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Coastwide and Barataria Basin Monitoring Plans for Louisiana's System-Wide Assessment and Monitoring Program (SWAMP)

Version II

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CPRA

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Preface

The purpose of this report is to describe the development of a coastwide monitoring plan for Louisiana with specific implementation recommendations for Barataria Basin. This cross-disciplinary research was conducted under the Coastal Ecology and People, Resources, and Technology (formerly the Human Dimensions) programs with additional support from the Physical Processes and Sediment Systems and the Natural Systems Modeling and Monitoring programs. Version I of the report was produced in February 2015 and a presentation was given to state, federal, and non-governmental representatives in April to communicate the main findings of the report and elicit feedback on the monitoring design and implementation strategy. As a result of the workshop and from comments received during the review of the report by CPRA, the report was revised to include additional data analysis, improved integration with existing monitoring efforts, and a conceptual diagram of the linkages between the human and natural systems. The revisions are incorporated into this Version II of the report.

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List of Acronyms

Acronym	Term
ACS	American Community Survey
ADCIRC	Advanced Circulation
AM	Adaptive Management
ASOS	Automated Surface Observing System
AVHRR	Advanced Very High Resolution Radiometer
AWOS	Automated Weather Observing System
AWQ	Ambient Water Quality
BICM	Barrier Island Comprehensive Monitoring
CDL	Cropland Data Layer
CDP	Census Designated Places
CORS	Continuously Operating Reference Stations
CPRA	Coastal Protection and Restoration Authority
CPUE	Catch Per Unit Effort
CRMS	Coastwide Reference Monitoring System
CV	Coefficient of Variation
CWPPRA	Coastal Wetlands Planning, Protection, and Restoration Act
DBH	Diameter at Breast Height
DO	Dissolved Oxygen
EMAP	Environmental Monitoring and Assessment Program
ET	Evapotranspiration
EwE	Ecopath with Ecosim
FEMA	Federal Emergency Management Agency
FFQI	Forested Floristic Quality Index
FIRM	Flood Insurance Rate Map
FQI	Floristic Quality Index
GIS	Geographic Information System
GLM	General Linear Model
GRTS	Generalized Random Tessellation Stratified

Acronym	Term
ICM	Integrated Compartment Models
IEA	Integrated Ecosystem Assessments
IRS	Independent Random Sampling
ISH	Integrated Surface Hourly
LCA	Louisiana Coastal Area
LDEQ	Louisiana Department of Environmental Quality
LDWF	Louisiana Department of Wildlife and Fisheries
LIDAR	Light Detecting and Ranging
LSU	Louisiana State University
LUMCON	Louisiana Universities Marine Consortium
MH	Multi-Hazard
MODIS	Moderate Resolution Imaging Spectroradiometer
MOE	Margins of Error
NASS	National Agricultural Statistics Service
NAVD88	North American Vertical Datum of 1988
NCDC	National Climatic Data Center
NDBC	National Data Buoy Center
NHD	National Hydrology Dataset
NOAA	National Oceanic and Atmospheric Administration
NPS	National Park Service
NTU	Nephelometric Turbidity Units
PET	Potential Evapotranspiration
QA/QC	Quality Assurance/Quality Control
SAS	Statistical Analysis Software
SE	Standard Error
SFHA	Special Flood Hazard Areas
SPOT	Satellite Pour l'Observation de la Terre
SWAMP	System-Wide Assessment and Monitoring Program
TM	Thematic Mapper

Acronym	Term
TN	Total Nitrogen
TNC	The Nature Conservancy
TP	Total Phosphorus
TSS	Total Suspended Solids
ULL	University of Louisiana at Lafayette
USACE	U.S. Army Corps of Engineers
USEPA	U.S. Environmental Protection Agency
USGS	U.S. Geological Survey
VIIRS	Visible Infrared Imagine Radiometer Suite
WAVCIS	Wave-Current-Surge Information System
ZCTA	Zip Code Tabulation Area

Glossary of Statistical Terms

Statistical Term	Symbol	Definition
Effect Size	none	Minimum detectable difference between two means, measured as the percentage change from the initial or current mean value.
Power	1-β	Probability of detecting a significant difference when a difference actually exists.
Standard Deviation	σ	Square root of variance.
Type I Error Rate	α	Probability of incorrectly rejecting the null hypothesis when then null hypothesis is true.
Type II Error Rate	β	Probability of failing to reject the null hypothesis when then null hypothesis is false.
Variance	σ2	Extent to which the data deviate from the mean.

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The Coastal Protection and Restoration Authority (CPRA) contributed to the concepts presented in this report as well as participated in project meetings and included Rick Raynie (SWAMP project manager), Karim Belhadjali, Bill Boshart, Rickey Brouillette, Honora Buras, Angelina Freeman, Mandy Green, Bren Haase, Ed Haywood, Syed Khalil, John Monzon, Jennifer Mouton, Jim Pahl, Carol Parsons Richards, Melanie Saucier, Leigh Anne Sharp, John Troutman, Chuck Villarrubia, and Dona Weifenbach. Subject matter experts were also convened to assist with refinement of the monitoring variables and objectives and review preliminary results and sampling designs and included Mark Hester of the University of Louisiana at Lafayette, Bryan Piazza of The Nature Conservancy, and Erick Swenson, Troy Blanchard, and Rex Caffey of Louisiana State University. Mary C. Christman of MCC Statistical Consulting provided statistical guidance and oversight and generated SAS code that was adapted for the analyses presented herein. Sarai Piazza of the U.S. Geological Survey, Al Hindrichs and Melinda Molieri of the Louisiana Department of Environmental Quality, Louisiana Department of Wildlife and Fisheries, and the U.S. Army Corps of Engineers Mississippi Valley Division New Orleans District provided data used in the analysis. Version I of this report was presented to an extensive group of individuals from state, federal, and non-governmental agencies and we thank those who provided written feedback that led to the refinements incorporated in this Version II, including Stephen Barnes and Eric Swenson of Louisiana State University, John Foret of the National Marine Fisheries Service National Oceanic and Atmospheric Administration, and Chris Swarzenski of the U.S. Geological Survey. Several individuals also assisted in identifying opportunities to leverage existing monitoring programs and resources including John Barras, Jim Flocks, and Greg Steyer of the U.S. Geological Survey, Dwight Bradshaw of the Louisiana Department of Environmental Quality, Maria Dillard and Tim Osborn of National Oceanic and Atmospheric Administration, Jeffrey Giering of the Governor's Office of Homeland Security and Emergency Preparedness, Lauren Land of Louisiana Sea Grant, Brian Lezina of the Louisiana Department of Wildlife and Fisheries, Shannon McArthur of the National Data Buoy Center, and Mathew Sanders of the Louisiana Office of Community Development.

The development of the ideas presented here was guided by a larger team at The Water Institute of the Gulf (the Institute) including Mead Allison, Tim Carruthers, Katelyn Costanza, Ehab Meselhe, Leland Moss, Joao Pereira, Denise Reed, Dallon Weathers, and Brendan Yuill.

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Executive Summary

The System-Wide Assessment and Monitoring Program (SWAMP) has been envisioned as a long-term monitoring program to ensure a comprehensive network of coastal data collection activities is in place to support the development, implementation, and adaptive management of the coastal protection and restoration program within coastal Louisiana. The Coastwide Reference Monitoring System (CRMS) and Barrier Island Comprehensive Monitoring (BICM) programs have been implemented under SWAMP, while other aspects of system dynamics, including offshore and inland water-body boundary conditions, nontidal freshwater habitats, riverine conditions, risk status, and protection performance, are not presently the subject of CPRA-coordinated monitoring. In order to implement these additional aspects of SWAMP, CPRA tasked The Water Institute of the Gulf to develop 1) a programmatic monitoring plan for evaluating the effectiveness of the coastal protection and restoration program on a coastwide scale, and 2) a Barataria Basin monitoring plan that will incorporate the elements of the programmatic plan with specific data collection activities designed to capture effects within the basin. Monitoring plans were developed for both the natural and human systems using an iterative process to identify the monitoring variables, objectives, and sampling design. The monitoring variables and objectives identified fall under the general categories of weather and climate, biotic integrity, water quality, hydrology, physical terrain, population and demographics, housing and community characteristics, economy and employment, ecosystem dependency, residential properties protection, and critical infrastructure and essential services protection. A rigorous statistical analysis, examination of modeling needs, and thorough reviews of previous planning and monitoring efforts were conducted to develop the sampling designs for the natural and human system monitoring plans. The plan relies heavily on the use of existing data, thus, coordination with other agencies and CPRA's existing monitoring programs (e.g., BICM, CRMS) is critical to the plan's success. Implementation of this plan will require development of quality control and quality assurance protocols, specific standardized operating procedures for each of the data collection efforts, a data management plan, and a reporting framework to contribute to decision making and reducing uncertainty in management actions.

Introduction

CONTEXT

The State of Louisiana and its partners have allocated considerable resources and have made long-term commitments to the restoration and management of wetland and aquatic resources in the coastal zone. Early project-specific monitoring efforts through the Coastal Wetlands Planning, Protection, and Restoration Act (CWPPRA) program in the early 1990s quickly became challenging as adequate reference areas were difficult to identify, and monitoring parameters were not consistent among projects. As a result, CWPPRA developed the Coastwide Reference Monitoring System-*Wetlands* (CRMS-*Wetlands*) for the System-Wide Assessment and Monitoring Program (SWAMP) to address these challenges and provide a pool of reference sites by which to evaluate the effectiveness of individual restoration projects, effectiveness of the overall program, and to provide a means to assess landscape change (Steyer et al., 2003a).

Although CRMS-*Wetlands* provides valuable data on wetlands across coastal Louisiana, a more comprehensive, systematic monitoring program is needed to meet the needs the state's coastal protection and restoration program, including predictive modeling and program assessment. In 2005, the Louisiana Coastal Area (LCA) Ecosystem Restoration Study Science and Technology Program proposed expanding CRMS-*Wetlands* to include coastal waters and barrier islands (U.S. Army Corps of Engineers, 2004). Although a formalized coastal waters program was not implemented, the monitoring of barrier islands was initiated by the Louisiana Department of Natural Resources (LDNR) under the Barrier Island Comprehensive Monitoring Program (BICM) and is now managed by the Coastal Protection and Restoration Authority (CPRA). While the ongoing monitoring and assessment of wetland systems and barrier islands through CRMS-*Wetlands* and BICM, respectively, has proven to be of value, other aspects of system dynamics, including offshore and inland water-body boundary conditions, nontidal freshwater habitats, riverine conditions, risk status, and protection performance, are not presently the subject of CPRA-coordinated monitoring. In addition, monitoring of some key aspects of the Louisiana coastal system is undertaken by other agencies or entities. To meet this need, SWAMP was re-envisioned as a long-term monitoring program to ensure a comprehensive network of coastal data collection activities is in place to support the development, implementation, and adaptive management of the coastal protection and restoration program within coastal Louisiana.

CPRA and The Water Institute of the Gulf (the Institute) have embarked on a series of tasks to advance the re-envisioned SWAMP to implementation. First, CPRA and the Institute developed the SWAMP Framework to identify the overarching goals of the monitoring program and to illustrate how the main drivers of system change influence specific system characteristics (e.g., salinity, population levels, etc.), using an influence diagram approach (Hijuelos et al., 2013). The influence diagram assisted in identifying the important parameters needed to support the restoration and protection program and to understand the overall system condition. Second, a review of existing monitoring programs within coastal Louisiana was conducted to develop a monitoring geodatabase that catalogues site locations, parameters collected at each site, frequency of data collection, and period of record. The Framework and monitoring inventory are used to prioritize monitoring needs, identify data gaps, and guide the development of the SWAMP monitoring plan presented in this report.

Building off these earlier efforts, CPRA tasked the Institute to progress SWAMP by developing 1) a programmatic monitoring plan for evaluating the effectiveness of the coastal protection and restoration program on a coastwide scale, and 2) a Barataria Basin monitoring plan that will incorporate the elements of the programmatic plan with specific data collection activities designed to capture effects within the basin. Barataria Basin has experienced severe land loss in recent decades (Couvillion et al., 2011) and has been the site of many restoration initiatives under CWPPRA. Louisiana's Comprehensive Master Plan for a Sustainable Coast includes a variety of projects, including barrier shoreline projects along the Gulf shoreline and several sediment diversion projects (CPRA (Coastal Protection and Restoration Authority), 2012). These projects, along with existing projects such as the Davis Pond Diversion, are expected to change many aspects of the system dynamics. The Barataria Basin also includes several rural communities, such as Lafitte, which are heavily dependent on natural resources and currently have no levee protection from storm surges. As such, Barataria Basin is an appropriate location to demonstrate the application of a system-wide approach to monitoring at the basin scale.

The ultimate goal of the monitoring plans are to obtain repeated long-term (e.g., years to decades) measurements that can be analyzed to detect change that may result from a variety of sources, including large-scale restoration and protection projects, environmental disturbances, changing climate, and other major drivers that impact the system. Attributing causes of change will require additional data collection beyond the intent or scope of SWAMP that is tailored for specific research questions of interest; however, the coastwide and basinwide monitoring programs will provide a baseline of information to serve as a foundation for cause and effect studies. CPRA established the geographic scope of the programmatic coastwide plan and the Barataria Basin plan with the Gulf boundary demarcated by the coastal zone and inland boundary by the 10-meter contour line (Figure 1).

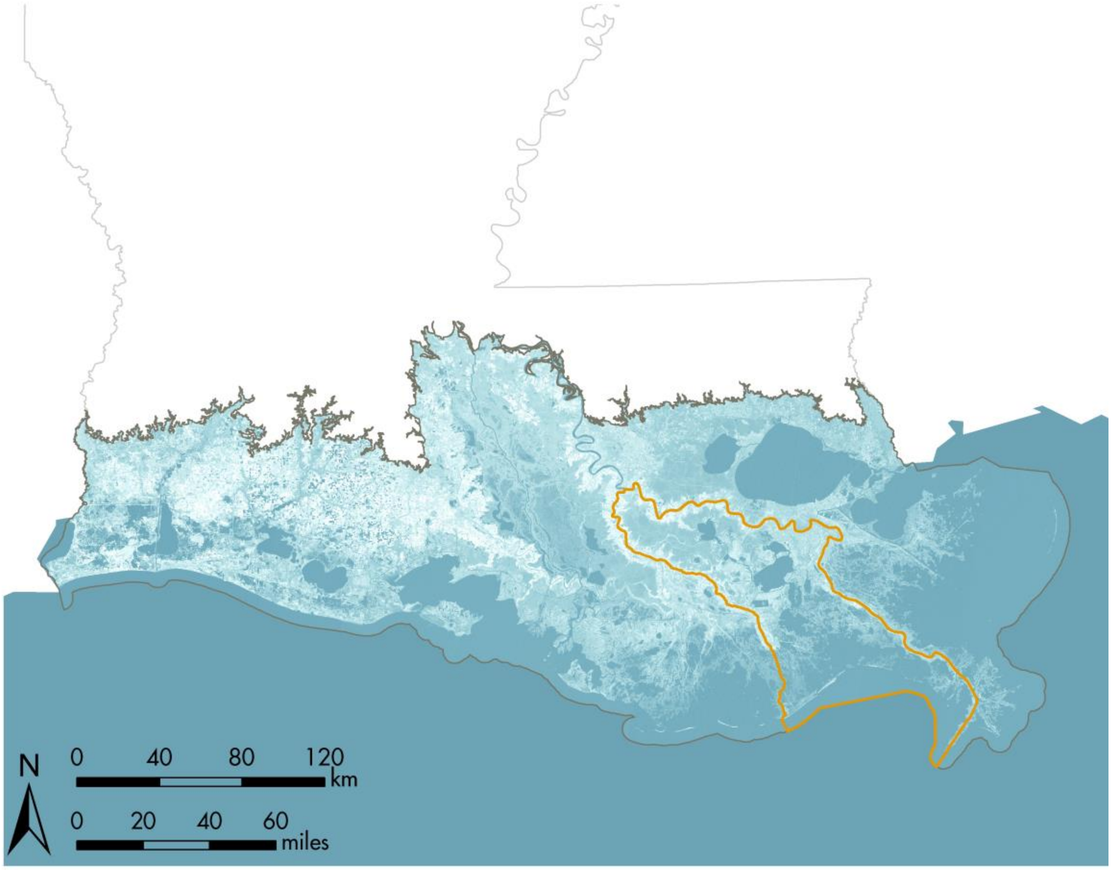

Figure 1. The geographic scope of the programmatic coastwide monitoring plan (grey boundary line) and the Barataria Basin monitoring plan (orange boundary line).

PROCESS

The development of large-scale environmental monitoring plans has been extensively discussed in the literature as it pertains to detecting change in ecological systems (Field et al., 2007; Gitzen et al., 2012; Wagner et al., 2013), development of indicators (Fennessy et al., 2007; Hershner et al., 2007; Nicholson & Jennings, 2004), and in the larger context of adaptive management (Williams et al., 2009). Although few large ecosystem-level socioeconomic monitoring plans have been implemented to date (Charnley & Stuart, 2006; Jackson et al., 2004; Sommers, 2001), the monitoring of social indicators has long been a crucial component of social impact assessments required for those projects that have environmental impacts on human communities (Interorganizational Committee on Principles and Guidelines for Social Impact Assessment, 2003; Kusel, 1996; Machlis et al., 1997). There is broad consensus that the key to a successful monitoring program is the development of (1) specific and relevant goals and objectives, and (2) survey designs that allow for drawing statistical inferences about the variable or resource of interest (Fancy et al., 2009; Legg & Nagy, 2006; Wagner et al., 2013). Also of importance are the creation of conceptual models to identify cause-effect relationships and describe the interactions among variables, as well as peer-reviewed protocols that describe the collection, management, analysis, and reporting procedures for the data (Fancy & Bennetts, 2012).

A long-term monitoring program can support adaptive coastal management by: (1) producing information on the status of critically important natural and socio-economic resources, (2) enabling assessments of how systems are changing, and (3) allowing determination of whether goals or targets are being achieved for both sustainable landscapes and resilient communities. In order to be successful, the quality, scale, and resolution of the data must be appropriate to meet the monitoring program's specific objectives. This includes consideration of error, accuracy, and bias which requires a statistical approach to ensure these components are examined during the planning and design of monitoring programs. A monitoring plan that fails to consider data quality or analytical needs may not support meaningful analysis and interpretation of data in the future. As a result, thorough planning of the objectives, analysis, design, and measurement choices must be conducted prior to the actual network deployment.

The process presented here provides the framework for implementing a comprehensive monitoring plan for both natural and human systems. The plan was designed to enable "nesting" of the Barataria Basin monitoring plan within the programmatic coastwide plan to ensure consistencies in designs such that basin-scale monitoring data can be used to assess program performance. Likewise, development of project-specific monitoring, although beyond the scope of SWAMP, could be designed to nest within the Barataria Basin monitoring plan, allowing consistency in designs and data collection methodologies across all scales where possible (Figure 2) and avoiding duplication of efforts. The plan uses an iterative process to identify the monitoring variables, objectives, and sampling design for both the natural and human systems of coastal Louisiana that can then be applied to the basin scale. Variables are elements of the natural and human systems that can be measured or calculated from measurements. The sampling design refers to the approach used to develop the proposed sample size and methodology for selecting site locations. The monitoring variables, objectives, and sampling design are identical for the programmatic coastwide and Barataria Basin monitoring plans, while the actual sample sizes differ at each of the scales. The process for developing the programmatic coastwide and Barataria Basin plans for the natural system is summarized as follows:

- identify monitoring variables and specific objectives;
- develop sampling design;
    - determine required sample spatial and temporal density using analytical approaches and expert knowledge of system dynamics and specify desired levels of precision and confidence for meeting the objectives;
    - establish methodology for selecting site locations; and
    - identify site locations in Barataria Basin.

The process for developing the programmatic coastwide and Barataria Basin plans for the human system is summarized as follows:

- identify monitoring variables and specific objectives;
- develop sampling design;
    - establish appropriate units of analysis and define functional socioeconomic communities;
    - determine methods using secondary data sources to monitor changes and trends in population and income distribution, employment by sector, education, housing type, and other social factors at the community level; and
    - identify primary data collection needs and establish methods to determine the required sample size for community surveys.

The approaches to developing the sampling design for the natural and human systems vary given the underlying differences among the data types, although they share many common themes. The natural system approach uses existing data from ongoing (or historical) monitoring programs to evaluate how these programs can be supplemented with additional data collection activities in order to improve confidence and levels of precision in the data. Conversely, the human system approach evaluates how the existing data can be analyzed to meet the monitoring variables and objectives, given that these secondary data sources, such as the American Community Survey (ACS), are fixed designs implemented by other agencies that cannot be directly augmented. Primary data collection needs and methods are then identified for those variables and objectives that cannot be met by the secondary data.

The report is structured as follows: The variables and objectives are first presented for both the natural and human systems to set the stage for the remaining discussions. The sampling designs are then described on the coastwide scale, separately for the natural and human systems, given the differences in data types, as previously described. The variables and sampling designs are then applied to the Barataria Basin domain to generate the Barataria Basin monitoring plan. For analyses conducted on both the basin and coastwide scale, the results are referenced within the Barataria Basin monitoring plan. The path forward section discusses additional steps necessary for implementing the plan. Appendix I contains influence diagrams for each of the variables. For the natural system, additional variable descriptions, methodologies, results, and justifications for the sample sizes and sample locations are provided in Appendix II. For the Human System, an example of how to use existing data to detect change is provided in Appendix III.

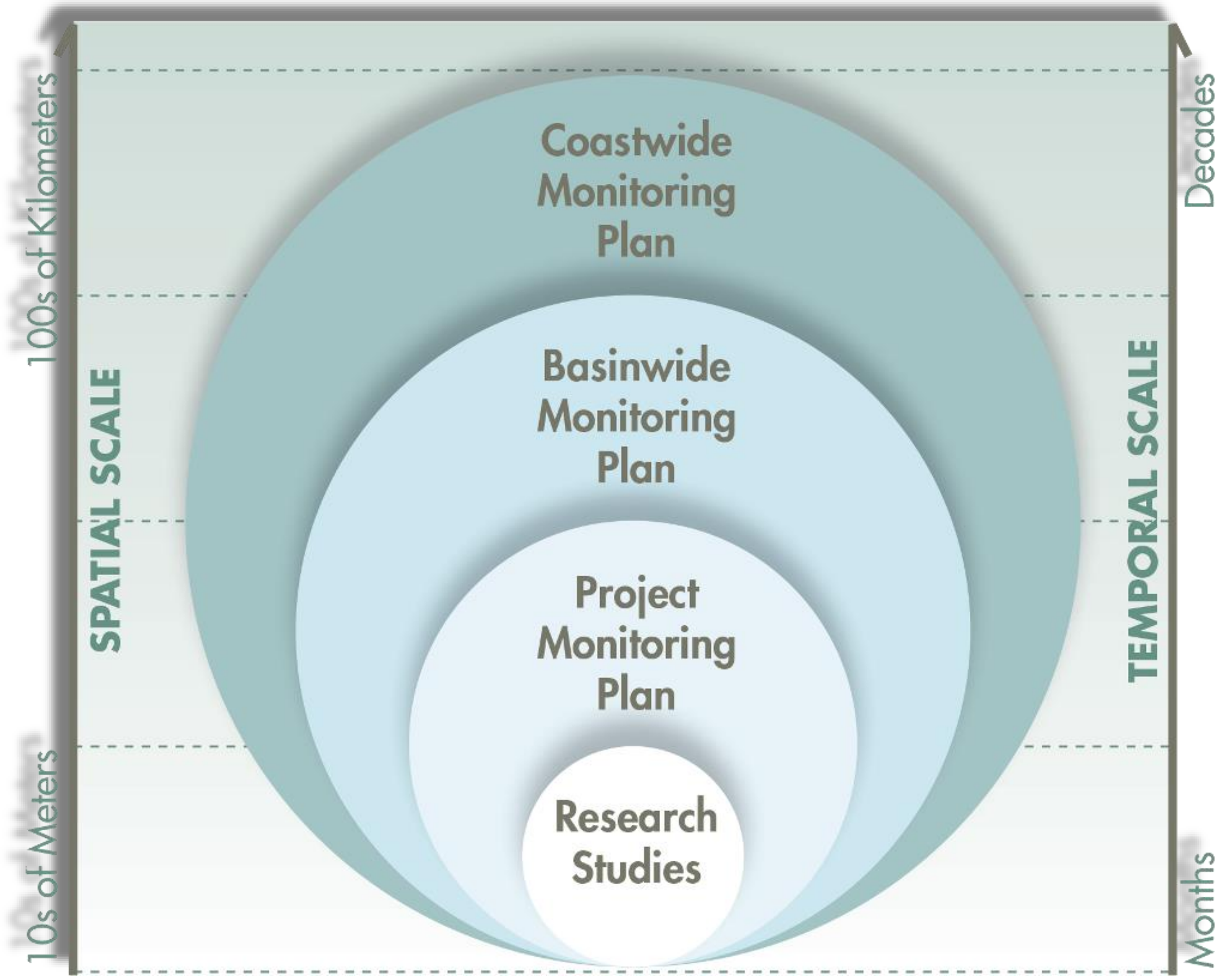

Figure 2. Nesting smaller-scale monitoring plans within larger-scale plans ensures a consistent framework for data collection activities.

Variables and Objectives

Clearly articulated goals and objectives provide the rationale for monitoring and inform the specification of what, where, when, and how to collect data (Gitzen & Millspaugh, 2012). As defined in the Framework, the goals of the monitoring program are to support CPRA activities by providing data on the natural and human environment that can be used to:

- document the drivers (natural and anthropogenic) and their effects on the system;
- provide early warning indications of changes in the system state;
- monitor the effects of natural or anthropogenic disturbances;
- reduce uncertainties regarding changing conditions or system state;
- evaluate the performance of coastal protection and restoration programs and support decision making;
- improve, validate, and calibrate numerical models; and
- support planning, engineering, and designing activities.

Building on the goals and variables identified in the SWAMP Framework as well as other efforts related to performance measures and long-term monitoring in coastal Louisiana (Hijuelos & Reed, 2013a; Steyer et al., 2004; Swenson & Swarzenski, 2004), a subset of monitoring variables was identified and these variables were prioritized, in coordination with CPRA, based on relevance to the coastal restoration and protection program. The influence diagrams developed in the SWAMP Framework are provided in Appendix I for the selected variables to illustrate general relationships between drivers and system responses. The variables were then grouped into eleven categories that represent various aspects of the system relevant to the wide-ranging activities of the coastal restoration and protection program. These categories are described in detail in the following sections. For each of the categories, a fundamental objective was developed in order to provide a broad rationale for monitoring the specific aspects of the system. Monitoring objectives were then established for each of the variables in order to articulate their need and purpose. This hierarchical approach of developing goals and objectives results in a focused description of why and what should be monitored. This information was then refined in coordination with subject matter experts experienced with collecting data in coastal Louisiana, including Mark Hester (University of Louisiana at Lafayette, ULL), Erick Swenson (Louisiana State University, LSU), Bryan Piazza (The Nature Conservancy, TNC), Darin Lee (CPRA), Troy Blanchard (LSU), and Rex Caffey (LSU). The combined expertise of these individuals includes water quality, vegetation, barrier islands, fisheries, demography, and natural resource economics. As part of the iterative process, additional refinements of the objectives and consolidation of variables occurred through the development of the plan.

NATURAL SYSTEM

The term "natural system" was used to describe the variables related to the coastal environment, excluding the human dimension. Natural resources critical for sustaining human ecosystems, such as agricultural yields and fishery landings, are specifically identified in the Human System section below. The variables identified include the main drivers of system change and those that reflect a number of system change mechanisms, primarily focusing on landscape or higher trophic dynamics. Collectively, the variables provide an understanding in a holistic sense of the potential impacts on system dynamics from a variety of drivers and are intended to be indicative of system condition or status rather than to be exhaustive. The monitoring variables and objectives related to natural systems monitoring were grouped in the following categories: weather and climate, biotic integrity, water quality, hydrology, and physical terrain.

Weather and Climate

Fundamental Objective: Determine weather and climate patterns for improving planning model predictions and aiding in the understanding of the drivers that impact the system.

Atmospheric and oceanic processes serve as drivers of coastal environmental change through their generation of weather, as defined by climatic variables, and extreme weather events (e.g., storms), as well as through control of oceanic boundary conditions (e.g., waves and currents). Key climatic variables needed for documenting drivers of coastal change include potential evapotranspiration (PET), precipitation, and wind speed and direction (Table 1; Figure 26). All of these variables are also used for the 2017 Coastal Master Plan Integrated Compartment Models (ICM) for either ground-truthing, initialization, calibration, or validation. Additional climatic variables that are often used as explanatory variables include air temperature and solar radiation and these can also be collected concurrently as part of the same sensor packages that collect the other variables of interest.

Table 1. Monitoring variables and objectives with supporting background information for weather and climate.

Monitoring Variable	Objective	Background
Potential Evapo-transpiration	Document PET patterns to support planning models and the characterization of evapotranspiration.	Evapotranspiration (ET) is the primary process by which wetlands lose water, thus, increases in ET as a result of climate change may lead to adverse effects on wetlands (Winter, 2000). Direct measurements of evapotranspiration can be challenging, so PET is a more typical metric and is defined as the total amount of liquid water that could be consumed (i.e., water demand) by regional vegetation and evaporated by solar energy.
Precipitation	Document precipitation patterns in support of planning models and the characterization of precipitation events.	Precipitation is a major component of the hydrologic cycle and influences the quantity of both surface water and groundwater. Precipitation depth defines the amount of terrestrial water introduced during a precipitation event and its intensity influences the amount of precipitation that is converted to runoff.
Wind	Document wind speed and direction to improve the understanding of the processes that impact water circulation and mixing, wave dynamics, and marsh edge erosion.	Winds associated with local weather, winter cold fronts, and tropical cyclones influence coastal water circulation patterns through increasing or decreasing water levels and resuspension and redistribution of particulates (Booth et al., 2000). Winds may also indirectly impact shorelines through wave attack, which can lead to erosion and damage to vegetative communities (Tonelli et al., 2010).

Biotic Integrity

Fundamental Objective: Document changes in the distribution and condition of biotic communities that represent important ecological elements and are responsive to system drivers.

Biotic integrity is a term used to describe the systems' elements (e.g., populations, landscapes), as well as the underlying processes that generate and maintain those elements (e.g., abundance fluctuation, soil formation; Angermeier & Karr, 1994). The monitoring variables selected for tracking the biotic integrity of terrestrial, pelagic, and benthic communities of the coastal environment include nekton community composition, oyster biomass, wetland soil condition, wetland vegetation community composition, and wetland vegetation biomass (Table 2). In addition to using these variables for assessing system status and response to drivers, many of these variables, with the exception of wetland biomass, are key inputs to the 2017 Coastal Master Plan either in the ICM, Ecopath with Ecosim (EwE), or Advanced Circulation (ADCIRC) models. Wetland biomass is a necessary parameter for the diversion planning studies, including those being conducted under the Mississippi River Hydrodynamic and Delta Management Study (MRHDMS).

Table 2. Monitoring variables and objectives with supporting background information for biotic integrity.

Monitoring Variable	Objective	Background
Nekton community composition	Document changes in species composition for commercially and recreationally important species, as well as, representative guilds of fish and shellfish to: (1) evaluate distributional patterns among freshwater, estuarine, and inshore shelf habitats, (2) quantify potential consumer resource availability within estuarine habitats, and (3) evaluate habitat association patterns.	Future large-scale changes in the coastal environment resulting from restoration activities and natural system drivers have the potential to substantially change the community composition and food web dynamics of the system (Piazza & La Peyre, 2011; Rozas & Minello, 2011). Nekton data collected using standardized gear can be used to measure relative abundance, to develop diversity indices, and to quantify potential consumer resource availability within estuarine habitats.
Oyster biomass	Document changes in oyster biomass to assess the status and trend of the resource across estuarine zones and evaluate habitat association patterns.	The distribution of oysters within an estuary is largely a function of salinity, freshwater input, depth, and substrate (Melancon et al., 1998), although sedimentation, coastal disturbances and overharvesting are also threats to their distribution (Oyster Technical Task Force, 2012). Storm surge and wave action can also result in the destruction of oyster reefs, killing of spat and juvenile oysters, or displacement of oysters onto habitats that cannot support them (Banks et al., 2007).
Soil condition	Document changes in soil condition (organic matter content and bulk density) to improve understanding of the effect of climate, hydrology, geomorphology, and management activities on wetlands sustainability.	Bulk density is used to estimate and evaluate many physical soil properties, such as porosity, water retention, buoyancy and compressibility (Ruehlmann & Körschens, 2009). Organic matter and mineral content of wetland soils are key determinants of soil development and are often used to describe the roles of organic accumulation—derived from above- and below-ground plant material—and mineral sediment deposition (Neubauer, 2008; Nyman et al., 2006). Both processes will vary with plant communities and other aspects of wetland dynamics, including soil inundation, drainage, redox potential, and other biogeochemical processes (Reddy et al., 2000).

Monitoring Variable	Objective	Background
Wetland vegetation biomass	Document changes in wetland above- and belowground biomass to improve understanding of the effect of climate, hydrology, geomorphology, and management activities on coastal habitats and plant productivity.	Wetland vegetation biomass refers to both the above- and belowground components of the plant. Biomass is a function of inundation, nutrient concentrations, soil properties, and for plants with C_3 metabolisms, atmospheric CO_2 (Bazzaz, 1990; Day et al., 2013; Kirwan & Guntenspergen, 2012). Measurements of biomass over time can be used to evaluate wetland primary productivity.
Wetland vegetation community composition	Document changes in forested and herbaceous wetland vegetation species composition to evaluate responses to episodic forcing events and improve understanding of the effect of climate, hydrology, geomorphology, and management activities in coastal habitats.	The species composition of communities found along the coast is a reflection of the relative influence of marine and terrestrial drivers and the underlying geologic setting of the region. Given their geographical position in low-lying coastal areas, wetlands face an array of climate-linked challenges, from rising sea levels to reduced freshwater input and drought conditions (Battaglia et al., 2012).

Water Quality

Fundamental Objective: Document changes in key water quality parameters in estuarine open water bodies from the Gulf of Mexico boundary to upland endpoints that are sensitive to system drivers and are critical for understanding system dynamics.

Water quality is an important attribute of estuaries that encompasses water characteristics including salinity, turbidity, dissolved oxygen (DO), chlorophyll a, and nutrients (total nitrogen, total phosphorus and silicate). These parameters inform understanding of the ecosystem status of pelagic and benthic communities, estuarine and marine wildlife, and soil properties of adjacent wetlands (Table 3; Figure 29 in Appendix I). Further, nearly all of these variables are inputs to the 2017 Coastal Master Plan models and MRHDMS.

Table 3. Monitoring variables and objectives with supporting background information for water quality.

Monitoring Variable	Objective	Background
Chlorophyll *a*	Document chlorophyll *a* concentrations as an indicator of algal biomass to characterize primary productivity and capture short-term changes that may result from influences of tides, river discharge, storms, management activities, or other events.	Chlorophyll *a* is as an indicator of pelagic primary production by phytoplankton (i.e., total quantity of carbon produced by primary producers) and indicates the presence of phytoplankton blooms in estuarine open waters. Phytoplankton blooms are controlled by several factors, such as nutrient loading, nutrient cycling, light availability, water residence time, temperature, and grazing by zooplankton and benthic filter feeders (Boyer et al., 2009).
Dissolved oxygen (DO)	Document DO concentrations within the estuary to characterize the health of open water bodies and to capture short-term changes that may result from tides, river discharge, storms, management activities, or other events.	DO is a measure of the amount of oxygen dissolved in water, in mg L^{-1} or percent saturation and enters surface water through the absorption of atmospheric oxygen and from primary production. DO is necessary for pelagic and benthic metabolic processes (i.e., respiration; (Kemp et al., 1992); reductions in DO levels can result in habitat shifts or changes in community structure of aquatic fauna (Rakocinski et al., 1992; Rozas et al., 2005) and nutrient release (Valiela, 1995).
Nutrient constituents	Characterize nutrient inputs and cycling by documenting concentration patterns of total nitrogen (TN), total phosphorus (TP), and silicate, in order to improve understanding of primary productivity within the estuary.	Measurements of estuarine water nutrient concentrations provides information on nutrient inputs to the system and potential effects upon biotic communities and eutrophication status (Bricker et al., 1999; Nixon, 1995). Total nitrogen, total phosphorus, and silicate are important for freshwater and marine phytoplankton production and inputs have shown large changes over time (Turner & Rabalais, 1991).

Monitoring Variable	Objective	Background
Salinity	Document changes in key estuarine isohalines in response to changes in freshwater and marine flux, sea level, and climate and to detect short-term changes in salinity that may result from tides, riverine inputs, storms, management activities, or other events.	Estuarine salinity patterns coincide with the distribution, growth, and productivity of nekton communities (Adamack et al., 2012; Minello et al., 2003; Zimmerman et al., 2000), zonation patterns of vegetation (Pennings et al., 2005), and ultimately the functions and services wetlands provide (Odum, 1988). As an essential characteristic of the coastal system, salinity is a key variable in ecological and hydrodynamic models and forecasting capabilities are limited by inadequate information of salinity patterns in the estuary (Habib et al., 2007).
Turbidity	Document turbidity in estuarine open water bodies to support planning models and to capture short-term changes that may result from tides, river discharge, storms, management activities, or other events.	Turbidity is a characteristic of estuarine water quality that quantifies the clarity of the water due to suspended particulates. Turbidity is influenced by phytoplankton blooms as well as riverine discharge and wind events which transport or resuspend particulates and affect water residence time (Allison et al., 2013; Cloern, 1987; Lane et al., 2007).
Suspended Sediment Concentration	Document suspended sediment concentration in littoral systems to allow for extrapolation of regional-scale sediment fluxes and improve understanding of the processes that deposit sediments.	The concentration of the total suspended solids (TSS) refers to the mineral:organic content and grain size information as a volumetric measurement in mg L^{-1}. Statistical relationships can also be developed in order to use measurements in Nephelometric Turbidity Units (NTU) as a predictor of TSS concentrations, if the relationships are based on measurements collected in the same place and time. TSS (in mg L^{-1}) is a critical input variable for calibrating and validating sediment transport in the state's planning models.

Hydrology

Fundamental Objective: Document hydrologic changes in open water bodies and major canals to improve understanding of drainage network and land-building potential.

Hydrology encompasses the movement and transport of water in response to natural process and anthropogenic events. Monitoring of current velocity, water level, and waves is essential for understanding physical changes to waterbodies, as well as the movement and transport of water itself (Table 4; Figure 30 in Appendix I). Water levels, currents, and waves are also key variables for the 2017 Coastal Master Plan effort.

Table 4. Monitoring variables and objectives with supporting background information for hydrology.

Monitoring Variable	Objective	Background
Current velocity	Identify significant large-scale circulation patterns in coastal water bodies from spatially, temporally, and depth-averaged velocities to support planning models and model development for sediment transport and deposition.	Currents are influenced by tides and winds, among other factors, and contribute significantly to the flow and exchange of freshwater, nutrients, sediments, and organic material between the Gulf of Mexico and estuaries. High-resolution measurements can meet the modeling needs of establishing boundary conditions and quantifying exchange points.
Water level	Document changes in water levels relative to vertical datum that may result from climate, sea levels, tides, river discharge, storms, management activities, or other events.	Water level refers to the depth of the water relative to a vertical datum, such as mean sea level or NAVD88. Tidal ranges in coastal Louisiana are relatively small (~0.3 m), but strong southerly winds can force water into estuaries and wetlands while northerly winds push water out, causing water levels to fluctuate (Inoue et al., 2008). Water levels have important implications on water quality dynamics and marsh surface responses to inundation.
Waves	Document wave dynamics (height, direction, period) to improve understanding of the processes that impact water circulation, mixing and marsh edge erosion in the estuarine and nearshore environment, and characterize offshore boundary conditions.	Wave generation is a function of fetch, such that the presence of emergent vegetation and other landforms can strongly limit the maximum wave heights (Fagherazzi & Wiberg, 2009). The expansion and deepening of open water bodies due to subsidence and erosional processes could lead to higher-energy waves, which, in turn, could contribute to morphological and ecological changes in the estuary.

Physical Terrain

Fundamental Objective: Determine topographical and areal changes of natural and built coastal landscapes in response to the cumulative effects of restoration and protection projects, natural processes, and other key drivers.

The physical terrain of the coastal environment in this context refers to natural land (e.g., wetlands, barrier islands, uplands, ridges) and constructed features (e.g., spoil banks). The coastal terrain serves a multitude of functions from buffering storms, filtering nutrients, pollutants, and sediments, and supporting a variety of flora and fauna. As a result, severe land loss threatens all aspects of the coastal ecosystem, from increasing fetch in open-water bodies to reducing habitat for ecologically important fish and wildlife. Bathymetry, surface elevation, and land area are monitored to track the physical changes to the landscape and are key variables for the 2017 Master Plan (Table 5).

Table 5. Monitoring variables and objectives with supporting background information for physical terrain.

Monitoring Variable	Objective	Background
Surface elevation	Document subaerial topographical changes over time relative to a vertical datum to develop digital elevation models and to contribute to spatial maps of relative sea-level rise rates.	Surface elevation refers to the height of the land surface relative to a vertical datum, such as mean sea level or NAVD88. Large, short-term changes in land elevation can occur because of changes in astronomical tides and meteorological conditions (e.g., pressure or wind-driven events) that influence subsurface processes, above ground production, and sediment deposition, among others factors (Cahoon et al., 2011). Long-term trends in elevation are a function of underlying tectonics, Holocene sediment compaction, sediment loading, glacial isostatic adjustment, surface water drainage and management, and sea level rise (Yuill et al., 2009).
Bathymetry	Document bathymetric changes to resolve long term (5-10 years) and storm-driven morphological evolution trends.	Detailed comparative bathymetric geometries provide insight into the change in the basin, local hydrodynamic regimes, and also littoral sediment availability and dynamics.
Land area	Document changes in land area distribution to evaluate wetlands, uplands, ridges, and barrier shoreline changes and improve understanding of the effect of climate, hydrology, geomorphology, and management activities on coastal habitats.	The natural landscape serves a multitude of functions, including buffering storms, filtering nutrients, pollutants, and sediments, as well as supporting a variety of flora and fauna. As a result, severe land loss threatens all aspects of the coastal ecosystem, from increasing fetch in open-water bodies to reducing habitat for ecologically important fish and wildlife (Chesney et al., 2000; Fagherazzi & Wiberg, 2009).

HUMAN SYSTEM

The human component of a coupled human-natural system is a coherent system of biophysical and social factors capable of adaptation and sustainability over time, exhibiting boundaries, resource flows, social structures, and dynamic continuity (Machlis et al., 1997). A number of critical resources are essential to sustain the human system, including natural resources, socioeconomic resources, and cultural resources. Changes to any of these critical resources have the potential to impact the overall well-being and sustainability of the human communities that rely on them. This is especially true of coastal Louisiana, where natural and anthropogenic alterations to the landscape may impact any of these critical resources in numerous ways, thereby placing many of the region's traditional renewable resource extraction cultures and communities at risk (Laska et al., 2005). The human system monitoring plan developed here identifies and quantifies changes to the coupled human-environmental ecosystem and the critical resources that sustain it.

One of the primary challenges for an effective human system monitoring plan is identifying relevant variables and available community scale data (Charnley & Stuart, 2006). Social variables have specific discrete, nominal, or continuous measures that are used to assess changes in human populations, communities, and social relationships resulting from a development project or policy change (Burdge, 1994). The monitoring plan to measure socioeconomic change in coastal Louisiana utilizes several variables, objectives, and approaches grouped into the following categories: population and demographics, housing and community characteristics, economy and employment, ecosystem dependency, residential properties protection, and critical infrastructure and essential services protection.

An effective socioeconomic monitoring plan should be able to identify changes in overall population, vulnerable population subgroups, including low income and minority populations, key economic sectors, housing characteristics, and property values to establish baseline information and determine if any social impacts are occurring within a defined study area (Colten & Hemmerling, 2014). This document presents a monitoring framework to assess change and trends within a broad suite of social and economic monitoring variables derived from a number of secondary data sources. The decennial census and ACS are the most comprehensive secondary datasets available upon which to develop baseline conditions, gathering information about population and income distribution, employment by sector, education, housing type, and other social factors at the community, county(parish), regional, and state levels. ACS is a nationwide, continuous survey designed to provide demographic, housing, social, and economic data for all established census geographies. It replaced the decennial census long form in 2010 and provides periodic measures that describe the average characteristics of population and housing over a 1-, 3-, and 5-year period of data collection. As shown in this report, there are some instances in which Census Bureau data will need to be supplemented by information from relevant state, parish, and municipal entities.

There are several limitations to using only secondary data sources to assess change in the human system. Chief among these limitations is data availability. In some cases, data on certain topics simply do not exist in any secondary data source. In other cases, the data may not be available at a scale useful for analysis. There are far more validated, stable, comprehensive data available at the parish level than other smaller levels of aggregation, such as the census block group or tract. In addition, the data that are available at this smaller level of aggregation tend to be less reliable (Jackson et al., 2004). Finally, it is difficult to establish causality from social indicators and monitoring variables alone, as inferences about individual actions cannot be drawn from the aggregate population. For certain variables presented here, specifically those related to the non-economic usage of natural resources, community-based longitudinal surveys will be needed to gather primary data not available in existing data sets.

Population and Demographics

Fundamental Objective: Determine changes in population at both individual and family scales. Any changes in demographic variables should also be identified, including the racial and ethnic makeup of local communities.

Social vulnerability involves the relative ability of an individual, household, or community to respond appropriately to changing environmental conditions (Levine et al., 2007). It is a function of exposure, sensitivity, and response, and it requires measurements of both environmental and social systems (Cutter & Finch, 2008). An effective coastwide human system monitoring plan must evaluate changes in community structure, including changes in overall population, the number of households, and the racial and ethnic makeup of the communities, particularly when management decisions have the potential to impact exposure levels (Table 6).

Table 6. Monitoring variables and objectives with supporting background information for population and demographics.

Monitoring Variable	Objective	Background
Number of households	Determine changes in the total number of family and nonfamily households in local population centers and occupational communities to improve understanding of the effects of management activities and coastal dynamics on community composition.	Households, in general, are much less likely to leave their community than are individuals (Gubhaju & De Jong, 2009). Increasing numbers of households in communities are therefore indicative of increasing levels of community resilience.
Total population	Determine changes in the total population in local population centers and occupational communities to improve understanding of the effects of management activities and coastal dynamics on population growth.	Population stability and the speed to which population levels are able to recover following extreme hazards events are predictive indicators of community resilience.
Race and ethnicity	Determine changes in the total number of minority residents in local population centers and occupational communities to identify areas of social justice concern and improve understanding of community composition and the effects of management activities and coastal dynamics on minority groups.	Racial and ethnic status often influences the ability of communities to adaptively respond to changing environmental conditions. The effect of racial and ethnic factors on adaptability is most likely seen the interaction of race and ethnicity with other drivers, particularly economic (Black et al., 2011).

Housing and Community Characteristics

Fundamental Objective: Determine changes to the housing characteristics of local communities. This includes changes in home ownership, vacancy rates, rent, and home values.

Housing and community characteristics are important variables for monitoring both community vulnerability and resilience. The value and quality of residential construction are both key elements of community resilience (Cutter et al., 2003). Additionally, the status of the housing market and residential occupancy rates are key indicators of community recovery following natural hazards events (Table 7).

Table 7. Monitoring variables and objectives with supporting background information for housing and community characteristics.

Monitoring Variable	Objective	Background
Residential stability	Document changes in residential movement to improve the understanding of how management activities and coastal dynamics affect population in-migration and out-migration in local population centers and occupational communities.	Residential stability is a key measure of resilience that establishes the length of time that people reside in the same household. Communities that maintain population levels through time exhibit higher amounts of residential stability and are therefore inherently more resilient than those communities with a large turnover in population.
Home ownership	Document changes in home ownership rates to improve the understanding of how management activities and coastal dynamics affect the overall viability of housing markets in local population centers and occupational communities	Increasing levels of home ownership are indicative of higher levels of community resilience. Low home ownership rates often point to a population that is either highly transient or without the financial resources for home ownership (Cutter et al., 2003).
Residential occupancy rates	Document changes to the number of vacant nonseasonal properties to improve understanding of how population shifts impact the physical structure and economic condition of local population centers and occupational communities.	The amount of vacant housing in a community is a measure of recovery from an environmental or economic shock. Higher levels of vacant housing suggest a loss of resilience, an indication that previous residents of the community have not returned to their previous residences.
Property values	Document changes to local rent and property values to improve the understanding of how management activities and coastal dynamics affect the real estate market in local population centers and occupational communities.	Changing property values are often indicative of changes in both economic conditions and quality of life within a community. These changes may be the result of inherent changes to the structure of the community, such as changing demographics or income levels, or they may be a reaction to an outside shock, such as a natural or technological hazard event.

Economy and Employment

Fundamental Objective: Determine changes to the income levels, poverty rates, and unemployment rates of families and individuals at the community level.

Economy and employment are key components of community resilience (Table 8). Many of these factors are highly co-dependent with other demographic factors such as race and ethnicity. The impacts of environmental and economic change on several different disadvantaged socioeconomic groups may be similar (Black et al., 2011). Socioeconomic status is a primary indicator of the ability of the population to respond to changing environmental conditions. Where communities are highly dependent on natural resource employment, for example, changing environmental conditions may result in a loss of economic opportunities or a shifting of job locations. Low-income residents are often unable to effectively adapt to these new conditions, often resulting in increased unemployment levels and higher poverty rates.

Table 8. Monitoring variables and objectives with supporting background information for economy and employment.

Monitoring Variable	Objective	Background
Economic activity	Determine changes in the number and type of businesses in local population centers and occupational communities to improve understanding of the effects of management activities and coastal dynamics on economic activity.	The ability of communities to retain and attract business is a key indicator of community resilience. Communities with a strong entrepreneurial culture experience improved economic outcomes, such as increasing median household income, lowering of poverty, and decreasing income inequality (Blanchard et al., 2012).
Income levels	Measure changes to individual and family income levels to improve the understanding of the effects management activities and coastal dynamics have on the income levels of local population centers and occupational community residents.	Socioeconomic status is a primary indicator of community resilience. Wealth and income directly impact the ability of residents to effectively adapt to changing social and environmental conditions, including the ability of residents to relocate or evacuate in response to natural hazards events (Black et al., 2011).
Poverty rates	Estimate 5-year changes in the total number of residents with income below the poverty line in local population centers and occupational communities to improve the understanding of poverty rates and the effects of management activities and coastal dynamics on low-income residents.	The percentage of the population living in poverty is a key social vulnerability and a direct measure of the community's ability to both evacuate and locate housing when faced with changing environmental conditions and natural hazards events (Levine et al., 2007).

Monitoring Variable	Objective	Background
Unemployment levels	Estimate changes to unemployment levels in local population centers and occupational communities to improve the understanding of the effects management activities and coastal dynamics have on the local economy, jobs, and employment.	The loss of business and therefore employment opportunities is a key driver of population outmigration and an indicator of a healthy economy, which enhances community resilience. The relocation of businesses out of local communities increases the costs of employment, resulting in greater joblessness, particularly among low income and minority residents (Fernandez, 1994).

Ecosystem Dependency

Fundamental Objective: Determine the degree to which local communities are reliant upon natural resources for their economic and social well-being. This includes employment based upon natural resource extraction as well as tourism and other recreational or cultural uses of natural resources.

Ecosystem dependency examines natural resources as they relate to community well-being (Table 9). Disruptions to ecological systems could impact coastal fisheries and other natural resource-based economic activities upon which many communities depend. The potential consequences of such disruptions are many and varied, including a loss of income, loss of subsistence food sources and a resultant decline of health, and ultimately out-migration of the population due to the loss of employment opportunities (Colten, 2014). Some of these nonmarket impacts of ecological change on natural resource-dependent communities can be identified using qualitative community survey methods.

Table 9. Monitoring variables and objectives with supporting background information for ecosystem dependency.

Monitoring Variable	Objective	Background
Natural resource extraction	Determine changes to levels of natural resource extraction within local communities to improve the understanding of the effect of biophysical processes on natural resources upon which resource-dependent occupational communities depend.	Environmental change can reduce crop, livestock, and fisheries productivity within a community, in addition to damaging assets used in the extraction of these resources (Black et al., 2011). Such impacts have the potential to reduce community resilience by reducing household income and community outmigration.

Monitoring Variable	Objective	Background
Cultural and traditional use of natural resources	Identify and measure change in the cultural and traditional uses of natural resources in local communities to improve the understanding of the role natural resources play in a resource-dependent occupational community's cultural heritage and subsistence.	The traditional renewable natural resource extraction cultures of the Louisiana coast rely on the integrity and health of the ecosystem for their well-being (Laska et al., 2005). The non-market uses of natural resources are important components in the cultural heritage of many coastal communities.
Natural resource-based employment	Identify changes in natural resource-based employment levels by sector (including agriculture, fisheries, and oil and gas) to improve the understanding of the effects of changing levels of natural resource availability on livelihoods and community structure in resource-dependent occupational communities.	Some occupations, especially those involving resource extraction, may be severely impacted by changing environmental conditions, natural hazard events, and technological disasters. Those workers engaged in agriculture may similarly suffer, as employment and income levels decline (Cutter et al., 2003)
Tourism and recreational use of natural resources	Identify and measure change in important recreational uses of natural resources in occupational communities to improve the understanding of the role that natural resource-based tourism and recreation play in local economies.	As environmental and economic changes increasingly impact levels of natural resource extraction in resource dependent communities, some residents adapt by developing alternate sources of income. The growth of ecotourism and sport fishing, for example, are growing industries in coastal Louisiana.

Residential Properties Protection

Fundamental Objective: Determine changes to the level of residential structural and nonstructural protection attained within local communities.

Louisiana's coastal zone is a highly dynamic environment, where land management decisions must necessarily integrate coastal restoration with coastal protection in order to reduce the social vulnerability of coastal communities (Peyronnin et al., 2013). Government policies have provided insurance subsidies and structural protection to encourage the development of coastal floodplains. Residential properties still located within flood hazard areas are clearly more vulnerable to changing environmental conditions. Some homeowners are able to partially reduce their risk by constructing within existing levee systems, while others may utilize nonstructural protection projects, such as flood proofing, retrofitting with individual mitigation measures, and elevating their homes (Table 10).

Table 10. Monitoring variables and objectives with supporting background information for protection of residential properties.

Monitoring Variable	Objective	Background
Residential risk reduction	Identify changes in the percentage and number of households in designated Special Flood Hazard Areas (SFHAs) at the census block group-level to improve the understanding of how management decisions and coastal dynamics influence community risk.	A common way to delineate the threat of flood is using the 100-year floodplain, also known as the Special Flood Hazard Area (SFHA) (Maantay & Maroko, 2009). The SFHA is a compilation of selected high risk zones (A and V zones) as designated by the Federal Emergency Management Agency (FEMA).
Households receiving structural protection	Identify changes in the percentage of households with structural protection to improve the understanding of how management decisions and coastal dynamics influence community risk and how this risk affects residential population growth.	The use of structural measures such as earthen levees, concrete walls, floodgates, and pump systems remains an effective tool in controlling floods and reducing flood losses in coastal communities.
Residential properties receiving nonstructural protection	Identify changes in the percentage and number of residential structures elevated above the 100-year floodplain, residential structures flood proofed or retrofitted with individual mitigation measures, and the percentage and number of acquisitions and buyouts to improve understanding of how management decisions and coastal dynamics influence community vulnerability.	Flood risks cannot be reduced purely by structural means such as building levees. Nonstructural project measures such as raising a building's elevation or flood proofing residential structures can effectively reduce residential risk levels (CPRA (Coastal Protection and Restoration Authority), 2012).

Critical Infrastructure and Essential Services Protection

Fundamental Objective: Determine the number of essential facilities and critical infrastructure (including hospitals, fire stations, police stations, schools, transportation facilities, fuel supply, water supply, wastewater treatment systems, electricity distribution systems, and flood protection systems) currently protected by structural and nonstructural projects.

The ability of a community to adapt to changing environmental conditions and rebound from coastal hazards events is dependent in large part on how quickly essential services can be restored. Coastal Louisiana has a complex system of public utilities and infrastructure that supports local communities. Because of the proximity of this infrastructure to the coast and the threat of powerful storm events, local and parish governments must construct and maintain additional infrastructure and engineering systems to protect them (Laska et al., 2005). Where large structural projects are not feasible, or where additional protective measures are desired, these essential facilities can be flood-proofed, retrofitted with individual mitigation measures, or elevated above base flood levels. Communities with well protected infrastructure are decidedly more resilient than those without (Table 11).

Table 11. Monitoring variables and objectives with supporting background information for the protection of critical infrastructure and essential services.

Monitoring Variable	Objective	Background
Risk reduction for essential facilities and critical infrastructure	Identify changes in the percentage and number of essential facilities and critical infrastructure located in SFHAs at the census block group-level to improve the understanding of how resilient communities are to risk.	Loss of sewers, bridges, water, communications, and transportation infrastructure compounds potential disaster losses and may place a heavy financial burden on smaller communities that lack the resources to rebuild (Cutter et al., 2003). The location of this infrastructure in areas of heightened flood risk increases the vulnerability of local communities.
Miles of levees created and maintained	Determine miles of newly created, federally certified levees and changes to existing levee alignments, geometries, elevations, and fortifications to improve understanding of how management decisions influence community risk.	As the density of people and infrastructure in floodplains increase, the use of structural measures such as levees remains an effective tool in controlling floods and reducing flood losses. However, these systems can fail due to the magnitude of flood events, or poor initial construction (Burton & Cutter, 2008; Campanella, 2010).
Number of essential facilities and critical infrastructure receiving structural protection	Identify changes in the percentage and number of essential facilities and critical infrastructure protected by structural projects.	The loss of infrastructure may place an insurmountable financial burden on smaller communities that lack the resource to rebuild (Cutter et al., 2003). To protect this infrastructure, local parishes and communities may need to construct and maintain additional engineering systems.
Public and commercial properties receiving nonstructural protection	Identify changes in the percentage and number of public and commercial structures elevated above the 100-year floodplain, commercial structures flood-proofed or retrofitted with individual mitigation measures, and the percentage and number of acquisitions and buyouts to improve understanding of how resilient communities are to risk.	The number of commercial and industrial buildings is an indicator of the economic health of a community. Potential losses in the business community present long-term issues with recovery after an event (Cutter et al., 2003). Nonstructural project measures such as raising a building's elevation or flood proofing public and commercial structures can effectively reduce risk levels (CPRA (Coastal Protection and Restoration Authority), 2012).

COUPLING OF THE NATURAL-HUMAN SYSTEMS

Although presented independently, the variables identified for the human and natural systems are closely coupled in Louisiana. Understanding of this coupled human-natural system requires knowledge of (1) the processes that link the human and natural systems, 2) interactions and feedback between the systems, and (3) how interactions between the human and natural systems occur within and across spatial and temporal scales (Liu et al., 2007). The relative strength of the coupling between the natural and human systems is hypothesized to be strongest when large areas of human-occupied land vulnerable to changes in the natural system are assigned monetary values by economic processes and measures are taken to protect these lands from damage (Werner and McNamara 2007). Such is the case for coastal Louisiana. The underlying properties of the natural system such as geology, climate, and the availability of natural resources have influenced where communities have developed while economic processes have allowed these communities to persist over time. The growth and development of these communities have in turn reshaped the natural system and the associated ecosystem services that the human system relies upon. On a shorter time frame, episodic events acting on the natural system, such as storms or droughts, often result in more immediate impacts on the human system, such as loss of economic viability or population shifts.

Although direct effects of the human system on the natural system, and vice versa, are often more apparent, the feedback between human and natural systems is less clear and requires an integrated analysis of coupled social-ecological systems. For coastal Louisiana, the SWAMP monitoring categories can be placed in a framework for an integrated analysis, based off the concepts of Chaplin et al. (2006) and the Millennium Ecosystem Assessment (2005a). The framework illustrates how the SWAMP variables are broadly linked within and between the natural and human systems and the potential interactions across spatial and temporal scales (Figure 3). These linkages include direct environmental impacts on the human system (e.g., flooding leading to loss of property), institutional responses to the environment (e.g., restoration activities leading to newly created land), and indirect pathways in which changes in the human and natural environments manifest themselves through changes in ecosystem dependency. For example, changes in biotic integrity can impact fisheries landings, a key measure of ecosystem dependency, which can in turn impact the socioeconomic characteristics of natural resource-dependent communities (Figure 3). These relationships may also cross scales, where large-scale processes within one system may impact both large and small scales in another. For example, changes in global market value of commercially important fisheries (large scale), can have implications on fishing pressure or natural resource-based employment and potentially reduced natural resource extraction within the basin (small scale). On the environmental side, variable overflow patterns in the Mississippi River, which are largely driven by upstream precipitation patterns (large scale), drive crawfish abundance in the Atchafalaya floodplain (small scale) and can lead to unpredictable wild harvest and be a stimulus to the development of crawfish aquaculture (McClain and Romaire, 2004). Through the monitoring of societal metrics related to human wellbeing and human resilience and monitoring of ecosystem condition and physical processes, SWAMP monitoring can provide the basis for an integrated understanding of the coupling of human and natural systems.

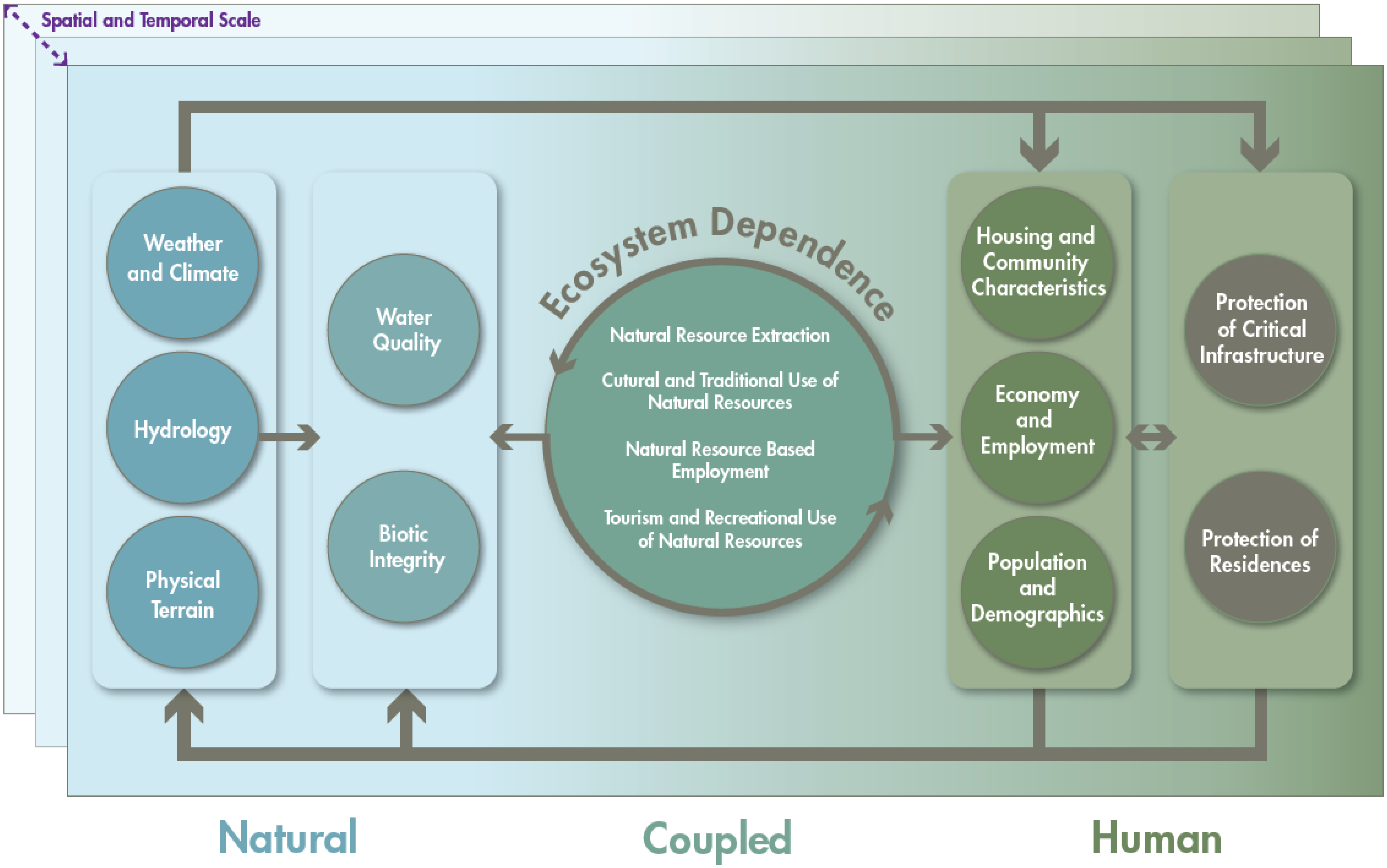

Figure 3. Conceptual diagram illustrating the concepts of a coupled human-natural system. Color gradient represents the direct linkages between these two systems. The arrows illustrate that interactions occur within the systems themselves and also the feedbacks that occur across the systems. The relative strength of these interactions is influenced by the scale at which they occur.

Natural System Sampling Design

BUILDING ON EXISTING MONITORING

Point and Continuous Sampling

The process of developing SWAMP relies heavily on the use of existing monitoring programs identified in the SWAMP inventory geodatabase. The SWAMP inventory illustrates a wealth of current data collection activities that are directly relevant to each of the monitoring categories identified within this report. A brief summary of the active monitoring programs that collect data relevant to SWAMP are provided below and how the data are integrated into the proposed monitoring plans for the Barataria Basin are described in detail in the Monitoring Plan and Appendix II. Weather and oceanographic data are mainly collected by the National Oceanic and Atmospheric Administration (NOAA) through several different weather observing systems available through their National Climatic Data Center (NCDC) and the National Data Buoy Center (NDBC), as well as select sites operated by the USGS, Louisiana Universities Marine Consortium (LUMCON) and Wave-Current- Surge Information System (WAVCIS; Figure 4). Data types collected at each station vary, but typically include some combination of wind speed and direction, gusts, barometric pressure, air temperature, water temperature, wave height, wave period, wave direction, and current speed and direction. Model predicted datasets are also available on larger scales from the NOAA National Weather Service's Advanced Hydrologic Prediction Service[1] and the NOAA Earth Systems Research Laboratory Physical Sciences Division[2]. Water quality data are collected by the Louisiana Department of Environmental Quality program, USGS, and the CPRA for the CRMS program (Figure 5). LDEQ AWQ measures water quality parameters discretely on a monthly basis every four years, while the USGS and CRMS programs monitor specific conductance, water temperature, salinity, and gauge height in real-time. Biotic integrity data are collected by the Louisiana Department of Wildlife and Fisheries (LDWF) and CPRA. LDWF collects fisheries-independent data using several different gear types that target specific aquatic habitats (e.g., shallow marsh edge habitats) and life stages of nekton, while CPRA samples community composition, accretion, and soil properties in herbaceous wetlands and swamp habitats for the CRMS program (Figure 6). Lastly, CPRA's BICM program collects data to assess and monitor changes in the aerial and subaqueous extent of islands, habitat types, sediment texture and geotechnical properties, environmental processes, and vegetation composition (Figure 7). Utilization of these existing monitoring programs is described in detail within the Natural Systems Monitoring Plan section below.

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[1] http://water.weather.gov/precip/

[2] http://www.esrl.noaa.gov/psd/data/gridded/data.narr.html

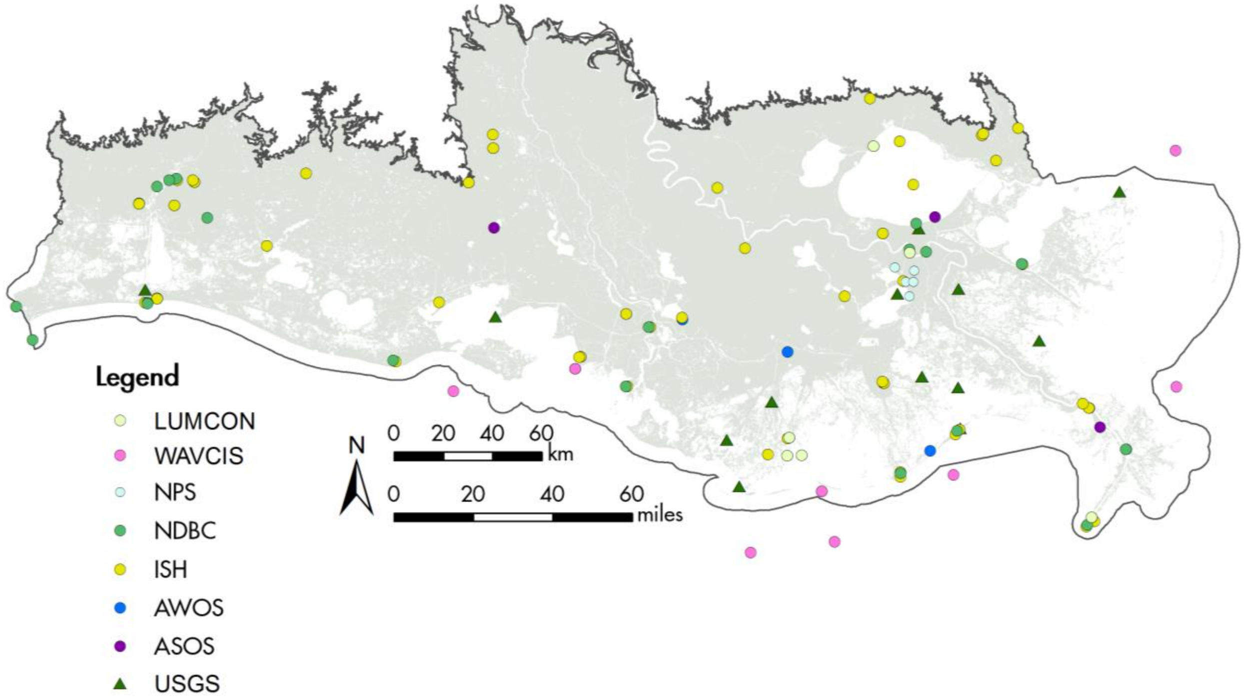

Figure 4. Existing weather and oceanographic monitoring sites. Legend key: Louisiana Universities Marine Consortium (LUMCON), Wave-Current-Surge Information System (WAVCIS), National Park Service (NPS), National Data Buoy Center (NDBC), Integrated Surface Hourly (ISH), Automated Weather Observing System (AWOS), Automated Surface Observing System (ASOS).

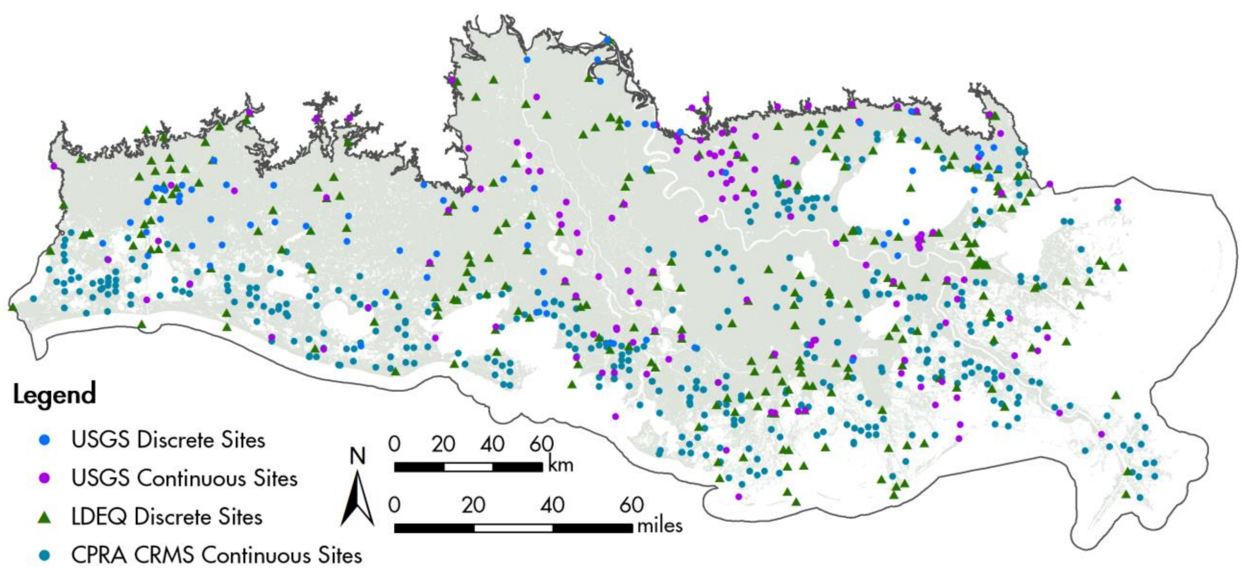

Figure 5. Existing water quality sites operated by USGS, LDEQ, and CPRA.

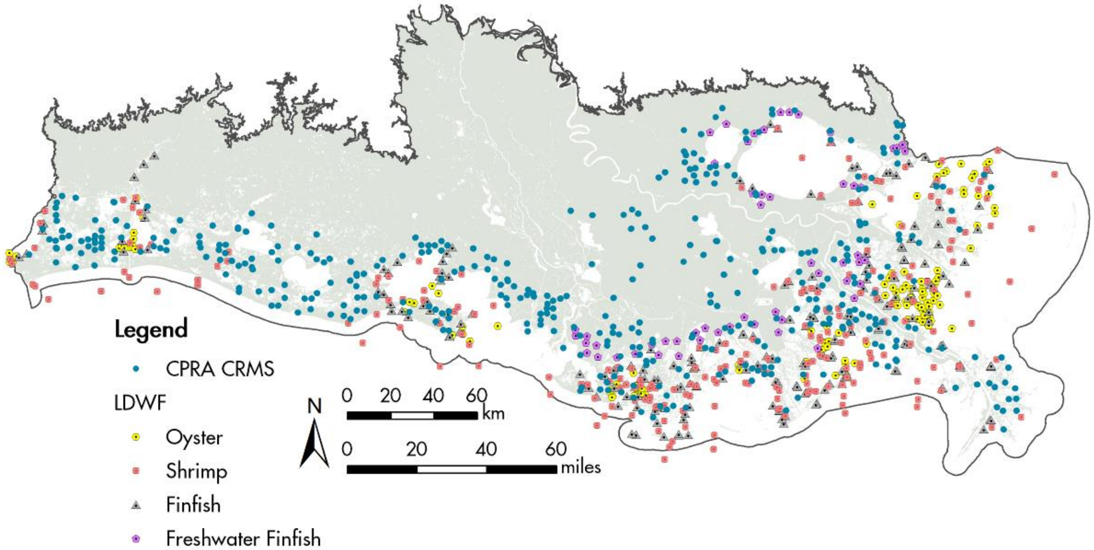

Figure 6. Existing biotic integrity sites operated by the LDWF for sampling nekton community composition and sites operated by CPRA for sampling wetland community composition and soil condition.

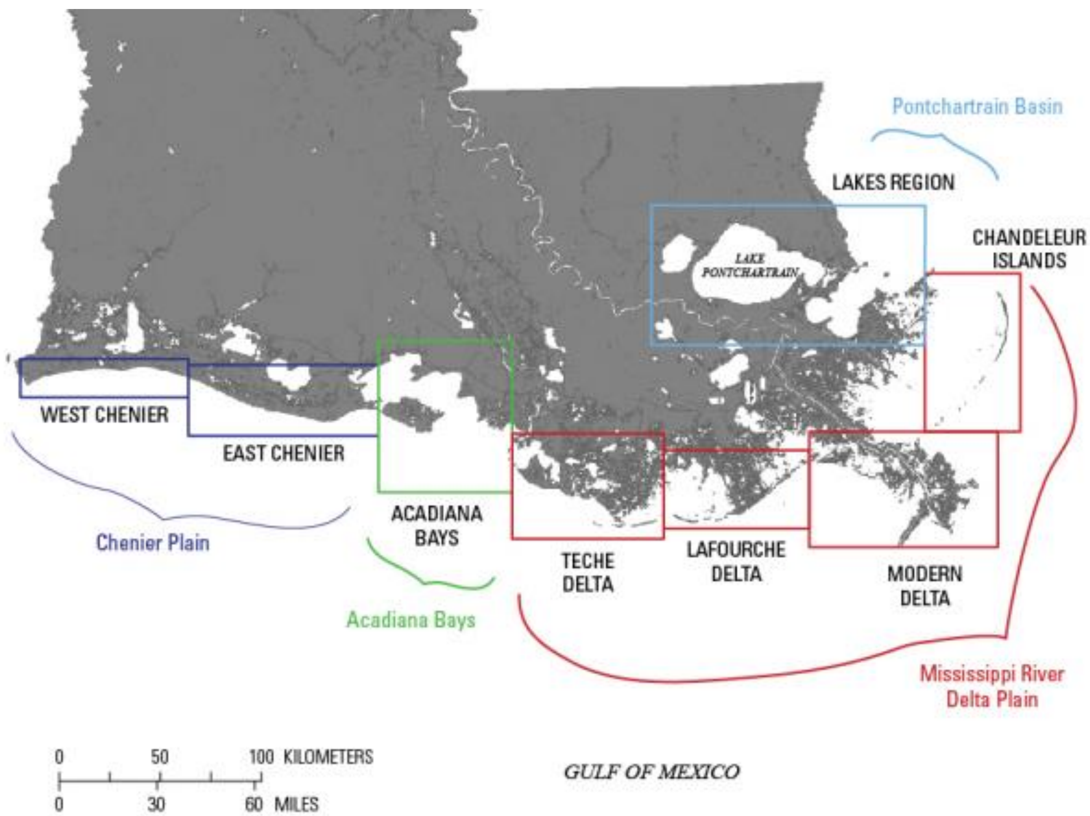

Figure 7. Geologic and physiographic setting (Pontchartrain Basin, Mississippi River Delta Plain, Acadiana Bays, and Chenier Plain) of the eight regions used in BICM analyses (the Lakes Region; Chandeleur Islands; Modern, Lafourche, and Teche deltas; Acadiana Bays; and the eastern and western Chenier Plain; Kindinger et al., 2013)).

Remote Sensing

Remotely sensed data are advantageous in that they allow for large spatial coverage and detection of spatial and temporal environmental gradients (Xie, 2008). A summary of satellite types and what they are used for are provided in Table 12. For water-based monitoring, remote sensing methodologies have successfully been used in Louisiana for mapping near surface temperature and total suspended sediment gradients using data from a variety of satellites includes NOAA's Polar Orbiting Environmental Satellites equipped with Advanced Very High Resolution Radiometer (AVHRR), the Earth Observing System fleet equipped with Moderate Resolution Imaging Spectroradiometer (MODIS) sensor, and the next generation Visible Infrared Imaging Radiometer Suite (VIIRS) (Myint and Walker, 2002; Walker et al., 2005). Accurate interpretations of these datasets into absolute values require atmospheric corrections and calibration against field data. These datasets can also be used qualitatively to identify the relative patterns in the environmental conditions, which may be helpful in calibrating hydrodynamic and water quality models. Remote sensing has been less successful in deriving salinity, chlorophyll *a*, and submerged aquatic vegetation in the coastal areas because high sediment concentrations in the water absorb light and decrease the reflectance, and require hyperspectral sensors and more sophisticated algorthims to identify each substance in the water (Klemas, 2011). Some success in estimating chlorophyll *a* concentrations has been shown outside the coastal areas, however (Walker and Rabalais, 2006). For land-based monitoring, Landsat Thematic Mapper (TM) imagery can be used for identifying wetlands and other land cover types, particularly when multi-temporal datasets can be acquired (Ozesmi and Bauer, 2002) and have been used to develop land-water maps in coastal Louisiana (Couvillion et al., 2011). Analysis requires baseline imagery of low-water conditions and repeated imagery allows of evaluation of areal changes over time (e.g., Wang and Xu, 2009). The benefit of these satellite derived datasets is the ability to cover large scales (coastwide) at frequencies not possible from ground-based measurements. These land-water maps are a critical component to the CRMS-Wetlands program. Estimates of biomass for emergent marsh vegetation are more difficult and are confounded by patch size, vertical stem morphology, high densities, and water inundation (Byrd et al., 2014). Although some remote sensing products have been incorporated into SWAMP already (e.g., land-water maps), the utility of other remote sensing is an area needing further research into how it can be effectively incorporated into SWAMP. As more efficient technologies and data processing algorithms evolve, it is envisioned that the data collection strategies within SWAMP will evolve as well.

Table 12. Satellite sensors for monitoring land cover, land surface properties, and land and marine productivity (from Millenium Ecosystem Assessment 2005b).

Platform	Sensor	Spatial Resolution at Nadir	Date of Observations
Coarse Resolution Satellite Sensors (> 1 km)			
National Oceanic and Atmospheric Administration–Television and Infrared Observation Satellite	AVHRR	1.1km (local area coverage) 8km (global area coverage)	1978–present

Platform	Sensor	Spatial Resolution at Nadir	Date of Observations
Systéme Probatoire pour la Observation de la Terre (SPOT)	VEGETATION	1.15KM	1998–present
Advanced Earth Observing Satellite - II	Polarization and Directionality of the Earth's Reflectances	7km x 6km	2002–present
SeaStar	Sea viewing Wide Field of View	1km (local coverage); 4km (global coverage)	1997–present
Moderate Resolution Satellite Sensors (250 m–1 km)			
Advanced Earth Observing Satellite - II	Global Imager	250m–1km	2002–present
Earth Observing System	MODIS	250–1,000m	1999–present
Earth Observing System	Multi-angle Imaging Spectroradiometer	275m	1999–present
Envisat	Medium Resolution Imaging Spectroradiometer	350–1,200m	2002–present
Envisat	Advanced Synthetic Aperature Radar	150–1,000m	2002–present
High Resolution Satellite Sensors (20 m–250 m)[a]			
SPOT	High Resolution Visible Imaging System	20m; 10m (panchromatic)	1986–present
European Remote Sensing Satellite	Synthetic Aperture Radar	30m	1995–present
Radarsat		10–100m	1995–present
Landsat	Multispectral Scanner	83m	1972–97
Landsat	TM	30m (120m thermal-infrared band)	1984–present
Landsat	Enhanced TM	30m	1999–present
Earth Observing System	Advanced Spaceborne Thermal Emission and Reflection Radiometer	15–90m	1999–present
Indian Remote Sensing	Linear Imaging Self-Scanner	23m; 5.8m (panchromatic)	1995–present
Very High Resolution Satellite Sensors (< 20 m)[a]			
Japanese Earth Resources Satellite	Synthetic Aperature Radar	18m	1992–98

Platform	Sensor	Spatial Resolution at Nadir	Date of Observations
Japanese Earth Resources Satellite	OPS	18mx24m	1992–98
IKONOS		1m panchromatic; 4m multispectral	1999–present
QuickBird		0.61m panchromatic; 2.44m multispectral	2001–present
SPOT–5	High-Resolution Geometric – High-Resolution Stereoscopic	10m; 2.5m (panchromatic)	2002–present

[a] *Data were not acquired continuously within the time period.*

METHODS FOR DETERMINING SAMPLE SIZE

The proceeding sections on the development of a sampling design are based on extensive review of the monitoring and statistical literature that largely focuses on the development of new monitoring programs. For SWAMP, there was a need to not only establish new monitoring, but also leverage data collection efforts through existing monitoring programs and integrate the monitoring across different spatial scales of interest. Although the plan identifies sites where existing monitoring takes place, the logistics and feasibility of utilizing these sites for SWAMP has yet to be considered. As a result, the sampling design methodologies seek to achieve statistical robustness irrespective of whether existing sites can be used in the SWAMP design.

Sample sizes for the natural system's monitoring variables were estimated using two approaches: analytical and expert knowledge. The analytical approach was used for variables in which the objective focused on monitoring status and trends and where data existed to conduct the analyses, either from research studies or existing monitoring programs. This included variables from water quality and biotic integrity categories. The expert knowledge approach was required for those variables predominantly required for planning models, whose objective was focused on conducting site-specific measurements rather than regional inferences, or where data were unavailable to conduct a power analysis. This included variables from the hydrology and physical terrain categories.

Power Analysis

In order to ensure that available resources are utilized efficiently and effectively, the development of a monitoring plan typically requires the evaluation of optimal survey designs and the evaluation of statistical power when statistical inferences are of interest (Field et al., 2005). The power of a statistical test, or the probability of detecting a significant difference when a difference actually exists, is a function of the significance level, sample size, variance, and effect size (i.e., minimum detectable difference; Zar, 2010). Although power and significance levels vary among applications and may be subjectively applied, they are useful in providing guidance for the amount of effort required to detect change. For instance, if a power analysis determines that an impractically large sample size is necessary to detect some desired minimum difference, it may be concluded that the time, effort, and expense to perform the monitoring is too high or an alternative metric may be preferable. Alternatively, if the sample size is already set through an established monitoring program, a power analysis can be carried out to calculate the minimum difference that is detectable given that sample size. This report evaluates both perspectives to determine the minimum detectable difference of existing monitoring programs given their current sample sizes and the effect of increasing sample sizes on the minimum detectable difference.

The power of a statistical test has these typical properties:

- power increases as the true population deviates from the null hypothesis (i.e., as larger changes occur),
- power increases as significance level (α) increases, and
- power increases when variability decreases (Urquhart et al., 1998).

Although the ability to detect trends is sensitive to the variability in the metric of interest, trend detection is still possible even with the presence of substantial variation (Urquhart et al., 1998). Environmental datasets generally have substantial variation associated with them, but the variance can often be broken down into key components: (1) site-to-site variation in the magnitude of the metric (i.e., site variance), (2) year-to-year variation expressed by all sites together (i.e., year variance), (3) average independent year-to-year variation at each site (i.e., interaction site*year variance), and (4) residual variance (i.e., variation not covered by site, year, and interaction (Larsen et al., 2004, 2001; Urquhart et al., 1998). The ability to detect trends within a network of sites is most sensitive to year-to-year and residual variances (Larsen et al., 2001). Site-to-site variance can be controlled by adding covariates that characterize the fundamental differences among sites (e.g., habitat types); year-to-year variance can only be controlled by either identifying covariant forcing factors (e.g., annual weather patterns such as wet or dry years) or extending the monitoring time frame; adding sites to a monitoring network only effects the interaction and residual variances; and more frequent sampling of sites within a year only influences residual variance (Larsen et al., 2004). A list of other common sources of higher residual variances and potential remedies are provided in Table 13.

Table 13. Common sources of variability in natural resources surveys with potential remedies (adapted from Reynolds, 2012).

Source	Description	Potential Remedy
Vague objectives	Failure to identify specific information and information quality required.	Thorough planning with peer review.
Frame errors	Differences between resource's spatial domain and the spatial domain targeted for monitoring.	Explicit documentation and assessment prior to sample selection.
Measurement bias and sampling variation	Changes in the sample unit values during measurement process; variation resulting from measuring only a subset of the sample frame (i.e., spatial domain).	Multiple measurements per site and/or increase number of sites; apply probabilistic site selection methods; use analysis that accounts for variation attributable to covariates.
Observer errors	Flawed protocols or bias between observers.	Tested and documented protocols; improve training and field guides; QA/QC processes.
Non-response or availability bias	Inaccessible sampling units.	Increase participation by land owners controlling access; modify sampling frame to eliminate inaccessible strata.
Data inaccuracies	Errors in recording, transcription, or management.	Automate data collection where possible; implement or improve QA/QC procedures including "in-field" error checking; develop metadata and archiving; regular re-assessments of data collection procedures; dedicated data management staff and procedures.
Analytical errors	Errors in conducting, interpreting, and presenting results; coding errors.	Peer review of statistical methods; development of analytical protocols; software testing, debugging, and documentation.

The power analysis approach used here was based on a set of assumptions that result in a conservative estimate of sample sizes (Zar, 2010). These assumptions were:

- the data are approximately normally distributed so that a t-test of the change in means is appropriate;
- the variance of the population is constant in time so that the standard deviation used is representative of the true standard deviation in different years;
- the sample sizes are balanced so that the same number of observations are taken each year; and
- the samples are randomly selected (i.e., simple random sampling design) from the study region (with equal probability) and there is no or little correlation among data points from one year to the next.

The last assumption potentially leads to estimated sample sizes that are larger than required because the correlation between observations taken repeatedly at a site influences the standard error of the estimator of change. Positive correlations decrease the standard error of the mean and larger positive correlations decrease the standard error more than smaller positive correlations. Although simulations have been used as an alternative power analysis approach when more complex sampling designs are of interest, it is critical that the assumed model used to generate the simulation reflects the complexities of the population and proposed sampling design, or else estimated means and standard errors may not reflect the true population (Melwani et al., 2006). However, given the large number of variables and objectives, the simulation approach was not practical and it was deemed more efficient to proceed with the power analysis as described below, under the assumption of simple random sampling. As a result, the results provided are considered conservative (i.e., there may be more samples than are actually needed to observe the change identified).

The power analysis approach was conducted on several of the water quality and biotic integrity variables listed in Table 2 and Table 3 to determine the sample size required to observe a given change (as a percentage) in the metric means over time (a given number of years) or in the means between factors (e.g., wetland types). Since power analyses are based on many assumptions, as described above, the resulting sample sizes are considered estimates and should not be construed as precise numbers. Thus, by conducting the analysis on several different variables within the water quality and biotic integrity categories, the collective results can be used to develop an appropriate sample size range for groups of variables. Although many of the variables may be represented by more than one response metric (e.g., biomass versus density, belowground versus aboveground biomass), it was not feasible to conduct the analysis on all possible metrics and it was assumed results from one metric could be used to infer sample size estimates of related variables and metrics (Table 14).

Table 14. Summary of variables for which a power analysis was conducted. Details on the power analysis for each variable can be found in Appendix II.

Monitoring Category	Monitoring Variable	Metric Used in Power Analysis
Water Quality	Chlorophyll *a*	Chlorophyll *a* concentration
	Dissolved oxygen (DO)	DO concentration
	Nutrient constituents	Total nitrogen and total phosphorus concentrations
	Salinity	Salinity concentration
	Turbidity	None. Sample size inferred from the collective results of the other variables within the water quality category.
	TSS	TSS concentration
Biotic Integrity	Herbaceous wetland vegetation biomass	Aboveground biomass
	Nekton community composition	Catch per unit effort by gear type
	Soil characteristics	Bulk density
	Wetland vegetation community composition	Marsh and swamp floristic quality indices

In order to perform a power analyses the following information was required:

- Type I error rate (α) for incorrectly rejecting the null hypothesis of no change between time points or factors;
- Type II error rate (β) for incorrectly failing to reject the null hypothesis when the alternative hypothesis of change is true; and
- effect size, here given as the percentage change from the initial or current mean value;
- standard deviation (σ) of the random variable under study.

Although power analyses are typically conducted to examine the power to detect change, power itself often has very little meaning outside the statistical literature and may not provide enough guidance for making decisions for selecting appropriate sample sizes. Instead, the effect size can be a useful measure in that it associates sample size estimates with actual changes that can be achieved (either reported in units of the metric or as a percentage). As a result, the main focus of the analysis was to examine the relationship between sample sizes and the effect size and also explore sensitivity to changes in spatial scales (i.e., subbasin, basinwide, and coastwide), while holding power constant. To conduct the power analysis, an "exemplary" dataset was created using data from existing monitoring program or research projects[3]. The data acquired are described for each variable in Appendix II.A general linear model (GLM) was fit to each response variable, y, with a fixed effect combination of covariates, x, that varied for each metric of interest in order to account for site-to-site variance and reduce the residual variance (Appendix II). The fitted model provided an estimate for the mean for each combination of factors, for the grand mean over all factor combinations, and an estimated error variance. In some cases, the variable required transformation— using either natural logarithm or square root—in order to approximate normality and satisfy the assumptions of the GLM. The means estimated by the GLM served as year 0 in the analysis and effect sizes (i.e., 1-36% change) were imposed in increments of 5% on every transformed mean and calculated for 5 continuous years to generate a 6-year time-series (i.e., year 0 plus 5 years of imposed percentage change). This time-series served as the exemplary dataset and each percentage change represents the effect size, or minimum detectable difference, as previously described. The exemplary dataset was then used to estimate sample sizes for detecting differences among factors (e.g., seasons) and for detecting a linear change over time for a particular effect size. Sensitivity of sample size estimates to the length of the time-series was also explored by running the analysis for 2, 4, or 6 contiguous years (annotated as +1, +3, and +5, respectively, in the graphs in Appendix II). SAS v9.3 was used for all analyses.

The final sample size selection was made by creating line graphs showing the relationship between the minimum detectable difference (percentage change) and sample size and visually identifying threshold points in which increasing sample size resulted in minimal gain in change detecting abilities (Figure 8). The sample sizes at the threshold points were then compared to sample sizes required to detect differences among factors in order to make a determination of what could (or couldn't) be detected given a particular

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[3] A random sampling design is required to assure that the estimates of the means and variances are unbiased. In many instances, it was unknown how the original sampling design was implemented and thus the estimated means and variances used may be biased and lead to inaccurate power estimates. However, proceeding with biased estimates does not prohibit the use of the results to inform sampling recommendations.

sample size. A summary of the recommended sample sizes are presented in the Monitoring Plan and detailed results of the analysis for each variable are presented in Appendix II.

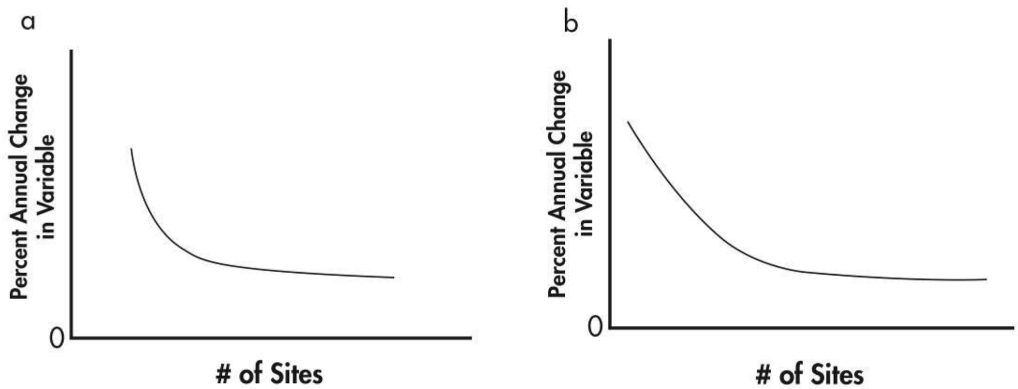

Figure 8. The hypothetical graphs illustrate the concept of threshold points in which a change in the x-axis results in a minimal change in the y-axis. In panel a, the slope is initially steep such that a small change in the x-axis results in a large change in the y-axis. In panel b, the slope is more gradual. In both cases, the line gradually tapers off, such that any change in the number of sites results in little to no change in change detection ability.

Expert Knowledge

Hydrodynamic and ecological models are used extensively in the coastal protection and restoration planning process. Model predictions are currently assessed with a computer-based decision support tool to make informed management decisions in the selection of restoration and protection projects (Groves & Sharon, 2013). Given the heavy reliance on predictive models for coastal planning, model improvement is a primary focus for the 2017 Coastal Master Plan (Coastal Protection and Restoration Authority, 2014). The development of SWAMP can support model improvement by providing data that can be used for parameterizations, calibration, and validation. However, there are many aspects to be considered when designing and implementing monitoring networks to support numerical modeling efforts, from reducing variances to improving predictions. For example, data limitations have previously been shown to contribute to large systematic and random errors in hydrological modeling (Habib et al., 2007). Meselhe and Rodrigue (2013) also identified general sources of uncertainties in model predictions:

- outdated, insufficient, inaccurate, or unrepresentative input data (bathymetry, topography, freshwater inflow volumes, sediment load, constituents load, etc.);
- poor or incomplete knowledge of the pertinent physical processes represented in the predictive models;
- approximations and numerical assumptions in the numerical schemes; and
- imperfect characterization of numerical and physical parameters in the formulations utilized in the models.

Data limitations were also frequently cited in the 2012 Master Plan and include:

- boundary conditions and physical processes of flow exchange; poor spatial coverage (CPRA, 2012 - Appendix D1);
- influence of wetland plant growth and belowground processes on vertical accretion (CPRA, 2012 - Appendix D2); and

- grazing, turbidity, and soil type to parameterize the response of plant species to these factors (CPRA, 2012 - Appendix D4).

Monitoring optimization methods have typically been employed to improve predictions or estimations of a single variable for a single model (e.g., salinity predictions in Barataria Basin, (Habib et al., 2007); contaminant concentrations in groundwater, (Zhang et al., 2005). Optimizing each and every planning model in coastal Louisiana for each variable identified was not practical. Instead, three general modeling needs, *spatial coverage, boundary conditions, and system exchange points*, applicable to basinwide modeling efforts, were identified from a review of the data limitations articulated in the 2012 Master Plan, review of responses collected in a modeling survey in coastal Louisiana (Steyer et al., 2004), workshop discussion during the development of the SWAMP Framework (Hijuelos et al., 2013), and discussions with modelers at the Institute.

Adequate *spatial coverage* is particularly important for validation and calibration such that sampling locations for a metric of interest should reflect different types of environments (e.g., shallow vs. deep; open water vs. channels). Improving spatial coverage can also help capture heterogeneity in the system and high gradient variability in order to improve model parameterization. *Boundary conditions* refer to the characteristics of the model's end points and are specified, not simulated (Adrien, 2004). The *exchange points* in this context refer to locations where water is conveyed between the marine and estuarine environment through the main tidal passes. Although exchange points occur throughout the coast, the tidal passes in the southern extent of the estuary were identified as critical exchange points in the modeling environment. These locations contribute significantly to the flow and exchange of freshwater, nutrients, sediments, and organic material between the Gulf of Mexico and estuaries. The selection of site locations on a coastwide scale was beyond the scope of this report, so the three modeling needs were used to optimize the number and placement of sites in Barataria Basin for the following monitoring variables:

- Weather and Climate: precipitation, wind, evapotranspiration
- Hydrology: current velocity, water level, waves
- Physical Terrain: bathymetry, land area, surface elevation

In some instances, modeling needs were used in conjunction with the power analysis to develop a recommendation on sample sizes and/or site locations. A summary of the recommended sample sizes and locations are presented in the Monitoring Plan and detailed justifications on sample sizes and site locations are provided for each variable in Appendix II.

METHODS FOR DETERMINING SITE LOCATIONS

Overview

Regional trend detection relies on data obtained from a network of sites that represents the target population of interest (Urquhart et al., 1998). Selecting site locations can be performed using probability-based or nonprobability-based sampling designs. Probability-based sampling designs are generally those that involve some stochastic component (e.g., random draws, random starting point, etc.) and are often employed, as they result in unbiased and defensible parameter estimates (McDonald, 2012). Those that lack a stochastic component are often selected using professional judgment or located haphazardly and may contain an underlying bias. Inferences cannot be made with any statistical basis beyond the selected location with nonprobability-based methods (McDonald, 2012). As a result, probability-based approaches are recommended for assessment of ecological data

Although several existing monitoring programs are well established in coastal Louisiana, their sample designs vary and in some instances there is little to no documentation as to how sites were originally selected. For the implementation of SWAMP, there will be a need to identify new site locations for monitoring of data that do not exist in any of the programs or site locations where there are an insufficient number of sites to detect change or meet the modeling needs previously identified. Typically, for a single parameter of interest, simple random sampling is an appropriate choice for estimating sample size when there is a lack of sufficient information available to identify appropriate strata[1] (McDonald, 2012). Alternatively, if information is available to identify strata, stratified random sampling with simple random samples within each stratum is a common approach as it should yield an estimator (in this case as the percentage change in time) with a smaller standard error. However, for multiple parameters, choice of strata[4] boundaries is complicated by the competing interests in minimizing variability of values for many different parameters within each stratum. Although numerous other probability-based sampling designs exist in the literature (Dixon & Chiswell, 1996; McDonald, 2012 and references therein), a design was needed for coastal Louisiana that included the following properties and would:

- allow optimization of the placement of sampling locations for estimations of more than one variable and numerous objectives;
- satisfy numerical modeling needs including spatial coverage, boundary conditions, and exchange points;
- achieve spatial balance across a large spatial scale;
- (i.e., reduce the amount of "clustering" of site locations in one geographic area);
- be able to nest data collected at the basin scale to the coastwide scale; and
- accommodate changes in the number of sampling locations (e.g., removal or addition of sites given changes in funding, constrained physical access to selected sites).

In order to meet the needs for coastal Louisiana outlined above, the Generalized Random Tessellation Stratified (GRTS) approach was chosen. GRTS produces a spatially balanced probability sample that works well with finite, linear, and areal resources with patterned or periodic responses (Stevens & Olsen, 2004). The GRTS design was developed as part of the U.S. Environmental Protection Agency (USEPA) Environmental Monitoring and Assessment Program (EMAP) and is currently used for the USEPA National Coastal Condition Assessment (USEPA, 2009), Minnesota Status and Trends Program (Minnesota Pollution Control Agency, 2006), Comprehensive Everglades Restoration Plan landscape monitoring (Philippi, 2005), California Status and Trends Program (Lackey & Stein, 2013), and many others. The GRTS design is often used in conjunction with a rotating panel design. A rotating panel design is a sampling strategy in which each panel contains a different collection of monitoring sites and

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[4] Optimal identification of strata occurs when every element (e.g., parameter value at a station location) within a stratum is more similar to the other elements in that stratum than to any element in any other stratum. This method of stratum identification decreases the within stratum variance for every stratum used in the sampling design.

the total number of sites is equal among panels. In year one of monitoring, a single panel of sites is visited according to the sampling frequency for the variable of interest (e.g., monthly, quarterly, etc.). The following year, a new panel of sites is visited and the pattern is repeated for a predetermined number of years (in this case, 3 years). Starting in year 4, the pattern recommences beginning with the panel from year one. The benefits of a rotating panel design relative to a design in which sites are visited each year are increased spatial coverage, improved estimation of status (i.e., size of the response), and reduced inadvertent impacts on the site itself, while still providing the ability to detect trends (Perles et al., 2014; Urquhart, 2012; Urquhart & Kincaid, 1999). The drawback of a rotating panel design is that the implementation of the design requires careful tracking to ensure the correct panel is sampled each year. Further, it may not be practical for sites in which permanent structures must be installed. Although the power to detect trends is marginally higher in "always revisit" designs in which sites are visited each year, always revisit designs have shown to result in less precise estimates of status and potential impacts to the site itself (Urquhart, 2012).

The GRTS design has been compared to other commonly used designs such as systematic sampling, simple random sample, and stratified random sample. Simulation studies suggest that the GRTS design significantly and consistently reduces sample variance, increases power to detect change, and reduces the necessary sample size (Lackey & Stein, 2013). The benefits of GRTS are as follows:

1. accommodates varying spatial sampling intensity,
2. spreads the sample points evenly and regularly over the domain,
3. allows augmentation of the sample after-the-fact, while maintaining spatial balance, and
4. accommodates varying population spatial density for finite and linear populations.

The methodology behind the GRTS design is less straightforward than many of the other commonly used designs and may require training to ensure the design is properly implemented. Further, each of the existing monitoring programs currently utilize a different design or use a different strata to select sites, thus some modifications to the GRTS design upon implementation will be needed in order to leverage existing sites.

Methodology

The GRTS design is based on a hierarchical, square grid placed over the target area. The grid is then subdivided until there is no more than one potential individual sample per grid cell. The hierarchical randomization process then maps the two-dimensional grid onto a one-dimensional line and a systematic sample is taken along the line. This results in samples that are in hierarchical random order and when mapped back on to two-dimensional space, exhibit a random distance between adjacent points. The GRTS design also allows for the use of a neighborhood variance estimator instead of the variance estimators that assume independent random sampling (IRS). The use of the neighborhood variance estimator can result in considerable reductions in the estimation of variance, e.g., 22-58% reductions (Lackey and Stein 2013), and as described above, smaller variances result in a higher power of the statistical test. Additional detail on the underlying algorithms and statistical properties of GRTS are described in Kincaid and Olsen (2013), Larsen et al. (2008), and Stevens and Olsen (2004).

GRTS was implemented by generating a coastwide master sample for water (Figure 10) using the *spsurvey* library in R v3.1.2 (Kincaid & Olsen, 2013). The master sample is a very large sample from which subsamples can be drawn to meet specific monitoring needs (Larsen et al., 2008). The subsamples in this context are the sample sizes recommended for SWAMP. Subsamples could also be project-specific monitoring or research study sites. In order to integrate different scales of monitoring, the master sample should be generated for the largest scale of analysis. The master sample can then be subset for any number of geographic domains, while remaining "nested" within the largest scale (e.g., coastwide; Figure 9). For this reason, the master sample was generated for the SWAMP coastwide boundary and subset using the Barataria Basin boundary file for development of the basinwide monitoring plan. The master sample could also be utilized for project-specific monitoring, using the project geographic boundary, in order to integrate project-specific monitoring with SWAMP. Critical to the use of the master sample is that sites must be selected for the order in which they were generated in *spsurvey*. If field inspection ultimately results in a site being unsuitable for monitoring, the next site in the ordered list must be used in order to maintain spatial balance of the GRTS design.

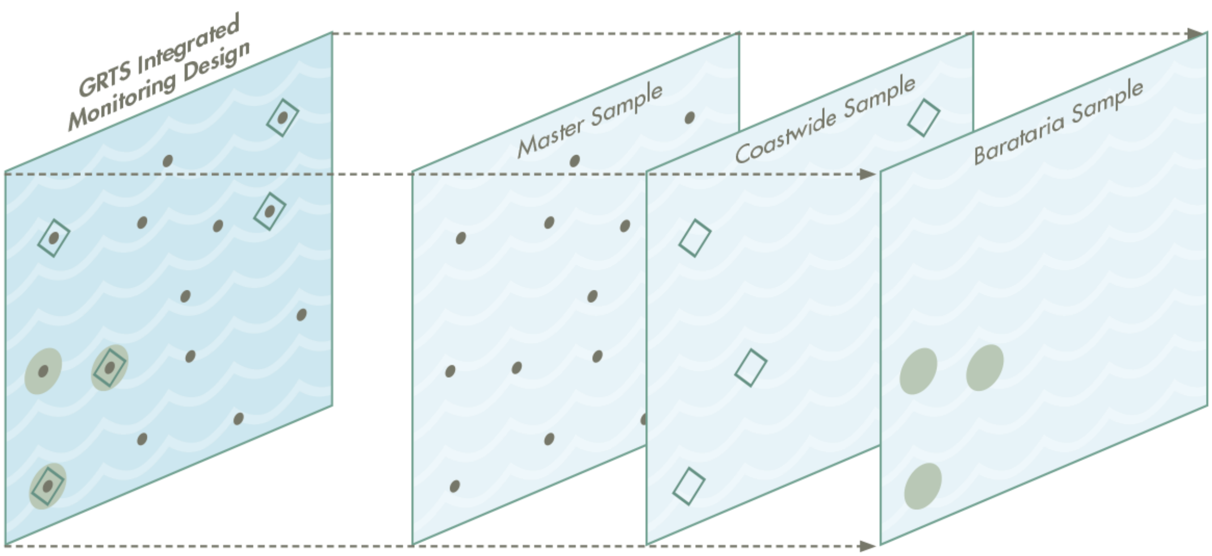

Figure 9. Hypothetical space illustrating the concept of the GRTS integrated monitoring design in which a master sample is generated to select coastwide and Barataria sites. Note that the coastwide sites located within the Barataria domain are also Barataria sites, but not all Barataria sites are needed for the coastwide network.

The master sample is most useful when it is generated using a detailed geographic layer representative of the area in which sampling will take place. The best available data to generate the geographic layer for the master sample was a wetland classification Geographic Information Systems (GIS) shapefile derived from satellite data (Couvillion et al., 2013) and the National Hydrography Dataset (NHD) geodatabase (details on the NHD can be found in Appendix II under the water quality variables). The NHD classification contains areal (e.g., bays) and linear (e.g. streams) features. Features within the SWAMP coastwide boundary classified as 'BayInlet', "SeaOcean", and "LakePond" were selected from the NHD dataset for generating the master sample. Next, areas less than 1 meter deep were identified using calibrated model output of water depth from the 2017 Master Plan Integrated Compartment Model (E. White, personal communication, June 2015) and removed as these features would be too shallow for the water-based sampling proposed in this plan. The master sample size was then determined by calculating the area of water within the coastwide boundary. The total area of water was then divided by 1 km^2 (i.e., 1 x 1 km grid), which resulted in 15,524 sites (Figure 10). The ordered list of sites generated in these master samples was then subset at the basin level (e.g., for Barataria Basin) to select site locations based on the sample sizes recommended in the Monitoring Plan below. Master samples were also generated for wetlands and offshore waters in the event that these may be useful in project-specific monitoring, rapid response programs, or individual research studies. They were not needed for SWAMP implementation in Barataria Basin as the wetland-based monitoring (e.g, biomass) could be conducted at existing CRMS locations, while offshore monitoring of waves could also utilize existing platforms. Thus, the selection of new sites for these land-based or offshore monitoring variables was not needed. The master sample was only used for the selection of new sites. If existing sites were available for incorporation into SWAMP, only the remaining sites needed to meet the recommended total sample size were selected from the master sample. In other words, the master sample and overall GRTS design is independent of existing monitoring sites.

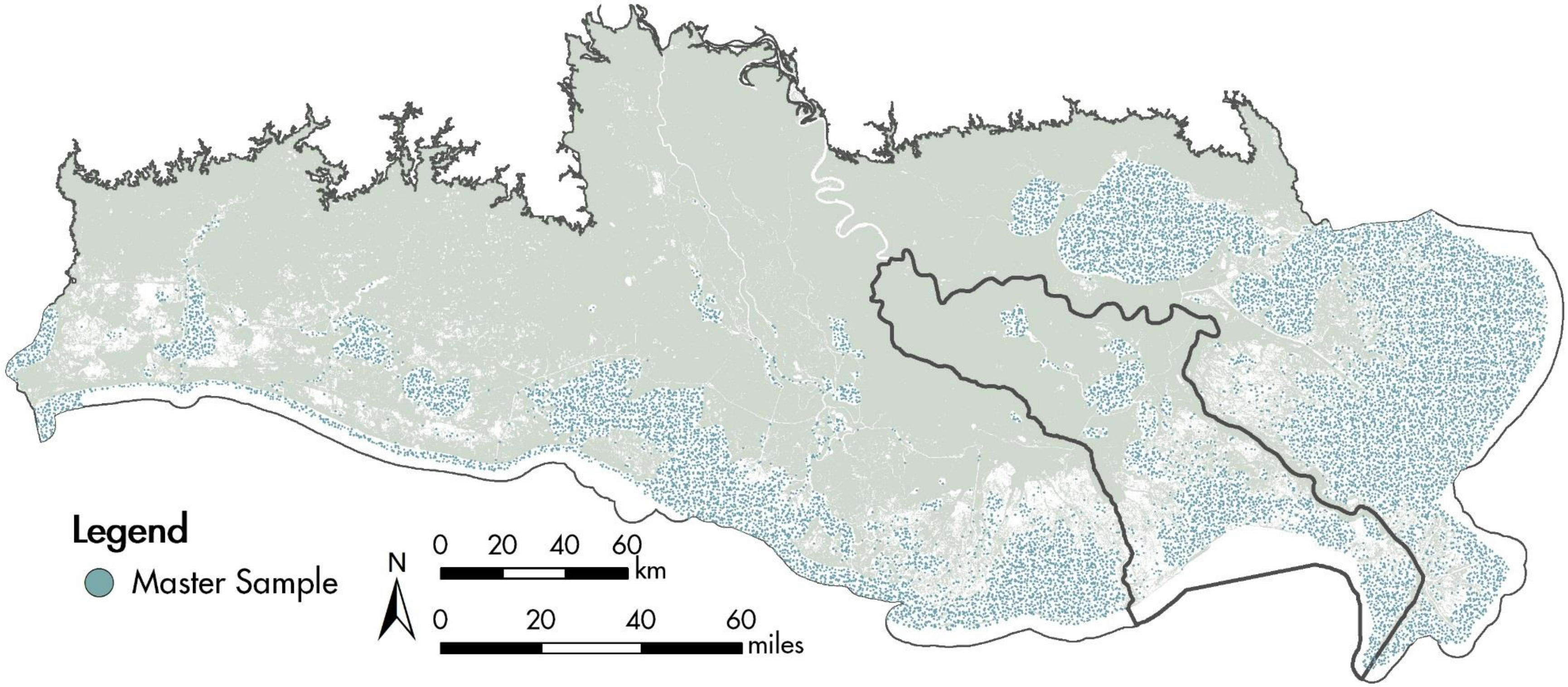

Figure 10. Master sample generated on the coastwide scale for water-based monitoring efforts.

Human System Sampling Design

METHODS FOR DETERMINING FUNCTIONAL COMMUNITIES

The human system monitoring plan is a framework to assess socioeconomic change and trends across coastal Louisiana and within specific hydrologic basins using a broad suite of social and economic variables derived from both primary and secondary data sources. Monitoring of the human system first requires defining the appropriate units of analysis, which can then be aggregated across a larger spatial extent to delineate functional community areas (e.g. local communities and parishes, and larger regional groupings such as economic or ecological impact areas). Within these functional communities, primary data collection can take place and/or secondary indicator data can be used to conduct statistical analyses of demographic change. To operationalize this, it is necessary to first define specific functional communities and then establish a viable method to delineate boundaries for the functional communities. The U.S. Forest Service noted the following challenges to establishing this type of natural system-based socioeconomic monitoring plan, most of which revolve around determining and defining the appropriate unit of analysis and delineating the spatial extent of the study communities:

- Determining an appropriate unit of analysis for monitoring;
- Defining and delineating "community" as a unit of analysis;
- Selecting sample communities and generalizing from the sample;
- Identifying relevant indicators for which community-scale data are available;
- Investing time and money for primary data collection; and
- Distinguishing the effects of management policy on communities from the effects of other social, economic, and ecological processes (Charnley & Stuart, 2006).

These functional community boundaries can be adapted to incorporate a number of specific units of analysis, such as census block groups and ZIP codes, for the SWAMP human system monitoring plan. Census and ACS data can be almost infinitely scaled (Phillips, 2003), allowing researchers to aggregate any number of units of analysis (e.g. census blocks and block groups) to a larger spatial extent or functional community area (e.g. local communities and parishes, and larger regional groupings such as economic or ecological impact areas). The same variables and objectives often can, and should, be applied to each aggregated unit of analysis at the coastwide and basin scale.

Four different geopolitical units of analysis can be adapted and used to address the objectives of the coastwide human system monitoring plan: parishes, census block groups, ZIP code areas, and census designated places (Figure 11). Block groups are the smallest inclusive unit of analysis for which all summary statistics are reported. Block group delineations do not, however, reflect meaningful community boundaries. For this reason, the coastwide human system monitoring plan aggregates existing block groups within larger and more socially meaningful functional community boundaries that can be analyzed to address many of the specific fundamental objectives of the plan (Doak & Kusel, 1996). General conceptualizations of community range from local geographic communities where people live, work, and interact in a common geographical area, such as a town or neighborhood, to communities of interest and occupational communities, where people are united by shared identification and interactions within an occupation. For this research, a number of functional communities will be derived that address the various socioeconomic monitoring objectives of the human system monitoring plan, using both established geographic population centers and occupational community groupings. The coastwide human system monitoring plan identifies changes within each established population center in the study area as well as within targeted natural resource dependent occupational communities. This also includes monitoring of the amount of natural resources extracted from the environment, specifically through fisheries and agriculture. Other functional community groupings monitored by the plan include populations sharing similar geographic vulnerabilities and environmental protection levels.

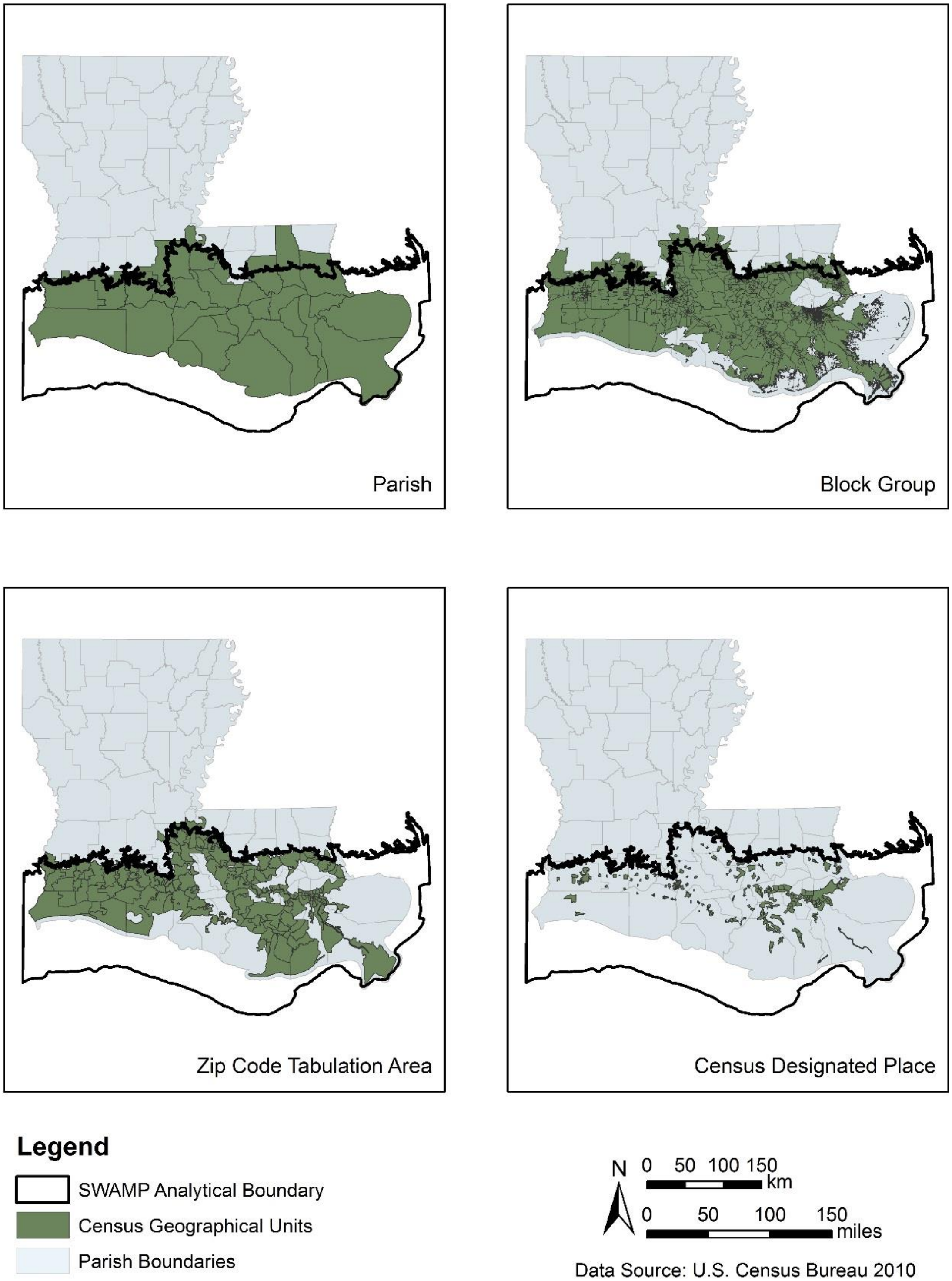

Figure 11. U.S. Census Bureau geographical units in coastal Louisiana

Geographic Communities

In general, parishes and towns do not coincide with communities for many types of social and environmental status and trend assessments. Moreover, analyses of those factors driving any observed socioeconomic changes often require a specificity and detail largely unobtainable with parish level data, particularly with large and heterogeneous parishes (Kusel, 2001). While parish or regional data may be too broad to effectively analyze socioeconomic change, administratively derived community boundaries may be too narrow. Functional community areas are typically not confined by political, administrative, or statistical boundaries (Parisi et al., 2003). Residents of small towns, for example, may commute to work or travel regularly to other towns for shopping, entertainment, socializing, schools, churches, public meetings, and other social functions (Blahna et al., 2003). In addition, many residents reside outside administratively established community boundaries, yet rely extensively on the services and organizational infrastructure of that community.

To understand socioeconomic change in coastal communities, analysis must focus on and isolate functional communities. One objective of the coastwide human system monitoring plan is to identify changes in population, housing, and economic characteristics within local population centers (Table 6 through Table 11). Population-based functional communities are based on proximity to compact central areas such as cities, towns, villages, and other concentrated population centers where residents are able to meet their daily needs (Taquino et al., 2002). The community boundary should include outlying population areas proximate to these places. Sociologists have often identified community areas by aggregating census units within a 5-10-mile radius around the geographic center of an established place, such as a city, town, village, or other census designated place. Other research suggests that distance itself has little socioeconomic value and that the geographical extent of analysis should be delineated based on travel time instead. Such a measure more accurately delineates the community areas where people are most likely to interact to meet daily needs (Parisi et al., 2003). This is particularly relevant in coastal Louisiana where residents are generally crowded together on narrow strips of high ground surrounded by broad expanses of uninhabited wetlands and large open water areas. Functional community boundaries in coastal Louisiana are best approximated by aggregating those census block groups around a U.S. Census Bureau designated compact central area based upon travel time. Adjusting for road variability, the traditional 5- to 10-mile aggregation distance translates into an average daily travel time of 10 minutes (Parisi et al., 2003; Taquino et al., 2002).

For this analysis, the aggregation procedure began by identifying both incorporated and unincorporated places within the SWAMP study area. Incorporated places are legally recognized political units with both social and government structure based upon their population size (Taquino et al., 2002). Unincorporated places are identified by the U.S. Census bureau as census designated places (CDPs).CDPs are settled concentrations of population that are identifiable by name, but are not legally incorporated under the laws of the state in which they are located. The Census Bureau draws CDP boundaries in coordination with local officials and these generally coincide with the boundary of an adjacent incorporated place.

The incorporated and unincorporated place boundaries were the basis for the travel time-based functional community boundaries. The Network Analyst function in the GIS software package ArcGIS v10.2 effectively models travel time-based distances using transportation network data and the established place boundaries (Wang, 2006). A 10-minute drive time buffer with its origin at the population weighted centroid of the community was derived (Figure 12).

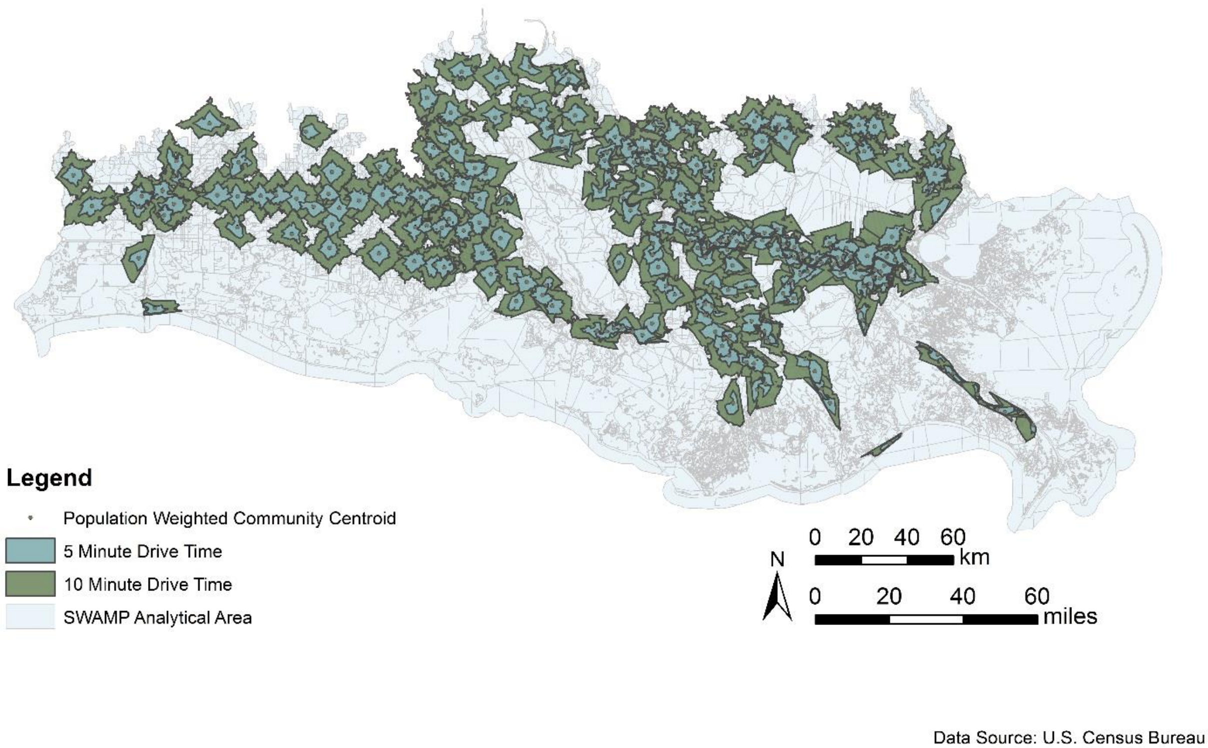

Figure 12. Community boundaries based on 10 minutes' travel time around central places

Once the community boundary was delimited, the census block groups contained within that boundary were aggregated to allow for further analysis of socio-economic change within the functional community. In many rural census block groups, a large proportion of the total area consists of unpopulated wetlands. Therefore, the aggregation of census block groups should be based on the population-weighted centroid rather than the geographic centroid of the block group. All census block groups whose population-weighted centroid fell within the functional community boundary were included as part of the 10-minute community. Census block groups falling outside of the 10-minute road network boundary were excluded from the geographic community areas.

Occupational Communities

Changing environmental conditions and policy actions taken to adapt to these conditions have the potential to impact certain communities more than others. In particular, populations that participate in - and depend upon - renewable natural resource extraction activities could be impacted dramatically by changes to the ecosystem (Laska et al., 2005). To effectively monitor socioeconomic change in coastal communities, it is vital to identify those elements that make these communities important, such as the significance of the area for supporting both the population and natural resources such as forests, fisheries, and tourism (Malone & La Rovere, 2005). Changes in the socioeconomic conditions of natural resource-dependent communities are essential components of any coastwide human system monitoring plan. County (parish) data tend to present too broad and diverse an area to adequately assess the levels of socioeconomic change within most natural resource-dependent communities. The larger the aggregation, the less likely the variables - whether they are median income, poverty, or unemployment - will have a relation to community resource activities (Kusel, 2001). As part of coastwide human system monitoring plan, occupational communities are delineated using geostatistical methods to identify significant clusters of coastal residents who self-identify in the U.S. Census as being employed in natural resources extractive industries. Many of the same variables used to measure change in local population centers (Table 6 through Table 11) will be used within the natural resource dependent occupational communities. Other targeted variables specifically related to ecosystem dependence (Table 9) are also monitored within these occupational communities.

Within the U.S. Census and the ACS, there is an important distinction between one's occupational classification and one's employment industry classification. According to the Bureau of Labor Statistics, the occupational classification reflects the type of job or work that the person does, while the industry classification reflects the business activity of their employer or company. For example, a clerical worker employed by a fishery would be classified as having an "Office and Administrative Support" occupation within an "Agriculture, Forestry, Fishing, and Hunting" industry. To capture the full impact of natural resource-related industries on a community, enhanced occupational boundaries should be determined using industry data reported by the census.

To establish these functional occupational community boundaries, it is necessary to locate clusters of census block groups with significantly high levels of natural resource employment relative to the surrounding block groups. The Spatial Statistics Tools in ArcGIS can perform a number of global and local tests for spatial autocorrelation. These tests determine the degree of clustering in the study area and determine where this clustering occurs and where statistical outliers are located. The Global Moran's I tool computes a single summary value (a z-score), which is used to describe the degree of spatial concentration or dispersion for the natural resource extraction employment within the study area. Comparing this summary value year by year indicates whether or not natural resource extraction is becoming more dispersed or more concentrated, overall (Scott & Janikas, 2010). Hot Spot Analysis (Getis-Ord Gi*) and Cluster and Outlier Analysis (Anselin Local Morans I) tools were used to determine regional clusters of high natural resource employment. The Getis-Ord Gi* statistic was used to identify local hotspots and clusters of natural resource-dependent census block groups (Getis & Ord, 1992; Ord & Getis, 1995). The Gi* statistic determines the spatial dependence between an observation and neighboring observations within a user-specified distance threshold. Gi* values are given as standard normal variances with an associated probability from the z-score distribution (Kracalik et al., 2012). Occupational community boundaries were established using the all census block groups with a Getis-Ord Gi* statistic equivalent to the 95% confidence interval (Figure 13).

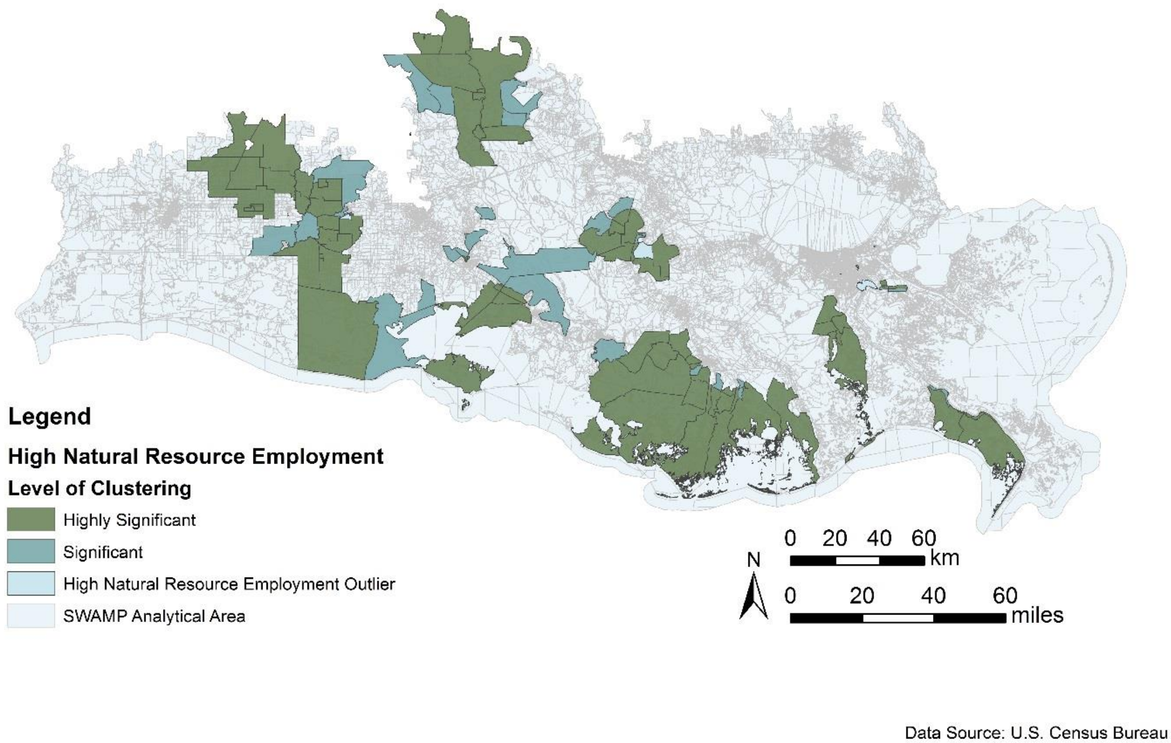

Figure 13. Community boundaries based on significant clustering of census block groups with high natural resource-based employment

Tests to detect the presence and location of spatial outliers, i.e., census block groups with high levels of natural resource employment not located within the derived occupational community boundaries, were also conducted. The presence of such outliers may be an indication of spatial instability at that location (Anselin, 1995). The Anselin Local Moran's I statistic was used to test for the presence of spatial outliers. As with the Getis-Ord Gi* statistic, the Local Moran's I values are given as standard normal variances. A low negative z-score (e.g., < -1.96) for a feature indicates a statistically significant (0.05 level) spatial outlier.

Physical Risk and Vulnerable Communities

Flood Zones

To effectively gauge the vulnerability of coastal populations to coastal hazards, the coastwide human system monitoring plan must track changes in the potential exposure of communities and the critical infrastructure they depend upon to coastal inundation and flood risk (Table 10). Whereas previous community delineation methods required derivation of analysis areas, the hazards and risk reduction analysis units can be derived from specific landscape features and hazard zones. The Federal Emergency Management Agency (FEMA), for example, uses a series of flood insurance rate maps (FIRMs) to determine whether or not a home is located in a 100-year flood zone, defined as an area with a 1% or greater chance of flooding in any given year. FEMA defines flooding as having an average inundation depth of one foot or greater. To effectively monitor the degree of exposure to flood risk in coastal Louisiana, the human system monitoring plan will estimate changes in the percentage of households located in the 100-year floodplain and FEMA v-zones (i.e., coastal areas subject to hazards associated with storm-induced waves) at the census block group level according to the most up to date FIRMs available. Any population-weighted block group centroids that fall within this special flood hazard area should be included as part of the community of analysis.

Structural and Nonstructural Protection

One objective of the coastwide human system monitoring plan is to determine how management decisions and coastal dynamics influence community risk and how resistant communities are to risk. Within coastal Louisiana, a combination of restoration, nonstructural, and targeted structural measures will provide increased flood protection for coastal communities and the strategic assets they rely upon (CPRA (Coastal Protection and Restoration Authority), 2012; Peyronnin et al., 2013). Structural projects for risk reduction include levees and floodgates. Sediment diversions and hydrologic restoration projects also utilize structural components, although these are employed primarily for coastal restoration purposes. Nonstructural projects examined as part of SWAMP include elevation, flood proofing, retrofitting buildings with individual mitigation measures, and voluntary acquisition of residential properties in areas where projected flood depths make elevation or floodproofing infeasible.

To monitor the protection of residential properties in coastal Louisiana, the coastwide plan will estimate changes in the percentage of households within structural protection zones, defined analytically as areas within levee polders and areas currently receiving 100- or 500-year protection according to CPRA (Table 10). Any population-weighted block group centroids that fall within these areas should be included as part of this functional community. In order to monitor change within the most physically vulnerable locations, SWAMP will also identify those census block groups located atop natural levees and those located in low-lying areas off of the natural levees. The plan will also monitor the total number of residential structures receiving nonstructural protection. These raw counts will be aggregated to the census block group level to allow for an effective comparison with other socioeconomic variables such as property values, levels of home ownership, and residential occupancy rates.

Another objective of the coastwide human system monitoring plan is to determine the number of essential facilities and critical infrastructure currently protected by structural and nonstructural projects (Table 11). Louisiana has a complex system of built infrastructure, as well as public utilities, in immediate proximity to the coast and highly vulnerable to the threat of tropical weather events (Laska et al., 2005).The protection of critical infrastructure is vital to the continued viability of coastal communities. The monitoring plan will utilize data obtained from the FEMA Hazus Multi-Hazard (MH) model to obtain residential and nonresidential structure counts at the census block level. FEMA Hazus- MH also provides locational data for critical infrastructure, which should also be aggregated to the census block level. All census blocks with their geographic centroid within the structural protection zones will be aggregated to develop this functional community boundary.

Natural Resource Extraction Study Areas

To effectively monitor change in coastal communities, SWAMP will identify changes in natural resource extraction, specifically fisheries landings and agricultural yields. For this analysis, the delimited locations where these resources are extracted are treated as functional communities because they are a function of human activities, though directly influenced by natural system factors. Unlike the functional communities derived previously (geographic, occupational, and physically vulnerable), however, the measures of change in natural resource extraction sites will be based purely on resource yield.

Fisheries Landings

Annual trip ticket data will be analyzed at both the coastwide and basin scales as part of the coastwide plan. Since 1999, commercial fishermen and licensed commercial seafood dealers have been required to report the volume and dockside value of commercial seafood landed in Louisiana as part of the Louisiana trip ticket program. Commercial seafood dealers and commercial fishermen must complete a record of the quantity and dockside value of the seafood exchanged at the "point of first sale" (Bharadwaj et al., 2012; Caffey et al., 2006). This individual trip information provides area-specific catch data that will improve the accuracy of stock assessments. Analyzed over time, individual trip information will also provide fishery managers with information on the impact of environmental changes and catastrophic events on the fishery (Louisiana Department of Wildlife and Fisheries, 2010). Variables included in the trip ticket report of each transaction include the identification of the species, the volume landed, the amount paid to the commercial fisherman, and the area fished. The ecosystem dependency portion of the coastwide human system monitoring plan focuses on monitoring the impacts of geophysical processes on the fisheries themselves (Table 9). Therefore, the coastwide plan will focus primarily on the areas fished as opposed to the ports where the fish were landed. For the coastwide analysis, basin-level trip ticket data will be utilized while subbasin data will be required to conduct the basin-level analyses.

Agricultural Counts

Monitoring changes in agricultural yield (Table 9) is problematic, given the geographic scale of the data available. Data are most widely available at the parish level, which, while useful for a coastwide assessment of agricultural shifts, does not lend itself to basin or subbasin level analyses. The LSU AgCenter's Department of Agricultural Economics and Agribusiness publishes an annual report that provides acreage, yield, and price data by parish for every commercially grown commodity in the state. This report, *Louisiana Summary: Agriculture and Natural Resources,* is a cooperative effort between parish and state Sea Grant Extension personnel. Because these data are published annually, they are effective in conducting agricultural damage assessments (Guidry & Pruitt, 2012). As with the LSU AgCenter data, the U.S. Department of Agriculture National Agricultural Statistics Service (NASS) provides its Census of Agriculture data at the parish level. These data are on a 5-year release schedule, although NASS began providing farm counts at the ZIP code level with its 5-year Census release beginning in 2007. While these data are not as extensive as those released by the LSU AgCenter, or even the parish-level Census of Agriculture, they can be used to assess changes in the total number and scale of operations at a subparish level.

One final means of monitoring change in agricultural land use patterns in coastal Louisiana involves using satellite imagery to identify shifts in landcover type. Since 1997, NASS has produced an annual crop-specific land cover product called the Cropland Data Layer (CDL). The CDL depicts more than 100 unique crop categories across the United States, and is delivered as a 30-m resolution raster image. The CDL is released annually and is delivered shortly after the growing season concludes (Mueller & Harris, 2013). While the CDL does not measure agricultural yield, it does provide a consistent method of monitoring the acreage of land dedicated to specific crops. Raster math and data analysis techniques within ArcGIS can be used to calculate total cropland acreages within any specified unit of analysis or functional community.

METHODS OF PRIMARY DATA COLLECTION

Study design and population sampling using community-based longitudinal surveying are two of the most important tools to monitor change in human communities. A survey is a research method for collecting information from a selected group of people using standardized questionnaires or interviews. Data from well-designed questionnaires - addressed to limited objectives - always enhance the understanding of community response to social change, whether planned or unintended (Burdge, 1994). A survey of individuals and households would allow researchers to operationalize hypotheses and customize data gathering at the individual level (Jackson et al., 2004). The survey process typically includes:

- determining delivery methods;
- selecting a sample;
- developing a questionnaire;
- pretesting the questionnaire;
- checking the reliability and validity of the questionnaire;
- administering the survey; and
- analyzing results (Virginia Commonwealth University, 2014).

Environmental economists have long used surveys to gather information about people's preferences, particularly when measuring nonmarket valuation of ecosystem goods and services, where techniques such as the travel cost method, contingent valuation, and choice modeling invariably employ some form of survey instrument (Fleming & Bowden, 2009). For this phase of the human system monitoring plan, community surveys will identify the cultural, traditional, and recreational utilization of ecosystem goods and services within Louisiana's coastal communities (Table 9). The following sections propose a mode of data collection and a methodology to determine sampling locations and to estimate sample sizes. The questionnaire itself would be typically designed, validated, and administered by survey consultants or subject matter experts.

For the ecosystem dependence portion of the human system monitoring plan, a mixed-mode survey methodology is recommended to reduce levels of nonresponse error. An analytical approach was taken to determine the sampling locations and estimate sample sizes for the human system's monitoring variables. Determinations of sampling locations follow similar procedures established previously to monitor change using secondary data sources, aggregating census geographies to correspond with certain functional communities. Sample size estimations are determined based upon a number of factors, both demographic and statistical.

Survey Methods

The use of community surveys ultimately culminates in the collection of primary data. Three general modes of data collection have traditionally been utilized in administering community surveys: face-to-face interviews, telephone interviews, and self-administered questionnaires (Visser et al., 2000). Each method has advantages and disadvantages relative to the other method. Researchers must consider several factors, including cost, characteristics of the population, and the desired response rate. Generally, face-to-face interviews are more expensive than telephone interviews, which are, in turn, usually more expensive than self-administered mail or internet questionnaire surveys of comparable size (Visser et al., 2000).

Land line-based telephone surveys have traditionally provided the most cost-efficient means of surveying individuals and households. During the past decade, however, participation in telephone surveys has declined dramatically due to factors such as the increased use of cellular telephones, growth of call screening technologies, and heightened privacy concerns resulting from increased telemarketing calls (Hu et al., 2011). Mail coverage remains a concern for general public surveys due to the relatively low response rates. It should be noted, however, that mail survey response rates have remained steady despite the large decline experienced for the telephone-based surveys (Dillman et al., 2009). More recently, self-administered email and web-based surveys have emerged as viable options. The comparatively low cost of web-based surveys is advantageous in that it enables large sample sizes and decreased sampling variance (Fleming & Bowden, 2009). The primary data collection portion of the human system monitoring plan uses a mixed-mode survey methodology combining mail and web-based self-administered questionnaires. The main justification for using multiple modes is to increase response rates in hopes of reducing the potential for nonresponse error.

While the actual design of the questionnaire should be determined by a qualified survey consultant, it should seek a mix of discussion style open-ended questions and more rigid closed questions (Kitchin & Tate, 2013). Open-ended questions are generally more descriptive in nature and, as a result, are more difficult to analyze quantitatively, often requiring some form of content analysis. Closed-ended questions, on the other hand, generate data that can be analyzed quantitatively. By combining descriptive and analytical answers, the questionnaire design will generate both factual and subjective data relating to people and their circumstances, behavior, attitudes, opinions, and beliefs (Kitchin & Tate, 2013).

Determining Sampling Locations

To address the primary data collection needs of the human system monitoring plan, it is necessary to determine the appropriate unit of analysis to sample. The community boundaries developed earlier in this report can be adapted for use in the survey analysis. As with the secondary data analyses, the appropriate units of analysis are variable and their selection is often times driven by specific policy needs. The basic sampling units to identify changes in ecosystem dependency in coastal Louisiana are those occupational communities with significant levels of natural resource employment. The ZIP code should be used as the primary unit of analysis for this portion of the research to allow survey consultants to more effectively target these communities for mail-based questionnaires.

Derivation of ZIP code analysis areas in SWAMP proceeded in two steps. First, cluster analysis was run on the U.S. Census Bureau's ZIP code boundaries, known as Zip Code Tabulation Areas (ZCTAs)[5]. The association of the ZCTA with the census blocks allows for detailed demographic analyses of ZIP code-level data. For SWAMP, cluster analysis was run using natural resource-based employment as the clustering factor, giving a ZIP code-based community boundary. After establishing these ZIP Code cluster boundaries, to assure that all communities with high levels of natural resource employment are sampled in the survey analysis, the boundaries were extended to incorporate any population-weighted

[5] It should be noted that, while similar, there are differences between ZCTA and U.S. Postal Service (USPS) ZIP codes. The USPS ZIP codes are based upon individual addresses and are stored as point files with no association with individual census blocks or other areal geographical features. The U.S. Census Bureau uses this address data to assign each census block to a specific ZCTA, which is a generalized approximation of the USPS Zip Code extents.

block group centroids included in the previously established occupational community boundaries. Noncontiguous census block groups will be assigned to the appropriate ZIP Code area and included in the analysis. This assures that all census block groups with high levels of natural resource employment are included in the sampling area. If policy needs dictate that specific towns or communities be sampled, the same methods can be utilized to identify ZIP code centroids within the geographic community boundaries derived earlier.

Estimating Sample Size

A survey generally aims to sample a portion of the population that is representative of the population as a whole. To calculate the minimum sample size required for accuracy in estimating proportions, the following decisions must be made:

1. decide on a reasonable estimate of key proportions (p) to be measured in the study;
2. decide on the degree of accuracy (B) that is desired in the study (e.g.0.01 or 0.05);
3. decide on the confidence level (C) you want to use. Usually 95% (which is equal to 1.96);
4. determine the size (N) of the population that the sample is supposed to represent; and
5. decide on the minimum differences you expect to find statistically significant.

This is expressed algebraically as:

$$n = \frac{(N)(p)(1-p)}{(N-1)\left(\frac{B}{C}\right)^2 + (p)(1-p)} \qquad \text{(Equation 1)}$$

Where:
n=complete sample size
N=size of population
P=proportion expected to answer a certain way (0.5 is most conservative)
B=acceptable level of sampling error (0.05 =±5%)
C=Z statistic associated with confidence interval (1.645 =90% confidence level; 1.960=95% confidence level; 2.576=99% confidence level)

To illustrate, within the Barataria Basin there are 17,077 people who reside in the 19 natural resource-dependent block groups within the occupational communities identified above. This population includes individuals residing in Plaquemines Parish (13 block groups), Jefferson Parish (five block groups), Assumption Parish (three block groups) and St. James Parish (one block group). Assuming a conservative 50/50 split in responses to each question, a sample size of 375 is needed to be 95% confident that that sample estimate is within ±5% of the true population value. The formula for this example is:

$$n = \frac{(17{,}077)(0.5)(1-0.5)}{(17{,}077-1)\left(\frac{0.05}{1.96}\right)^2 + (0.5)(1-0.5)} = 375 \qquad \text{(Equation 2)}$$

When conducting a survey, it is necessary to estimate what the expected response rate will be. The sample size estimated above is the number of completed questionnaires needed to achieve the minimum sample size needed for accuracy. It is necessary to incorporate the expected response rate when deciding how many surveys to send out.

$$Response\ Rate = \frac{Number\ of\ Usable\ Surveys\ Returned}{Number\ of\ Surveys\ Mailed - Number\ of\ Surveys\ "Not\ Deliverable"} \qquad \text{(Equation 3)}$$

To estimate the number of surveys required to achieve the necessary sample size (n) calculated in Equation 2, the number of surveys required is calculated from:

$$Surveys\ Required = \frac{n}{[(1-U)RR]} \qquad \text{(Equation 4)}$$

Where:
n=the required sample size
U=the estimated proportion that is not deliverable
RR=the estimated response rate (proportion)

Using data from the above example, if it is determined that a sample size of 375 will allow for reasonable precision and confidence for your estimate, and it is estimated that 5% of the mail will be undeliverable and that there will be a response rate of 10%, it is estimated that 3,947 surveys will need to be mailed. The formula for this example is:

$$Surveys\ Required = \frac{375}{[(1-0.05)0.10]} = 3{,}947 \qquad \text{(Equation 5)}$$

DETECTING CHANGE IN HUMAN SYSTEM DATA

Detecting Change Using Secondary Data

After deriving functional community boundaries, the human system monitoring plan uses statistical analyses of block group level data published by the U.S. Census Bureau to measure demographic change within these functional communities. ACS is the most current population data published by the Census Bureau and the census block group is the finest geographical level at which all data are available.

There are methodological considerations that need to be made when using ACS data. Because ACS samples only 3 million addresses per year, the Census Bureau needs to combine population or housing data from multiple years to produce reliable numbers for small counties (parishes), neighborhoods, and other local areas (Census Bureau, 2008). Areas with a population of at least 20,000 will be published using three years of pooled data, while smaller areas, such as census tracts and block groups, require 60 months of pooled ACS samples (Starsinic & Tersine, 2007). Because data are pooled across years, rates of change cannot be calculated on an annual basis. In addition, overlapping multiyear periods between different 5-year ACS estimates preclude an easy comparison of these estimates. As a result, comparisons over time can only be made on 5-year ACS estimates without overlapping years (e.g., 2005-2009 and 2010-2014).

All data based on samples, such as ACS and the census long form samples, include a range of uncertainty. The Census Bureau reports the 90% confidence interval and provides margins of error (MOE) on all ACS estimates. MOE describes the precision of the estimate at a given level of confidence. The confidence level associated with MOE indicates the likelihood that the sample estimate is within a certain distance from the population value. Confidence levels of 90%, 95%, and 99% are commonly used in practice to lessen the risk associated with an incorrect inference. MOE provides a concise measure of the precision of the sample estimate in a table and is easily used to construct confidence intervals and test for statistical significance (Census Bureau, 2008). MOEs published by the Census Bureau can be adapted and used to develop a number of statistics that can be analyzed to detect change between communities and over time. An example of detecting change using ACS data is provided in Appendix III.

Detecting Change Using Primary Data

If multiple surveys are conducted using the same closed-ended questions over time, it is possible to analyze patterns in the data and detect change. To compare two estimates over time, it is necessary to determine whether any observed difference is statistically significant or due to chance. As with the ACS data, the tests for significance of change in survey data use the estimates and their corresponding standard errors. In order to derive the standard error, we must first calculate the margin of error in the sample. Using the sample size and population size of the community, a margin of error is calculated from:

$$B = C\sqrt{\frac{p(1-p)}{n} - \frac{p(1-p)}{N}} \qquad \text{(Equation 6)}$$

To illustrate using the previous example, if the completed sample size (n) is 500 and the population size (N) is 17,077, the margin of error (i.e. sampling error) at the 95% confidence interval with a 50/50 split would be 0.043 or ±4.3% of the true population value. The formula for this example is:

$$B = 1.96\sqrt{\frac{0.5(1-0.5)}{500} - \frac{0.5(1-0.5)}{17{,}077}} = 0.043 \qquad \text{(Equation 7)}$$

Once the margin of error is known, the standard error can be derived (Equation 13) and the significance of any observed change can be determined (Equation 19).

Monitoring Plan

NATURAL SYSTEM

The monitoring plan includes continuous and discrete monitoring of the natural system. In this context, continuous monitoring refers to the collection of data using an automated data recording system that is permanently deployed at a site with a constant and evenly spaced sampling interval (e.g., hourly). Data can be retrieved remotely via cellular or satellite communications (if properly equipped) or by periodically downloading the data from the internal recording system. Discrete monitoring refers to the collection of data using any instrumentation that is temporarily deployed by an observer and then removed at the end of the collection period. Sample intervals are typically longer with discrete monitoring (e.g., monthly) and require an observer to revisit the site to obtain each sample. In some cases, both continuous and discrete measurements are recommended for a given variable. Detailed methodologies and analytical results of the power analysis are provided for each variable in Appendix II. Here, a summary is provided showing site locations and sample sizes, including utilization of existing monitoring programs in Barataria Basin (Table 15). Selection of sites on a coastwide scale was beyond the scope of this report, but inferences to how many sites may be needed on a coastwide scale are provided for select variables.

Weather and Climate

Key climatic variables needed for documenting drivers of coastal change and improving planning-models' predictions include precipitation, wind, and evapotranspiration. Precipitation is a major component of the hydrologic cycle and influences the quantity of both surface water and groundwater. Excessive precipitation results in increased riverine discharge and potentially increased inundation of riparian zones and wetlands, while drought conditions can lead to anoxic soil conditions (Michener et al., 1997). Winds associated with local weather, winter cold-fronts, and tropical cyclones influence coastal water circulation patterns through increasing or decreasing water levels and resuspension and redistribution of particulates (Booth et al., 2000). Winds may also indirectly impact shorelines through wave attack which can lead to erosion and damage to vegetative communities (Tonelli et al., 2010). Because direct measurements of evapotranspiration can be difficult to collect, potential evapotranspiration is a more typically used metric and is the total amount of liquid water that could be consumed (i.e., the water demand) by regional vegetation and evaporated by solar energy. Precipitation and winds are measured continuously, while PET is estimated from measurements of solar radiation, temperature, humidity, and land cover.

It is recommended that three real-time meteorological sensors be added to Barataria Basin on either existing platforms or in conjunction with the new water quality or hydrology continuous stations described below (Figure 14). Other variables such as barometric pressure, solar radiation, and air temperature are typically packaged with these sensors without substantially adding to costs, and can be useful in ancillary investigations of ecosystem processes. Data availability and continuity of the existing datasets is currently being coordinated by CPRA to determine their long-term utility. The proposed sample size estimate also assumes radar and model derived datasets from NOAA, as previously described, will continue to be available for obtaining gridded datasets of precipitation and wind. On the coastwide scale, these gridded datasets are also critical given their large spatial coverage and can be ground-truthed using existing meteorological stations present coastwide. Any additional meteorological sensors beyond those recommended for the Barataria Basin should be considered during the planning and implementation of SWAMP for those basins.

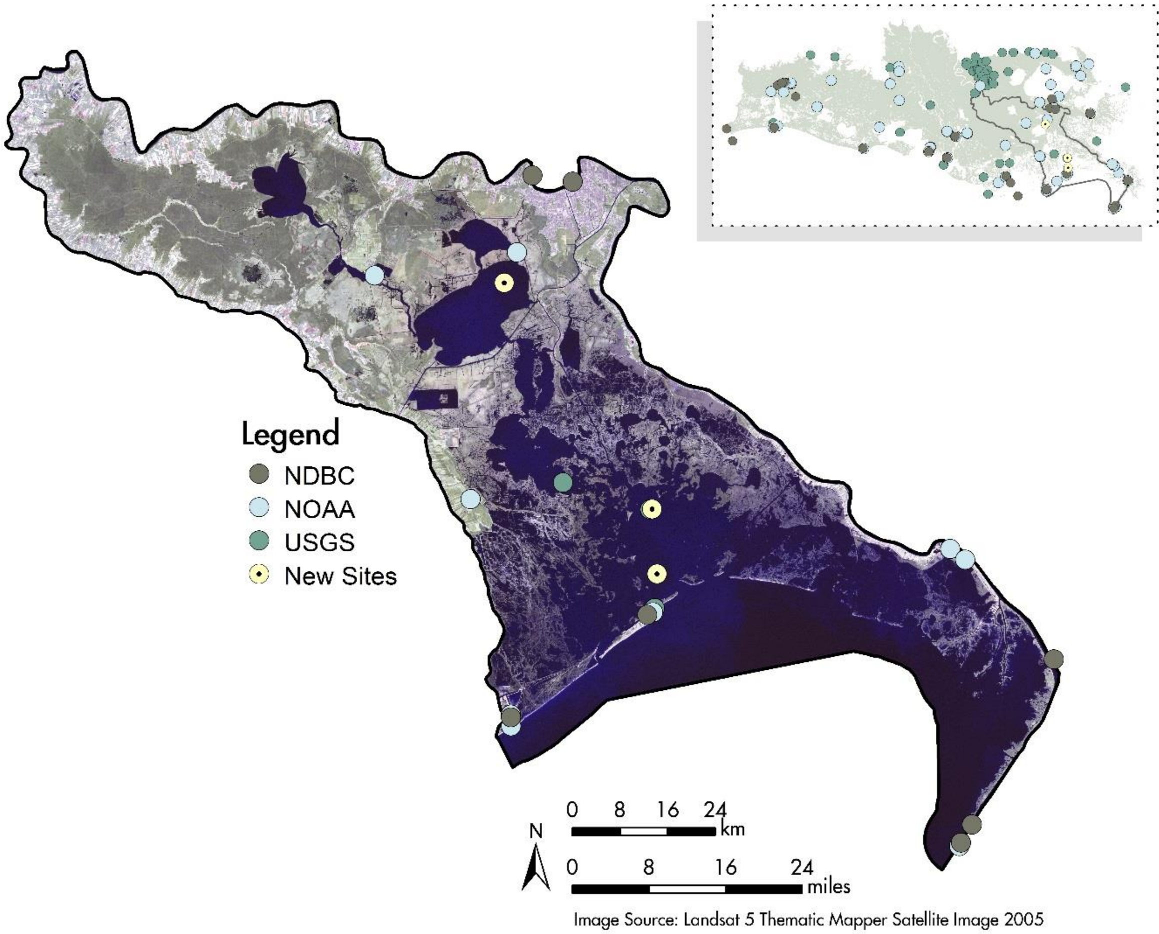

Figure 14. Existing and proposed weather and climate sites. Actual parameters collected at each existing site vary and may include wind, precipitation, or both. Proposed sites should include both.

Biotic Integrity

Nekton Community Composition and Oyster Biomass

Louisiana's coastal ecosystem supports abundant and diverse nekton communities that play an important role in the recreational and commercial fishing industries. Brown and white shrimp, blue crab, bay anchovy, and oysters are some of the key species in the region that contribute to the fishing industries. Survival and recruitment of these individuals are largely driven by estuarine water quality, primary production, and physical habitat characteristics, such as marsh edge or substrate composition (Chesney et al., 2000; Zimmerman et al., 2000), which in turn are influenced by riverine inputs into the system (Piazza & La Peyre, 2011). Future large-scale changes in the coastal environment resulting from restoration activities and natural system drivers have the potential to substantially change the community composition and food web dynamics of the system (Piazza & La Peyre, 2011; Rozas & Minello, 2011). Reliable predictions of future changes are difficult to obtain given the diversity of nekton species occurring at different life stages within the estuaries and the resulting complex trophic food web that interacts with the local environment (Chesney et al., 2000).

In order to meet the monitoring objective for nekton community composition, sampling must be effective at detecting changes in both residents and transients in order to fully capture the diversity of species and their life stages in the estuary and their response to basinwide changes. As a result, the following additions to LDWF's marine monitoring program are recommended. First, results of the power analysis indicate that the current number of gillnet stations is adequate for select species, assuming the sites are visited every month (Figure 47). Efforts to randomize selection of sites using the GRTS approach could help reduce bias in the data that may be present due to the use of non-probability based methods to select sites and ultimately improve estimates of population means and variances and change detection abilities (McDonald, 2012). Second, the 16-foot trawl sample size should be increased by 10 sites in order to improve the effectiveness in detecting trends in the penaeid shrimps (Figure 48). All sites (new and existing) should be sampled monthly, at a minimum. The GRTS approach was used for the selection of new trawl sites (Figure 15). Third, results of the analysis indicate the 50-foot seines are only effective for detecting changes that are 25-30% per year for juvenile bay anchovy and grass shrimp, and even higher changes for blue crabs, brown and white shrimp, Gulf menhaden, and sheepshead minnows (Figure 50 in Appendix II), which is likely a result of the low and variable catch efficiency of the gear (Rozas & Minello, 1997). Although there is no agreed upon universal threshold for what constitutes biologically significant change, the seines were least effective across multiple species in detecting change, potentially limiting their utility in future analyses. The use of other gears should be considered, such as drop samplers or throw traps, which would allow for estimates of biomass, a critical parameter in many fishery models such as Ecopath with Ecosim and the Comprehensive Aquatic Systems Model, and would more effectively sample the shallow shoreline and edge habitats (Rozas & Minello, 1997). A three-year pilot study with overlapping seine and drop sample data collection would enable comparison of the gear types and quantification of their relative effectiveness at capturing particular species and life stages of interest. Currently, LDWF is also testing the utility of cast nests in conjunction with seine sampling to determine their effectiveness. Fourth, for LDWF's freshwater program, results of the power analysis indicate that the existing sample size of 16 electrofishing sites in Barataria Basin is sufficient for detecting changes in largemouth bass over time. Lastly, to improve the oyster monitoring program, mapping of oyster reefs is needed to accurately characterize the substrate and determine the size of the existing oyster beds. Upon completion of the oyster survey, the GRTS master sample could be categorized into oyster versus non-oyster habitats in order to select additional sites for monitoring. Further, the frequency of oyster sampling should be increased to 2 to 4 times a year in order to track seasonal changes in oyster biomass and survival. For coastwide monitoring, results of the power analysis indicate that existing sample sizes are sufficient for detecting change at the coastwide scale.

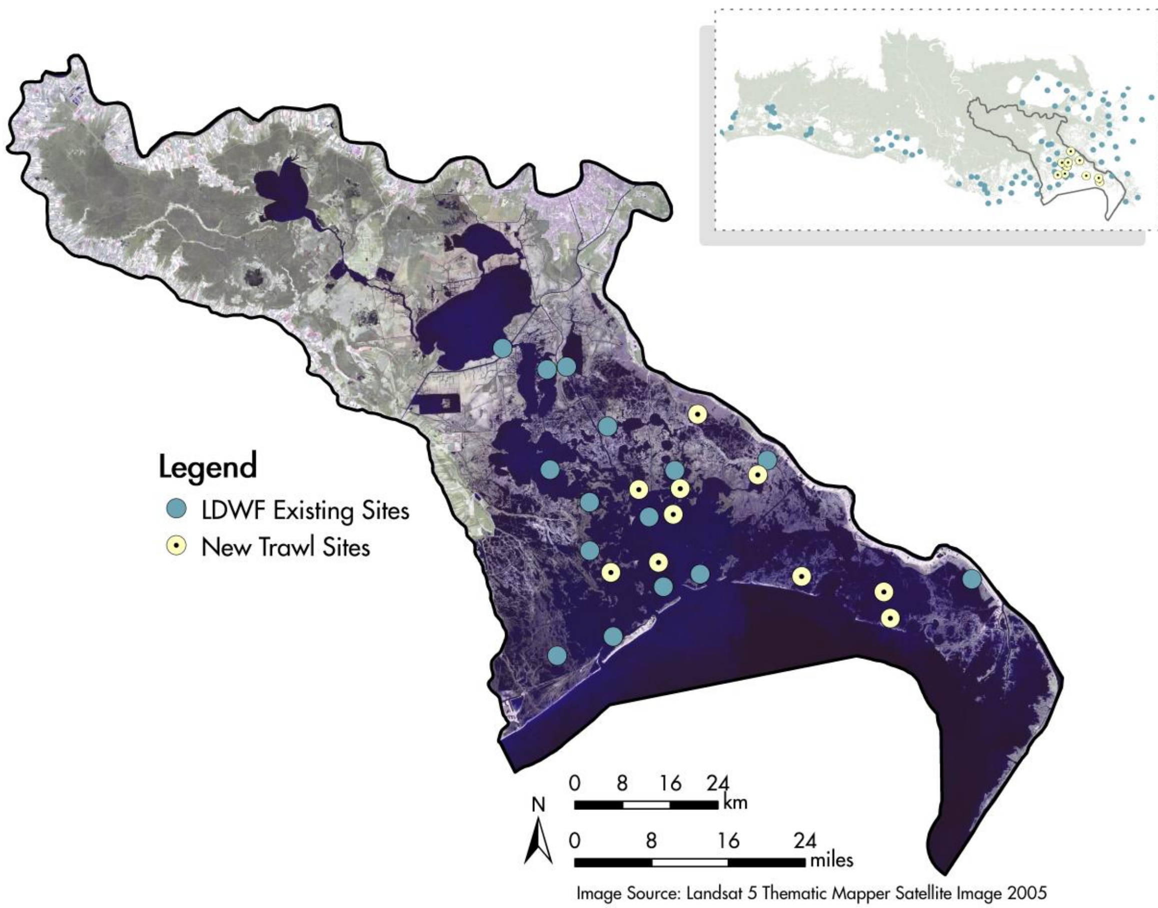

Figure 15. Existing and proposed 16-foot trawl sites for monitoring nekton community composition.

Vegetative Community Composition

Herbaceous wetlands in Louisiana occur along the interface between the marine and terrestrial environment, receiving influence on the seaward end from tides and tropical systems, and on the landward side from freshwater inflows and frontal storms (Battaglia et al., 2012). The composition of species found along the coast is a reflection of the relative influence of these forcings and the underlying geomorphology of the region. In Barataria Basin, *Spartina alterniflora, Distichlis spicata*, and *S. patens* can be found in high salinity while *Panicum hemitomon, Eleocharis spp*., and *Sagittaria lancifolia* can be found in the fresher portions of the basin (Visser et al., 1998). Coastal forested wetlands occupy elevations above that of freshwater and saltwater marshes and are typically inundated for most of the growing season (April – October), although periodic draw downs are necessary for seedling establishment (Keim et al., 2006). Given their geographical position in low-lying coastal areas, they face an array of climate-linked challenges, from rising sea levels to reduced freshwater input and drought conditions. Forested wetlands exposed to increasing saltwater intrusion as a result of rising sea levels and a subsiding coast, and a lack freshwater inflows, are at risk of tree death and forest dieback (Doyle et al., 2007). Critical to the survival of the slow-growing species that dominate forested swamps is the recruitment of new individuals, which may be hindered by the salinity and flooding stress.

Monitoring of herbaceous and forested wetlands is currently conducted through the CRMS program and includes measures of species composition, cover, and average height of the dominant species (Figure 53). A continuous salinity and water level recorder is also stationed at each site. The results of the power analysis for herbaceous wetlands indicate that 24 sites are required for detecting moderate changes (~15% annual change) in vegetative community composition on an annual basis in Barataria Basin. On the coastwide scale, 75-160 sites are required for detecting changes in vegetative community composition. There are currently 54 existing herbaceous wetland sites with the CRMS program in Barataria Basin and 390 coastwide, thus no additional stations are recommended at this time. The results of the power analysis for forested wetlands indicate that the existing sample size of 11 sites is adequate for detecting small changes (~11%) in Barataria Basin over 5-year time spans, but not annually. Given the slow growth rate of forested wetlands, changes in species composition will not be evident over annual time scales and thus the 5-year time span is likely more appropriate for monitoring forests. As a result, no additional sites are recommended at this time. Other indices that are more sensitive to changes in forest communities over annual time scales should be explored if capturing short-term changes is of interest. Further, monitoring of land area (under the Physical Terrain category) can also be used in combination with *in situ* monitoring to assess land use and land cover changes at a larger scale.

Wetlands Biomass and Soil Condition

Wetland biomass refers to both the above- and below-ground components of the plant, typically separated by live and dead materials. Biomass production contributes to soil organic matter content and elevation changes and is affected by inundation, nutrient concentrations, soil properties, and for plants with C_3 metabolisms, atmospheric CO_2 (Bazzaz, 1990; Day et al., 2013; Kirwan & Guntenspergen, 2012). Measurements of biomass over time can be used to evaluate wetland primary productivity in response to management activities and ecosystem drivers. Bulk density is used to estimate and evaluate many physical soil properties, such as porosity, water retention, buoyancy and compressibility (Ruehlmann & Körschens, 2009). Organic matter and mineral content of wetland soils are key determinants of soil development and are often used to describe the roles of organic accumulation - derived from above- and below-ground plant material - and mineral sediment deposition (Neubauer, 2008; Nyman et al., 2006). Both processes will vary with plant communities and other aspects of wetland dynamics, including soil inundation, drainage, redox potential, and other biogeochemical processes (Reddy et al., 2000).

The results of the power analysis for herbaceous wetlands indicate that 21 sites are needed for detecting moderate changes (~11% annual change) in biomass (aboveground and belowground) and soil condition (organic matter and bulk density) over five-year time periods in Barataria Basin. On the coastwide scale, 75 sites are required for detecting changes. The existing CRMS sites can be utilized for biomass collection, if collection occurs outside the 200 m x 200 m current data collection area, due to the destructive nature of biomass collection. Biomass and soil condition have already been collected at seven CRMS sites as part of a basinwide modeling effort to understand the effect of diversions on adjacent wetlands. Thus, 14 additional sites were randomly selected from the available CRMS sites to complete the sample size of 21. The 14 sites were proportionally allocated to each of the vegetation types identified by CRMS, such that 3 sites were selected from fresh, 2 sites from intermediate, 3 sites from brackish, and 6 sites from saline marshes (Figure 16).

No data were available to assess the ability to detect changes in biomass or soil condition of forested wetlands. As a result, the existing CRMS sample size of 11 sites is recommended for monitoring biomass and soil condition of forested wetlands, with an assessment of power once these initial data becomes available.

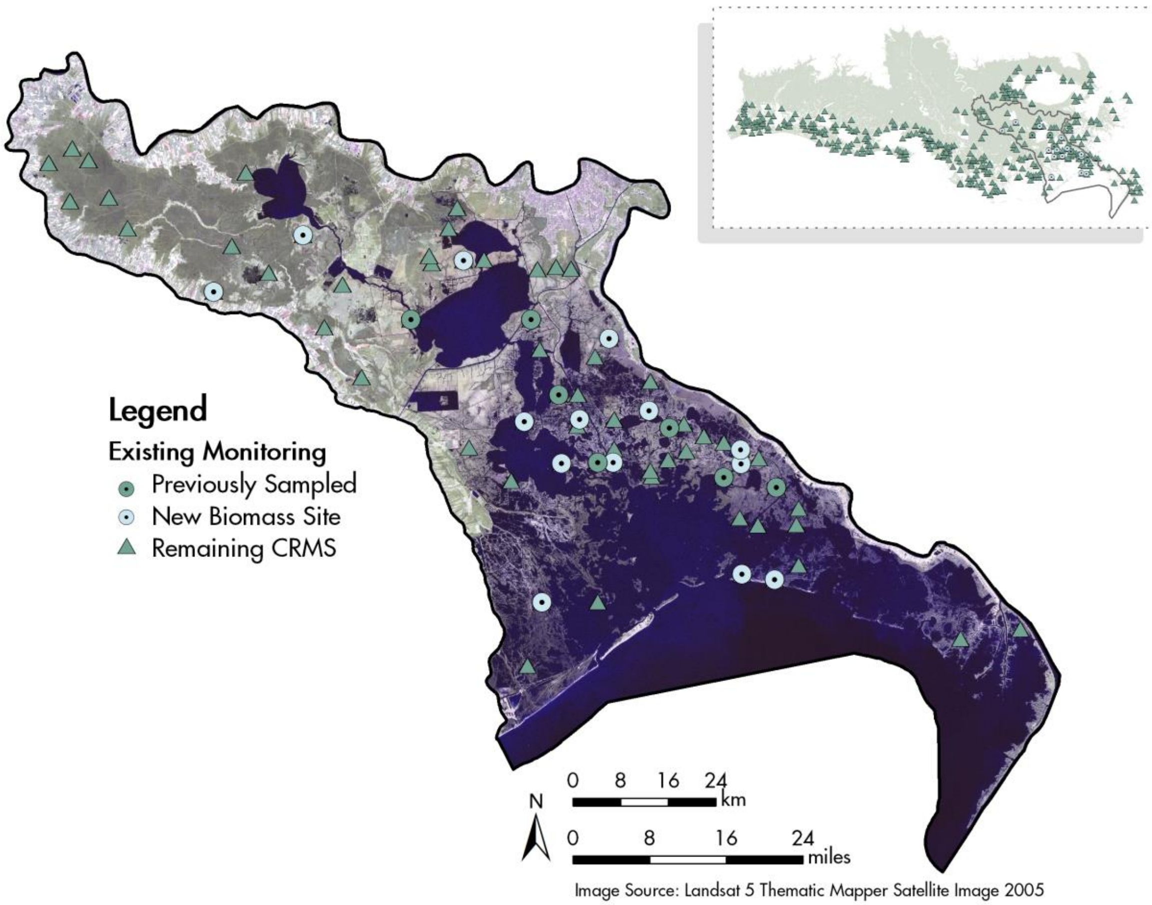

Figure 16. New sites for sampling wetland biomass and soil condition.

Water Quality

Chlorophyll *a* is an indicator of pelagic primary production by phytoplankton (i.e., total quantity of carbon produced by primary producers) and indicates the presence of phytoplankton blooms in estuarine open waters, measured as general fluorescence units, or calculated to $\mu g\ L^{-1}$. Chlorophyll fluorescence can be measured continuously *in situ* using a chlorophyll fluorescence sensor, or discretely through the collection of water samples and laboratory analysis. Phytoplankton blooms are controlled by several factors, such as nutrient loading, nutrient cycling, light availability, water residence time, and grazing by zooplankton and benthic filter feeders (Boyer et al., 2009). As organic matter - originating from excessive primary production or other inputs - sinks to the bottom and decomposes, bottom waters can become oxygen-deficient. Low DO levels can further be exacerbated by thermal and salinity stratification in the water column which prevents water column mixing, leading to low DO levels on the bottom and higher DO levels on the surface (Sklar & Browder, 1998). DO concentrations and stratification are also influenced by abiotic conditions such as water temperature, flooding level, water movement (Kaller et al., 2011), and nutrient loading (Rabalais & Turner, 2001). DO also tends to have a strong diurnal cycle, typically linked to the biotic and abiotic factors mentioned above. Given that most forms of aquatic life require a specific range of dissolved oxygen concentrations for respiration - outside of which can be harmful - DO can be used as an indicator of the overall health of the open water bodies and, when measured continuously, can be used to track hypoxic events (< 2 ppm). Measurement of estuarine water nutrient concentrations directly provides information on nutrient inputs to the system and potential effects upon biotic communities and eutrophication status (Bricker et al., 1999; Nixon, 1995). Total nitrogen and total phosphorus are measured in either mg L^{-1} or μM from a nonfiltered sample and provide a measure of the combined dissolved inorganic (NH_4^+, NO_2^-, NO_3^- or PO_4^{3-}), particulate organic (e.g., phytoplankton) and particulate inorganic (e.g., sediment) components of the water column (USEPA, 2001). While estuarine and marine systems tend to be nitrogen limited, phosphorus has an important role in the production of freshwater phytoplankton communities, which can include the plume of the Mississippi River (Anderson et al., 2002; Sylvan et al., 2006). Silicate is an essential nutrient for diatoms, and changes in concentration, measured in μM, can influence plankton and copepod communities with potentially large implications throughout the pelagic food web (Turner et al., 1998). Estuarine salinity patterns coincide with the distribution, growth, and productivity of nekton communities (Adamack et al., 2012; Minello et al., 2003; Zimmerman et al., 2000), zonation patterns of vegetation (Pennings et al., 2005), and ultimately the functions and services wetlands provide (Odum, 1988). As an essential characteristic of the coastal system, salinity is a key variable in ecological and hydrodynamic models and forecasting capabilities are limited by inadequate information of salinity patterns in the estuary (Habib et al., 2007). Lastly, turbidity is a characteristic of estuarine water quality that quantifies the clarity of the water due to suspended solids and is a measurement of transmission of light in NTU. The concentration of the total suspended solids (TSS) is quantified by collecting a water sample and processing it in the laboratory to yield mineral: organic content and grain size information as a volumetric measurement in mg L^{-1}. Statistical relationships can also be developed in order to use measurements in NTU as a predictor of TSS concentrations, if the relationships are based on measurements collected in the same place and time. Turbidity is influenced by phytoplankton blooms as well as riverine discharge and wind events which transport or resuspend particulates and affect water residence time (Allison et al., 2013; Cloern, 1987; Lane et al., 2007). Turbidity indicates the ability for growth and survival of pelagic and benthic organisms, such as fish, shellfish, and seagrasses. TSS (in mg L^{-1}) is a critical input variable for calibrating and validating sediment transport in the state's planning models. As a result, both measures are needed as part of a monitoring program.

The results of the power analysis indicate 22 discrete sites would be adequate to detect small to moderate changes in mean annual chlorophyll *a*, DO, nutrients, salinity, turbidity, and TSS concentrations from one year to the next in the Barataria Basin. The sample size is also sufficient for detecting larger changes (25-40%) on a smaller scale (subbasin) in the Barataria Basin. Six of those 22 discrete sites should also implement continuous monitoring stations for chlorophyll fluorescence, DO, salinity, and TSS to capture short-term changes within the basin and draw inference from the discrete measurements. These short-term changes will be useful for documenting the duration of phytoplankton blooms and hypoxic events and for developing statistical relationships between turbidity and TSS. Once an adequate time series of continuous data is available (≥ 3 years), a power analysis could be run to determine whether the sample size is adequate.

Three active USGS platforms that collect salinity and one inactive platform can be leveraged for installing continuous sensors of the variables listed above and also used for discrete sampling. Thus, 18 new sites are necessary to meet the recommended sample size of 22, two of which will also be designated as continuous sites (Figure 17). The 18 additional sites were selected using the GRTS approach described in the "Natural System Sampling Design" (see Figure 10 for master sample) and thus overlap with other water-based monitoring sites that utilized the master sample (e.g., nekton community composition). The two sites selected for continuous monitoring are located in the southern portion of the basin to maximize spatial coverage and capture the marine influence. An additional continuous station beyond the 22 recommended has also been proposed by CPRA in order to monitor water quality in the vicinity of oyster leases (Figure 17).

As previously mentioned, there are also 64 CRMS sites within smaller waterbodies and canals. This sample size was deemed sufficient for monitoring these waterbody types. Further, LDEQ also collects some of the water quality parameters on a less frequent basis and does not always sample the entire basin within the same year. As a result, years in which LDEQ does monitor in the Barataria Basin will result in an increased sample size and added benefit to the dataset.

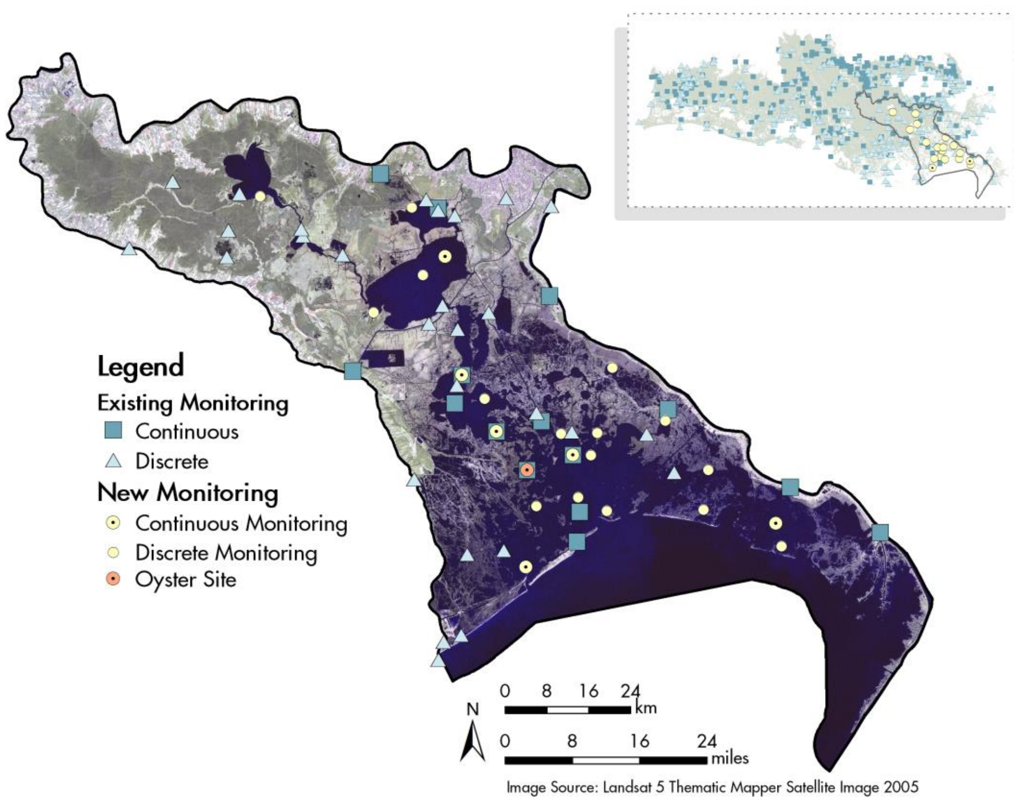

Figure 17. Existing and new locations for continuous and discrete monitoring of water quality variables.

Hydrology

Water Levels

Water level refers to the height of the water surface relative to a common datum (e.g., mean sea level, NAVD88, etc.). Short-term fluctuations in water level occur as a function of tides and weather patterns including cold fronts and tropical events, while long-term climate change contributes to increases in sea level. Astronomical tidal ranges in coastal Louisiana are relatively small (~0.3 m), but strong southerly winds can force water into estuaries and wetlands while northerly winds push water out, causing water levels to fluctuate up to a meter (Inoue et al., 2008; Kemp et al., 1980). Flooding of the marsh surface can result in the accumulation of sediments and organic matter which promotes below- and aboveground biomass production and ultimately results in vertical accretion of the marsh surface (Cahoon et al., 2006; Turner et al., 2002). Excessive flooding, however, may negatively impact vegetation by creating anaerobic conditions, accumulating toxic compounds, and altering nutrient cycling, impacting survival, growth, and productivity (DeLaune et al., 1987; Pezeshki, 2001; Webb & Mendelssohn, 1996). Water level data are currently collected in numerous channels, lakes, bays, ponds, tidal creeks, and bayous adjacent to wetlands as part of CRMS, in select bays and lakes by the USGS, and in some tidal channels reported through the NDBC (Figure 18).

Continuous records of water level will support modeling needs as well as research efforts aimed at understanding physical and biological processes in the Barataria Basin. The existing CRMS network is sufficient for characterizing water levels adjacent to wetlands, while the open-water system should be expanded. A total of 15 to 22 permanent stations would be sufficient to provide adequate spatial coverage throughout the basin. This number corresponds to the sample size required for detecting salinity changes, as discussed in the Water Quality section. At this time, six additional water level recorders are recommended for the Barataria Basin in addition to the nine stations operated by USGS (Figure 18). Four sites overlap other water-based monitoring sites proposed in this plan (i.e., water quality and fisheries) and two were manually selected in order to order to fill spatial gaps in the central and eastern portions of Barataria Bay. Instruments should be programmed to collect data at a minimum of every hour.

Waves and Currents

Wind-generated waves in the nearshore coastal environment contribute to the resuspension and transport of bed materials and are a main causative agent for marsh edge erosion in coastal Louisiana (Booth et al., 2000; Trosclair, 2013; Watzke, 2004). Wave generation is a function of fetch, such that presence of emergent vegetation and other landforms can strongly limit the maximum wave heights (Fagherazzi & Wiberg, 2009). The expansion of open water bodies due to subsidence and erosional processes could lead to higher-energy waves in the Barataria Basin, which in turn could contribute to morphological and ecological changes in the estuary. For instance, wave-induced marsh edge erosion results in the release of significant quantities of sediment and organic matter back into the water column, potentially impacting biogeochemical cycles in estuaries and the adjacent continental shelf (Wilson & Allison, 2008). Typical nearshore wave heights in coastal Louisiana vary from 0.07 to 0.8 m, with heights up to 2 m reported during cold-fronts and tropical cyclones (Georgiou et al., 2005), although data are sparsely available. Waves are typically characterized by their height, period, and direction, which can be used to calculate additional metrics such as wave power. At the time of this report, there were no active monitoring stations collecting wave measurements in the Barataria Basin. As a result, continuous records of wave heights and directions along a transect are recommended in order to evaluate the propagation of waves into the basin. Wave instruments that also measure currents are preferred as this would also allow for deconvolving the wave versus current boundary layer effects that erode sediment from the bay floor. Wave stations within Barataria Bay would also enable examination of increases in wave power, due to increase in fetch, and the interaction between waves and marsh edge erosion. Sites were selected preferentially along a transect that extended from offshore into Barataria Bay and takes advantage of exiting platforms and instrumentation (Figure 18). There are USGS platforms adjacent to the two northern wave transects proposed and these may serve as an option for installing the waves and currents instrumentation. Two existing monitoring sites exist offshore, WAVCIS station CSI09 and Louisiana Offshore Oil Port station LOPL1, although it is unclear whether these will be maintained in the long-term. Further, additional wave sites could be implemented as part of a rapid response program to respond to extreme weather, oil spills, or other events that warrant larger spatial coverage of wave data.

Circulation patterns in coastal water bodies of Louisiana are also driven in part by currents. Inlet currents are influenced by tides and winds, among other factors, and contribute significantly to the flow and exchange of freshwater, nutrients, sediments, and organic material between the Gulf of Mexico and estuaries. Rapid relative sea level rise and erosional processes have increased Barataria Bay's tidal prism and tidal exchange, subsequently leading to an increase in the cross-sectional area of major tidal inlets (Georgiou et al., 2005). As a result, quantifying the transport of waterborne materials through these inlets is of critical importance, particularly in the modeling context. High-resolution measurements in these inlets can meet the modeling needs of establishing boundary conditions and quantifying exchange points. Further, current measurements in conjunction with wave measurements in open waterbodies will also help determine critical shear stress for remobilizing bay bottom sediments. Given that currents often change direction due to tides or seasonal flow patterns, temporally averaged values are typically needed to estimate the net movement of water and sediment.

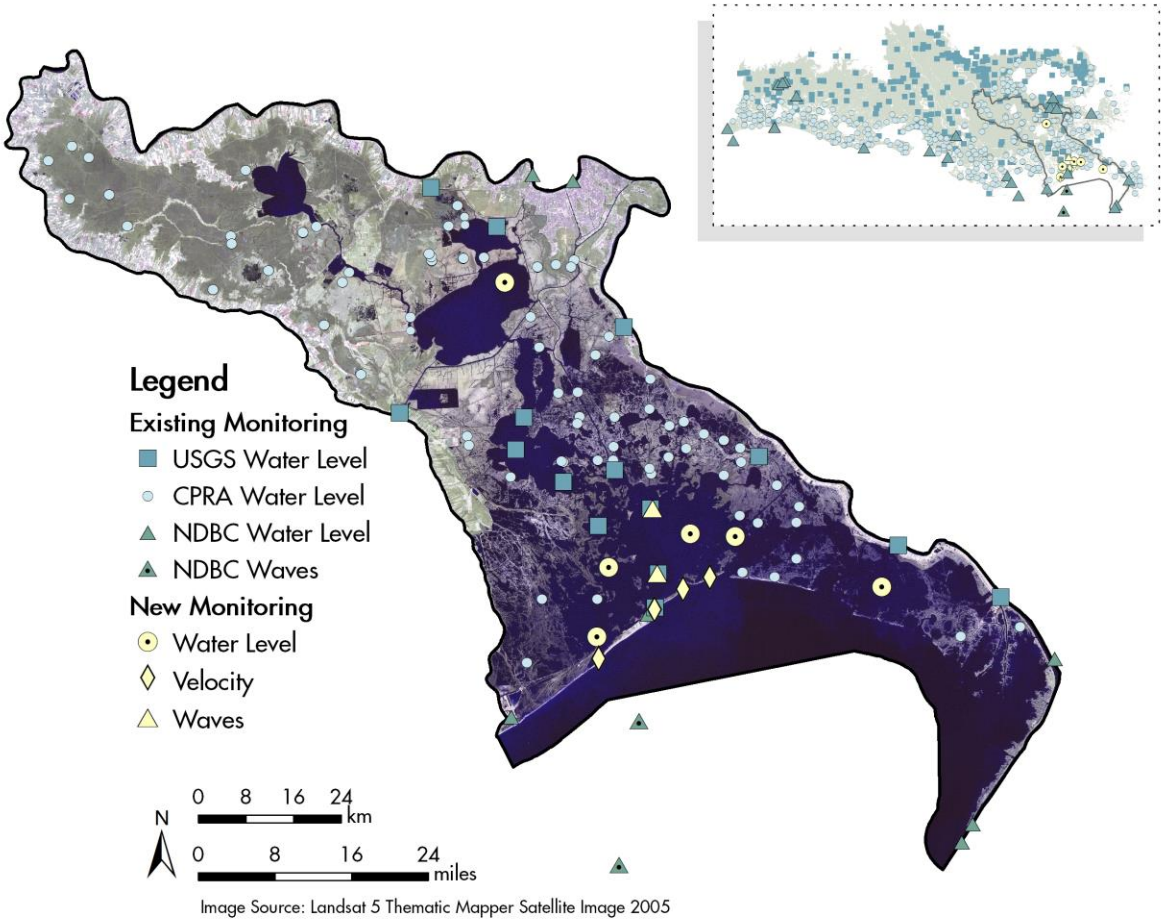

Figure 18. Existing and new site locations for waves, velocity, and water level.

Physical Terrain

Land Area

Land in the context of SWAMP refers to the area of natural landscape features (e.g., marshes, forests, barrier islands). Change in land and water area over time reflects both land gain and the conversion to open water. The natural landscape serves a multitude of functions from buffering storms, filtering nutrients, pollutants, and sediments, and supporting a variety of fauna. As a result, severe land loss threatens all aspects of the coastal ecosystem, from increasing fetch in open-water bodies to reducing habitat for ecologically important fish and wildlife.

As part of the CRMS program, satellite imagery (e.g., Landsat TM multi-spectral imagery) is acquired every three years for regional assessment of changes in land and water distribution (Folse et al., 2008). In concert with these efforts, the U.S. Geological Survey conducts landscape analysis to look at land cover changes and document land loss (Couvillion et al., 2011). Continued support to these programs is recommended in order to document land use and land cover changes over time and supplement the wetland community composition monitoring variable discussed under the biotic integrity category.

Surface Elevation

Surface elevation refers to the height of the land surface relative to a vertical datum (e.g., mean sea level, NAVD88, etc.). The relatively flat topographic setting and high subsidence rates in coastal Louisiana makes it particularly vulnerable to chronic but gradual changes in sea level, threatening large extents of coastal marshes and freshwater swamps with increased inundation. Large, short-term changes in wetland elevation can occur because of changes in tides and meteorological conditions (e.g., wind-driven events) that influence subsurface processes occurring below the root zone (Cahoon et al., 2011). Long-term trends in marsh production and ultimately soil elevation vary in response to precipitation or freshwater input (McKee et al., 2004), sediment and nutrient supply (Day et al., 2008; DeLaune & Pezeshki, 2003; Nyman et al., 1990), and sea level (Morris et al., 2002), as well as localized subsidence rates (Yuill et al., 2009). Temporal patterns of subsidence suggests subsurface fluid withdrawal may be an important driver in some regions (Kolker et al., 2011), but numerous influential processes govern regional subsidence rates including underlying tectonics, Holocene sediment compaction, sediment loading, glacial isostatic adjustment, and surface water drainage and management (Yuill et al., 2009).

Light detecting and ranging (LIDAR) data provide the best available method to obtain elevations over large spatial extents, although the vertical accuracy of these data (nonvegetated vertical accuracy of 19.6-39.2 cm at 95-percent confidence level; J. Barras personal communication, June 2015) prevents their use for monitoring small elevation changes. While some spatial maps of subsidence rates across the deltaic plain have been developed through Master Planning efforts, they are largely based on expert knowledge and could be improved to guide restoration and modeling. Significant effort has been made in recent years to quantify rates of elevation change. Three methods are presently being utilized: long-term tide gages, Continuously Operating Reference Stations (CORS), and surface elevation tables at CRMS sites. Extending measurements of elevation change to subaqueous shallow water bodies is recommended using the CORS real time stations on platforms hosting other proposed instrumentation. Future (CRMS and CORS deployments) could be installed to depths optimized by modeling and examination of existing subsidence data. The construction of two CORS stations is being planned in the Barataria Basin near Port Fourchon and Port Sulphur (Figure 19) by a NOAA-funded five-state consortium along the northern Gulf of Mexico (T. Osborn, personal communication, July 2015). Leveraging of this new network is recommended. Secondarily, a subset of the water level measuring stations should be surveyed to NOAA standards to utilize as eventual long-term tide gauge stations to supplement the one at Grand Isle, LA. This would provide a measurement of sea level change that integrates deeper subsidence as well as shallow subsidence and eustatic effects.

Bathymetry

Bathymetric data are needed to resolve long-term (5-10 years) and storm-driven morphological evolution trends, although more frequent measurements (annual) may be needed for select tidal passes in response to storm events, for example. Bathymetry information is important for setting up numerical model grids for hydrodynamic, sediment transport and land-building models. Bathymetry data are not systematically collected within estuarine open water bodies, although these data are sporadically collected in individual water bodies to meet specific project and modeling needs. Bathymetry data around barrier islands are currently collected regularly as part of the Barrier Island Comprehensive Monitoring Program (BICM).

The dynamic and detailed geomorphology of waterbody features that are complex and rapidly evolving (e.g., tidal inlets and ebb/flood tide deltas) are best represented with a 100% coverage multibeam survey. Changes in the inlet throat geometry, ebb deltas, and flood deltas are interrelated and provide an insight into the change in the whole basin, into local hydrodynamic regime, and also into littoral sediment availability and dynamics. Their potential expansion with sea level rise and/or storms, by increasing tidal prism in Barataria Bay, would also cause profound alteration to basin ecological and physical evolution. This 100% coverage bathymetry is feasible as these areas are relatively limited in spatial extent compared to the overall Barataria Basin submerged areas. It is suggested that repeat surveys at these locales punctuate the generalized survey scheme at shorter intervals. In the remaining Barataria Basin, planned survey lines were drawn and are of two categories: channel lines and bay lines (Figure 19). Regularly spaced (200-500 m) multibeam transects across open water bodies (bay lines) are suggested. Complete (100% coverage) multibeam is not feasible due to the cost of the survey time required. The channel lines follow discreet waterways that are known or appear to be navigable from aerial imagery. As such, they are thought to be significant conduits for water flow. Single-track multibeam down each canal axis is suggested given their limited lateral extent and variability in water depth. The actual 'channels' surveyed may require adjustments after encountering field conditions. In any case, the lines surveyed at the outset of the monitoring should be reoccupied in subsequent surveys to account for change. CPRA is currently working with a subcontractor to begin data collection in the fall of 2015.

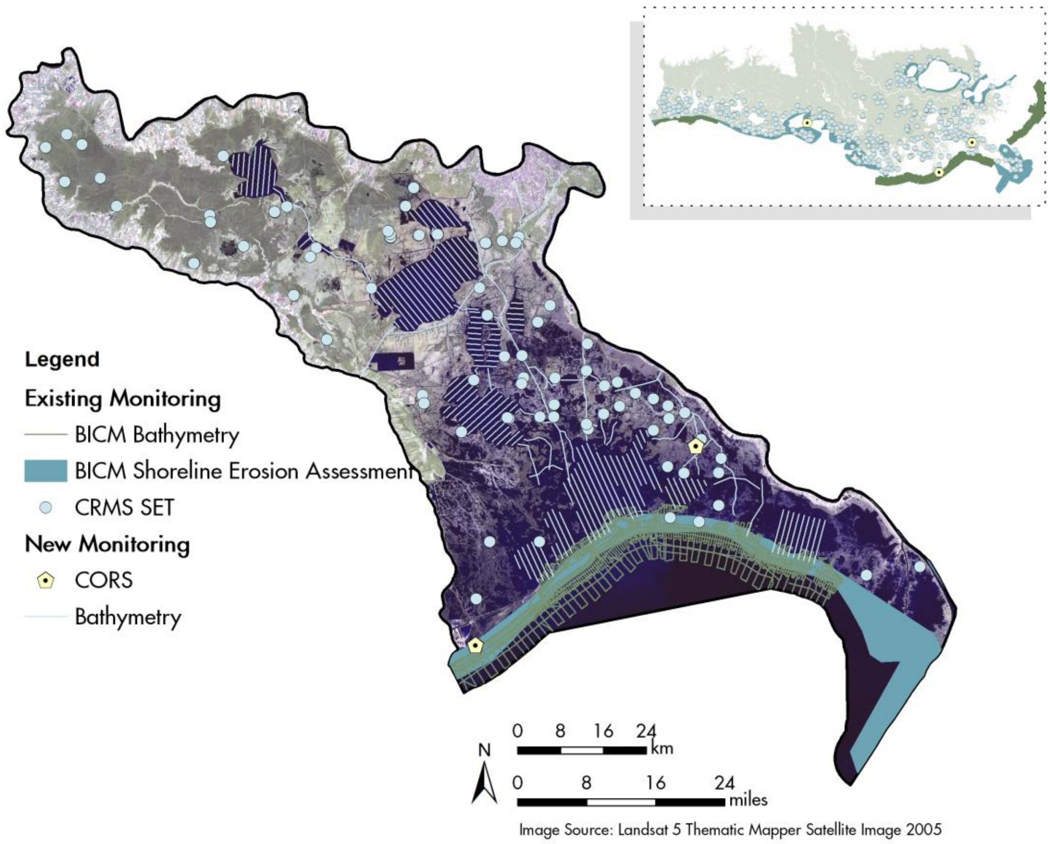

Figure 19. Site locations for measuring surface elevation and bathymetry, including existing site surveys conducted through BICM and CRMS programs. CORS site locations are approximate and under development by NOAA.

Table 15. Recommended sample sizes for the Barataria Basin natural system monitoring plan. The sample sizes are provided as a range depending on the level of change (i.e., effect size) that can be detected. The ranges are representative of the minimum and maximum for the collective set of variables within a category. See Appendix I for change detecting information on an individual variable basis and justification for the sample sizes provided.

Monitoring Category	Variable	Existing Monitoring in Barataria Basin		New Sites for Barataria Basin		Sample Size Method	Site Selection Method
		Number of Sites	Sampling Frequency	Number of Additional Sites	Sampling Frequency		
Weather and Climate	**Potential Evapo-transpiration**	Calculated, not measured directly.					
	Precipitation	16 sites plus gridded datasets from NOAA	Sub-hourly	3	Sub-hourly	Expert Knowledge	Utilize existing platforms
	Wind	14 sites plus gridded datasets from NOAA	Sub-hourly	3	Sub-hourly	Expert Knowledge	Utilize existing platforms
Biotic Integrity	**Nekton Community Composition**	25 gillnet, 15 trawl, 20 seine sites; 16 electrofishing	Variable: Weekly to quarterly	10 16-foot trawls; supplement 50-foot seines with drop samplers	Monthly	Power Analysis	GRTS
	Oyster biomass	7 square meter	Annually	15	Semi-annually to Quarterly	Expert knowledge	Should conduct oyster mapping prior to site selection
	Soil condition	CRMS: 11 forested wetlands and 54 herbaceous wetlands	Once every ten years	None	N/A	Power Analysis on herbaceous wetlands only	Utilize CRMS sites

Monitoring Category	Variable	Existing Monitoring in Barataria Basin		New Sites for Barataria Basin		Sample Size Method	Site Selection Method
		Number of Sites	Sampling Frequency	Number of Additional Sites	Sampling Frequency		
	Wetland vegetation biomass	CPRA: 7 CRMS	Once	14 plus revisit 7 existing sites	Once every five years	Power Analysis on herbaceous wetlands only	Utilize CRMS sites
	Wetland vegetation community composition	CRMS: 11 forested wetlands and 54 herbaceous wetlands	Annually	None	Annually	Power Analysis	Utilize existing CRMS sites
Water Quality	**Chlorophyll *a***	No existing stations	N/A	22	Monthly	Power Analysis	GRTS
				6	Sub-hourly	Expert knowledge	
	Dissolved oxygen (DO)	LDEQ: 8 within larger open waterbodies LDWF: 60 within the mid to lower basin	LDEQ: Monthly, every four years LDWF: Variable	22	Monthly	Power Analysis	GRTS
				6	Sub-hourly	Expert knowledge	
	Nutrient constituents	LDEQ: 8 within larger open waterbodies	Monthly, every four years	22	Monthly	Power Analysis	GRTS
	Salinity	USGS: 10 CPRA: 65	Hourly	6	Hourly	Power Analysis	GRTS
	Turbidity	LDEQ: 8 within larger open waterbodies	LDEQ: Monthly, every four	22	Monthly	Power Analysis	GRTS

Monitoring Category	Variable	Existing Monitoring in Barataria Basin		New Sites for Barataria Basin		Sample Size Method	Site Selection Method
		Number of Sites	Sampling Frequency	Number of Additional Sites	Sampling Frequency		
		LDWF: 60 within the mid to lower basin	years LDWF: Variable	6	Sub-hourly	Expert knowledge	
	Total Suspended Solids	LDEQ: 8 within larger open waterbodies LDWF: 60 within the mid to lower basin	LDEQ: Monthly, every four years LDWF: Variable	22	Monthly	Power Analysis	GRTS
Hydrology	**Current Velocity**	No existing sites	N/A	4	Hourly	Expert Knowledge	Expert knowledge
	Water level	USGS: 10 CPRA: 65	Hourly	6	Hourly	Power Analysis	GRTS; Expert knowledge
	Waves	WAVCIS: 1 Oil Platform: 1	Hourly	2	Hourly	Expert Knowledge	Utilize existing USGS platforms
Physical Terrain	**Bathymetry**	CPRA: Barrier islands (BICM)	BICM every 5-10 years	Tidal inlets; regularly spaced transects in open water bodies; single-track multibeam down canals	Variable (annual to decadal)	Expert Knowledge	Expert knowledge
	Land Area	CRMS Coastwide	3-5 years	None	N/A	Expert knowledge	None
	Surface Elevation	CPRA: 65 SETs NOAA: 2 CORS (in planning phase)	Semi-annually	None	N/A	Expert knowledge	None

HUMAN SYSTEM

The Barataria Basin human system monitoring plan uses social indicators and monitoring variables combined with targeted primary data collection to address the socioeconomic objectives of SWAMP. The variables and objectives related to the monitoring of socioeconomic change in coastal Louisiana were grouped into the following categories: population and demographics, housing and community characteristics, economy and employment, ecosystem dependency, protection of residential properties, and protection of critical infrastructure and essential services. A summary of monitoring variables, data sources, and sampling information is provided in Table 16. As previously discussed, detecting change using secondary data requires a two-part approach: the derivation of functional community boundaries, and the statistical analysis of social and economic change within these boundaries. Census block group data were aggregated into larger and more socially meaningful units to develop a number of functional community areas.

- Geographic Communities – For monitoring of population centers, the plan recommends using administrative boundaries extended using existing road networks to create a 10-minute drive time buffer around the population-weighted center of the community (Figure 20). All census block groups with their population-weighted centroid within the derived community boundary were aggregated to create the functional geographic communities.
- Occupational Communities – Clusters of census block groups with a high level of natural resource employment were identified using industry data reported by the census, not occupational data. Global and local tests for clustering are used to determine the degree of clustering in the study area and to determine where this clustering occurs and where statistical outliers are located. These population clusters defined the functional occupational communities (Figure 21). For primary data collection, any population-weighted ZIP code centroids that fall within the occupational community boundaries should be included as part of the occupational community unit. The ZIP code should be used as the primary unit of analysis, to more effectively target these communities for mail-based questionnaires (Figure 22). The plan recommends sampling these communities on a 5-year cycle, with additional sampling conducted as changing environmental conditions warrant. Similarly, if policy needs dictate that specific towns or communities be sampled, the same methods can be utilized to identify ZIP code centroids within defined geographic community boundaries derived from the administrative boundaries.
- Physical Risk and Vulnerable Communities – FEMA's FIRMs enable the identification of households located within the 100-year floodplain and FEMA v-zones (Figure 23). All census block groups with their population-weighted centroid within these special flood hazard areas were aggregated to create risk-based functional communities. Similarly, households residing in census block groups located atop natural levees and/or receiving structural protection were aggregated in the same manner, allowing the plan to monitor the proportion of the population requiring and receiving structural protection (Figure 24).

Table 16. Recommended data sources and sampling design for the Barataria Basin human system monitoring plan.

See the human system sampling design for information on deriving the functional community types identified under the site selection method.

Monitoring Category	Variables	Data Type	Data Source	Sampling Frequency	Site Selection Method
Population and Demographics	Number of Households	Secondary	5-year ACS block group estimates of *Household Type (Including Living Alone)*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
	Total Population	Secondary	5-year ACS block group estimates of *Total Population*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
	Race and Ethnicity	Secondary	5-year ACS block group estimates of *Race* and *Hispanic or Latino Origin*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
Housing and Community Characteristics	Residential Stability	Secondary	5-year ACS block group estimates of *geographical mobility in the past year for current residence*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
	Home Ownership	Secondary	5-year ACS block group estimates of *tenure of occupied housing units*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
	Residential Occupancy Rates	Secondary	5-year ACS block group estimates of *occupancy status of housing units*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
	Property Values	Secondary	5-year ACS block group estimates of *median gross rent* and *median value of owner-occupied housing units*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
Economy and Employment	Economic Development	Secondary	FEMA Hazus-MH block level *Building Count by Occupancy*[2] data	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
	Income Levels	Secondary	5-year ACS block group estimates of *Median Household Income in the Past 12 Months*	5-year within communities	Geographic Communities

Monitoring Category	Variables	Data Type	Data Source	Sampling Frequency	Site Selection Method
			5-year ACS block group estimates of *Per Capita Income in the Past 12 Months*[1]	Annual between communities	Occupational Communities
	Poverty Rates	Secondary	5-year ACS block group estimates of *Poverty Status in the Past 12 Months for Unrelated Individuals*	5-year within communities	Geographic Communities
			5-year ACS block group estimates of *Poverty Status in the Past 12 Months for Families*[1]	Annual between communities	Occupational Communities
	Unemployment Levels	Secondary	5-year ACS block group estimates of *Employment Status for the Population 16 Years and Over*[1]	5-year within communities	Geographic Communities
				Annual between communities	Occupational Communities
			Louisiana Workforce Commission Unemployment Insurance Claims	Annual	Parish
Ecosystem Dependency	Natural Resource Extraction	Secondary	USDA Census of Agriculture ZIP code agricultural yield data	5 Year	Natural Resource Extraction Sites
			LSU AgCenter parish agricultural totals	Annual	
			LDWF trip ticket zone fisheries landings data		
			LDNR oil and gas production data		
	Cultural and Traditional Uses of Natural Resources	Primary	Multistage or clustered random sampling survey methods (~4000 surveys needed)	5 Year	Occupational Communities
	Natural Resource-Based Employment	Secondary	5-year ACS block group estimates of employment in agriculture, forestry, fishing and hunting, and oil and gas extraction	5-year within communities	Occupational Communities
				Annual between communities	
	Tourism and Recreational Use of Natural Resources	Primary	Multistage or clustered random sampling survey methods (~4000 surveys needed)	5 Year	Occupational Communities
Residential Properties Protection	Residential Risk Reduction	Secondary	5-year ACS block group estimates of *Household Type (Including Living Alone)*[1]	5-year within communities.	Physical Risk and Vulnerable Communities
			FEMA digital flood maps	Annual between communities	
	Households Receiving Structural Protection	Secondary	5-year ACS estimates of *Household Type (Including Living Alone)*[1]	5-year within communities	Physical Risk and Vulnerable Communities
			USACE levee locations data	Annual between communities	
	Residential Properties Receiving Nonstructural Protection	Secondary	GOHSEP mitigated structures data	5 Year	Physical Risk and Vulnerable Communities

Monitoring Category	Variables	Data Type	Data Source	Sampling Frequency	Site Selection Method
Critical Infrastructure and Essential Services Protection	Risk Reduction for Critical Facilities	Secondary	FEMA Hazus-MH block level *Essential Facilities, Lifeline Utility Systems* and *Transportation Systems*[2] data GOHSEP Severe Repetitive Loss Data	5 Year	Physical Risk and Vulnerable Communities
	Miles of Levees Created and Maintained	Secondary	USACE levee locations data USACE Levee Safety Action Classification Data	Annual	Physical Risk and Vulnerable Communities
	Number of Critical Facilities Protected by Levees	Secondary	FEMA Hazus-MH block level *Essential Facilities, Lifeline Utility Systems* and *Transportation Systems*[2] data USACE Levee Polder data	5 Year	Physical Risk and Vulnerable Communities
	Public and Commercial Properties Receiving Nonstructural Protection	Secondary	GOHSEP mitigated structures data	5 Year	Physical Risk and Vulnerable Communities

[1] *Terms used specifically by ACS.*
[2] *Terms used specifically in the Federal Emergency Management Agency (FEMA) Hazus-MH database.*

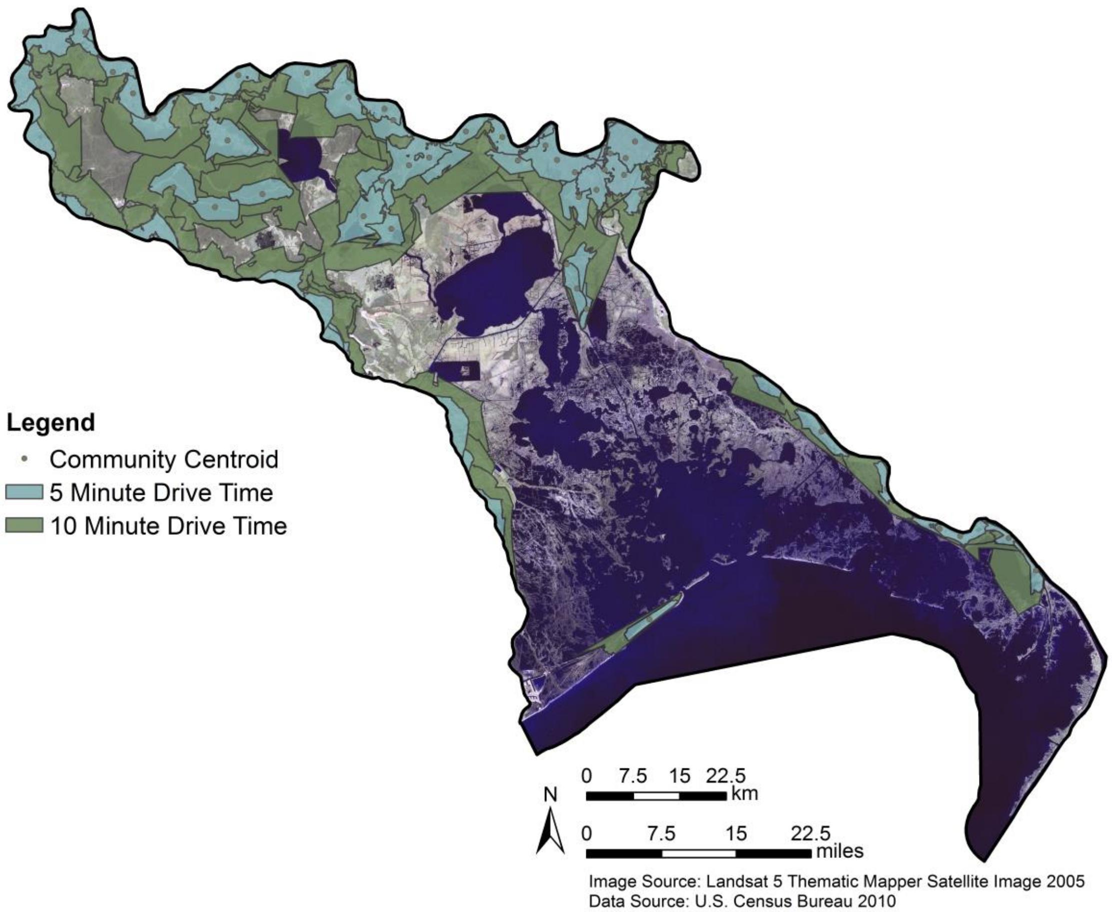

Figure 20. Map of site locations for population-based geographical functional communities based upon driving time from the population weighted centroid of the community.

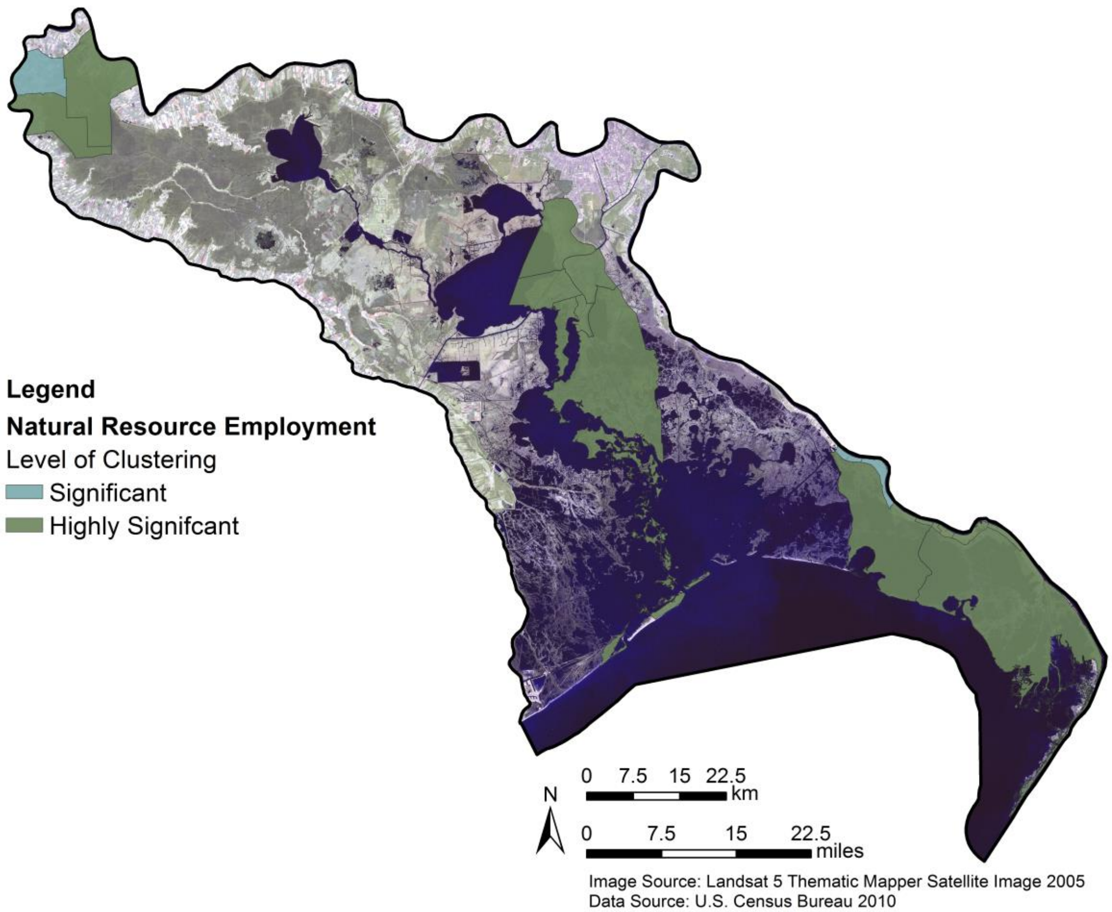

Figure 21. Map of site locations for functional communities based upon clusters of renewable natural resource dependent census block groups.

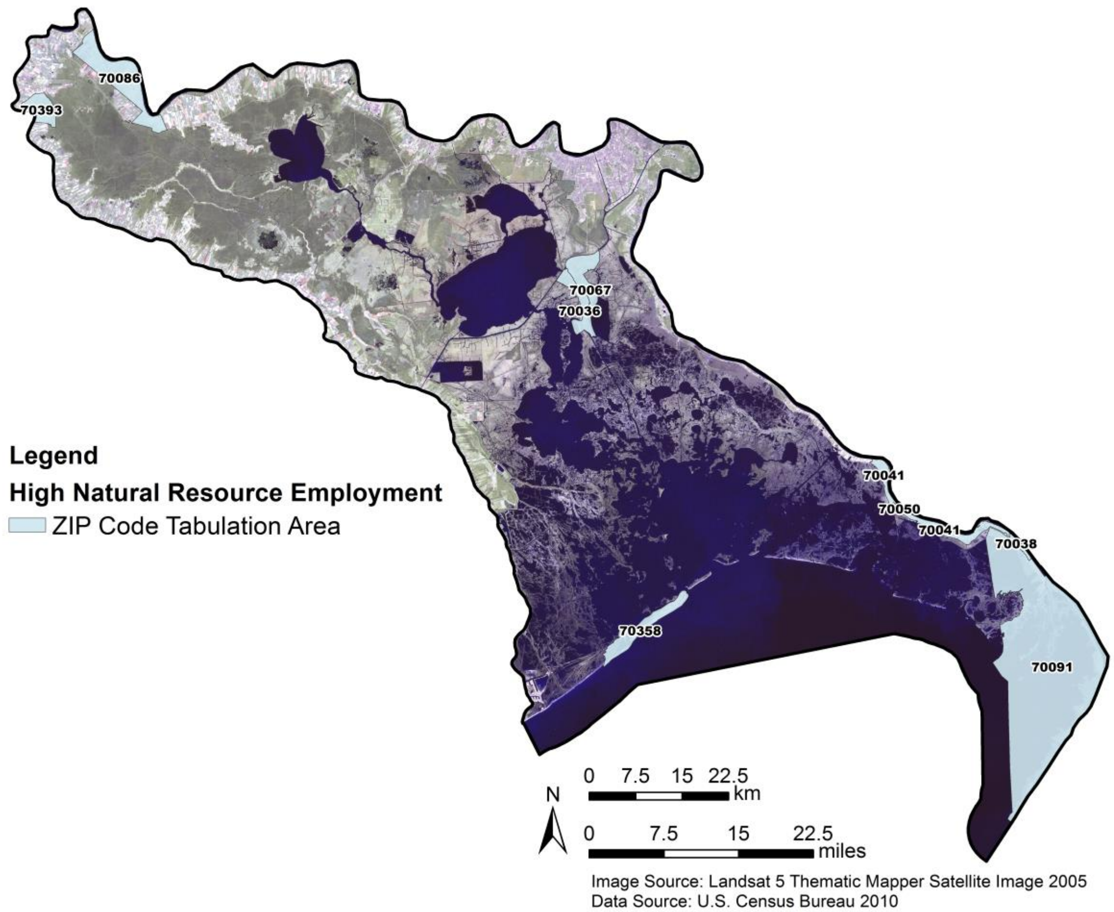

Figure 22. Map of site locations for ZIP code-based functional communities based upon renewable natural resource dependent census block groups.

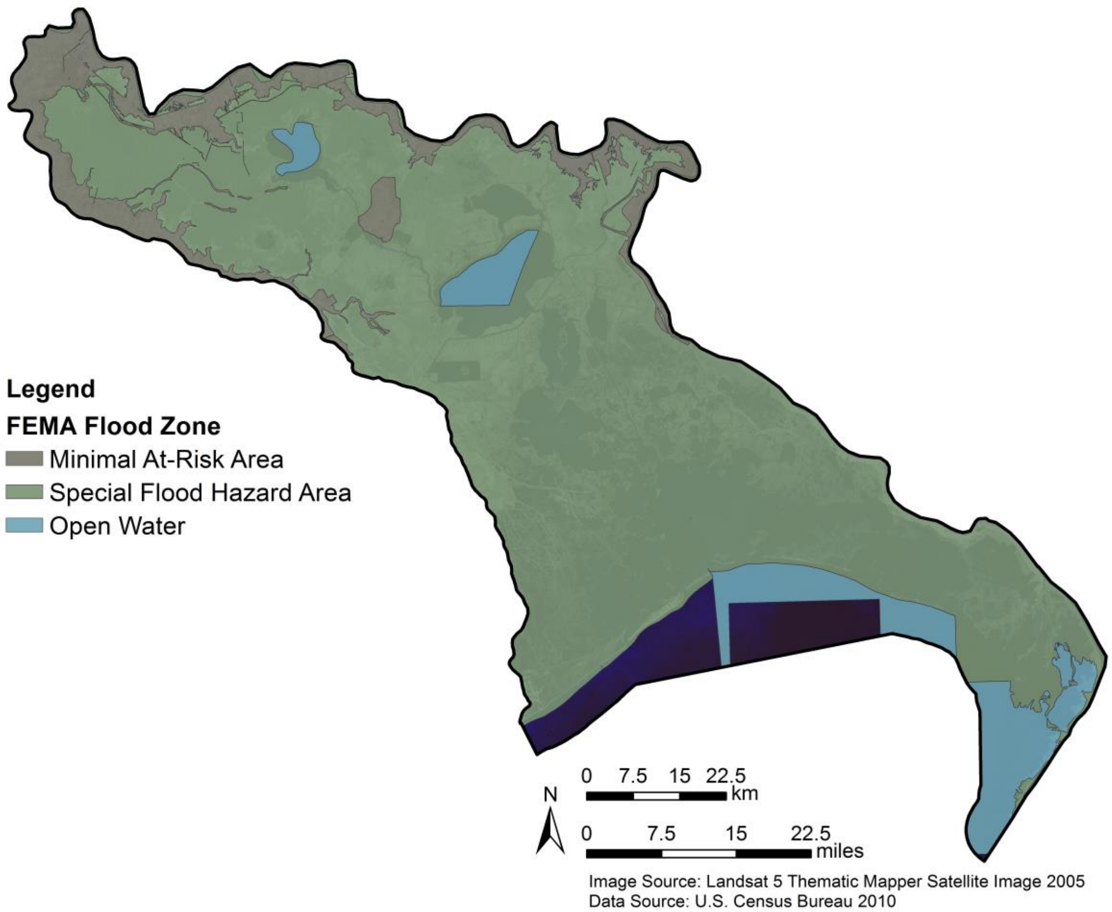

Figure 23. Map of site locations for functional communities based upon flood risk derived from FEMA Flood Insurance Risk Maps. Special Flood Hazard Areas consist of the FEMA 100-year floodplain and v-zones.

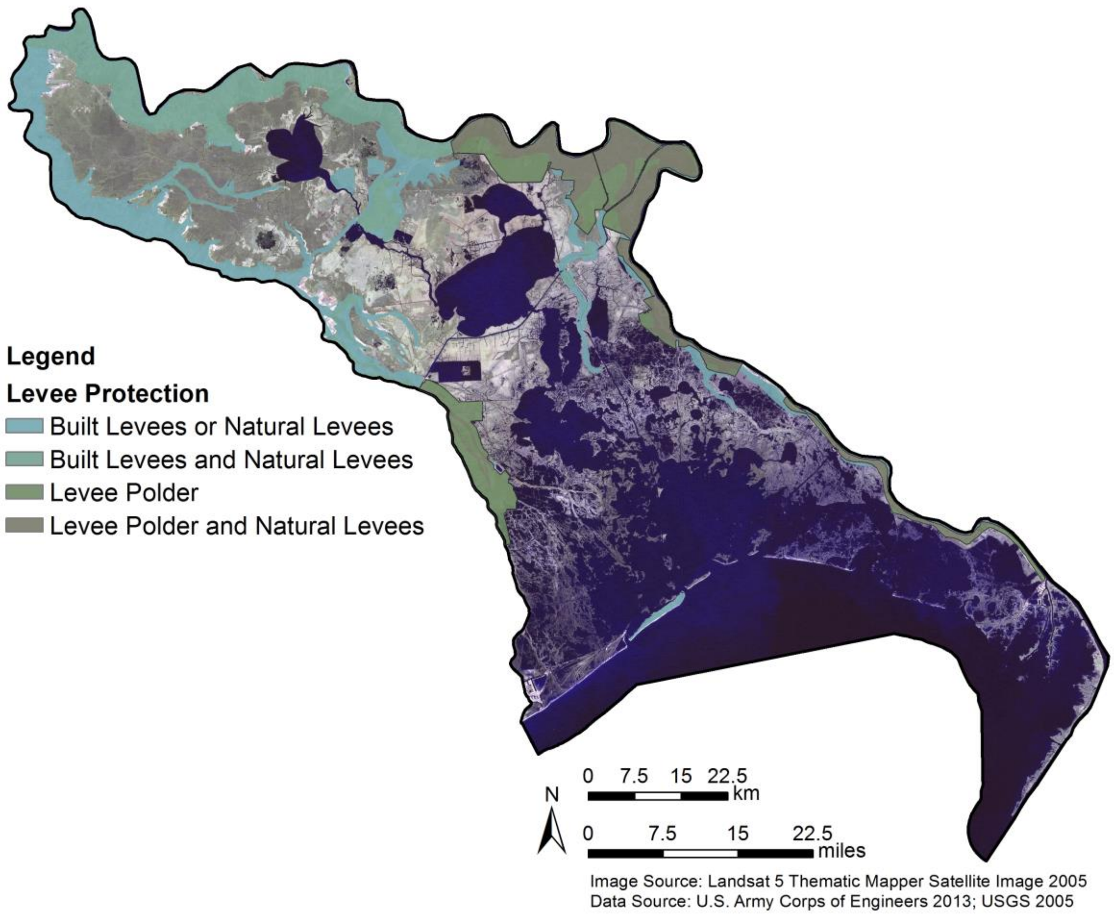

Figure 24. Map of site locations for functional communities based upon presence of natural levees, constructed levees, and levee polders.

Path Forward

This report describes an integrated plan for monitoring the natural and human systems within the Barataria Basin of coastal Louisiana and coastwide. A rigorous statistical analysis and thorough reviews of previous planning and monitoring efforts resulted in the development of this comprehensive plan. The plan relies heavily on the use of existing data, thus, coordination with other agencies and CPRA's existing monitoring programs (e.g., BICM, CRMS) is critical to the plan's success. Collectively, the variables provide an understanding in a holistic sense of the potential impacts on system dynamics from a variety of drivers and are intended to be indicative rather than exhaustive of system condition. As a result, there were some aspects of the system not included in the plan, such as monitoring of wildlife species, submerged aquatic vegetation, and economic impacts on local businesses, that warrant additional discussion with subject matter experts prior to their inclusion to determine their relevance in the SWAMP framework and to the coastal protection and restoration program. Further, the exclusion of any variable does not necessarily mean the variables should be excluded from any project-specific monitoring.

Prior to implementation of this plan, SWAMP will require development of quality control and quality assurance protocols, specific standardized operating procedures for each of the data collection efforts, a data management plan, and a reporting framework to contribute to decision making and reducing uncertainty in management actions. Protocols and standardized operating procedures have previously been developed for many of the major monitoring programs and research efforts in coastal Louisiana and could serve as a guide for many of the variables identified herein.

Several monitoring programs exist in coastal Louisiana as documented in the SWAMP inventory geodatabase[65] and summarized in the Introduction. In many cases, it is unknown whether probability-based methods were employed in the selection of sites. In order to integrate these existing monitoring programs for analysis of system change, the use of nonprobability-based designs in conjunction with the probability-based design proposed herein warrants additional discussion with statistical experts and those from other large-scale monitoring programs that have faced similar issues. The statistical literature provides some guidance on appropriate methodologies for combining datasets from nonprobability- and probability-based designs (Brus & De Gruijter, 2003; Cox & Piegorsch, 1996; Elliott, 2009), but there is no general consensus. The analysis of existing data generated from sites in which probability-based methods were used in selecting site locations, in conjunction with new data generated from sites in which the GRTS was used, does not pose any critical statistical concerns. This does not imply that the GRTS design can be applied post hoc to designs created using other probability-based methods.

The implementation of this plan will result in a wealth of information that can be used in the Adaptive Management framework and contribute to the "knowledge base" (The Water Institute of the Gulf, 2013). Data streams in and of themselves, however, are not sufficient; formal synthesis and quantitative analyses are needed for making informed management decisions (Levin et al., 2009; Williams et al., 2009). The use of Integrated Ecosystem Assessments (IEA) or Adaptive Management (AM) have been proposed for

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[6] For more information on the SWAMP GIS data inventory, contact info@thewaterinstitute.org.

large scale ecosystem management to inform management of entire systems (Samhouri et al., 2013; Schreiber et al., 2004), including coupled natural-human sytems such as those monitored in SWAMP. Many of the concepts presented in IEA and AM have already been initiated at different scales for coastal Louisiana, through multiple efforts by several agencies and organizations. Drivers and pressures upon the system were identified for the Barataria Basin (Northern Gulf Institute Ecosystem Team, 2010) and a conceptual framework of the key system drivers was developed on a coastwide scale as part of a related SWAMP planning effort (Hijuelos et al., 2013). Several research efforts have also explored indicator development for use in evaluating coastal restoration efforts (Cretini et al., 2012; Snedden & Swenson, 2012; Stagg et al., 2013) and coastal protection efforts (Hijuelos & Reed, 2013a), evaluating water quality condition (Louisiana Department of Environmental Quality, 2008), and quantifying success of the fish and wildlife conservation strategy (Lester et al., 2005). This SWAMP plan extends the sectoral approach taken in these and other efforts to allow for the use of IEA or AM in the management of fully coupled natural-human systems.

In addition, report cards at the CRMS site, CWPPRA project, basin, and coastwide scales have been developed using indices developed from CRMS data to assess wetland hydrology, vegetation, and soil. The development of ecological- and/or management-related thresholds for the identified indicators have not yet been developed, but this could be achieved through analysis of existing data and literature synthesis of relevant ecosystem monitoring frameworks. Upon the completion of thresholds, the application of the SWAMP monitoring framework into a reporting framework could be applied in a Louisiana coastal system report card, to regularly assess basinwide and coastwide performance in achieving sustainable landscapes and resilient communities (Figure 25).

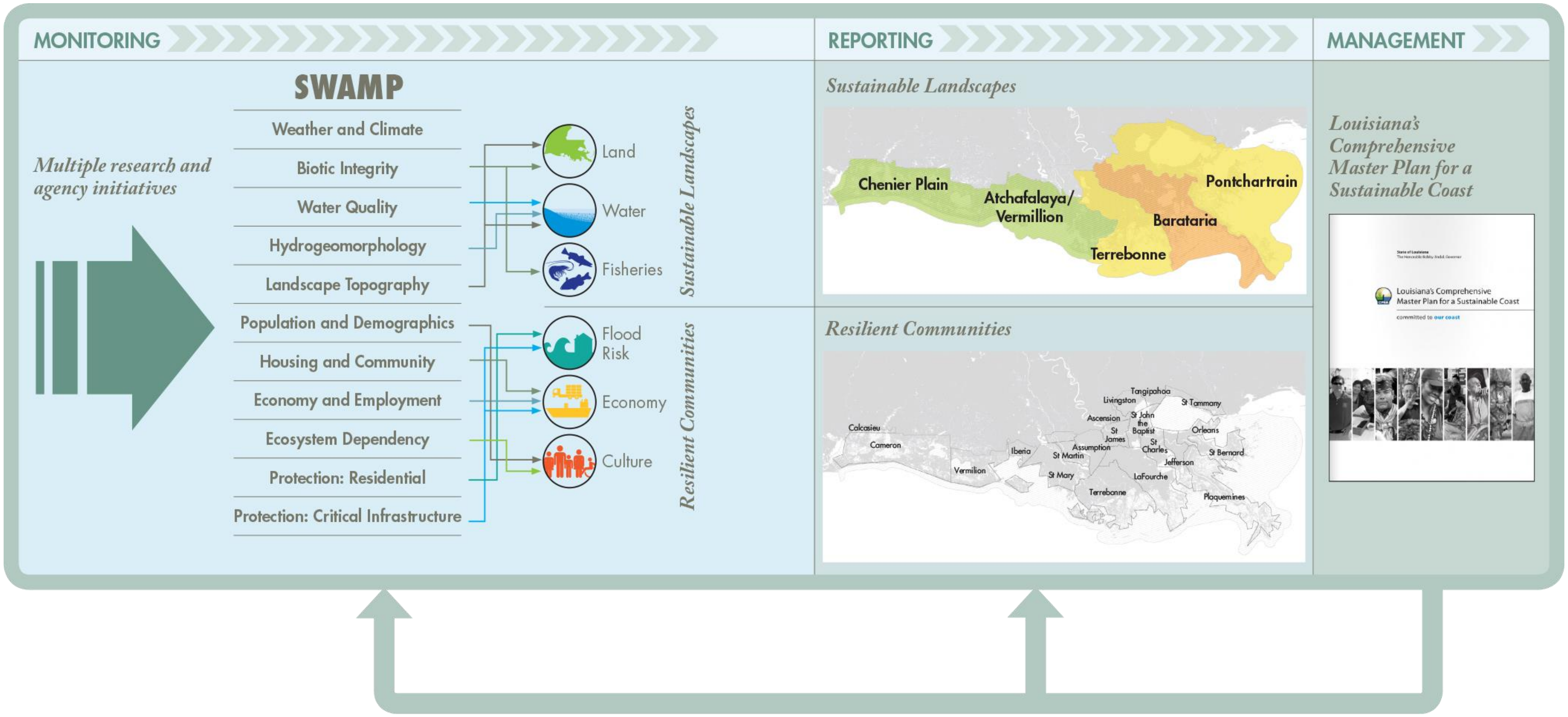


Figure 25. Application of the SWAMP monitoring framework to a report card for coastal Louisiana. More information on the concept of developing a report card for coastal Louisiana can be found in Hijuelos & Reed (2013b).

Appendix I Influence Diagrams

As part of an earlier effort for identifying the key parameters required to understand system change, an influence diagram approach was employed to illustrate how the main drivers of system change influence specific system characteristics. The diagrams were designed to illustrate general relationships between drivers and system responses and were not intended to serve as comprehensive conceptual models. This approach did function as a guide for identifying important key parameters (e.g., those that reflect a number of system change mechanisms) and understanding in a holistic sense the potential impacts on system dynamics from a variety of drivers. Influence diagrams were developed separately for the restoration and protection monitoring frameworks, although common drivers exist between the two. A full description of the influence diagrams can be found in Hijuelos et al. (2013). This appendix contains a subset of the full diagram to illustrate the parameters (i.e., variables) selected for SWAMP. Given the large size of the diagrams, some are depicted as two separate diagrams to separately show the "inputs" and "outputs" of the variables.

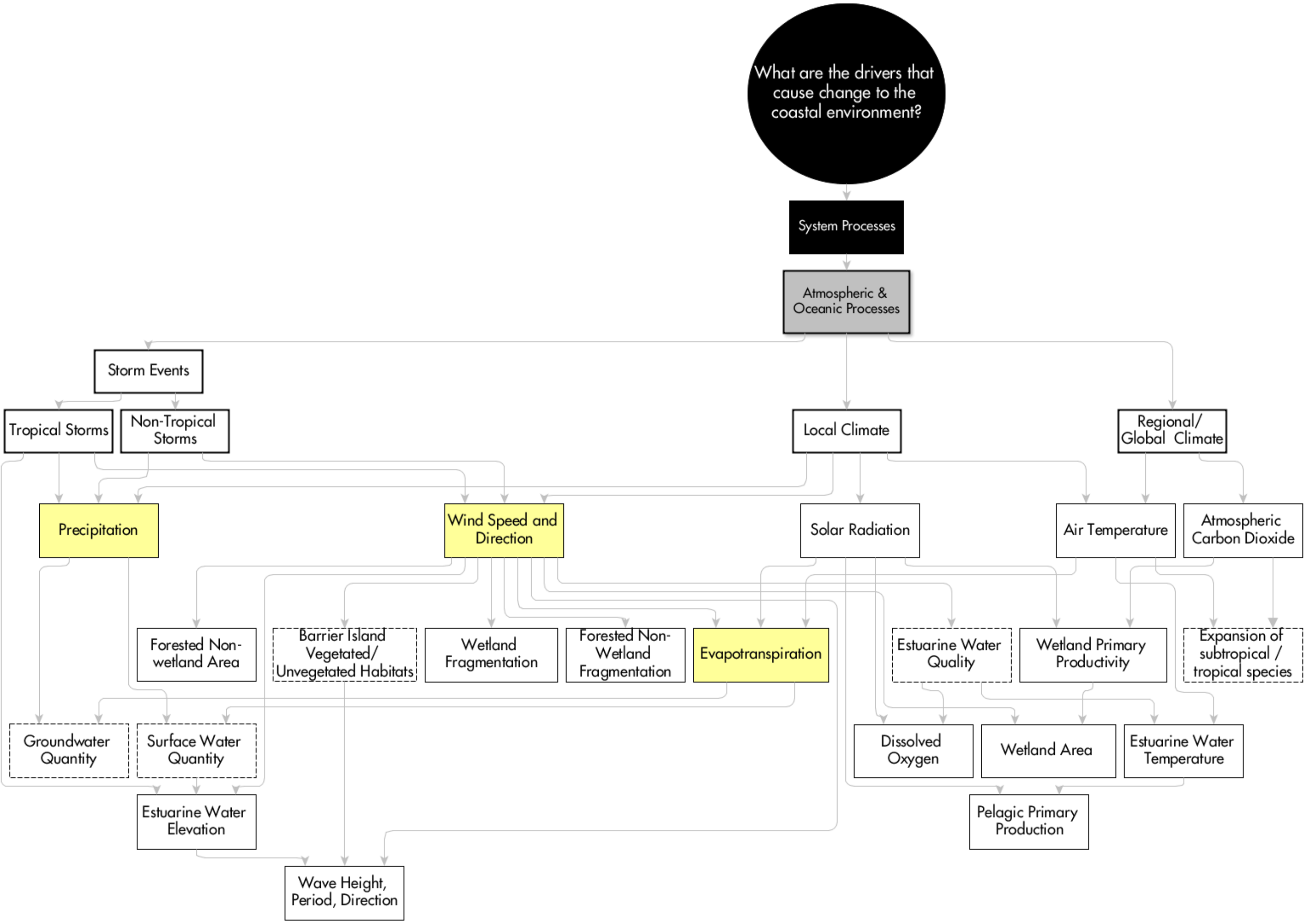


Figure 26. Weather and climate variables (in yellow) selected from the SWAMP Framework influence diagram (Hijuelos et al., 2013).

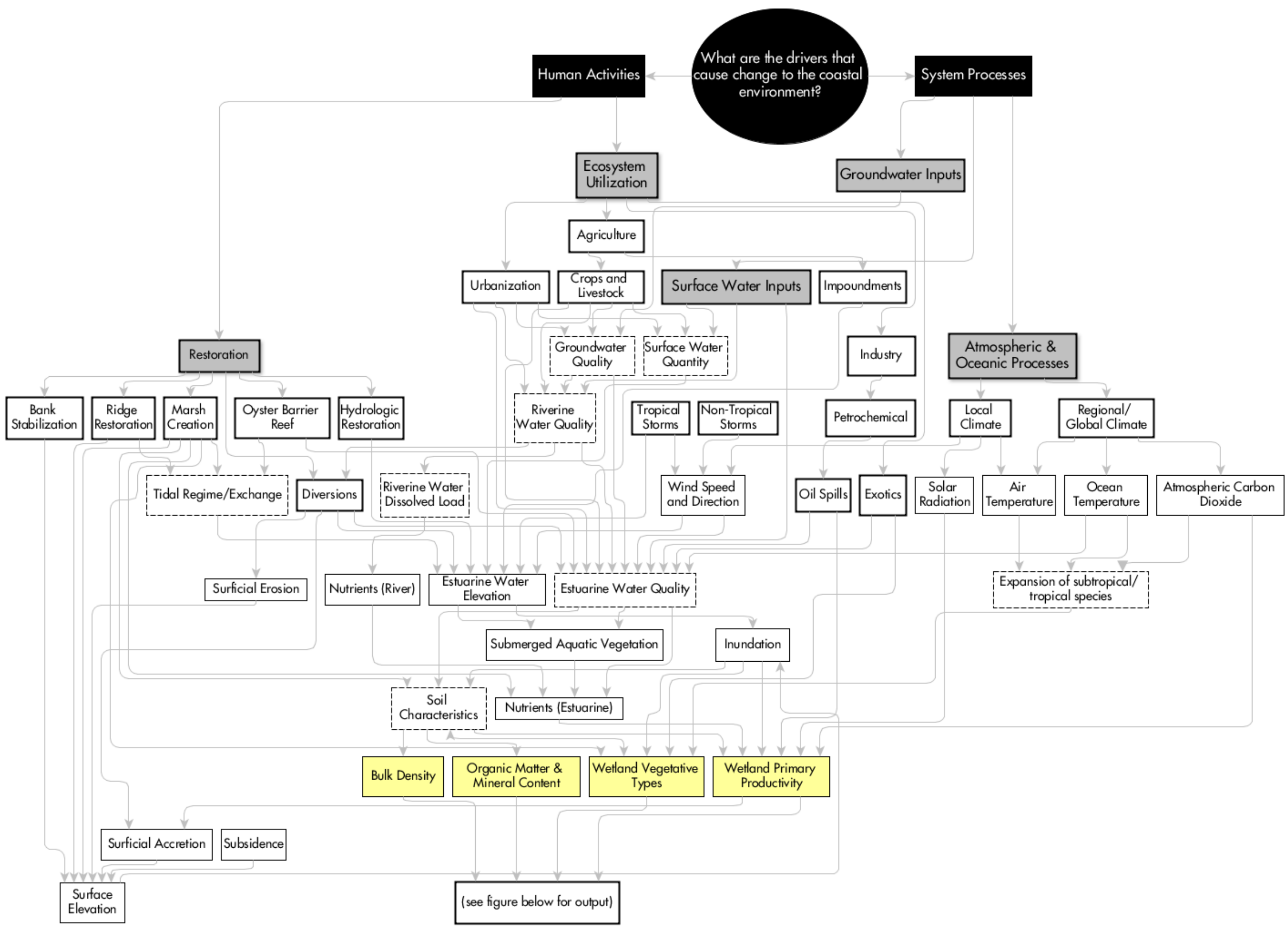


Figure 27a. Biotic integrity variables related to wetlands (in yellow) selected from the SWAMP Framework influence diagram showing (A) drivers or variables that influence wetlands.

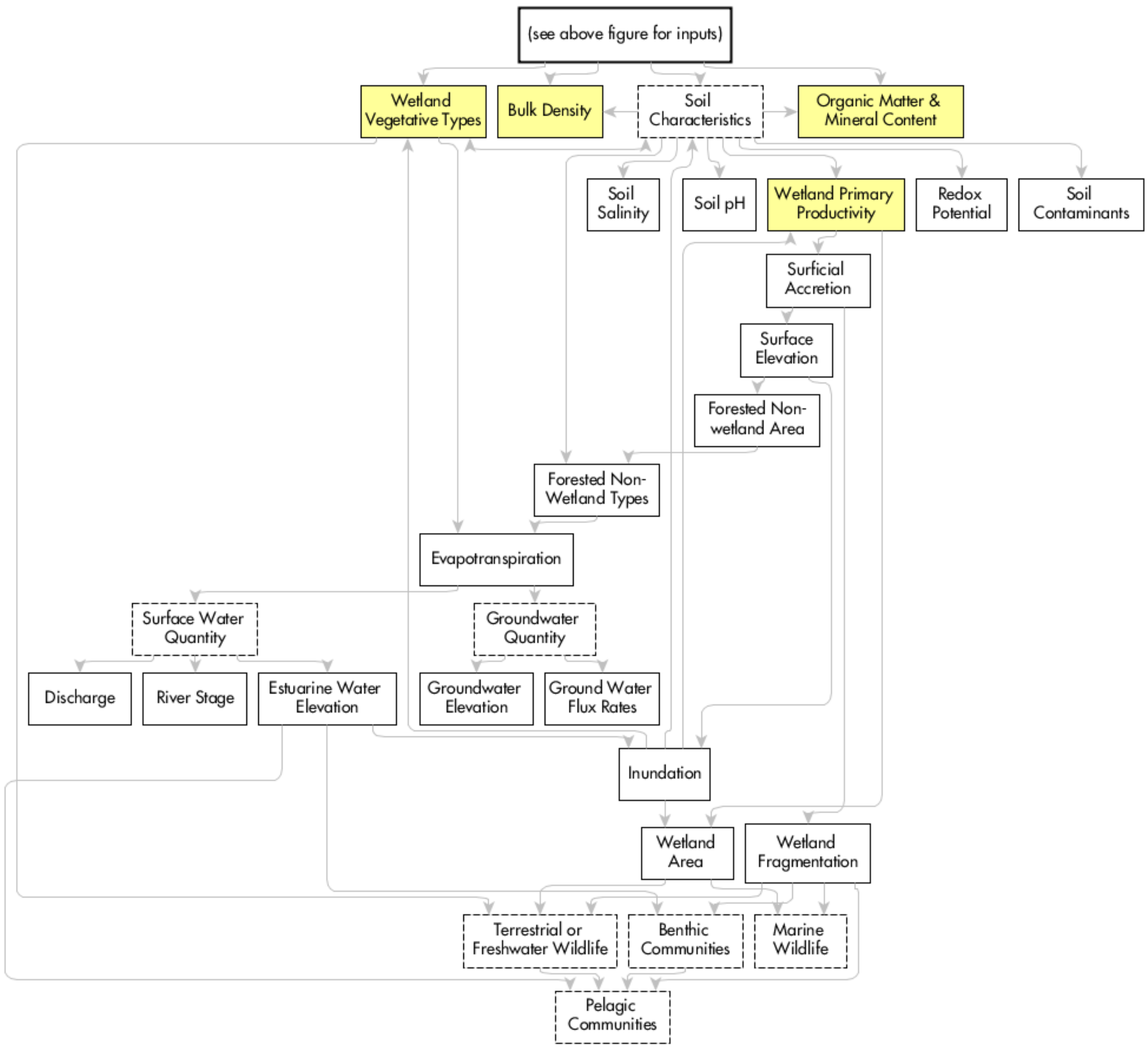


Figure 27b. Biotic integrity variables related to wetlands (in yellow) selected from the SWAMP Framework influence diagram showing (B) wetlands influence on other variables (Hijuelos et al., 2013).

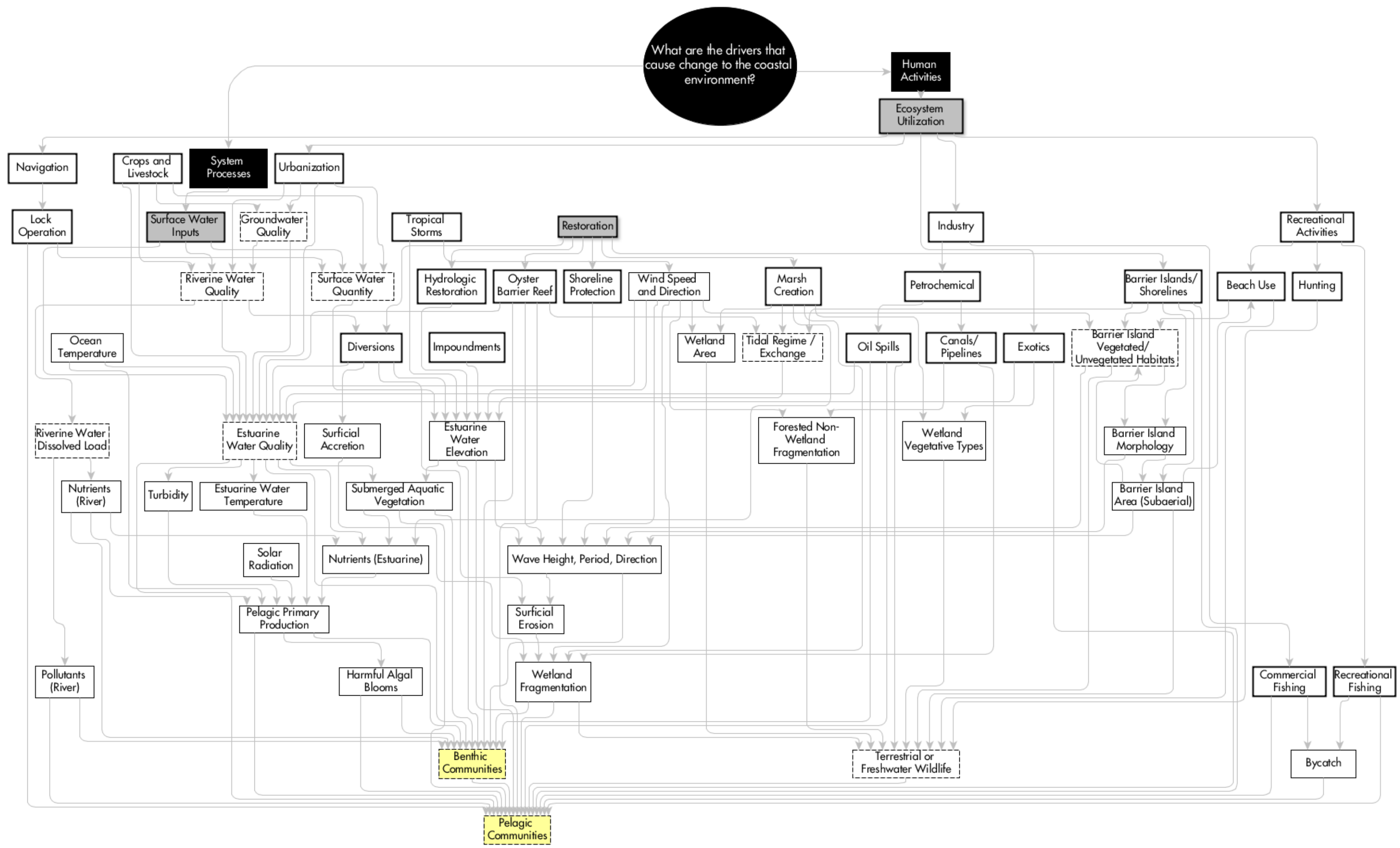
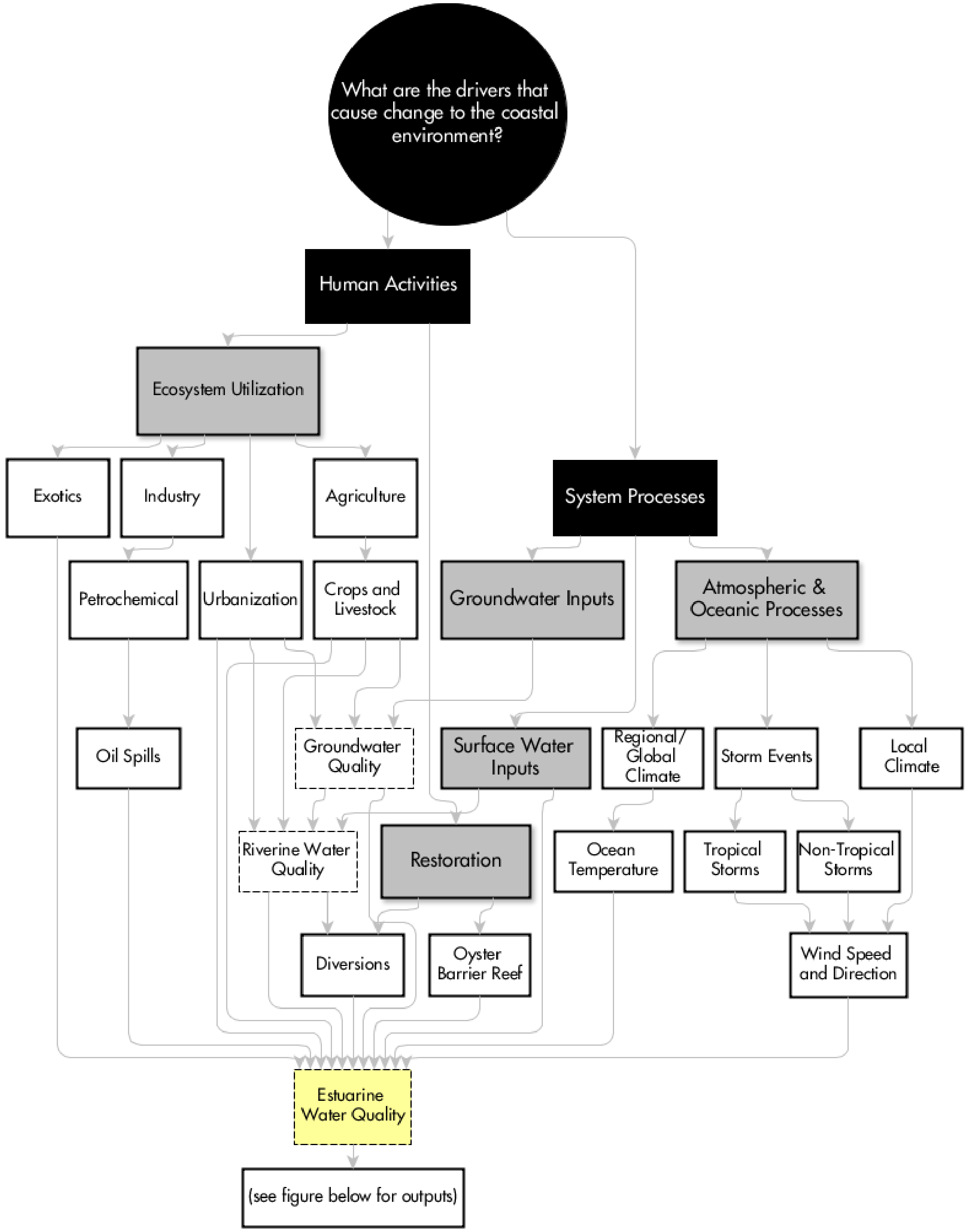


Figure 28. Biotic integrity variables related to pelagic and benthic communities (in yellow) selected from the SWAMP Framework influence diagram (Hijuelos et al., 2013).

A



What are the drivers that cause change to the coastal environment?
Human Activities
System Processes
Ecosystem Utilization
Exotics
Industry
Agriculture
Petrochemical
Urbanization
Crops and Livestock
Groundwater Inputs
Atmospheric & Oceanic Processes
Oil Spills
Groundwater Quality
Surface Water Inputs
Regional/ Global Climate
Storm Events
Local Climate
Riverine Water Quality
Restoration
Ocean Temperature
Tropical Storms
Non-Tropical Storms
Diversions
Oyster Barrier Reef
Wind Speed and Direction
Estuarine Water Quality
(see figure below for outputs)

B

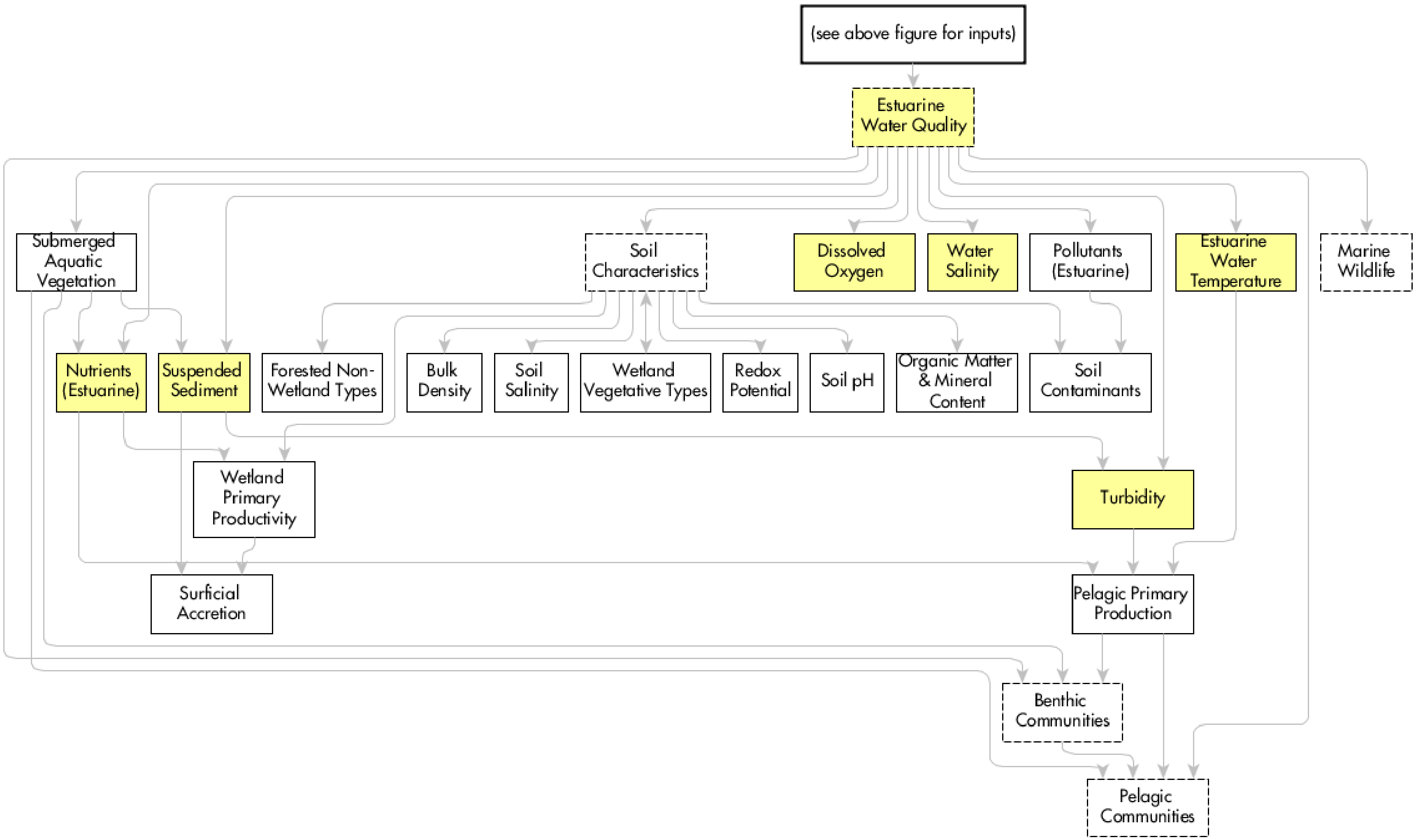


Figure 29. Water quality variables (in yellow) selected from the SWAMP Framework influence diagram showing (A) drivers or variables that influence water quality and (B) water quality influence on other variables (Hijuelos et al., 2013).

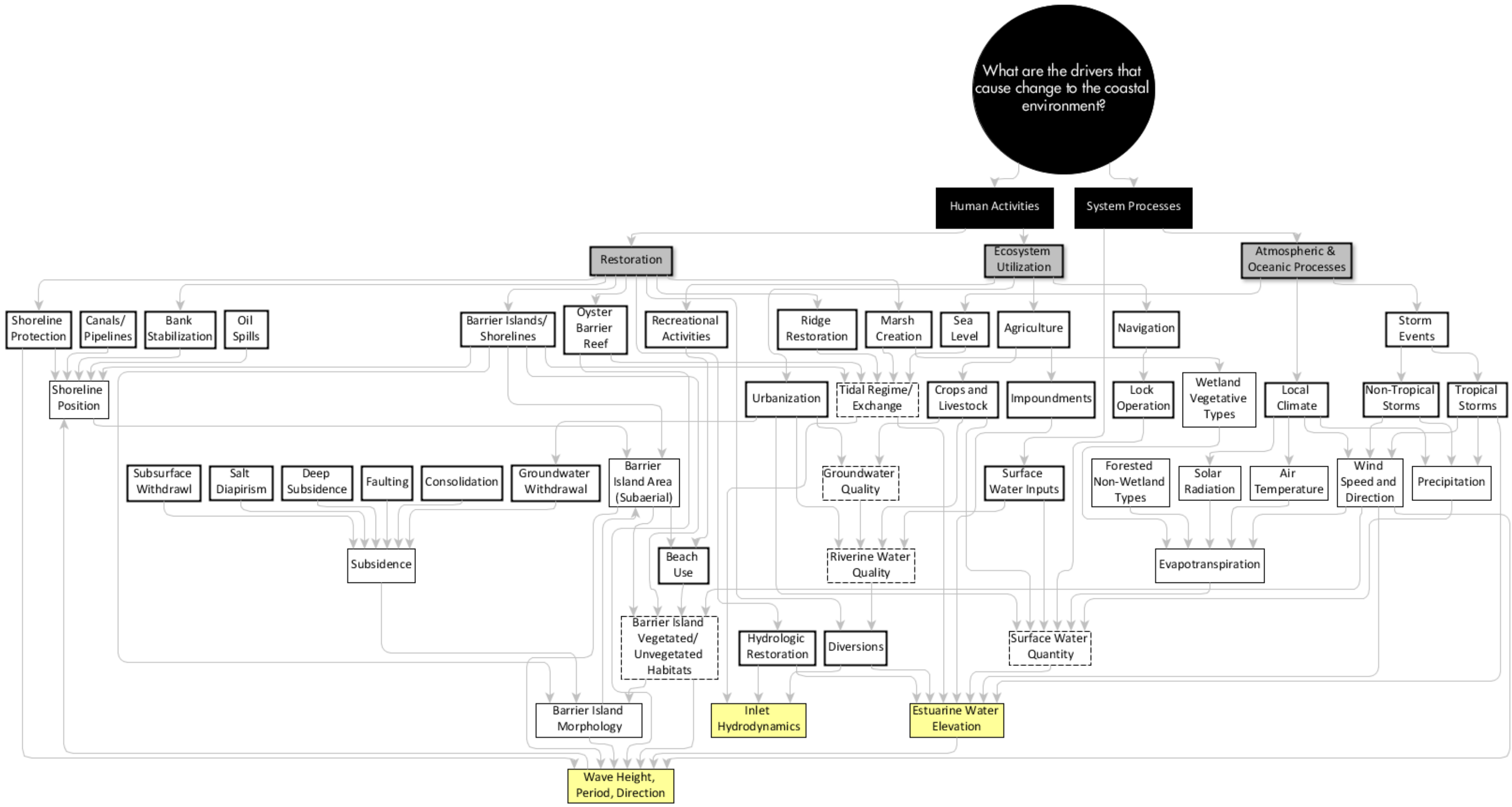


Figure 30. Hydrology variables (in yellow) selected from the SWAMP Framework influence diagram showing drivers or variables that hydrology (Hijuelos et al., 2013).

Appendix II Analytical Results

Water Quality

Power analyses were conducted on water quality variables at the coastwide, basinwide, and subbasin scales, depending on data availability. The purpose of the power analysis was to identify an appropriate sample size for detecting changes at different spatial and temporal scales. A more rigorous analysis was conducted on the basin and subbasin scales given the initial priority for implementing SWAMP within the Barataria Basin. A more generalized analysis and interpretation of results was performed on the coastwide scale in order to approximate how the sampling design for the Barataria Basin would scale coastwide. As a result, the LDEQ AWQ program datasets were used on the coastwide analysis, whereas a compilation of datasets from the Davis Pond monitoring program, USGS, and LDEQ were used in order to conduct a more rigorous analysis for the Barataria Basin Pilot study.

CHLOROPHYLL A

Power Analysis

At the time of this report, there were no active chlorophyll *a* measurements (continuous or discrete) in the estuarine open water bodies within Barataria Basin or coastwide. As a result, historical data collected within Barataria Basin were used in the analysis. No coastwide analysis could be conducted.

Chlorophyll *a* concentrations were obtained from the historical U.S. Army Corps of Engineers (USACE) Davis Pond monitoring program to create the exemplary dataset (as defined in the "Natural System Sampling Design" in the main report). As part of the monitoring program, water samples were obtained on a monthly basis throughout the Barataria Basin from 1998-2009 (Figure 31). It is unknown how the original sampling locations were selected, but it was assumed for the analysis that some element of randomness was incorporated into the selection of sites. The NHD was then used to classify the monitoring site locations into waterbody types. The NHD contains geographic information on the drainage network and classifies features such as rivers, streams, canals, lakes, ponds, coastline, dams, and stream gauges. The features were consolidated such that sites were classified as either open water (e.g., lakes, ponds) or channels (e.g., streams, canals). The sites were further classified based on their position in the estuary (upper, middle, and lower subbasins as indicated in Figure 31) and the season in which they were collected. The natural logarithmic transformation was used in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting a GLM to the log-transformed chlorophyll *a* concentrations with the interaction term season*waterbody type*subbasin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors.

The following hypotheses were then tested for the power analysis:

1. at least one subbasin mean differs significantly from another subbasin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. waterbody type means are significantly different from one another;
4. the means in year 0 differ significantly from the means in year 1, averaged over all waterbody types, seasons, and subbasins;
5. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins;
6. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins.

Hypotheses 4 through 6 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Further, hypotheses 2 through 6 were conducted for each subbasin independently in order to evaluate how sample size requirements may differ at a subbasin scale relative to the basin scale. Although standard deviation may differ when calculated at the basin versus subbasin scale, the basin scale estimate of standard deviation was used in the subbasin analysis. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in alpha (α) generally results in a need for larger sample sizes (Zar, 2010). Alpha and power were also held constant across analyses. As a result, the only information not held constant between the basin and subbasin scale analyses was the estimated means for each of the factors (season, waterbody type, subbasin). This allowed for exploring the sensitivity of the analysis to the means calculated at the different spatial scales.

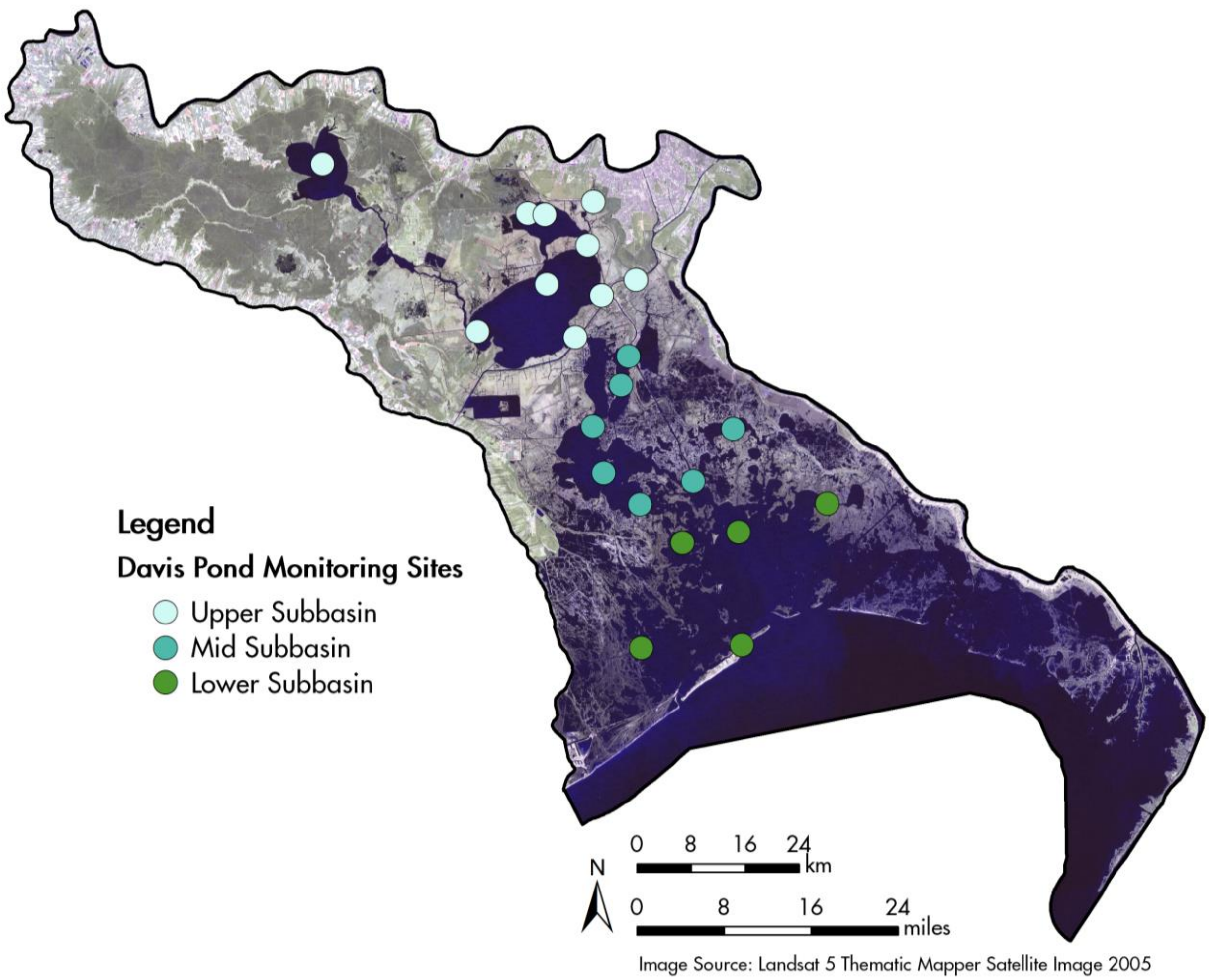


Figure 31. Chlorophyll *a* site locations for the historical USACE Davis Pond Monitoring Program. Sites were classified into subbasins using the USACE categorization.

Results

Barataria Basin

The results of the power analysis on the basinwide scale indicate that detecting differences in seasonal means within a year, or linear trends in the annual mean over years, can be achieved with a moderate sample size (6-12 sites), while detecting changes between subbasins means or between waterbody types means requires a substantial increase in sample size (Table 17). Detecting a linear pattern in the annual means over time, averaged over all factors, is sensitive to the effect size applied (Figure 32). However, a threshold point is evident in Figure 32, where an increase in sample size beyond 9 results in a very small shift in the percentage of change. For example, from a sample size of 1 to 9, the difference in the y-axis is approximately 20%, while a change from 9 to 18 only results in a change of 5%. Also evident in the graphs is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 17. Chlorophyll *a* summary results of the power analysis for hypotheses 1 through 6 on the basinwide scale.

Hypothesis	% Change[i]	Average Change (µg L^{-1})[ii]	# of Sites
1: Differences among subbasin means	n/a	0.93	80
2: Differences among seasonal means	n/a	3.10	10
3: Differences among waterbody type means	n/a	0.14	> 1000
4: +1 years of data	20% - 15%	4.16 – 2.95	6-11
5: +3 years of data	8% - 6%	1.26-0.92	6-11
6: +5 years of data	~6%	0.92	6-11

[I] *Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.*
[ii] *The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from yearr 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

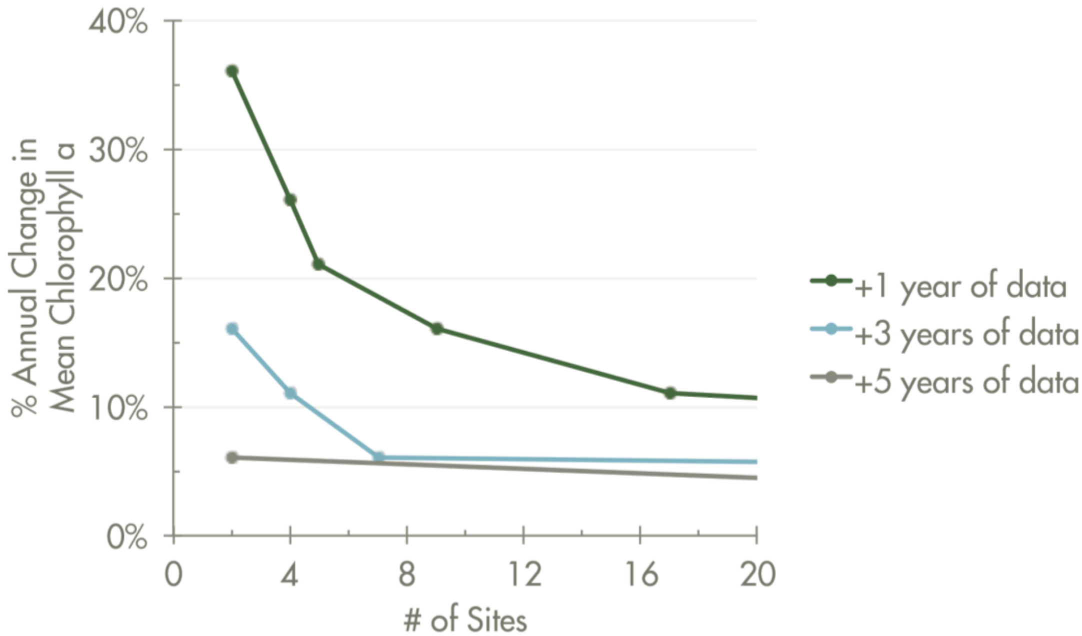


Figure 32. Results of the power analysis on the basinwide scale for hypotheses 4 through 6 indicating the percent change in mean chlorophyll *a* that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.42. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on square-root-transformed values.

Subbasin

The results of the power analysis on the subbasin scale exhibit comparable sample size requirements for each hypothesis for an individual subbasin as they do for the basin as a whole (Table 18 and Figure 33). The reason for the consistency in the estimates stems from the similarities in the means among subbasins such that the basinwide mean is representative of the mean calculated on a subbasin scale. As a result, if subbasin scale questions are of interest, the total sample size for the basin would be approximately three times larger than if the question of interest is on a basinwide scale.

Table 18. Chlorophyll *a* summary results of the power analysis for hypotheses 2 through 6 by subbasin.

Upper Subbasin

Hypothesis	% Change[i]	Average Change (µg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	2.30	14
3: Differences among waterbody type means	n/a	0.38	658
4: +1 years of data	20-15%	3.56-2.53	11-7
5: +3 years of data	7-6%	1.10-0.92	11-7
6: +5 years of data	6-5%	0.92-0.76	11-7

Mid-Subbasin

Hypothesis	% Change[i]	Average Change (µg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	3.78	8
3: Differences among waterbody type means	n/a	0.26	> 1000
4: +1 years of data	20-15%	4.70-3.33	10-6
5: +3 years of data	6%	1.20	10-6
6: +5 years of data	6-5%	1.20-0.99	10-6

Lower Subbasin

Hypothesis	% Change[i]	Average Change (µg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	4.55	5
3: Differences among waterbody type means[iii]	n/a	n/a	n/a
4: +1 years of data	20-15%	4.43-3.14	10-6
5: +3 years of data	6%	1.14	10-6
6: +5 years of data	6-5%	1.14-0.94	10-6

[i] Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.
[ii] The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

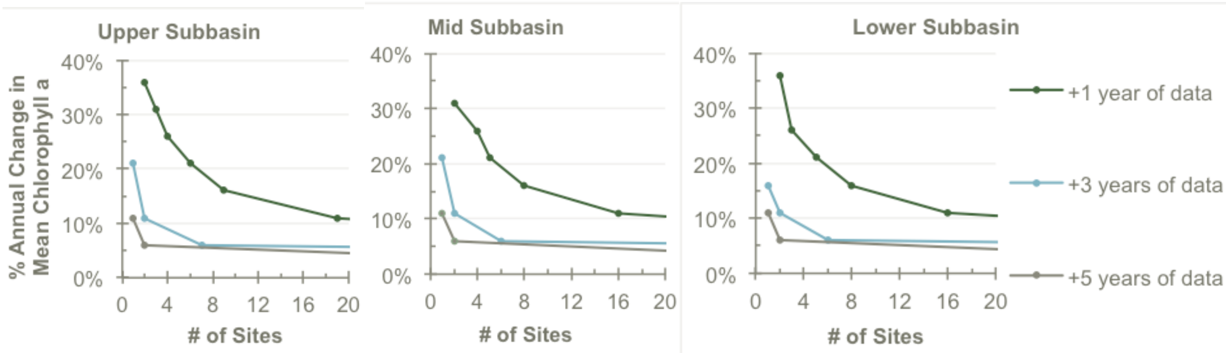


Figure 33. Results of the power analysis for each subbasin for hypotheses 4 through 6 indicating the percent change in mean chlorophyll *a* that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.816. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including year 0 baseline).

DISSOLVED OXYGEN

Power Analysis

There are no active measurements of continuous DO within the Barataria Basin. Discrete measurements are collected as part of several different monitoring programs including the LDEQ Ambient Water Quality (AWQ) monitoring program and, more recently, the Louisiana Department of Wildlife and Fisheries (LDWF) fisheries independent monitoring program. The LDEQ AWQ program samples on a monthly basis in the Barataria Basin every four years, while the LDWF program frequency of sampling is dependent upon the gear type used for the fisheries sampling and varies from weekly to monthly to annually at select locations (see Figure 46 for LDWF site locations).

Coastwide

DO concentrations were obtained from the LDEQ AWQ program to create the exemplary dataset (as defined in the "Natural System Sampling Design" in the main report). LDEQ AWQ measures water quality parameters discretely on a monthly basis for one year and repeats every four years (Figure 5). It was assumed for the analysis that some element of randomness was incorporated into the selection of their monitoring sites. The sites were then categorized into basins using the Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA) basin designations, as used by other CPRA monitoring programs. The data were normally distributed and therefore satisfied the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting GLMs to DO concentrations, separately, with the interaction term season*basin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one basin mean differs significantly from another basin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. the means in year 0 differ significantly from the means in year 1, averaged over all seasons and basins;
4. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins;
5. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins.

Hypotheses 3 through 5 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Alpha (α) and power were also held constant across analyses at the different spatial scales. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in α generally results in a need for larger sample sizes (Zar, 2010). As a result, the focus of the analysis was to evaluate how sample size requirements change in response to the means of each of the factors calculated at the different spatial scales.

Barataria Basin

DO concentrations were obtained from both the LDEQ AWQ program and the historical USACE Davis Pond monitoring program to create the exemplary dataset (as defined in the "Natural System Sampling Design" in the main report). As part of the Davis Pond monitoring program, water samples were obtained on a monthly basis throughout the Barataria Basin from 1998-2009 (Figure 34), while the LDEQ data collection dates back to 1978. In some instances, DO readings were recorded on the bottom and surface of the water, and in other cases it was not specified where the reading was taken. Thus, if more than one reading was provided, an average was taken to represent one DO level for the site. It is unknown how the original sampling locations were selected in either case, but it was assumed for the analysis that some element of randomness was incorporated in the selection of sites. The NHD was then used to classify the monitoring site locations into waterbody types. The NHD contains geographic information on the drainage network and classifies features such as rivers, streams, canals, lakes, ponds, coastline, dams, and stream gauges. The features were consolidated such that sites were classified as either open water (e.g., lakes, ponds) or channels (e.g., streams, canals). The sites were further classified based on their position in the estuary (upper, mid-, and lower subbasins as indicated in Figure 34) and the season in which the data were collected. The square-root transformation was used in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting a GLM to the square-root-transformed DO concentrations with the interaction term season*waterbody type*subbasin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one subbasin mean differs significantly from another subbasin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. waterbody type means are significantly different from one another;
4. the means in year 0 differ significantly from the means in year 1, averaged over all waterbody types, seasons, and subbasins;
5. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins;
6. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins.

Hypotheses 4 through 6 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Further, hypotheses 2 through 6 were conducted for each subbasin independently in order to evaluate how sample size requirements may differ at a subbasin scale relative to the basin scale. Although standard deviation (σ) may differ when calculated at the basin versus subbasin scale, the basin scale estimate of standard deviation was used in the subbasin analysis. Alpha (α) and power were also held constant across analyses. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in α generally results in a need for larger sample sizes (Zar, 2010). As a result, the focus of the analysis was to evaluate how sample size requirements change in response to the means of each of the factors calculated at the different spatial scales.

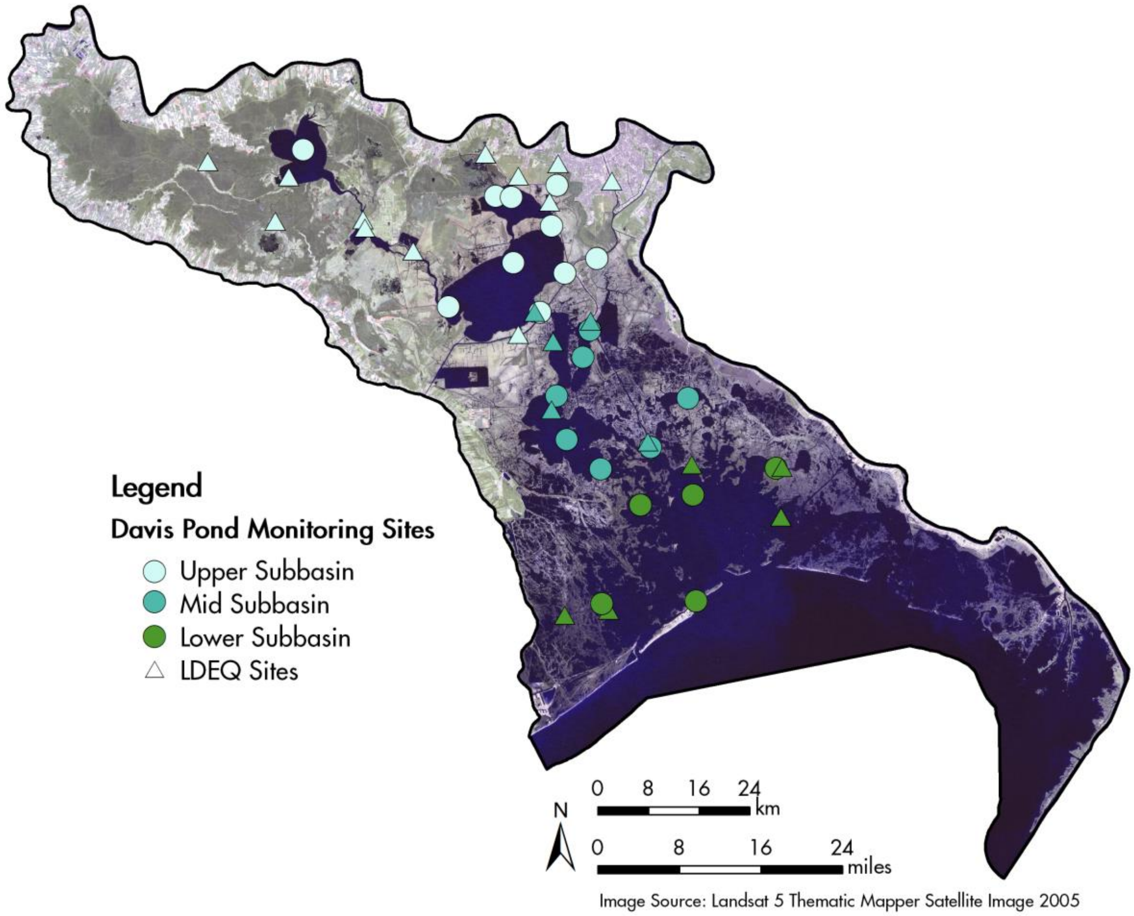


Figure 34. Dissolved oxygen site locations for the historical USACE Davis Pond Monitoring Program including those sampled by LDEQ as part of their Ambient Water Quality Monitoring Network. Sites were classified into subbasins using the USACE categorization.

Results

Coastwide

The results of the power analysis on the coastwide scale indicate that all hypotheses could be tested with a small sample size (10-34 sites; Table 19). Generally, large sample size requirements indicate that the difference being tested is relatively small or that standard deviation is large relative to the difference being tested.

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
1: Differences among basin means	n/a	0.78	14
2: Differences among seasonal means	n/a	0.22	4
4: +1 year of data	11-16%	0.16-0.23	10-34
5: +3 years of data	6%	0.09	4
6: +5 years of data	6%	0.09	4

Barataria Basin

The results of the power analysis on the basinwide scale indicate that all hypotheses could be tested with a moderate sample size (6-14 sites; Table 19). Detecting a linear pattern in the annual means over time, averaged over all factors, is sensitive to the effect size applied (Figure 35). However, a threshold point is evident in Figure 35 where an increase in sample size beyond 10 results in a very small shift in the percentage of change. For example, from a sample size of 4 to 10, the difference in the y-axis is approximately 5%, while an increase from 10 to 20 sites only results in a change of less than 1%. Also evident in the graphs is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 19. Dissolved oxygen summary results of the power analysis for hypotheses 1 through 6 on the basinwide scale.

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
1: Differences among subbasin means	n/a	0.90	14
2: Differences among seasonal means	n/a	1.84	4
3: Differences among waterbody type means	n/a	1.18	10
4: +1 years of data	10-6%	1.45-0.85	6-10
5: +3 years of data	~5%	0.71	6-10
6: +5 years of data	3-1%	0.42-0.13	6-10

i Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.

ii The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

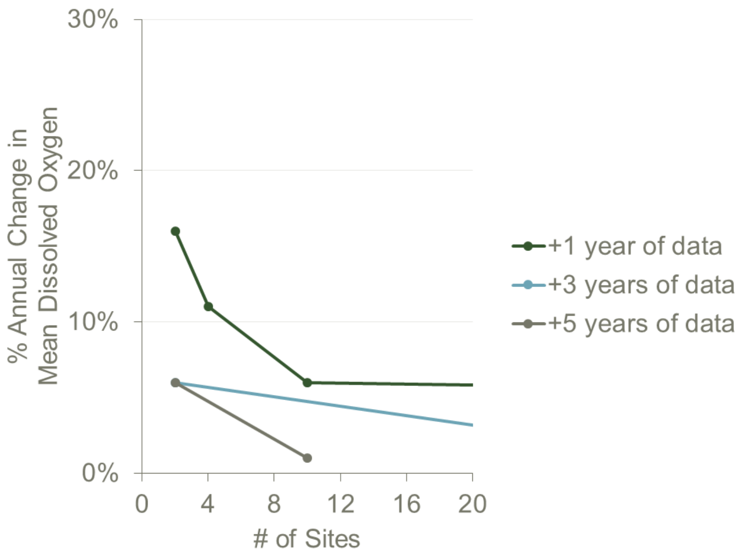


Figure 35. Results of the power analysis on the basinwide scale for hypotheses 4 through 6 indicating the percent change in mean dissolved oxygen that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.42. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on square-root-transformed values.

Subbasin

The results of the power analysis on the subbasin scale exhibit comparable sample size requirements for each hypothesis for an individual subbasin as they do for the basin as a whole (Table 20 and Figure 36). The only exception is the mid-subbasin hypothesis for detecting changes among waterbody types. The large sample size required (113 sites) for the mid-subbasin is because the average change is extremely small (0.35 mg L^{-1}), indicating that differences do not exist between the waterbody types (Table 20). The consistency in the estimates stems from the similarities in the means among subbasins such that the basinwide mean is representative of the mean calculated on a subbasin scale. As a result, if subbasin scale questions are of interest, the total sample size for the basin would be approximately three times larger than if the question of interest is on a basinwide scale.

Table 20. Dissolved oxygen summary results of the power analysis for hypotheses 2 through 6 by subbasin.

Upper Subbasin

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	1.78	4
3: Differences among waterbody type means	n/a	2.25	3
4: +1 year of data	20-11%	2.73-1.44	5-10
5: +3 years of data	6%	0.77	5-10
6: +5 years of data	6-5%	0.77-0.63	5-10

Mid-Subbasin

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	1.91	4
3: Differences among waterbody type means	n/a	0.35	113
4: +1 year of data	20-11%	3.32-1.75	3-8
5: +3 years of data	6%	0.93	3-8
6: +5 years of data	6-5%	0.93-0.77	3-8

Lower Subbasin

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	1.80	4
3: Differences among waterbody type means	n/a	0.82	20
4: +1 year of data	20-11%	3.09-1.62	3-10
5: +3 years of data	6%	0.87	3-10
6: +5 years of data	6-5%	0.87-0.72	3-10

i Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.
ii The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

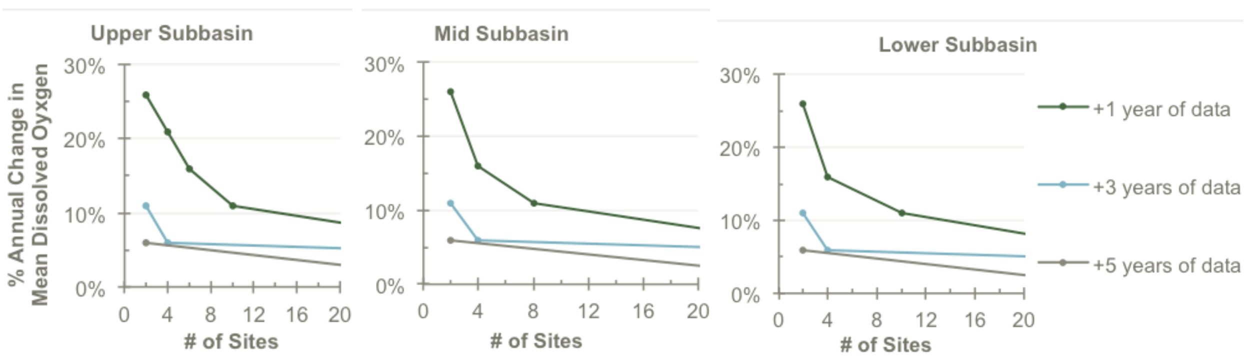


Figure 36. Results of the power analysis for each subbasin for hypotheses 4 through 6 indicating the percent change in dissolved oxygen that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.42. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on square-root-transformed values.

NUTRIENTS

Power Analysis

Nutrient concentrations are measured as part of the LDEQ AWQ statewide monitoring program. The LDEQ AWQ program samples on a monthly basis in the Barataria Basin every four years.

Coastwide

Total nitrogen (TN) and total phosphorus (TP) concentrations were obtained from the LDEQ AWQ program to create the exemplary dataset (as defined in the "Natural System Sampling Design" in the main report). LDEQ AWQ measures water quality parameters discretely on a monthly basis for one year and repeats every four years (Figure 5). It was assumed for the analysis that some element of randomness was incorporated into the selection of their monitoring sites. The sites were then categorized into basins using Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA) basin designations, as used by other CPRA monitoring programs. The natural log transformation was used on both TN and TP in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting GLMs to the natural log-transformed TN and TP concentrations, separately, with the interaction term season*basin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one basin mean differs significantly from another basin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. the means in year 0 differ significantly from the means in year 1, averaged over all seasons and basins;
4. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins;
5. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins.

Hypotheses 3 through 5 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Alpha (α) and power were also held constant across analyses at the different spatial scales. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in α generally results in a need for larger sample sizes (Zar, 2010). As a result, the focus of the analysis was to evaluate how sample size requirements change in response to the means of each of the factors calculated at the different spatial scales.

Basinwide and Subbasin

TN and TP concentrations were obtained from both the LDEQ AWQ program and the historical USACE Davis Pond monitoring program to create the exemplary dataset (as defined in the "Natural System Sampling Design" in the main report). As part of the Davis Pond monitoring program, water samples were obtained on a monthly basis throughout the Barataria Basin, while the LDEQ data collection dates back to 1978 (Figure 34). It is unknown how the original sampling locations were selected in either case, but it was assumed for the analysis that some element of randomness was incorporated into the selection of sites. The NHD was then used to classify the monitoring site locations into waterbody types. The NHD contains geographic information on the drainage network and classifies features such as rivers, streams, canals, lakes, ponds, coastline, dams, and stream gauges. The features were consolidated such that sites were classified as either open water (e.g., lakes, ponds) or channels (e.g., streams, canals). The sites were further classified based on their position in the estuary (upper, mid-, and lower subbasins as indicated in Figure 34) and the season in which they were collected. The square-root transformation was used on both TN and TP in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting GLMs to the square-root-transformed TN and TP concentrations, separately, with the interaction term season*waterbody type*subbasin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one subbasin mean differs significantly from another subbasin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. waterbody type means are significantly different from one another;
4. the means in year 0 differ significantly from the means in year 1, averaged over all waterbody types, seasons, and subbasins;
5. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins;
6. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins.

Hypotheses 4 through 6 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Further, hypotheses 2 through 6 were conducted for each subbasin independently in order to evaluate how sample size requirements may differ at a subbasin scale relative to the basin scale. Although standard deviation (σ) may differ when calculated at the basin versus subbasin scale, the basin scale estimate of standard deviation was used in the subbasin analysis. Alpha (α) and power were also held constant across analyses at the different spatial scales.

Results

Coastwide

The results of the power analysis on the coastwide scale indicate that detecting linear trends in the annual TN mean over years could be achieved with a relatively small sample size between 27-57 sites (

Table 21) and a smaller sample size for detecting annual changes in TP (10-34; Table 22). Detecting changes among seasons, however, requires a larger sample size for TP (260) because of the relatively small average change that occurs among season (0.01 mg L^{-1}). Generally, large sample size requirements indicate that the difference being tested is relatively small or that standard deviation is large relative to the difference being tested.

Table 21. Total nitrogen summary results of the power analysis for hypotheses 1 through 5.

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
1: Differences among basin means	n/a	0.31	7
2: Differences among seasonal means	n/a	0.05	50
3: +1 year of data	16-11%	0.05-0.03	27-57
4: +3 years of data	11-6%	0.03-0.02	7-20
4: +5 years of data	6%	0.02	7

Table 22. Total phosphorus summary results of the power analysis for hypotheses 1 through 5.

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
1: Differences among basin means	n/a	0.05	10
2: Differences among seasonal means	n/a	0.01	260
3: +1 year of data	11-6%	0.03-0.02	10-34
4: +3 years of data	6-5%	0.01-0.02	4-28
5: +5 years of data	6-1%	0.01-0.002	4-37

Barataria Basin

The results of the power analysis on the basinwide scale indicate that detecting linear trends in the annual TN mean over years could be achieved with a relatively small sample size (5-10 sites; Table 23) and a slightly higher sample size for detecting annual changes in TP (7-16; Table 24). In order to detect differences among subbasins, TN requires substantially more samples than TP (35 vs.4 sites), because the average change between subbasins is very small (0.077 mg L^{-1} TN; Table 23). Detecting changes among seasons and waterbody types requires large sample sizes for both TN and TP. Generally, large sample size requirements indicate that the difference being tested is relatively small or that standard deviation is large relative to the difference being tested.

Detecting a linear pattern in the annual means over time, averaged over all factors, is sensitive to the effect size applied (Figure 37 and Figure 38). However, a threshold point is evident in Figure 37 where an increase in sample size beyond 10 results in a very small shift in the percentage of change. For example, from a sample size of 5 to 10, the difference in the y-axis is approximately 9%, while an increase from 10 to 20 sites only results in a change of less than 1%. Also evident in the graphs is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time. The same patterns occur for TP, as well (Figure 38).

Table 23. Total nitrogen summary results of the power analysis for hypotheses 1 through 6.

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
1: Differences among subbasin means	n/a	0.077	35
2: Differences among seasonal means	n/a	0.041	67
3: Differences among waterbody type means	n/a	0.055	237
4: +1 years of data	20-11%	0.176-0.093	5-10
5: +3 years of data	6%	0.050	5-10
6: +5 years of data	6-5%	0.050-0.041	5-10

Table 24. Total phosphorus summary results of the power analysis for hypotheses 1 through 6.

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
1: Differences among subbasin means	n/a	0.063	4
2: Differences among seasonal means	n/a	0.012	86
3: Differences among waterbody type means	n/a	0.017	60
4: +1 years of data	20-11%	0.047-0.025	7-16
5: +3 years of data	6%	0.013	7-16
6: +5 years of data	6-5%	0.013-0.011	7-16

i Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.

ii The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

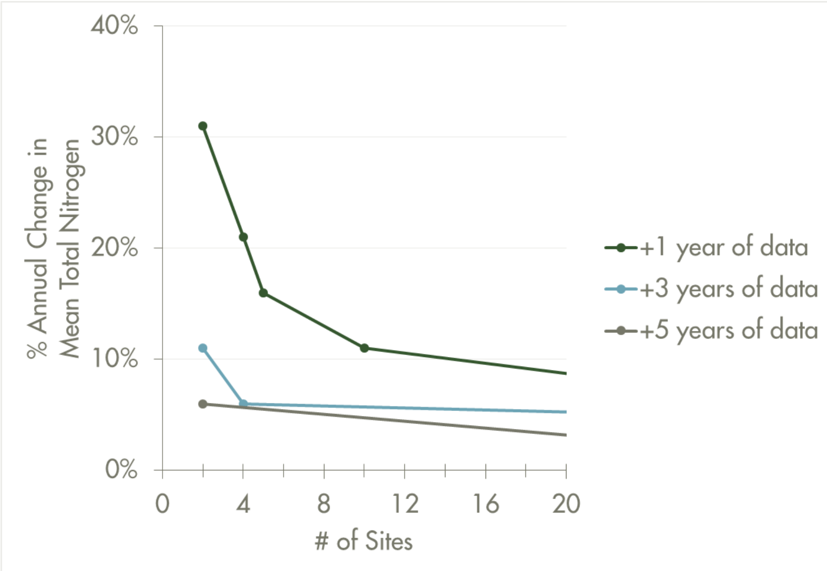


Figure 37. Results of the power analysis on the basinwide scale for hypotheses 4 through 6 indicating the percent change in TN that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.186. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including year 0 baseline). Percent change is based on square-root-transformed values.

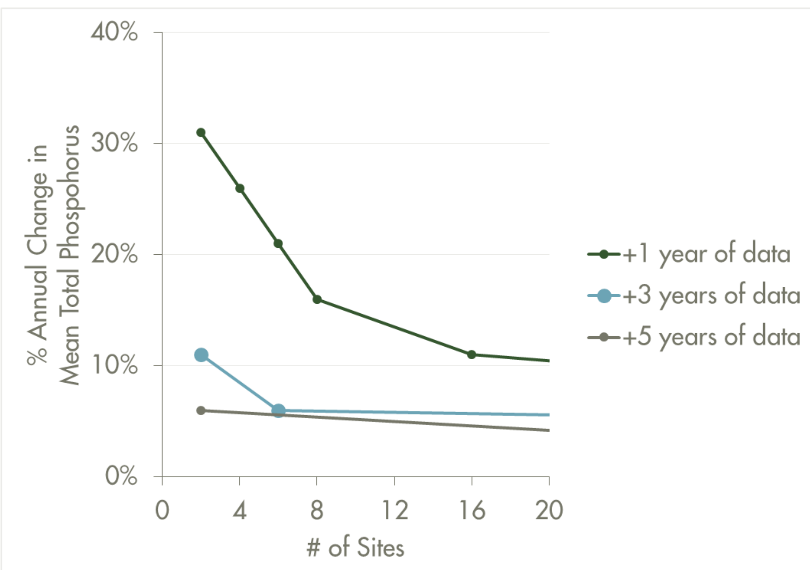


Figure 38. Results of the power analysis on the basinwide scale for hypotheses 4 through 6 indicating the percent change in TP that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.121. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including year 0 baseline). Percent change is based on square-root-transformed values.

Subbasin

The results of the power analysis on the subbasin scale exhibit comparable sample size requirements for detecting linear trends through time for an individual subbasin as they do for the basin as a whole (Figure 39 and Figure 40). An exception is the mid-subbasin hypothesis for detecting changes among waterbody types. The large sample size required (> 1000 sites) for the mid-subbasin is because the average change is extremely small (0.006 mg L^{-1}), indicating that there are not strong differences between the waterbody types for either TN or TP (Table 25 and Table 26). The consistency in the estimates stems from the similarities in the means among subbasins such that the basinwide mean is representative of the mean calculated on a subbasin scale. As a result, if subbasin scale questions are of interest, the total sample size for the basin would need to be increased.

Table 25. Total nitrogen summary results of the power analysis for hypotheses 2 through 6 by subbasin.

Upper Subbasin

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	0.050	45
3: Differences among waterbody type means	n/a	0.052	60
4: +1 years of data	20-11%	0.196-0.103	4-9
5: +3 years of data	6%	0.0549	4-9
6: +5 years of data	6-5%	0.0549-0.0456	4-9

Mid-Subbasin

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	0.034	91
3: Differences among waterbody type means	n/a	0.006	> 1000
4: +1 years of data	20-11%	0.174-0.092	4-10
5: +3 years of data	6%	0.0490	4-10
6: +5 years of data	6-5%	0.0490-0.0406	4-10

Lower Subbasin

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	0.192	91
3: Differences among waterbody type means	n/a	n/a	> 1000
4: +1 years of data	20-11%	0.145-0.076	4-10
5: +3 years of data	6%	0.0407	4-10
6: +5 years of data	6-5%	0.0407-0.0338	4-10

i Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.

ii The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

Table 26. Total phosphorus summary results of the power analysis for hypotheses 2 through 6 by subbasin.

Upper Subbasin

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
2: Differences among seasonal means	n/a	0.010	164
3: Differences among waterbody type means	n/a	0.92	4
4: +1 years of data	20-15%	0.070-0.051	6-10
5: +3 years of data	6%	0.020	6-10
6: +5 years of data	6-5%	0.020-0.016	6-10

Mid-Subbasin

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
2: Differences among seasonal means	n/a	0.013	54
3: Differences among waterbody type means	n/a	0.104	> 1000
4: +1 years of data	20-11%	0.046-0.024	5-10
5: +3 years of data	6%	0.013	5-10
6: +5 years of data	6-5%	0.013-0.011	5-10

Lower Subbasin

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
2: Differences among seasonal means	n/a	0.016	29
3: Differences among waterbody type means	n/a	0.055	27
4: +1 years of data	20-11%	0.028-0.015	5-12
5: +3 years of data	6%	0.008	5-12
6: +5 years of data	6-5%	0.008-0.007	5-12

[i] Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.
[ii] The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

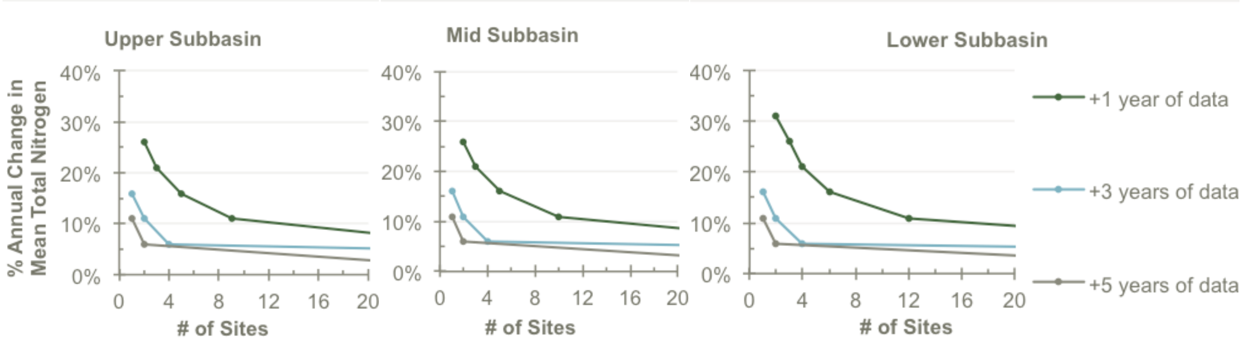


Figure 39. Results of the power analysis for each subbasin for hypotheses 4 through 6 indicating the percent change in TN that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.186. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on square-root-transformed values.

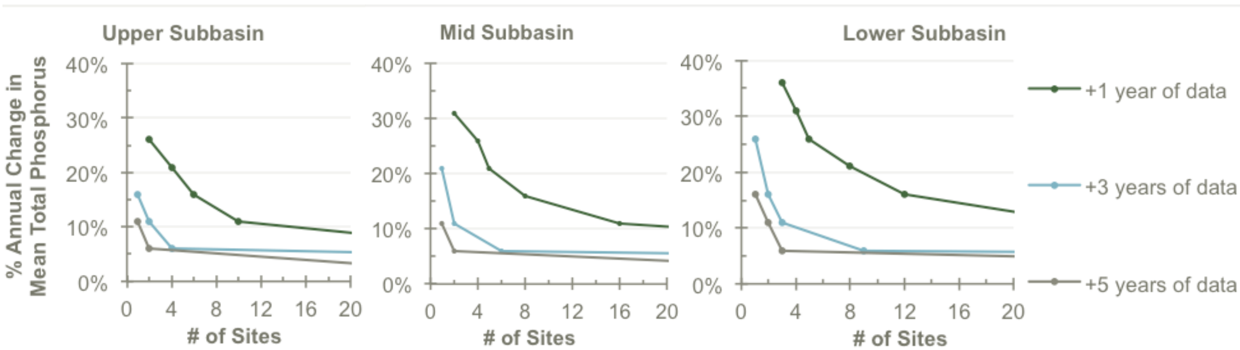


Figure 40. Results of the power analysis for each subbasin for hypotheses 4 through 6 indicating the percent change in TP that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.122. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on square-root-transformed values.

SALINITY

Power Analysis

An existing network of salinity gauges is located in canals, bayous, and ponds adjacent to wetlands as part of the Coastwide Reference Monitoring System (CRMS) and in the larger open waterbodies operated by the U.S. Geological Survey (Figure 41).

Coastwide

Salinity concentrations were obtained from the LDEQ AWQ program to create the exemplary dataset (as defined in the “Natural System Sampling Design” in the main report). LDEQ AWQ measures water quality parameters discretely on a monthly basis for one year and repeats every four years (Figure 5). It was assumed for the analysis that some element of randomness was incorporated into the selection of their monitoring sites. The sites were then categorized into basins using the Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA) basin designation, as used by other CPRA monitoring programs. The natural-logarithmic transformation was used on monthly mean salinity in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting GLMs to salinity concentrations with the interaction term season*basin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one basin mean differs significantly from another basin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. the means in year 0 differ significantly from the means in year 1, averaged over all seasons and basins;
4. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins;
5. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins.

Hypotheses 3 through 5 were conducted for different effect sizes (e.g., 1-36%) as described in the “Natural System Sampling Design” in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Alpha (α) and power were also held constant across analyses at the different spatial scales. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in α generally results in a need for larger sample sizes (Zar, 2010). As a result, the focus of the analysis was to evaluate how sample size requirements change in response to the means of each of the factors calculated at the different spatial scales.

Barataria Basin and Subbasin

Salinity data were obtained from CRMS monitoring program and USGS Louisiana Water Science Center (Figure 41) to create the exemplary dataset (as defined in the “Natural System Sampling Design” in the main report). The data were collected at a minimum once every hour. In order to obtain an accurate representation of average monthly conditions, only sites that contained at least 20 days’ worth of data were used in the analysis for that month. The CRMS program used a stratified random design with proportional allocation in the selection of sites (Steyer et al., 2003b), but it is unknown how the original sampling locations were selected for the USGS sites and it was assumed for the analysis that some element of randomness was incorporated into the selection of sites. The NHD was then used to classify the monitoring site locations into waterbody types. The NHD contains geographic information on the drainage network and classifies features such as rivers, streams, canals, lakes, ponds, coastline, dams, and stream gauges. The features were consolidated such that sites were classified as either open water (e.g., lakes, ponds) or channels (e.g., streams, canals). Given the disproportional number of canal sites (n = 89) versus the open water sites (n = 11), the analyses were run separately in order to determine whether there were sufficient sites for detecting changes within the open water bodies. The sites were further classified based on their position in the estuary (upper, mid-, and lower subbasins as indicated in Figure 41) and the season in which the data were collected. The natural-logarithmic transformation was used on monthly mean salinity in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting GLMs to the natural log transformed salinity with the interaction term season*subbasin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one subbasin mean differs significantly from another subbasin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. the means in year 0 differ significantly from the means in year 1, averaged over all seasons and subbasins;
4. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all seasons and subbasins;
5. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all seasons and subbasins.

Hypotheses 3 through 5 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Further, hypotheses 2 through 5 were conducted for each subbasin independently in order to evaluate how sample size requirements may differ at a subbasin scale relative to the basin scale. Although standard deviation (σ) may differ when calculated at the basin versus subbasin scale, the basin scale estimate of standard deviation was used in the subbasin analysis. Alpha (α) and power were also held constant across analyses at the different spatial scales. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in α generally results in a need for larger sample sizes (Zar, 2010). As a result, the focus of the analysis was to evaluate how sample size requirements change in response to the means of each of the factors calculated at the different spatial scales and waterbody types.

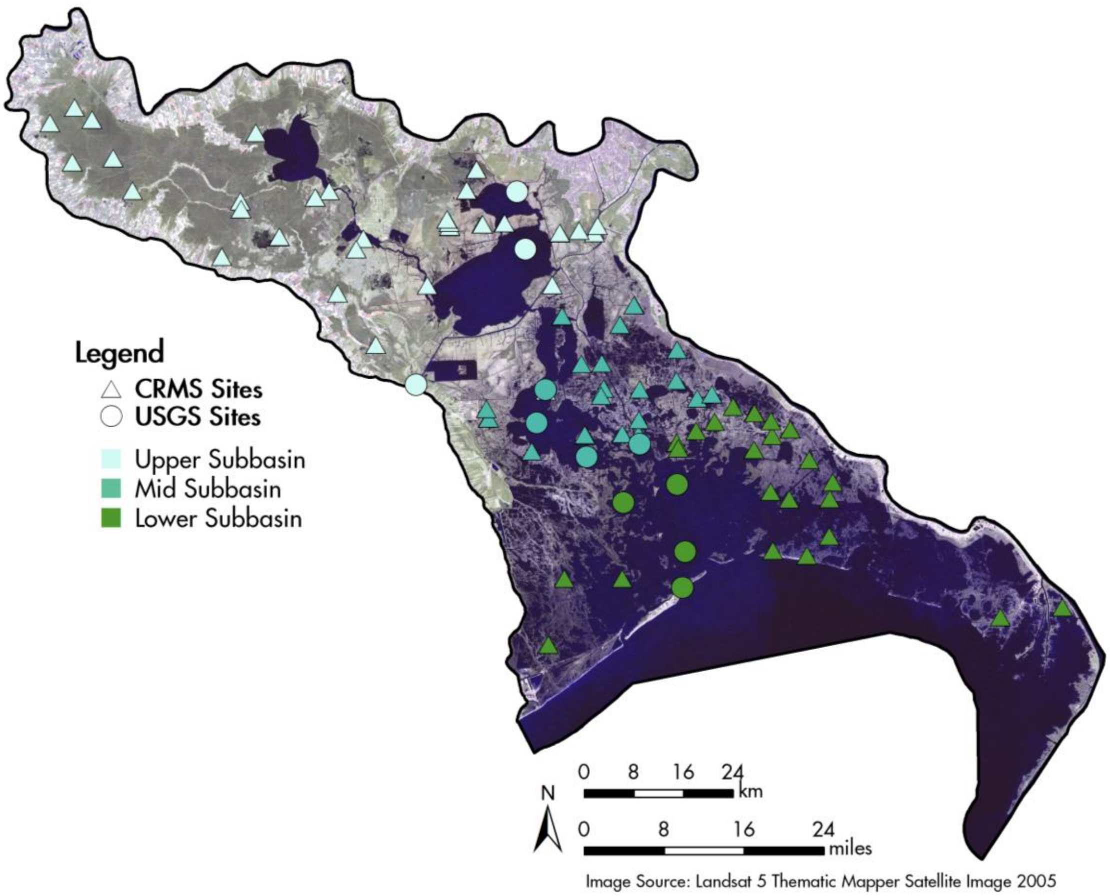


Figure 41. Site locations for the CRMS and USGS continuous salinity gauges.

Results

Coastwide

The results of the power analysis indicate that all hypotheses could be tested with a sample size between 34-115 sites (Table 27). Detecting differences among seasons or basins requires a sample size on the lower end given that the average change is relatively large (Table 27). Detecting changes from one year to the next or over multiple years requires different sample sizes depending on the level of change detectable and the number of years for testing this change. The longer data are collected, the ability to detect change improves.

Table 27. Salinity summary results of the power analysis for hypotheses 1 through 5 on the coastwide scale.

Hypothesis	% Change[i]	Average Change (ppt)[ii]	# of Sites
1: Differences among basin means	n/a	1.79	7
2: Differences among seasonal means	n/a	0.47	34
3: +1 year of data	20-25%	0.31-0.40	75-115
4: +3 years of data	11-16%	0.16-0.24	37-120
5: +5 years of data	6-10%	0.08-0.14	18-37

[i] *Detecting differences within basins and seasons was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.*
[ii] *The average change was calculated as the average difference among means for basins and seasons from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

Barataria Basin

The results of the power analysis on the basinwide scale indicate the existing CRMS sites occupying canals and bayous adjacent to wetlands are sufficient for detecting seasonal and annual changes within the canals. Thus, the remaining discussion pertains to the analysis of the open waterbodies. The results for the open waterbody type indicate that all hypotheses could be tested with a moderate sample size (15-22 sites; Table 28). Detecting a linear pattern in the annual means over time, averaged over all factors, is sensitive to the effect size applied (Figure 42). However, a threshold point is evident in Figure 42 where an increase in sample size beyond 20 results in a very small shift in the percentage of change. For example, from a sample size of 12 to 20, the difference in the y-axis is approximately 5%, while an increase from 20 to 40 sites still only results in a change of 5%. Also evident in the graphs is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 28. Salinity summary results of the power analysis for hypotheses 1 through 5 on the basinwide scale.

Hypothesis	% Change[i]	Average Change (ppt)[ii]	# of Sites
1: Differences among subbasin means	n/a	4.7	3
2: Differences among seasonal means	n/a	0.7	15
3: +1 years of data	20-15%	0.22-0.15	15-22
4: +3 years of data	6%	0.06	15-22
5: +5 years of data	6-5%	0.06-0.05	15-22

[i] *Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.*
[ii] *The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

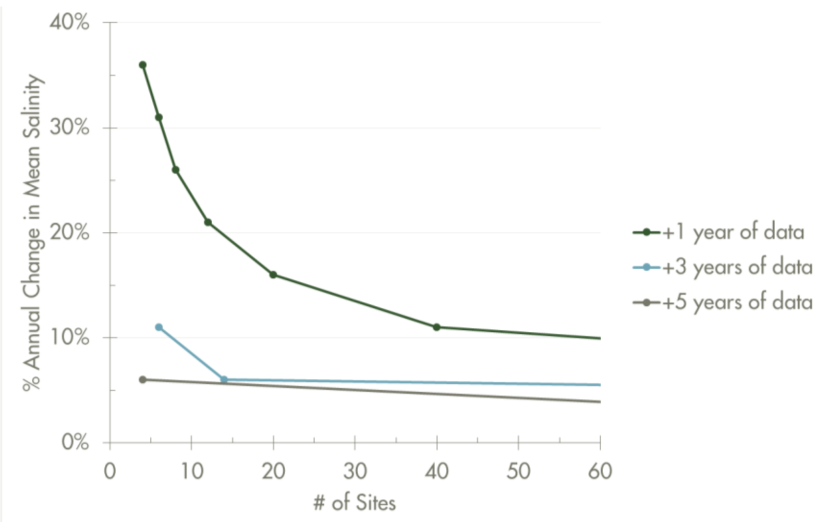


Figure 42. Results of the power analysis on the basinwide scale in open waterbodies for hypotheses 3 through 5 indicating the percent change in mean salinity that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=1.07. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on natural logarithmic transformed values.

Subbasin

The results of the power analysis for open waterbodies on the subbasin scale exhibit higher sample size requirements for detecting linear trends in the upper and mid-subbasins than the lower subbasin (Table 29 and Figure 44). This results from the lower salinity values present in the upper and mid-subbasins such that when the percent change is converted to salinity units, the change is actually very small (< 0.1 ppt in the upper subbasin, < 1.0 ppt in the mid-subbasin, and 1-4ppt in the lower subbasin Table 29). As a result, if subbasin scale questions are of interest and detecting small changes in the freshwater portions of the basins is of importance, then the allocation of sites across the subbasins should not be equal.

Table 29. Salinity summary results of the power analysis for hypotheses 2 through 5 by subbasin.

Upper Subbasin

Hypothesis	% Change[i]	Average Change (ppt)[ii]	# of Sites
2: Differences among seasonal means	n/a	0.1	17
3: +1 years of data	25-20%	0.08-0.07	19-30
4: +3 years of data	9-6%	0.03-0.02	19-30
5: +5 years of data	6%	0.02	19-30

Mid-Subbasin

Hypothesis	% Change[i]	Average Change (ppt)[ii]	# of Sites
2: Differences among seasonal means	n/a	1.3	9
3: +1 years of data	30-25%	0.70-0.56	23-32
4: +3 years of data	11-8%	0.23-0.17	23-32
5: +5 years of data	6%	0.12	23-32

Lower Subbasin

Hypothesis	% Change[i]	Average Change (ppt)[ii]	# of Sites
2: Differences among seasonal means	n/a	2.7	18
3: +1 years of data	20-15%	3.7-2.6	10-16
4: +3 years of data	7-6%	1.1-0.9	10-16
5: +5 years of data	6-5%	0.9-0.8	10-16

[i] *Detecting differences within seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.*
[ii] *The average change was calculated as the average difference among means for seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

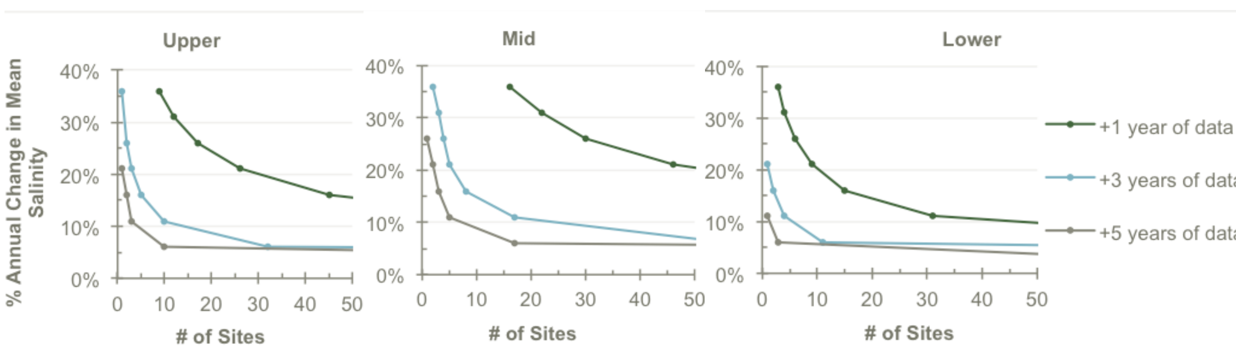


Figure 43. Results of the power analysis for each subbasin in open waterbodies for hypotheses 3 through 5 indicating the percent change in mean salinity that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=1.07. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on square-root-transformed values.

Power Analysis

At the time of this report, the LDEQ collected discrete water quality samples on a monthly basis to measure TSS (among other variables), although the monitoring in the Barataria Basin only occurs every four years. The Louisiana Department of Wildlife and Fisheries more recently has begun collecting turbidity data in conjunction with their fisheries independent monitoring program. The frequency of sampling is dependent upon the gear type used for the fisheries sampling and varies from weekly to monthly to annually at select locations (see Figure 46 for LDWF site locations).

Coastwide

TSS concentrations were obtained from the LDEQ AWQ program to create the exemplary dataset (as defined in the "Natural System Sampling Design" in the main report). LDEQ AWQ measures water quality parameters discretely on a monthly basis for one year and repeats every four years (Figure 5). It was assumed for the analysis that some element of randomness was incorporated into the selection of their monitoring sites. The sites were then categorized into basins using the Coastal Wetlands Planning, Protection and Restoration Act (CWPPRA) basin designation, as used by other CPRA monitoring programs. The natural-logarithmic transformation was used on monthly mean TSS in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting GLMs to TSS concentrations with the interaction term season*basin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one basin mean differs significantly from another basin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. the means in year 0 differ significantly from the means in year 1, averaged over all seasons and basins;
4. the means in years 0 through 2 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins;
5. the means in years 0 through 4 are linearly related and have a slope significantly different from zero, averaged over all seasons and basins.

Hypotheses 3 through 5 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Alpha (α) and power were also held constant across analyses at the different spatial scales. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in α generally results in a need for larger sample sizes (Zar, 2010). As a result, the focus of the analysis was to evaluate how sample size requirements change in response to the means of each of the factors calculated at the different spatial scales.

Barataria Basin

The power analysis was conducted on TSS, under the assumption that the recommendations provided for the other water quality variables (DO, chlorophyll *a*, TN, TP) and the results of the TSS analysis can be used to guide the sample size estimate for discrete measurements of turbidity. Concentrations of TSS were obtained from both the LDEQ AWQ program and the historical USACE Davis Pond monitoring program to create the exemplary dataset (as defined in the "Natural System Sampling Design" in the main report). As part of the Davis Pond monitoring program, water samples were obtained on a monthly basis throughout Barataria Basin from 1997 to 2009 and LDEQ collected TSS data during this time, as well (Figure 34). It is unknown how the original sampling locations were selected, but it was assumed for the analysis that some element of randomness was incorporated in the selection of sites. The NHD was then used to classify the monitoring site locations into waterbody types. The NHD contains geographic information on the drainage network and classifies features such as rivers, streams, canals, lakes, ponds, coastline, dams, and stream gauges. The features were consolidated such that sites were classified as either open water (e.g., lakes, ponds) or channels (e.g., streams, canals).The sites were further classified based on their position in the estuary (upper, middle, and lower subbasins as indicated in Figure 34) and the season in which data were collected. The natural logarithmic transformation was used in order to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting a GLM to the log-transformed TSS concentrations with the interaction term season*waterbody type*subbasin. These terms were used to reduce the residual mean square error and provide an estimate of the mean for each combination of factors. The following hypotheses were then tested for the power analysis:

1. at least one subbasin mean differs significantly from another subbasin mean;
2. at least one seasonal mean differs significantly from another seasonal mean;
3. waterbody type means are significantly different from one another;
4. the means in year 0 differ significantly from the means in year 1, averaged over all waterbody types, seasons, and subbasins;
5. the means in years 0 through year 2 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins;
6. the means in years 0 through year 4 are linearly related and have a slope significantly different from zero, averaged over all waterbody types, seasons, and subbasins.

Hypotheses 4 through 6 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +3, and +5 years of data, respectively. Further, hypotheses 2 through 6 were conducted for each subbasin independently in order to evaluate how sample size requirements may differ at a subbasin scale relative to the basin scale. Although standard deviation may differ when calculated at the basin versus subbasin scale, the basin scale estimate of standard deviation was used in the subbasin analysis. Alpha (α) and power were also held constant across analyses. It is already well established in the statistical literature that an increase in standard deviation, an increase in power, or a decrease in α generally results in a need for larger sample sizes (Zar, 2010). As a result, the only information not held constant between the basin and subbasin scale analyses was the estimated means for each of the factors (season, waterbody type, subbasin). This allowed for exploring the sensitivity of the analysis to the means calculated at the different spatial scales.

Results

Coastwide

The results of the power analysis indicate that all six hypotheses could be tested with a sample size between 10-77 sites (Table 30). Detecting differences among seasons or basins (hypotheses 1 and 2) requires a sample size on the lower end (10), because average differences among seasons or basins are large (10.58 mg L^{-1}). Detecting changes over time requires different sample sizes depending on the level of change detectable and the time period for testing this change.

Table 30. Turbidity summary results of the power analysis for hypotheses 1 through 6 on the coastwide scale.

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
2: Differences among seasonal means	n/a	10.58	10
3: Differences among basin means	n/a	10.58	10
4: +1 year of data	6-11%	6.02-12.04	7-24
5: +3 years of data	1-6%	0.92-6.02	4-77
6: +5 years of data	1-6%	0.92-6.02	4-24

Barataria Basin

The results of the power analysis on the basinwide scale indicate that detecting linear trends in the annual mean over years can be achieved with a moderate sample size (3-8 sites) while detecting changes within any of the factors (i.e., subbasins, seasons, waterbody types) requires a substantial increase in sample size (Table 31). Detecting a linear pattern in the annual means over time, averaged over all factors, is sensitive to the effect size applied (Figure 44). However, a threshold point is evident in Figure 44 where an increase in sample size beyond 8 results in a very small shift in the percentage of change. For example, from a sample size of 2 to 8, the difference in the y-axis is approximately 10%, while an increase from 8 to 16 sites only results in a change of less than 5%. Also evident in the graphs is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 31. Turbidity summary results of the power analysis for hypotheses 1 through 6 on the basinwide scale.

Hypothesis	% Change[i]	Average Change (mg L^{-1})[ii]	# of Sites
1: Differences among subbasin means	n/a	8.08	22
2: Differences among seasonal means	n/a	5.32	52
3: Differences among waterbody type means	n/a	0.50	> 1000
4: +1 years of data	11-20%	14.90-32.10	8-3
5: +3 years of data	6%	7.42	8-3
6: +5 years of data	5-6%	6.07-7.42	8-3

[i] Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.
[ii] The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from y 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

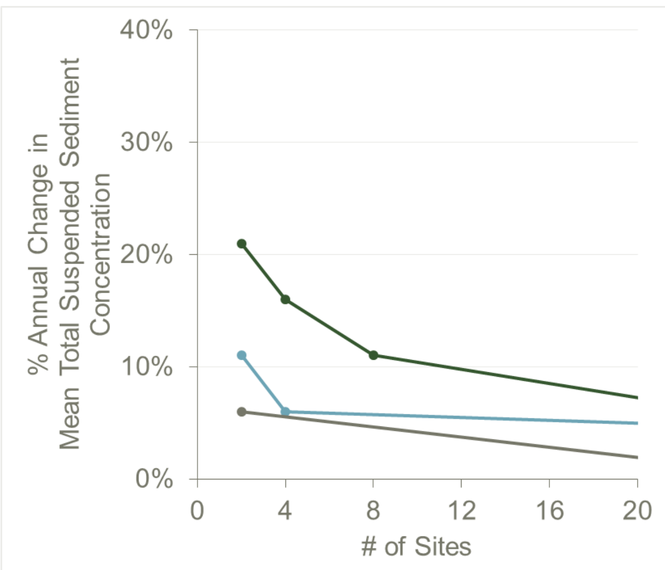


Figure 44. Results of the power analysis for TSS on the basinwide scale for hypotheses 4 through 6 indicating the percent change that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.86. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on natural logarithmic transformed values.

Subbasin

The results of the power analysis on the subbasin scale exhibit comparable sample size requirements for each hypothesis for an individual subbasin as they do for the basin as a whole (Table 32). The reason for the consistency in the estimates stems from the similarities in the means among subbasins such that the basinwide mean is representative of the mean calculated on a subbasin scale. As a result, if subbasin scale questions are of interest, the total sample size for the basin would be approximately three times larger than if the question of interest is on a basinwide scale.

Table 32. Turbidity summary results of the power analysis for hypotheses 2 through 6 by subbasin.

Upper Subbasin

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
2: Differences among seasonal means	n/a	9.66	12
3: Differences among waterbody type means	n/a	7.42	24
4: +1 years of data	11-20%	9.64-22.95	8-4
5: +3 years of data	6%	9.64-22.95	8-4
6: +5 years of data	5-6%	9.64-22.95	8-4

Mid-Subbasin

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
2: Differences among seasonal means	n/a	9.88	20
3: Differences among waterbody type means	n/a	4.27	130
4: +1 years of data	11-20%	14.89-36.12	7-3
5: +3 years of data	6%	14.89-36.12	7-3
6: +5 years of data	5-6%	14.89-36.12	7-3

Lower Subbasin

Hypothesis	% Change[i]	Average Change ($mg\ L^{-1}$)[ii]	# of Sites
2: Differences among seasonal means	n/a	13.89	12
3: Differences among waterbody type means	n/a	13.84	15
4: +1 years of data	11-20%	16.33-39.78	7-3
5: +3 years of data	6%	16.33-39.78	7-3
6: +5 years of data	5-6%	16.33-39.78	7-3

[i] Detecting differences within subbasins, seasons, and waterbody types was based on the changes that have historically occurred within those categories. The effect size was not manually adjusted as was done with the trend analysis.
[ii] The average change was calculated as the average difference among means for subbasins, seasons, and waterbody types from the exemplary dataset and as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

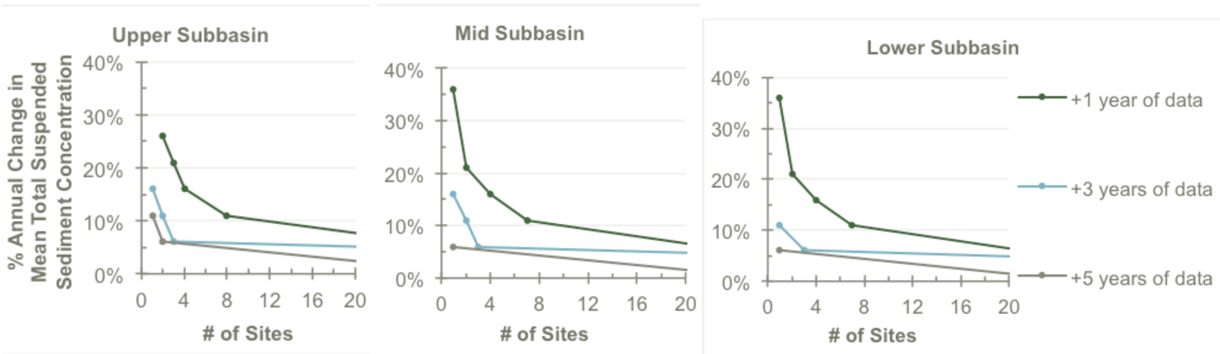


Figure 45. Results of the power analysis for each subbasin for hypotheses 4 through 6 indicating the percent change that can be detected given a range of sample sizes with α=0.05, β≥0.80, σ=0.86. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +3, and +5 years of data equate to 2, 4, and 6 years of data in total (including baseline, year 0). Percent change is based on square-root-transformed values.

Biotic Integrity

NEKTON COMMUNITY COMPOSITION AND OYSTER BIOMASS

Overview

Collection of fish and shellfish using standardized gear can be used as an indicator of relative abundance and can be used to develop diversity indices and to quantify potential consumer resource availability within estuarine habitats. Standardized gear also target specific size classes, which provides an opportunity to examine ecological differences among life stages of a given species (Livingston, 1988). The LDWF Fisheries Independent Monitoring program employs a variety of gear types, including trawls, seines, and gillnets, intended to target particular groups of fish and shellfish, although all species caught are recorded in the database. The program also samples oysters within a square meter plot. The meter square samples provide a measure of oyster density collected annually during the summer months at several sites along the public oyster grounds within the Barataria Basin. Given the low sampling frequency and small spatial scale, it was determined that the data may not be representative of the true oyster population in the basin. As a result, the power analysis was only conducted on marine species caught with trawls, seines, and gillnets, and freshwater species caught using boat electrofishing, as described below.

Power Analysis

The coastwide and basinwide analyses were conducted on catch per unit effort (CPUE) of different fish and shellfish species for the 16-foot trawl, 50-foot seine, 750-foot experimental gillnet, and electrofishing. CPUE is a measure of relative abundance and, due to the variable catch efficiency of different gear types, should be estimated separately for each gear type. The 16-foot trawls are sampled bi-weekly during November through February and weekly from March through October at fixed stations to provide abundance indices and size distributions for penaeid shrimps, crabs, and finfish (bottom fish) in the larger inshore bays and Louisiana's territorial waters (LDWF, 2002). Preliminary examination of the data for the period 2003- 2013 revealed the 16-foot trawls were efficient at catching blue crab, white shrimp, brown shrimp, grass shrimp, Gulf menhaden, and bay anchovy. With the exception of grass shrimp, species represent key economic fisheries. Grass shrimp was included because it is a marsh resident species and tracking changes in both transients and residents is of particular importance in response to large-scale environmental perturbations and management actions. The 50-foot seines have historically been sampled once or twice per month at fixed stations within each coastal basin by LDWF to provide abundance indices and size distributions of the small fishes and invertebrates using the shallow shoreline habitats of the estuaries (LDWF, 2002). Preliminary examination of the data for the period 2003-2013 revealed the 50-foot seines were efficient at catching blue crab, white shrimp, brown shrimp, grass shrimp, sheepshead minnow, Gulf menhaden, and bay anchovy. Both grass shrimp and sheepshead minnow are marsh resident species. The 750- foot experimental gill nets have historically been sampled once per month at fixed stations from October through March and twice per month from April through September to provide abundance indices and sizes for adult finfish such as spotted seatrout, Gulf menhaden, and red drum (LDWF, 2002). Preliminary examination of the data for the period 2003-2013 revealed the 750-foot gill nets were efficient at catching Gulf menhaden and spotted seatrout. Although spotted seatrout is not a marsh resident species, females show strong fidelity for natal estuaries, which may limit their ability to respond to large-scale changes in the system (Callihan et al., 2013). Lastly, electrofishing is conducted in 15-minute time steps up to four times a year in freshwater rivers, lakes, and bayous. It is primarily used for sampling largemouth bass populations. As a result, the analysis was conducted strictly on largemouth bass. The natural-logarithmic transformation was used in all analyses to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting a GLM to the CPUE of each of the species for each gear type with month and subbasin (mid- and lower, only) as a covariate. Given the large number of species and gear types analyzed, the analysis was focused on a single hypothesis for each species. The following hypothesis was tested for the power analysis:

1. the means in year 0 differ significantly from the means in year 1.

The hypothesis was conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report.

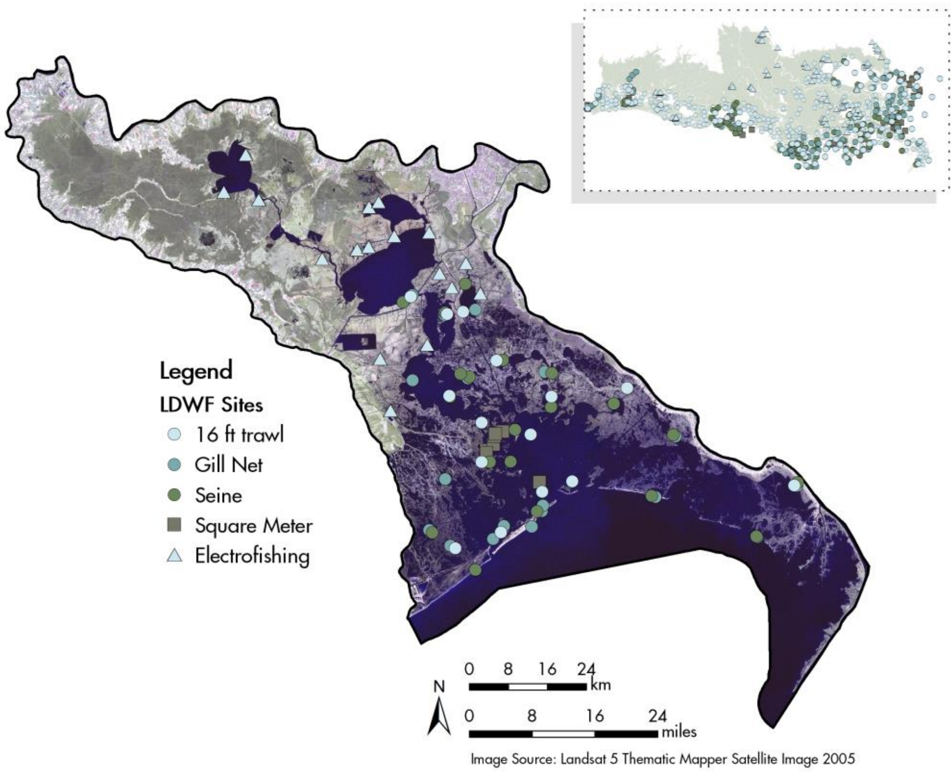


Figure 46. Existing LDWF sites that sample nekton community composition in the mid- and lower subbasins of Barataria Basin.

Results

Coastwide

The 750-foot gill net is effective at detecting between 25-35% change in mean annual CPUE of adult Gulf menhaden and adult spotted seatrout with a sample size of 52, which represents the current number of gill net sites that are sampled on an annual basis coastwide by LDWF. There are a total of 107 sites from which the 52 are randomly selected in a given year. If all 107 of LDWF's gillnet sites were sampled in a year, then the ability to detect change would only improve to 20-25%. As a result, increasing the sample size does not result in substantial benefits and is thus not recommended at this time. The 16-foot trawl is most effective at the current sample size (92 sites) for detecting changes between 10-20% for juvenile blue crab, juvenile brown shrimp, and grass shrimp, and between 5-10% for juvenile and adult bay anchovy and juvenile Gulf menhaden. The 50-foot seine was also effective at detecting between 10-15% for juvenile white and brown shrimp, juvenile blue crab, and grass shrimp, and 5-10% change for juvenile bay anchovy and juvenile Gulf menhaden based on the current sample size of 102. The electrofishing gear is capable of detecting trends in largemouth bass as small as 6% based on a sample size of 86 sites coastwide. As a result, the existing sample sizes are all sufficient for detecting trends on the coastwide scale, although there is variation between gear types and species in the change that it is possible to detect.

Barataria Basin

Detecting a linear change in the annual means over time depends on the effect size and gear type. The 750-foot gill net is effective at detecting 25% changes in mean annual CPUE of adult Gulf menhaden and adult spotted seatrout with a sample size of 25, which represents the current number of gill net sites sampled by LDWF (Figure 47). In order to detect a 20% change in either species, the sample size would need to increase from 25 to 40 sites. The 16-foot trawl is most effective at the current sample size (15 sites) for detecting changes in juveniles and adult bay anchovies, and juvenile blue crab and juvenile brown and white shrimp, but least effective for grass shrimp and juvenile Gulf menhaden (Figure 48). Increasing the 16-foot trawl sample size from 15 to 20 would allow for detecting 20% annual changes in juvenile blue crab and juvenile brown and white shrimp. The electrofishing gear at the current sample size of 16 sites is capable of detecting a 15% change in largemouth bass from one year to the next (Figure 49). The 50-foot seine is the least effective out of all the gear types tested at detecting trends on the basinwide scale. At the current sample size of 20, a 25% change can be detected in juvenile bay anchovy and grass shrimp, while only 30% (and higher) for all other species tested (Figure 50). The inefficiency of seines in capturing small nekton has previously been reported, resulting in low and variable catch efficiencies (Rozas & Minello, 1997).

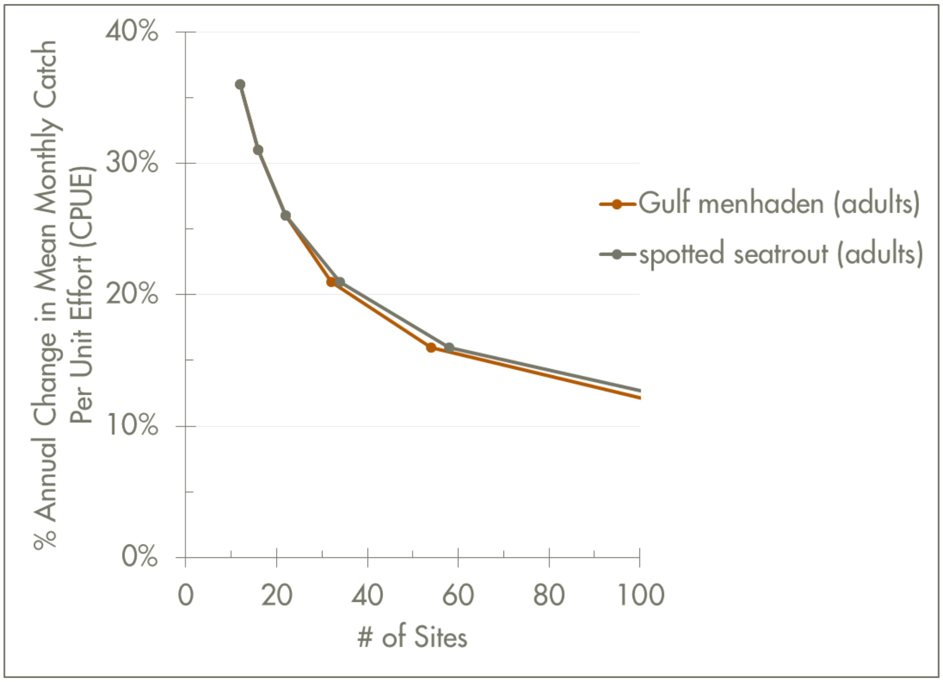


Figure 47. Results of the power analysis for the 750-foot gill net on the basinwide scale indicating the percent change that can be detected in CPUE given a range of sample sizes (α=0.1, β≥0.80, σ=see Table 33).

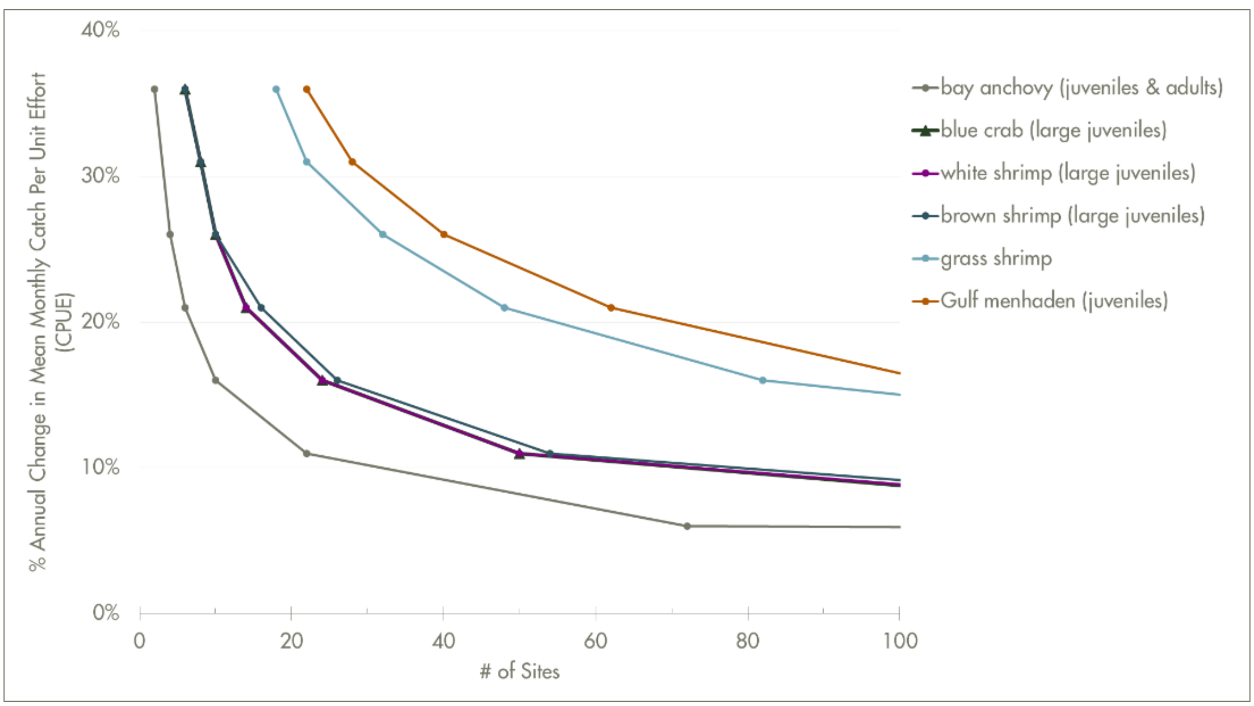


Figure 48. Results of the power analysis for the 16-foot trawl on the basinwide scale indicating the percent change that can be detected in CPUE given a range of sample sizes (α=0.1, β≥0.80, σ=see Table 33). The blue crab line (green with triangle symbol) overlaps the white shrimp line (pink with circle symbol) on the graph.

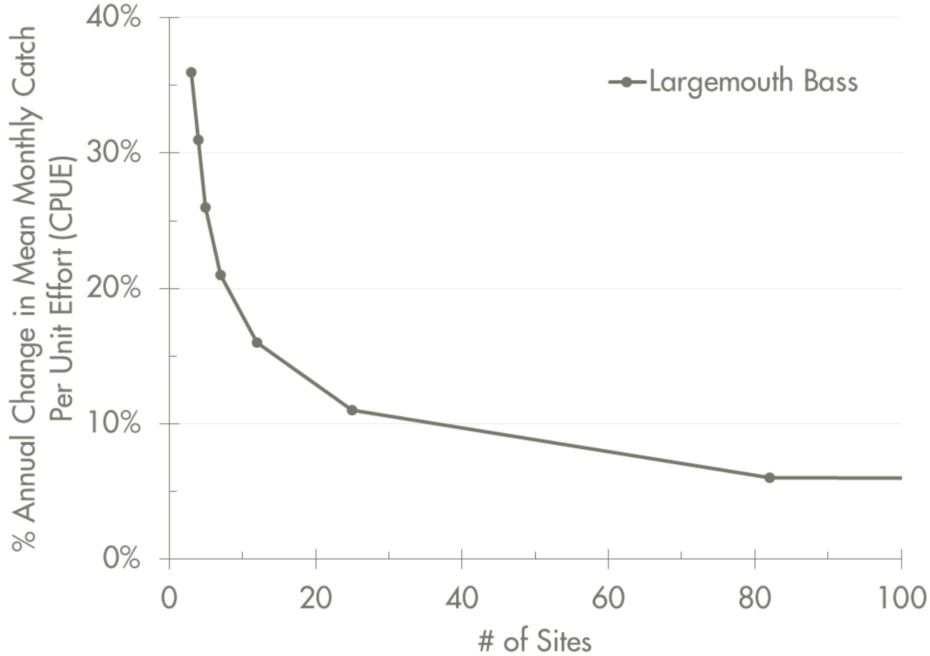


Figure 49. Results of the power analysis for electrofishing on the basinwide scale indicating the percent change that can be detected in CPUE given a range of sample sizes (α=0.1, β≥0.80, σ=see Table 33).

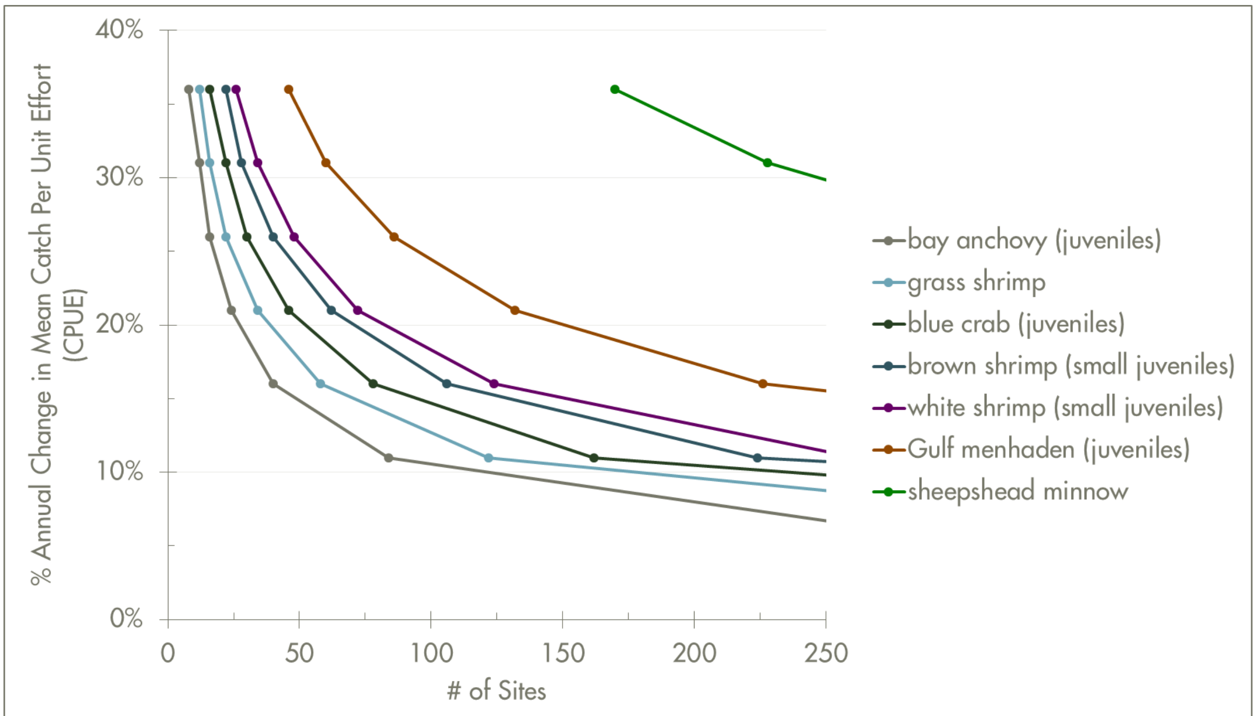


Figure 50. Results of the power analysis for the 50-foot seine on the basinwide scale indicating the percent change that can be detected in CPUE given a range of sample sizes (α=0.1, β≥0.80, σ=see Table 33).

Table 33. Standard deviations used in the power analysis for each of the fish and shellfish species and gear type.

Species	Gear Type	Standard Deviation (σ)	
		Barataria Basin	**Coastwide**
Blue crab	Trawls	0.84	1.36
White shrimp	Trawls	1.27	1.41
Gulf menhaden	Trawls	0.86	0.97
Grass shrimp	Trawls	0.76	1.77
Brown shrimp	Trawls	1.23	2.06
Bay anchovy	Trawls	1.71	1.83
White shrimp	Seine	0.71	1.73
Bay anchovy	Seine	1.81	1.75
Brown shrimp	Seine	0.88	1.98
Gulf menhaden	Seine	1.26	1.16
Grass shrimp	Seine	1.50	2.62
Sheepshead minnow	Seine	0.49	N/A
Blue crab	Seine	0.74	0.91
Gulf menhaden	Gill net	1.13	2.27
Spotted seatrout	Gill net	0.85	1.17
Largemouth bass	Electrofishing	1.08	1.02

WETLAND BIOMASS AND SOIL CONDITION

Overview

Wetland biomass refers to both the above- and below-ground components of the plant, typically separated by live and dead materials. Biomass production contributes to soil organic matter content and elevation changes and is affected by inundation, nutrient concentrations, soil properties, and for plants with C_3 metabolisms, atmospheric CO_2 (Bazzaz, 1990; Day et al., 2013; Kirwan & Guntenspergen, 2012). Measurements of biomass over time can be used to evaluate wetland primary productivity in response to management activities and ecosystem drivers. Bulk density is used to estimate and evaluate many physical soil properties, such as porosity, water retention, buoyancy and compressibility (Ruehlmann & Körschens, 2009). Organic matter and mineral content of wetland soils are key determinants of soil development and are often used to describe the roles of organic accumulation - derived from above- and below-ground plant material - and mineral sediment deposition (Neubauer, 2008; Nyman et al., 2006). Both processes will vary with plant communities and other aspects of wetland dynamics, including soil inundation, drainage, redox potential, and other biogeochemical processes (Reddy et al., 2000). There is no existing monitoring program of wetland biomass in coastal Louisiana. Soil condition data (organic matter and bulk density) are collected upon establishment of new CRMS sites and repeated measurements are taken at the sites every 10 years.

Power Analysis

The analysis was conducted using aboveground biomass and soil bulk density obtained from a research study in herbaceous wetlands (Piazza et al., 2011). Similar results were found for both aboveground biomass and soil bulk density, so the remaining discussion is limited to aboveground biomass for simplicity. The data were collected four times a year from 2006- 2007 and sites were selected to overlap with the CRMS program. The square-root transformation was used to approximate normality and satisfy the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting a GLM to the transformed means with season and wetland type (i.e., fresh, intermediate, brackish, and saline marsh as defined in the study) as covariates. The low sample sizes within each basin prevented use of basin as a covariate. The following hypotheses were then tested for the power analysis:

1 at least one wetland type mean differs significantly from another wetland type mean;
2. the means in year 0 differ significantly from the means in year 1, averaged over all basins.
3. the means in years 0 through 5 are linearly related and have a slope significantly different from zero, averaged over all basins;
4. the means in year 0 differ significantly from the means in year 4, averaged over all basins.

Hypotheses 2-4 were conducted for different effect sizes (e.g., 1-36%) as described in the "Natural System Sampling Design" in the main report and are referenced shorthand in the tables and figures as +1, +5 years of data, and once every 5 years, respectively. Further, hypotheses 1-4 were conducted at the coastwide and basinwide scale in order to evaluate how sample size requirements may differ over spatial scales. For the basin scale analysis, data from both Barataria and Breton basins were used so that all wetland types would be present in the analysis. This assumes the data collected in Breton Basin is representative of soil conditions in Barataria Basin and the sample size estimates from the analysis can be applied to Barataria Basin or Breton Basin. Although season was included as a covariate in the model to reduce the residual variance, it was not included in the power analysis because measurements are not expected to vary seasonally and would only be collected once in a given year for SWAMP.

Results

Coastwide

The results of the power analysis on the coastwide scale indicate that detecting linear trends in the annual mean from one year to the next requires a moderate sample size, however, a longer time step enables much finer changes to be detected (Table 34). Detecting a linear pattern in the annual means over time, averaged over all factors, is also sensitive to the effect size applied (Figure 51). However, a threshold point is evident in Figure 51 where an increase in sample size beyond 112 results in a very small shift in the percentage of change. Also evident in the graphs is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 34. Herbaceous wetland aboveground biomass summary results of the power analysis for the hypotheses on the coastwide scale.

Hypothesis	% Change	Average Change (g m^{-2})[i]	# of Sites
1: Differences among wetland types	n/a	272.9	56
2: +1 years of data	16-11%	475.8-319.5	56-112
3: +5 years of data	6%	170.2	56-112
4: Once every 5 years	6-5%	170.2-141.1	56-112

[i] The average change in aboveground biomass (g m-2) was calculated as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.

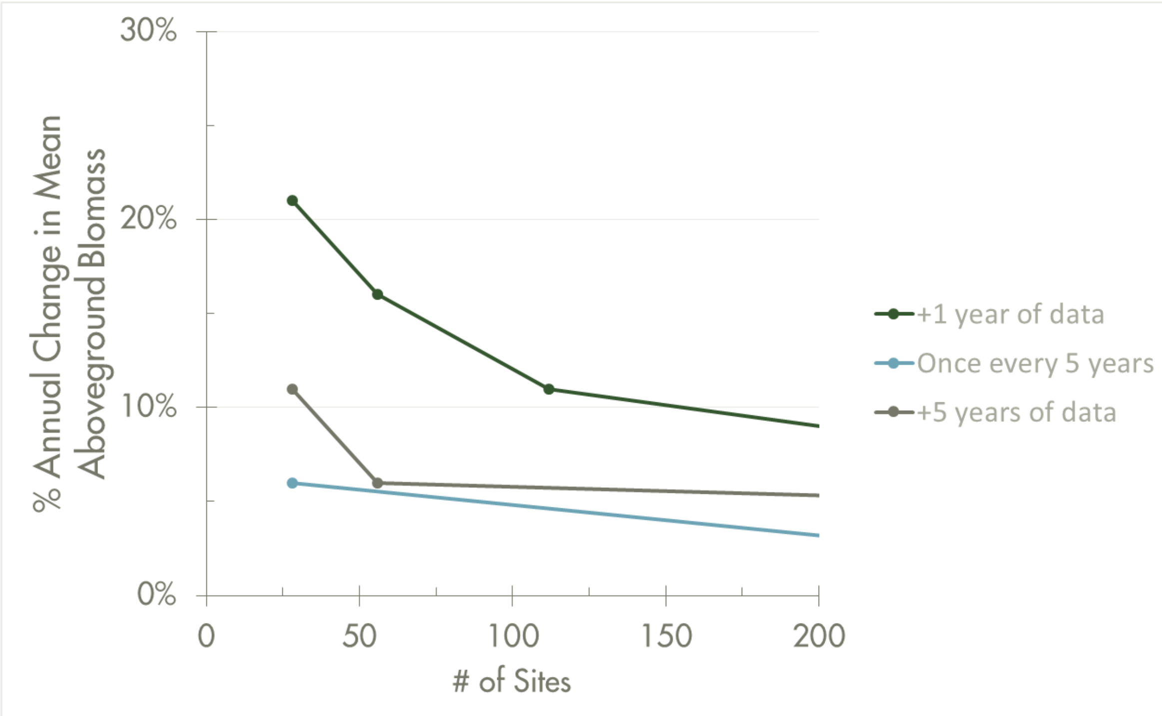


Figure 51. Results of the power analysis on the coastwide scale indicating the percent change in aboveground biomass that can be detected given a range of sample sizes (α=0.05, β≥0.80, σ=9.94). Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +5, and once every 5 years of data equate to 2, 6, and 2 years of data in total (including baseline), respectively.

Barataria Basin

The results of the power analysis on the basinwide scale indicate that detecting linear trends in the annual mean from one year to the next requires a substantial sample size, however, a longer time step enables much finer changes to be detected (Table 35). Detecting a linear pattern in the annual means over time, averaged over all factors, is also sensitive to the effect size applied (Figure 52). However, a threshold point is evident in Figure 52 where an increase in sample size beyond 63 results in a very small shift in the percentage of change. Further, the graphs indicate that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 35. Herbaceous wetland aboveground biomass summary results of the power analysis for the hypotheses on the basinwide scale.

Hypothesis	% Change	Average Change (g m^{-2})[i]	# of Sites
1: Differences among wetland types	n/a	406.9	63
2: +1 years of data	20-16%	494.2-388.2	45-63
3: +5 years of data	6%	138.8	45-63
4: Once every 5 years	6-5%	138.8-115.3	45-63

[i] *The average change in aboveground biomass (g m^{-2}) was calculated as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

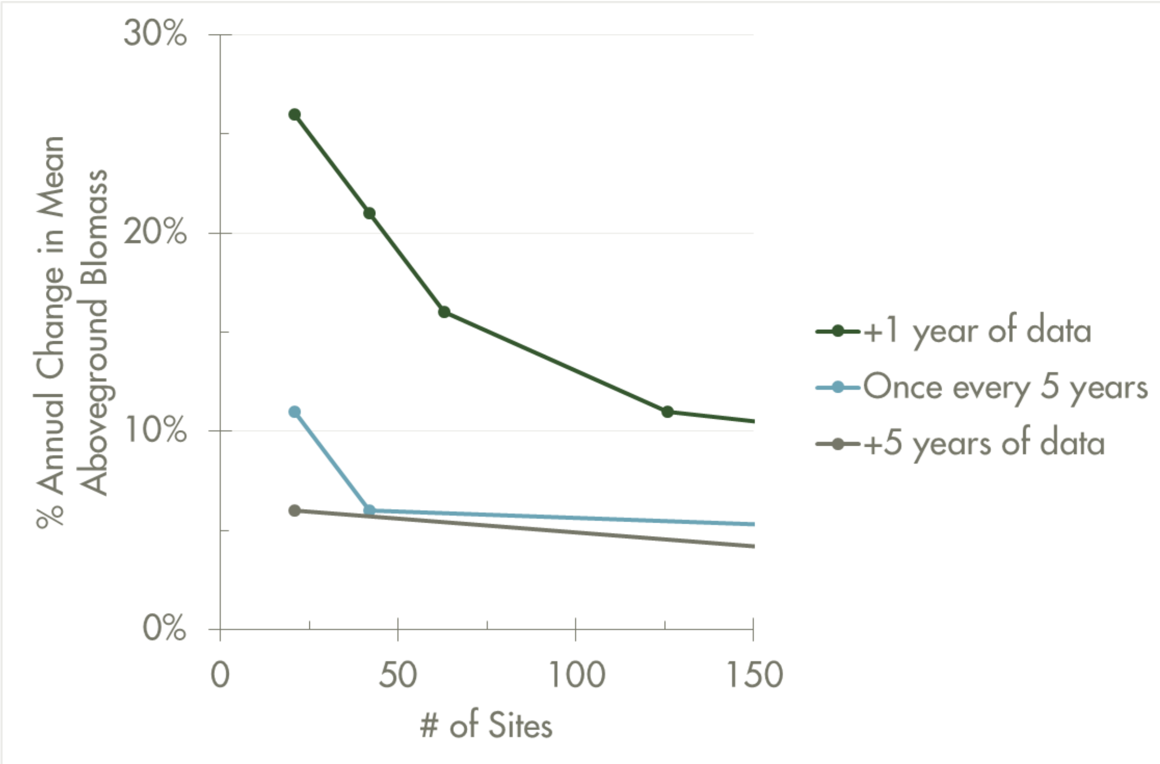


Figure 52. Results of the power analysis on the basinwide scale indicating the percent change in aboveground biomass that can be detected given a range of sample sizes (α=0.05, β≥0.80, σ=9.65. Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +5, and once every 5 years of data equate to 2, 6, and 2 years of data in total (including baseline), respectively.

WETLAND COMMUNITY COMPOSITION

Overview

Monitoring of herbaceous and forested wetlands is currently conducted through the CRMS program and includes measures of species composition, overstory and understory diameter at breast height (DBH), understory plant height, and canopy cover (Figure 53). A continuous salinity and water level recorder, rod surface elevation tables, and vertical accretion plots are also stationed at each site.

Power Analysis

The power analysis was conducted using the Floristic Quality Index (FQI) calculated for each herbaceous wetland site and the Forested FQI (FFQI) for forested wetlands. FQI is used as a measure of wetland condition in the CRMS program and is calculated from species percent cover (both native and non-native species) and a coefficient of conservatism score which ranks species based on their relative tolerance to disturbance and fidelity to specific environmental conditions (Cretini et al., 2012). The FQI and FFQI was calculated annually from 2007- 2013. The CRMS program used a stratified random design with proportional allocation in the selection of sites (Figure 53; Steyer et al., 2003b). FQI scores approximated normality and satisfied the assumptions of the GLM. Estimated means and variance were generated for the exemplary dataset by fitting a GLM to the FQI scores with basins as a covariate. The following hypotheses were then tested for the power analysis:

1. at least one basin mean differs significantly from another basin mean;
2. the means in year 0 differ significantly from the means in year 1, averaged over all basins.
3. the means in years 0 through 5 are linearly related and have a slope significantly different from zero, averaged over all basins;
4. the means in year 0 differ significantly from the means in year 4, averaged over all basins.

Hypotheses 2-4 were conducted for different effect sizes (e.g., 1-36%) as described in the “Natural System Sampling Design” in the main report and are referenced shorthand in the tables and figures as +1, +5 years of data, and once every 5 years, respectively. Further, hypotheses 2-4 were conducted at the coastwide and basinwide scale in order to evaluate how sample size requirements may differ over spatial scales. Hypothesis 1 is only relevant to the coastwide scale analysis.

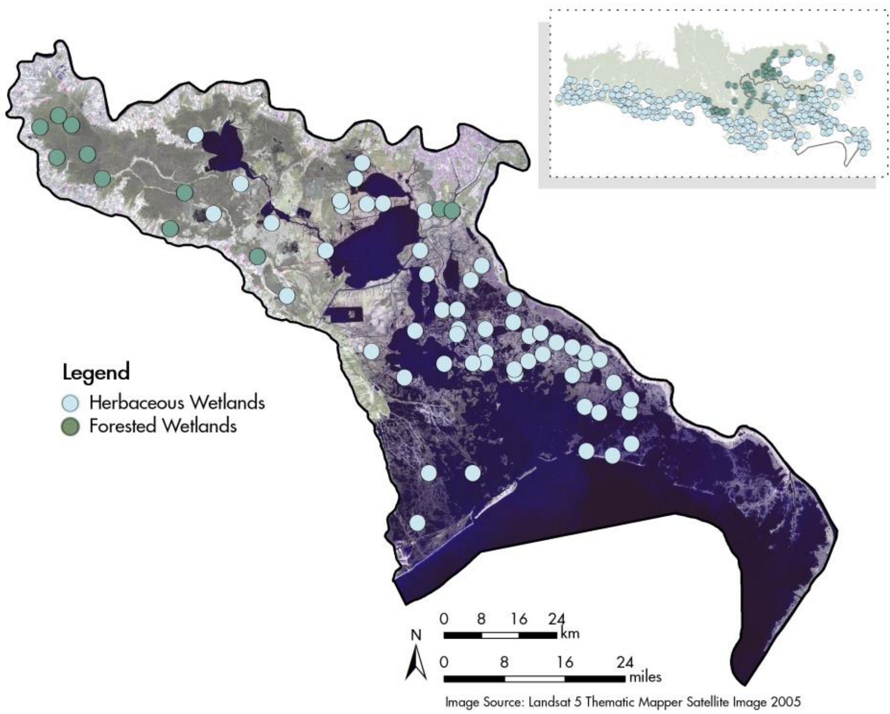


Figure 53. Existing CRMS sites in Barataria Basin used in the power analysis.

Results for Forested Wetlands

Coastwide

The results of the power analysis on the coastwide scale indicate that detecting linear trends in the annual mean from one year to the next requires a sample size of greater than 100, however, a longer time step enables much finer changes to be detected at half the sample size (Figure 54). Detecting a linear pattern in the annual means over time, averaged over all factors, is also sensitive to the effect size applied (Figure 54). However, a threshold point is evident in Figure 54 where an increase in sample size beyond 35 results in a very small shift in the percentage of change for the once every 5 years sampling regime. For example, from a sample size of 20 to 35, the difference in the y-axis is 5%, while a change from 35 to 110 results in only a change of 5%. Also evident in the graphs is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 36. Forested wetland FFQI summary results of the power analysis for the hypotheses on the coastwide scale.

Hypothesis	% Change	Average Change (FFQI)[i]	# of Sites
1: Differences among basins	n/a	8.9	25
2: +1 years of data	25-20%	7.9-9.9	100-160
3: +5 years of data	6%	2.4	50
4: Once every 5 years	10%	3.9	55

i *The average change in FFQI units was calculated as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

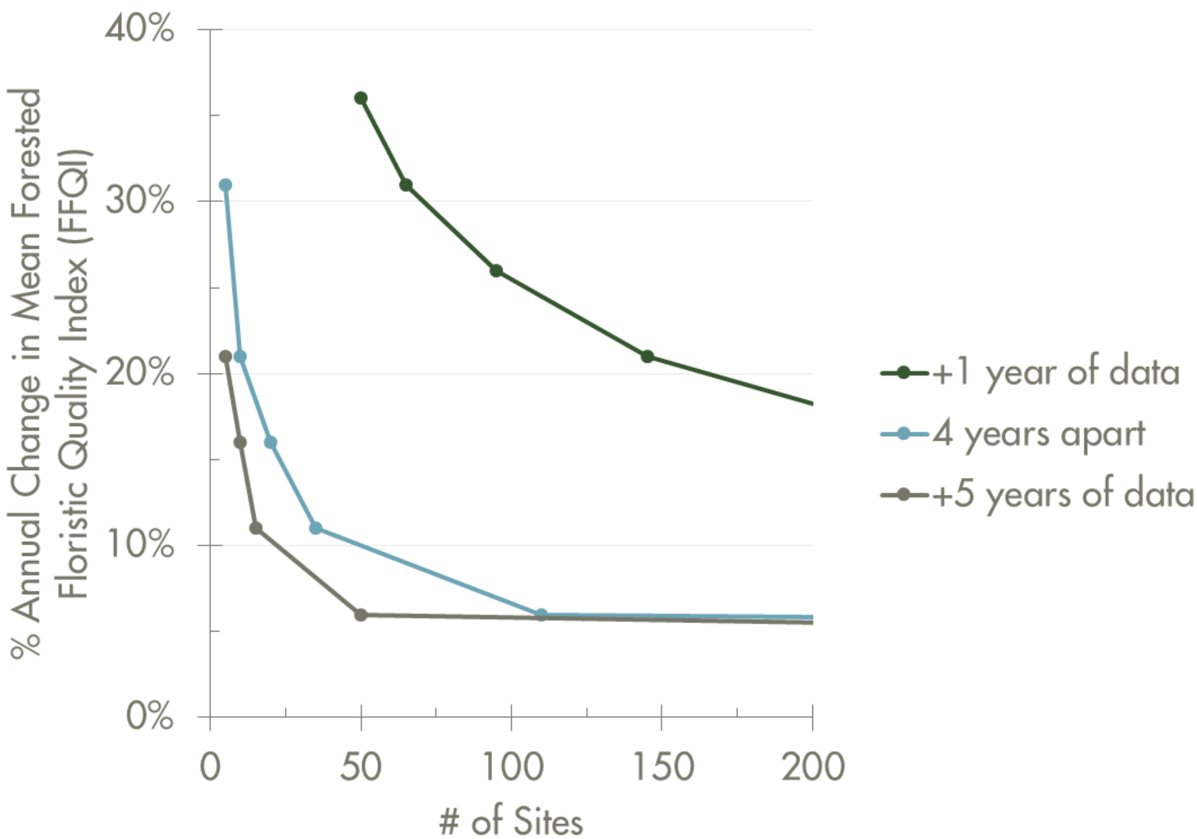


Figure 54. Results of the power analysis on the coastwide scale indicating the percent change that can be detected given a range of sample sizes (α=0.05, β≥0.80, σ=24.77). Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +5, and 4 years apart of data equate to 2, 6, and 2 years of data in total (including baseline), respectively.

Barataria Basin

The results of the power analysis on the basinwide scale are similar to those on the coastwide scale and indicate that detecting linear trends in the annual mean from one year to the next requires a substantial sample size, however, a longer time step enables much finer changes to be detected (Figure 55). Detecting a linear pattern in the annual means over time, averaged over all factors, is also sensitive to the effect size applied (Figure 55). However, a threshold point is evident in Figure 55 where an increase in sample size beyond 23 results in a very small shift in the percentage of change, for the once every 5 years sampling regime. For example, from a sample size of 11 to 23, the difference in the y-axis is 5%, while a change from 23 to 75 results also results in a change of 5%. Further, the graphs indicate that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 37. Forested wetland FFQI summary results of the power analysis for the hypotheses on the basinwide scale.

Hypothesis	% Change	Average Change (FFQI)[i]	# of Sites
1: +1 years of data	25-20%	9.5-11.9	75-120
2: +5 years of data	6%	2.85	23
3: Once every 5 years	6%	2.85	75

[i] *The average change in FFQI units was calculated as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

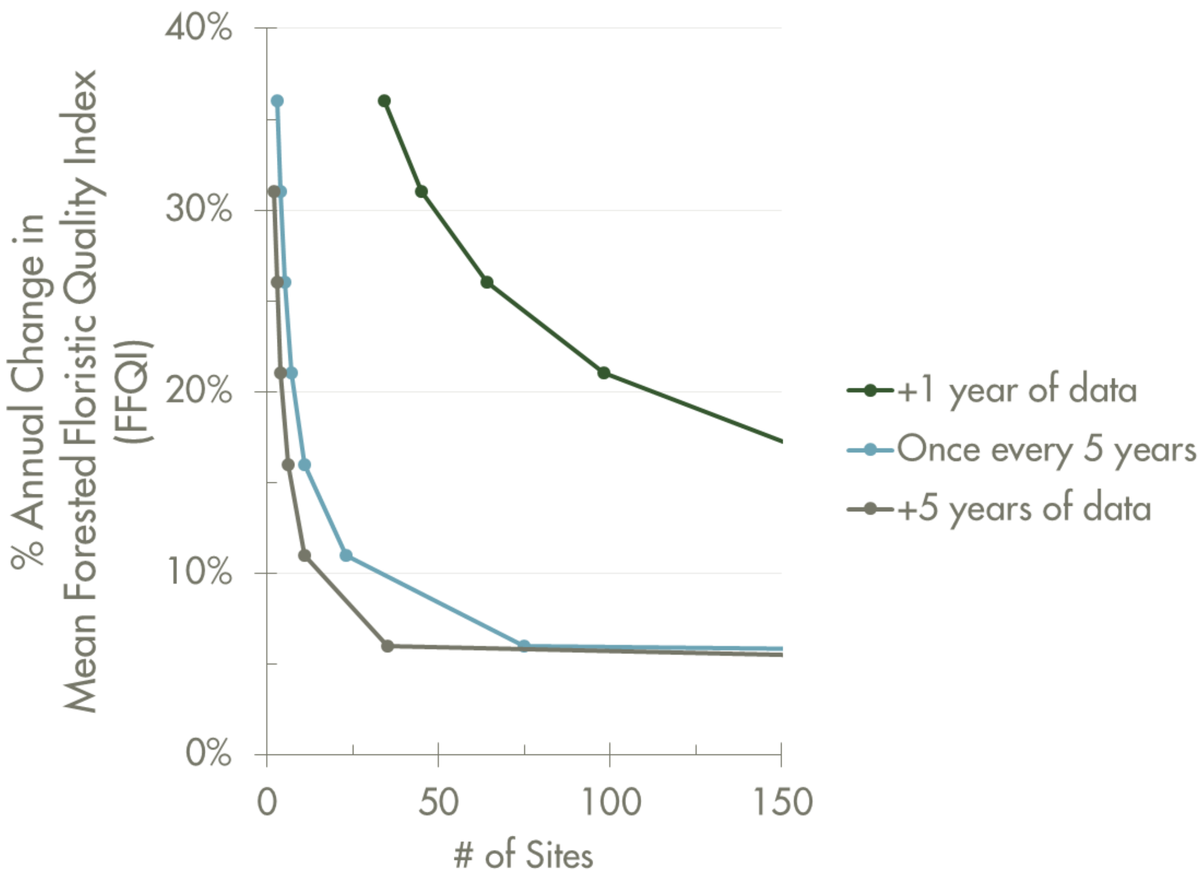


Figure 55. Results of the power analysis on the basinwide scale indicating the percent change that can be detected given a range of sample sizes (α=0.05, β≥0.80, σ=24.9). Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +5, and once every 5 years of data equate to 2, 6, and 2 years of data in total (including baseline), respectively.

Results for Herbaceous Wetlands

Coastwide

The results of the power analysis on the coastwide scale indicate that detecting linear trends in the annual mean from one year to the next requires a substantial sample size, however, a longer time step enables much finer changes to be detected (Table 38; Figure 56). Detecting a linear pattern in the annual means over time, averaged over all factors, is also sensitive to the effect size applied. However, a threshold point is evident where an increase in sample size beyond 120 results in a very small shift in the percentage of change. For example, when increasing the sample size from 60 to 120, the difference in the y-axis is 5%, while increasing the sample size from 120 to 330 still results in a change of 5%, despite the larger increase in sample size (Figure 56). Also evident in the graph is that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 38. Herbaceous wetland summary results of the power analysis for the hypotheses on the coastwide scale.

Hypothesis	% Change	Average Change (FQI)[i]	# of Sites
1: Differences among basins	n/a	12.6	90
2: Differences among wetland types	n/a	16.0	60
3: +1 years of data	15-10%	5.6-8.4	160-75
4: +5 years of data	6-5%	3.4-2.8	160-75
5: Once every 5 years	6-4%	3.4-2.2	160-75

***i** The average change in FQI units was calculated as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

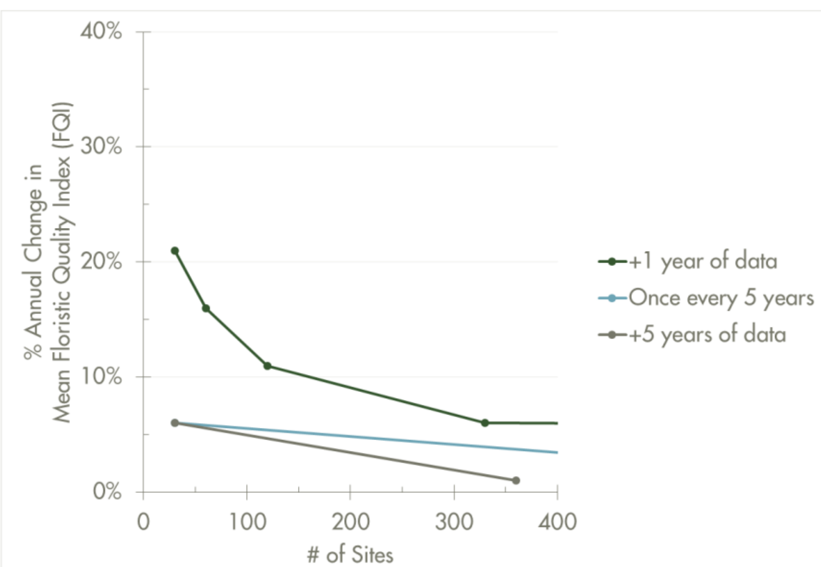


Figure 56. Results of the power analysis on the coastwide scale indicating the percent change that can be detected given a range of sample sizes (α=0.05, β≥0.80, σ=15.4). Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +5, and once every 5 years of data equate to 2, 6, and 2 years of data in total (including baseline), respectively.

Barataria Basin

The results of the power analysis on the basinwide scale indicate that detecting linear trends in the annual mean from one year to the next requires a substantial sample size, however, a longer time step enables much finer changes to be detected (Table 39; Figure 57). Detecting a linear pattern in the annual means over time, averaged over all factors, is also sensitive to the effect size applied. However, a threshold point is evident in Figure 55 where an increase in sample size beyond 24 results in a very small shift in the percentage of change for the once every 5 years sampling regime. For example, from a sample size of 16 to 24, the difference in the y-axis is 5%, while a change from 24 to 48 results also results in a change of 5% (Figure 57). Further, the graphs indicate that as data are collected for longer periods of time, smaller changes can be detected, assuming the change is constant through time.

Table 39. Herbaceous wetland summary results of the power analysis for the hypotheses on the basinwide scale.

Hypothesis	% Change	Average Change (FQI)[i]	# of Sites
1: Differences among wetland types	n/a	10.5	32
2: +1 years of data	15-10%	10.4-7.0	27-65
3: +5 years of data	6%	4.2	8
4: Once every 5 years	6-5%	4.2-3.5	12

[i] *The average change in FQI units was calculated as the average difference among means from year 0 to year 1 based on the effect size applied to the exemplary dataset as indicated in the "% change" column.*

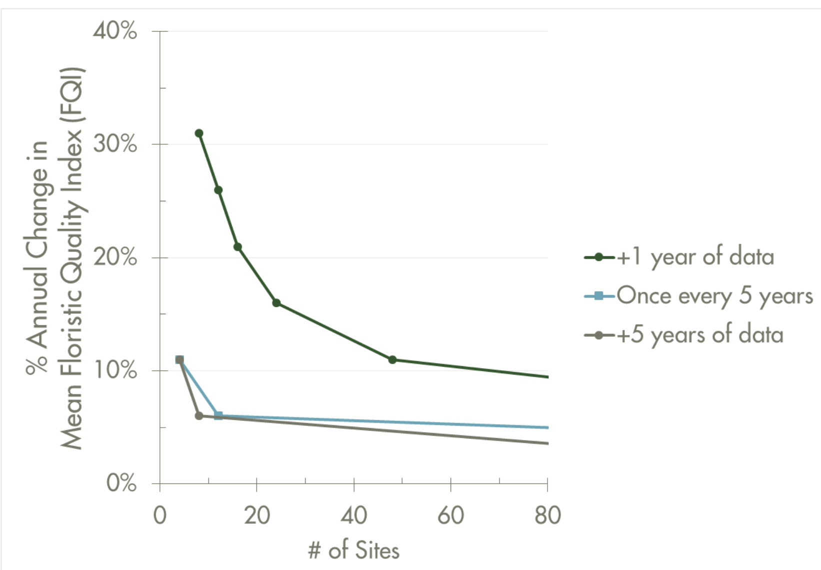


Figure 57. Results of the power analysis on the basinwide scale indicating the percent change that can be detected given a range of sample sizes (α=0.05, β≥0.80, σ=12.9). Legend indicates the number of years of data collection post-baseline (year 0). Thus, +1, +5, and once every 5 years of data equate to 2, 6, and 2 years of data in total (including baseline), respectively.

Detecting Change Using ACS Data

To monitor socioeconomic change at the community level, as defined in main report, it is necessary to analyze aggregations of census block groups. Areas with populations of less than 20,000, such as small towns, census tracts, and census block groups, will have annual ACS updates based on five previous years of data. Because sampling error generally increases as the sample size decreases, sampling error will be most apparent with these small census geographies (Williamson, 2008). However, the reliability of the population estimates can be improved by aggregating these estimates to a higher geographic level (Census Bureau, 2008).

The MOE for the aggregated count is calculated as:

$$MOE_{agg} = \pm\sqrt{\sum_c MOE_c^2} \qquad \text{(Equation 8)}$$

where MOE_c is the Margin of Error of the c^{th} component.

The example below illustrates how to calculate the MOE for the estimated total number of vacant houses within the 19 census block groups that have been identified previously as being significant (at the 95% confidence interval) clusters of natural resource employment and outlier census block groups with high levels of natural resource employment in the 2006-2010 ACS 5-year estimates (Table 40).

Table 40. Vacant housing units[1] in natural resource-dependent block groups in the Barataria Basin (2006-2010).

Block Group	Estimate	Margin of Error
220070503001	74	81
220750507004	31	52
220510279011	50	45
220070501001	63	64
220750508001	89	68
220750507001	44	54
220750502001	57	93
220750507002	39	51
220510279012	216	75
220510279021	451	85
220930405002	20	31
220070501002	86	85
220750507003	117	82
220750506002	31	35
220750508002	105	59
220750505003	36	45
220510280001	27	43
220510279023	248	125
220750506001	34	41

1 Data from ACS estimate of occupancy status of housing units

The aggregate estimate for all census block groups in the study area is 1,819 vacant houses. Using MOEs of the individual block group estimates, we calculate the MOE for the aggregate estimate by calculating the square root of the sum of the squared MOEs.

$$MOE_{agg} = \pm\sqrt{(81)^2 + (52)^2 + (45)^2 + (64)^2 + \cdots} = \pm 296 \qquad \text{(Equation 9)}$$

Thus, the derived estimate of the number of vacant houses in the natural resource-dependent census blocks in the Barataria Basin in the time period 2006-2010 is 1,819 and the MOE for the estimate is ±296.

Note that the Census Bureau standard for published MOEs is the 90% confidence level. To use a MOE corresponding to a different confidence level, it is necessary to multiply the published MOE by an adjustment factor (1.645 =90% confidence level; 1.960=95% confidence level; 2.576=99% confidence level).

Conversion of the published ACS MOE to the MOE for a different confidence level can be expressed as:

$$MOE_{95} = \frac{1.960}{1.645} MOE_{ACS} \qquad \text{(Equation 10)}$$

$$MOE_{99} = \frac{2.576}{1.645} MOE_{ACS} \qquad \text{(Equation 11)}$$

Where MOE_{ACS} is the published 90% MOE for the estimate.

For the above example, the MOE corresponds to a 95% confidence level using the aggregated MOE. In this case, the MOE would be derived as follows:

$$MOE_{95} = \frac{1.960}{1.645}(296) = \pm 353 \qquad \text{(Equation 12)}$$

In this case, the derived estimate of the number of vacant houses in the natural resource-dependent census blocks in the Barataria Basin in the time period 2006-2010 calculated to the 95% confidence level would be 1,819 with a MOE for the estimate of ±353.

The same process can be used to derive the estimated total number of vacant houses in the same study area using the 2008-2010 ACS 5-year estimates (Table 41).

In this example, the derived estimate of the number of vacant houses in the natural resource-dependent census blocks in the Barataria Basin in the time period 2008-2012 is 1,689 and the MOE for the estimate is ±257, calculated at the 90% confidence interval.

Table 41. Vacant housing units1 in natural resource-dependent block groups in the Barataria Basin (2008-2012)

Block Group	Estimate	Margin of Error
220750507003	32	50
220750507004	33	53
220750507001	36	41
220750506002	10	18
220750506001	26	23
220750507002	12	19
220750508002	19	31
220750502001	54	85
220750508001	40	40
220750505003	51	44
220070501001	147	87
220070501002	84	78
220070503001	65	71
220510279012	165	65
220510279023	140	89
220510280001	24	40
220510279021	676	107
220510279011	0	12
220930405002	75	48

[1] *Data from ACS estimate of occupancy status of housing units*

DETERMINING THE SAMPLING ERROR OF POPULATION ESTIMATES

The decennial census long form and ACS are both estimates derived from a sample of the population. As such, these estimates will generally not equal the population value because the survey did not measure all members of the population (U.S. Census Bureau, 2008). The standard error (SE) provides a quantitative measure of the extent to which an estimate derived from the sample survey can be expected to deviate from the true population value (U.S. Census Bureau, 2008). Similarly, the coefficient of variation (CV) provides a measure of the relative amount of sampling error that is associated with the sampling estimate. The CV is a function of the overall sample size and the size of the population of interest. In general, as the estimation period increases the sample size increases and the size of the CV decreases. These measures of variability and sampling error are important factors used to conduct tests of significance and analyze and interpret ACS data.

To derive the SE, divide the positive value of the MOE by the appropriate factor associated with that MOE. When using published ACS data estimated to the 90% confidence level, the SE can be expressed as:

$$SE = \frac{MOE_{ACS}}{1.645} \qquad \text{(Equation 13)}$$

Where *MOEACS* is the positive value of ACS published MOE or the aggregated ACS MOE derived from the published data for the estimate.
The CV can be calculated from the SE derived above.

$$CV = \frac{SE}{\hat{X}} \times 100 \qquad \text{(Equation 14)}$$

Where
X is the ACS estimate
SE is the derived SE for the ACS estimate.

In the example above, the MOE associated with the number of vacant houses in natural resource-dependent block groups in the Barataria Basin estimated over the 2006-2010 time period is ±296. Estimated over the 2008-2012 time period, the MOE for the same location is ±257.The SEs for the estimates would be derived as:

$$SE_{2010} = \frac{296}{1.645} = 180 \qquad \text{(Equation 15)}$$

$$SE_{2012} = \frac{257}{1.645} = 156 \qquad \text{(Equation 16)}$$

Using these values along with the aggregated estimates, it is possible to determine the CV for the estimated number of vacant houses in natural resource-dependent block groups in the Barataria Basin for each of the ACS survey periods.

$$CV_{2010} = \frac{180}{1{,}819} \times 100 = 9.89\% \qquad \text{(Equation 17)}$$

$$CV_{2012} = \frac{156}{1{,}689} \times 100 = 9.24\% \qquad \text{(Equation 18)}$$

This means that the amount of sampling error present in the estimate is as little as 10% of the size of the estimate.

DETERMINING THE STATISTICAL SIGNIFICANCE WHEN COMPARING TWO ESTIMATES

When comparing two estimates, it is necessary to determine whether the observed difference is statistically significant or likely due to chance. The tests for significance of chance in ACS estimates use the estimates and their corresponding SEs. Algebraically, the significance test can be expressed as:

$$If \left| \frac{\hat{X}_1 - \hat{X}_2}{\sqrt{SE_1^2 - SE_2^2}} \right| > Z_{CL},$$

$$then\ the\ difference\ between\ estimates\ \ddot{X}_1\ and\ \ddot{X}_2\ is\ statistically\ signifcant\ at\ the\ specified\ confidence\ level, CL \qquad \text{(Equation 19)}$$

Where X_i is estimate i (=1,2)
SE_i is the SE for the estimate i (=1, 2)
Z_{CL} is the critical value for the desired confidence level.

Ideally, when comparing estimates from two multiyear periods of the same geography, change over time is best evaluated with multiyear estimates that do not overlap (e.g. comparing 3-year estimates from 2006-2008 with 3-year estimates from 2009-2011). Because most of the socioeconomic units of analysis used in SWAMP are based upon geographical units that are only released in the 5-year ACS (census blocks, block groups, and ZIP Code Tabulation Areas) and the first 5-year ACS covered the years 2005-2009, the first true comparison of nonoverlapping 5-year ACS estimates across the same geographical area cannot be conducted until the release of the 2010- 2014 ACS release sometime in 2015.

In some cases, it may be necessary to compare estimates from two overlapping time periods. In such situations, it is important to note that any observed differences are driven by the nonoverlapping years. For example, when comparing the house vacancy data used previously (based upon two overlapping 5-year ACS estimates, 2006-2010 and 2008-2012), the difference estimate should not be interpreted as a reflection of change from 2010 through 2012. Rather, because data for 2008, 2009, and 2010 are included in both estimates, any observed change would be driven by differences in the estimates in 2006-2007 and 2011-2012. To account for this sample overlap when comparing overlapping multiyear samples, the standard error calculation is modified and the test of statistical significance would follow the same process outlined above, with one modification to the significance test formula.

$$\left|\frac{\hat{X}_1-\hat{X}_2}{\sqrt{(1-C}\sqrt{SE_1^2+SE_2^2}}\right| > Z_{CL}, \mathit{then\ the\ difference\ between\ estimates}\ \hat{X}_1\ \mathit{and}\ \hat{X}_2\ \mathit{is\ statistically\ signifcant\ at\ the\ specified\ confidence\ level}, CL$$ (Equation 20)

Where X_i is estimate i (=1, 2)
C is the fraction of the overlapping years.
SEi is the SE for the estimate i (=1, 2).
ZCL is the critical value for the desired confidence level.

The example below uses data on the total number of vacant houses within the 19 census block groups with high levels of natural resource employment in the 2006-2010 and 2008-2012 ACS 5-year estimates (Tables 1 and 3). In this example, the periods 2006-2010 and 2008-2012 overlap for three out of five years, so the fraction of overlapping years is 0.6.

$$\left|\frac{\hat{X}_1-\hat{X}_2}{\sqrt{(1-C}\sqrt{SE_1^2+SE_2^2}}\right| = \left|\frac{1{,}819-1{,}689}{\sqrt{(1-0.6\sqrt{(180)^2+(156)^2}}}\right| = 0.86$$ (Equation 21)

Since the test value (0.86) is less than the critical value for a confidence level of 90% (1.645), the difference in estimates is not statistically significant. Thus, we cannot be certain that the observed difference in the number of vacant housing units in the study area between the two time periods was not due to chance.

CALCULATING MARGINS OF ERROR FOR DERIVED PROPORTIONS

When monitoring change in coastal communities, it is often necessary to derive proportions and percentages of the population where the numerator is a subset of the denominator. For example, when analyzing unemployment in natural resource-dependent communities, it necessary to examine the number of unemployed persons as a percentage of the total labor force, defined by the U.S. Census Bureau as those persons age 16 and over.

To calculate the MOE for derived proportions, the following algebraic calculation is used:

$$MOE_p = \frac{\pm\sqrt{MOE_{num}^2 - (\hat{p}^2 \times MOE_{den}^2)}}{\hat{X}_{den}} \qquad \text{(Equation 22)}$$

Where MOE_{num} is the MOE of the numerator.

MOE_{den} is the MOE of the denominator.

$\hat{p} = \frac{\hat{X}_{num}}{\hat{X}_{den}}$ is the derived proportion.

X_{num} is the estimate used as the numerator of the derived proportion.

X_{den} is the estimate used as the denominator of the derived proportion.

Table 42. Households in poverty[1] in natural resource-dependent block groups in the Barataria Basin (2008-2012).

Block Group	Households in Poverty	Margin of Error	Total Households	Margin of Error
220750507003	0	12	190	106
220750507004	0	12	41	29
220750507001	0	12	51	42
220750506002	0	12	143	77
220750506001	33	38	245	76
220750507002	6	23	155	71
220750508002	85	49	283	85
220750502001	12	21	926	164
220750508001	4	7	138	62
220750505003	38	43	87	52
220070501001	74	69	372	111
220070501002	87	72	627	129
220070503001	19	22	476	106
220510279012	53	26	813	96
220510279023	67	40	548	135
220510280001	44	49	199	75
220510279021	17	27	166	69
220510279011	33	36	237	68
220930405002	104	58	544	71

1 *Data from ACS estimates of Poverty Status in the Past 12 Months by Household*

The example below shows how to derive the MOE for the estimated percentage of households in poverty in natural resource-dependent block groups within the Barataria Basin based on the 2008- 2012 5-year ACS (Table 37).

The aggregate estimate for all households in poverty for all natural resource-dependent census block groups in the study area is 676, while the total number of households is estimated to be 6,241. The estimated proportion of household in poverty in the study area is:

$$\hat{p}_{agg} = \frac{\ddot{X}_{poverty}}{\hat{X}_{total}} = \frac{676}{6{,}241} = 0.1083 \qquad \text{(Equation 23)}$$

Where $X_{poverty}$ is the ACS estimate of households in the study area that are at or below the poverty level and X_{total} is the ACS estimate of the total number of households in the study area.

Using the MOEs of the individual block group estimates, we calculate the MOE for the aggregate estimates by calculating the square root of the sum of the squared MOEs.

$$MOE_{pov\,agg} = \pm\sqrt{(12)^2 + (12)^2 + (12)^2 + (12)^2 + (38)^2 \ldots} = \pm 167 \qquad \text{(Equation 24)}$$

$$MOE_{tot\,agg} = \pm\sqrt{(106)^2 + (29)^2 + (42)^2 + (77)^2 + (76)^2 \ldots} = \pm 399 \qquad \text{(Equation 25)}$$

The MOE for the estimated proportion is:

$$MOE_{agg} = \frac{\pm\sqrt{(167)^2 - [(0.1083)^2 \times (399)^2]}}{6{,}241} = 0.026 \qquad \text{(Equation 26)}$$

Thus, the derived estimate of the proportion of households in poverty in natural resource-dependent block groups within the Barataria Basin is 0.1083, with a MOE of 0.026. In other words, approximately 10.83% of the households in the census block groups are at or below the poverty level, with a margin of error of 2.6%.

The same calculations can be run on the 236 census block groups in the Barataria Basin that are not significantly reliant upon natural resource employment. The aggregate estimate for all households in poverty in these census block groups is 11,918 while the total number of households is estimated to be 117,524. The estimated proportion of households in poverty in the study area is therefore:

$$\hat{p}_{agg} = \frac{\ddot{X}_{poverty}}{\hat{X}_{total}} = \frac{11{,}918}{117{,}524} = 0.1014 \qquad \text{(Equation 27)}$$

Where $X_{poverty}$ is the ACS estimate of households in the study area that are at or below the poverty level and X_{total} is the ACS estimate of the total number of households in the study area.

Using MOEs of the individual block group estimates, it is possible to calculate the MOE for the aggregate estimates by calculating the square root of the sum of the squared MOEs

$$MOE_{pov\,agg} = \pm\sqrt{(55)^2 + (24)^2 + (57)^2 + (55)^2 + (12)^2 \ldots} = \pm 790 \qquad \text{(Equation 28)}$$

$$MOE_{totagg} = \pm\sqrt{(155)^2 + (97)^2 + (82)^2 + (110)^2 + (108)^2 \ldots} = \pm 1{,}744 \quad \text{(Equation 29)}$$

The MOE for the estimated proportion is:

$$MOE_{agg} = \frac{\pm\sqrt{(790)^2 - [(0.1014)^2 \times (1{,}744)^2]}}{117{,}524} = 0.007 \quad \text{(Equation 30)}$$

Thus, the derived estimate of the proportion of household in poverty in census block groups within the Barataria Basin that are not significantly reliant upon natural resource employment is 0.1014 with a MOE of 0.007. In other words, approximately 10.14% of the households in the census block groups are at or below the poverty level, with a margin of error of 0.7%.

To determine if the observed difference is significant, we must determine the SE as in the previous example and then conduct a significance test. In this example, the MOE associated with the percentage of households in poverty in natural resource-dependent block groups in the Barataria Basin is being compared to the percentage of households in poverty throughout the rest of the Barataria Basin, both estimated over the 2008- 2012 time period (Table 38).

Table 43. Percentage household poverty in select census block groups in the Barataria Basin (2008-2012).

Block Group Status	Estimate	Margin of Error
Resource-Dependent	0.1083	0.026
Not Resource-Dependent	0.1014	0.007

The SEs for the estimates would be derived as:

$$SE_{resource} = \frac{0.026}{1.645} = 0.158 \quad \text{(Equation 31)}$$

$$SE_{not\ resource} = \frac{0.007}{1.645} = 0.004 \quad \text{(Equation 32)}$$

$$\left|\frac{\hat{X}_1 - \hat{X}_2}{\sqrt{SE_1^2 + SE_2^2}}\right| = \left|\frac{0.1083 - 0.1014}{\sqrt{(0.026)^2 + (0.007)^2}}\right| = 0.26 \quad \text{(Equation 33)}$$

Since the test value (0.26) is less than the critical value for a confidence level of 90% (1.645), the difference in estimates is not statistically significant. Thus, this test analysis shows there is no significant difference between the number of households in poverty in natural resource-dependent block groups and block groups that are not heavily reliant on natural resource employment.

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