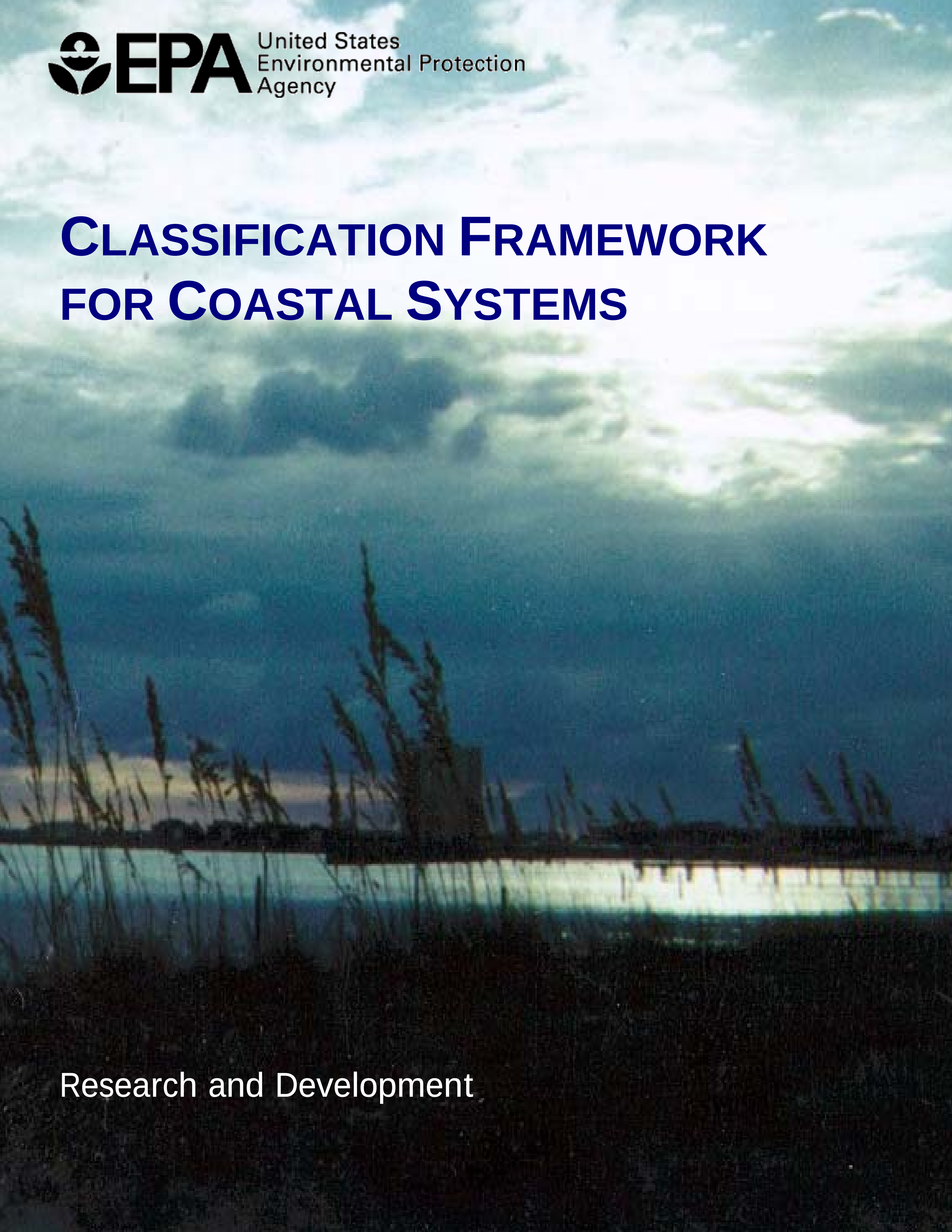
EPA United States Environmental Protection Agency

CLASSIFICATION FRAMEWORK FOR COASTAL SYSTEMS



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Classification Framework for Coastal Systems

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Notice

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List of Acronyms

303(d)	Section of the federal Clean Water Act requiring states to periodically prepare a list of all surface waters impaired by pollutants
305(b)	Section of the federal Clean Water Act requiring each state to prepare a water quality assessment report every two years.
ANCOVA	Analysis of Covariance
AVS	Acid Volatile Sulfides
BASINS	Better Assessment Science Integrating Point and Non-Point Sources
CA&DS	Coastal Assessment and Data Synthesis
CAF	Coastal Assessment Framework
CART	Classification and Regression Tree
CDA	Coastal Drainage Area
CHAID	Chi-Square Automatic Interaction Detector
DCP	Dissolved Concentration Potential
EDA	Estuarine Drainage Area
EMAP	Environmental Monitoring and Assessment Program
EPA	United States Environmental Protection Agency
EROS	Earth Resources Observing Systems
FEMA	Federal Emergency Management Agency
GAP	Gap Analysis Program
GIS	Geographic Information Systems
GLEAMS	Groundwater Loading Effects from Agricultural Management Systems model
GLEI	Great Lakes Environmental Indicators
HUC	Hydrological Unit Code
HUMUS	Hydrologic Unit Model for the United States
IBI	Index of Biotic Integrity
IWI	Index of Watershed Indicators
LIDAR	Light Detection and Ranging (remote sensing technology)
LTER	Long Term Ecological Research
MATC	Maximum Acceptable Toxicant Concentration
MRPP	Multi-response Permutation procedures
NAO	North Atlantic Oscillation
NCA	National Coastal Assessment
NEP	National Estuaries Program
NHD	National Hydrography Database
NHEERL	National Health and Environmental Effects Research Laboratory
NLCD	National Land Cover Data
NMDS	Non-Metric Dimensional Scaling
NOAA	National Oceanic and Atmospheric Association
NOS	National Ocean Service
NPDES	National Pollutant Discharge Elimination System
NPLD	National Pesticide Loss Database

List of Acronyms (continued)

NRC	National Research Council
NRCS	Natural Resources Conservation Service
NRI	National Resources Inventory
NSI	National Sediment Inventory
NWI	National Wetland Inventory
OHDNR	Ohio Department of Natural Resources
PAH	Polycyclic Aromatic Hydrocarbon
PC1	First Principal Component
PC2	Second Principal Component
PC3	Third Principal Component
PCA	Principal Components Analysis
PCB	Polychlorinated Biphenyls
PCS	Permit Compliance System
PRE	Particle Retention Efficiency
PRISM	Parameter-elevation Regressions on Independent Slopes Model
Q2	Peak discharge with 2-year Recurrence Interval
R-EMAP	Regional Environmental Monitoring Assessment Program
RF1	Reach File 1
SPARROW	Spatially Referenced Regression of Watershed Attributes
SCS	Soil Conservation Service
STAR	Science to Achieve Results
STATSGO	State Soil Geographic database
STORET	Storage and Retrieval (EPA's Largest Computerized Environmental Data System)
SWAT	Soil and Water Assessment Tool
SYSTAT	Statistics software
TAES	Texas Agricultural Experiment Station
TEU	Toxicity Equivalent Unit
TM	Thematic Mapper
TMDL	Total Maximum Daily Load
TSS	Total Suspended Solids
USDA	United States Department of Agriculture
USFWS	United States Fish and Wildlife Service
USGS	United States Geological Survey
WIDNR	Wisconsin Department of Natural Resources

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EXECUTIVE SUMMARY

This report contains initial results from the Diagnostics Committee, produced under the U.S. Environmental Protection Agency (EPA) Aquatic Stressors Framework (USEPA, 2002a). The goal of Diagnostics Research is to provide tools to simplify diagnosis of the causes of biological impairment, in support of State and Tribe 303(d) impaired waters lists. The Diagnostics Workgroup has developed conceptual models for four major aquatic stressors that cause impairment: nutrients, suspended and bedded sediments, toxics, and altered habitat. The conceptual models form the basis for classification of aquatic systems according to their sensitivity to these stressors. The proposed classification framework should enable a more refined approach for quantifying stressor-response relationships over broad geographical scales.

A coastal classification framework was constructed which encompasses watersheds and coastal wetlands in both Great Lakes and marine coastal states in the conterminous U.S. This report provides an overview of the components of the classification framework: 1) a review of existing classification schemes and examination of their relevance for different management goals, 2) a conceptual model for classification based on risk from stressors, 3) coastal classification databases for both Great Lakes and marine coastal states, 4) a description of potential approaches to classification, 5) application of an empirical approach for classification to coastal estuarine systems, 6) a regional test of a watershed classification framework based on data from Lake Michigan coastal riverine wetlands, and 7) plans for Stage II of the coastal classification framework.

As the most developed areas in the nation, coastal areas are valuable ecological and economic resources affected by multiple, interacting stressors. A classification framework is required to describe and inventory near-coastal communities, understand stressor impacts, predict which systems are most sensitive to stressors, and manage and protect ecosystem resources. Numerous approaches have been proposed to classify aquatic resources. Classification schemes have included geographic, hydro-dynamic, and habitat-based characteristics and have been applied to wetlands, fluvial systems, near coastal waters, and estuaries. With the exception of classification systems developed to explain differences in estuarine susceptibility to eutrophication, few existing classification schemes address system response or susceptibility to multiple stressors.

Three primary factors control the action of pollutants in aquatic ecosystems: 1) the residence time of water and pollutant in the system, 2) the natural processing capacity of the system for the pollutant including the pathways that decompose, bind, bioaccumulate, or sequester the material, and 3) ancillary factors that modify the form of a pollutant, the rate of processing, or the kind of action the pollutant exerts within the ecosystem (Figure ES-1). We can evaluate these factors in a manner that quantitatively determines the effective dose of a pollutant for different types of ecosystems. Characteristic properties related to residence time, processing capacity, and modifying factors can be used to differentiate classes of ecosystems that develop different biologically effective concentrations of a material when loaded with a given quantity of that pollutant. The problem can be further simplified by grouping pollutants according to their mode of action such that an ecosystem processes all compounds in a class in a similar manner. In this case, we can express the bioeffective concentration in aggregate units (i.e., standard toxicity units).

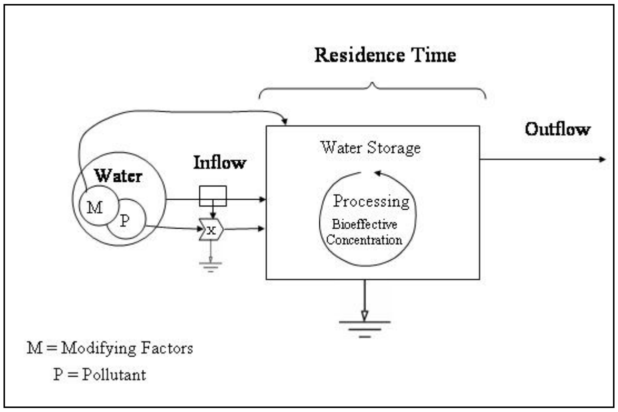

Figure ES- 1. Conceptual energy systems model of the factors controlling the action of stressors in aquatic ecosystems.

To test the conceptual model for risk-based classification, we constructed databases for 1) hydrologic regimes in coastal Great Lakes and marine coastal states, 2) a subset of 155 coastal riverine wetlands in the Great Lakes and their associated watersheds, and 3) estuarine systems along the marine coast of the conterminous U.S. To support prediction of flow responsiveness of coastal watersheds for the Great Lakes, we constructed databases from U.S. Geological Survey (USGS) reports containing nonlinear regression parameters for 2-year peak flow magnitudes. We compiled raw data on peak flows and watershed characteristics for all drainage basins associated with USGS gauging stations chosen for flood frequency analysis from these same reports.

Simon et al. (2003) had identified a subset of 155 Great Lakes coastal riverine wetlands for monitoring using a probability-based survey design for a Regional Environmental Monitoring and Assessment Program (R-EMAP) project. We delineated watersheds associated with these coastal wetlands and characterized these with respect to land cover, soil properties, climatic variables, watershed and soil storage indicators, and indicators of the "flashiness" of hydrologic regimes (Figure ES-2).

All 145 Estuarine Drainage Areas (EDAs) and 58 associated Coastal Drainage Areas (CDAs) in the conterminous U.S. within the National Oceanic and Atmospheric Association's (NOAA) Coastal Assessment and Data Synthesis (CA&DS) database were included in estuarine databases (NOAA, 2003a). Estuarine databases include data on physical and hydrologic characteristics of estuaries and both indirect and direct indicators of exposure (loadings or concentration, land cover, risk indices) for nutrients, suspended sediments, and toxics, and modifying factors (Figure ES-3).

Classification approaches can be applied either *a priori* or *a posteriori*. We base *a priori* classification on a conceptual model or hypothesis concerning expected differences in behavior of ecological response along stressor gradients as a function of watershed or water body characteristics. We have developed and tested *a priori* classification strategies based on conceptual models of watershed hydrology, determining discriminating factors for classification based on hydrological endpoints as integrators of expected ecological effects (Detenbeck et al., 2000; Detenbeck et al., 2003a or 2003b). In future work, we will apply simple canonical models of stressor effects and interactions to determine discontinuities in stressor-response surfaces for estuaries as a function of water-body retention time, modifying factors, and processing capacity (Campbell et al., 2003; Stefan et al., 1995; Stefan et al., 1996). *A posteriori* classification is based on analysis and interpretation of available data. Water-body classes can be derived empirically both through indirect and factor-based methods, using cluster analysis of water-body and watershed characteristics, and through direct and response-based approaches, using Bayesian approaches to determine natural breakpoints in assessment endpoints as a function of stressor gradients and classification factors (Breiman et al., 1984; Kass, 1980).

Using subsets of the classification databases, we applied and tested three approaches to classification of coastal systems. We identified classification factors and breakpoints associated with watersheds of varying flow-responsiveness levels through Classification and Regression Tree (CART) analysis of the gauging station watershed database. We used the magnitude of two-year peak flows normalized to watershed area as an indicator of flow-responsiveness of watersheds or "flashiness" of hydrologic regimes (Figure ES-2). We applied flow-regime classes derived for watersheds in the Lake Michigan basin to watersheds associated with coastal riverine wetlands monitoring in the Region 5 R-EMAP project. We successfully used flow-regime types to explain differences among classes in response of nutrients, chlorophyll, thermal regime, and periphyton communities in coastal wetlands along land cover gradients. Finally, we developed an empirical classification of estuarine systems using cluster analysis on physical and hydrological data (Figure ES-3).

Stage II of the classification framework will include improvements in spatial extent and resolution of coastal units, incorporation of additional classification factors, application of empirical and model-based approaches for classification to coastal systems (both watersheds and coastal wetlands), and testing of classification systems using data gathered through the Environmental Monitoring and Assessment Program (EMAP), National Coastal Assessment (NCA), and R-EMAP in the Great Lakes. Initial classifications will be refined using data from intensively monitored systems from different classes. In addition, we will explore model-based approaches to classification of coastal systems.

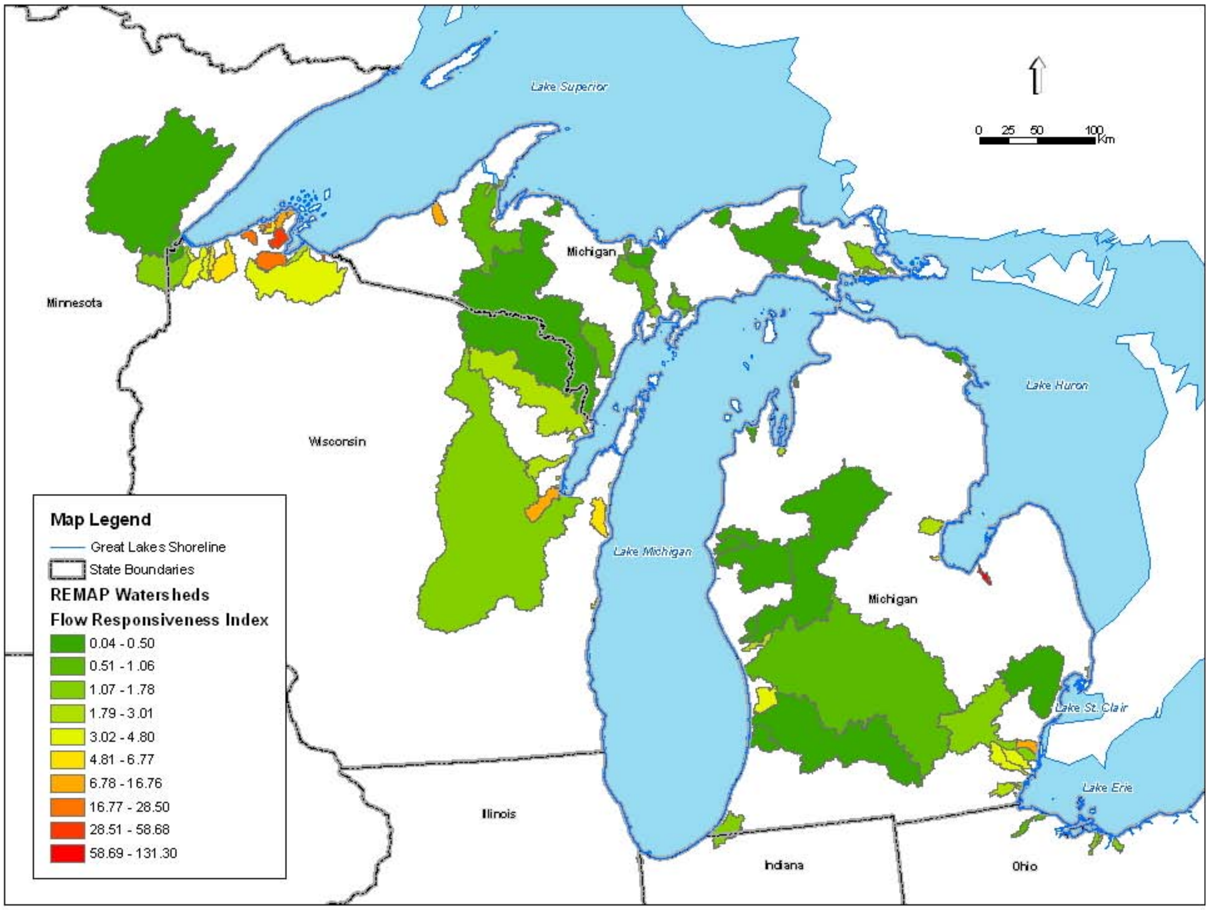

Figure ES- 2. Watersheds associated with 110 R-EMAP Great Lakes coastal riverine wetlands, characterized by flow responsiveness index. Flow responsiveness index is defined as 2-year peak flood volume and watershed depressional storage volume.

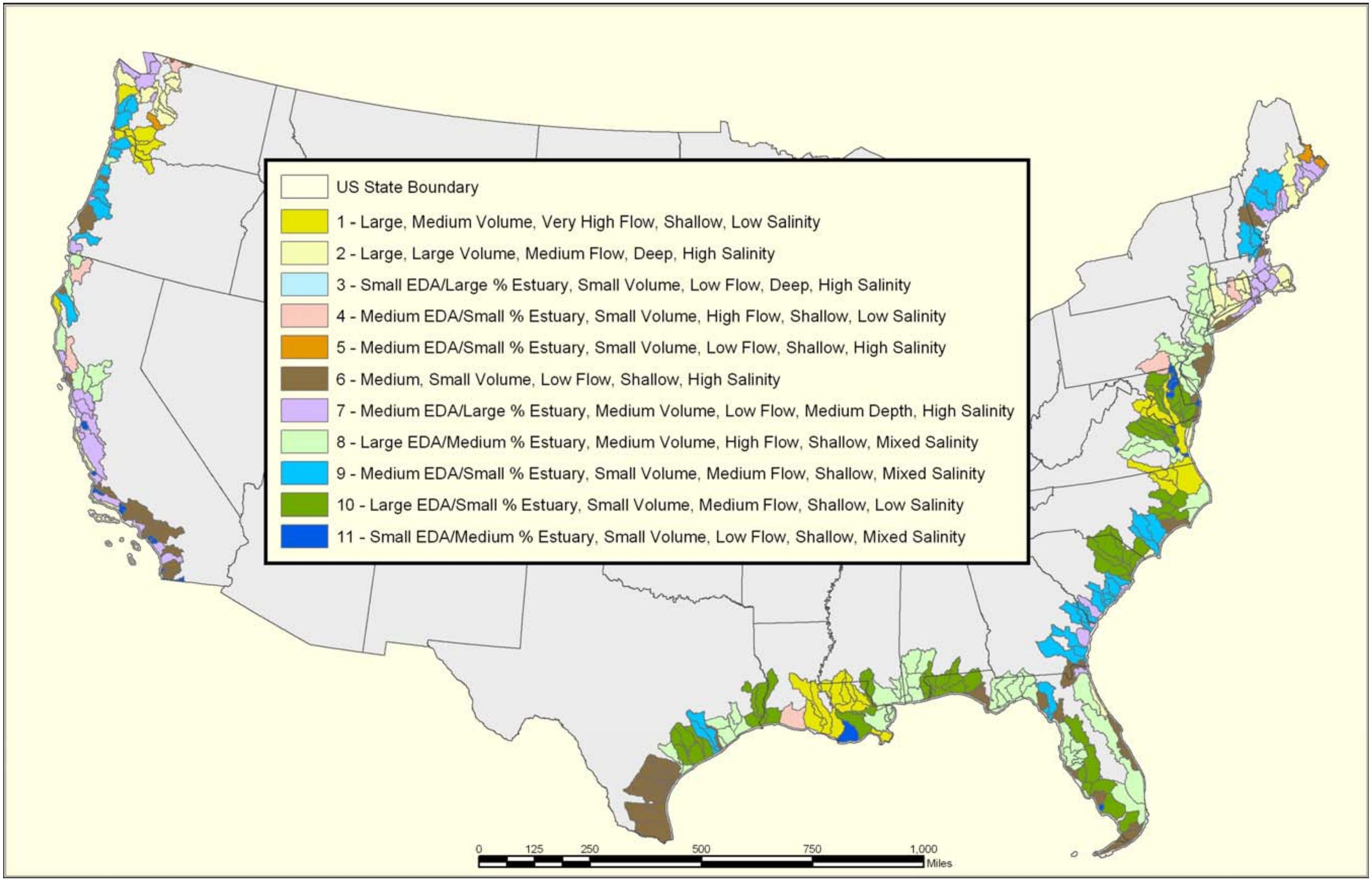

Figure ES- 3. Estuarine areas classified through cluster analysis of physical and hydrological variables.

I. INTRODUCTION

Coastal areas are some of the most developed areas in the nation and are a source of many valuable resources. These include: 1) fish and shellfish, which support commercial and recreational fisheries, 2) extensive water areas that support boating, swimming, and other water-related recreational activities, 3) water supplies for cooling, and 4) a large dilution and flushing capacity, which reduces concentrations of wastes from many municipal and industrial points of discharge. Because a large proportion of the nation's population lives in coastal areas, environmental pressures threaten the resources that make the coast so desirable (USEPA, 1995; 2001a).

Aquatic Stressors Framework

EPA's common management goal is to maintain ecological integrity by protecting aquatic systems against the degradation of habitat, loss of ecosystem functions and services, and reduced biodiversity. To contribute to this common goal through ecological effects research, the EPA National Health and Environmental Effects Research Laboratory (NHEERL) developed the Aquatic Stressors Research Framework and Implementation Plan (USEPA, 2002a). EPA designed this research framework to develop scientifically valid approaches for protecting and restoring the ecological integrity of aquatic ecosystems from the impacts of multiple aquatic stressors.

Stressors of Concern

Dorward-King et al. (2001) define stressors as environmental factors that have the potential to cause a significant change in an organism, population, community, or ecological system. Stressors may act simultaneously or sequentially at an intensity, duration, and frequency of exposure that results in a change in ecological condition (USEPA, 2000). In estuarine systems, stressors with natural origins include temperature, salinity, and suspended sediment load while stressors from anthropogenic sources include single chemical classes, such as pesticides, mixtures of chemicals of different classes (e.g., wastewaters), or a combination of chemicals and habitat degradation. For the present classification, our research focused on aquatic ecosystem stressors derived from anthropogenic sources or activities with the greatest potential for causing adverse effects, including habitat alteration, nutrients, excessive suspended and bedded sediments, toxic chemicals, and interactions among the four. The research will attempt to isolate natural stressor effects from those derived from anthropogenic sources (USEPA, 2002a). Furthermore, we will assume that sufficient information on the ecological effects of many toxic chemicals exists although information on effects of chemical mixtures is not available.

Diagnostics Objectives

To support implementation of Section 303(d) of the Clean Water Act and other regulatory programs, NHEERL's Diagnostics research focuses on the need to diagnose causes of biological impairment within an integrated framework linking watersheds with receiving water. The starting point for diagnostics research is the need to respond to reports of biological impairment, non-attainment of aquatic life use, and other indications of adverse effects (e.g., toxicity). Initial assessments can also record evidence of multiple potential causes of impairment and conflicting lines of evidence that might complicate a diagnosis. Thus, the endpoint for the diagnostic process includes both the definition of the primary causes of impairment as well as the allocation of observed effects among multiple potential stressors, and the assessment of potential interactive effects among stressors.

In developing a research plan, we considered the States' implementation stages (i.e., monitoring, diagnosis, restoration). We then linked these implementation stages to the critical path for research. The following are four primary objectives for diagnostics research:

- Provide a framework for interpreting cause-and-effect relationships, including:
  - Conceptual ecosystem models based on appropriate mechanisms of action to improve stressor related impairment decisions
  - Conceptual models to define the natural conditions of ecosystems and watersheds and their driving factors for quantifying degree of impairment and for setting restoration goals
  - Classification frameworks that explain variation in the response of individuals, populations, communities, and ecosystems to individual stressors and to combinations of stressors at regional, watershed, water body, and habitat scales.
- Develop single-stressor diagnostic methods and models to determine the primary source for biological impairment of aquatic ecosystems.
- Develop methods and models to allocate causality among multiple stressors and to diagnose interactions among them.
- Develop methods and models capable of forecasting the ecological benefits of source reductions, to investigate stressor interactions, and to assess the gains and losses realized by various alternatives for restoration and remediation.

Need for a Coastal Classification System

Risk to Coastal Systems

Coastal systems at the interface between land and sea, or between land and the Great Lakes, are highly productive and diverse. These areas of dynamic inter-change for both fresh and oceanic waters, sediments, and organic and inorganic chemicals create both opportunities and risks for organisms, populations and communities (Hobbie, 2000). Increases in coastal human population density and the concomitant changes in land use affect rates of interchange, which in turn affect harvests of fish and shellfish and recreational opportunities for human populations.

The U.S. National Research Council (NRC; 1994) has outlined some important interchanges and associated risks to coastal ecosystems that may result from increases in human uses and population density. Habitats such as seagrass meadows and emergent marshes are vital nursery areas for important commercial fishery species, yet are affected by dredging, filling, and increased sediment loads. Land use alterations and water diversions change the seasonal pattern and amount of freshwater inflow along with the supply of organic and inorganic nutrients and the amount of sediment transported into coastal systems. Nutrients from treated wastewater discharges and agricultural runoff have increased causing depletion or decreases in oxygen in bottom waters and shifts in species dominance resulting in harmful algal blooms. Industrial activities release toxic contaminants such as polycyclic aromatic hydrocarbons (PAHs) and heavy metals in some areas. Formerly, abundant populations of finfish and shellfish have been overexploited, reducing stocks and altering natural cycles. Loss or decline of natural populations and the introduction of nonindigenous species has resulted in loss of biodiversity and degradation of resource populations. Changes in climate and weather patterns affect precipitation and salinity, circulation patterns and transport of nutrients, which can also affect biological production and diversity. In short, coastal resources will be subject to increasingly complex interactions as human population pressure increases. Understanding these complex interactions poses a significant challenge to researchers and managers.

Classification by Sensitivity to Common Stressors

Although coastal areas are diverse, complex and heavily utilized, they may show similar patterns that can be useful for classifying coastal systems. Specifically, coastal systems may show commonalities in their sensitivity to stressors that can be used as classification parameters to aid diagnosis. Estuaries most susceptible to pollution have a poor ability to dilute or flush sediments, toxins or dissolved substances (NOAA, 1989). Thus, physical and hydrologic characteristics can be used to predict the susceptibility of coastal systems.

The NRC (2000) considered the role of both biological and physical factors in influencing estuarine susceptibility to nutrients. NOAA had previously identified the following physical factors as predictors of sensitivity: physiography, dilution due to area-volume relationships and mixing processes, water residence time and flushing rate, and stratification, to which NRC added hypsography, or the relative areal extent of land surface elevation and depth, and loading (Bricker et al., 1999). Loading includes nutrient load derived from both watershed and atmospheric inputs, suspended material load, which reduces light penetration through the water column, dissolved and particulate organic matter load, and toxin loads (PAHs, metals, pesticides and other classes of chemicals as well as mixtures of classes). We suggest that the loads derived from sediment, including biotic and abiotic particles, nutrients, and toxins, are also influential in these systems.

Biological factors that determine estuarine response to stressors like nutrient overenrichment include primary production, grazing rates, and denitrification (NRC, 2000). Major types of primary producer communities include emergent marshes, seagrasses, benthic macroalgae, periphyton, and phytoplankton in marine coastal systems, and macrophyte, periphyton, and phytoplankton in Great Lakes coastal wetlands. Communities dominated by marshes are likely to be shallow with short residence times, while plankton-dominated systems may be deeper with longer residence times. Changes in grazing pressure at different trophic levels, may result in changes in food webs, system function and sensitivity to stressors. Processes like denitrification, sulfate reduction and methane generation are all biogeochemical processes in coastal systems, and are likely to determine system sensitivity to the affected pollutants. Biological factors are less well characterized, for the most part, compared to physical factors, and should be a target for future classification and modeling efforts.

Client Needs

Managers and researchers need classification frameworks to understand, protect and manage coastal resources. A successful classification scheme will accomplish several key tasks needed by EPA clients: (1) describe and inventory near coastal communities and habitat types, (2) identify and help set priorities for conservation efforts, (3) aid in the management of ecosystem resources, and (4) help target future research needs. Classification frameworks are logical approaches to organizing and grouping information about ecological systems. Because we compare systems based on data, we can use classification frameworks as logical organizing structures and repositories for data collected from a variety of contributors. Once managers have established a common terminology and organized categories of data in a database, they can conduct inventories to determine the extent and distribution of different ecosystem types and potential stressor effects.

Classification frameworks and the information base required to develop them can assist environmental managers in their efforts to set water or sediment criteria, establish reference conditions, determine the cause of impairment, and predict changes in environmental condition. Water quality criteria for chemicals are concentrations that, when not exceeded, protect aquatic life and human health according to available scientific information. Biological criteria are narrative or numerical descriptions of the desired biological condition of aquatic communities inhabiting particular types of water bodies (Detenbeck, 2001). Reference conditions describe characteristics of water body segments least impaired by human activities, i.e., those habitat conditions that may exist in pristine areas or those conditions attainable through management actions. Establishment of water quality criteria can be aided not only by describing expected reference conditions for naturally-occurring substances or communities, but also by identifying classes of aquatic systems with differential sensitivity to pollutants.

Determining impairment and diagnosing its cause(s) are requirements of sections 305(b) and 303(d) of the Clean Water Act. Under section 305(b) states and tribes are required to assess the status of water bodies and to identify suspected causes of impairment. Section 303(d) requires preparation and submission of listings of impaired water bodies that violate water quality standards or exceed water quality criteria or biocriteria. Grouping of systems by class can simplify the problem of determining the cause of observed ecological effects. Classes behave differently under the influence of the stressor of concern. Once we define classes and categorize responses, we can predict changes in environmental condition resulting from restoration actions, habitat alterations, or increased contaminant loading with greater confidence.

Classification can assist environmental managers in meeting water quality standards by supporting implementation of the Total Maximum Daily Load (TMDL) program initiated as part of the Clean Water Act. A TMDL is the projected load of a pollutant that will result in compliance with a water quality standard. Of the 40,000 water bodies currently identified in the nation, 21,000 river segments, lakes, and estuaries have been identified as being in violation of one or more standards (NRC, 2001). States must develop plans for TMDLs that will result in attainment of water quality standards under an ambitious time schedule. In addition, most plans will require controlling nonpoint source pollution, which is more difficult to quantify and manage than point sources.

For each water body, managers must diagnose the cause(s) of impairment prior to specifying a TMDL. Classification can help to establish the expected ecological conditions for water bodies by class, which would help to determine if impairment exists. We can simplify determination of the cause(s) of impairment for thousands of systems by developing robust classification schemes that identify groups of coastal ecosystems that behave in a similar manner in the presence of a stressor. A useful classification framework will provide regional, state, and tribal regulatory authorities a tool to collapse the over 40,000 water bodies requiring TMDLs into a more manageable number of water body classes, each class composed of individual water bodies with common, stressor-sensitive characteristics. For example, estuaries with slower turnover times are more susceptible to the effects of nutrient loading and may form one logical class. For defined water body classes, managers could create a TMDL template or plan for remediating the impairment, which they could apply to all of the water bodies within the class with minor adjustments on a case-by-case basis. This method would eliminate the need for 40,000 unique TMDLs and remediation plans.

Finally, classification systems can serve to target current and future research needs. In building a database for classification, research gaps readily become apparent. These gaps point to opportunities for empirical studies to complete data sets and may help to determine which missing data are most important to obtain. Analysis of classification databases may reveal important couplings between physical, biogeochemical, and ecological processes. Numerical modeling simulations may be a useful approach for better understanding these couplings and interactions, and may address important issues like spatial and temporal variation (Geyer et al., 2000). Establishing meaningful and measurable response indicators and causal links between loads and response to stressors within ecosystems are also important areas for research. Combining food web models and chemical fate models could allow better prediction of exposure and response within aquatic ecosystems (Baird et al., 2001). Studies comparing observed loads and responses among classes of coastal ecosystems combined with modeling approaches will advance our abilities to make responsible decisions that will protect coastal ecosystems.

Properties and Limitations of Existing Classification Systems

Efforts to develop classification systems have focused principally on terrestrial and freshwater systems, and on specific regions and habitat types, as well as on entire nations. Researchers have studied a few coastal systems and their watersheds intensively, but have not yet expanded broad-scale classification efforts to coastal and estuarine ecosystems (Edgar et al., 2000). Researchers have conducted even fewer studies to compare susceptibility or responses to stressors among or across coastal ecosystems.

Although none of the 25 classification systems we reviewed specifically met our needs for a coastal classification based on susceptibility to stressors (Appendix E), each provided approaches and information to build upon. Three geographic mapping efforts divided the U.S. into regions with common features based on overlays of existing landscape and climatic data (Bailey, 1976; Keys et al., 1995; Omernik, 1987; USGS, 1999). These geographic efforts served to define and compartmentalize the entire country into similar climatic units, aiding environmental management and conservation efforts to inventory and define natural resources. Although comprehensive, climatic units are more relevant to terrestrial systems and result in an impractical number of classes for our purposes.

Scientists have designed another group of classification frameworks for inventory and management of wetlands (Chow-Fraser, Albert, 1998; Cowardin et al., 1979; Day et al., 1988; Detenbeck, 2001; Keough et al., 1999; Shaw, Fredine, 1956). The most widely used of these, developed by Cowardin et al. (1979), divides environments into groups in a manner similar to a taxonomic key. Broad categories of habitat types are successively divided in hierarchical fashion into groups with more aspects in common, cascading down to numerous, well-defined classes with many common features. These systems add considerations of biological diversity, hydrology and retention time, but lack a qualitative framework making susceptibility to stressors difficult to predict or measure (Jay et al., 2000). At the level of refinement necessary for considerations of susceptibility to stressors, these systems still result in a large number of classes.

Fluvial systems and watersheds are the focus of five additional frameworks that use hydrology, geomorphology, and sediment transport as classification parameters (Montgomery, Buffington, 1993; Rosgen, 1994; Poff, Ward, 1989; USGS, 2003g; Detenbeck et al., 2000). These systems result in smaller numbers of classes, and are relevant to classifying aquatic habitats for the coastal Great Lakes. They are not designed for direct application to estuaries, nor are they directly applicable to stressor susceptibility determinations.

Several classification frameworks, published since the 1950s and 1960s, have addressed estuaries. Two are simplified to elements of stratification and circulation (Hansen, Rattray, 1966; Strommel, Farmer, 1952). Two more recent systems add forcing processes like wind and waves (Jay et al., 2000), or employ hierarchical clustering methods with both quantitative and subjective data for Australia (Digby et al., 1998). Allee et al. (2000), developed a system including biological criteria that was modeled after the hierarchical framework developed for wetlands by Cowardin et al. (1979). Two additional estuarine efforts include biological aspects. Briggs (1974) outlined zoogeographic regions based on the distribution of indigenous marine organisms, and the Nature Conservancy has adapted their freshwater classification framework to estuarine habitats for the conservation of biodiversity and specific species of interest (Beck, Odaya, 2001).

Four classification systems address susceptibility to stressors in a more direct way. Sklar and Browder (1998) identify the potential impacts of alterations to freshwater flow, comparing effects from individual stressors to multiple stressor effects. This study provided an in-depth examination of Gulf of Mexico systems and additional research may demonstrate broader applicability. Stefan et al. (1996) used a modeling approach to predict habitat susceptibility to global climate change. They considered trophic status and interacting stressors, although only in closed, northern lake systems. Ferreira (2000) developed an estuarine quality index. This decision support system addressed vulnerability, but required fish and benthic community diversity measures and sediment quality indicators that may not be widely available. Finally, NOAA considered estuarine susceptibility to nutrient over-enrichment (NOAA, 1989; Bricker et al., 1999). Using these calculations and metrics, managers can classify estuaries effectively based on nutrient susceptibility, but must rely partially on subjective measures, and are unable to consider other stressors to aquatic systems using these methods.

When maintaining habitat inventories and prioritizing habitats for conservation efforts or examining reference conditions are the only goals considered, the state of science for classification of Great Lakes coastal habitats is similar to the state of science for marine estuaries. Existing habitat classification frameworks for wetlands and deepwater (Cowardin et al., 1979) and ecoregion or ecological unit classification frameworks (Keys et al., 1995; Maxwell et al., 1995; Omernik, 1987) are generally applicable to the Great Lakes as well as other regions of the U.S. For Great Lakes coastal wetlands, McKee et al. (1992) suggest a modification of Cowardin's system, incorporating landscape position (system), depth zone (littoral vs. limnetic subsystems), vegetative or substrate cover (class and subclass), and modifiers of ecoregions, water level regimes, fish community structure, geomorphic structure, and human modification. More detailed habitat type classifications for both coastal and inland aquatic systems in the Great Lakes basin are in progress through the USGS Gap Analysis Program (USGS, GAP, 2003a). In this approach, managers and researchers use physical, chemical, and hydrological characteristics of streams or coastal habitats to classify habitat types and relate them to organism presence or absence and biological community types. For streams and rivers of the upper Midwest, Robertson et al. (2001) have demonstrated that they can improve predictions of reference condition for nutrient concentrations by applying the ecozone concept. Robertson et al. (2001) identified both natural and combined natural and anthropogenic watershed characteristics that discriminate among classes of watersheds with different ranges of nutrient concentrations. Previously, managers and researchers had neither tested the ecoregion nor the ecozone classification approaches specifically for Great Lakes coastal habitats. However, results from a recent EPA R-EMAP project (Simon et al., 2003) will provide an opportunity to test ecoregion and ecozone definitions of reference condition for both nutrients and indices of biotic integrity.

In contrast to the state of the science for classification of aquatic habitat types and reference condition, the science for classification of Great Lakes coastal habitats based on relative susceptibility to stressors is in its infancy. One exception is the construction of an Environmental Sensitivity Index for both marine and Great Lakes shorelines by NOAA; however, NOAA constructed this index specifically to predict sensitivity to spills of oil and other hazardous substances (USEPA, 2001c; NOAA, 2003c). Researchers have proposed numerous Great Lakes coastal wetland classification schemes, but have focused either on vegetation type or on some combination of geomorphology and geologic origin, without establishing any conceptual or empirical relationships between wetland type and susceptibility to stressors (Chow-Fraser, Albert, 1998; Keough et al., 1999; Maynard, Wilcox, 1997; Minc, Albert, 1998; Great Lakes Commission, 2001).

Conceptual Models

The conceptual framework for evaluating causes of biological impairment within aquatic ecosystems of the U.S. is comprised of a hierarchical, modular set of diagnostic methods and models and an ecosystem classification scheme (Figure 1). Together, these tools should simplify and improve the accuracy of water body evaluations, which the federal government, states, and tribes carry out under Sections 305(b), and 303(d) of the Clean Water Act. The conceptual overview described here provides the basis for developing and testing our classification system.

Context for Model Development and Classification

One of our goals is to simplify the process of diagnosing the causes of impairment by classifying ecosystems based on differences in their response to stressors. A second goal is that our models and classification system simplify and facilitate management at the watershed scale. To accomplish these goals we need to understand and predict the actions of stressors on aquatic ecosystems within their watersheds. Thus, the nature of watersheds, aquatic ecosystems and stressors set the context for model development. We define *fundamental watersheds* here as networks of ecosystems that are linked by flow of water and have a terminal connection to the open sea or to one of the Great Lakes (Figure 2). They serve as the largest watershed scale system within which we must manage wetlands, stream segments, lakes and estuaries to ensure that limits established for pollutants and habitat alteration will be effective.

Our classification system uses the properties of fundamental watersheds as input data and organizes the information in this way. We can define a stressor as an injury or impairment to an ecosystem that results from the overuse of one or more ecosystem components or processes. In general, this condition is the result of a change or perturbation of the normal (long-term or natural) suite of energy inputs to a place (the energy signature, Figure 3) that results in a change in the normal or expected functioning of the ecosystem under the old signature.

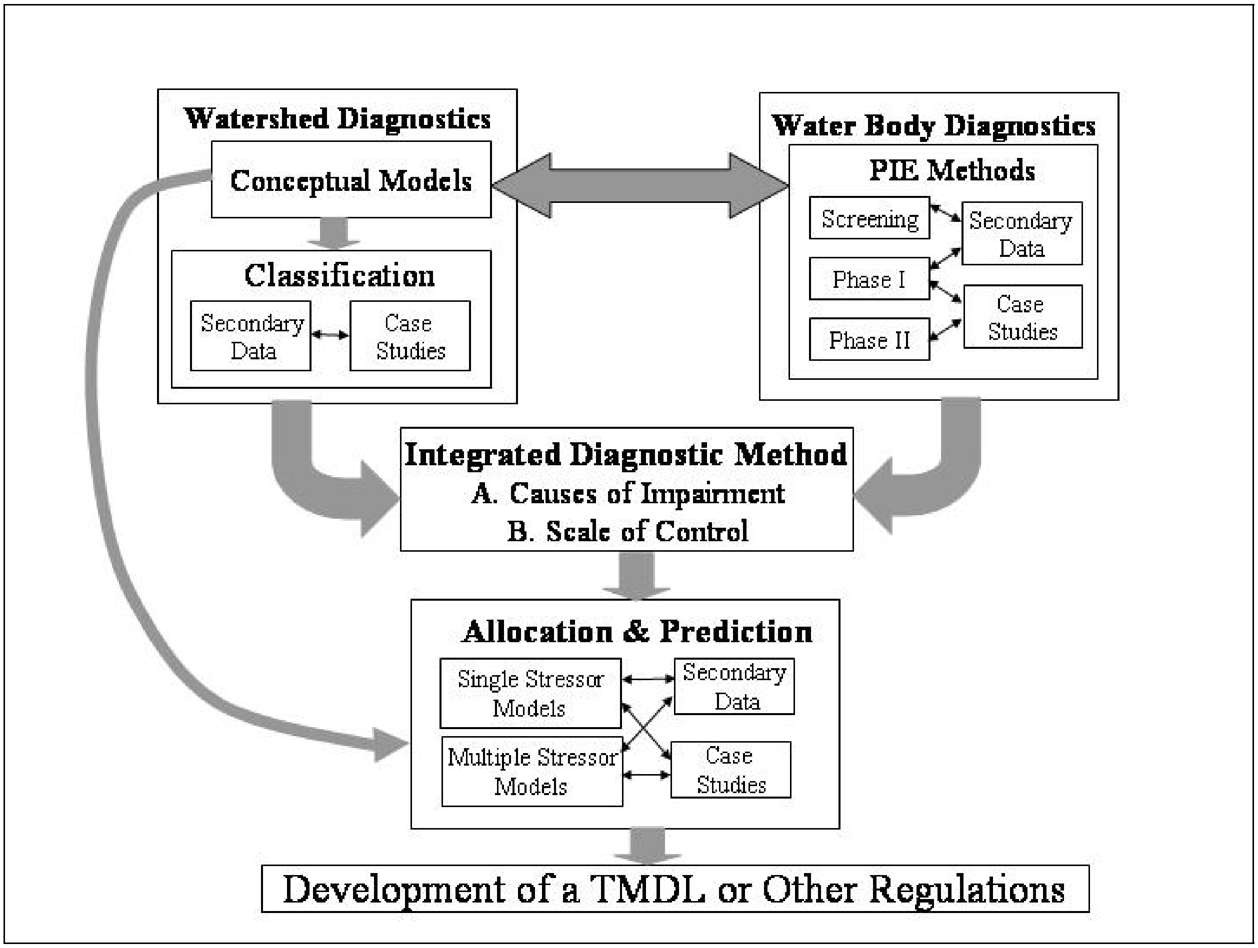

Figure 1. Generalized critical path for Diagnostics Research showing role of classification and conceptual models. PIE = Pollutant Identification Evaluation.

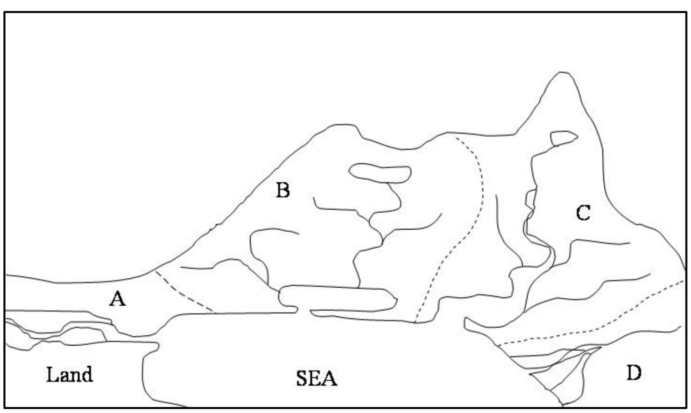

Figure 2. Network of ecosystem units arranged on the landscape within fundamental watersheds A, B, C, and D.

A conceptual representation of the impact pathway that results in stress in an ecosystem is a simple chain of cause and effect:

> Human activities ⇒ pollutant sources ⇒ presence of the stressor in the environment, e.g., the concentration of a pollutant ⇒ observed effect, e.g., a biological impact.

For a classification system to be useful in simplifying diagnosis of the causes of impairment to aquatic ecosystems, it must be able to discriminate groups of systems based on differences in their response to stress and to a particular stressor. The four classes of stressors we are considering, nutrients, suspended and bedded sediments, toxics, and altered habitat, each have different mechanisms of action within ecosystems. Therefore, we expect that the system groupings found by a classification scheme will differ based on the factors that control the behavior of aquatic ecosystems under the influence of one or more of these stressors. Development of a TMDL is determined on a pollutant-by-pollutant basis. Thus, there is a need to understand the mechanisms of stressor action and the behavior of systems under stress on a pollutant-by-pollutant basis. We developed a second conceptual model for the network of system interactions controlling the behavior of stressors within fundamental watersheds but did not use these watershed models in our initial classification research.

The Conceptual Model Used as a Basis for Classification

We developed a hierarchical, modular framework for constructing the conceptual models needed to diagnose the causes of impairment in aquatic ecosystems. At the highest level of aggregation, we used a set of simple standardized models (Figure 4) to describe the links between watershed units and their aquatic ecosystems on the landscape. We illustrate the common and distinguishing properties of the four canonical models used to represent aquatic ecosystems with different hydrological properties in Figure 4. The base unit for each of these models is a water body (river reach, lake, or estuary) and its watershed. We must specify the characteristics of the water body, including its geometric and geomorphic properties along with the loading of the material stressor from the surrounding watershed and the quantity of the material that is stored within the system. We hypothesize that three primary factors control the stressful actions of pollutants in aquatic ecosystems. They are (1) the residence time of water and pollutant in the system, (2) the natural processing capacity of the system for the pollutant including the pathways that decompose, bind, take-up, or sequester the material, and (3) ancillary factors that modify the form of a pollutant, the rate of processing, or the kind of action the pollutant exerts within the ecosystem. We can evaluate these three factors in a manner that quantitatively determines the effective dose of a pollutant experienced in ecosystems of different kinds. We hypothesize that different ecosystems will have characteristic properties related to residence time, processing capacity, and modifying factors that together can be used to differentiate classes of ecosystems that develop different biologically effective concentrations of a material when loaded with a given quantity of that pollutant. We can further simplify the problem by grouping pollutants according to their mode of action such that an ecosystem processes all members of a class in a similar manner. In this case, we can express the bioeffective concentration in aggregate units, i.e., standard toxicity units.

The factors that we have used to construct the conceptual models for diagnosis when quantitatively evaluated give an expression for the exposure of the ecosystem to biologically active concentrations of a particular stressor.

Residence *	Bioeffective	= Exposure
Time	Concentration	(g m^{-3} - days)
(days)	(g m^{-3})	

We base our classification system on the premise that effective exposure will differ for particular pollutants or classes of pollutants across estuaries and Great Lakes coastal wetlands of different kinds. The first term of the expression given above depends on the physical forces and flows that control the residence time of pollutants in the system, whereas the second term depends on the biological and chemical factors that determine processing capacity for the material. Modifying factors are forcing functions or materials that alter the effect of stressor action. When the effects of modifying factors are applied to exposure calculations given above, the effective exposure results.

System Properties Controlling the Effects of Stressors

Residence Time

This generic property measures the average time period a molecule of water derived from riverine sources resides in the estuary. The longer the residence time, the longer freshwater and dissolved constituents will remain in the estuary. Shallow systems exhibit properties that magnify stress, e.g., increased concentrations of riverine inputs, internal waste products and lower salinities. However, shallow systems also decrease stress by removing some of the dissolved constituents through decreased freshwater residence times. Large estuarine systems by virtue of their lower surface area to volume ratio should have lower concentrations of waste products and, therefore, be less stressful. However, because of longer residence times deeper areas of the estuary can accumulate these organic degradation products resulting in anoxia with concomitant changes in other critical populations, communities and ecosystem functions. As a result, residence time of both freshwater and seawater systems are important determinants of the ecological state of estuarine systems.

Ecosystem processing capacity

Biological, chemical, and physical processes alter the bioavailable concentrations and residence time of materials entering the ecosystem. These processes consist of absorption and desorption onto particles, chemical and biological uptake, transformation and degradation. As a result of these processes, anthropogenic materials and pollutants can be either removed from the system with no adverse affects or accumulate in various compartments (e.g., sediments) of the aquatic system where adverse ecological effects can occur. Any foreign material that reduces or interferes with the rate at which these processes occur can result in further system degradation due to the changes in removal rates of other compounds normally found at low concentrations. The rate of processing of major compounds (e.g., nutrients) could be ecosystem specific and, therefore, be a determinant in the classification of an ecological system.

Modifying factors

Modifying factors alter the relationship between exposure and effect. For example, aluminum is toxic at low pH but not at a higher pH. Therefore, a calculated exposure to aluminum would result in greater mortality at pH 5 than at pH 7. Another example of a modifying factor is water column turbidity, which alters the amount of carbon fixation realized from a given concentration of phosphorus and/or nitrogen. Processes that alter the residence time of the system such as changes in the flow regime can also change the effective exposure of the ecosystem to a pollutant by altering the time it has to react with the biota. For example, the amount of watershed storage in fresh water systems can influence the amount of biological and chemical processing, flow regime effects on habitat, and biological condition of fish communities in fresh water aquatic ecosystems (Detenbeck et al., 2000). We should also consider factors that control the relationship between an observed biological attribute and exposure to a pollutant as modifying factors, e.g., storage in fresh water systems, salinity in salt water systems, and pH (Table 1)

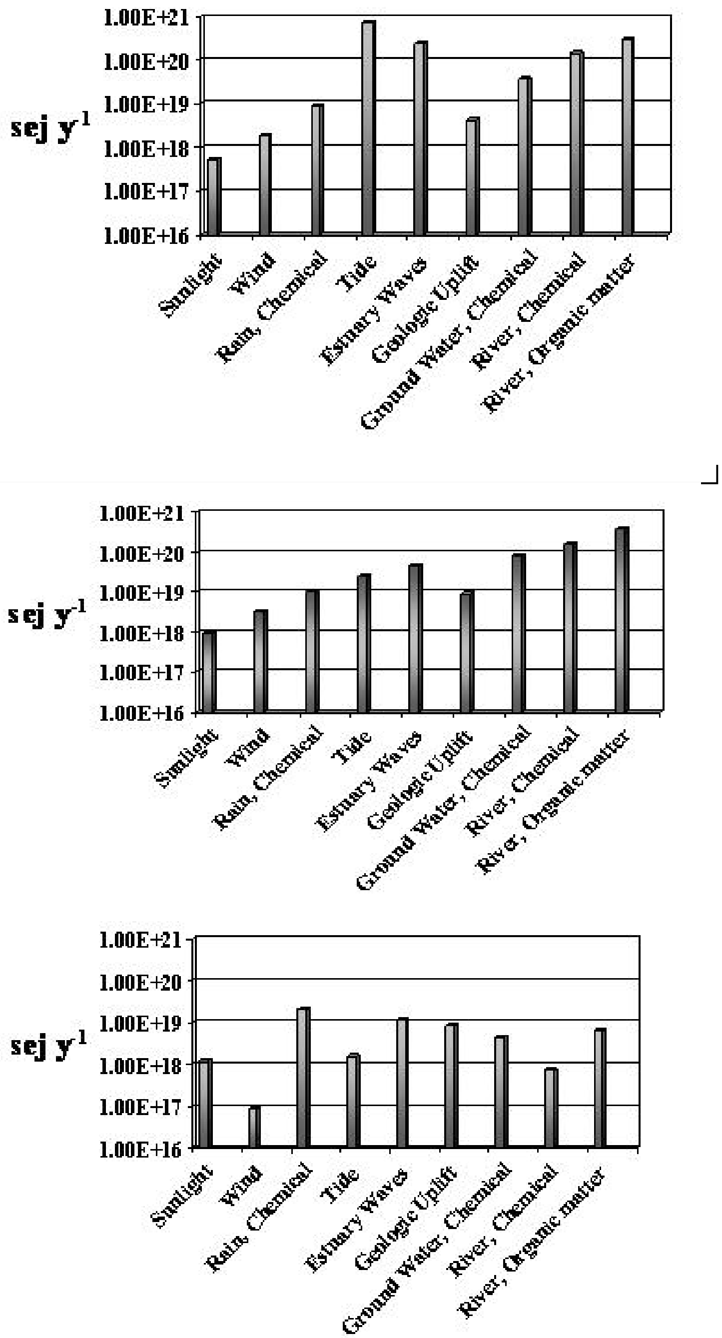

Figure 3. Emergy signatures for a) top: a micro-tidal estuary (Cobscook Bay, ME), b) middle: a fluvial estuary (York River, VA), and c) bottom: a lagoon (Mosquito Lagoon, Florida), from Campbell 2000).

Figure 4. Conceptual canonical energy system models of the factors controlling the action of stressors in a system with a) top left: unidirectional water flow, b) top right: unidirectional flows and two different processing capacities, e.g., stratified system (water column or water plus sediment column); c) bottom left: bi-directional flows, or d) bottom right: bi-directional flows and two different processing capacities.

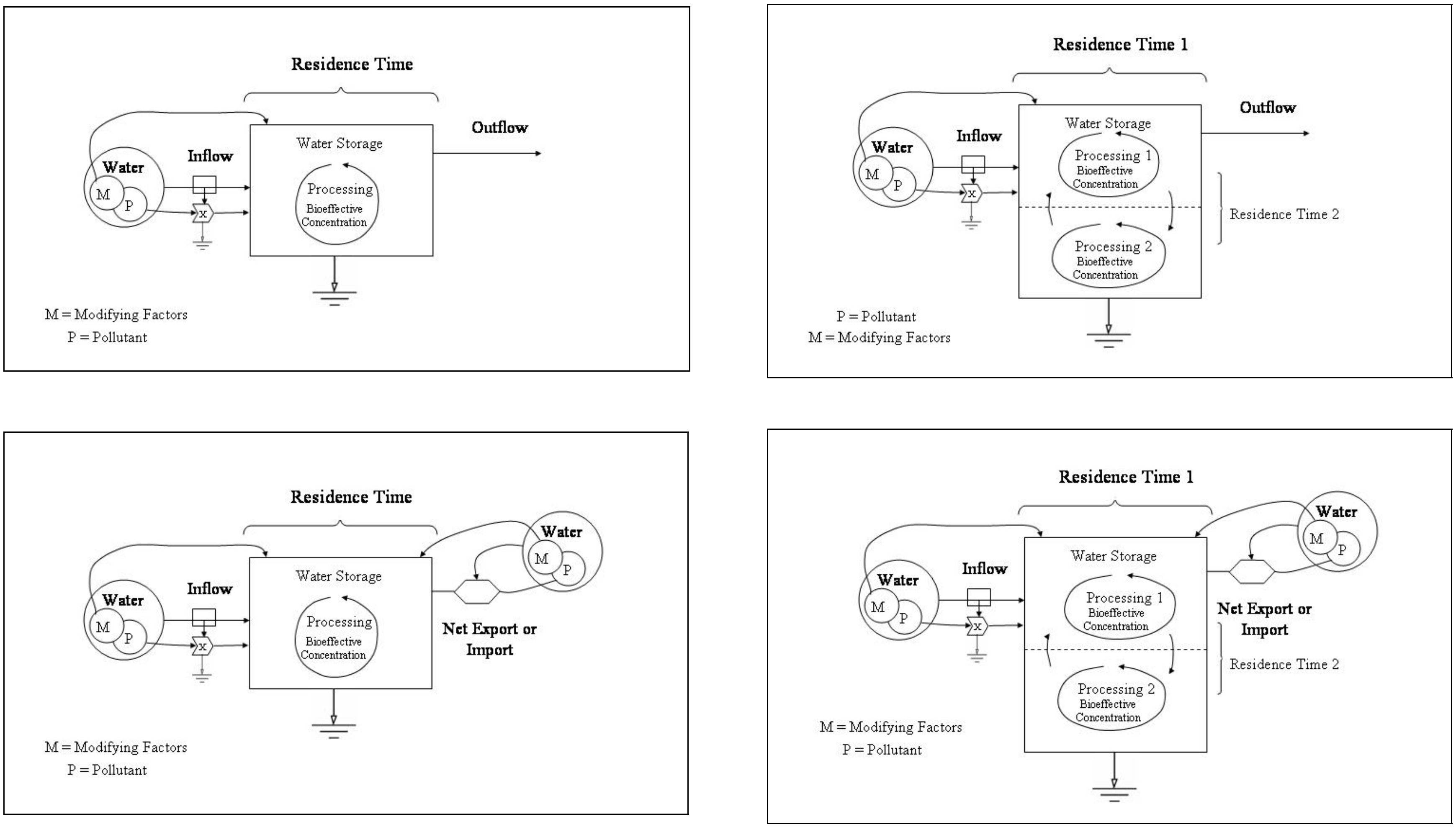

Table 1. Modifying factors and processing rates relevant for major aquatic stressors.

Modifying factors	Processing rates
Toxics	
Total and dissolved organic carbon	Biotic, abiotic degradation (photolysis, hydrolysis)
Acid volatile sulfide	Bioaccumulation, uptake
PH	Denitrification and nitrification, primary production
Ionic strength (salinity, hardness)	
Temperature	
Redox potential (oxic vs. anoxic)	
Total suspended solids	
Photic depth	
Nutrients	
Total suspended solids	Primary production and respiration
Other nutrients, Redfield ratio effects	Remineralization (bacteria)
Temperature	Grazing rates, food web and chain changes
Dissolved oxygen	Nitrification and denitrification
Hardness	
Hypsography (depth distribution)	
Organic matter loading, shift processes	
Suspended and embedded sediments	
Shear force	Filter feeding
Grain size distribution	Bioturbation
Large scale structure	Physical resuspension (storm events)
Flow magnitude and duration, flashiness	Large-scale hydrologic
	Normal channel and basin evolution

II. APPROACH

Methods Applied for Stage I Classification Database

Database structure

We compiled separate databases for classification of estuarine and Great Lakes coastal watersheds and wetlands. Both databases will eventually contain the same components, i.e., information on system morphometry and hydrology needed to estimate retention time, watershed characteristics determining hydrologic regime and/or loadings for stressors and modifying factors, and ecological exposure and effects data necessary to test the classification systems. In the Stage I database, some components of the estuarine database are more complete than those for coastal Great Lake wetlands, while data for Great Lakes coastal watersheds are available at a finer scale of spatial resolution. The delineation of finer scale watersheds for Great Lakes coastal wetlands allowed us to develop indicators of hydrologic regime for individual systems, while for estuarine systems, only regional thresholds were derived for the Stage I database. This situation reflects the current availability of data, and will be rectified during development of the Stage II database. The components of the databases and sources of data are described below.

<u>Estuaries</u>

Any geographical classification requires standard spatial units. The base unit for this classification framework was a unique combination of USGS 8-digit Hydrologic Unit Codes (HUCs) and Estuarine Drainage Area/Coastal Drainage Area (EDA/CDA) defined by NOAA. Watersheds are delineated by USGS using a nationwide hierarchical system based on surface hydrologic features (Seaber et al., 1987). The hydrologic unit system divides the U.S. sequentially into finer and finer drainage basin subdivisions, with regions as the largest unit (2-digit code) and cataloging units as the fourth level subdivision (8-digit code).

The Coastal Assessment Framework (CAF) (NOAA, 2003d) is a consistently derived, watershed-based, national digital spatial framework that is similar to the 8-digit HUC system. The main difference between CAF and HUC lies in the method by which NOAA sub-divides 8-digit HUCs into EDAs and CDAs where the limits of tidal influence within an estuary or coastal drainage area are incorporated. An EDA is that component of an estuary's entire watershed that empties directly into waters affected by the tides. EDAs may be composed of a portion of a single hydrologic unit, an entire hydrologic unit, more than one hydrologic unit, or several complete hydrologic units and portions of several adjacent hydrologic units. Every EDA has both a land and water component. A CDA is generally defined as that component of an entire watershed that meets the following three criteria: 1) it is not part of any EDA or a corresponding FDA (fluvial drainage area), 2) it drains directly into an ocean, an estuary, or the Great Lakes, and 3) it is composed only of the HUC that is closest to the ocean or shoreline.

Our unique spatial referencing unit for coastal watershed classification is based primarily on the USGS 8-digit HUCs, modified in some areas along the coast by sub-dividing or combining the HUCs using the EDA/CDA boundaries. We identified 8-digit HUCs that drained into an ocean or estuary. For the conterminous U.S. we selected 277 HUCs that were directly associated with the coast. We also identified EDAs and CDAs located along the U.S. coast. Of the 348 EDAs and CDAs listed in the CAF, we selected a total of 203 (145 EDAs and 58 CDAs) for our classification database.

The HUCs and EDA/CDAs were overlaid on a map of the U.S. using GIS. HUCs were geographically referenced to EDA/CDAs. There were 240 one-to-one matches of HUCs to EDA/CDAs. Differences in the methods of delineating EDA/CDAs from HUCS resulted in 64 EDA/CDAs that overlapped the boundaries of more than one HUC and 44 HUCs that overlapped the boundaries of more than one EDA/CDA (Figure 5).

We developed unique identification codes for 348 classification units that enabled us to reference either a HUC or EDA/CDA depending on our needs and whether data was aggregated by HUC or EDA/CDA. Five final databases were generated for use in classification and future stressor-response modeling: 1) physical and hydrologic characteristics, 2) land cover statistics, 3) stressor loads, 4) in situ stressor concentrations, and 5) modifying factors. Measurements or indicators of exposure (stressors, loadings, landcover) are not intended to be used to classify systems but to test for differences in response among classes to stressor gradients. An additional standard spatial unit database contained both EDA and HUC identifiers so that data could be merged from sources referenced by either EDA or HUC. The physical and hydrologic characteristics of EDAs were used to classify estuaries into groups whose members had similar characteristics. This database included area, volume, flow, tides, depth, and salinity for each EDA (Appendix A-1.2). Most of the variables were derived directly from CA&DS. CA&DS is a national- and regional-level database and mapping analysis tool designed to access, synthesize, assess, and apply nationwide data sets to priority coastal issues such as estuarine eutrophication, essential fish habitat, coastal monitoring, and sustainable development (NOAA, 2003a).

Where CA&DS data were incomplete, data from the Estuarine Eutrophication Survey (NOAA, 1996; NOAA, 1997a-c; NOAA, 1998) were used. Average salinity and depth were calculated from EMAP data, where point locations sampled from 1990-2000 were geo-referenced to EDAs.

<u>Great Lakes</u>

Spatial units for Great Lakes systems were the coastal riverine wetlands and their associated watersheds. Unlike the case for estuaries, receiving water bodies could be defined at a finer scale, and watershed boundaries scaled appropriately. A recently completed inventory of coastal riverine wetlands in the Great Lakes identified a total of 283 sites (Simon et al., 2003). The classification database for the Great Lakes includes data for those 150 coastal riverine wetlands and associated watersheds for which response variables have been measured through the EPA Region 5 Great Lakes Coastal Wetlands R-EMAP (Simon et al., 2003). Although 8-digit HUC boundaries for coastal drainage areas in the Great Lakes are defined in CA&DS, the spatial resolution of these hydrologic unit boundaries is too coarse to provide the base coverage for a classification system for Great Lakes coastal wetlands. To develop the National Watershed Boundary Database, delineation of 10- and 12-digit HUCs has begun for the Great Lakes states, but is not yet complete (Legleiter, 2001). For the current classification database, watershed boundaries for Great Lakes coastal riverine wetlands were either imported from existing state watershed coverages or 12-digit HUCs, delineated through an automated process using digital elevation models (Franken et al., 2001) or digitized onscreen in an ArcInfo Geographic Information. System (GIS) using 1:24,000 topographic maps (digital raster graphics files) and 1:100,000 National Hydrography Database (NHD) stream coverages as a backdrop (USGS, 2003b).

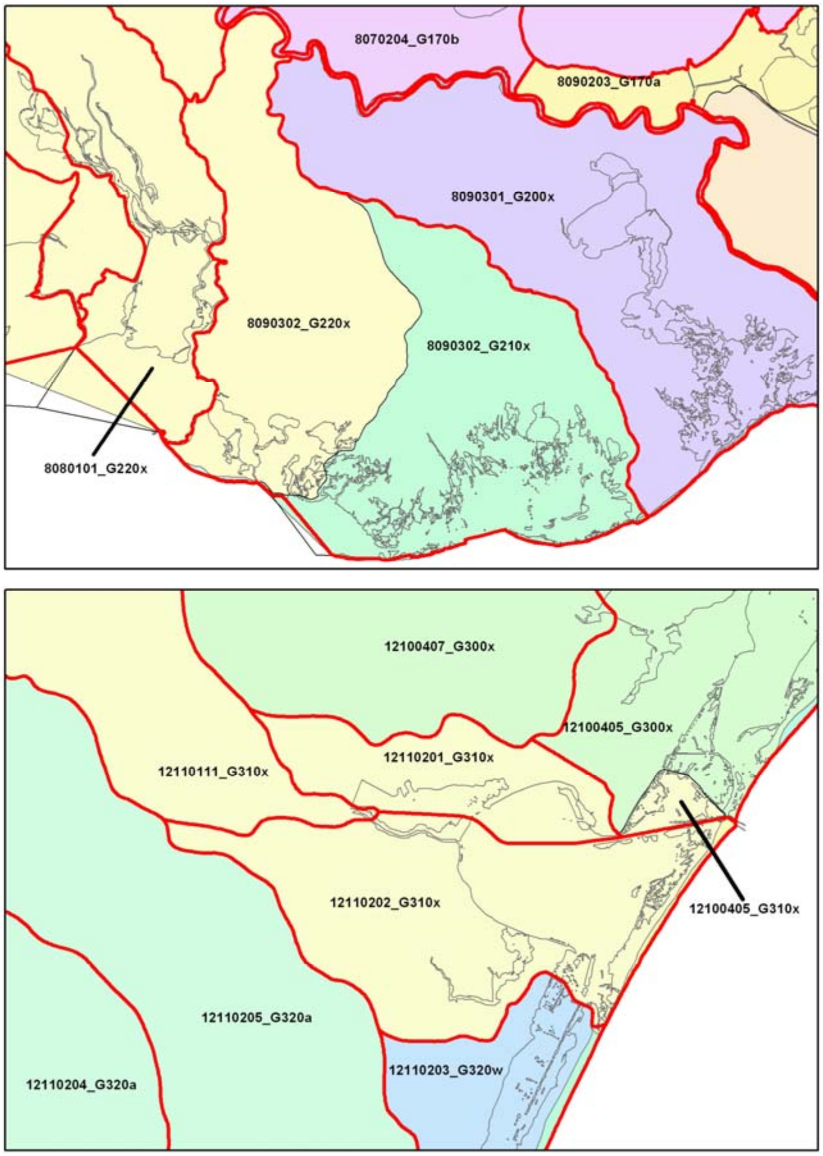

Figure 5. a) HUC 8090302 (West Central Louisiana Coastal) overlapped two EDAs (G210x-Terrebonne/Timbalier Bays and G220x-Atchafalaya/Vermillion Bays) resulting in two unique spatial units for classification (8090302_G210x and 8090302_G220x), b) EDA G310x (Corpus Christi Bay) overlapped four HUCs (12110111-Lower Nueces, 12110201-North Corpus Christi Bay, 12110202-South Corpus Christi Bay, and 12100405-Aransas Bay) resulting in four unique spatial units for classification (12110111_G310x, 12110201_G310x, 12110202_G310x, and 12100405_G310x). Yellow and green areas = EDA and red outline = HUC.

The full population of Great Lakes coastal riverine wetlands was defined operationally for the Region 5 R-EMAP according to the following criteria:

- ❖ wetland area
- ❖ surface connection to the lake
- ❖ proximity to the Lake (must be within 10-20' elevation above lake level)
- ❖ subset of all coastal wetlands (drowned-river mouth and riverine wetlands) extracted based on
  - ➢ association with 2nd order streams or larger (1:24,000) OR
  - ➢ association with 1st order streams if tributary is outflow of a lake or pond.

A list-based sample frame of all coastal Great Lakes wetlands was developed based on an inventory generated by USFWS (1981a-f) and supplemented by identification of wetlands using marsh symbols present on 1:24000 topographic maps, presence of emergent or floating vegetation on digital orthophoto quadrangle aerial photos, and experience of local wetlands experts (Simon et al., 2003). A subset of 22 coastal riverine wetlands in the Lake Michigan basin was selected for sampling in 2000 using a probabilistic survey design with unequal probability weighting for ecoregion classes and three wetland areal size classes (<100 acres, 100-1000 acres, and >1000 acres). In 2001, this set of coastal riverine wetlands was supplemented with sites selected through a second probabilistic survey design for the four Great Lakes within EPA Region 5 (Lakes Superior, Michigan, Huron, and Erie) and associated connecting channels, for a sample total of 155 coastal riverine wetlands. To distribute sampled sites more evenly among chosen categories, the second survey design included unequal probability weighting by Great Lake or connecting channel class and by wetland size class (Simon et al., 2003).

Five separate databases were generated for Great Lakes coastal systems. These include: 1) a database of watershed characteristics and hydrologic variables for selected USGS gauging stations in coastal Great Lakes states (Glatfelter, 1984; Holtschlag and Croskey, 1984; Jacques and Lorenz, 1988; Krug et al., 1992; Lumia, 1991; Sauer et al., 1983; Stedfast, 1986), 2) derived hydrologic thresholds by state climatological region that define boundaries among hydrologic regime classes based on watershed characteristics, 3) characteristics and hydrologic regime class for watersheds associated with a subset of 155 coastal riverine wetlands, 4) coastal riverine wetland attributes for the subset of 155 coastal riverine wetlands, and 5) biological condition estimates for the subset of 155 coastal riverine wetlands. Hydrologic thresholds in the second database were derived for all coastal marine states as well.

Databases to characterize hydrologic regime class of Great Lakes coastal systems were derived by compiling data from state-level USGS reports on watershed characteristics related to peak and base flows (see Jennings et al., 1993 for summary). USGS and state partners first divide each state into homogeneous hydroclimatological regions. Gaging stations are identified with long-term time series adequate to define peak flows for recurrence intervals ranging from 2 to 100 years. For each region, equations have been developed to predict peak flows based on watershed characteristics. Watershed characteristics to be included in each analysis are chosen on a state-by-state basis but typically include contributing drainage area, main channel slope, and a subset of other variables such as watershed storage (lake + wetland and watershed area), minimum soil permeability, and precipitation (e.g., 2-year, 24-hour rain event magnitude, annual snowfall, annual average precipitation) (Jennings et al., 1993).

For each hydroclimatological region within each state, a combination of visual graphical analysis and CART techniques were applied to identify hydrologic thresholds (Wilkinson, 1999). We define a hydrologic threshold as a region of rapid change in a hydrologic metric such as peak discharge for a 2-year recurrence interval normalized by watershed area as a function of other watershed characteristics. For example, hydrologic thresholds that have been derived and tested for some regions of the Great Lakes include a watershed storage threshold of 5-10% and a mature forest threshold of 50% (Detenbeck et al., 2000). Below these thresholds, area-normalized peak flow increases exponentially, such that threshold values can be used to predict which watersheds will have stable versus flashy hydrologic regimes.

Watershed characteristics were derived for each of the 155 Great Lakes coastal riverine wetlands sampled under the EPA Region 5 R-EMAP. For Stage I of the database, watershed characteristics included land cover as an indicator of stressors such as potential nutrient, sediment, and toxics inputs, along with two derived watershed flashiness indices. Coastal riverine wetland characteristics included wetland location and wetland area in forested, emergent, and submerged wetland classes, as defined in National Wetlands Inventory and state wetland inventory coverages. Initial estimates of coastal wetland areas were taken from (USFWS 1981a-f).

Data Sources for Stressor Exposure(s)

In the initial version of the classification database, data for stressor exposures were compiled only for coastal watersheds along the marine coast, using the EDA/CDA and HUC units described above. For the Great Lakes watersheds, only land cover for coastal riverine wetland watersheds has been compiled because most other information sources include data that have already been aggregated to the level of 8-digit HUCs.

<u>Land Cover</u>

USGS and EPA created the National Land Cover Data (NLCD), (Vogelmann et al., 2001), for the conterminous U.S. based on early to mid-1990s, 30-meter Landsat Thematic Mapper (TM) satellite imagery. The NLCD consists of 21 level II land cover classes (Figure 6) (Vogelmann et al., 2001). To derive acreage statistics for each spatial referencing unit or EDA, we performed a matrix overlay of our spatial referencing unit dataset with the NLCD.

For Great Lakes coastal watersheds, land cover classes were aggregated to the following categories: agricultural, nonagricultural grasslands, commercial and residential, forested, wetlands, barren, mining, and open water (Table 2). For estuaries, NLCD level II land cover classes were aggregated to level I classes to produce area estimates for water, shrubland, grassland, non-natural woody, developed, barren, forested, agricultural, and wetland land cover classes (Appendix A-2.1).

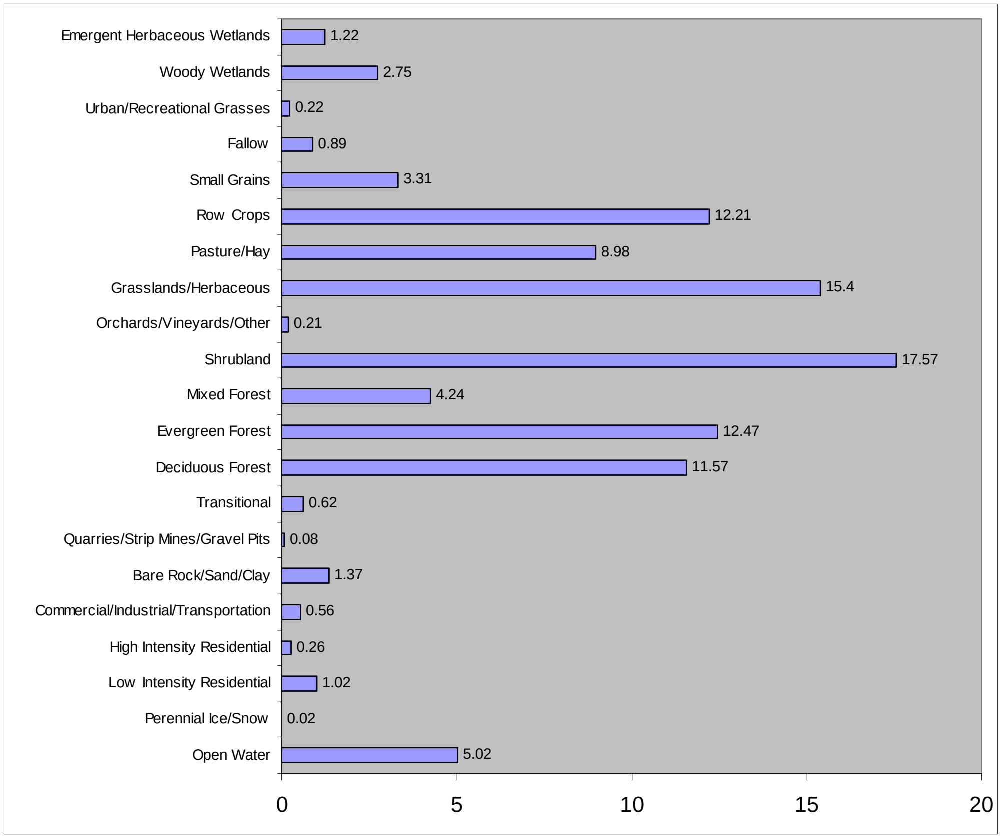

Figure 6. Breakdown of NLCD land cover classes for coastal EDAs and CDAs.

Table 2. Aggregation of land-cover categories for Great Lakes and estuarine watershed databases.

<table>
<tr><th>Original NLCD Class</th><th>Aggregated Class for Great Lakes</th><th>Aggregated Class for Estuaries</th></tr>
<tr><td>Open Water</td><td>Open Water</td><td>Water</td></tr>
<tr><td>Low Intensity Residential</td><td rowspan="3">Commercial/Residential</td><td rowspan="3">Developed</td></tr>
<tr><td>High Intensity Residential</td></tr>
<tr><td>Commercial/Industrial/Transportation</td></tr>
<tr><td>Bare Rock/Sand/Clay</td><td rowspan="2">Barren</td><td rowspan="3">Barren</td></tr>
<tr><td>Transitional</td></tr>
<tr><td>Quarries/Strip Mines/Gravel Pits</td><td>Mining</td></tr>
<tr><td>Deciduous Forest</td><td rowspan="3">Forested</td><td rowspan="3">Forested</td></tr>
<tr><td>Evergreen Forest</td></tr>
<tr><td>Mixed Forest</td></tr>
<tr><td>Shrubland</td><td>Shrubland</td><td>Shrubland</td></tr>
<tr><td>Orchards/Vineyards/Other</td><td rowspan="6">Agricultural</td><td>Non-Natural Woody</td></tr>
<tr><td>Pasture/Hay</td><td rowspan="5">Agricultural</td></tr>
<tr><td>Row Crops</td></tr>
<tr><td>Small Grains</td></tr>
<tr><td>Fallow</td></tr>
<tr><td>Urban/Recreational Grasses</td></tr>
<tr><td>Grasslands/Herbaceous</td><td>Non-agricultural grasslands</td><td>Herbaceous Upland Natural/Semi-Natural Vegetation</td></tr>
<tr><td>Woody Wetlands</td><td rowspan="2">Wetlands</td><td rowspan="2">Wetlands</td></tr>
<tr><td>Emergent Herbaceous Wetlands</td></tr>
</table>

Risk from Groundwater Nitrate Inputs

Groundwater nitrate risk was obtained from USGS (2003c). Nitrate risk is based upon input factors (population density and nitrogen loading) and aquifer vulnerability factors (soil drainage and woodland and cropland ratio in agricultural areas). The USGS calculated the soil drainage class from the State Soil Geographic (STATSGO) database (USDA, 2001). Categorical values were converted to numbers and threshold values determined. Soils with a hydrologic group value of <2.5 were considered well-drained; soils ≥2.5 were considered poorly drained. The woodland and cropland ratio was calculated from the 1992 Census of Agriculture. The data were divided into two groups: those with a woodland and cropland value <0.3 and ≥0.3. Population density was calculated from 1990 census data by dividing number of people in a block group by the total area of the block group. These data were divided into two groups: regions having ≤386 people/km² and regions with >386 people/km². Nitrogen loading was calculated by adding input from fertilizer, manure and atmospheric deposition (Battaglin and Goolsby, 1994). Nitrogen loading was divided into two groups: ≤2100 kg/km² and >2100 kg/km². These four data sets were added together to create four risk categories (Table 3). Groundwater nitrate collected from wells less than 100 ft deep generally verified the nitrate risk patterns. This national coverage was matched to the HUC and EDA/CDA units described earlier

Table 3. Categories of risk for groundwater nitrate inputs.

Risk Category	N Loading	Population Density	Hydrologic Group	Woodland/ Cropland Ratio
High Risk	>2100 kg/km²	>386 people/km²	<2.5	<0.3
Moderately High Risk	>2100 kg/km²	>386 people/km²	≥2.5	≥ 0.3
Moderately Low Risk	≤2100 kg/km²	≤ 386 people/km²	<2.5	<0.3
Low Risk	≤2100 kg/km²	≤ 386 people/km²	≥2.5	≥ 0.3

Risk from Pesticides

Risk from pesticides from agricultural sources was derived from the USDA NRCS National Pesticide Loss Database (Goss et al., 1998, NPLD). Goss et al. (1998) applied the pesticide fate and transport model from Groundwater Loading Effects from Agricultural Management Systems (GLEAMS) to scenarios for 243 pesticides applied to120 generic soils for 20 years of daily weather from each of 55 climate stations. They then used data from the NPLD, along with data from the 1992 National Resources Inventory (NRI), on crop type and 1990-1993 pesticide use data (application rate by crop) from Gianessi and Anderson (1995). Estimates of pesticide loss from the NPLD were imputed onto the 170,000 field sample points in the NRI database according to soil type, geographic location, and pesticide. Predicted concentrations were compared to Maximum Acceptable Toxicant Concentrations (MATCs) to derive threshold exceedance units at each point, then multiplied by the number of acres treated and summed over points in each watershed to create aggregate measures of risk. Two risk indices available from Natural Resources Conservation Service (NRCS) at the 8-digit HUC scale were included in the EDA database: 1) Acres (1,000) by watershed where the potential leaching concentration at the bottom of the root zone exceeds a multiple of one or more water quality thresholds for fish, and 2) Acres (1,000) by watershed where the potential runoff concentration at the edge of the field exceeds a multiple of one or more water quality thresholds for fish.

<u>Loadings</u>

The classification database for stressor loads includes total and point source nitrogen and phosphorus, total suspended solids, and indicators of toxic contaminant and sediment loads (Appendix A-3.2). Nitrogen and phosphorus loads were derived from the USGS Spatially Referenced Regression on Watershed Attributes (SPARROW) model for point and non-point sources of nutrients (Smith and Alexander, 2000; Smith et al., 1997). The loadings encompass both point and non-point sources estimated empirically, based on data collected from approximately 400 long-term stream monitoring sites, nutrient sources and physical characteristics of the watershed (Battaglin and Goolsby, 1994). Datasets generated using the SPARROW model include watershed total nitrogen and total phosphorus export and yield by source, as well as percent contribution to total load by source (fertilizer, livestock waste, atmosphere, non-agriculture; Smith and Alexander, 2000). Additional point source loads for nitrogen, phosphorus, and total suspended solids were compiled from Permit Compliance System (PCS) data housed in the Better Assessment Science Integrating point and Nonpoint Sources (USEPA, 2003a, BASINS). Total nitrogen and phosphorus loads were calculated by averaging loads over time for each National Pollutant Discharge Elimination System (NPDES) identification code and then summing loads across all NPDES codes by HUC.

Twenty-nine chemical loads were also compiled from the PCS. A principal component analysis (PCA) was conducted to reduce this data set to three principal components representing PAHs, metals, and pesticides.

Sediment load data are not currently in the classification database; however, a hydrologic unit model for the U.S. (HUMUS; TAES, 2000) has been developed to estimate runoff, and sediment, phosphorus and nitrogen loads to coastal areas. HUMUS utilizes four input data types (land use, soil survey, digital elevation, and climate). For the current version of the database, we have included a relative ranking for the potential for sediment delivery to HUCs, based on data from the HUMUS database, was obtained from the Index of Watershed Indicators (IWI) database (USEPA, 2003i). The relative rank of watersheds based on this parameter estimates the potential for possible water quality problems from instream sediment loads.

<u>In Situ Stressor Exposure Levels</u>

Nutrients

In situ nutrient concentrations were obtained from EMAP NCA and BASINS (USEPA, 2003a; 2003b) databases (Appendix A-4.1). Water quality data collected in 2000 for NCA included dissolved inorganic nitrogen (nitrate, nitrite and ammonia), which species were summed for the stressor exposure database. Where data gaps existed, nitrogen data from the BASINS database were utilized to complement the EMAP nutrient database. Total Kjeldahl nitrogen and total phosphorus concentrations were extracted from the BASINS database and averaged by HUC. All data were geo-referenced to EDAs.

Suspended Sediments

As a surrogate for suspended sediment concentrations, total suspended solids (TSS) data were obtained from EPA's Storage and Retrieval (STORET) data summaries provided in the BASINS database. TSS concentrations were averaged by HUC and geo-referenced to EDA. TSS concentrations are also included in the stressor exposure database as a modifying factor.

Toxics

Sediment contaminant concentrations were obtained from EMAP and were converted to toxic units for metals, pesticides, polychlorinated biphenyls (PCBs), and PAHs. Sediment toxicity information was obtained from three sources: National Sediment Inventory (NSI) (USEPA, 1996), STORET and EMAP. NSI data and STORET data were sorted first by freshwater or marine location. STORET data were sorted into freshwater or marine using the website options; NSI data were sorted based upon the descriptors included in the state-by-state database. NSI data and STORET data were then sorted by the presence or absence of 32 toxic substances and 5 modifying factors (Table 4). Using best professional judgment and available data in the literature, these toxics were chosen as the most commonly occurring in sediments; choices were consistent with summaries in the NSI report (USEPA, 1998). Five modifying factors were chosen for their ability to assist in interpretation of the bioavailability of the toxics (Table 1). Entries containing any of the listed toxics were chosen for further consideration if they contained either HUC location or latitude- longitude coordinates that could be associated with an 8-digit HUC.

Table 4. Effects level for diagnostic screening.

Toxic Chemical Name	Water-only Toxicity Value (µg/L) [A]		Sediment Toxicity Value (See footnotes for units)		Sediment Concentration Units[1,2]
	Freshwater	Marine	Freshwater	Marine	
Total Ammonia[B]	4.68 (pH 6.5) 4.15 (pH 7) 1.71 (pH 8) 0.342 (pH 9)	11 (pH 7) 1.1 (pH 8) 0.14 (pH 9)	Use water-only values	Use water-only values	
Metals					
Cadmium	2.2	9.3	0.99[C]	1.2[C]	µg/g dwt
Copper	9.0	3.1	31.6[C]	34[C]	µg/g dwt
Chromium	11[D]	50[D]	43.4[C]	81[C]	µg/g dwt
Mercury	0.77	0.94	0.18[C]	0.15[C]	µg/g dwt
Nickel	52	8.2	22.7[C]	21[C]	µg/g dwt
Zinc	120	81	120[C]	150[C]	µg/g dwt
Organics					
Pesticides					
Chlordane	0.0043	0.004	3.24[E]		ng/g dwt
Chlorpyrifos	0.041	0.0056			ng/g dwt
Total DDTs	0.001	0.001	5.28[E]	1.58[E]	ng/g dwt
Diazinon[I]	0.05				ng/g dwt
Dieldrin	0.056	0.0019	12000[F]	28000[F]	ng/g OC
Total Endosulfans	0.056	0.0087			ng/g dwt
Endrin	0.036	0.0023	5400[F]	990[F]	ng/g OC
Pyrethroids (Permethrin)[I]	0.024				ng/g dwt
Total PCBs	0.014	0.03	35[E]	60[E]	ng/g dwt
Polycyclic Aromatic Hydrocarbons (PAHs)[G]					
Acenaphthene	55.9		491000[F]		ng/g OC
Acenaphthylene	307		452000[F]		ng/g OC
Anthracene	20.7		594000[F]		ng/g OC
Benzo(a)anthracene	2.23		841000[F]		ng/g OC
Benzo(b)fluoranthene	0.68		979000[F]		ng/g OC
Benzo(k)fluoranthene	0.64		981000[F]		ng/g OC

Toxic Chemical Name	Water-only Toxicity Value (μg/L) [A]		Sediment Toxicity Value (See footnotes for units)		Sediment Concentration Units[1,2]
	Freshwater	Marine	Freshwater	Marine	
Benzo(ghi)perylene	0.44		1100000[F]		ng/g OC
Benzo(a)pyrene	0.96		965000[F]		ng/g OC
Chrysene	2.04		844000[F]		ng/g OC
Dibenzo(a,h)anthracene	0.28		1120000[F]		ng/g OC
Fluoranthene	7.11		80[H]		ng/g dwt
Fluorene	39.3		538000[F]		ng/g OC
Indeno(1,2,3-cd)pyrene	0.28		1120000[F]		ng/g OC
Naphthalene	194		385000[F]		ng/g OC
Phenanthrene	19.1		596000[F]		ng/g OC
Pyrene	10.1		697000[F]		ng/g OC
Total Dioxins	$1.4 * 10^{-8}$		-		

Dwt = dry weight OC = organic carbon

[A] Water Quality Criteria (WQC) or Final Chronic Values (FCV) from USEPA (1989; 1999b,c; 2003e,f,g)
[B] mg/L, freshwater values assume 20˚C and marine values assume 20˚C and 30‰.
[C] From MacDonald et al. (2000a) and Long et al. (1995) in μg/g dry weight.
[D] Chromium VI.
[E] From MacDonald et al. (2000a,b) and Long et al. (1995) in ng/g dry weight.
[F] From USEPA (2003e,f,g) in ng/g organic carbon.
[G] Freshwater and marine values are identical.
[H] From USEPA (1999a).
[I] Diazinon and pyrethroid values are from Illinois water quality standards. (http://www.epa.state.il.us/water/water-quality-standards/water-quality-criteria-list.pdf)

Note 1: Using the units above, sediment dry weight concentrations can be converted to sediment organic carbon normalized concentrations using the following:

Sediment Concentration$_{OC}$ = Sediment Concentration $_{dwt}$ ÷ (Sediment organic carbon (in %) * 0.01)

Note 2: Using the units above, toxic units are calculated as follows:

Toxic Units$_{\text{dry weight}}$ = Sediment Concentration$_{\text{dry weight}}$ ÷ Sediment Toxicity Value$_{\text{dry weight}}$

Toxic Units$_{\text{organic carbon}}$ = Sediment Concentration$_{\text{organic carbon}}$ ÷ Sediment Toxicity Value$_{\text{organic carbon}}$

Note 3: Diazinon and pyrethroid values are from Illinois water quality standards (http://www.epa.state.il.us/water/water-quality-standards/water-quality-criteria-list.pdf). These values are lower than those observed in surveys of peer-reviewed literature with one exception Schulz and Liess, (2000), indicate that fenvalerate, a synethetic pyrethroid, has an effect level lower than the Illinois chronic water quality criterion (0.024 μg/L). In their paper, fenvalarate with a one hour exposure, at a concentration of 0.001 μg/L has an effect on the temporal emergence of the caddis fly. In addition the same paper states that 0.01 μg/L affects the dry weight of adults. The WQC number was used because the fenvalerate number is an outlier (order of magnitude lower than the rest), and while fenvalerate is a synthetic pyrethroid, it is not one often measured in waters and sediments, and we have based the pyrethroid number on permethrin concentrations

Data Sources for System Properties Affecting Retention Time

Most morphometry data were only available for estuarine systems. For Great Lakes coastal riverine wetlands, only preliminary estimates of wetland area are included in Stage I of the classification database.

Estuaries

Morphometry of estuaries includes measures of area, depth and volume. There are five measures of area within the database derived from CA&DS which were converted from square miles to square kilometers. The total area of the EDA represents land and water area for the watershed. Estuary area represents water area for the watershed. Mixing zone area represents the area in the estuary where salinity ranges from 0.5 to 25 ppt. The sea zone area represents the area in the estuary where salinity is >25 ppt. The tidal freshwater zone represents the area in the estuary where salinity is <0.5 ppt. Depth of the estuary in meters was obtained from EMAP, averaged over time and space. If depth or volume was not available for an EDA from EMAP data, the average depth or estuary volume was extracted from NOAA's Estuarine Eutrophication Survey Regional Reports (NOAA, 1996; NOAA, 1997a-c; NOAA, 1998). All depth values were converted from feet to meters. Volume was converted from cubic feet to cubic meters. Where estuarine volume was missing, it was estimated by multiplying estuary area by average depth.

Tidal Range

Tidal height and tidal prism volume were obtained from CA&DS. Average tidal height was calculated as the means of the height differences or ratios measured from NOAA National Ocean Service (NOS) tide gauge stations and converted from feet to meters. Tidal prism volume was calculated from the salinity zone mean range value or the salinity mean tide value multiplied by two. The salinity zone tidal value (depth) multiplied by salinity zone area (i.e., tidal freshwater zone, mixing zone, seawater zone) provided volume for each salinity zone. The tidal prism volume was calculated as the sum of all salinity zone volumes. If tide information was not available for all three salinity zones, the estuary mean range was used or the estuary mean tide value multiplied by two. This value was converted from cubic feet to cubic meters.

Riverine discharge

Average monthly river flow was obtained from CA&DS. These values were obtained from the annual long-term flow average of gauged rivers from USGS. Where such data were missing, average daily inflow values were converted to monthly and were substituted from NOAA's Estuarine Eutrophication Survey Regional Reports (NOAA, 1996; NOAA, 1997a-c; NOAA, 1998).

Salinity-based Indicators of Retention Time

We estimated the dissolved concentration potential (DCP) of a pollutant as a function of pollutant load, the volume of freshwater in the estuary, freshwater inflow, and total estuarine volume. The volume of freshwater in the estuary was calculated using the freshwater fraction method:

$$F_{fw} = (SO-S)/SO) \text{ where,}$$

F_{fw} = Freshwater fraction,
SO = Boundary Salinity, and
S = Average salinity.

Average salinity data were obtained from the EMAP database for surface and bottom waters. Boundary salinities were designated as 35 ppt unless average salinities in the estuary were hypersaline (>35 ppt). In those cases with salinities >35 ppt, boundary salinities were based on averaged salinity and rounded up to the nearest whole number. For example, if the average salinity was 38.5 ppt, then the boundary salinity was set at 39 ppt. This procedure eliminated negative values for the volume of freshwater in the estuary.

The volume of freshwater was calculated using:

$$V_{fw} = F_{fw} \times V_{tot} \text{ where,}$$

V_{fw} = volume of freshwater in the estuary,
F_{fw} = Freshwater fraction, and
V_{tot} = Estuarine volume.

Estuarine volume data were obtained, by EDA, from the Estuarine Eutrophication Survey (NOAA, 1996). Where no data were available for EDAs or CDAs, volume was estimated by multiplying average depth from EMAP data and estuarine area from CA&DS.

DCP was calculated using the following equation (NOAA, 1989):

$$DCP = L(V_{fw}/I_{fw})(1/V_{tot}) \text{ where,}$$

DCP = Dissolved concentration potential,
L = Pollutant Load,
V_{fw} =Volume of freshwater in the estuary,
I_{fw} = Average freshwater inflow (daily average river flow), and
V_{tot} = Estuarine volume.

In order to compare relative DCP values among EDAs, a constant pollutant load (L) was assigned to each EDA. Relative DCP values can be used to estimate the concentration of a pollutant expected in an estuary assuming that its concentration is entirely controlled by physical processes.

Particle retention efficiency (PRE) estimates the ability of an estuary to trap suspended particles (i.e., the time a particle remains in an estuary). PRE is calculated using the formula (NOAA, 1989):

$$PRE = C/I \text{ where,}$$

C = Volume of the estuary, and
I = freshwater inflow.

Because both nutrients and toxic substances can bind to particles entering the estuary, it is necessary to include PRE when evaluating *in situ* concentrations and loads. In addition, PRE can be applied to sediment loads.

Modifying factors are variables that change the equilibrium or rate of material processing, e.g., pH changes the bioeffective concentration of many toxic metals and turbidity changes the maximum productivity rate associated with a given nutrient supply rate. The following variables have been identified as "modifying factors", factors that affect the equilibrium or rates of nutrient processing and are included in the classification database. Associations between primary stressors and potential modifying factors were described in Table 1.

Sediment total organic carbon and acid volatile sulfide concentrations were obtained from EMAP. Average dissolved oxygen concentrations, water temperature, salinity, and pH were calculated from surface and bottom measurements from EMAP NCA databases. Where gaps existed, values were extracted from the BASINs database. Values were geo-referenced to EDAs and HUCs.

Total suspended solids, total chloride, sulfate concentrations, hardness and alkalinity as calcium carbonate in water, and specific conductance were derived from the BASINS database. Average values by HUC were geo-referenced to EDA.

Great Lakes

Morphological data for Great Lakes wetlands are less available and less well developed than those for estuaries; thus in Stage I, emphasis was placed on creating a geospatial inventory of coastal wetlands based on hydrogeomorphic class. A GIS database was constructed to support the identification and classification of Great Lakes coastal wetlands along the U.S. shoreline for each of the four Great Lakes included in the Great Lakes R-EMAP project: Lakes Superior, Erie, Huron, and Michigan. Coastal wetlands associated with connecting channels and Lake St. Clair were also included. The GIS database consists of a fine-resolution shoreline coverage for each of the lakes and connecting channels, the most accurate hydrography coverages available for each Great Lakes basin, a compilation of the most up-to-date digital wetland inventory coverages for the Great Lakes basin, a point coverage of Great Lakes coastal wetlands developed from Herdendorf's records (USFWS, 1981a-f) which were supplemented by locations derived from local experts, and an elevation contour denoting the upper extent of lake level influence. The shoreline coverage was constructed from 1:24,000 state hydrography where available, supplemented by the NOAA medium resolution shoreline vector for other states (Illinois, Indiana). The hydrography coverage was constructed from 1:24,000 state hydrography where available, supplemented by 1:24,000 digital line graph (DLG) coverages for the state of Ohio. Digital wetland inventory coverages were compiled from the National Wetlands Inventory (USFWS, 2003), Wisconsin Wetlands Inventory (WIDNR, 2003), Ohio Wetlands Inventory (OHDNR, 2003), and New York wetlands inventories developed by the state and by the Adirondack Park Agency. Wetland inventory coverages were queried to extract the wetland polygons expected to be associated with coastal wetland areas. A coastal zone was defined by intersecting the Lake Michigan Basin with a buffered version of the Great Lakes high-water elevation contour. In future versions of the Great Lakes coastal wetlands database, coastal wetlands will be identified by intersecting wetlands inventory coverages with buffered shoreline and stream and river hydrography segments, and then classifying these according to proximity to lake (mainland and island) shorelines and streams or rivers.

Hydrologic Regimes

Two sources of data were used to define hydrologic regime classes of Great Lakes and marine coastal watersheds. These included 1) the derivation of empirical hydrologic thresholds for state hydro-climatological regions based on USGS datasets (Ries and Crouse, 2002), and 2) the derivation of watershed flashiness indices (Great Lakes coastal watersheds only). In future versions of the classification database, all coastal watersheds will be assigned to hydrologic regime types based on regions defined by Saco and Kumar (2000).

Two different approaches for the development of watershed indicators of hydrologic regime were tested. The first approach relied on visual analysis of empirical relationships derived by USGS between flood magnitude of given return intervals and associated watershed attributes (Detenbeck et al., 2000; Jennings et al., 1993). Flood prediction equations created by the USGS are of the form:

$$Q_n = A^a B^b C^c$$

where Q_n = peak flow with recurrence interval of n years
A, B, C = watershed attributes

Typically, watershed area is one predictive variable; other variables commonly included are main channel slope (S) and watershed storage (ST, fraction of watershed area covered by lakes and wetlands). In some regions, soil permeability (SP) or texture, precipitation (snowpack

(SN) or 2-year, 24-hour rainfall event (I24_2)), and land cover (% forest, % urban or impervious surface area) are also included. The exponent for watershed area (A) is typically close to 1, so it is reasonable to normalize peak flows for watershed area (Qn/A). Graphical analysis can be used to examine plots of single predictors (e.g., Qn/A vs ST) or combined predictor variables (e.g., Qn/A vs ST *SP) to determine thresholds of response. Where exponents have a common sign, it is appropriate to examine multiplicative terms; where exponents of equation variables have different signs, it is appropriate to examine ratios of variables. We also supplemented graphical analysis with CART analysis in SYSTAT to determine if thresholds could be identified in a more quantitative fashion (Wilkinson, 1999).

We developed a second, model-based approach for development of indicators of hydrologic regime to combine effects of changing land cover and variation in watershed storage. Runoff volume from peak snowpack or from a design storm (2-year, 24-hour event) was compared with estimated watershed storage volume. Runoff volume was calculated as maximum potential snowmelt, the water equivalent of total snowfall for a watershed, or as runoff expected from a design rainfall event, using the Soil Conservation Service (SCS) curve number approach (Neitsch et al., 2002). Design storm magnitudes were derived by scanning isopleth maps (Huff and Angel, 1992) and converting these to grid coverages in ArcInfo. Mean snowfall was estimated based upon geospatial coverages derived from the Parameter-elevation Regressions on Independent Slopes Model (Daly et al., 1994, PRISM). We estimated watershed storage volume using different weighting factors for lake and wetland class polygons from wetland inventory coverages. For the latter, we used digital NWI coverages where available, supplemented by Wisconsin Wetland Inventory coverages. We estimated soil hydrologic group (Types A, B, C, and D) coverage and average slope using STATSGO layers (USDA, 1994), and derived land cover class coverage from the NLCD (Vogelmann et al., 2001).

Methods for Developing and Testing Classification System

Data Reduction Methods

If too many correlated variables are included in the final analysis, the results may not be robust. The purpose of an initial data reduction step is to identify those sets of variables that are strongly correlated so that redundant information is not included in the final analysis. Three methods were used to reduce the number of variables analyzed: PCA of stressor indicators and exposure data, non-metric dimensional scaling (NMDS) to reduce dimensionality of biological community data, and calculation of toxicity equivalent units (TEUs).

PCA was used to reduce the number of variables for contaminant load data. Annual average loads (lb/yr) for 29 contaminants were compiled from PCS available through BASINS (Table 5). The first three principal components accounted for 76% of the variation With some individual exceptions the eigenvectors were weighted on PAHs for the first principal component (PC1), metals for the second principal component (PC2), and pesticides for the third principal component (PC3). We substituted these three principal components for the actual load data in our database.

The magnitude of anthropogenic contamination in estuaries is an important criterion for testing any classification system. The number and magnitude of the concentrations of these contaminants, however, is highly variable among estuaries, which makes spatial comparison complex and unwieldy. For simplification, a toxic units approach was used to reduce the number of variables related to contaminant exposure. The measured concentration of each contaminant in surface water and sediment was

.

Table 5. Contaminant loads available from Permit Compliance System.

Metals	Pesticides	PAHs
Cadmium	Chlordane	Acenaphthene
Copper	Chlorpyrifos	Acenaphthylene
Chromium	Total DDTs	Anthracene
Mercury	Diazinon	Benzo(a)anthracene
Nickel	Dieldrin	Benzo(b)fluoranthene
Zinc	Total Endosulfans	Benzo(k)fluoranthene
	Endrin	Benzo(ghi)perylene
		Benzo(a)pyrene
		Chrysene
		Dibenzo(ah)anthracene
		Fluoranthene
		Fluorene
		Indeno(123-cd)pyrene
		Naphthalene
		Phenanthrene
		Pyrene

divided by the corresponding toxicity values (Table 4), which are based upon proposed marine sediment quality guidelines. The resulting fractions for all contaminants were then summed for each estuary and presented as a whole number for sediment. These two values can then be compared among estuaries for similar media where higher numbers indicate a greater likelihood of toxicity.

Methods for A Priori Development of Classes

Classification approaches can be applied either *a priori* or *posteriori*. *A priori* classification is based on a conceptual model or hypothesis concerning expected differences in behavior of ecological response along stressor gradients as a function of watershed or water body characteristics. In contrast, *a posteriori* classification is driven by analysis and interpretation of available data. We developed and tested *a priori* classification strategies based on conceptual models of watershed hydrology by determining discriminating factors for classification based on hydrological endpoints as integrators of expected ecological effects (Detenbeck et al., 2000).

Model-based and hydrologic integration

The hydrologic regime can be used as an integrating factor to indicate the sensitivity of aquatic systems to stressors (Clausen and Biggs, 2000; Detenbeck et al., 2000; Poff and Ward, 1989). Detenbeck et al. (2000), have derived hydrologic thresholds based on watershed characteristics that control magnitude and frequency of peak flows (Breiman et al., 1984; Kass, 1980; Jennings et al., 1993). Thresholds are determined as the level of some watershed characteristic below or above which 2-year flood discharge and watershed area increases sharply and exponentially. Peak flows with 2-year recurrence interval (Q2) values were used as the response variable because floods with a 2 - 2.5 year return interval are known to have the greatest influence on channel morphology, transporting the greatest amount of sediment and associated pollutants (Rosgen, 1996). A database of peak flow statistics and relevant watershed characteristics was compiled from records for USGS gauging stations with long-term discharge records, using data reported as part of the USGS National Flood Frequency program (USGS, 2003e, f). The database includes all Great Lakes states and marine coastal states with estuarine systems, as identified in CA&DS. Hydrologic thresholds were derived from the database by using a combination of CART analysis and piecewise linear regression (Breiman et al., 1984; Wilkinson, 1999). CART was applied to determine the identity and magnitude of variables associated with significant shifts in area-normalized peak flows. Piecewise linear regression analysis was used to determine breakpoints in the slope of cumulative frequency plots of Q2/area values > regional median values as a function of classification variables such as watershed storage. Threshold parameters were applied to Great Lakes coastal riverine wetland watersheds for which long-term flow records were unavailable to classify them into stable versus flashy hydrologic regime categories. Thresholds will ultimately be applied to coastal estuarine watersheds for which flow records are unavailable, as predictors of the type of hydrologic regime present.

Approaches for A Posteriori Development of Classes

Physical and hydrologic characteristics were compiled for each of the estuarine classification units from several sources. Parameters included area, volume, flow, tides, depth, and salinity. Because the frequency of missing values was high and often data were unavailable at the HUC level, we aggregated the original matrix up to 203 EDA/CDAs. This involved taking the sum or average across classification units (or HUCs) associated with each EDA/CDA as appropriate. This procedure reduced the frequency of missing values to 15%. The matrix used for classification of physical and hydrologic characteristics was 203 rows (EDA/CDAs) by 15 columns (Appendix A-1.2). All numeric values were log-transformed. Remaining missing values were imputed using the multiple imputation procedure, PROC MI, available in SAS/STAT (SAS Institute, 2001). Multiple imputation provides a useful strategy for dealing with data sets with missing values. Instead of filling in a single value for each missing value, Rubin's (1987) multiple imputation procedure replaces each missing value with a set of plausible values that represent the uncertainty about the right value to impute. PROC MI yielded five completed data sets differing only in the plausible imputed missing data values. These five data sets were found to be not significantly different from each other, so one data set was chosen at random to be analyzed by the cluster routine available in PRIMER (Plymouth Marine Lab). Average-linkage cluster analysis was performed on normalized Euclidean distances using PRIMER. Eleven clusters or groups of EDA/CDAs were identified from examining the dendogram result from the cluster analysis. Box-plots for each variable used in the cluster analysis were examined to compare the mean, median, 25th and 75th percentiles, minimum and maximum values across clusters. This resulted in the derivation of labels to describe the properties of each cluster of EDA/CDAs.

Tests of Classification Approaches for Coastal Watersheds

An initial test of *a priori* hydrologic classes developed for Lake Michigan watersheds was done through analysis of covariance (ANCOVA) of Great Lakes coastal wetland R-EMAP data using hydrologic regime classes, loading or land cover gradients vs. stressor and exposure metrics and biological response vs. exposure or land cover gradients (Detenbeck et al., 2003b)

III. RESULTS

Estuaries

The final geographic coverage used in cluster analysis for classification of estuarine coastal systems contained 203 unique classification units, representing EDA/CDAs and HUCs as described in the methods section. Each unit was identified by an EDA/CDA code and an estuary name.

The final database used in cluster analysis for classification of estuarine coastal systems contained 15 physical and hydrologic parameters for each of 203 classification units (Appendix A-1.2). The physical and hydrologic database was not complete. Every parameter had at least one missing value except for the area of the estuarine drainage area (km^2). The frequency of missing values is indicated in Table 6. Imputation procedures were used so that the final database contained no missing values.

Cluster Analysis of Estuarine Systems

In agglomerative hierarchical cluster analysis using Euclidean distance, individual units with the lowest dissimilarity are joined first. Size of the estuarine drainage area and estuary area were the primary variables contributing to the separation of clusters, although volume, flow, depth and salinity contributed as well. Comparisons of the means between clusters were used to describe the properties of the clusters. We grouped the means of primary variables into large, medium and small according to the values shown in Table 7. If the EDA area and percent of the EDA that is defined as estuary fell in the same size group, the label simply indicates large, medium or small as the first descriptor. If, however, those two variables fell in different groups, the label indicates both (e.g., Large EDA / Small % Estuary). The labels are intended to be generally descriptive of the properties of the estuaries within each cluster. The values in Table 7 represent the average values for the physical and hydrological variables for the estuaries within each cluster. This does not mean that every estuary in a cluster falls within the values in Table 7. Eleven clusters and the number of EDA/CDAs in each cluster are listed in Table 8. Finally, the clusters were mapped on the geographic coverage of EDAs (Figure 7) and the estuaries within each cluster were listed in Appendix D1.

Some of the classes showed clearly distinct characteristics. The last class to be identified by the cluster analysis included the Chesapeake Bay Mainstem, Potomac River, the tidal portion of the Mississippi River, and the Columbia River. This large, river-dominated class had the highest average river flow, lowest average salinity, and largest watershed areas when compared with all other classes. The second to last class included Long Island Sound, Cape Cod Bay, Puget Sound and San Pedro Channel Islands. On average, this class had the largest estuarine area, largest volume, and was the deepest of all other classes. The class containing the smallest estuaries with the shallowest depths included primarily estuaries and sub-estuaries located in California and the Mid-Atlantic (e.g., Chester River, Elk/Sassafras Rivers, Tijuana Estuary, Waquoit Bay, Mission Bay, Morro Bay). The first two estuaries to join in the cluster analysis (i.e., most similar) were in this class: Morro Bay and Anaheim Bay. It is important to reiterate that not every estuary fits the general characteristics of the class. Cluster analysis identifies patterns and similarities, the interpretation of which is often subjective. In Stage II of this classification effort, we will enhance this classification by using an improved database and applying the conceptual models described earlier.

Table 6. Frequency of missing values for physical and hydrologic parameters.

Parameters	**Missing Values**	
	Frequency	Percent
Area of Estuary (km^2)	6	3%
Area of Estuarine Drainage Area (km^2)	0	0%
Mixing Zone Surface Area (km^2)	57	28%
Seawater Zone Surface Area (km^2)	57	28%
Tidal Freshwater Zone Surface Area (km^2)	57	28%
Average Tide Height (m)	24	12%
Average Monthly River Flow (m^3/day)	15	7%
Maximum Monthly River Flow (m^3/day)	27	13%
Estuarine Volume (10^9 m^3)	20	10%
Tidal Prism Volume (10^9 m^3)	12	6%
Average Bottom Salinity (ppt)	36	18%
Average Surface Salinity (ppt)	36	18%
Average Depth (m)	19	9%
Dissolved Concentration Potential of Pollutant (DCP in mg/L)	47	23%
Time for Freshwater to Displace Entire Volume of Estuary (PRE)	31	15%

Table 7. Ranges of values for classification variables, used to describe clusters.

Variable	Large/High/Deep	Medium	Small/Low/Shallow
EDA Area (km^2)	> 6000	2000 - 6000	< 2000
% Estuary	> 30	10 – 30	< 10
Estuary Volume (10^9 m^3)	> 20	2 – 20	< 2
River Flow (m^3/day)	> 100 25 – 100	10 – 25	< 10
Depth (m)	> 10	5 – 10	< 5
Salinity	> 25	10 - 25	< 10

Great Lakes

The final geographic coverage for Great Lakes coastal riverine wetlands and associated watersheds included 155 (55%) of the 283 total systems chosen through a probability-weighted survey design process, and distributed among all of the Great Lakes and connecting channels except for Lake Ontario. The database of watershed characteristics, hydrologic variables, and associated CART-derived thresholds for hydrologic regimes in coastal watersheds includes data from all Great Lakes states and from all coastal marine states in the conterminous U.S., with the exception of Virginia and Alabama.

The Great Lakes coastal wetlands and watersheds database is complete for all base data: watershed area, wetland area, land cover, soils, and climatic variables, and for derived flashiness indicators. To date, hydrologic thresholds have only been derived and tested for Lake Michigan coastal watersheds (n = 55).

The database of hydrologic variables and drainage basin characteristics for gauged watersheds in coastal and Great Lakes states is currently inconsistent with respect to variables included, because data were derived from reports produced by different state USGS offices and state agencies (USGS, 2003f) which derived variables using a variety of manual versus digital techniques. All equations predicting peak discharge contained a term for watershed area or contributing drainage area. Of the remaining categories of variables representing natural features, channel or basin slope (32 % of cases) and annual precipitation, snowfall or precipitation intensity (29% of cases) were most often significantly related to peak flows. Variables related to depressional storage or soil and underground storage were also frequently included (32 % of cases total), with inclusion of depressional storage being more common. Given the historic loss of wetlands throughout the U.S., variation in surficial storage has both natural and anthropogenic components. Land cover was rarely found to be a significant factor affecting peak runoff in rural watershed (10% of cases), but some measure of urbanization or impervious surface area was found to be a significant predictor of peak flows for all urban studies and for one statewide study (Table 9).

Derivation of Hydrologic Regime Classes for Watersheds in Coastal and Great Lake States

CART analysis successfully discriminated among classes of watersheds by state or by state and hydrologic region combinations based on flow responsiveness. Mean 2-year peak flow per unit watershed area differed among classes by 3-4 orders of magnitude within each region of the country (Great Lakes, Atlantic coast, Gulf coast, Pacific coast), although variation was somewhat less for the Atlantic and Pacific coastal states (Figures 9 a-d). Categories of variables identified through CART analysis as the best discriminators among watershed peak flow classes normalized for drainage basin area (Q2/A) are summarized for all coastal and Great Lakes states in Table 10, and are listed in complete form in Appendix C-1.1. Average percent reduction in error produced by CART analyses was 55% (range = 10 – 83%) for analyses conducted on all rural watersheds within individual states, 58% (range = 16 - 94%) for analyses conducted on rural watersheds within hydrologic regions by state, and 58% (37 - 76%) for analyses conducted on urban watersheds. For both rural and urban watershed analyses combined, the most frequent predictor variables identified were slope (54%), basin shape or lag time (40%) and depressional or soil storage variables (30%). For analyses conducted with data from entire states, ignoring hydrologic regions, storage was less commonly identified as an explanatory variable (reduction from 30% to 21%). However, for rural watersheds analyzed by hydrologic region within coastal and Great Lake states, depressional and soil storage variables were retained as significant predictors in 50% of cases.

Table 8. Estuarine classes resulting from cluster analysis of physical and hydrologic variables.

Estuarine Class	Number of EDA/CDAs in Class
Large Area, Very High Flow, Shallow, Low Salinity	9
Large Area, High Volume, Deep, High Salinity	16
Small EDA/Large % Estuary, Low Volume, Low Flow, High Salinity	2
Medium EDA/Small % Estuary, Low Volume, High Flow, Low Salinity	6
Medium EDA/Small % Estuary, Low Volume, Low Flow, High Salinity	2
Medium Area, Low Volume, Shallow, Mixed Salinity	37
Medium Area and Volume, High Salinity	37
Large Area, High Flow, Shallow, Mixed Salinity	23
Medium EDA/Small % Estuary, Low Volume, High Flow, Mixed Salinity	24
Large EDA/Small % Estuary, Low Volume	23
Small Area, Low Volume, Low Flow, Shallow, Mixed Salinity	24

Table 9. Frequency of variable inclusion by state and hydrologic region in equations predicting peak discharge for coastal and Great Lakes states.

	Water-shed area	Slope	Storage - surficial	Soil storage	Imper-vious surface area	Forest	Precipi-tation	Runoff	Temp-erature	Eleva-tion	Shape
RURAL CASES (n=28)	28	17	11	6	1	4	10	2	0	5	4
URBAN CASES (n=13)	12	2	2	0	12	0	2	0	0	0	0
TOTAL CASES (n=41)	40	19	13	6	13	4	12	2	0	5	4

Derivation of model-based flow classes for Great Lakes coastal wetland watersheds demonstrated a wide gradient of flow regimes, from those predicted to be stable (peak 2-year flood volume: watershed depressional storage volume < 1) to those predicted to be extremely flashy (ratio > 10; Figure 10).

Initial Testing of Classification Frameworks

To date, watershed hydrologic regime classes have only been derived and tested for Lake Michigan coastal riverine wetlands. Overall, hydrologic regime classes were more successful than either nutrient ecozones (Robertson et al., 2001) or Omernik's nutrient ecoregions (Omernik et al., 2002) in explaining differences in sensitivity of water quality and biological response to land cover gradients and nutrient concentrations. With minor exceptions, classification of Lake Michigan coastal riverine wetlands by either Robertson's nutrient ecozones or Omernik's nutrient ecoregions showed no significant differences in reference condition (y-intercept) or response (slope) in regressions of surface water nutrient concentration versus fraction watershed developed.

Hydrologic Thresholds for Subwatersheds in Lake Michigan Basin

Hydrologic thresholds for peak flows were similar conceptually for Michigan and Wisconsin, based on the product of indicators for soil permeability and watershed storage, although the exact variables included in analyses differed among states (Detenbeck et al., 2003b). Hydrologic thresholds for Michigan Hydrologic Regions 1-3 were all based on the product of fraction coarse substrate (outwash + coarse glacial till) with fraction channel storage (fraction main channel in wetlands), although the position of the threshold was higher for Region 2 than for Regions 1 and 3.

The hydrologic threshold for Wisconsin Hydrologic Region 4 was similar in construct to those developed for Michigan, but was based on a product of soil permeability and watershed storage (percent watershed area covered by lakes and wetlands).

Relationship Between Watershed Flashiness Indicators Derived for Lake Michigan Basin

The significance of relationships between empirical hydrologic thresholds and model-based flashiness indicators was not guaranteed, because model-based indicators explicitly included the interaction of land cover with precipitation, soils and storage attributes in modifying peak flows, whereas empirical hydrological thresholds did not. Model-based flashiness indicators for rain- versus snowmelt-based events are strongly correlated for Lake Michigan coastal wetland watersheds ($r^2 = 0.90$, $p < 0.0001$). In addition, the magnitude of the model-based flashiness indicator for rain events was significantly higher for flashy watersheds as compared to stable watershed classes, as assigned by the empirical models for peak flows (Kruskal-Wallis test, $p = 0.001$; (Detenbeck et al., 2003).

Hydrologic Thresholds and Flashiness Indices as Predictors of Water Quality and Biotic Condition in Lake Michigan Coastal Riverine Wetlands

With the exception of nitrate, log-transformed surface water concentrations of nutrients, suspended solids, and turbidity in Lake Michigan coastal riverine wetlands were significantly correlated with the model-based index of watershed flashiness for rainfall events. For total phosphorus, total nitrogen, turbidity, and total suspended solids in coastal wetlands, the relationship between fraction of watershed developed and surface water concentrations differed significantly between stable and flashy watershed classes, with the slope of the relationship being lower for flashy watersheds ($p < 0.05$). For soluble reactive phosphorus, ammonium, and nitrate + nitrite-nitrogen, surface water concentrations increased significantly with fraction watershed developed, but neither slope nor y-intercept varied among stable versus flashy watershed classes ($p > 0.05$; Detenbeck et al., 2003).

Midsummer temperature of Lake Michigan wetland tributaries and of coastal riverine wetlands differed significantly among hydrologic classes, and no additional variability could be explained by including wetland latitude in ANCOVAs. Midsummer temperatures were 4 - 5 degrees (EC) lower in tributaries and wetlands associated with stable hydrologic regimes as compared to flashy hydrologic regimes (Detenbeck et al., 2003b).

Fish IBI scores in Lake Michigan coastal riverine wetlands differed significantly among stable versus flashy watershed classes, but did not respond linearly to fraction watershed developed, either within watershed classes or in the combined data set ($p > 0.05$). Fish IBI scores also were significantly related to the model-based index of flashiness for rainfall events ($p = 0.006$). In contrast, plant IBI scores for 2001 sites decreased significantly with fraction watershed developed, but neither the slope nor y-intercept for the relationship differed among watershed classes (Detenbeck et al., 2003b).

Both phytoplankton chlorophyll *a* and periphyton chlorophyll (mg chl $a \cdot cm^{-2}$) increased exponentially as a function of surface water total P in Lake Michigan coastal riverine wetlands. For phytoplankton, responses differed by hydrologic class, with higher chlorophyll *a* levels at low total phosphorus for wetlands with stable hydrologic regimes as compared to those with flashy hydrologic regimes. Periphyton composition also changed along a watershed development gradient, with increases in green and blue-green algae, and concomitant decreases in diatoms, occurring at lower levels of development for coastal wetlands with stable hydrologic regimes (Detenbeck et al., 2003b).

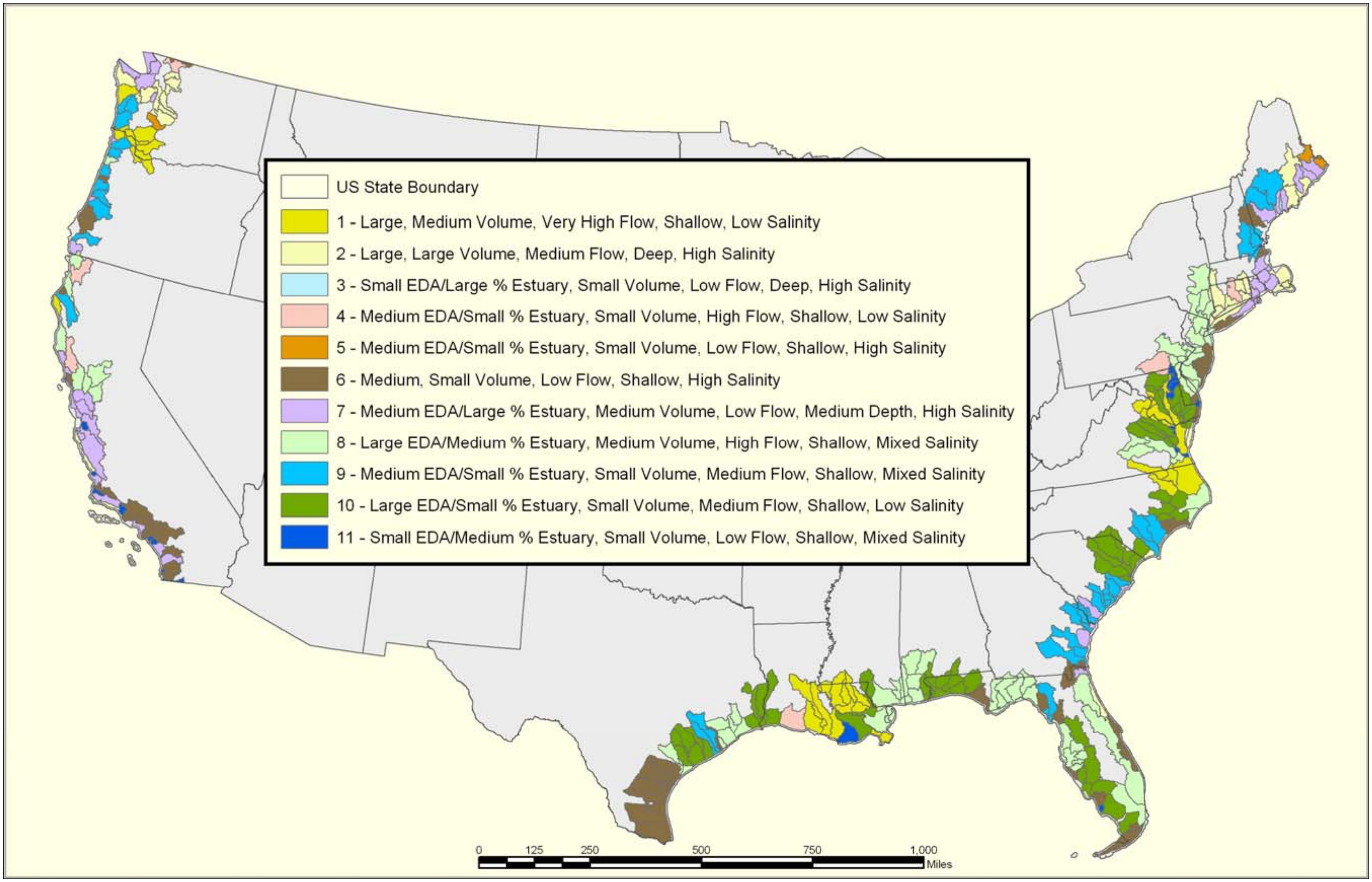

Figure 7. Estuarine classes resulting from cluster analysis of physical and hydrological variables.

Table 10. Categories of variables identified through CART analysis by state, region, and urban area that best discriminate among area-normalized peak flow classes for coastal and Great Lake states.

	Analysis for full state, rural watersheds		**Analysis by region, rural watersheds**		**Analysis by urban area**		**Total**	
	Cases	Percent of total	Cases	Percent of total	Cases	Percent of total	Cases	Percent of total
Watershed area	4	14%	4	20%	0	0%	8	14%
Slope	14	48%	15	75%	2	25%	31	54%
Storage – surficial	4	14%	8	40%	0	0%	12	21%
Soil storage	2	7%	2	10%	1	13%	5	9%
Impervious surface area	1	3%	1	5%	4	50%	6	11%
Forest	2	7%	6	30%	0	0%	8	14%
Precipitation	5	17%	3	15%	1	13%	9	16%
Runoff/ Evap	2	7%	3	15%	0	0%	5	9%
Temperature	1	3%	2	10%	0	0%	3	5%
Elevation	2	7%	4	20%	0	0%	6	11%
Shape/ Lag time	9	31%	10	50%	4	50%	23	40%
Region	3	10%	0	0%	0	0%	3	5%
Potential total	29		20		8		57	

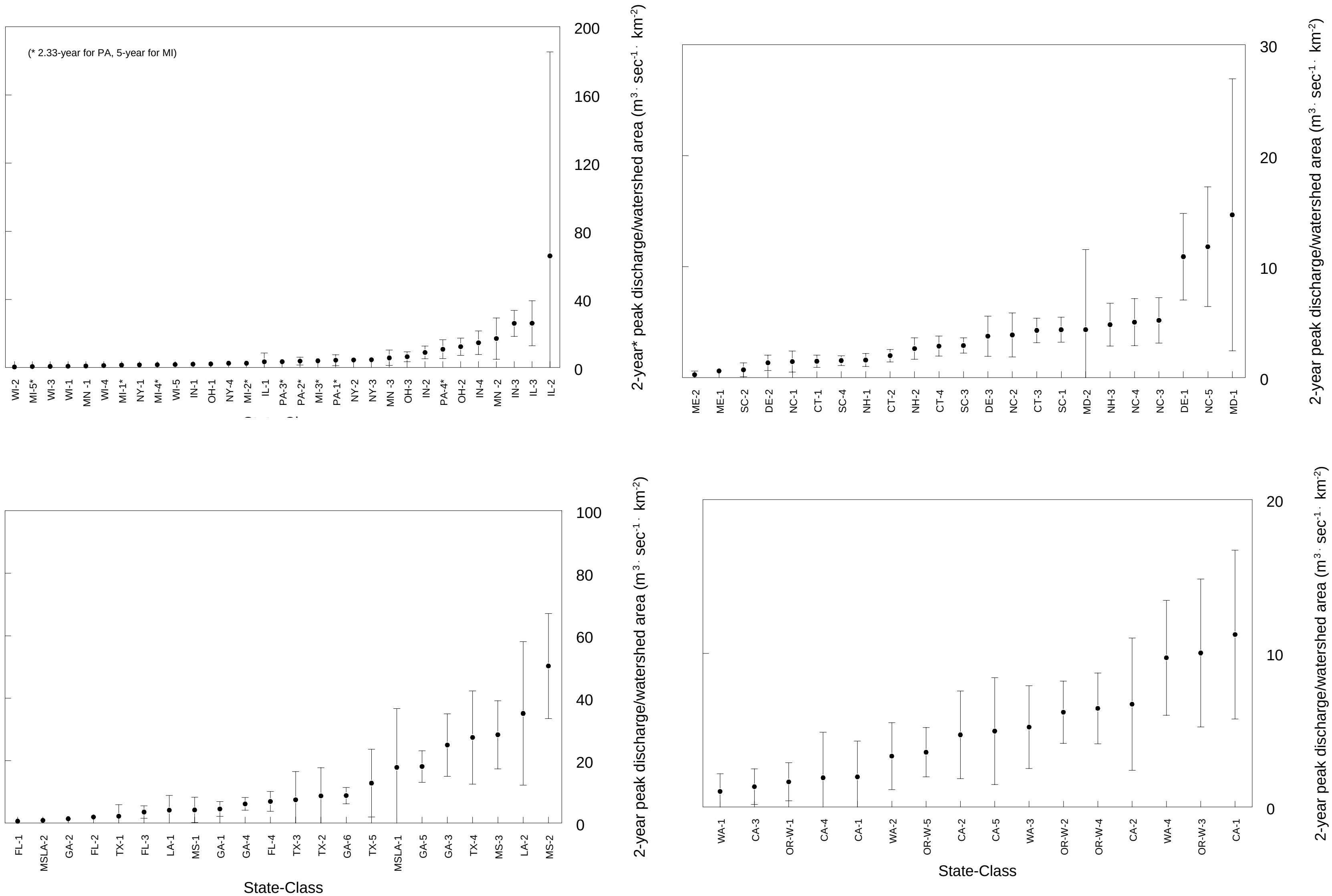

Figure 8. Peak 2-year flow classes identified through CART analysis of data from USGS gauging stations. Top left: Great Lakes states, top right: Atlantic coastal states, bottom left: Gulf states, bottom right: Pacific coast states.

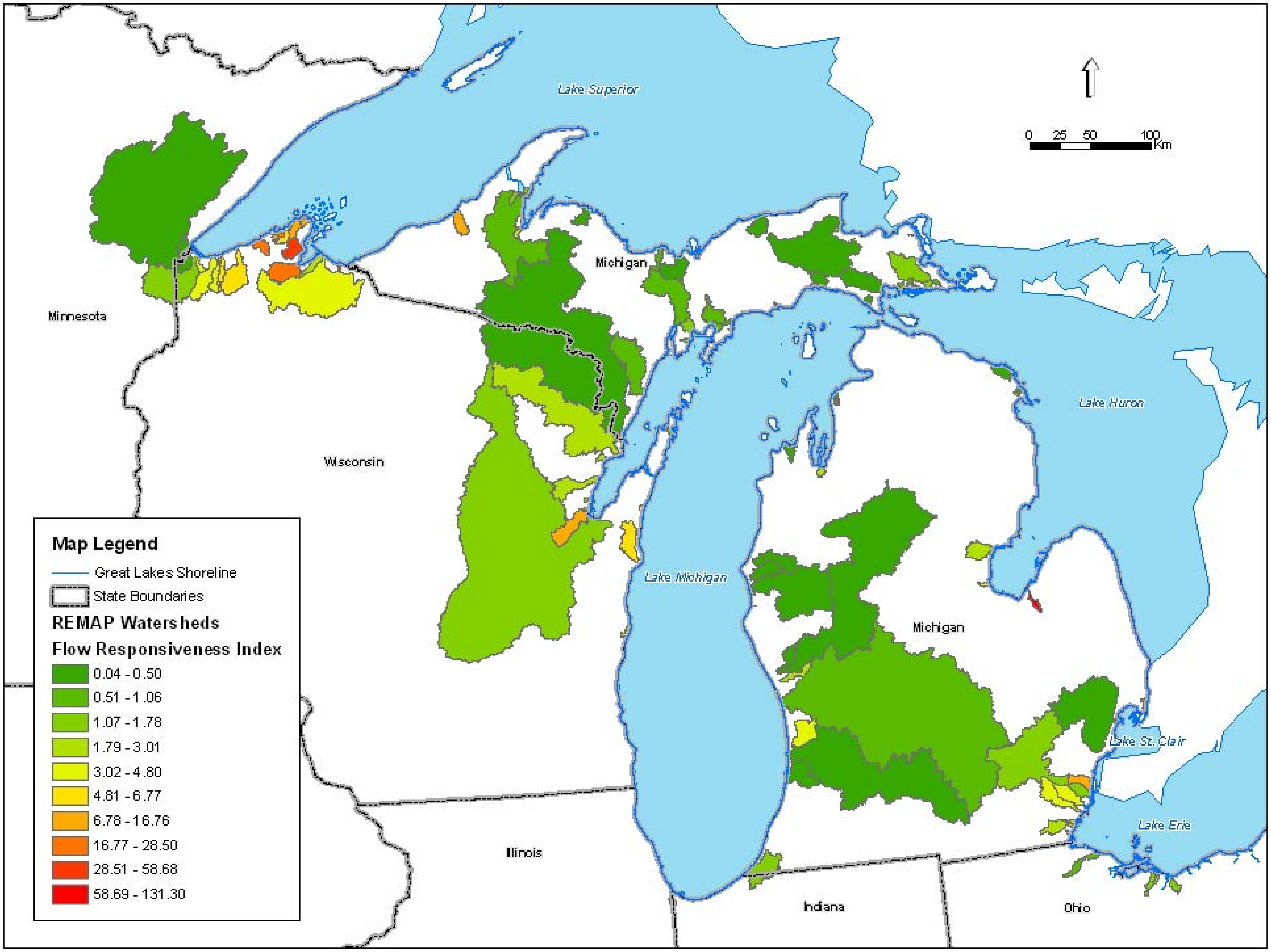

Figure 9. Flow responsiveness watershed index (peak 2-year flood volume and watershed depressional storage volume) for watersheds associated with Great Lakes coastal riverine wetlands.

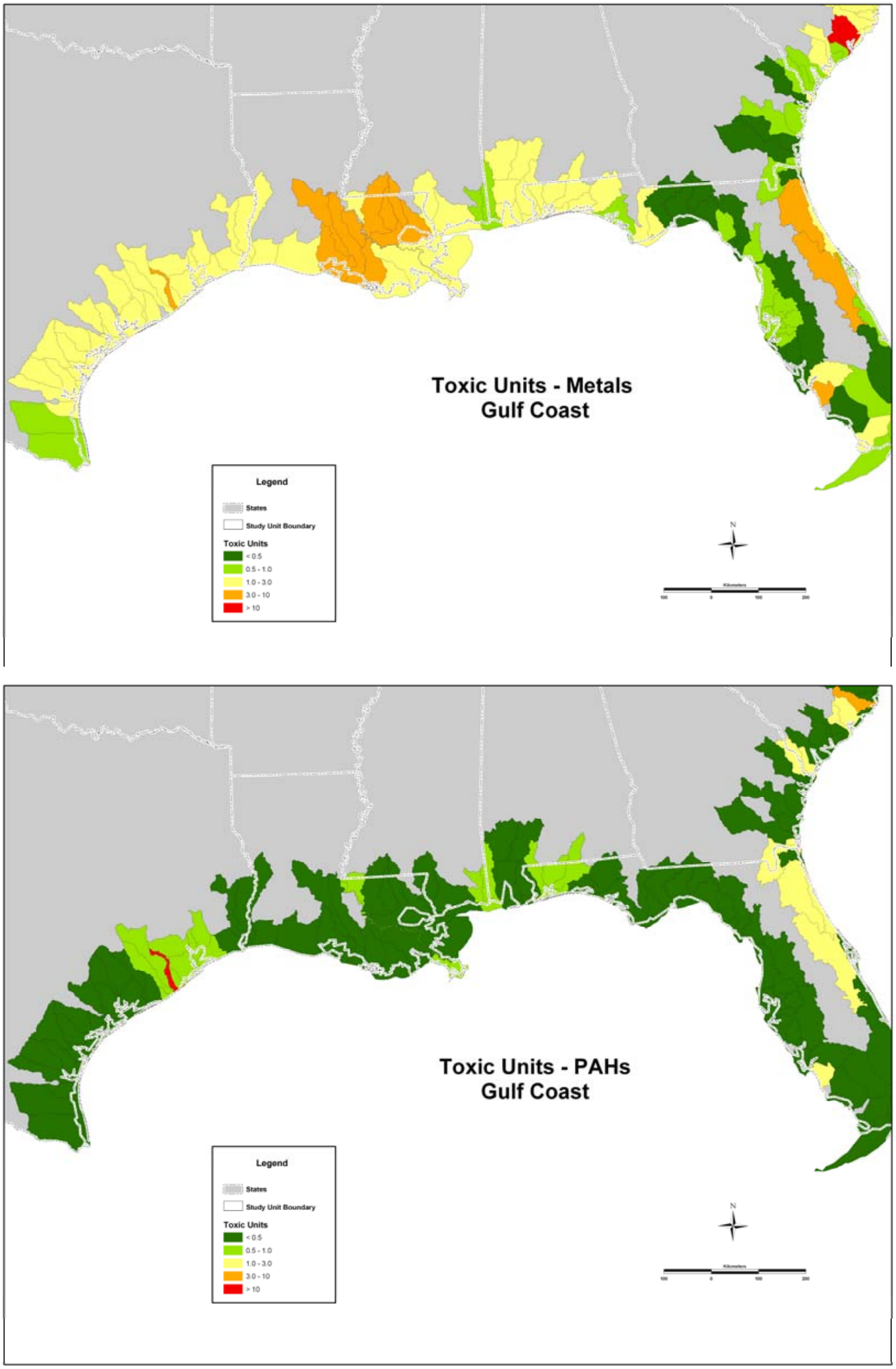

Figure 10. Average total toxic equivalent units for PAHs (top) and metals (bottom) within estuarine sediments of Gulf of Mexico, color-coded for associated EDAs and CDAs.

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IV. STAGE II PLANS

We will build upon the Stage I classification framework by improving geographic coverage, reassessing scale issues, filling in missing values and missing parameters in the database, adding data sources on coastal condition, and evaluating different approaches for testing the coastal classification framework. Specific examples of these improvements are included in the following text. In addition, we will improve consistency between estuarine and Great Lakes databases by including more and better estimates of physical and hydrological variables for Great Lakes coastal wetlands. We will explore the implications of using average retention time in estuaries versus examining temporal patterns in retention time. Finally we will supplement the Stage I database with additional modifying factors and indicators of key ecosystem processes.

Geographic Coverage

Extent

Currently, the coastal estuarine classification database covers the full set of estuaries in the conterminous United States as defined in CA&DS. In the future, we will expand the geographic extent of the database to include systems in Alaska and Hawaii. In the first version of the database, watershed characteristics were included only for EDAs and CDAs, i.e., those 8-digit HUCs immediately upstream of EDAs. In the future, we will expand the database to include upstream fluvial drainage areas that are hydrologically connected to estuarine watersheds.

The Great Lakes coastal riverine wetland and watershed database currently includes only those coastal riverine wetlands sampled as part of the 2000-2001 EPA Region 5 R-EMAP project on coastal Great Lakes wetlands (Simon et al., 2003), and specifically excludes Lake Ontario as it is outside of EPA Region 5. Future versions of the classification database will include all of the Great Lakes and connecting channels. Contingent upon GIS resource support, we will delineate watersheds for remaining coastal riverine wetlands using state watershed boundaries and the National Watershed Boundary Database as a starting point, and refined using watershed delineation tools developed through an interagency agreement with USGS (2002). An alternative, but less desirable option, would be to characterize the full set of "reachsheds" defined by the Natural Resources Research Institute under EPA Science to Achieve Results (STAR) grant to the Great Lakes Environmental Indicators (GLEI) project (University of Minnesota, 2003). Investigators have defined the watersheds feeding coastal reaches (reachsheds) for the entire Great Lakes shoreline using endpoints defining lengths of the shoreline, i.e., reaches identified in NOAA's medium resolution shoreline vector database (NOAA, 2003b).

Scale of Units

The most recent guidance from EPA Office of Water indicated that the proper scale for TMDLs was an important issue that should be addressed (USEPA, 2003c). The level of spatial resolution for marine EDAs is adequate in some regions for addressing TMDL issues but not in others. Using a combination of local knowledge, coastal states' definition of reporting units for 305(b) reports and 303(d) listing (shapefile coverages available from EPA, 2002i) and shoreline reaches defined in NOAA's medium resolution shoreline vector coverage (NOAA, 2003b), we will examine the boundaries of EDAs to determine areas needing improved spatial resolution. Although the level of spatial resolution in current EDAs might be adequate for TMDL purposes, different stressors might be better detected at different scales (Edgar and Barrett, 2002; Morrisey et al., 1992). Finer-scale studies should also allow investigation of variability within estuaries.

Parameter Improvements

Loadings

The Stage I classification database lacks quantitative measures of suspended solids loadings, nutrient loading data of appropriate spatial resolution, and complete geographic coverage for toxics exposure data for all of the Great Lakes and marine coastal states. Refinements to the Stage II database will address these issues. We will obtain improved estimates of suspended sediment loadings by calculating actual loads from USGS databases (USGS, 2003d). For EDAs with complete data, we will compare results with the EPA IWI index of potential sediment loading from the USDA HUMUS database to determine if we can use these data to calibrate the IWI relative ranking index (USEPA, 2003i; TAES, 2000). An additional data source for sediment yield data may include the Soil and Water Assessment Tool (USDA, 2002; SWAT). SWAT is a river basin scale model developed to quantify the impact of land management practices in large, complex watersheds and can now be readily parameterized in a GIS using AGWA (Miller et al. 2002).

We will obtain improved estimates of nutrient loadings from the next version of the SPARROW model through direct collaboration with the USGS. Version 2 of the nationwide SPARROW database has been improved by developing continuous estimates of nutrient loading by stream reach rather than just at the outlets of 8-digit HUCs, and will include inputs from upstream HUCs (R. Alexander, U.S. Geological Survey, personal communication).

The current database only includes toxicity loadings estimates from EPA's PCS database and sediment toxics data from the NSI and STORET for marine estuaries. In future versions of the database, we will expand nutrient, sediment, and toxics loading and exposure data to include Great Lakes coastal riverine wetlands. In cooperation with EPA Office of Water, we will screen the PCS database for outliers to improve the quality of toxics loading estimates.

Retention Time Estimates

The current version of the marine EDA classification database includes estimates of retention time and the related parameters, particle retention efficiency (PRE) and dissolved concentration potential (DCP), which were calculated using readily available salinity data from EMAP and average values for freshwater discharge. We will improve the spatial and temporal resolution of the salinity portion of the database by requesting data from coastal state monitoring programs. Using data from well-characterized systems, we will assess the degree of error inherent in calculating retention time from standard comprehensive data sources like EMAP.

The current database includes values for average tidal volume derived from CA&DS. In future work, we will examine the effects of temporal variation in tidal volumes on residence time. We will also assess temporal variability in retention time indirectly through classification of systems by hydroclimatic region (Saco and Kumar, 2000) and hydrologic regime (naturally stable or regulated vs. flashy; (Detenbeck et al., 2000). We will improve the USGS database supporting derivation of hydrologic regime classes by standardizing the parameters included and regionalization schemes across state boundaries.

We will improve hydrological and physical databases for EDAs by filling in missing data where possible from NOAA's coastal morphometry databases. We can estimate values for missing hydrologic data using regional equations for prediction of flow (Koltun and Whitehead, 2001). We will improve hydrological and physical databases for Great Lakes coastal wetlands by estimating average discharge for ungauged systems, using regional equations (e.g., (Koltun and Whitehead, 2001) and estimates included in the EPA Reach File 1 (RF1) database (USEPA, 2003h). We will refine area estimates for Great Lakes coastal riverine wetlands to distinguish among different wetland cover classes (e.g., open water vs. emergent vs. forested). We will examine the feasibility for assessing coastal wetland volumes by digitizing changes in wetland open water boundaries for wet versus dry years (with associated known high and low lake levels). We will assess improvements in coastal bathymetry based on data from Light Detection and Ranging (LIDAR) initiatives coordinated by the Federal Emergency Management Agency (FEMA) as another source of fine resolution digital elevation data for direct calculation of wetland volume using GIS.

We will record hydrologic regime types for all coastal tributaries as defined by Saco and Kumar (2000) through spectral analysis of discharge time series. Saco and Kumar (2000) defined three distinct hydrologic regime types: 1) a long seasonal (LS) mode, 2) a short seasonal (SS) mode, and 3) a high small-scale (HSS) mode. The LS mode is characterized by a seasonal cycle of streamflow associated with either sustained or frequent above average flow conditions across several months. The SS mode is similar to the LS mode, but above average flow conditions occur over a period of only 2-3 months, with higher peaks of short duration overriding them. The HSS mode is associated with very high variability at timescales of 6 days to 1 month.

Modifying Factors

The Stage I database contains data on modifying factors that were readily available from EMAP, STORET, and the National Sediment Inventory.
Data on some modifying factors such as acid volatile sulfide (AVS) were incomplete. Data on other modifying factors were available but require further analysis before they can be used. We will expand modifying factors included in the coastal classification database to include:

⇒ improved estimates of suspended sediment concentrations. The USGS has compiled data on mineral and organic suspended sediments from their monitoring programs into a single database (USGS, 2003d).

⇒ values of dissolved organic carbon. DOC in the water column interacts with suspended sediments by influencing light penetration, and influences partitioning of organic toxins and the effect they exert.

⇒ estimates of photic depth. The Gallegos model allows derivation of predictive relationships for extinction coefficients based on dissolved organic carbon, chlorophyll *a*, and total suspended solids data from EMAP (Gallegos, 2001).

⇒ Morphometric interactions with the photic zone. We can calculate change in % estuarine bottom within the photic zone as a function of increased suspended solids or chlorophyll *a*.

⇒ AVS predictions. We will assess the feasibility of predicting AVS from readily available data (e.g., organic carbon, redox potential, Fe, particle size) based on systems with complete data sets.

⇒ aluminum: heavy metal ratios. These ratios can be used to correct for natural background in metals content.

⇒ energy regime. NOAA's Environmental Sensitivity Index for coastal systems contains indicators of the energy regime (NOAA, 2003c).

System Processing Capacity

Processing capacity is determined by the normal cycle of interactions processing materials in natural systems; generally, rate functions that are driven or limited by internal or external modifying factors, e.g., denitrification, carbon and nitrogen fixation, primary production, and grazing. The current version of the coastal classification database does not include any direct measurements or indicators of system processing capacity, although most of the data required to estimate denitrification potential is available. In future iterations of the database, we will include indicators of:

⇒ N processing potential. Dissolved inorganic N [DIN] in the water column of an aquatic system as the result of the integration of total system processes (nitrification, denitrification, sediment remineralization, etc.) = the difference between the measured [DIN] in the water column and the conservative [DIN] expected in the water column from riverine inputs. The determination of these variables will be system dependent and incorporates flushing time, volume, river flow, riverine nutrient inputs, etc.

⇒ biological filtering capacity. Shellfish bed area will be used as an indicator of biological filtering capacity, based on information in CA&DS.

⇒ coastal wetland extent. We will combine NWI and state wetland inventory data as necessary.

⇒ primary productivity potential. We will explore whether productivity varies systematically as a function of climatic factors such as mean annual temperature and seasonality (Phytosociological Research Center, 1995).

The processing capacity of estuaries for nutrients is dependent upon a combination of physical and biological factors. *In situ* concentrations of nutrients and toxics are indicators of an estuary's ability to process contaminants based on pollutant load, flushing factors, mixing, and biogeochemical cycling. Initial classification resulting from cluster analysis incorporated physical and hydrological parameters and DCP of pollutants based on a standardized load. By comparing *in situ* nutrient concentrations within an estuary to the DCP calculated based on actual or estimated load (SPARROW), we can evaluate the processing capacity of the estuary. If nutrient concentrations measured in the water column are below the DCP calculated for the estuary, it can be assumed that the rate of removal due to internal processes, whether biological or physical, exceeds the rate of regeneration due to internal processes. Conversely, if nutrient concentrations exceed the DCP, then internal regeneration exceeds removal by internal processes. While the DCP calculation includes flushing, it does not account for internal or recycled nutrients. In order to compare the processing capacity within and among estuarine classes, we need to compare the *in situ* concentrations to the DCP. Based on physical and hydrological data, we can assign three subclasses to systems based on system response to nutrient load: below capacity, at capacity, or above capacity. We will use case studies to validate class assignments within this scheme and to provide further information on the processes driving the system response. These processing rates include, but are not limited to, the following:

Nitrification
Denitrification
Sediment Phosphorus Regeneration
Primary Production
Bacterial Production
Sediment Nutrient Flux Rates
Oxygen Metabolism (sediment and water column oxygen demand)

Data for these processes are not available for every unit; however, investigators have quantified these rates in several well-studied estuarine systems. By comparing process rates in these systems between and among classes, we could validate class designations based on the DCP. Intensively studied systems for which processing rate data are most likely available include:

Class I	Chesapeake Bay Mainstem, Albermarle Sound
Class II	Puget Sound, Long Island Sound
Class III	Damariscotta River
Class IV	Connecticut River, Klamath River
Class VI	Florida Bay, Corpus Christi Bay
Class VII	Buzzards Bay, San Francisco Bay
Class VIII	Tampa Bay, Galveston Bay, Pamlico Sound
Class IX	Great Bay, Charleston Harbor
Class X	Pensacola Bay, Neuse River
Class XI	Waquoit Bay

Data associated with processes for many of the estuaries can be obtained from the National Estuaries Program (USEPA, 2003d; NEP) or those associated with coastal Long-Term Ecological Research (LTER) sites (Florida Coastal Everglades LTER, Georgia Coastal Ecosystems LTER, and Plum Island LTER).

Data Sources on Coastal System Condition

National Coastal Assessment

EMAP has monitored and assessed the condition of coastal estuarine systems in the U.S. since 1990. In addition to indicators of stressor exposure and habitat condition, benthic macroinvertebrate and fish community data have been collected to determine biotic integrity. Several benthic indices of condition have been developed through EMAP NCA for different biogeographic regions of the U.S: Virginian Province (Paul et al., 2001; Weisberg et al., 1993), Chesapeake Bay (Weisberg et al., 1997), Carolinian Province (Van Dolah et al., 1999), Gulf of Mexico (Engle and Summers, 1999). These multimetric indices combine measures of abundance, species richness and diversity, and relative abundance of sensitive species to distinguish between reference and degraded benthic communities. In the regions of the U.S. for which a benthic condition index has not yet been developed (i.e., the Pacific West Coast and the Northeast), measures of diversity were used to assess benthic condition. The original benthic community data and calculated indicators were available from EMAP (USEPA, 2003b).

Great Lakes Regional Environmental Monitoring and Assessment Program

Data on condition of 155 Great Lakes coastal riverine wetlands were obtained from a EPA Region V R-EMAP project (Simon et al., 2003). For testing of Phase I of the classification database, indices of biotic integrity (IBIs) and associated metrics for vegetation, macroinvertebrates, and fish communities were available only for a subset of Lake Michigan sites. Subsequent phases of the classification database can be tested using the full dataset, which will include fish IBIs and metrics for all 155 sites.

Testing of Estuarine Classification System

Classification approaches can be applied either *a priori* or *posteriori*, as discussed previously. We will explore additional approaches, both empirical- and model-based.

Improvements in A Priori Testing

The significance and robustness of classes identified in Stage I through cluster analysis will be tested using the nonparametric multi-response permutation procedures (MRPP) available in PC-ORD software (Mielke, 1984). Discriminant function analysis will then be applied to determine which watershed and estuarine characteristics can be used to discriminate among hydromorphological types. After applying stepwise discriminant analysis to narrow down the range of explanatory flow or velocity metrics, we will use the selected subset of metrics to define linear discriminant functions, using PROC DISCRIM (SAS Institute, 1990). Classification error rates will be estimated using the CROSSVALIDATE option.

Development of Model-Based Classes for Testing

Simple mechanistic models can be used in conjunction with physically-based empirical classes of estuaries or coastal riverine wetlands to determine critical differences in behavior among systems, based on predictions of stressor levels or ecological assessment endpoints. For example, Stefan et al. (1996) has used this approach to predict loss of habitat volume in different physically-based classes of lakes in response to climate change. In Stefan et al.'s (1996) work, habitat volume was described as a function of temperature and dissolved oxygen requirements for different thermal guilds of fish.

In the next year, we will use our conceptual models and the database for estuaries presented in this paper to develop and test stressor-based classification systems. We will apply simple canonical models of stressor effects and interactions to determine discontinuities in stressor-response surfaces for estuaries as a function of water-body retention time, modifying factors, and processing capacity (Campbell et al., 2003; Stefan et al., 1995; Stefan et al., 1996). We illustrate our planned approach in Figure11. The aquatic systems to be classified include water bodies and their watersheds. Any system defined in this way can be classified, *e.g.*, a stream reach and its watershed, an estuary and its drainage area, a lake and its watershed. The classes will be based primarily on water body characteristics and are stressor specific. Basic information for the pollutant (stressor) will be determined along with the loading rate from the adjacent watershed, watersheds upstream, the atmosphere, and the ocean for estuaries. In addition, we will determine the stored quantity of the pollutant presently residing in the aquatic system. Implicit in the discussion that follows is the assumption that all the information needed for each step in the model-based classification will be present in the database. In the next year, we may have to augment the existing database with needed information.

We will first apply the classification process for a unit load of pollutant and predict the expected biologically effective concentrations for different classes of aquatic systems. The first step in classification is to place the system to be classified into one of the four canonical models controlling residence time (Figure 11). Once this is accomplished, we will divide the systems into ranges of average temperature and into one of two classes (Continuous or discontinuous) based on the way materials are processed. Thus, we will distinguish between temperate and tropical systems at this step. Temperature determines the rate of metabolic processing of the pollutant processing above, we will determine the average residence time for the system and the relevant range of temporal variation. If residence time varies markedly over the area of the system under study, we will divide the system into subsystems and analyze each subsystem separately. We will separate systems into residence time classes, which will be determined based on the chronic dose-response characteristics of the particular stressor. Knowing the variation of turnover with time will allow us to partition a system into more than one residence time class, if necessary.

Once we have divided systems into classes based upon residence time, we will split classes again using factors that control processing capacity, e.g., the ratio of wetland to water body area, dissolved organic carbon, or AVS. Once again, we could use two or more classes based on the processing capacity of the wetland for the various pollutants. We hypothesize that the presence or absence of wetlands will be the factor of greatest importance after temperature in processing pollutants. Wetlands are both a response variable an indicator of processing capacity. Initially, the distribution of wetlands is determined by natural factors. However, wetlands can be lost through direct physical stressors (dredging, fill) as well as through indirect stressors (eutrophication) which hamper the growth of submerged aquatic vegetation. The loss of vegetation is expected to create a feedback effect, further limiting the retention of sediments and nutrients within an estuarine system.

We will consider other processing factors at this stage based on the particular pollutant being evaluated. At this point, we will estimate the bioeffective concentration expected in the class and multiply it by the residence time to determine an exposure. We will construct the expected exposure-effect relationship for the pollutant from past studies in the literature and predict the effects on biological output variables from the exposures determined for each class.

Next, we will consider the effects of modifying factors to determine the alterations in the biological impacts expected in particular systems. We will group modifying factors according to their effects on the pollutant. We will combine those that have a positive (decreased response effect) and those that have a negative (increased response effect) to estimate the net effect on the biological response. Once we have determined a positive or negative effect then we will apply it to the exposure calculated above to determine an effective exposure in the system containing modifying factors. If not modifying factors are present, the exposure value determined above is the effective exposure and it passes directly to the bottom line (Figure 11). We hypothesize that effective exposure will characterize sets of aquatic systems where similar biological effects will be observed.

Next we will apply the actual loads entering the aquatic systems and determine the effective exposures. We will plot the observed values for the biological output variables from the aquatic systems against the effective exposures to construct an exposure-effect curve for the pollutant. We will compare this relationship to the one expected from past studies. We can expect system classes to plot as a family of curves on the exposure-effect plane or as a single curve on the effective exposure-effects plane. Managers could allow greater loading in a class of aquatic systems that is less sensitive to the pollutant to attain a given level of effect deemed acceptable.

Approaches for A Posteriori Development of Classes

We will derive water-body classes empirically both through indirect and factor-based methods, using cluster analysis of water-body and watershed characteristics, and through direct and response-based approaches, using Bayesian approaches to determine natural breakpoints in assessment endpoints as a function of stressor gradients and classification factors (Breiman et al., 1984; Kass, 1980).
Indirect classification procedures such as cluster analysis use information on the variation

of potential classification variables among coastal watersheds and wetlands. In contrast, response-based classification procedures use information on both independent variables (classification factors, stressor indicators) and dependent variables (ecological assessment endpoints such as indices of biotic integrity). Procedures that can be used to empirically discriminate differences among classes in response of ecological endpoints along stressor gradients include Bayesian techniques such as CART (Breiman et al., 1984) and Chi-square Automatic Interaction Detector (CHAID, see (Kass, 1980). CART produces a binary tree in which a response variable is sequentially separated into two classes, using either categorical variables or breakpoints for continuous variables. CHAID is analogous to CART, but extends the procedure to multiple classes at each level of the tree. Unlike parametric procedures such as canonical correlation analysis, CART and CHAID do not require assumptions of normality, homoscedasticity, or additivity of effects. The techniques are ideally suited for teasing out interactions among factors, e.g., the interaction between stressor or exposure gradients and watershed and water body classes. Interaction terms between categorical and continuous variables also can be explicitly included in a model to tease out differences between main effects and interaction terms, analogous to what is done in an analysis of variance (Statsoft, Inc., 2003).

Spatio-temporal classification

Classification approaches can be applied to distinguish among system behaviors either based on spatial differences among systems at one point in time, or among system behaviors over climatic cycles. We will explore a spatio-temporal classification approach, which defines spatial aggregations of watershed units based on similarities in system hydrology across climatic cycles (Saco and Kumar, 2000). Climate change can determine the magnitude and timing of freshwater flow and nutrient delivery to coastal systems from rivers, as well as directly affecting marine and freshwater organisms through alterations in salinity and temperature (Chang et al., 2001; Drinkwater et al., 2003; Staile et al., 2003). Coastal systems, at the interface of fresh and salt water, can be expected to be especially vulnerable. Climatic cycles driven by El Nino, El Nino-Southern Oscillation, and the North Atlantic Oscillation (NAO) can affect different regions of the coast differently during the same time period (Cayan et al., 1998; Dettinger et al., 1998; Walker et al., 2002). Hydroclimatic temporal regimes defined by Saco and Kumar (2000) will be tested as part of an *a priori* classification scheme. Rather than focusing on differences in hydrologic response within a region of homogeneous climate, hydroclimatic regimes take into account differences among regions in hydrologic response over time related to atmospheric circulation patterns. Based on spectral analysis of long-term discharge records from U.S. coastal segments, Saco and Kumar (2000) identified three classes of temporal regimes based on strength of seasonality and frequency of high flows. Once watersheds have been separated into hydroclimatic regimes, and the atmospheric forcing functions identified for each region, response data can also be categorized by position along climatic cycles, using indicators such as the NAO index, or Palmer's drought index applied at a regional scale (Cayan et al., 1998; Dettinger et al., 1998; Walker et al., 2002).

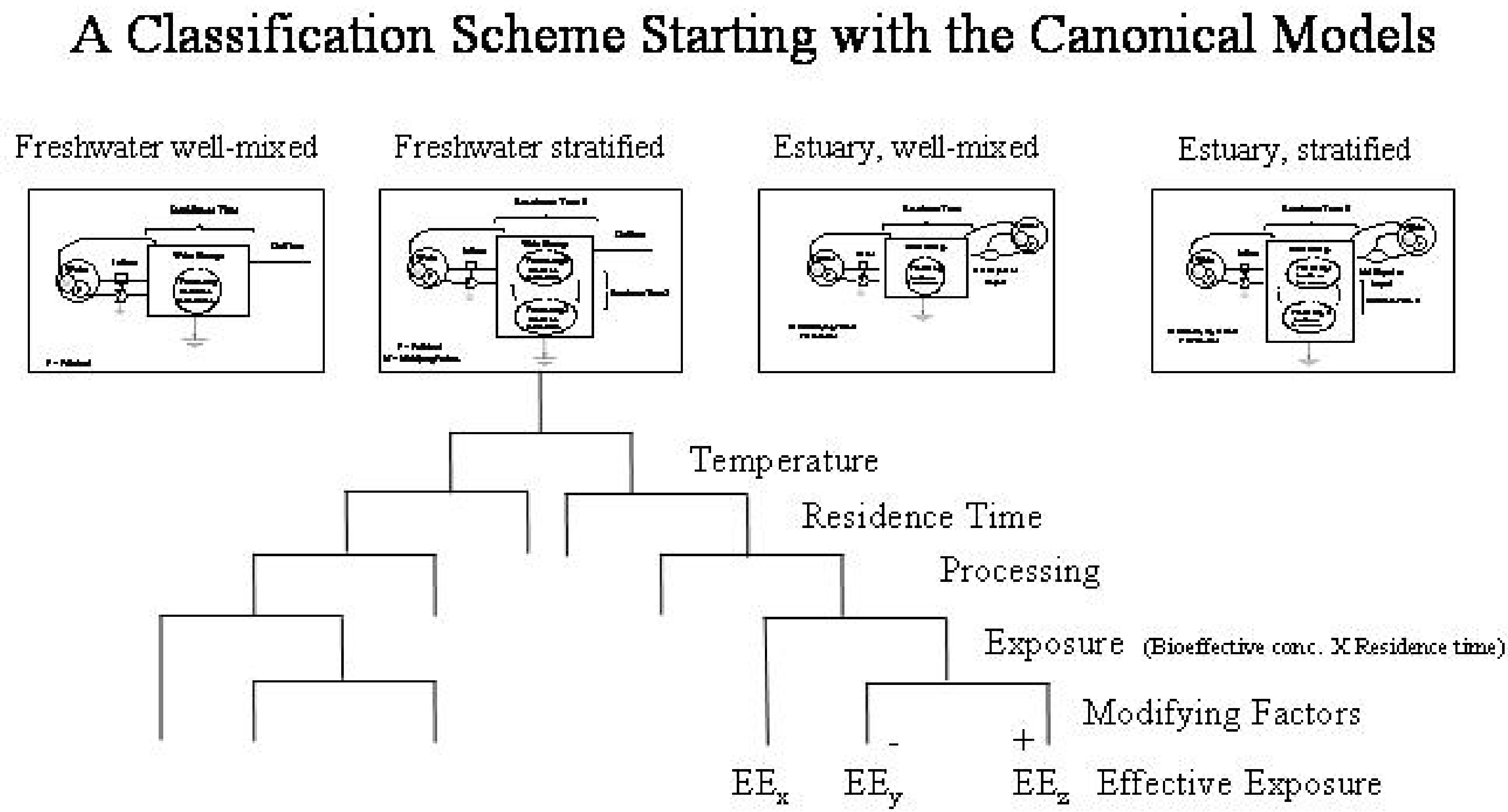

Figure 11. A classification tree to group estuaries by effective exposure regimes based on our conceptual model of the controlling factors.

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