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MARYLAND CHESAPEAKE BAY WATER QUALITY MONITORING PROGRAM

ECOSYSTEMS PROCESSES COMPONENT (EPC)

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Executive Summary 2015

The analytical work conducted by the Ecosystem Processes Component (EPC) of the Chesapeake Bay Water Quality Monitoring Program during FY 2015 encompassed four distinct efforts and these included the following:

1. Assessments of dissolved oxygen criteria failure rates, duration of failure periods, and exploration of conditions leading to low dissolved oxygen conditions and overall oxygen variability. These analyses explored the majority of the ConMon database and used a variety of quantitative tools (z-score metrics, modeling, time-series analysis) to discern biological versus physical drivers of oxygen variability.

2. An analysis of variability and long-term trends in watershed management, in-stream nutrient concentrations, nutrient loads, and water quality responses in the Corsica River estuary during the 2005-2013 period. This effort aimed to understand the effects of the targeted watershed management efforts in the Corsica watershed on estuarine conditions and utilized an extensive suite of long term biomonitoring data, ConMon data, land-use data, stream gauging, and monitoring, and BMP implementation time-series for data analysis and modeling.

3. A comparative analysis of 19 tributaries of the Chesapeake Bay to understand variability in chlorophyll-a including an analysis of biological, watershed, and physical drivers and a comparison of predictive models. The result of this effort is a simple composite model of nitrogen load, residence time, and depth that is highly predictive for chlorophyll-a across 18 of the 19 tributaries analyzed.

4. PI Testa of the EPC program began his co-chairmanship of the Chesapeake Bay Program Integrated Trends Analysis Team.

In the following section key findings from the FY 2015 EPC work are summarized:

Dissolved Oxygen Criteria Assessments:

- Data from 91 ConMon stations were analyzed for both percent failure and duration of failure events relative to established DO criteria. Both instantaneous (< 3.2 mg L^{-1}) and 30-day mean (< 5 mg L^{-1}) criteria were analyzed. We also computed hours of hypoxia (less than 2 and 3.2 mg L^{-1}) and collated the associated temperature, chlorophyll-a, salinity, and pH data.
- We tested a field of explanatory variables based on ConMon measurements of temperature, salinity, and chlorophyll-a and aggregated as daily minimum, maximum, or mean values to predict DO criteria. Using an all-possible subsets regression framework, we evaluated candidate models and ranked them according to Akaike criterion to winnow down the candidate models and evaluate what factors measured in the CONMON program are most explanatory of DO criteria failures.
- To explore the variability of the dataset over time and visualize emergent trends, we computed z-scores for a subset of the ConMon stations (n=24). Z-scores standardize

measurements to the station's long term mean and standard deviation and can be used in color maps to evaluate how variable the measurements are over time and whether the general direction of change for a given station is for improving or declining water quality. This first look at a subset of stations revealed some locations where seasonality is strong and has been consistent (Newport Creek, Sycamore Point), improvements at Piscataway Creek, and unchanged, consistently poor water quality at Bishopville Prong.

- Spectral analysis of a subset of the 91 ConMon stations revealed strong tidal and diurnal variability in dissolved oxygen, pH, and chlorophyll-a. While the diurnal signal (driven by photosynthesis (P) and respiration (R)) was more dominant for oxygen, salinity was dominated by tidal-timescale variation, suggesting that for most stations, photosynthesis and respiration drive oxygen variation. For these stations, we expect that nutrient reductions, which reduce P and R, should improve oxygen conditions. For stations where tides dominate, physical variability may overwhelm biologically-induced changes.
- Hypoxia duration and oxygen criteria failure were strongly correlated with chlorophyll-a during summer in the Corsica River, as well as several smaller tributaries (e.g., Magothy, Severn), but relationships were much weaker for deeper, larger estuaries (e.g., Patuxent, Potomac).

Corsica River Water Quality and Habitat Assessment:

- We analyzed a comprehensive data set of water quality variables, nutrient loads, watershed characteristics, and BMP implementation in the Corsica River watershed and estuary, allowing for an assessment of the major drivers of nutrient loading, the association of various BMPs with changes in stream nutrient concentrations and loads, and changes in water quality during the past decade.
- A large increase in cover cropping in the watershed after 2010 corresponds to declines in the concentration of TN and nitrate in two of the three streams that were routinely sampled from 2005-2013. In contrast, no declines in dissolved or total phosphorus were found. Declines in nitrogen concentrations were largest during summer (June to August) and fall (September to November) periods.
- Despite the long-term declines in stream nitrogen concentration in the two tributaries, no declines in nitrogen load were found, primarily because stream flow was slightly higher in the most recent 5 years and the largest stream in the upper watershed (Old Mill Stream) did not have declining nutrient concentrations.
- Measured TN loads compared favorably with the Phase 5 CBP watershed model loads, while TP loads derived from composite samplers that measured storm events were much higher than the Phase 5.3 TP loads.
- No clear evidence for improvements in water quality in the estuary was found, although summer ecosystem respiration and oxygen criteria failure were reduced at Sycamore Point after 2007.

Predicting Chlorophyll-a in Shallow Tributaries of the Chesapeake Bay:

- We evaluated variability in (and controls on) chlorophyll-a in 19 shallow tributaries of the Chesapeake Bay using data analysis and model selection from a suite of composite metrics that include measures of nutrient load, residence time, and depth.
- Cluster analysis revealed similarities and differences between the tributaries, where deeper mesohaline tributaries grouped separately from the shallower, more freshwater tributaries. The highly eutrophic Back River and SAV-dominated Piscataway Creek appeared to be unique. This separation is highlighted by the fact that chlorophyll-a and river flow are positively correlated in deeper, mesohaline tributaries, but negatively correlated in shallow, oligohaline or tidal fresh tributaries.
- Cluster analysis also indicates that geomorphic and physical variables grouped together, while nutrient concentrations and chlorophyll-a grouped together. This result suggests that there may be non-linear relationships between biogeochemical and physical characteristics that will not be easily discerned using linear regression techniques.
- A model selection approach using Bayesian ranking metrics (Akaike Criterion and associated weights) resulted in the selection of a composite metric including measures of nutrient load, residence time, and depth to explain variability in chlorophyll-a broadly across 18 of the 19 small estuaries, with relatively high statistical power (r^2 = 0.43, AIC = 814.18).

Chapter 1

Introduction and Objectives

J.M. Testa, L.A. Harris, W.R. Boynton, C.L.S. Hodgkins, J.L. Humphrey, and M.C. Day

1-1 BACKGROUND AND THE ECOSYSTEM PROCESSES COMPONENT (EPC) OF THE BIOMONITORING PROGRAM 1

1-2 NUTRIENT EFFECTS AND CONCEPTUAL MODEL OF WATER QUALITY PROCESSES IN CHESAPEAKE BAY SYSTEMS 3

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1-1 Background and the Ecosystem Processes Component (EPC) of the Biomonitoring Program

The first phase of the Chesapeake Bay Program was undertaken during a period of four years (1984 - 1987) and had as its goal the characterization of the existing state of the Bay, including spatial and seasonal variation, which were keys to the identification of problem areas. During this phase of the program, the EPC measured sediment-water oxygen and nutrient exchange rates and determined the rates at which organic and inorganic particulate materials reached deep waters and Bay sediments. Sediment-water exchanges and depositional processes are major features of estuarine nutrient cycles and play an important role in determining water quality and habitat conditions. The results of EPC monitoring have been summarized in a series of interpretive reports (Boynton et al., annually from 1984 through 2011; and Bailey et al., 2008). The results of this characterization effort have confirmed the importance of deposition and sediment processes in determining water quality and habitat conditions. Furthermore, it is also now clear that these processes are responsive to changes in nutrient loading rates (Boynton and Kemp, 2008). Much of these data played a key role in formulating, calibrating and verifying Chesapeake Bay water quality models and these data are continuing to be used as the “gold standard” against which the sediment model is further tested and refined (e.g., Brady et al., 2012; Testa et al., 2013). We have also created a web-accessible and complete Chesapeake Bay sediment flux data base that is available to all interested parties (www.gonzo.cbl.umces.edu).

The second phase of the program effort, completed during 1988 through 1990, identified interrelationships and trends in key processes monitored during the initial phase of the program. The EPC was able to identify trends in sediment-water exchanges and deposition rates. Important factors regulating these processes have also been identified and related to water quality conditions

(Kemp and Boynton, 1992; Boynton et al., 1991; Cowan and Boynton, 1996; Boynton and Kemp, 2008).

In 1991 the program entered its third phase. During this phase the long-term 40% nutrient reduction strategy for the Bay was re-evaluated. In this phase of the process, the monitoring program was used to assess the appropriateness of targeted nutrient load reductions as well as provide indications of water quality patterns that will result from such management actions. The preliminary re-evaluation report (Progress Report of the Bay-wide Nutrient Reduction Reevaluation, 1992) included the following conclusions: nonpoint sources of nutrients contributed approximately 77% of the nitrogen and 66% of the phosphorus entering the Bay; agricultural sources were dominant followed by forest and urban sources; the "controllable" fraction of nutrient loads was about 47% for nitrogen and 70% for phosphorus; point source reductions were ahead of schedule and diffuse source reductions were close to projected reductions; further efforts were needed to reduce diffuse sources; significant reductions in phosphorus concentrations and slight increases in nitrogen concentrations have been observed in some areas of the Bay; areas of low dissolved oxygen have been quantified and living resource water quality goals established; simulation model projections indicated significant reductions in low dissolved oxygen conditions associated with a 40% reduction of controllable nutrient loads. These results have recently been re-evaluated, modified and new goals established since 1991.

During the latter part of 1997, the Chesapeake Bay Program entered another phase of re-evaluation. Since the last evaluation, programs had collected and analyzed additional information, nutrient reduction strategies had been implemented and, in some areas, habitat improvements had been accomplished. The overall goal of the 1997 re-evaluation was the progress assessment of the program and the implementation of necessary modifications to the difficult process of restoring water quality, habitats and living resources in Chesapeake Bay. During this portion of the program, EPC was further modified to include 1) development of intensive spatial water quality mapping; 2) intensive examination of SAV habitat conditions in major regions of the Chesapeake Bay and development of a high frequency shallow water monitoring protocol (ConMon) that has been extensively implemented in many regions of the Bay and tributary rivers.

During the past several years (2008-2014) the EPC of the Biomonitoring Program has further evolved to focus on data analysis of water quality issues. Specifically, the EPC has accomplished the following: 1) rescued a rare, high quality, near-continuous and long-term water quality data set collected in the mesohaline portion of the Patuxent estuary from 1963-1969 and made this data set generally available; 2) examined multiple sites using dataflow results for a better understanding of the spatial features of water quality and factors, both local and remote, influencing these water quality distributions; 3) used ConMon data sets to assess DO criteria attainment and duration of low DO events in near-shore areas using a variety of computational approaches; and 4) developed an algorithm for computing community-scale primary production and respiration using ConMon data for purposes of developing another metric of water quality and relating these fundamental ecosystem processes to important controlling factors such as nutrient loading rates. The specific goals of the FY2015 EPC Program are provided later in this chapter.

The Chesapeake Bay Water Quality Monitoring Program was initiated to provide guidelines for restoration, protection and future use of the mainstem estuary and its tributaries and to provide evaluations of implemented management actions directed towards alleviating some critical pollution problems. A description of the complete monitoring program, which has evolved substantially over time, is provided in the following documents: Magnien et al. (1987), Chesapeake Bay Program web page: http://www.chesapeakeBay.net/about/programs/monitoring

In addition to the EPC program portion, the monitoring program also has components that measure:

1. Freshwater, nutrient and other pollutant input rates at 9 river fall line locations.
2. Chemical, biological and physical properties of the water column at fixed locations in the mainstem Bay and tributary rivers.
3. High frequency (15 minute intervals) chemical, biological and physical properties of the water column at selected shallow water locations (ConMon Program) and high spatial resolution (Dataflow Program) surface water properties also at selected locations.
4. Benthic community characteristics (abundances, biomass and indices of health).
5. SAV distribution and density

1-2 Nutrient Effects and Conceptual Model of Water Quality Processes in Chesapeake Bay Systems

During the past three to four decades much has been learned about the effects of natural and anthropogenic nutrient inputs (e.g., nitrogen, phosphorus, silica) on such important estuarine features as phytoplankton production, algal biomass, seagrass abundance and distribution and oxygen conditions in deep waters (Nixon, 1981, 1988; Boynton et al., 1982; Kemp et al., 1983; D'Elia et al., 1983; Garber et al., 1989; Malone, 1992; Kemp and Boynton, 1992; Boynton and Kemp, 2008; Boynton et al., 2014). While our understanding is not complete, important pathways regulating these processes have been identified and related to water quality issues. Of particular importance here, it has been determined that 1) algal primary production and biomass levels in many estuaries (including Chesapeake Bay) are responsive to nutrient loading rates, 2) high rates of algal production and algal blooms are sustained through summer and fall periods by recycling of essential nutrients that enter the system during the high flow periods of the year, which occur in late winter and spring 3) the “nutrient memory” of estuarine systems is relatively short (one to several years for nitrogen and longer for phosphorus), 4) submerged aquatic vegetation (SAV) communities are responsive to water quality conditions, especially light availability, that is modulated both by water column turbidity regimes and epiphytic fouling on SAV leaf surfaces and 5) dissolved oxygen regimes are influenced both by the biology and physics of these systems and that near-shore and off-shore DO regimes exhibit important differences.

Nutrients and organic matter enter the Bay from a variety of sources, including sewage treatment plant effluents, fluvial inputs, local non-point drainage and direct rainfall on Bay waters. Dissolved nutrients are rapidly incorporated into particulate matter via biological, chemical and physical mechanisms. A portion of this newly produced organic matter sinks to the bottom, decomposes and thereby contributes to the development of hypoxic or anoxic conditions and loss of habitat for important infaunal, shellfish and demersal fish communities. Eutrophic (nutrient enriched) conditions favor the growth of a diverse assemblage of estuarine bacteria that play a major role in consuming dissolved oxygen and the subsequent development of hypoxic and anoxic conditions. The regenerative and large short-term nutrient storage capacities of estuarine sediments ensure a large return flux of nutrients from sediments to the water column that can sustain continued high rates of phytoplanktonic growth and biomass accumulation. Continued growth and accumulation supports high rates of deposition of organics to deep waters, sustaining hypoxic and anoxic conditions typically associated with eutrophication of estuarine systems. To a considerable extent, it is the magnitude of these processes that determines water quality conditions in many zones of the Bay. Ultimately, these processes are driven by inputs of organic matter and nutrients from both natural and anthropogenic sources. If water quality management programs are instituted and loadings of organic matter and nutrients decrease, changes in the magnitude of these processes are expected and will serve as a guide in determining the effectiveness of strategies aimed at improving Bay water quality and habitat conditions. The schematic diagram in Figure 1-1 summarizes this conceptual eutrophication model where increased nitrogen (N) and phosphorus (P) loads result in a water quality degradation trajectory and reduced N and P loads lead to a restoration trajectory. There is ample empirical evidence for the importance of N and P load variation. For example, water quality and habitat conditions change dramatically between wet and dry years, with the former having degradation trajectory characteristics and the latter, restoration trajectory characteristics (Boynton and Kemp, 2000; Hagy et al., 2004; Kemp et al., 2005). However, the exact temporal sequence of restoration may range from simple and rapid reversals to complex and lengthy processes (Kemp and Goldman, 2008).

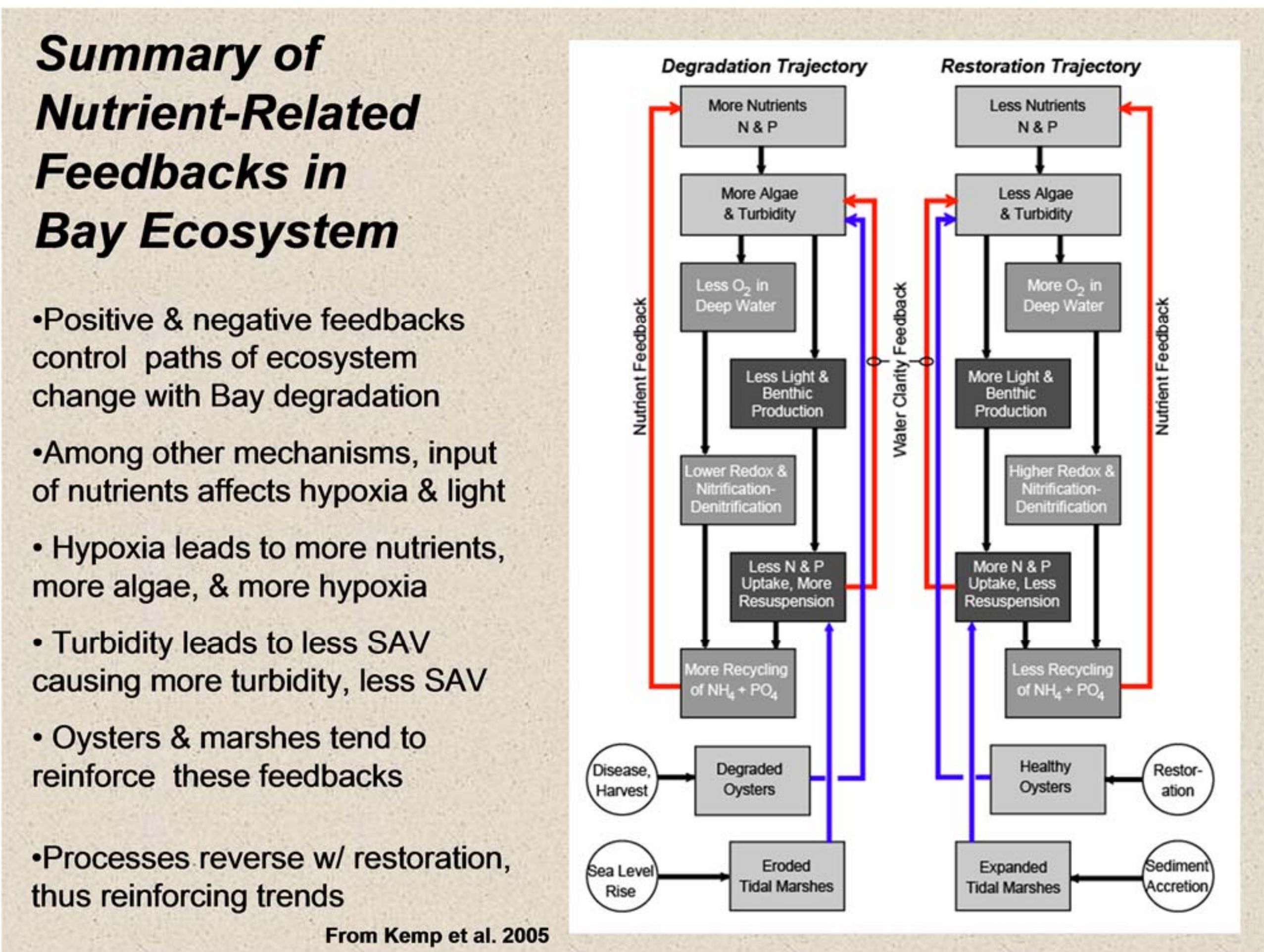

Figure 1-1. A simplified schematic diagram indicating degradation and restoration trajectories of an estuarine ecosystem. Figure was adapted from Kemp et al., 2005.

Within the context of this conceptual model, monitoring program data analysis has focused on SAV and other near-shore contemporary and historical habitat and water quality conditions to evaluate water quality criteria attainment. Recent EPC efforts have addressed management needs to understand the relative importance of local or regional drivers in controlling water quality and how quickly the biotic system may respond to changes in nutrient or sediment inputs from the watershed. Given the growing realization of the effects of climatic (i.e., “unmanageable”) forces in driving variability in water quality and potentially masking trends associated with nutrient reduction efforts, we have focused on understanding the competing roles of climate and nutrient-driven biogeochemical processes in FY2015.

1-3 General and Specific Objectives of the EPC Program

The EPC has undergone multiple and significant program modification since its inception in 1984 but its overall objectives have remained consistent with those of other Monitoring Program Components. The specific objectives of the FY2015 EPC program were as follows:

1. Provide a continuation and enhancement of the analysis of ConMon data from FY2014, with an emphasis on (1) understanding broad patterns of nutrient loading effects in these shallow systems, (2) applying quantitative tools to describe variability in the ConMon data associated with physical variability (e.g., tides), (3) choosing ideal locations to be sentinel sites moving forward, and (4) analyses to inform the development of the new ConMon program, including requirements for sensor density, deployment plans, and alternative measures of criteria failure.
2. Provide an analysis of the (now) long-term changes in the Corsica River estuary associated with BMP implementation and other factors. This analysis serves as an update and extension of a previous analysis done by EPC PIs (Boynton et al., 2009). This analysis provides important information concerning lag times relative to BMP implementation as well.
3. Provide a multivariate statistical analysis of controls on chlorophyll-a in the shallow-water tributaries of Chesapeake Bay
4. One of our team (WRB) continued to be involved with the emerging Bay Program workgroup examining Bay water quality for trends and developing explanations of those trends. Other EPC Program PIs (JMT, LAH) continued their participation in STAC. This effort tied EPC activities to those of criteria assessment, trend analyses, land-estuarine linkages and other water quality issues investigated or reviewed by various Bay Program workgroups and formal committees.
5. Activities in the EPC program were coordinated with other components of the Maryland Chesapeake Bay Water Quality Monitoring Program. To be more explicit, during the FY2015 effort we used data from the River Input monitoring program, the Chesapeake Bay Landscape modeling effort, the long-term tidal water quality monitoring program, ConMon program and Dataflow program. We also utilized a vast dataset for the Corsica River estuary from the Maryland Department of Natural Resources. During the past several years we have become more skilled at efficiently obtaining and utilizing these diverse data sets.

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Chapter 2

Evaluation of Criteria Failures on DO and Chlorophyll-a Variability in ConMon with New Quantitative Tools and Metrics

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2-1 Introduction

The shallow waters of Chesapeake Bay are important habitats for submerged plants (SAV), benthic algae, and a variety of larger benthic and pelagic organisms. As a consequence of estuarine geomorphology, these shallow habitats tend to be located at the land-estuarine interface, which makes these environments the initial recipients of terrestrially-based nutrient and sediment inputs. Much of the shallow habitat within Chesapeake Bay is within tributaries, where nutrient concentrations are relatively high and rates of primary production and respiration are correspondingly large. Therefore, short-term variations in chlorophyll-a, pH, and dissolved oxygen tend to be extreme relative to more open water areas, making shallow environments sensitive to temporary blooms of algae, depletion of oxygen, and high pH. Because quantification of these variations is key to understanding how these shallow environments will fare in the face of nutrient load reductions, tools and data sets that consider the shallows are increasingly useful for coastal water management.

The continuous monitoring (ConMon) program in Maryland shallow waters provides detailed time series of water quality information that can be applied to water quality assessments at many tributary and mainstem Bay sites in Maryland. These data offer some of the best information for understanding hourly to interannual dynamics of DO and other conditions (e.g., water clarity, temperature, salinity, pH, and chlorophyll-a) relevant to sustaining aquatic organisms. Here and in the past, the Ecosystem Processes Component (EPC) examined ConMon data in terms relevant to regulatory compliance, used these data to develop indicators of estuarine condition or health, and related these metrics to variables (e.g., chlorophyll-a, temperature, etc.) that represent processes that control criteria compliance due to both manageable factors (e.g., nutrient loading) and climate-related, unmanageable factors (e.g., temperature, tidal mixing).

This work builds on a growing body of analysis aimed at deriving meaningful metrics of water quality condition *and* understanding the factors that control shallow-water processes and variability. In 2012, various approaches for developing water quality assessments and metrics were presented and in the ensuing years progress has been made relative to implementing these approaches. In 2014, algorithms were developed to compute various DO criteria failures (e.g., instantaneous, monthly, etc.) and to compute the duration of DO criteria failures at 56 ConMon locations spanning a range from highly to less eutrophicated sites and sites located in small tributaries of tributary rivers to sites exposed to the mainstem Bay. Now we aim to continue the analysis from 2014, but approaching the ConMon data with new quantitative tools that aim to (1) relate criteria failures to “normal” conditions at the site, as some sites are more naturally susceptible to failures than others, (2) examine new measures of central tendency and variability (z-score, standard deviation), and (3) apply spectral analysis to understand tidal effects and other periodic and largely “non-controllable” influences (e.g., wind events).

2-2 Methods

2-2.1 ConMon Program and Maryland ConMon Database

Continuous monitoring data from 2001 to 2014 for all stations (Fig. 2-1, Table 2-1) were obtained from the Maryland Department of Natural Resources Tidewater Ecosystems Assessment division (B. Cole) in electronic (.txt) file format.

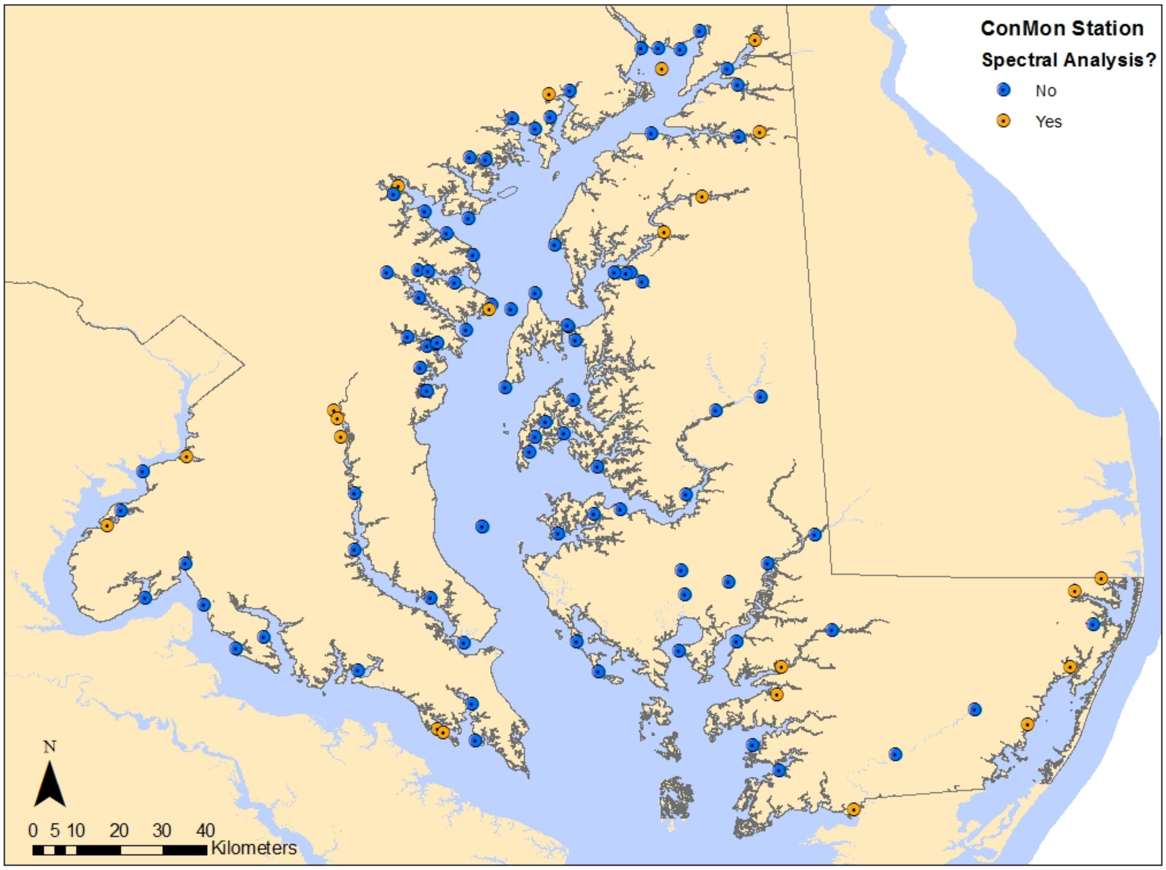


Figure 2-1. Station locations in Continuous monitoring database. Orange circles represent stations where spectral analysis was performed.

Because of the near-continuous characteristic of these measurements, a data set with no error and complete days was developed using an R (www.R-project.org) program. Data with failing or invalid codes (as detailed in the MDDNR QAPP: Michael et al., 2013), missing data, and duplicates were isolated. These rows in their entirety were removed to provide a complete and error free dataset. The date was then expanded into separate month, day, and year columns for future analysis. This standardization was essential for our model averaging exercise and z-scores so that equal samples were available for all days used in the analyses.

For each 15 minute interval, non-attainment of the instantaneous (DO <3.2 mgL^{-1}) and 30-day DO criteria (DO <5.0 mg L^{-1}) were calculated. This dataset was then aggregated by each day and station into total hours per day, non-attainment of DO criteria at the 3.2 and 5 mgL^{-1} level (expressed as a percent (%) of failures and total hours below DO criteria values). Water quality parameters were also aggregated as minimum, maximum, and mean DO, salinity, temperature, and chlorophyll-a by day and station. Days that did not have readings for all 24 hours were filtered from the dataset to ensure that only complete days were used for analysis (Table 2-2).

Table 2-1. Listing of all stations in Continuous monitoring database with their associated three letter acronym, station code, and years deployed. Stations highlighted in blue indicate those included in past reports.

System	Station name	Acronym	Code	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Annemessex River	Big Ann	BAN	XBJ3220											X	X	X	
Bohemia River	Long Point	BOH	XJI8369							X	X	X					
Bush River	Church Point	BCP	XJG7461								X	X	X				
Bush River	Lauderick Creek	LAU	XJG4337			X	X	X	X	X							
Bush River	Otter Point	OPC	XJG7035			X	X	X	X	X	X	X	X	X	X	X	X
Chesapeake Bay	Annapolis CBIBS	NAP	XGF7832											X	X		
Chesapeake Bay	Dominion-Gooses - Bottom	GOB	XEF3551										X	X	X	X	X
Chesapeake Bay	Dominion-Gooses - Surface	GOO	XEF3551										X	X	X	X	X
Chesapeake Bay	Downs Park	DWN	XHF6841									X	X	X			
Chesapeake Bay	Fort Howard	HOW	XIF1735									X	X	X			
Chesapeake Bay	Gratitude	THX	XHG8442									X	X	X			
Chesapeake Bay	Love Point	LUV	XHG2318									X	X	X			
Chesapeake Bay	Sandy Point East	SPE	XHF0561				X	X	X	X							
Chesapeake Bay	Sandy Point South	SPS	XHF0460				X	X	X	X	X	X	X	X	X	X	X
Chesapeake Bay	Stump Point	STU	XKH2870							X	X	X					
Chesapeake Bay	Susquehanna Flats	FLT	XKH0375							X	X	X	X	X	X	X	X
Chester River	Deep Landing	DEE	CHE0348			X	X	X	X								
Chester River	Kent Narrows Inside	KNI	XGG8359							X	X	X					
Chester River	Kent Narrows outside	KNO	XGG8458							X	X	X					
Chester River	Rolphs Warf	ROL	XIH0077			X	X	X	X								
Chicamacomico River	Drawbridge	CCM	CCM0069	X	X	X											
Choptank River	Harris Creek Downstream	HAD	XFG2810													X	X
Choptank River	Harris Creek Profiler	PRO	XFG4618												X	X	X
Choptank River	Harris Creek Upstream	HAU	XFG6431													X	X
Choptank River	High Banks	HBK	CHO0417						X	X	X						
Choptank River	Horn Point	HPL	XEH5622						X	X	X						
Choptank River	Jamaica Point	JAM	XEI7405						X	X	X						
Choptank River	Mulberry Point	MUL	XFG5054						X	X	X						
Coastal Bay	Bishopville Prong	BSH	XDM4486			X	X	X	X	X	X	X	X	X	X	X	X
Coastal Bay	Greys Creek	GYK	XDN6921								X	X	X	X	X	X	X
Coastal Bay	Newport Creek	NPC	NPC0012						X	X	X	X	X	X	X	X	X
Coastal Bay	Public Landing	PUB	XBM8828					X	X	X	X	X	X	X	X	X	X
Coastal Bay	Turville Creek	TUV	TUV0021			X	X	X	X	X							
Corsica River	Emory Creek	EMO	XHH5046					X	X								
Corsica River	Possum Point Bottom	PPB	XHH4931						X	X	X	X	X	X	X	X	X
Corsica River	Possum Point Surface	PPT	XHH4931						X	X	X	X	X	X	X	X	X
Corsica River	Sycamore Point	COR	XHH3851					X	X	X	X	X	X	X	X	X	X
Corsica River	The Sill Bottom	SIB	XHH4916						X	X	X	X	X	X			
Corsica River	The Sill Surface	SIL	XHH4916						X	X	X	X	X	X			

Table 2-1. Continued

System	Station name	Acronym	Code	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Eastern Bay	CBEC	CBE	XGG6667					X	X	X	X						
Eastern Bay	Hambleton Point	HAM	XFG9164				X	X	X								
Eastern Bay	Kent Point	KNT	XGF0681				X	X	X								
Elk River	Hollywood Beach	HOL	XKI0256							X	X	X					
Elk River	Locust Point Marina	LOC	XKI3890							X	X	X					
Fishing Bay	Bestpitch	BST	TRQ0088			X	X	X									
Fishing Bay	Fishing Bay	FSB	XCH8097			X	X	X									
Gunpowder River	Aberdeen	GUN	XJG2718			X	X	X									
Gunpowder River	Mariner Point	MPP	XJF4289			X	X	X									
Honga River	House Point	HPT	XCG9168								X	X	X				
Honga River	Muddy Hook Cove	HON	XCG5495								X	X	X				
Little Choptank	Casson Point	LIL	XEG2646					X	X	X							
Little Choptank	Garys Creek	GAR	XEG4991					X	X	X							
Magothy River	Cattail Creek	CAT	CTT0014	X				X									
Magothy River	Stonington	MAG	XHF3719	X	X	X											
Magothy River	Whitehurst	WHI	CTT0001		X	X											
Manokin River	Manokin	MAN	XBI6387											X	X	X	
Middle River	Cutter Marina	MDR	MDR0038			X	X	X									
Middle River	Strawberry	STP	FRG0002			X	X	X									
Nanticoke	Sharptown	SPT	XEJ2464												X	X	X
Nanticoke	Tyaskin	TYA	XCI9167												X	X	X
Nanticoke	Vienna	VNA	XDJ8905												X	X	X
Northeast River	Carpenters Point	CAR	XKH2797							X	X	X					
Northeast River	Charlestown	NOR	XKI5022							X	X	X					
Patapsco River	Fort Armistead	ARM	XIE2581									X	X	X			
Patapsco River	Ft. McHenry	MCH	XIE5748				X	X	X	X	X	X	X	X	X	X	
Patapsco River	Ft.Smallwood	SMA	XHF9808									X	X	X			
Patapsco River	Masonville Cove	MSV	XIE4741									X	X	X	X		
Patapsco River	Masonville Cove Pier	MSC	XIE4742													X	X
Patuxent River	Benedict	BCT	XED0694			X	X	X									
Patuxent River	CBL	CBL	XCF9029			X	X	X									
Patuxent River	Iron Pot Landing	IPL	WXT0013			X	X	X	X	X	X	X	X	X	X	X	X
Patuxent River	Jug Bay	JUG	PXT0455			X	X	X	X	X	X	X	X	X	X	X	X
Patuxent River	Kings Landing	KNG	PXT0311			X	X	X	X								
Patuxent River	Mataponi	MTI	MTI0015			X	X	X	X	X	X	X	X	X	X	X	X
Patuxent River	Pin Oak	PIN	XDE4587			X	X	X	X	X							
Pocomoke River	Pocomoke City	POC	POK0187												X	X	X
Pocomoke River	Pocomoke Sound	SOU	XAJ5327												X		
Pocomoke River	Shelltown	SHL	POK0009												X	X	X
Pocomoke River	Snow Hill	SNO	POK0316												X	X	X
Potomac River	Blossom Point	BLO	XDB4544						X	X	X						
Potomac River	Breton Bay	BBY	XCD5599						X	X	X	X					
Potomac River	Fenwick	FEN	XFB0231				X	X	X	X	X						
Potomac River	Indian Head	IND	XEB5404									X	X	X	X		
Potomac River	Mattawoman Creek	MAT	XEA3687				X	X	X	X	X	X	X	X	X	X	X
Potomac River	Piney Point	PNY	XBE8396				X	X	X	X	X						
Potomac River	Piscataway Creek	PIS	XFB2184				X	X	X	X	X						
Potomac River	Popes Creek	POP	XDC3807						X	X	X						
Potomac River	Port Tobacco	PRT	XDB8884							X	X						
Potomac River	St Georges Creek	SGC	XBF7904						X	X	X	X	X	X	X	X	X
Potomac River	Swan Point	SWN	XCC8346						X	X	X						
Potomac River	Wicomico	WIB	XCC9680						X	X	X						
Rhode River	SERC	RHO	XGE3275				X	X	X								

Table 2-1. Continued

System	Station name	Acronym	Code	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Sassafras River	Betterton Beach	BET	XJH2362						X	X	X	X	X	X			
Sassafras River	Budds Landing	BUD	XJI2396							X	X	X	X	X	X	X	X
Sassafras River	Georgetown Yacht Basin	GYB	XJI1871						X	X							
Severn River	Ben Oaks	BEN	SEV0116		X	X											
Severn River	Sherwood	SHW	XHE1973		X	X											
South River	Beards Creek	BDS	XGE7059				X	X	X								
South River	Cedar Point	CED	XGE5984					X									
South River	Harness Creek Down	HCD	ZDM0001				X		X	X	X			X	X		
South River	Harness Creek Up	HCU	ZDM0002				X		X	X	X						
St Marys River	Sage	SAG	XBF6843				X	X									
St Marys River	St. Marys	SMC	XCF1440								X	X					
Susquehanna River	Havre de Grace	SUS	XKH2949							X	X	X	X	X	X	X	X
Transquaking River	Decoursey Bridge	TRQ	TRQ0146	X													
Tred Avon River	Tred Avon	TAV	XFG0995									X					
West River	Chesapeake Yacht Club	CYC	XGE0320											X	X	X	
West River	Shady Side	WSR	XGE0284				X	X	X								
Wicomico River	Little Monie Creek	LMN	LMN0028						X	X	X	X	X	X	X	X	
Wicomico River	Upper Ferry	UPF	WIW0144						X	X	X						
Wicomico River	Whitehaven	WHV	XCJ6023						X	X	X						
Williston Lake	Williston Lake	WLK	XFI9597												X	X	X

= stations included in past reports (EPC 31)

Table 2-2. Sample of a daily-aggregated ConMon dataset at 4 stations in 2001

DATE	STATION	Layer	COUNT	FAIL 3.2	PCT.FAIL 3.2	FAIL 5	PCT.FAIL 5	DO MIN	DO MAX	DO MEAN	temp MIN	temp MAX	temp MEAN	sal MIN	sal MAX	sal MEAN	chl MIN	chl MAX	chl MEAN
5/2/2001	CCM0069	BS	24	0	0	0	0	8.04	10.37	9.223	20.53	24.42	22.51	0.12	0.29	0.196	62.7	80.2	71.22
5/2/2001	CTT0014	BS	24	0	0	0	0	5.77	8.21	7.07	19.62	21.21	20.28	4.98	5.18	5.091	10.4	37.2	19.34
5/2/2001	TRQ0146	BS	24	0	0	0	0	6.47	8.8	7.549	19.99	25.26	22.63	0.3	0.89	0.548	35.8	54.3	43.12
5/2/2001	XHF3719	BS	24	0	0	0	0	9.89	12.84	11.46	15.61	17.91	16.61	5.2	6.66	5.837	14.8	34	24.26
5/3/2001	CCM0069	BS	24	0	0	0	0	6.69	9.26	8.371	22.4	25.72	24.06	0.15	0.39	0.263	55	90.7	64.55

2-2.2 Information-Theoretic Statistical Approach

Our initial efforts to explore explanatory models of DO criteria failure invoked the use of model averaging techniques outlined by Burnham and Anderson (2002). We were particularly interested in determining whether measurements of temperature, salinity, or chlorophyll-a taken as part of the ConMon program were useful in predicting daily failures of the dissolved oxygen criteria. Solubility of oxygen in water is a function of pressure and temperature according to the ideal gas law, and this solubility increases in fresh waters (Pilson, 2012). In the Chesapeake Bay, increased organic matter as a consequence of eutrophication is typically a function of *in situ* autochthonous carbon production from primary production and so we might also assume that criteria failures coincide with higher chlorophyll-a concentrations. Taking into consideration temperature, salinity, and chlorophyll-a concentrations, our model averaging approach evaluated all possible subsets of models using the aforementioned dataset, where models were evaluated for 3 potential independent indicators; non-attainment of the instantaneous (DO <3.2 mgL^{-1}: “3.2FAIL”) and 30-day DO criteria (DO <5.0 mg L^{-1}: “5FAIL”), as well as the daily calculated dissolved oxygen minimum (DO_MIN).

Our model selection followed the methods also outlined in chapter 4. Candidate models are ranked according to the second-order bias correction, Akaike Information Criteria (AIC), and the adjusted coefficient of multiple determination ($adjr^2$) following the approach of Burnham and Anderson (2002). The $adjr^2$ is based on the coefficient of determination, r^2, but adjusted for the number terms in the model. The AIC is a tool for model selection calculated from the Kullback-Leibler distance between model i and the "true" model that generated the data. The Kullback-Leibler distance is the amount of information lost when using model i to approximate the true model. The best model has the smallest Kullback-Leibler distance and thus the smallest AIC. Akaike weights (w_i) determine the relative support of each candidate model, providing insight into which variables are of interest in predicting dissolved oxygen. Regression analyses were completed using the R-statistical package (http://www.r-project.org/), and specifically the "leaps" and "cards" libraries.

2-2.3 Z-Score Metrics

A challenge of evaluating such a large dataset, spanning space and time, is finding useful tools to visualize emergent trends. One approach we applied to this problem was the calculation of z-scores across the stations for temperature, salinity, dissolved oxygen, and chlorophyll-a measurements. The z-score or standard score is computed by standardizing a given measurement to both the long term station mean and standard deviation of the time series in the following way:

$$z = \frac{x - \mu}{\sigma}$$

where x is the measurement, μ is the mean of the time series, and σ is the standard deviation. We then scaled these z-scores using color coding, where cooler colors (i.e. blues) correspond to lower values and warmer colors are higher. This color coding was reversed for the daily dissolved oxygen minimum so that warmer (i.e. reds) colors correspond with values of lower DO relative to long term means. This analysis was done for the daily aggregated dataset, focusing on the two failure criteria, and daily aggregated data for minimum dissolved oxygen, maximum temperature, and average chlorophyll-a. An initial ordination analysis of the dataset revealed high similarity among values for each of the variables and this led to our selection of minimum, maximum, or mean according to our interest in how chlorophyll-a, temperature, and dissolved oxygen might relate to water quality for a given day. Z-scores were computed for 24 of the 25 stations in Table 2-3.

2-2.4 Spectral Analysis

One key consideration for the ConMon data is the extent to which the cycling of DO, pH, and other variables occurs primarily over each day, over a tidal cycle, or over longer time-scales (e.g., months, a year). This cycling is relevant in understanding the extent to which tidal variation drives the variation of oxygen and chlorophyll-a, or alternatively, to what extent diel variation in phytoplankton growth and respiration drives oxygen dynamics. In the former case, strong tidal influences may overwhelm variation in DO associated with nutrient-fueled phytoplankton growth and would make the site particularly vulnerable or independent of nutrient impacts. Alternatively, in the absence of strong tidal influence, clear diel cycles of DO might indicate a strong daily metabolic pattern that suggests a key role for nutrient-fueled phytoplankton growth.

In order to identify the time-scales of variability at ConMon sites, we applied time-series analysis to the DO, salinity, fluorescence, and pH data to a subset of the ConMon stations (n=25, Fig. 2-1 detailed in Table 2-3). The analysis used Fourier Transformations of the data to identify periodicity within the time-series, and we utilized the fast Fourier transform (FFT) function in Matlab to analyze all data sets (Matlab v8.1.0.604 (R2013a)). The results of this analysis are illustrated by plots of the power spectral density, a measure of variance, against the temporal frequency, or cycles per day. In this case, power spectral density (hereafter PSD) has the units of measure (e.g., mg L^{-1} for DO) squared per cycle per day, while frequency is in cycles per day (e.g., 1 cycle per day is periodicity of daily solar cycle). The frequencies at which large peaks in PSD occur represent key time-scales of variation at the site; for example, a station with a PSD peak at ~2 cycles per day and ~0.003 cycles per day would indicate high variability at tidal (2/day) and annual (0.003/day or 1/year) time-scales.

Table 2-3. Station names, codes, tidal range (m) and depth (m) for 25 stations analyzed with spectral analysis and Z-score metrics

Station	Code	Years Available	Tidal Range	Station Depth
Otter Point	XJG7035	2003-2014	1.25	5.0
Sandy Point South	XHF0460	2004-2014	0.97	18.7
Susquehanna Flats	XKH0375	2007-2014	1.9	1.6
Deep Landing	CHE0348	2003-2006	1.19	1.6
Rolphs Warf	XIH0077	2003-2006	1.19	1.4
Bishopville Prong	XDM4486	2003-2014	1.53	1.8
Greys Creek	XDN6921	2008-2014	1.53	1.0
Newport Creek	NPC0012	2006-2014	0.46	1.0
Public Landing	XBM8828	2005-2014	0.53	1.2
Possum Point	XHH4931	2006-2014	1.19	3.6
Sycamore Point	XHH3851	2005-2014	1.19	2.0
The Sill	XHH4916	2006-2011	1.19	4.9
Locust Point Marina	XKI3890	2007-2009	2.17	1.6
Ft. McHenry/Baltimore Harbor	XIE5748	2003-2013	1.13	10.6
Iron Pot Landing	WXT0013	2003-2014	1.82	3.7
Jug Bay	PXT0455	2003-2014	1.82	2.6
Mattaponi	MTI0015	2003-2014	1.17	2.5
Shelltown	POK0009	2012-2014	1.16	2.5
Mattawoman Creek	XEA3687	2004-2014	1.24	2.4
Piney Point	XBE8396	2004-2008	1.24	2.1
Piscataway Creek	XFB2184	2004-2008	1.24	2.3
St Georges Creek	XBF7904	2006-2014	1.24	2.1
Budds Landing	XJI2396	2007-2014	1.21	1.3
Little Monie Creek	LMN0028	2006-2013	1.76	1.9
Whitehaven	XCJ6023	2006-2008	1.76	1.5

Several steps were required to perform the time-series analysis. First, all missing data needed to be replaced with a value, and we interpolated linearly between the last observation before a gap and the first observation after the gap to generate replaced values. This method does not impart any new variability into the time-series. Secondly, the data were detrended in Matlab (function "detrend") to remove any long-term trends from the data; the resulting time-series has a mean of zero (Fig. 2-2). Once the detrended data sets with equally spaced (in time) values were computed, the FFT analysis and PSD plots were generated (Fig. 2-2).

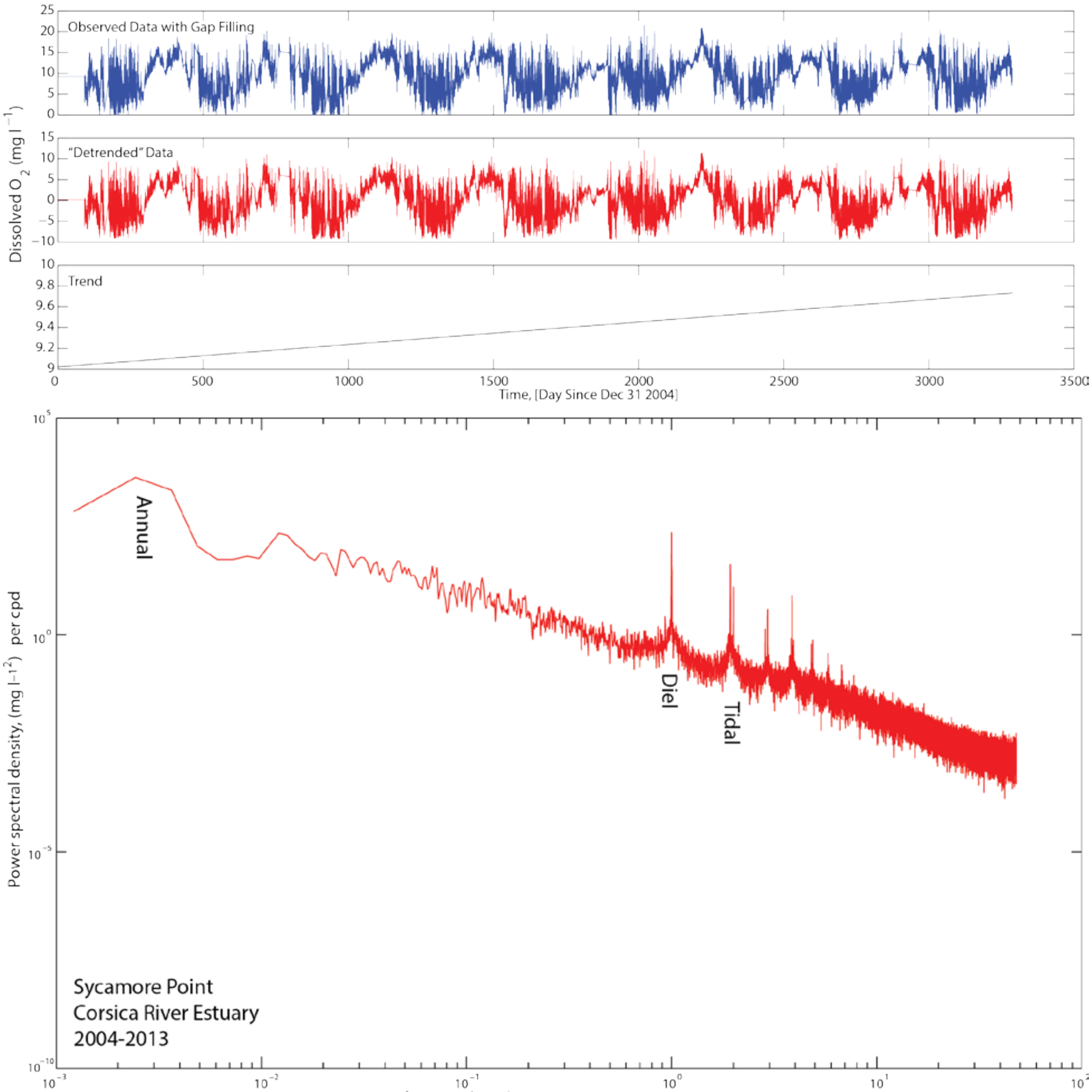


Figure 2-2. Example time-series of spectral analysis of DO at Sycamore Point in the Corsica River estuary, including (top panel) observed DO data with missing data filled by linear interpolation, (2nd from top) detrended DO time series with zero mean, (2nd from bottom) linear trend in data, and (bottom panel) PSD diagram illustrating large peaks at tidal, diel, and annual time scales.

2-3 Results and Discussion

2-3.1 Database Characteristics

Our analysis of ConMon data spanned 91 stations over the course of 14 years in every major Maryland tributary, the Maryland Coastal Bays, and the mainstem of the Chesapeake Bay (Fig. 2-1). Nearly 200 km^2 of water was covered with 71,211 total samples, including dissolved oxygen, temperature, salinity, chlorophyll-a, and pH. To our knowledge, no previous effort has analyzed such a large contemporaneous data set for these high-frequency measurements.

2-3.2 Model Selection Approaches

The all possible subsets analysis focused on three potential sets of variables as listed below:

1. $3.2FAIL \sim MINTemp + MAXTemp + MEANTemp + MINSal + MAXSal + MEANSal + MINChl + MAXChl + MEANChl$
2. $5FAIL \sim MINTemp + MAXTemp + MEANTemp + MINSal + MAXSal + MEANSal + MINChl + MAXChl + MEANChl$
3. $MINDO \sim MINTemp + MAXTemp + MEANTemp + MINSal + MAXSal + MEANSal + MINChl + MAXChl + MEANChl$

Each of these analyses resulted in 72 possible models, representing various combinations of the nine dependent variables describing temperature, salinity, and chlorophyll-a measurements. The ratio of sample size to dependent variables for all models was greater than 7,000, well above the ratio criterion of 40-60 suggested for use of the AIC metric (Anderson 2008). Models for each of the 3 analyses were ranked from lowest to highest AIC values, after which Akaike weights were computed (w_i) to determine the relative support of each candidate model. Burnham and Anderson (2002) suggests that the level of empirical support for a model with a ΔAIC greater than 10 is very low, and this threshold permitted selection of top models for each failure criteria.

Table 2-4 reports the results of the model selection exercise for measurements related to non-attainment of the instantaneous (DO <3.2 mgL^{-1}) criterion. Six model candidates attained ΔAIC values that were larger than 10, however adjusted r^2 for these models were particularly low. These top ranked models all included at least 7 of the dependent variables. While the model selection exercise easily weeded out models of lower explanatory power, the particularly low adjusted r^2 values do not give confidence for prediction of this criterion from contemporaneously measured temperature, salinity, and chlorophyll-a. The 30-day DO criteria (DO <5.0 mg L^{-1}) also yielded clear candidates for models with better explanatory power (Table 2-5) and these models all included a majority of the dependent variables, but adjusted r^2 values were low (~0.15).

In contrast, the dataset using daily minimum dissolved oxygen concentrations as the independent variable resulted in a clear difference between the top ranked models and those with ΔAIC greater than 10. The adjusted r^2 for these candidate models was much higher, with values ~0.51. Table 2-6 describes the statistics for these top ranked models and we suggest that these results should be used for development of predictive multiple regression equations to be used collectively to predict minimum dissolved oxygen concentrations.

Table 2-4. Model selection results for non-attainment of the instantaneous (DO <3.2 mgL^{-1}) criterion.

Model rank	Independent variables	adj r^2	AIC	Δ AIC	ω_i
1	tempMAX, tempMEAN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.08	65304.17	0.00	0.86
2	tempMIN, tempMAX, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.08	65310.03	5.86	0.34
3	tempMIN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.08	65310.24	6.07	0.46
4	tempMAX, tempMEAN, salMIN, salMEAN, chlMIN, chlMAX, chlMEAN	0.08	65311.71	7.54	0.41
5	tempMIN, tempMEAN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.08	65311.97	7.80	0.61
6	tempMAX, tempMIN, tempMEAN, salMIN, salMEAN, chlMIN, chlMAX, chlMEAN	0.08	65313.71	9.54	0.65

Table 2-5. Model selection results for 30-day DO criteria (DO <5.0 mg L^{-1}).

Model rank	Independent variables	adj r^2	AIC	Δ AIC	ω_i
1	tempMAX, tempMIN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.15	104545.46	0.00	0.55
2	tempMAX, tempMIN, salMIN, salMAX, salMEAN, chlMAX, chlMEAN	0.15	104546.93	1.47	0.58
3	tempMAX, tempMIN, tempMEAN, salMIN, salMAX, salMEAN, chlMAX, chlMEAN	0.15	104548.46	3.00	0.63
4	tempMIN, tempMEAN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.15	104551.71	6.25	0.34
5	tempMAX, tempMIN, salMIN, salMEAN, chlMIN, chlMAX, chlMEAN	0.15	104552.68	7.23	0.32
6	tempMIN, tempMEAN, salMIN, salMAX, salMEAN, chlMAX, chlMEAN	0.15	104553.23	7.77	0.35
7	tempMAX, tempMIN, salMIN, salMEAN, chlMAX, chlMEAN	0.15	104553.79	8.33	0.42
8	tempMAX, tempMIN, tempMEAN, salMIN, salMEAN, chlMIN, chlMAX, chlMEAN	0.15	104554.27	8.81	0.56
9	tempMAX, tempMIN, tempMEAN, salMIN, salMEAN, chlMAX, chlMEAN	0.15	104555.36	9.90	0.73

Table 2-6. Model Selection results for dataset using daily minimum dissolved oxygen concentrations.

Model rank	Independent variables	adj r^2	AIC	Δ AIC	ω_i
1	tempMEAN, salMIN, salMAX, chlMIN, chlMAX, chlMEAN	0.51	42692.95	0.00	0.28
2	tempMAX, tempMEAN, salMIN, salMAX, chlMIN, chlMAX, chlMEAN	0.51	42693.43	0.47	0.31
3	tempMAX, tempMIN, tempMEAN, salMIN, salMAX, chlMIN, chlMAX, chlMEAN	0.51	42693.98	1.03	0.33
4	tempMIN, tempMEAN, salMIN, salMAX, chlMIN, chlMAX, chlMEAN	0.51	42694.90	1.95	0.32
5	tempMEAN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.51	42694.94	1.99	0.45
6	tempMAX, tempMEAN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.51	42695.43	2.47	0.65
7	tempMIN, tempMEAN, salMIN, salMAX, salMEAN, chlMIN, chlMAX, chlMEAN	0.51	42696.90	3.95	0.90

2-3.3 Z-Score Metrics

Color-coded maps of the z-scores for the two failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values are shown in the figures on the following pages. We have grouped stations so that z-scores indicative of seasonal variability are together (Newport Creek, Greys Creek, Bishopville Prong, Little Monie Creek, Ft. McHenry, Sycamore Point, and Mattaponi). Stations that have some variability in temperature that is seasonal, but where values for the failure criteria have not changed over time (Sandy Point South, Locust Point Marina, Iron Pot Landing: *Please note that there could have been failures throughout the time series at these three stations, it's just that those failures are not variable!)*. Stations where failure criteria seem to be improving (Rolphs Warf, Jug Bay, Susquehanna Flats, Piscataway, St. Georges Creek, Public Landing). Stations that are getting worse (Deep Landing, Budds Landing). And stations that are all over the place for DO criteria (Shelltown, Otter Point, Possum Point, Mattawoman Creek, Piney Point, The Sill). The degree to which the maps reflect changes from blue to red reflect the variability that a given station has experienced over the time frame for which we have ConMon data. So, for example, stations like Newport Creek or Sycamore Point exhibit variability that is seasonal, but the strength of that variability does not appear to have changed over the time frame for which we have measurements. For a station like Piscataway Creek, we can visualize a "cooling" over the time series, with less incidents of DO failure, chlorophyll-a concentrations that shift below the long term mean, DO minimum values that are improving, and temperature conditions that remain seasonal in nature. Recall that the DO minimum z-scores were transformed by multiplication of -1 so that the cooler, blue colors indicate an improvement (higher DO concentrations) to assist in visually interpreting the z-score maps. A challenge of comparing the maps over the dataset is related to the unequal sampling for each station's time series. So, for example, The Ft. McHenry station appears to exhibit bluer colors in more recent years, but this also corresponds to more numerous available measurements per year since 2009. Should the EPC pursue this tool in future efforts, we recommend some standardization of sampling frequency.

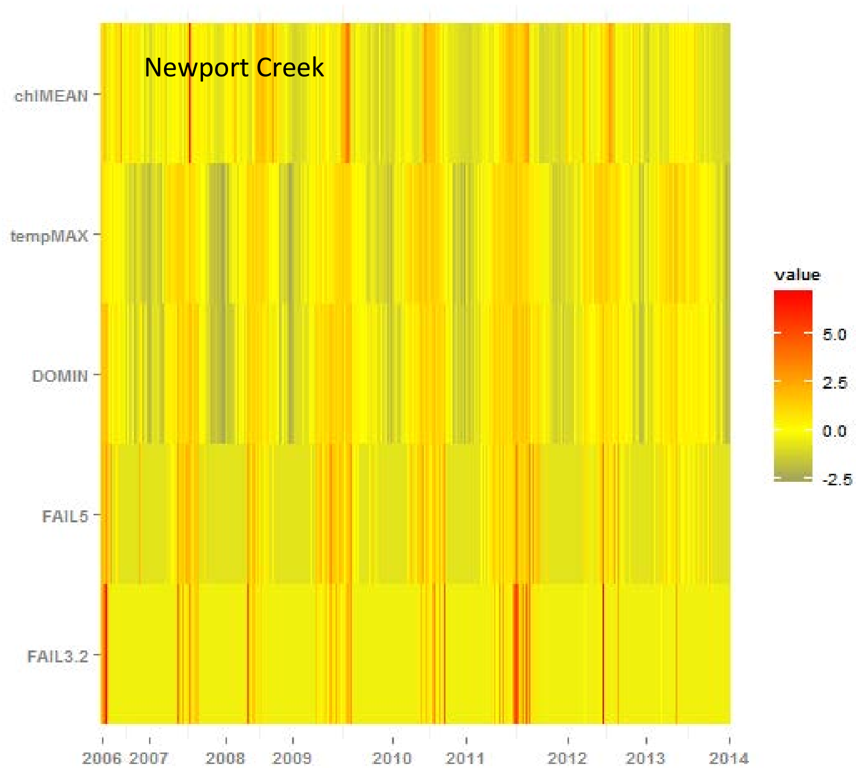
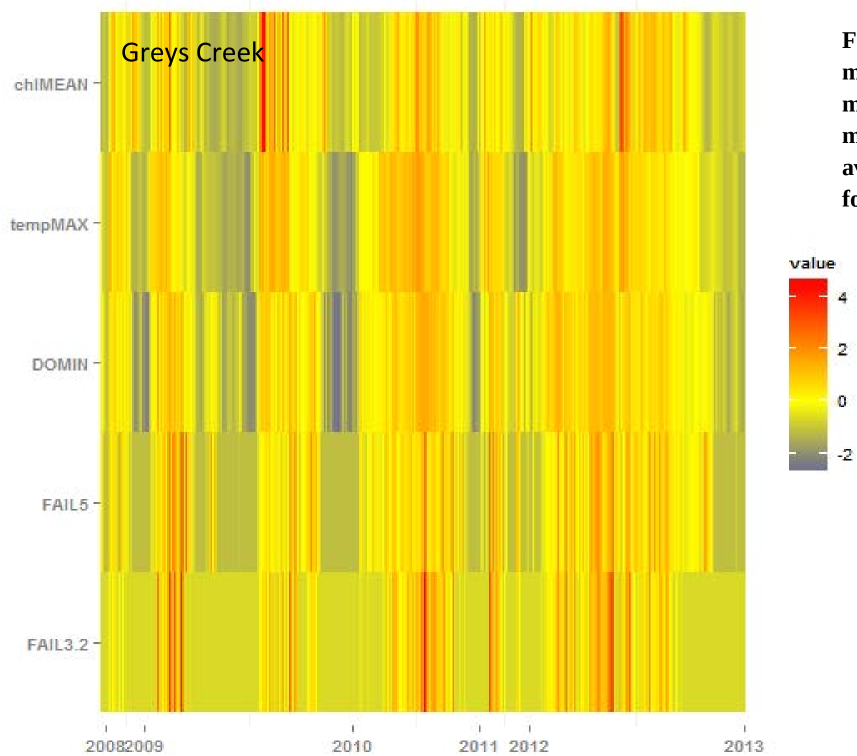


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



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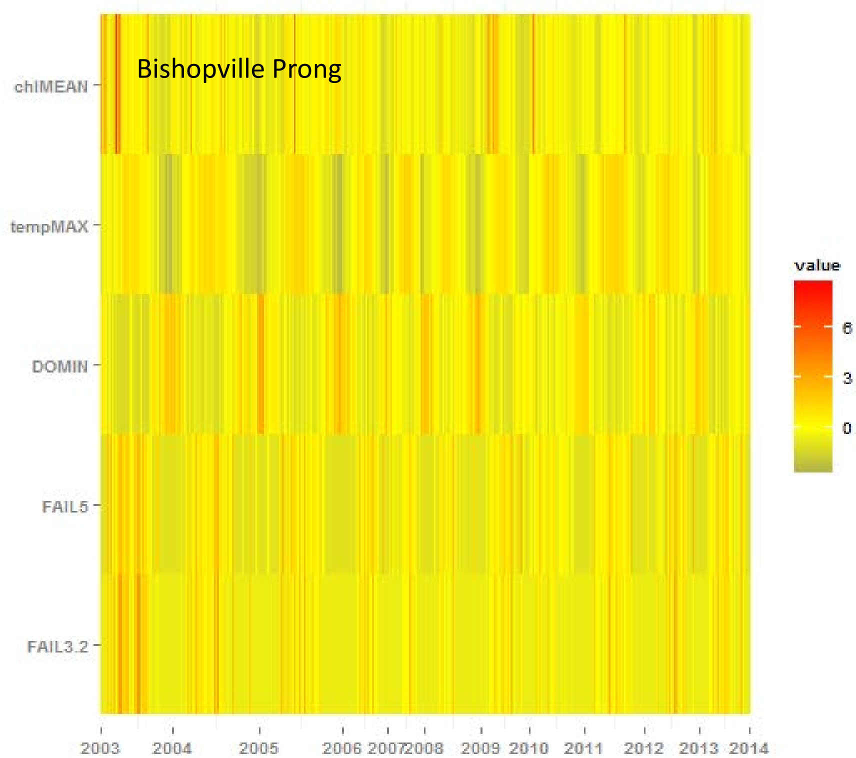

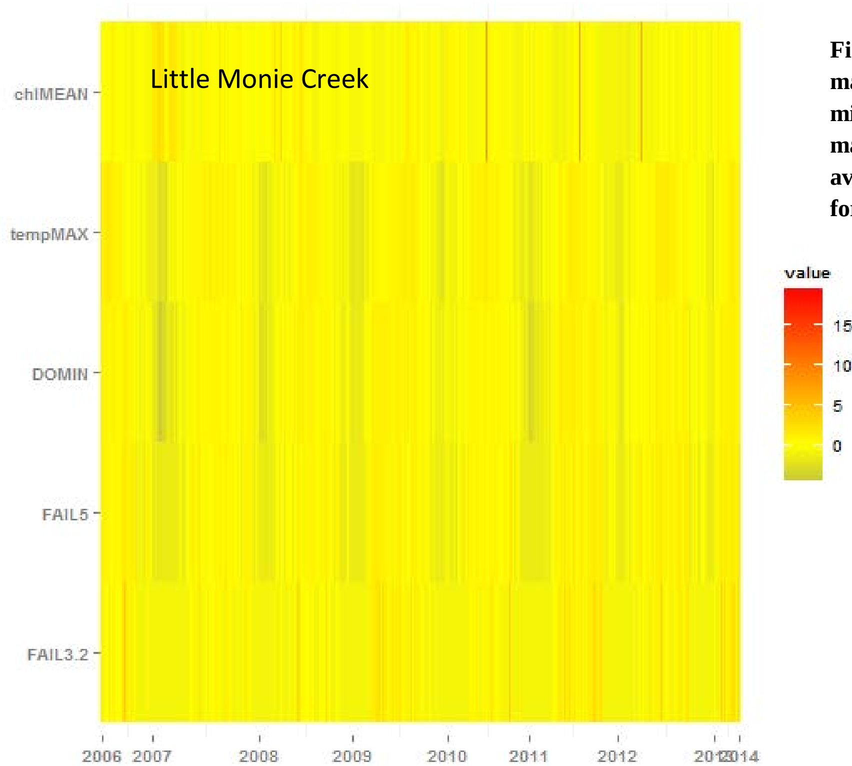

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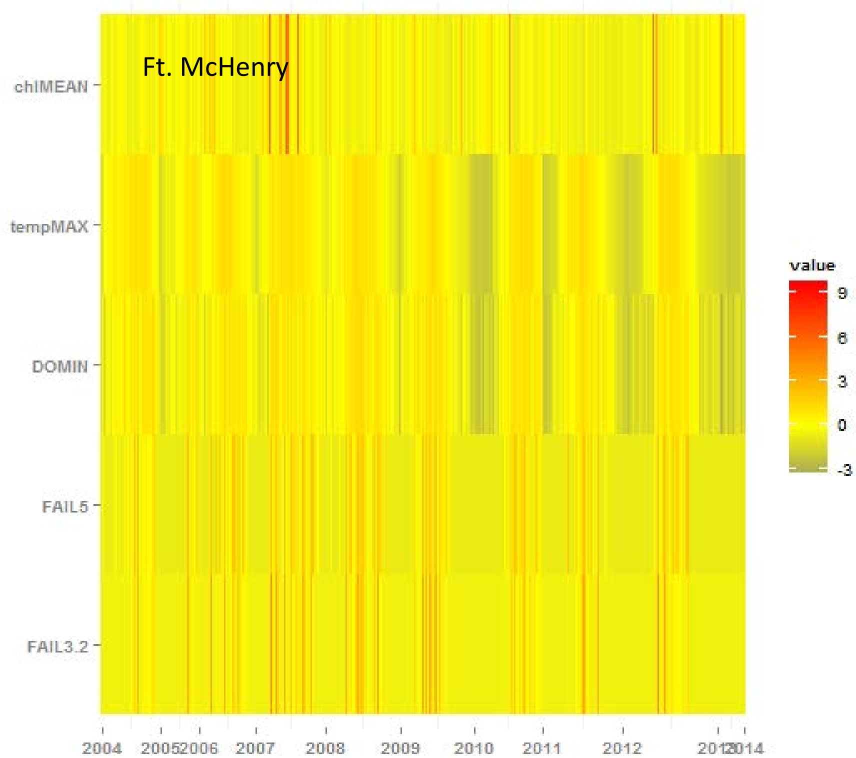

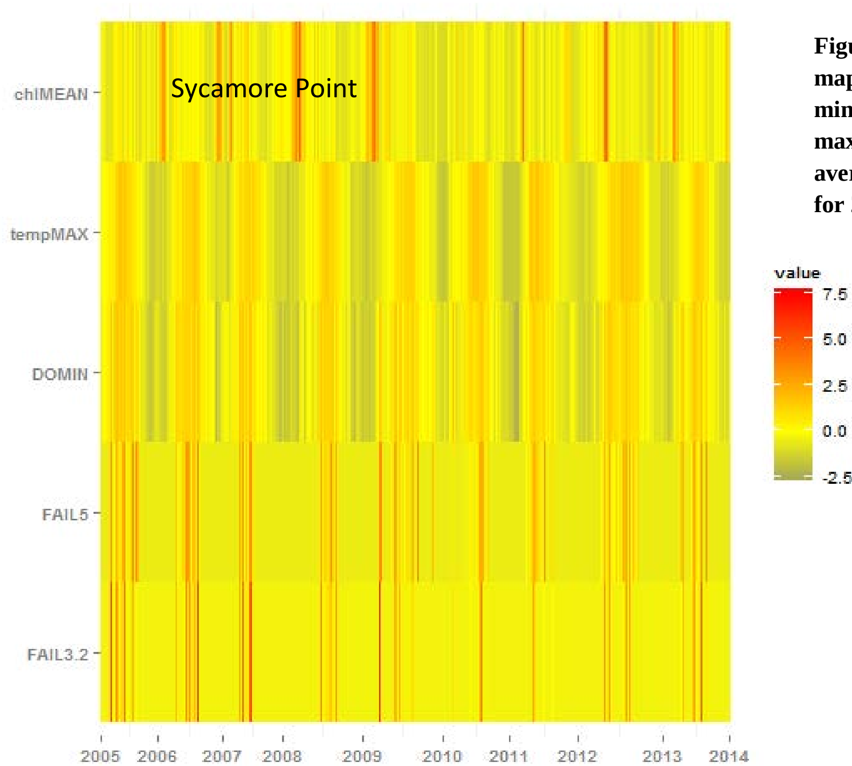

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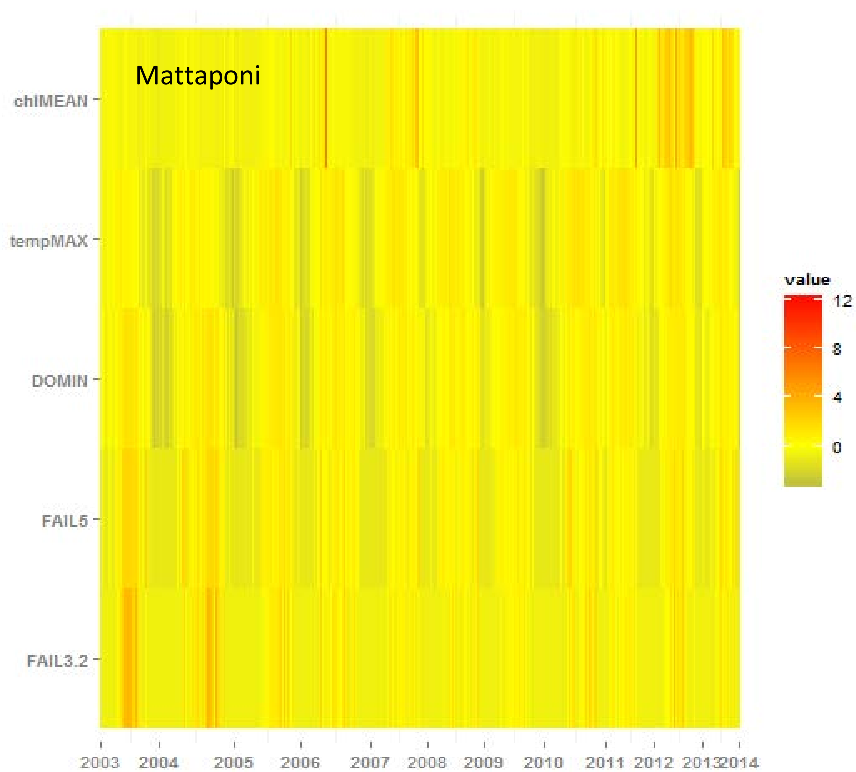


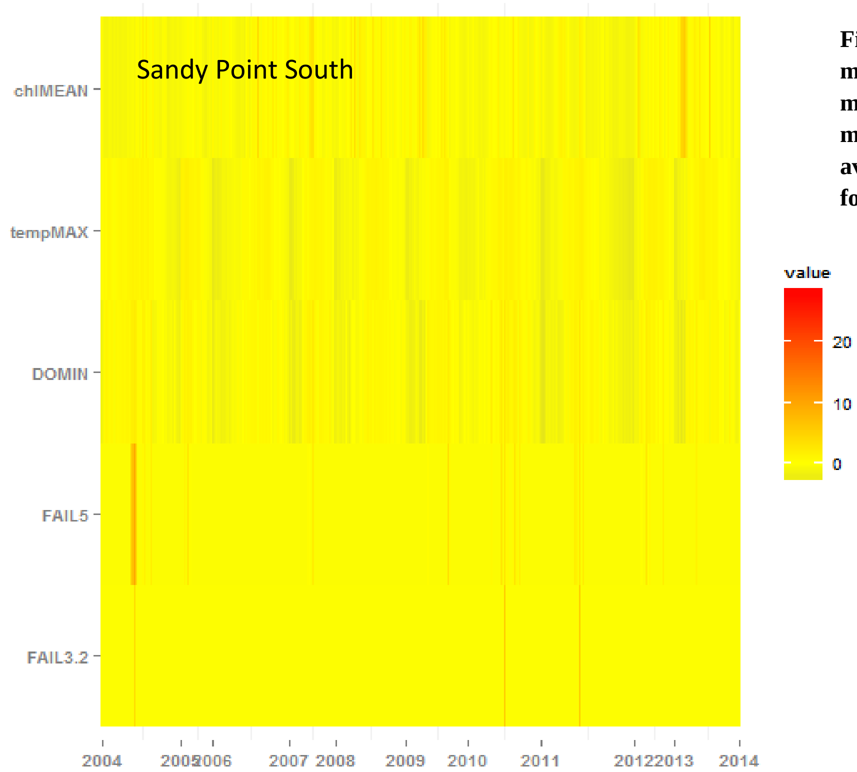
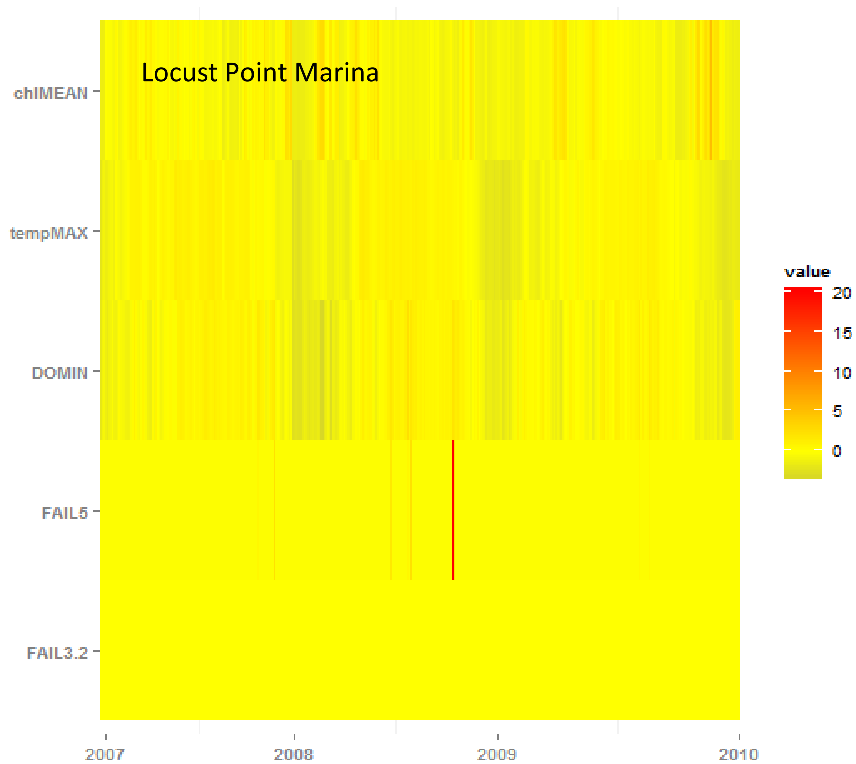


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



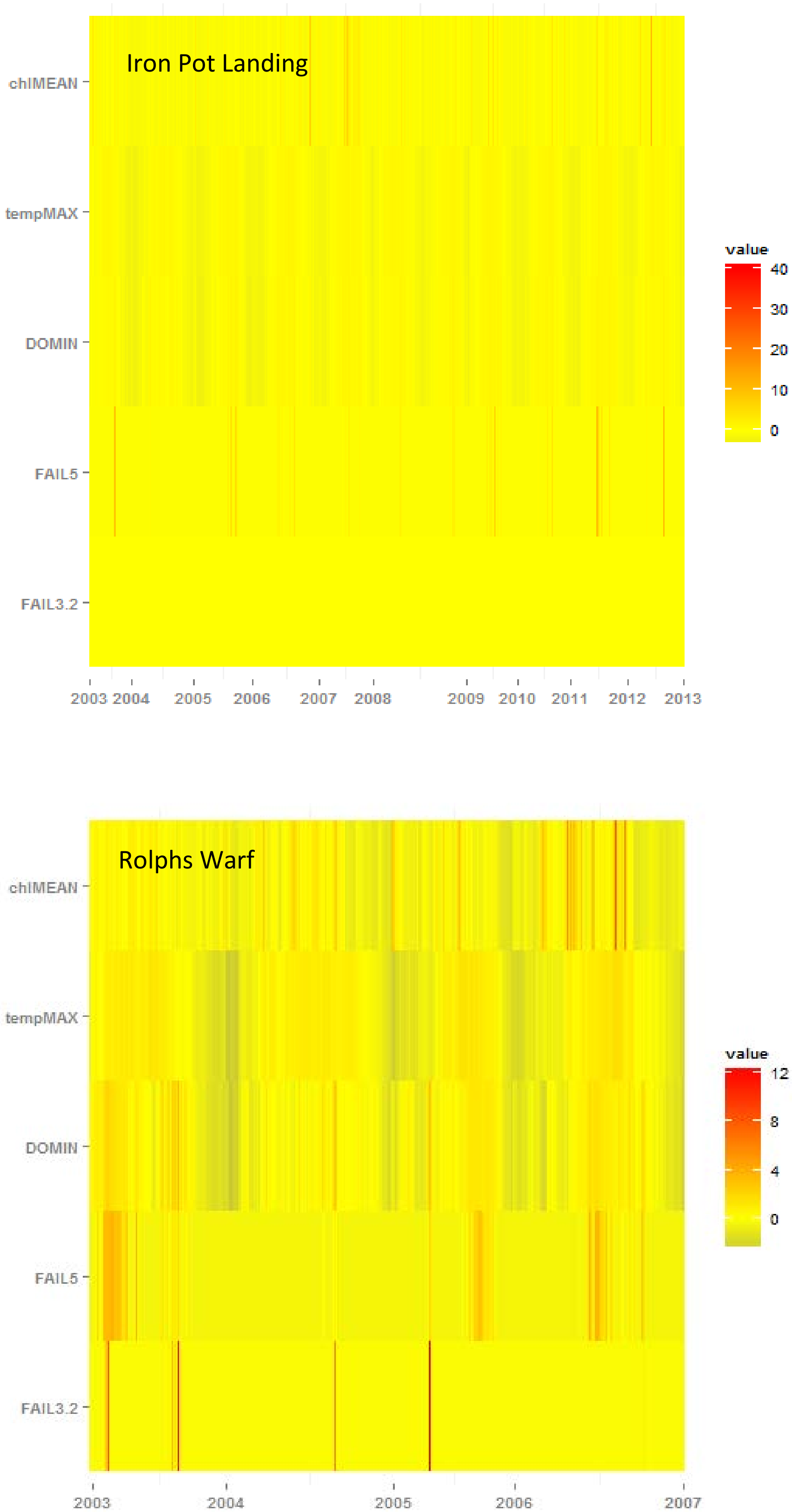
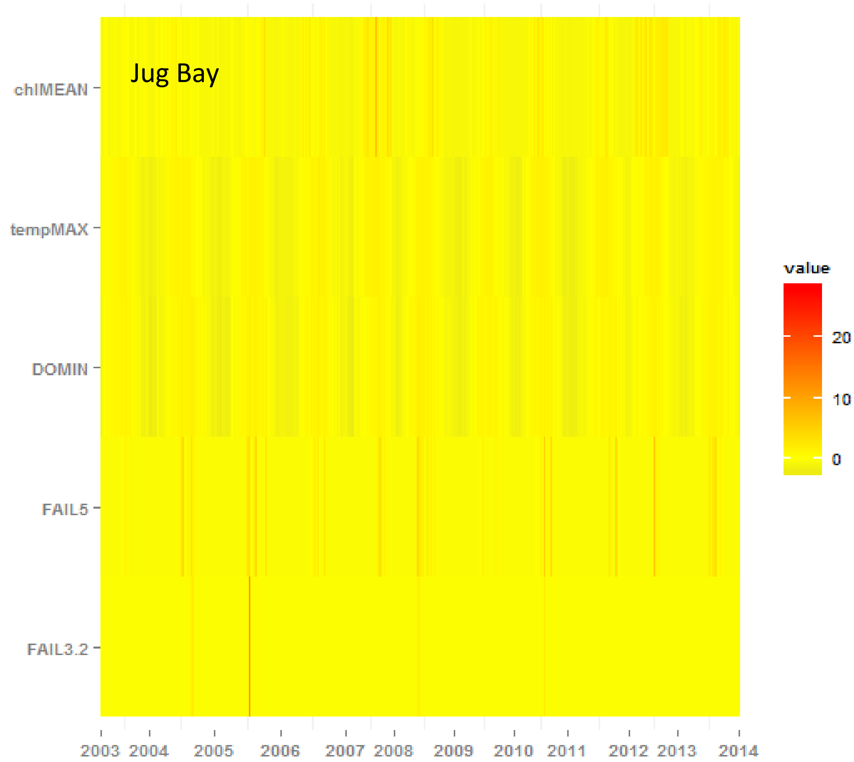


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



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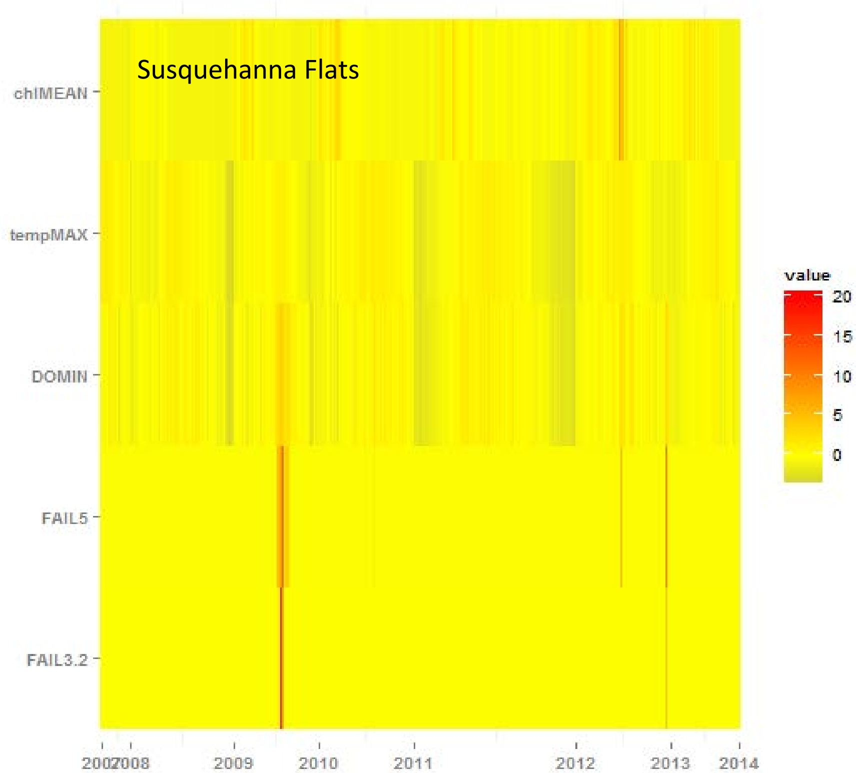


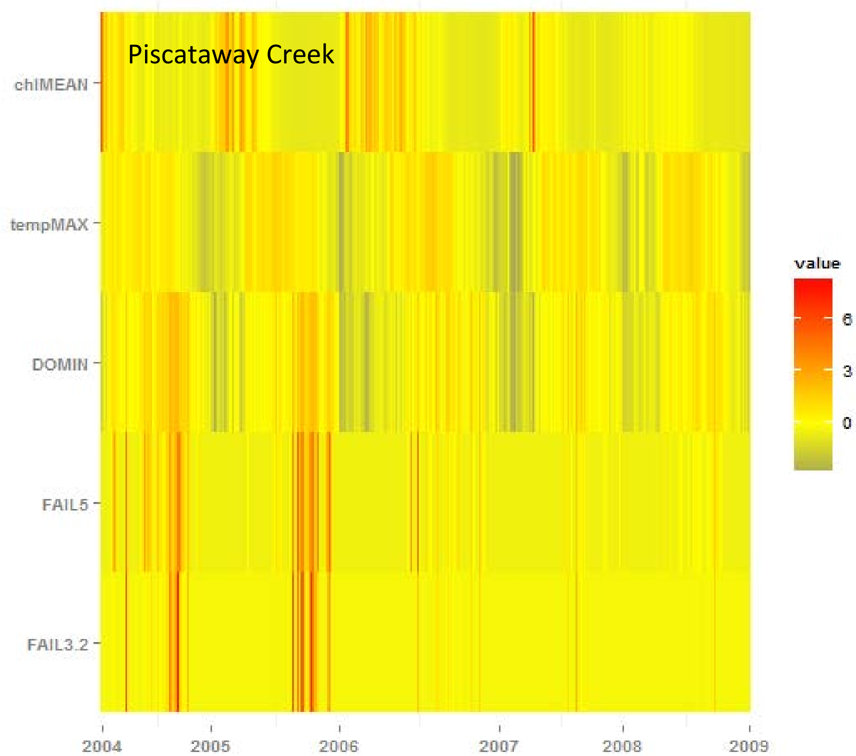
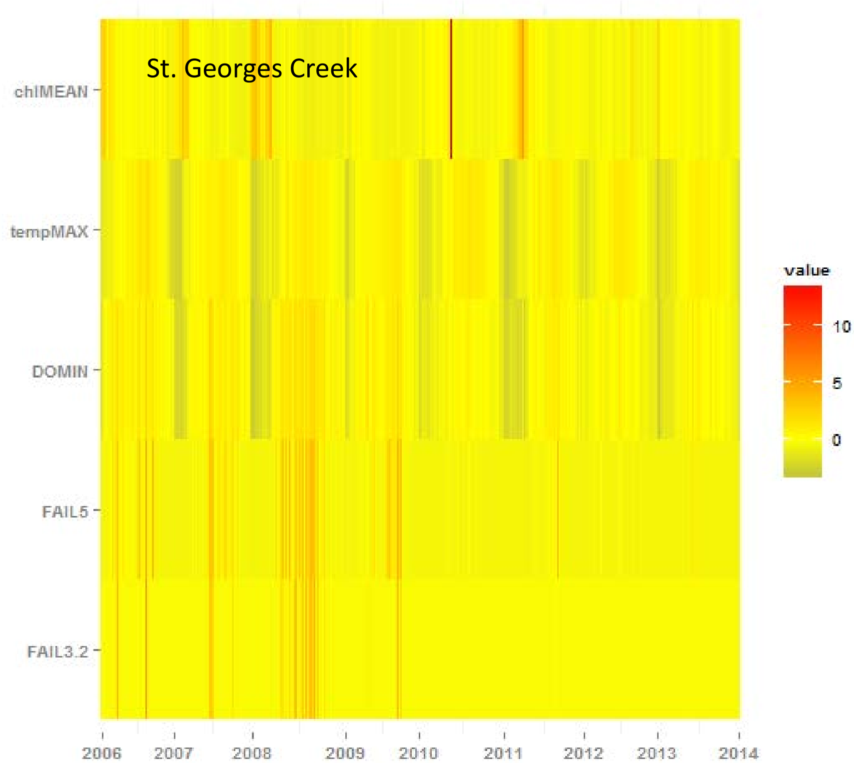


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



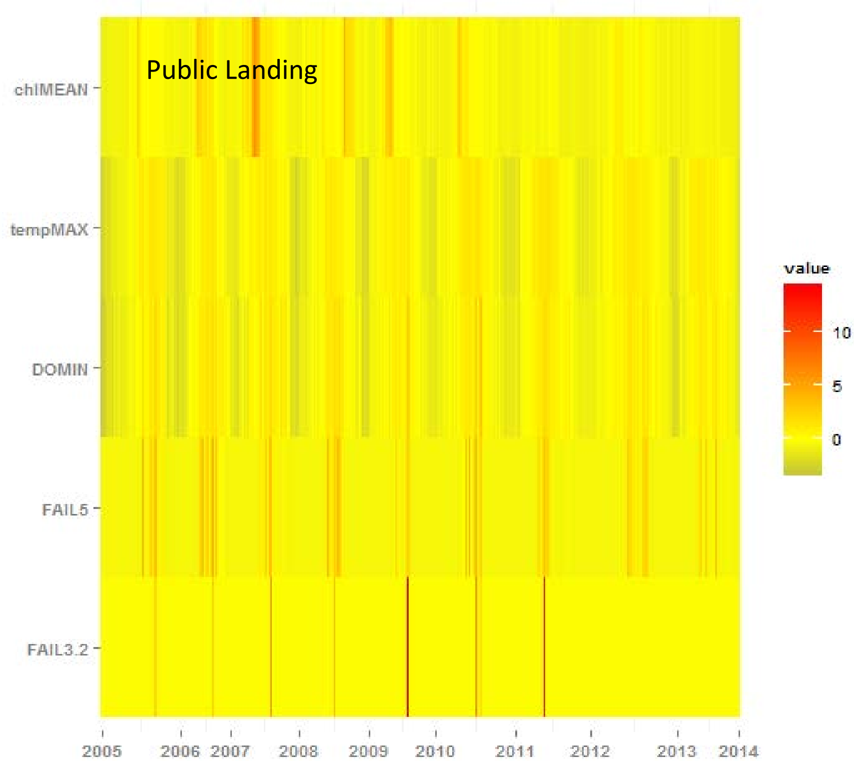
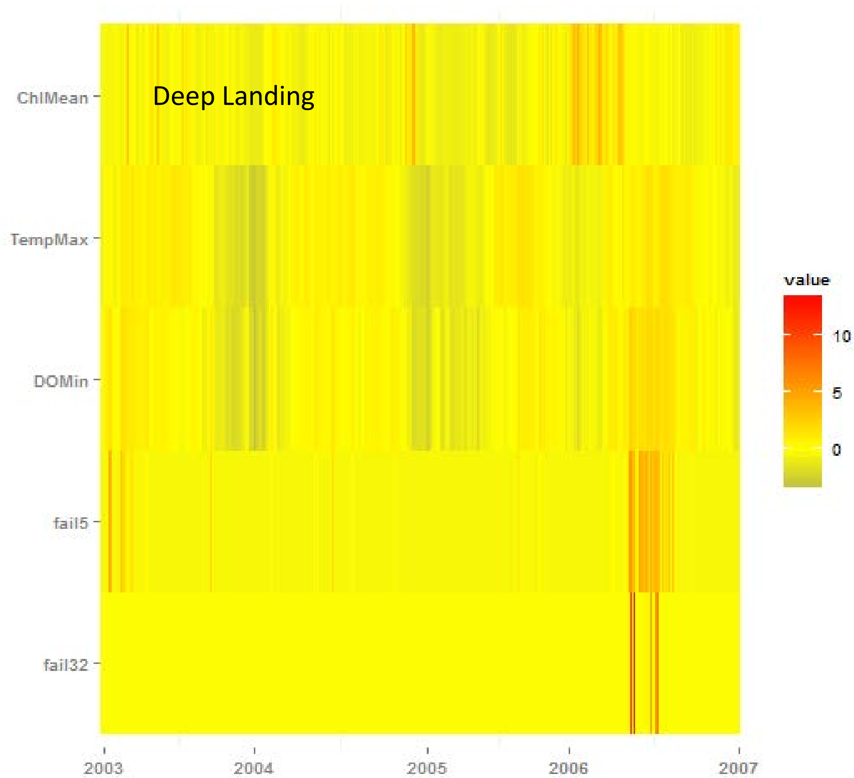


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



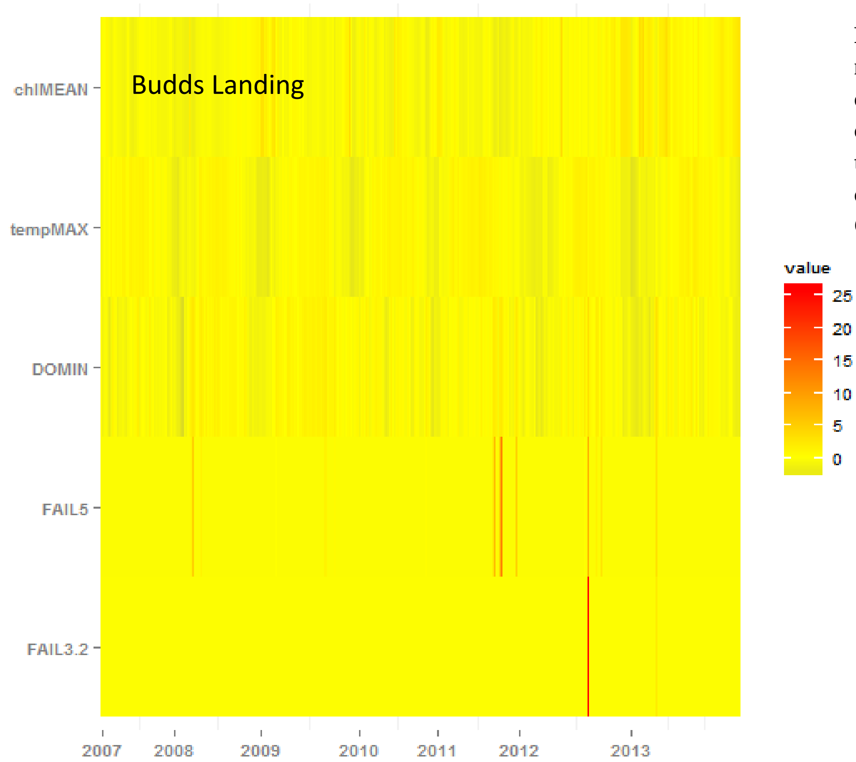
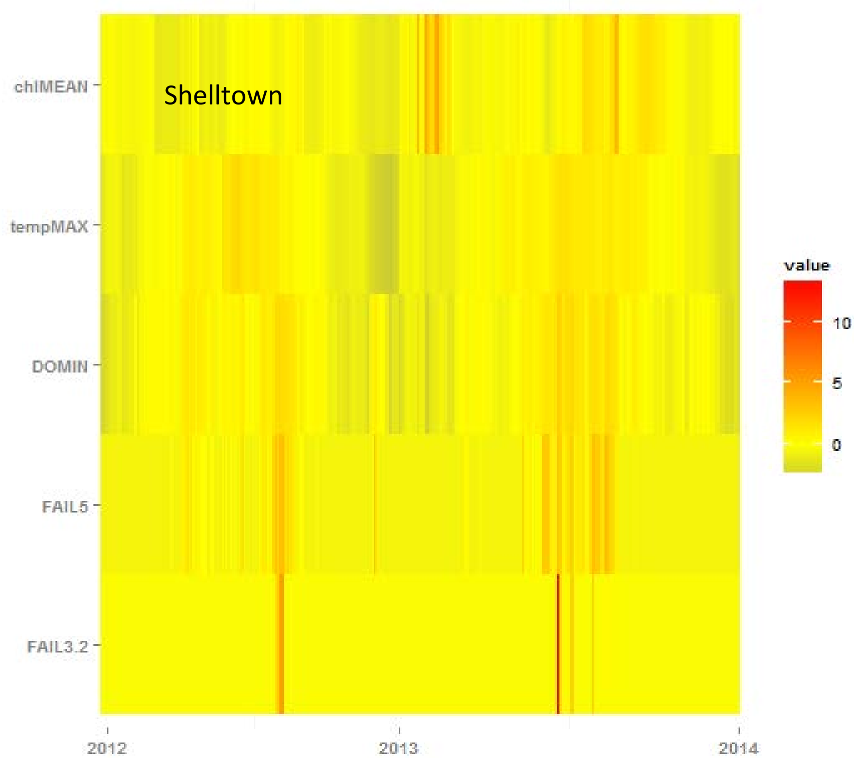


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



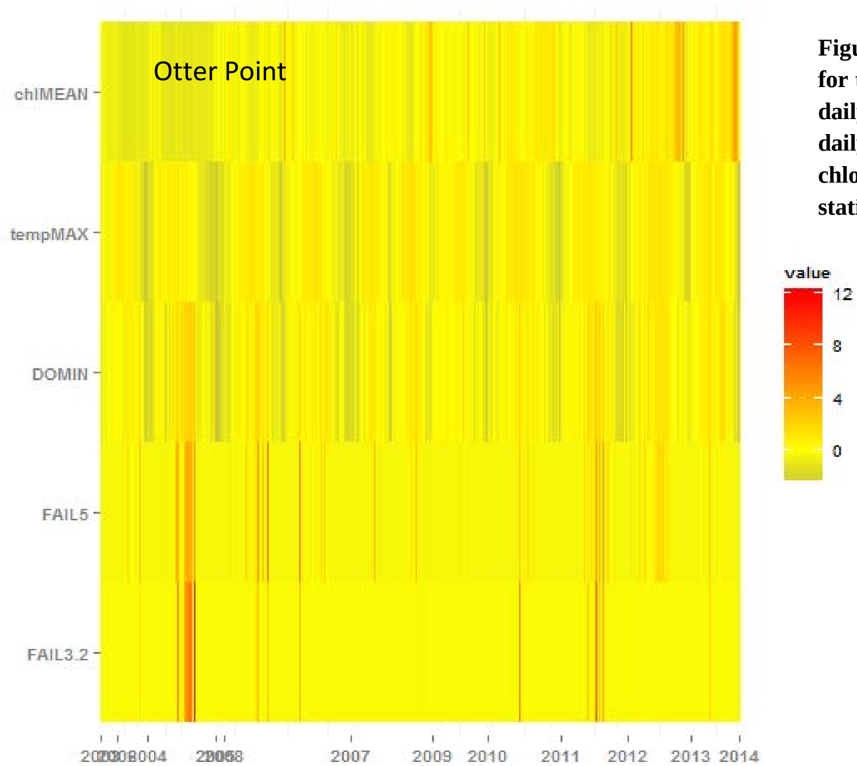
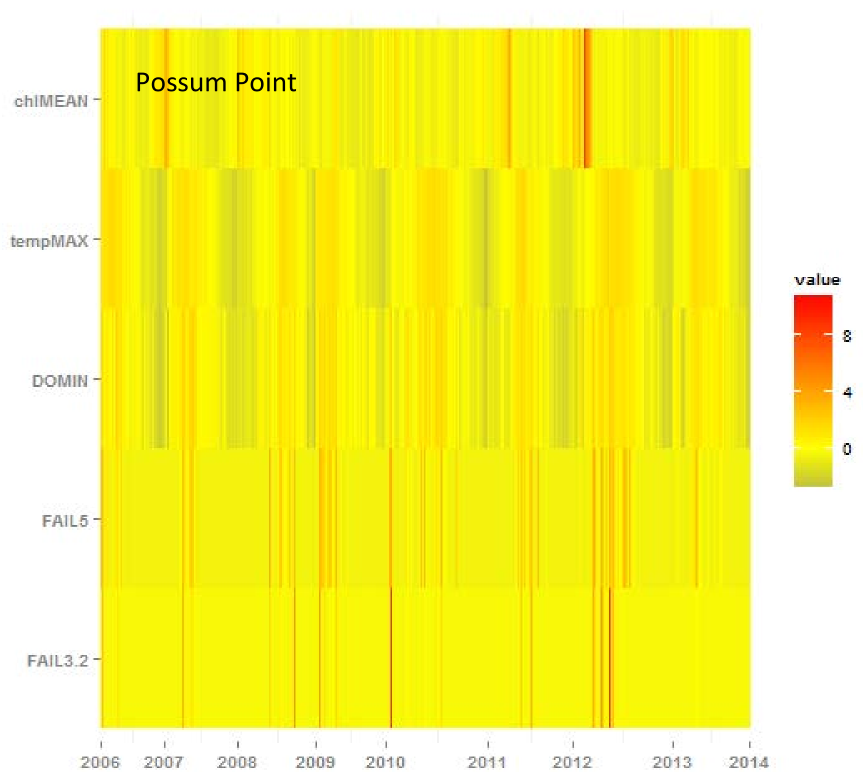


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



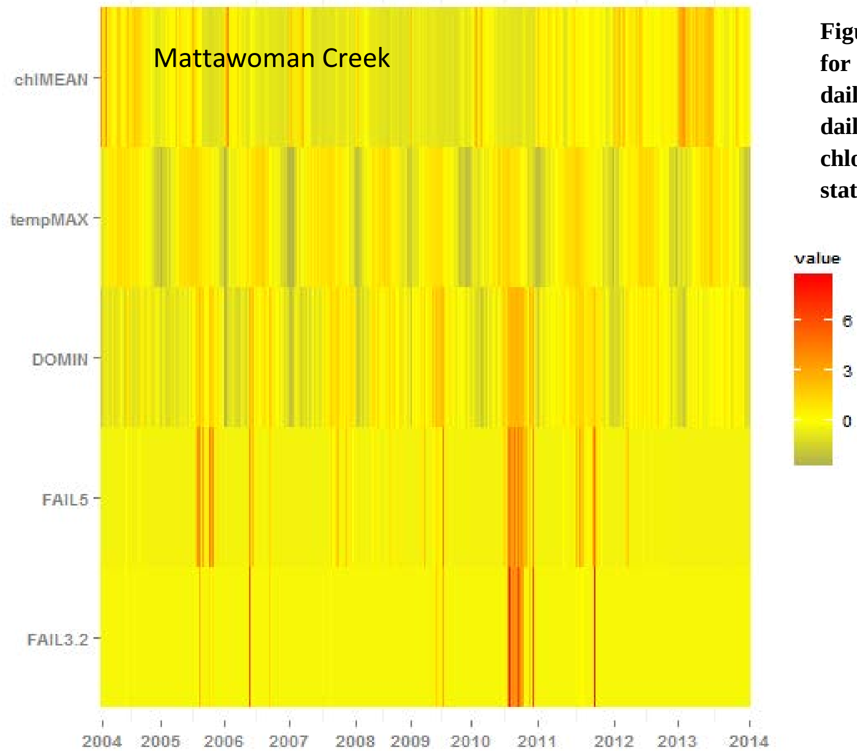
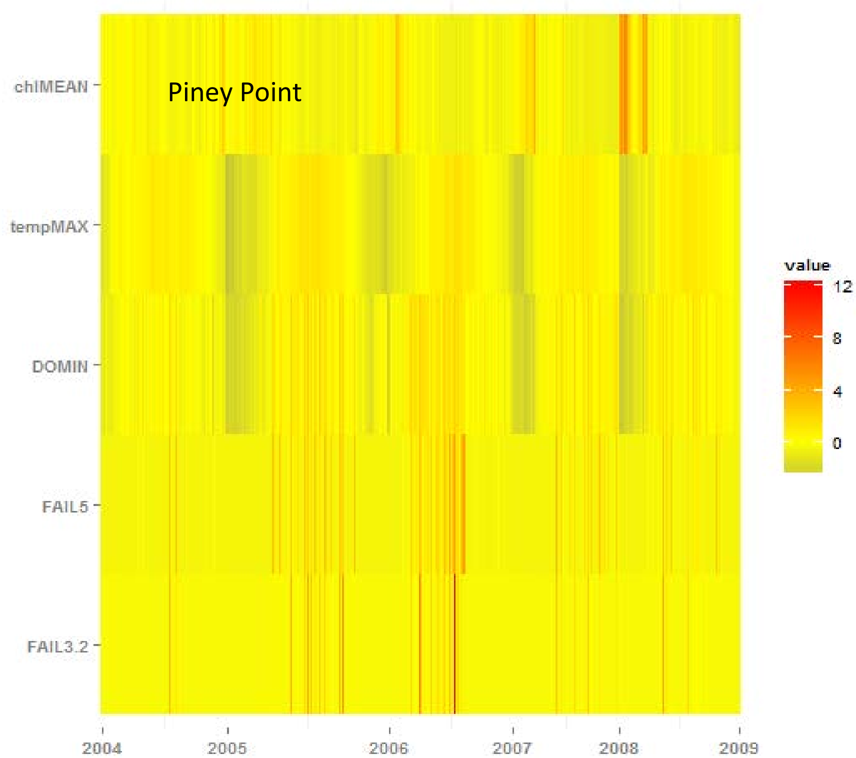


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon stations



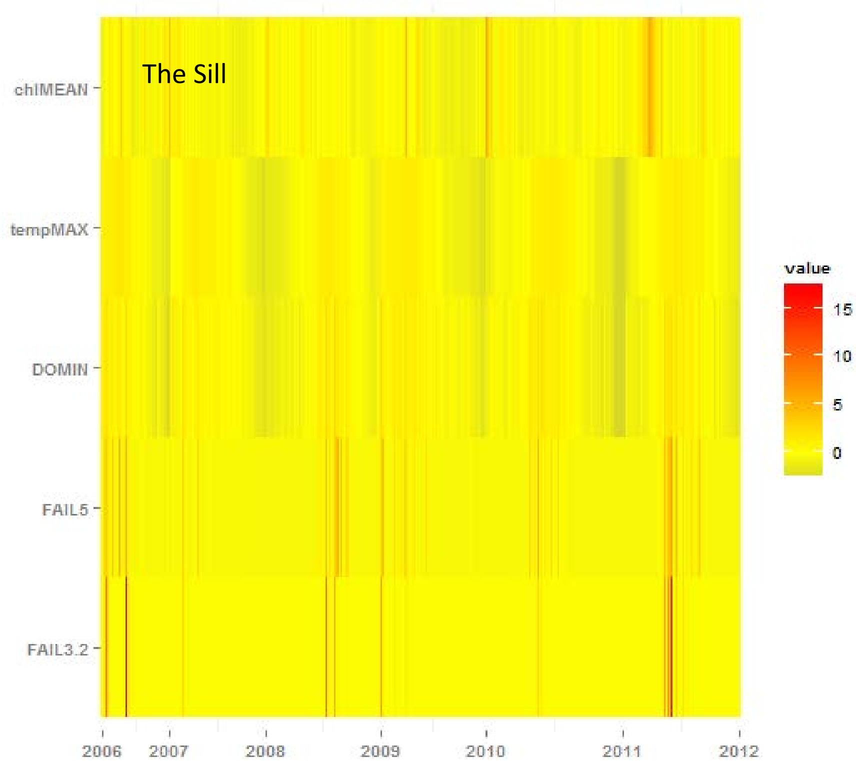


Figure 2-3. Color-coded z-score maps for two DO failure criteria, minimum daily DO concentrations, maximum daily temperature, and average daily chlorophyll-a values for 24 ConMon station

2-3.4 Spectral Analysis

2-3.4.1 Dominant Time-Scales of Water Quality Variability

Throughout the ConMon dataset, three clear timescales were dominant in the data, including annual, diurnal (1 cycle per day), and tidal (2 cycles per day). For stations that lacked sampling over the entire annual cycle, the annual PSD was weak so we could not compare the PSD across all 25 stations. Thus we focused our analysis on the relative magnitude of the power spectral density at the diurnal and tidal time scales. For each station and variable, we computed the sum of PSD values (y-axis in Figure 2-2) around the target frequency (0.9-1.1 for diurnal, 1.9-2.1 for tidal). We then compared the diurnal PSD versus the tidal PSD for all stations, revealing the dominant frequency of variability for each variable. For salinity, PSD was always larger at the tidal frequency, indicating the obvious dominance of tides in driving sub-daily salinity variation (Fig. 2-4). In contrast, diurnal variation in DO was higher than that for salinity at all but 3 of the 25 sites, indicating a biologically-driven dissolved oxygen cycle at these sites (Fig. 2-4). It is in these 22 systems that we expect oxygen variability, and thus criteria failure, to be a potential function of nutrient loading. For pH, we found a slightly more even mix of tidally- and diurnally-dominated signals (6 out of 25 sites), indicating the potential for both biologically-driven variation and buffering associated with inputs of higher salinity water with tidal fluctuations (Fig. 2-4).

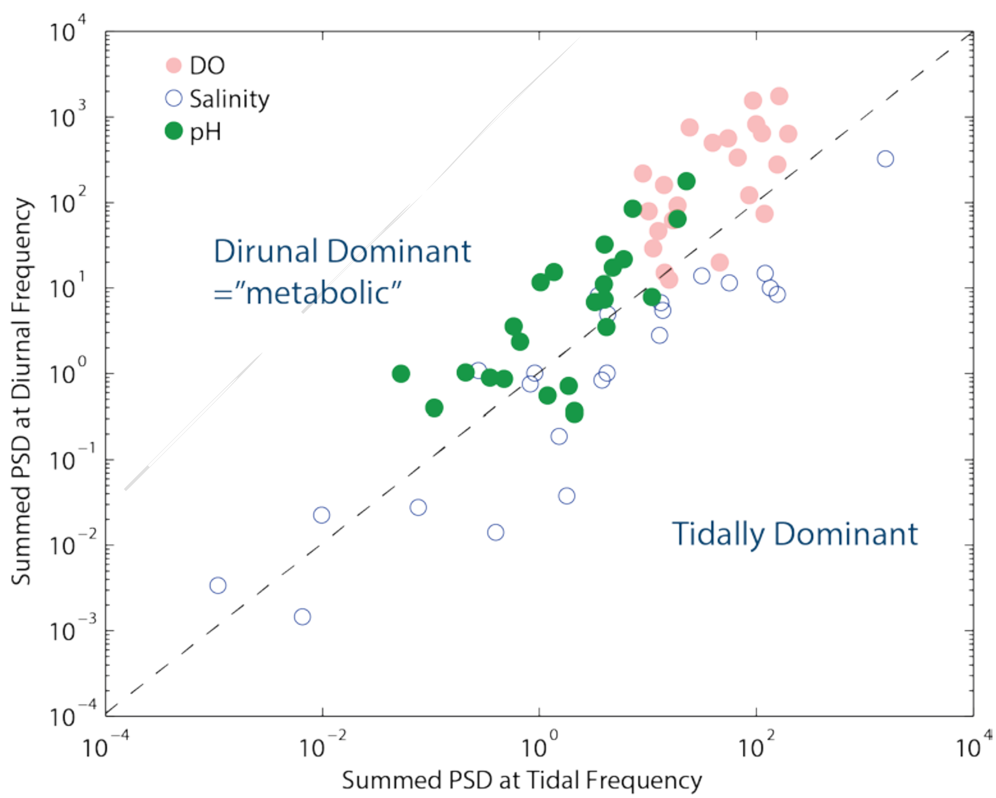


Figure 2-4. Relationship of sum PSD at tidal and diurnal frequencies for salinity, DO, and pH at 25 ConMon stations.

2-3.4.2 Contrasting Sites: Key Diurnal and Tidal Signals

The key question then becomes, “Why do these stations have different strengths of the diurnal signal for DO and pH?” We presume that high diurnal variability at a station is the result of high metabolic activity associated with elevated phytoplankton concentrations or dense SAV populations, especially where tidal forcing and atmospheric exchange are relatively weak. The diurnal signal can be weakened if tides deliver water from adjacent locations with higher or lower oxygen concentrations, which can confound the local rate of change. In our summary of 25 ConMon stations, the eight stations with the highest diurnal signal represent a range of habitat types and nutrient states. For example, Newport Creek (Md Coastal Bays), Sycamore Point, Budds Landing, and Fort McHenry are eutrophic sites that have high nutrient concentrations and elevated chlorophyll-a levels relative to nearby locations (Fig. 2-5). Piscataway Creek and Susquehanna Flats are dominated by dense SAV beds whose metabolism is high, driving large diurnal swings in DO and pH. Otter Point Creek (Bush River) and Mattaponi (Patuxent River) have large DO signals, but the reasons for these high signals are less clear. Although this assessment is somewhat qualitative at this point, the stations we would expect to be most dominated by diurnal signals are those with high biological activity. In contrast, the sites where the tidal signal is stronger than or equal to the diurnal signal (Shelltown, Deep Landing, Whitehaven, The Sill (bottom); Fig. 2-5) suggest strong tidal influences at the sites and indicate that these sites are either not eutrophic or that a potentially strong metabolic component is masked by strong tidal inputs. Regressions of local tidal range with the tidal salinity PSD were weak and insignificant, suggesting a factor beyond simple tidal height in controlling tidally-induced variability. Future analysis of these patterns might be useful for removing tidally-induced variability from the DO data to more clearly examine and quantify criteria failure and metabolic rates (production and respiration).

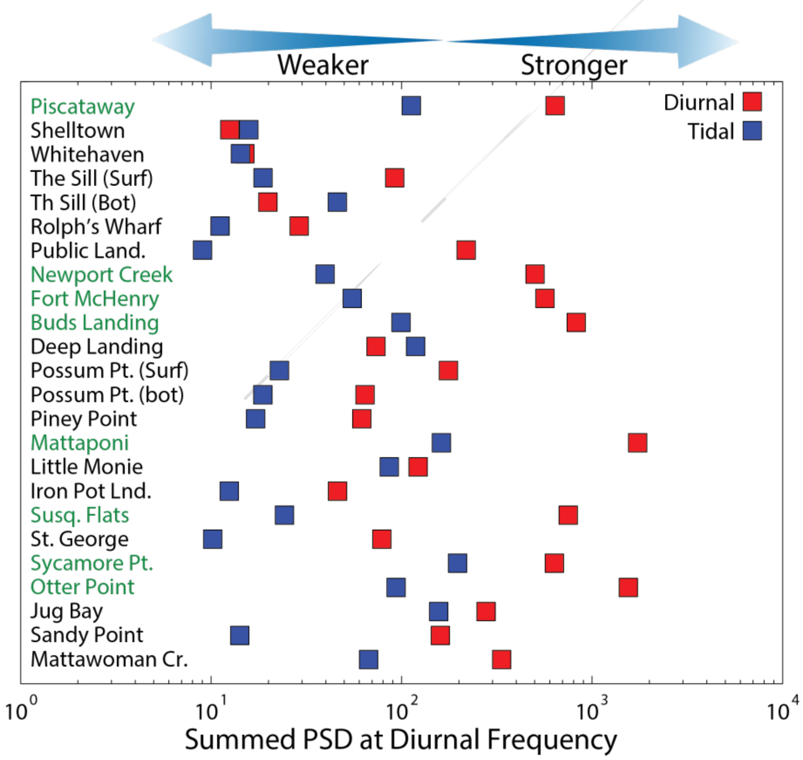


Figure 2-5: Summed PSD for DO at all stations for both the diurnal and tidal frequencies. Station names are to the right, where the eight stations with the largest diurnal variability are denoted with green text.

2-3.4.3 Relationship of DO to pH and Chlorophyll-a

For variables that represent biological activity, such as pH, DO, and chlorophyll-a, we would expect strong correlations between the diurnal variability in these variables across sites. Strong diurnal DO signals are strongly correlated with diurnal pH signals (Fig. 2-6, top), indicating that primary production and respiration concurrently impact DO and pH (via CO_2 changes). A similar relationship was not found between diurnal DO variability and chlorophyll-a (Fig. 2-6, bottom). This lack of clear linear, univariate relationship between DO and chlorophyll-a is also a take-home message from our model selection exercise. Our analyses suggest that, at a minimum, multiple regressions are more appropriate for predicting DO and nonlinear models should also be considered.

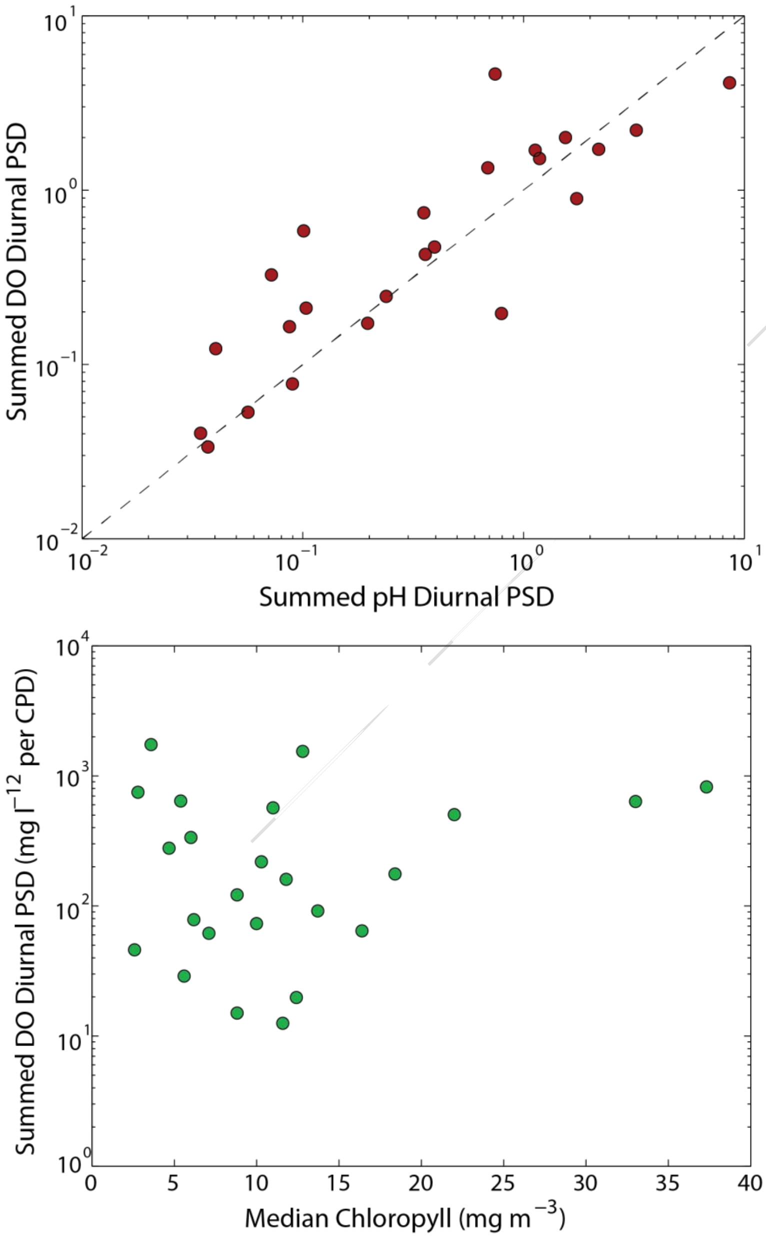


Figure 2-6. (top) Relationship of the sum diurnal DO PSD and the sum diurnal pH PSD at 25 ConMon stations. PSD is normalized to the mean for each variable, as DO PSD is roughly an order of magnitude higher than pH. (bottom) Relationship of the sum diurnal DO PSD and the median chlorophyll-a at each site.

2-3.5 Hypoxic Hours and Criteria vs Chlorophyll-a

We would expect strong relationships between chlorophyll-a and low oxygen conditions in systems where phytoplankton production, biomass, and respiration is large enough to drive oxygen dynamics and where biological oxygen cycling is the dominant driver of oxygen variability. We plotted mean summer (June-August) chlorophyll-a against four metrics of oxygen deficit at all ConMon stations: 1) total hours below 2 mg L^{-1} 2) total hours below 3.2 mg L^{-1} 3) the % instantaneous failure when 2 mg L^{-1} threshold oxygen level and 4) the % instantaneous failure of 3.2 mg L^{-1} threshold oxygen level. The results reveal a wide variety of relationships between indices of phytoplankton biomass and the tendency for depleted oxygen. In the highly eutrophic Corsica River, positive relationships between chlorophyll-a and both hypoxia and criteria failure highlight the association of high phytoplankton respiration and oxygen depletion (Fig. 2-7). A strong driver of this correlation is the Sycamore Point stations, where dense phytoplankton communities and shallow depths allow for long durations of low-oxygen conditions.

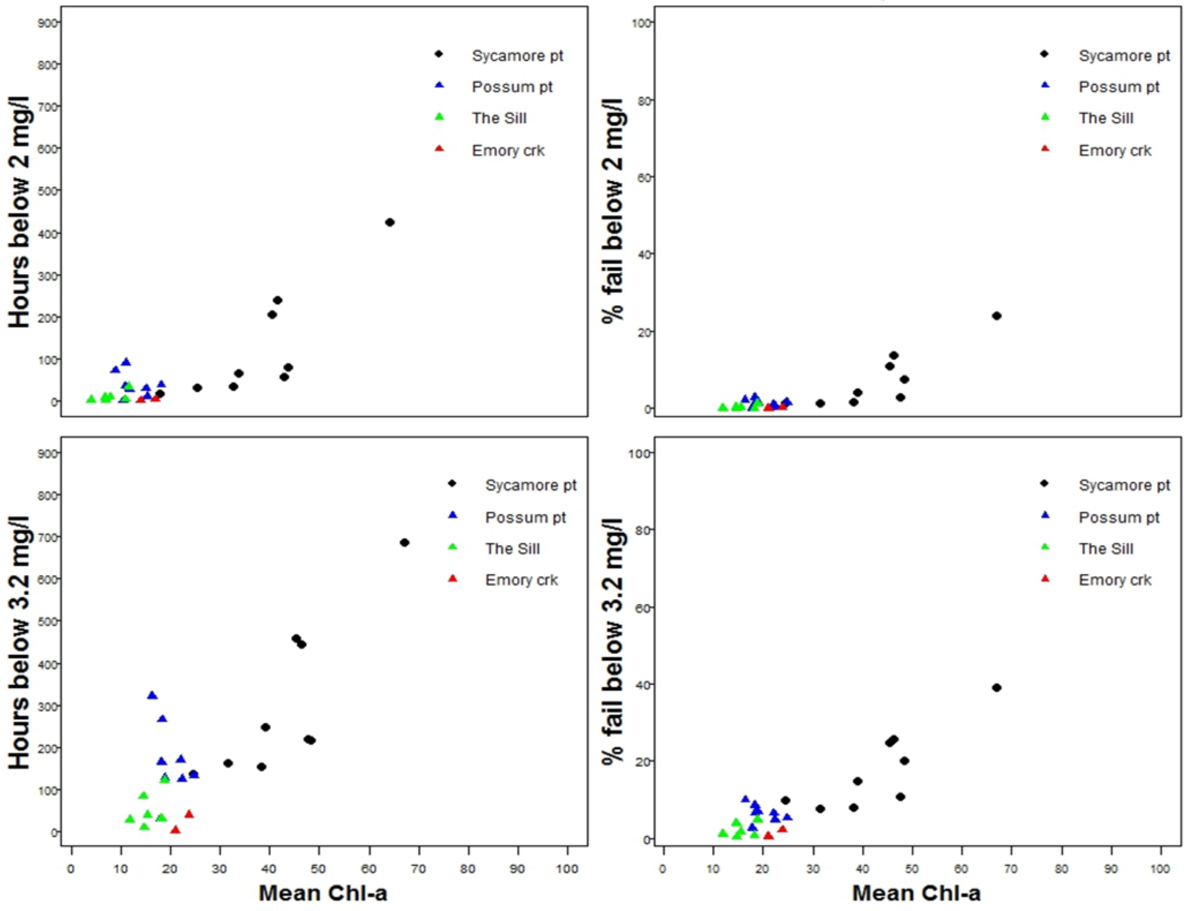


Figure 2-7. Relationship between mean summer chlorophyll-a and four different oxygen metrics at Sycamore Point, Possum Point, The Sill and Emory Creek in the Corsica River estuary.

Such simple correlations between criteria failure and chlorophyll-a were not found within the deeper, more mesohaline stations (Fig. 2-8), but positive relationships were found for the smaller, northern stations (Fig. 2-9). In total, these varied relationships reveal the complexity of the relationship between phytoplankton biomass and the tendency for a system to fail a particular criteria for dissolved oxygen, highlighting the importance of local physical circulation and other physical variables (Table 2-6).

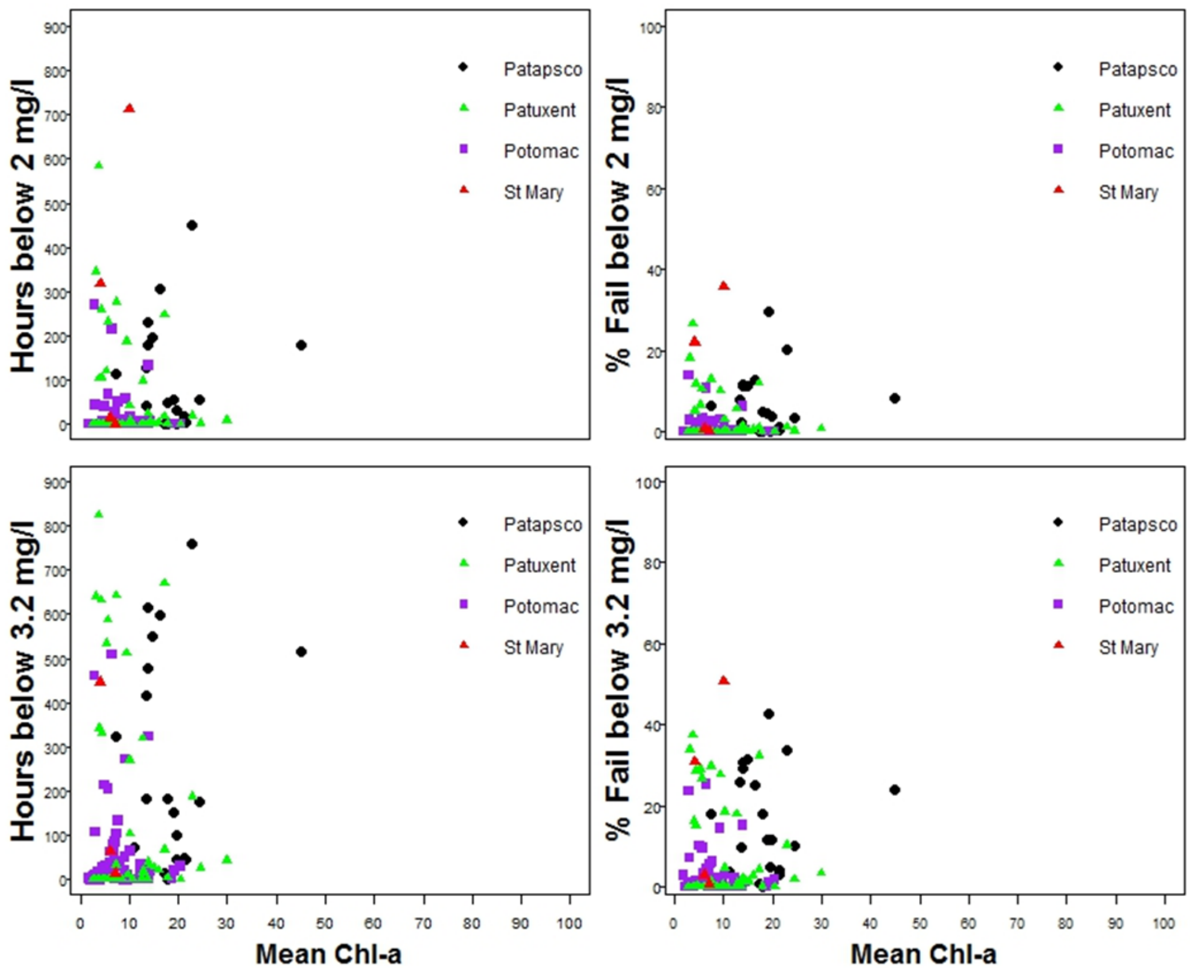


Figure 2-8. Relationship between mean summer chlorophyll-a and four different oxygen metrics in the Patapsco, Patuxent, Potomac, St. Mary's estuaries.

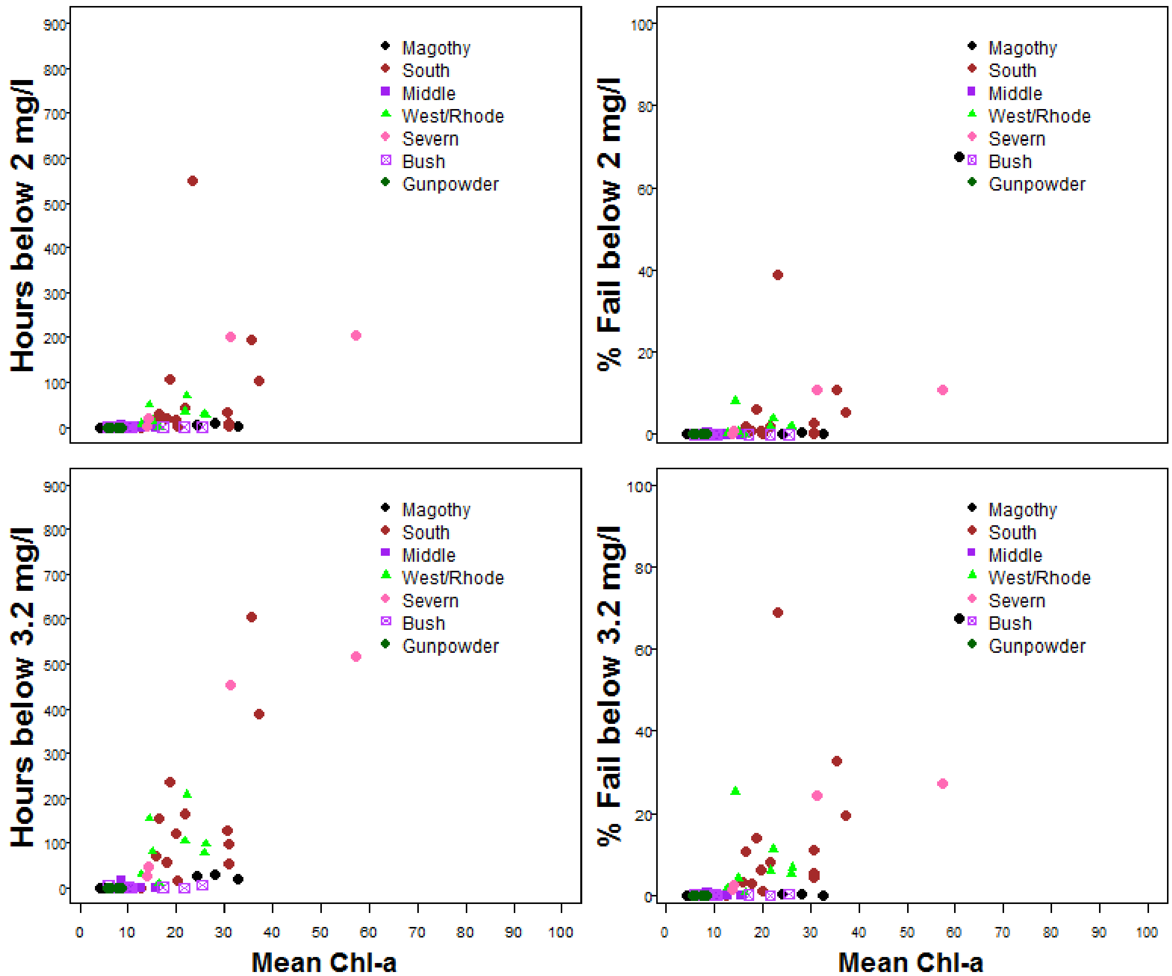


Figure 2-9. Relationship between mean summer chlorophyll-a and four different oxygen metrics in the Magothy, South, Middle, West/Rhode, Severn, Bush, and Gunpowder estuaries.

2-4 Conclusions and Recommendations

The analyses presented in this chapter underscore the importance of both local physical conditions and biological processes in driving variations in water quality over multiple time scales. New quantitative tools were applied to relatively long time-series for 91 ConMon stations, revealing high variability among the sites in terms of criteria failure and the association of criteria failure with a single variable, such as chlorophyll-a. Model selection tools revealed the importance of temperature, salinity, and chlorophyll-a in driving criteria failure, which emphasizes the (1) diverse drivers of variation in DO and (2) the potential to predict criteria failure from data supplied by the ConMon sensors themselves. More specifically:

- To explore the variability of the dataset over time and visualize emergent trends, we computed z-scores for a subset of the ConMon stations (n=24). Z-scores standardize measurements to the station's long term mean and standard deviation and can be used in color maps to evaluate how variable the measurements are over time and whether the general direction of change for a given station is for improving or declining water quality. This first look at a subset of stations revealed some locations where seasonality is strong and has been consistent (Newport Creek, Sycamore Point), improvements at Piscataway Creek, and unchanged, consistently poor water quality at Bishopville Prong.

• Spectral analysis of a subset of the 91 ConMon stations revealed strong tidal and diurnal variability in dissolved oxygen, pH, and chlorophyll-a. While the diurnal signal (driven by photosynthesis (P) and respiration (R)) was more dominant for oxygen, salinity was dominated by tidal-timescale variation, suggesting that for most stations, photosynthesis and respiration drive oxygen variation. For these stations, we expect that nutrient reductions which reduce P and R, should improve oxygen conditions. For stations where tides dominate, physical variability may overwhelm biologically-induced changes.

• Hypoxia duration and oxygen criteria failure were strongly correlated with chlorophyll-a during summer in the Corsica River, as well as several smaller tributaries (e.g., Magothy, Severn), but relationships were much weaker for deeper, larger estuaries (e.g., Patuxent, Potomac).

Although the tools presented in this chapter are informative from a perspective of understanding all of the drivers on dissolved oxygen variability in shallow Chesapeake locations, future work would (1) build new predictive variables into the model selection exercise, (2) examine how the spectral properties of the variables change over time, and (3) develop a scheme to use the ConMon data to remove tidal and advective variation for DO time series.

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Chapter 3

Tributary Water Quality and Habitat Assessment: Corsica River Estuary

J.M. Testa, C.L.S. Hodgkins, W.R. Boynton, J.L. Humphrey, and L.A. Harris

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3-1 Introduction

One of the recent goals of TMAW and NTWG (Non-Tidal Work Group) has been to more closely link conditions in the watersheds of the Chesapeake Bay (e.g., trends in loads of water, N, P and sediments) to water quality and habitat conditions in tidal areas of the Bay. These workgroups have conducted several joint meetings each year to improve the flow of information, share evaluation approaches and generally develop a better understanding of land-estuary linkages for technical and public audiences. The EPC program has played a direct role in this effort. This group has now completed four case studies of areas of the Bay where strong management actions have reduced nutrient loads. From this effort it is clear that we now need to quantify the response of some of these systems to these nutrient load changes. The work described in Chapter 3 is a continuation of the effort to examine land – estuary linkages.

In the recent past the EPC group has conducted detailed tidal water evaluations, most recently for Mattawoman Creek, a tributary of the Potomac River estuary (Boynton et al., 2013). These evaluations included water and nutrient inputs (using multiple data sets and estimation approaches), estimates of exchange with other tidal systems, water quality conditions and trends, habitat assessments (focused on SAV), development of mass balance nutrient budgets, and development of simple statistical models linking nutrient inputs (and changes in inputs) to water quality and habitat conditions. In some of these evaluations thresholds and response lag times were also considered. These are complicated and time consuming activities but well worth the effort, especially considering the amount of money spent on nutrient load reductions. These analyses are particularly important for the shallow inlets that empty into the major Chesapeake Bay tributaries, as these inlets are the initial reactors for land-derived nutrient loads from much of the coastal plain watersheds.

In 2009, members of this team completed an ecological assessment of one such inlet, the Corsica River estuary, using available data to frame the following: (1) the status of the estuary, (2) the expected outcomes of nutrient management in the watershed, (3) the identified data gaps, and (4) the establishment of baseline conditions for the restoration effort (Boynton et al., 2009). Five years later, a decade-long time-series of nutrient loading, oxygen, and chlorophyll-a data have been collected in the estuary, in addition to the documentation of BMP implementation in the watershed. This presents a rare and novel opportunity to understand how successful the restoration has been to date. Specifically, Boynton et al. (2009) used relationships between nutrient load, chlorophyll-a, light availability, and oxygen concentrations in the Corsica estuary to predict improvements in SAV habitat and hypoxia duration for a given nitrogen load reduction. Considering our previous efforts in the Corsica River estuary, we are well-positioned to build on our knowledge of the system with the availability of a diverse collection of data that we have previously assembled and analyzed.

3-2 Methods and Data Sources

Our assessment of variability and change in the Corsica River estuary utilized a variety of data types spanning the watershed-stream-estuary continuum. We assessed the location and type of BMP implementation over the past decade (e.g., cover cropping, rain garden, septic upgrades) and used these changes to quantify their potential role in reducing nutrient loads to one sub-watershed of the Corsica watershed (Gravel Run). We also assessed trends in stream nitrogen and phosphorus concentrations based on regular (week-fortnightly) sampling in three large streams (Gravel Run, Three Bridges Branch, Old Mill Stream; Fig. 3-1) and twice-annual synoptic surveys (spring and fall) across 20+ stations in the watershed. For the three large streams, we used nutrient concentrations and streamflow rates to estimate nitrogen and phosphorus loads to the estuary for the years 2007-2012 and compared these loads to watershed model-derived loads and estimates from a watershed nitrogen loading model (NLM; Valiela et al., 1997, 2000). Finally, we used these loads to interpret changes in concentration and variability in oxygen, nutrient, and chlorophyll-a in the estuary, as well as estimates of metabolic properties, hypoxia duration, and numeric oxygen criteria failure based on ConMon data.

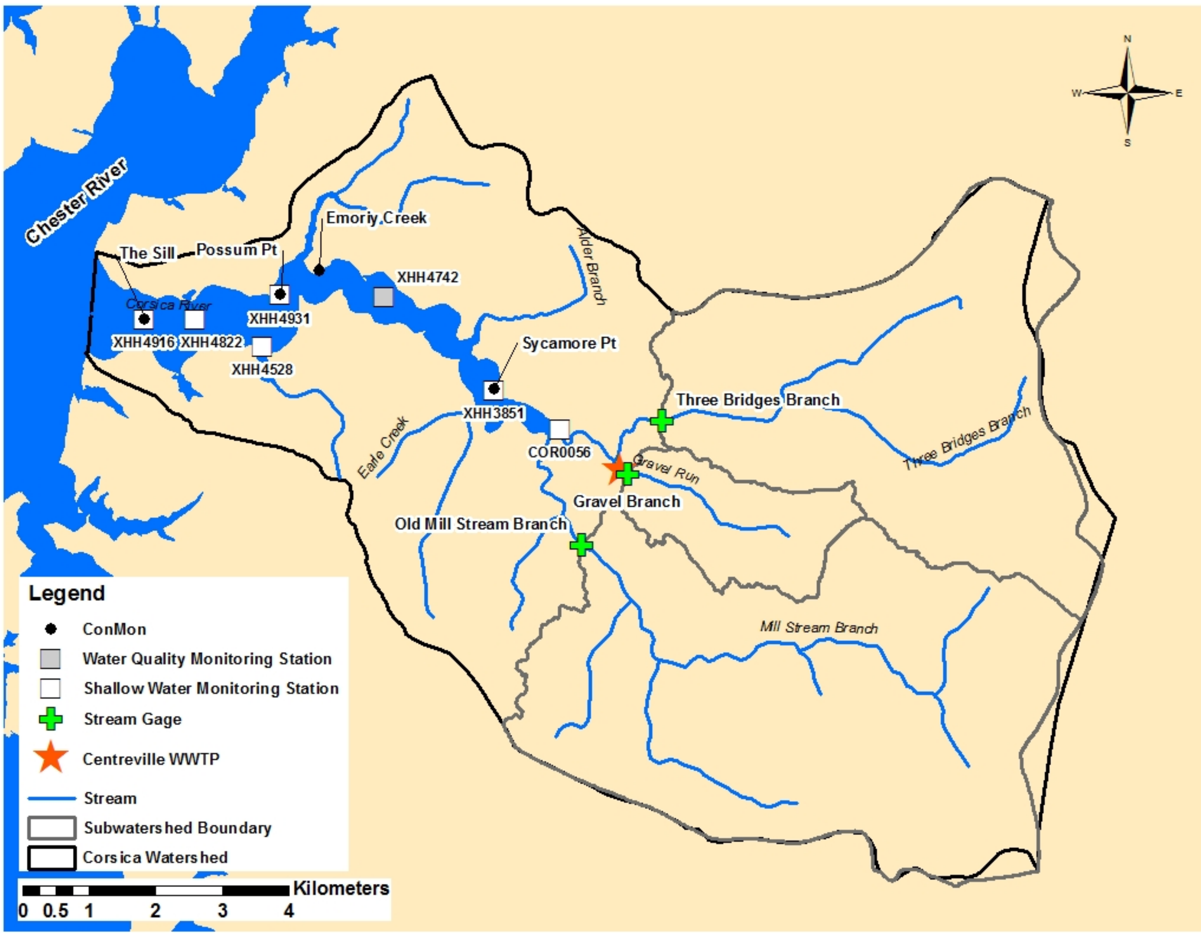


Figure 3-1. A map of the Corsica River estuary watershed and sub-watersheds, stream network, monitoring stations, and the Centreville wastewater treatment plant.

3-2.1 Best Management Practices (BMP) Implementation

We were provided data for the implementation of Best Management Practices (BMPs) in the Corsica watershed by the Maryland Department of the Environment (Quentin Forrest, personal communication). These unique BMP efforts have been documented since 2005 and collated by MDE from the various town and county agencies who oversaw their implementation. The majority of the BMPs were implemented in the upper watershed, especially in the town of Centreville (Fig. 3-2). For each BMP, we examined location (latitude, longitude), size (acres treated), and Maryland Assessment Scenario Tool (MAST) category. We also utilized a separate dataset for cover crop implementation, that identified the sub-watershed where the cover crops were planted (Three Bridges Branch, Old Mill Stream, Gravel Run), the type of crop (both cover and food), the planting date, and the acres covered.

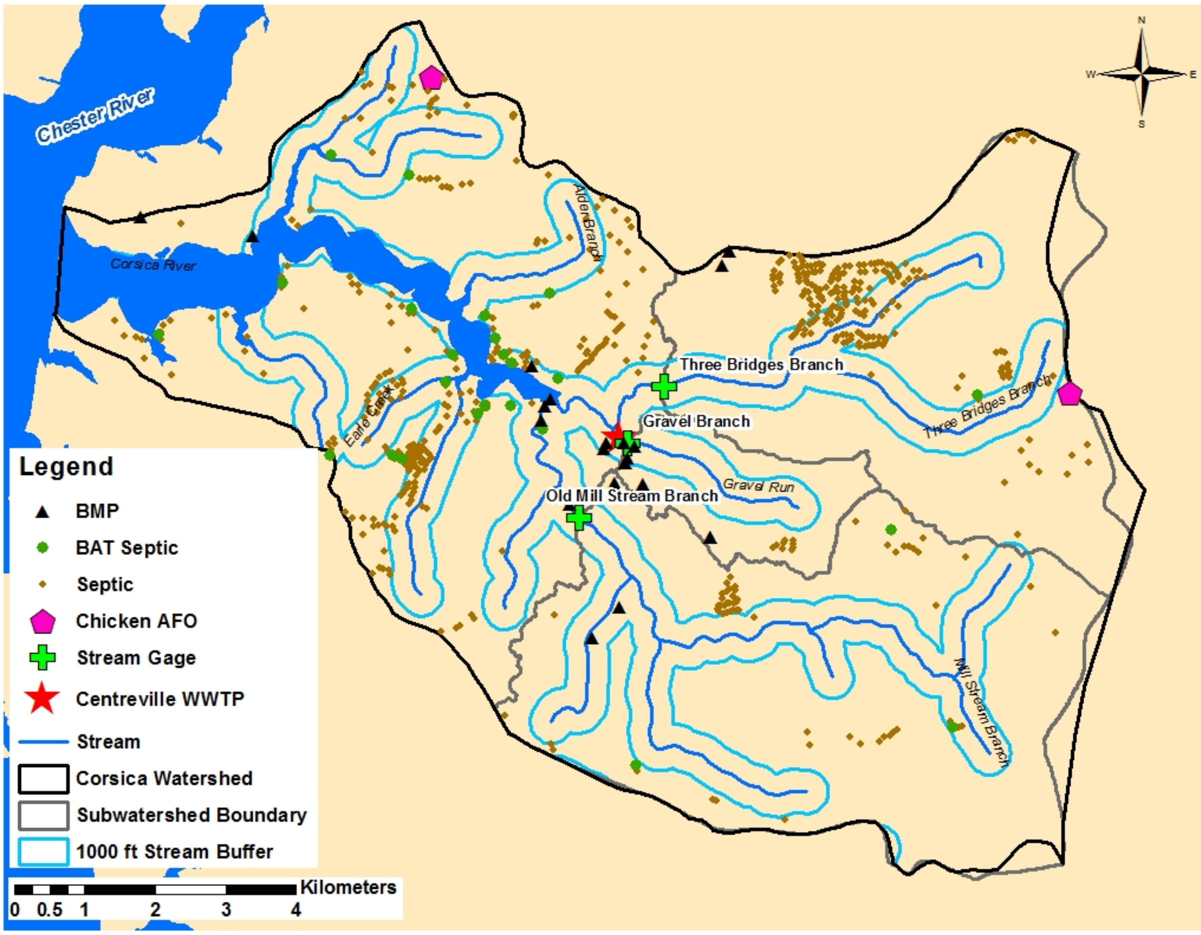


Figure 3-2. A map showing, the 1000ft stream buffer area (light blue), traditional and BAT septic, poultry operations, and BMP locations within the Corsica River estuary watershed.

3-2.2 In-Stream Nutrient Concentrations

We examined concentrations of TN, TP, NO_{23}^-, NH_4^+, and PO_4^{3-} for the years 2005-2013 in each gauged tributary of the upper watershed (Three Bridges Branch (TBB), Gravel Run (GVL), Old Mill Stream (OMS); Fig. 3-1). Three stream concentration datasets were available; (1) bi-weekly grab sample concentrations (representing base flow conditions) in each of the three streams for all variables mentioned above, (2) flow-weighted, weekly concentrations of TN and TP collected by composite samplers that sampled baseflow at regular intervals but were triggered to sample more frequently under high flow conditions, and (3) concentrations of TN, TP, NO_{23}^-, and PO_4^{3-} measured during synoptic surveys completed one time in spring (February-April) and one time in fall (August-November) at 43 stations for the years 2005-2013. All nutrient concentrations were collected by the Maryland Department of the Environment (MDE) and reported by station, date, and concentration in milligrams N or P per liter.

3-2.3 Estimates of Nutrient Loading

Nitrogen loading model

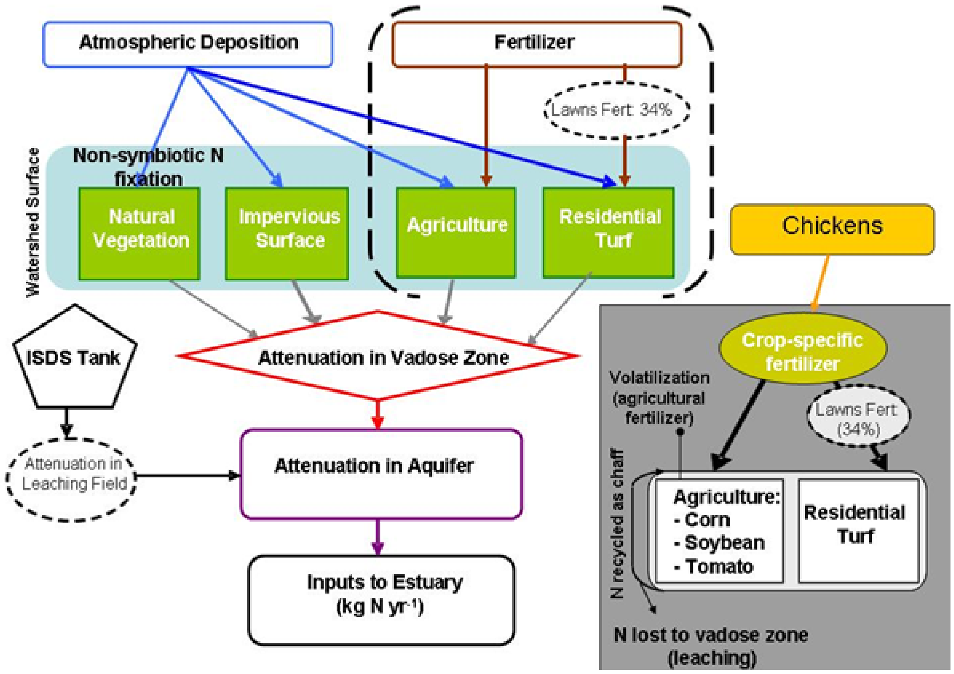


Figure 3-3. Schematic of the nitrogen loading model adapted from Valiela et al. (1997) and Cole (2005).

The nitrogen loading model (NLM) we explored here was initially developed by Valiela et al. (1997) but has more recently been adapted to the Delmarva by Giordano et al. (2011). The NLM is an automated Microsoft Excel worksheet that calculates nitrogen loads upon entering a number of input variables (Table 3-1). Inputs include: atmospheric deposition, point sources, population (on septic), poultry, estuary surface area, agricultural and non-agricultural land cover, fertilization rates and agricultural yield. Giordano et al. (2011) and Cole (2005) adapted the Valiela et al. (2000) implementation to incorporate poultry and agricultural practices common to the Delmarva Peninsula. Figure 3-3 pictures the processes described by this model, where inputs of nitrogen are applied to various watershed land uses before being attenuated in the vadose zone and aquifer. Attenuation coefficients vary by land use type. Volatilization of chicken litter, nitrogen yields extracted from the watershed via agricultural harvests, and nitrogen fixation by legume crops are also incorporated and described in detail by Giordano et al. (2011) and in our newest version posted at http://netsim.vims.edu/netsims/brush/DelCBM_beta3/index.html. We used ESRI ArcMap 10.0© spatial analyst toolbox to mask land cover files to the Corsica watershed. Chicken animal feeding operation (AFO) locations from MDE for all years used in this analysis were confirmed using aerial imagery. Numbers of chickens per AFO per year were assumed to be the same across all years.

Agriculture land cover was available at the county level. To scale down to the Corsica watershed we calculated the ratio of Agricultural land in the watershed to Agricultural land in the county using CBP land cover data series. The ratio was then multiplied by Queen Anne's County crop specific areas from the US Department of Agriculture's National Agricultural Statistics Service to estimate crop area for the watershed. Attenuation coefficients were taken from an ongoing modeling effort supported by Delaware, Maryland, and Virginia Sea Grant including co-PI Harris.

Table 3-1. List of NLM data inputs and sources.

Input	Source
Surface Area	Boynton et al., 2013
Point Sources	Chesapeake Bay Program Nutrient Point Source Database (2001)
Atmospheric Deposition	National Atmospheric Deposition Program/NTN Site MD13 (2014)
Septic	Maryland Department of the Environment (2011)
Land Cover	Chesapeake Bay Program Land Cover Series (1992, 2001, 2006)
Poultry	Maryland Food System Map/Maryland Department of the Environment (2012)
Agriculture Land Cover	USDA NASS quickstats (2014)

Watershed Model Loads

We received modeled nutrient loads from the Chesapeake Bay Program Watershed model (US EPA, 2010) from Phase 5.3 (1986-2005), phase 5.3.2 (2002-2011), and phase 6 prototype (1995-2014). Data files were received in individual files for monthly and annual loads by year. Monthly files were loaded into R, combined using R function rbind, subsetted by unique cell ID that corresponded with Corsica land river segments (A24035EU0_4260_0000 and A24035EU0_4471_0000) and then data were summed to annual and seasonal scales for analysis.

We also estimated annual loads of TN, TP, NO_{23}^{-}, NH_4^{+}, and PO_4^{3-} for the years 2007-2012 using Beale's unbiased ratio estimate. Loads were computed for each gauged tributary of the upper watershed (Three Bridges Branch (TBB), Gravel Run (GVL), Old Mill Stream (OMS)) and separate computations were made using bi-weekly grab sample concentrations (representing base flow conditions) and also flow-weighted, weekly concentrations of TN and TP collected by composite samplers that were triggered to sample under high flow conditions. All nutrient concentrations were collected by the Maryland Department of the Environment (MDE). A continuous, daily record of streamflow was measured at TBB by the United States Geological Survey, while weekly flow estimates were made by MDE at Old Mill Stream and Gravel Run. Because streamflow was highly correlated between TBB and both GVL and OMS, we estimated daily streamflow for GVL and OMS from the TBB record. This was done by using linear regressions of weekly TBB flow with weekly GVL and OMS (r^2= 0.38, 0.87, respectively (p<0.05)) to extrapolate daily GVL and OMS flow from the daily TBB record. Beale's unbiased ratio estimator (hereafter Beale's) allows for the computation of annual nutrient loading from daily streamflow records (Q) and less frequent streamflow measurements.

To compute a "biased" estimate for each day where a nutrient concentration is measured, a daily nutrient flux (i.e., load) is computed as the product of the streamflow that day (x_i) and the concentration (y_i). A mean flux is then computed for all days where concentrations were sampled (m_y), as well as the mean discharge of those days (m_x) and the mean discharge (u_x) over the entire year. To compute the annual load, simply multiply the ratio of mean sample flux (m_y) over mean discharge over those days (m_x) by the mean annual daily discharge (u_x): [Annual Flux = ($u_x \cdot (m_y / m_x)) \cdot 365$]. This simplified approach, however, is biased by the discharge on the days where nutrient concentrations were measured. To render the load estimate "unbiased", the simple annual flux estimate is multiplied by a second ratio, described by the equations below, where the numerator is the sum of the product of the mean flux and the mean sample discharge ($m_y \cdot m_x$) subtracted from each individual measured flux ($x_i y_i$) and divided by the degrees of freedom (1/n-1), where n is the number of concentration samples. This summed number is then divided by the product of the mean flux and the mean sample discharge ($m_y \cdot m_x$), then multiplied by 1/n, and finally added to one. The denominator of the ratio is the product of the number of samples and the mean discharge subtracted from each individual stream flow. These values are then summed and again multiplied by the degrees of freedom. This summed number is then divided by the mean sample discharge (m_x), then multiplied by 1/n, and finally added to one. This ratio effectively removes bias in the load estimate by comparing the measured fluxes and discharges to the rest of the hydrograph and yields a discharge weighted annual flux estimate.

$$\tilde{\mu}_y = \mu_x \frac{m_y}{m_x} \left(\frac{1 + \frac{1}{n} \frac{S_{xy}}{m_x m_y}}{1 + \frac{1}{n} \frac{S_{x^2}}{m_x^2}} \right)$$

$$S_{xy} = \frac{1}{(n-1)} \sum_{i=1}^{n} (x_i y_i - m_y)(x_i - m_x)$$

$$S_{x^2} = \frac{1}{(n-1)} \sum_{i=1}^{n} (x_i - m_x)^2$$

Where $\tilde{\mu}_y$ is equal to the estimated load, $\tilde{\mu}_x$ is mean daily discharge over an annual cycle, m_y is the mean daily loading for days on which concentrations were determined, m_x is the mean daily discharge for those days on which concentrations were determined, and n is equal to the number of days on which concentrations were determined. Individual measured flows and concentrations are represented by x_i and y_i, respectively (Dolan et al., 1981). Beale's ratio estimator has proven to be highly reliable and is recommended if the relationship between discharge and concentration is weak, if the data are skewed, and if the data are not normally distributed (Richards and Holloway, 1987; Richards, 1998).

3-2.4 Fixed Station Tidal Water Quality Data

Concentrations of chlorophyll-a, nitrate+nitrate (NO_{23}^{-}), ammonium (NH_4^{+}), phosphate (PO_4^{3-}), total nitrogen (TN), and total phosphorus (TP) at fixed tidal water quality monitoring stations in the Corsica estuary (Fig. 3-1) from 2005 to 2013 were collated from the Chesapeake Bay Program data hub. These surface water concentrations were measured roughly every month using standard methods (CBP, 2001).

3-2.5 Statistical Analysis Linking Watershed and Estuary

We performed numerous linear regressions using the functions lm and summary.lm with the statistical software R (R Core Team, 2014). Regressions were performed using spring (Jan-Apr) and summer (June to August) means. We chose to examine composite loads from Three Bridges Branch, because the time record was most complete, to interpret changes in water clarity (Secchi disk), chlorophyll-a concentrations in the estuary, as well as estimates of metabolic properties, and numeric oxygen criteria failure based on ConMon and monitoring station data. Chlorophyll-a and Secchi disk depth data were averaged across all monitoring stations in the Corsica River (Fig. 3-1). ConMon stations Sycamore Point and Possum Point have the longest time-series available and were therefore used for dissolved oxygen criteria failure and metabolic rate variables in this analysis.

3-2.6 Computing Community Production and Respiration from O_2 Time-Series

The basic concept and method for computing community production and respiration was developed by Odum and Hoskin (1958) and, with numerous modifications, has been used since for estimating these rate processes in streams, rivers, lakes, estuaries, and the open ocean. The technique is based on following the oxygen concentration in a body of water for a 24 hour period. During hours of daylight, oxygen concentration increases in the water due to the release of O_2 as a by-product of photosynthesis. During hours of darkness, O_2 concentration declines due to O_2 consumption by both primary producers and all other heterotrophs. The rate processes (gross photosynthesis, Pg*; nighttime respiration, Rn) are estimated by computing the rate of change in O_2 concentrations during day and night periods. This rate of change is then corrected for O_2 diffusion across the air-water interface and the result is an estimate of Pg* and Rn. ConMon data are exactly the type of data needed for these computations in that all the needed variables are measured (dissolved oxygen, temperature, and salinity), the measurement frequency is high (15 minute intervals) and the measurement period is for 9 or more months. It is very rare when a rate process can be estimated with such temporal intensity.

Based on earlier work by Burger and Hagy (1998) for calculating community metabolism from near-continuous monitoring data, an automated Excel spreadsheet (Metabolism.xls) was developed by Mr. David Jasinski and utilized here with Microsoft's Visual Basic for Applications (VBA) programming language (Boynton et al., 2012). We computed metabolic rates based on ConMon data for Sycamore Point, Possum Point, and the Sill for surface sensors only based on the data set described in Chapter 1. Briefly, sunrise and sunset times for each date are calculated based on the latitude and longitude of the station and used to compute a "Metabolic Day", which begins at sunrise on the current day and continues to the observation immediately before sunrise on the following day. The change in DO, time, air/sea exchange, and oxygen flux is then calculated between each consecutive observation and sums of these changes are calculated for each metabolic day for the periods between sunrise and metabolic dawn, metabolic dawn and metabolic dusk, metabolic dusk and sunset, and sunset and the following sunrise. From these sums, 6 metabolic variables are calculated:

rn = Nighttime (sunset to following sunrise) summed rates of DO flux corrected for air/water diffusion.

rnhourly = rn divided by the number of nighttime hours

pa = The sum (both positive and negative) of oxygen flux (corrected for air-water diffusion) for the dawn, day and dusk periods.

pa_star = summed oxygen flux (corrected for air-water diffusion) for the day period

pg = pa + daytime respiration. Daytime respiration = rnhourly * (number of hours of daytime+dawntime+dusktime).

pg_star = pa_star + daytime respiration as defined above.

Air-water diffusion of oxygen is considered in these computations and the diffusion correction is based on the difference between observed DO percent saturation and 100% saturation multiplied by a constant diffusion coefficient. For these computations a diffusion coefficient of 0.5 g O_2 m^{-2} hr^{-1} was selected as generally representative of conditions frequently encountered in estuarine tributary situations (Caffrey, 2004).

One of the primary assumptions of this method is that temporal changes in DO measured by the continuous monitors are due solely to metabolism (i.e., oxygen production from photosynthesis and oxygen loss from respiration) occurring at the station and not due to advection of water masses with different oxygen conditions moving past the instrument. Because the Chesapeake Bay is a tidal system, this may not always be the case. Depending on the hydrodynamics of a given station, this assumption may be more or less realistic and may also be variable from date to date. One way of censoring dates where DO is affected by advection is to preview the data graphically prior to metabolism calculations and determine if there is a relationship between salinity and DO. Large changes in salinity suggest moving water masses and therefore, advection. These dates could then be flagged and reviewed before metabolism variables are calculated.

3-3 Results and Discussion

3-3.1 BMP Implementation Over Space and Cover Cropping Over Time

The implementation of BMPs in the Corsica River watershed has been relatively aggressive with a diversity of BMP types implemented over the past decade. These BMPs include, but are not limited to, the construction of bioretentive structures and rain gardens, permeable pavement, urban forest and grass buffers, bioswale, and the installation of best available technology (BAT) septic systems (Fig. 3-2, 3-4). Over half of these BMPs have been implemented within the 100 foot stream buffer, while nearly all new septic BAT systems reside in this buffer zone (Fig. 3-2).

Figure 3-4. Examples of stormwater BMPs in the Corsica River watershed, including a vegetated storm water retention area on the corner of Kidwell and Pennsylvania Ave. (left) and a bioswale system on Quail Run Dr. (right).

We used a watershed budget nitrogen loading model (NLM, see below) to estimate changes in nitrogen loading from Gravel Run in response to the non-agricultural BMPs that have been implemented there. NLM used standard values applied to the Maryland Assessment Scenario Tool (MAST) to estimate the load reductions that might be expected from each BMP type. We checked these values against a review of relevent BMPs that attempted to assess ranges of nitrogen reduction for a variety of ecological engineering practices (Passeport et al., 2013). The resulting load reduction was less than 1% (Fig. 3-5) and indicated that current non-agricultural BMP implementation (small-scale stormwater management) should not be expected to substantially reduce nitrogen loads.

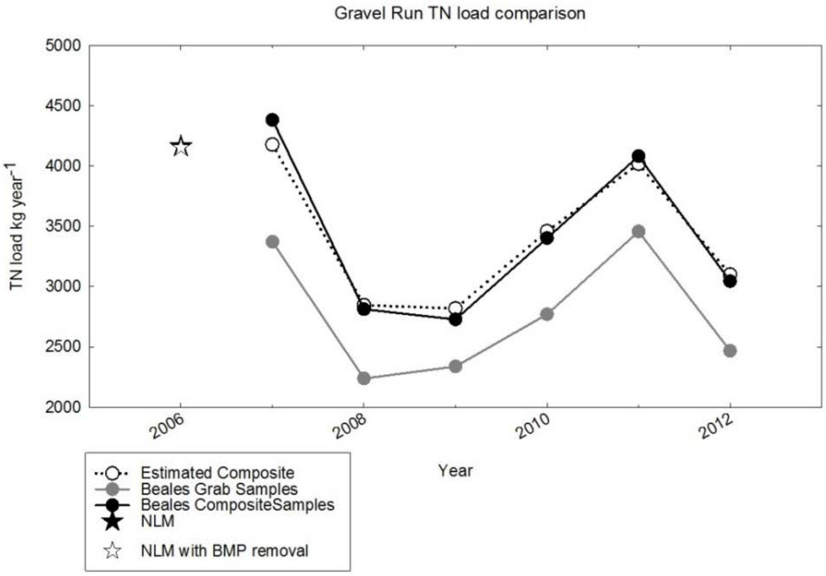


Figure 3-5. TN load comparison of two methods of load calculations at Gravel Run, NLM calculations with BMP implementation (white star) and without BMP implementation (black star). Data are from MDE, 2014.

An incentive program has resulted in an increasing level of cover crop planting in the watershed, resulting in 6000 total acres planted in 2014 (compared to ~2000 acres in 2006-2010; Fig. 3-6). The majority of these cover crops were planted in the latter two weeks of September and the first week of October. It has been documented that cover cropping results in a 63-83% reduction in root zone (15 to 105 cm deep) nitrate concentrations (e.g. Staver and Brinsfield, 2008), depending on the type of cover crop used (e.g., barely, rye, wheat). Specifically, fallow corn with no cover crops had a root zone nitrate concentration of 17.5 mg N/l, while cover cropping reduced nitrate concentrations to 5.5 mg N/l for barely, 3.0 mg N/l for rye, and 6.5 mg N/l for wheat. Given these large reductions, we expect to see a reduction in baseflow nutrient concentrations in adjacent streams as a result, but with some lag between the time of more intensive cover cropping and reduced N concentrations.

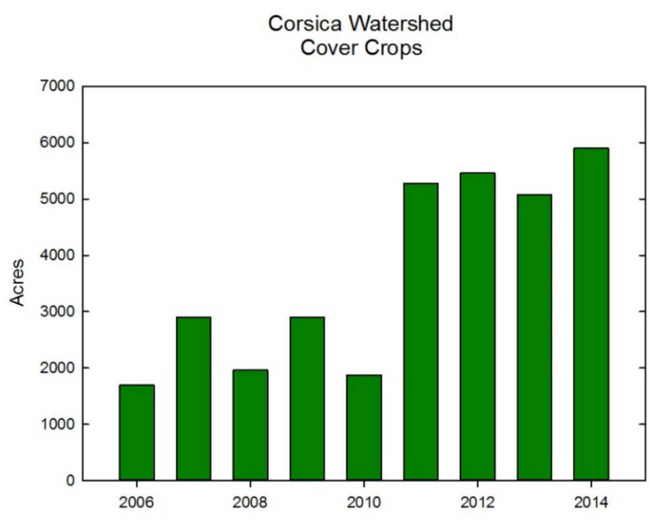


Figure 3-6. Time-series of cover crop acreage in the Corsica River watershed, illustrating a near-tripling in cover crop acreage from 2010 to 2011 and after.

3-3.2 In-Stream Nutrient Concentrations

Long-term (2005-2013) records of in-stream concentrations of TN, TP, NO_{23}^-, and PO_4^{3-} indicate different patterns for the three gauged systems in the Corsica watershed. Concentrations of TN, TP, and NO_{23}^-indicate declining trends in Gravel Run and Three Bridges Branch, with no apparent changes in any variables in Old Mill Stream (Fig. 3-7). Prior work has identified statistically significant declines in TP and TN concentrations at Three Bridges Branch and Gravel Run, and significant declines in TN and TP load at Gravel Run, but no significant changes for any concentration or load in Old Mill Stream (Spooner et al., 2014). Although the most likely explanation for the declines in observed TN and TP concentration is the implementation of cover cropping, declines were not found in Old Mill Stream (where cover cropping has increased substantially) and we currently lack a tool to quantitatively link cover crop-induced groundwater nutrient concentrations to reductions in stream concentrations. Finally, although Gravel Run was the one stream where nutrient loads declined significantly, this stream contributes less than 5% of the total upper Corsica basin loads for all nutrient species (Fig. 3-8)

A more detailed view of temporal changes in nutrient concentrations is illustrated by time-series of seasonally-averaged values over the time-series. Mean nutrient concentrations for the winter-spring (January to May), summer (June to August), and Fall (September to November) periods for Gravel Run, Three Bridges Branch, and Old Mill Stream (Fig. 3-9) indicate that declines in summer and fall TN and NO_{23}^- are apparent in all streams, whereas declines in TP and PO_4^{3-} are not evident. Because stream flows tend to be lower during summer and early fall periods, declines in TN and NO_{23}^- during these periods may be reflective of baseflow conditions, which would indicate a reduction in groundwater concentrations of NO_{23}^- (NO_{23}^- dominates the TN pool; Fig 3-9).

We analyzed the time series of in-stream, base flow nutrient (NO_{23}^-, NH_4^+, PO_4^{3-}, TN, TP) concentrations for significant trends using the Seasonal Kendall test of trend (Hirsch et al., 1982). Significant declining trends in NO_{23}^- and TN concentration were found for Gravel Run, but not for the other two tributaries. These trends were driven by declines in May-September concentrations. No significant trends were found for PO_4^{3-} or TP, despite the apparent declines in concentration during the September to November period.

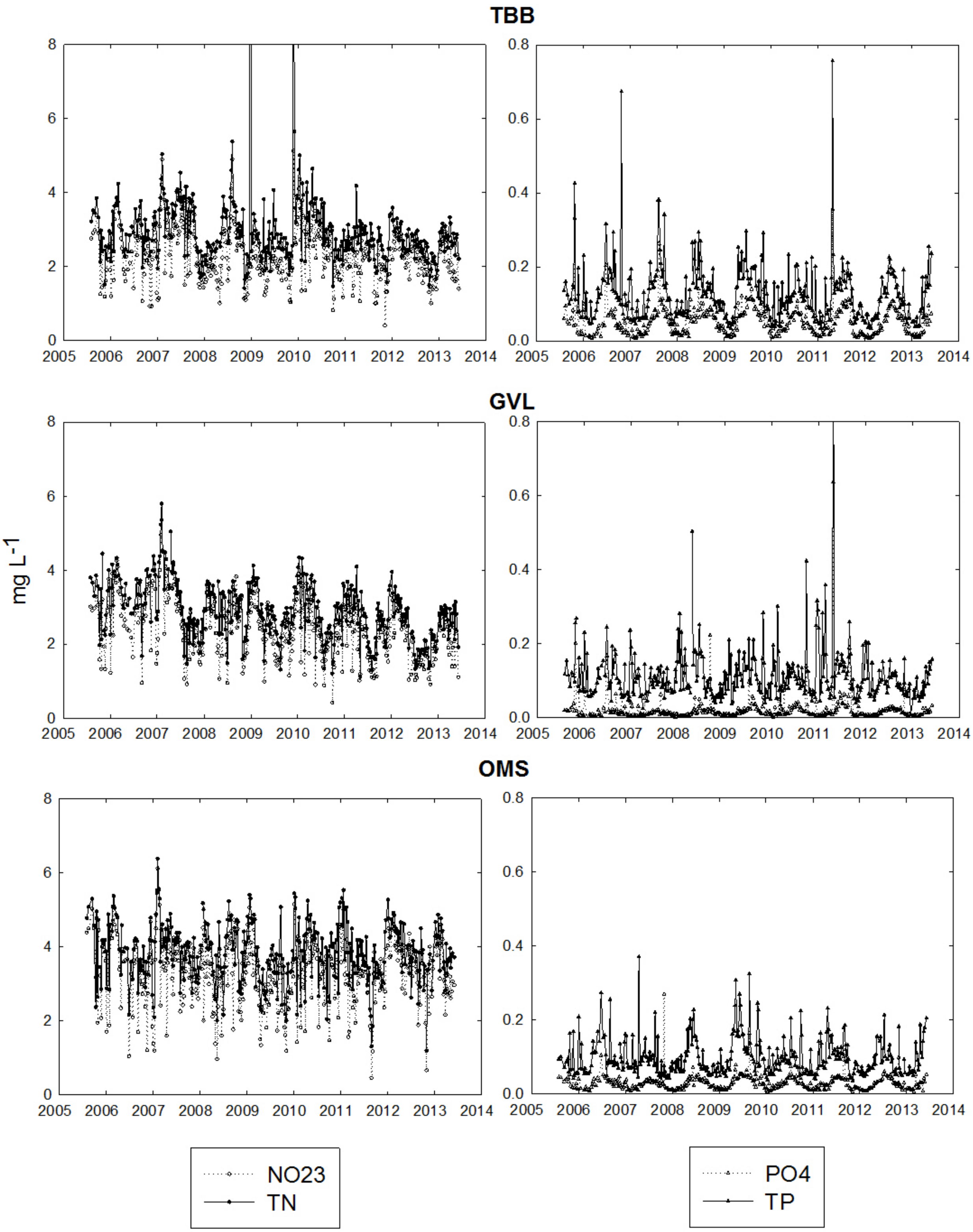


Figure 3.7. Time-series of nutrient concentrations at the three primary streams of the upper Corsica watershed from 2005-2013.

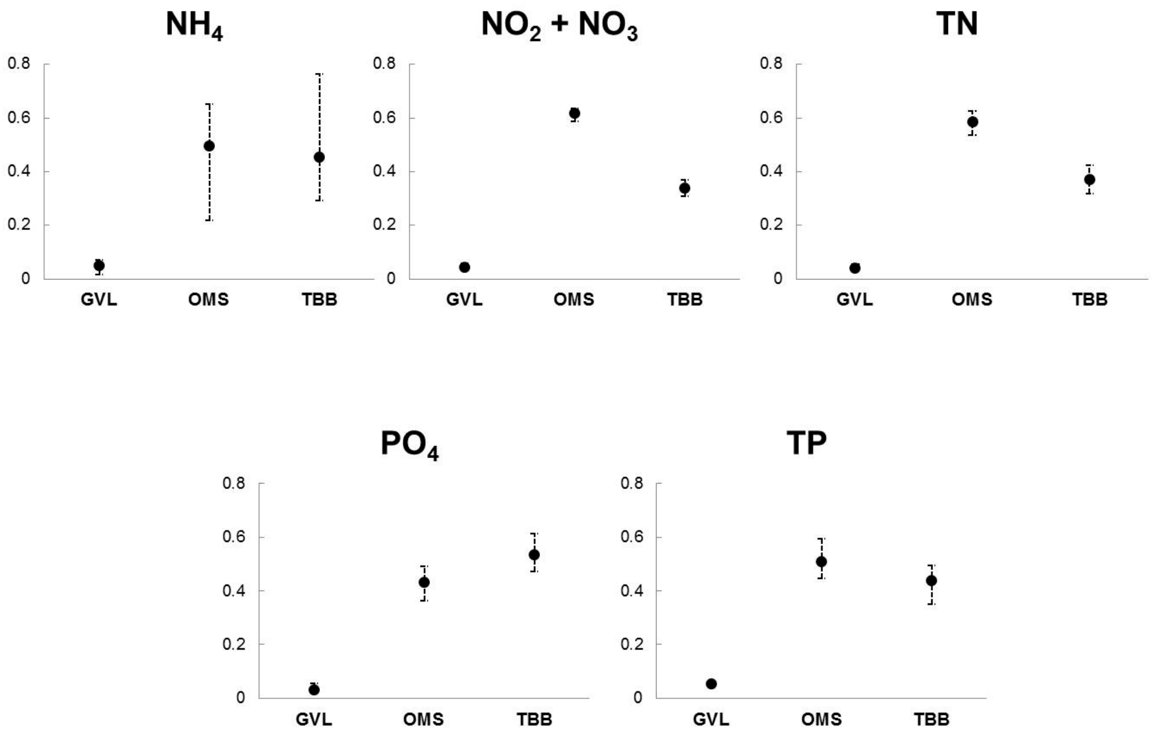


Figure 3.8. Mean fraction of total nutrient load to the upper Corsica watershed contributed by each sub-basin for the time period 2007-2012. Error bars indicate minimum and maximum fraction of total nutrient load.

Figure 3-9. Time-series (2005-2013) of seasonally-averaged concentrations of all nutrients measured during bi-weekly grab samples at Three Bridges Branch, Old Mill Stream, and Gravel Run. Note log scale for NH_4^+.

3-3.3 Loading Comparison

We compared nutrient loads from three phases of the Chesapeake Bay Programs watershed model (USEPA, 2010) for total nitrogen (TN) and total phosphorus (TP) for the entire Corsica River watershed (Fig. 3-10). Though each phase of the model covered difference time frames, there was overlap between all three phases from 2002 to 2005 and overlap between phase 5.3.2 and phase 6 prototype from 2002-2011, and phase 5.3 and 6 from 1995 to 2005. Overall the three models have similar patterns for TN and TP. However, beginning in 2007, the phase 6 prototype output predicts much higher loads than phase 5.3.2. The phase 5.3.2 model is a detailed mechanistic simulation of the watershed processes for a small representative area in each land use and county. The phase 6 prototype is built from simple relationships extracted from multiple lines of evidence, including complex mechanistic simulations (G. Shenk, personal communication, 2015). Given the preliminary nature of these simulations, we hesitate to interpret these discrepancies.

In addition to comparisons among the WSM loads, we computed TN loads with the nitrogen loading model (NLM (Fig. 3-10. upper panel)). Estimates generated from NLM were limited to two years, 1992 and 2001, due to data availability. Results from NLM were consistent with modeled loads for both years, and notably aligned with the lower range of loads during the 1985-2013 period. We would expect NLM to correspond to the lower load (and thus flow) years, as this model does not include the effects of flow-stimulated increases in nitrogen loading.

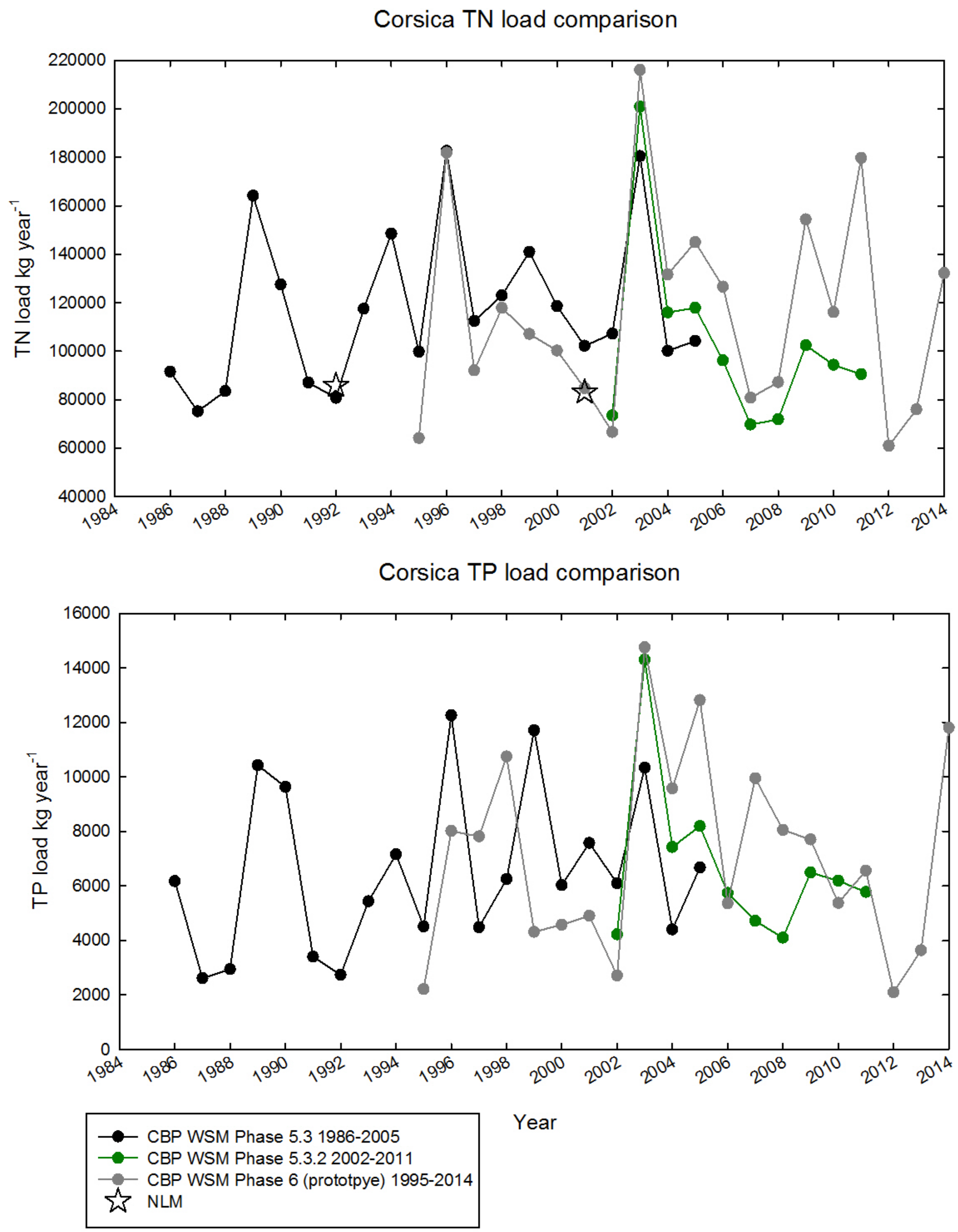
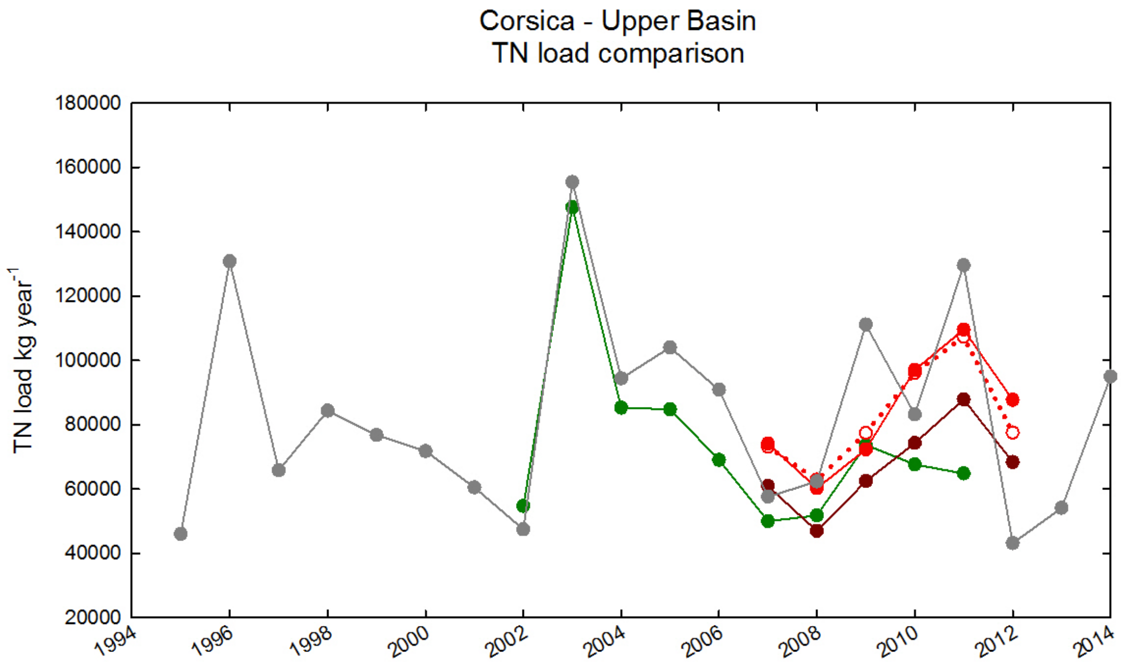


Figure 3-10. TN and TP load comparisons in the Corsica River watershed for 4 different watershed models.

Given the CBPs unique segmentation scheme mentioned earlier in this chapter, we were also able to directly compare modeled loads (Phase 5.3.2 and 6 prototype) to the upper Corsica River watershed to loads estimated from grab and composite samples collected in the three sub-watersheds in the upper basin. Loads from Phase 5.3 were not used in this analysis because they were outputs for the whole Corsica River watershed and therefore not applicable. Figure 3-11 shows that all TN load estimates performed quite well, which is interesting given the fact that the watershed model has not been calibrated to the Corsica watershed. However, when we examine the TP loads, there is a large difference between composite load estimates and the remaining loads. Old Mill Stream had very high TP concentrations for this period of time. In coastal plain streams like the Corsica watershed, large amounts (>50%) of bioavailable phosphorus can be bound to particles that have eroded from land and are transported in large quantities during storm events. Consequently, the majority of P loading to estuaries likely occurs during high flow periods when the majority of TSS is also transported. This is especially true in the coastal plain where highly erodible soils are most affected by high flow conditions during storms. Recent research has also suggested that groundwater phosphorus is more mobile than previously thought, and precipitation-induced flushing of groundwater could also increase P flux during storms. Therefore, P loading estimates made using measurements of phosphorus under base flow conditions will underestimate P loads. The current watershed model calibration (e.g., Phase 5.3), which was performed using base-flow concentrations, appears to be underestimating the phosphorus loading from the Corsica River watershed.



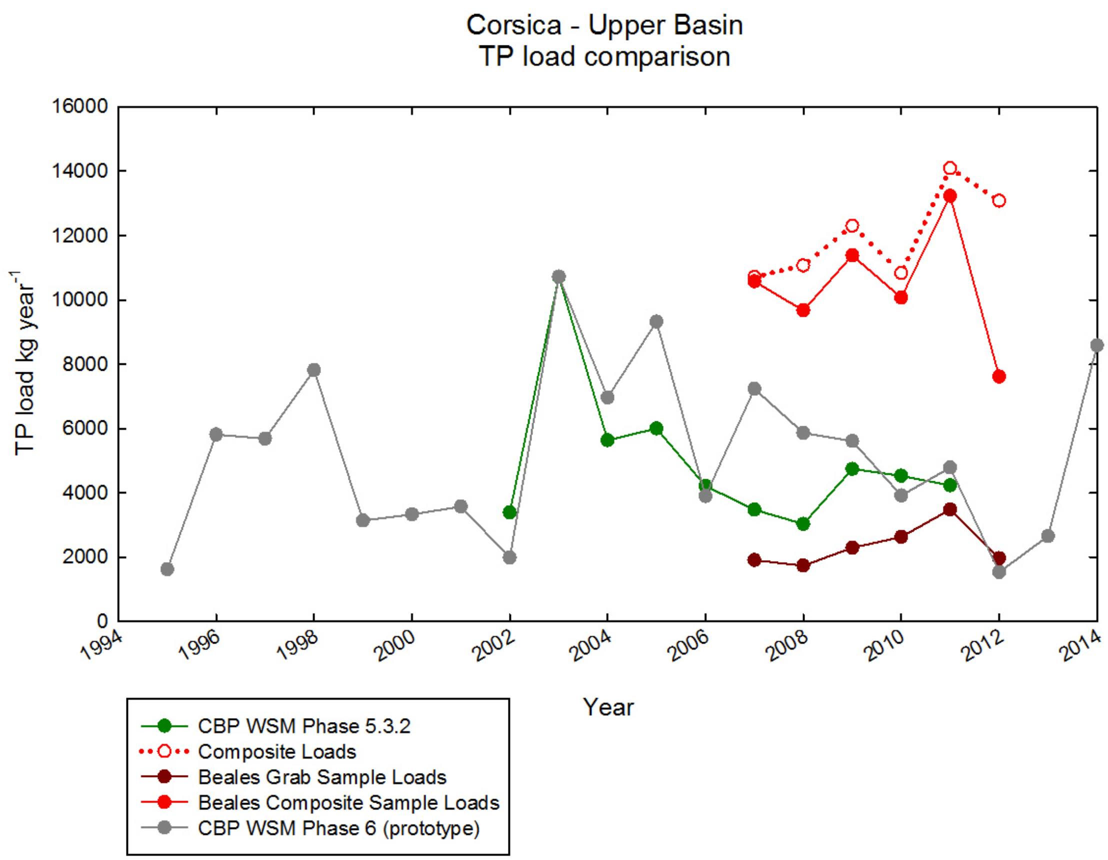


Figure 3-11. TN and TP load comparisons between watershed models and observation-based estimates in the upper Corsica River watershed.

3-3.4 Water-Quality Time-Series in the Estuary

It is instructive to analyze temporal changes in estuary nutrient concentrations as an initial indicator of changes in the estuary resulting from nutrient loads. We illustrate temporal changes in all measured nitrogen and phosphorus species in Figure 3-12 where data are averaged over different seasons within the year (January-April, June-August, September-November). Few clear patterns emerge from these data, except that there are no significant patterns in the concentrations consistent with limited reductions in nutrient loads from Gravel Run and no reductions in load from Old Mill Stream, the major upper watershed stream. Similarly, we detected no significant changes in chlorophyll-a in the estuary (data not shown).

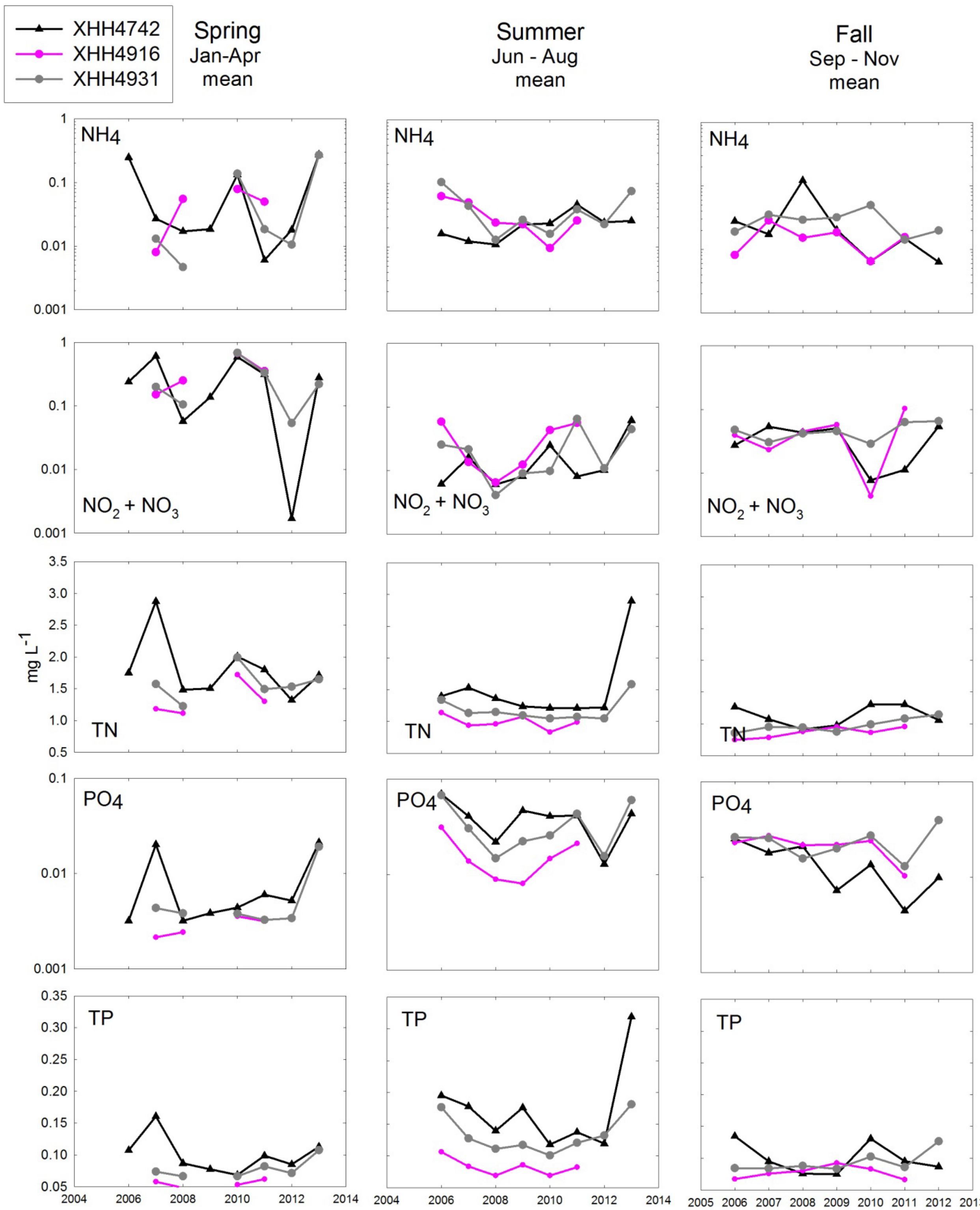


Figure 3-12. Time-series (2005-2013) of seasonally-averaged concentrations of all nutrients measured during monthly grab samples at three stations in the Corsica river estuary.

We explored the relationship between nutrient loading and estuarine nutrient concentration with the dual goal of (1) documenting that high loads translate into high in-estuary concentrations and (2) using the in-estuary concentrations to validate the nutrient loading estimates. Annual mean concentrations for both TN and TP at three stations within the estuary were related to annual TN and TP loads computed from both the grab samples and composite samples (Fig. 3-13) There is a clear positive relationship between TN loads for both grab and composite samples and TN concentrations at the lower estuary stations (XHH4916 and XHH4931), but somewhat less clear relationship with the middle-estuary station (XHH4792; Fig 3-13). For TP, relationships between grab-sample based loads and in-estuary concentrations were weak, while relationships between composite-sample based loads and in-estuary concentrations were better (Fig. 3-13). This reveals that nitrogen loads and concentrations are well linked in the Corsica estuary, but this is not true for TP. These analyses also reveal that composite loads better represent the true TP loading, given that correlations between load and concentration are much better with this method, and what is expected because TP loads are highest with storm flows (captured in the composite loads but not the grab sample loads).

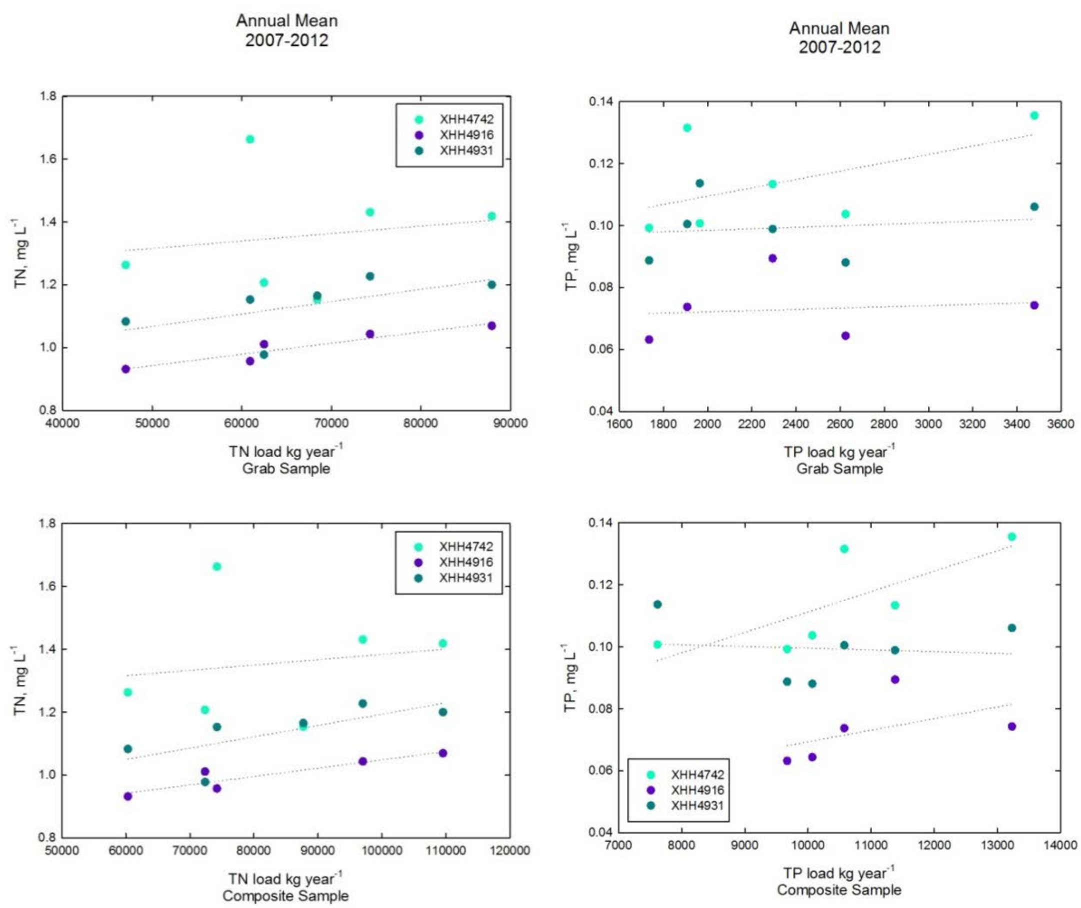


Figure 3-13. Relationships between annually-averaged concentrations of TN and TP at three stations in the Corsica estuary with composite and grab sample based nutrient loads from Three Bridges Branch, Old Mill Stream, and Gravel Run.

3-3.5 Corsica River Estuary Metabolic Processes

We computed metabolic rates (Gross Primary Productions; Pg*, Respiration; Rn, and Net Ecosystem Metabolism; NEM) for nine years in the Corsica estuary and we present rates for Sycamore Point in Figure 3-13. These rates indicate clear seasonal patterns in Pg* and Rn that follow the annual temperature cycle (Fig. 3-14), with peak rates in June, July, and August. Interestingly, in 2007, 2010, 2011, and 2013, relatively high rates of Pg* during March coincided with seasonal peaks in chlorophyll-a, but did not have characteristically high rates of Rn (Fig. 3-14). This latter pattern is typical of a spring bloom condition in larger, open estuaries and coastal seas and leads to spring peaks in NEM. In years where this spring Pg* peak was not present, NEM tends to peak in mid-summer, indicating that temperature-induced increases in respiration cause Rn to not fully compensate for increases in Pg* during the productive mid-summer period. Time-series of metabolic rates at The Sill, Possum Point, and Sycamore Point do not indicate any long-term trends, except for a decline in the peak rates of Rn over time at Sycamore Point (Fig. 3-15). This decline is associated with a reduction in the instantaneous and 30-day criteria failures at Sycamore Point after 2007, which is one of the few clear signs of change toward a less eutrophic state in the Corsica estuary overall.

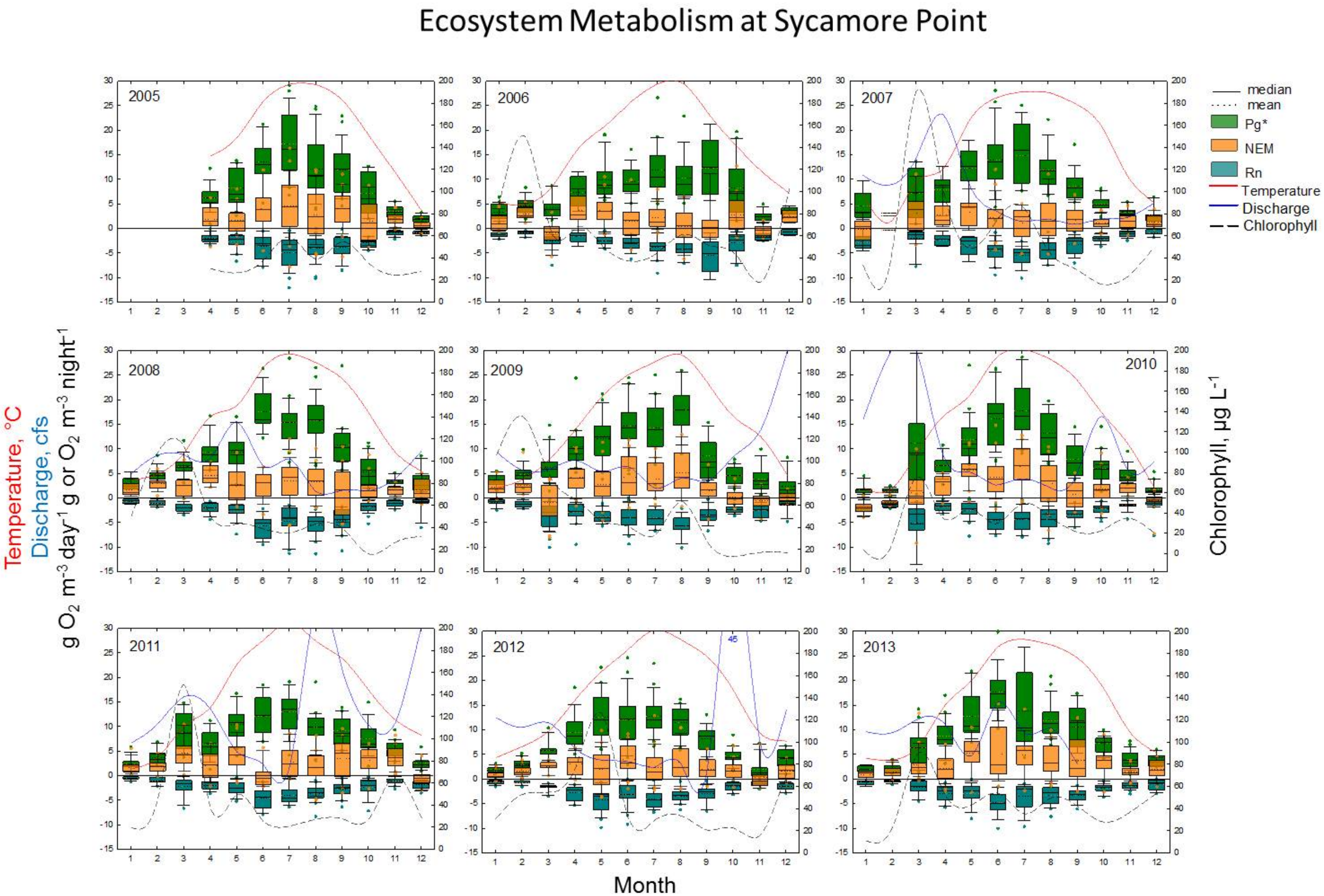


Figure 3-14. Annual cycles of Gross Primary Production (Pg*), respiration (Rn), Net Ecosystem Metabolism (NEM), temperature, chlorophyll-a, and discharge at Three Bridges Branch for nine years at Sycamore Point.

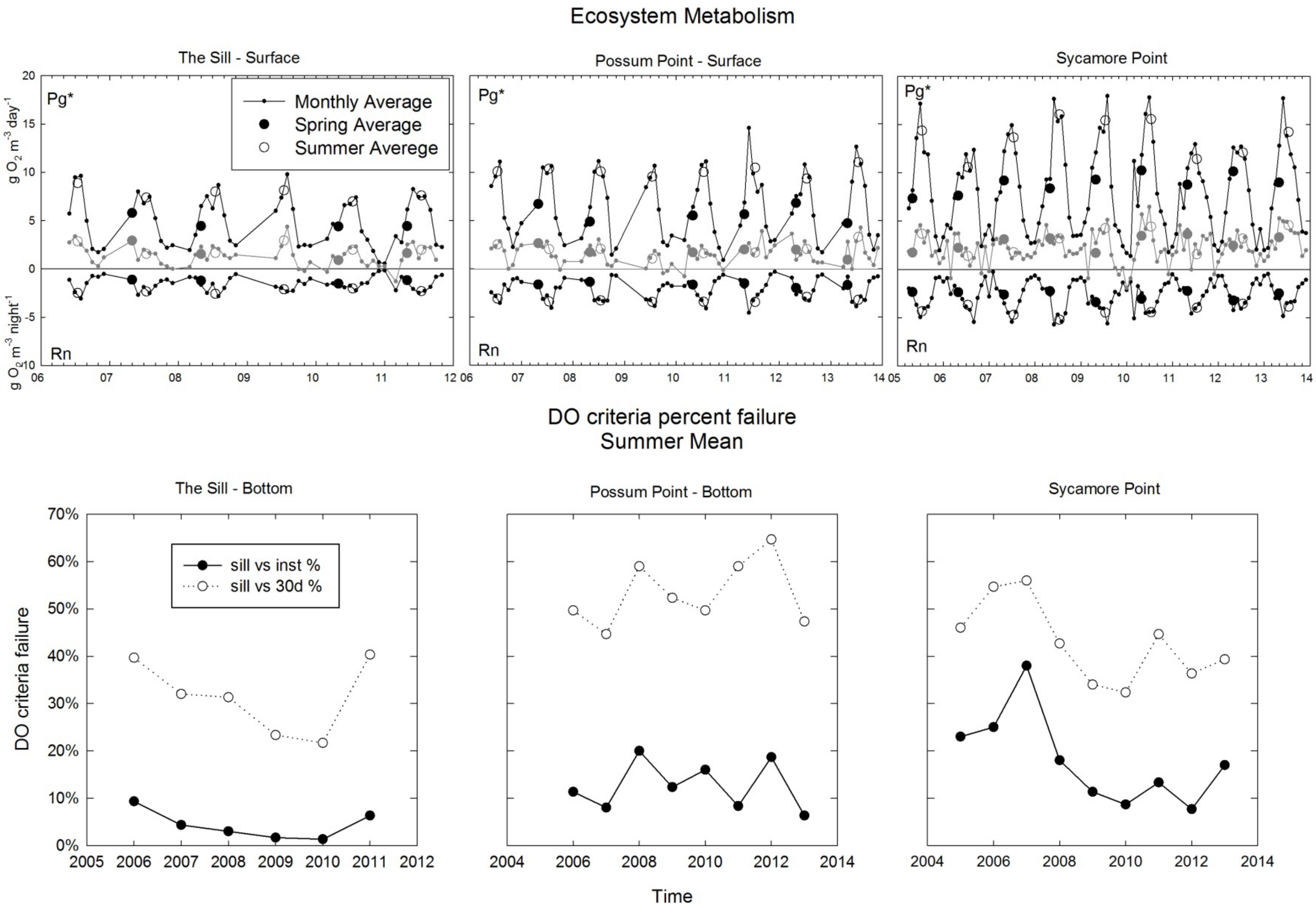


Figure 3-15. (top panel) Time-series (2006-2012) of monthly computations and seasonal means for Gross Primary Production (Pg*), respiration (Rn)), Net Ecosystem Metabolism (NEM) at The Sill, Possum Point, and Sycamore Point. Pg* (positive values) and Rn (negative values) are represented with black circles and lines. NEM is represented by grey circle and liness. (bottom panel) Time-series of the %time of instantaneous and 30-day criteria failure for the same 3 stations.

3-3.6 Results in Context of Goals

The Action Plan for the Corsica River estuary set an ambitious goal of providing a test case for watershed and estuarine restoration, and many of the aggressive actions in the watershed appear to have resulted in modest improvements in water quality. Later season (primarily fall) nitrogen concentrations have declined in each gaged tributary of the upper watershed, and for Gravel Run and Three Bridges Branch, modest overall nitrogen concentrations have declined over time. Although we lack quantitative evidence at this time, the aggressive implementation of cover crops appears to be the most likely contributor to these observed concentration declines, considering that the majority of cover crops were planted in September or early October and this fall period is when the nutrient declines in streams were most evident. However, given that freshwater input has been high in recent years (Fig. 3-16) and that Old Mill Stream, the largest of the three streams, has not had large concentration declines, basin-scale nitrogen (and phosphorus) loading have not declined over the 2006-2013 period.

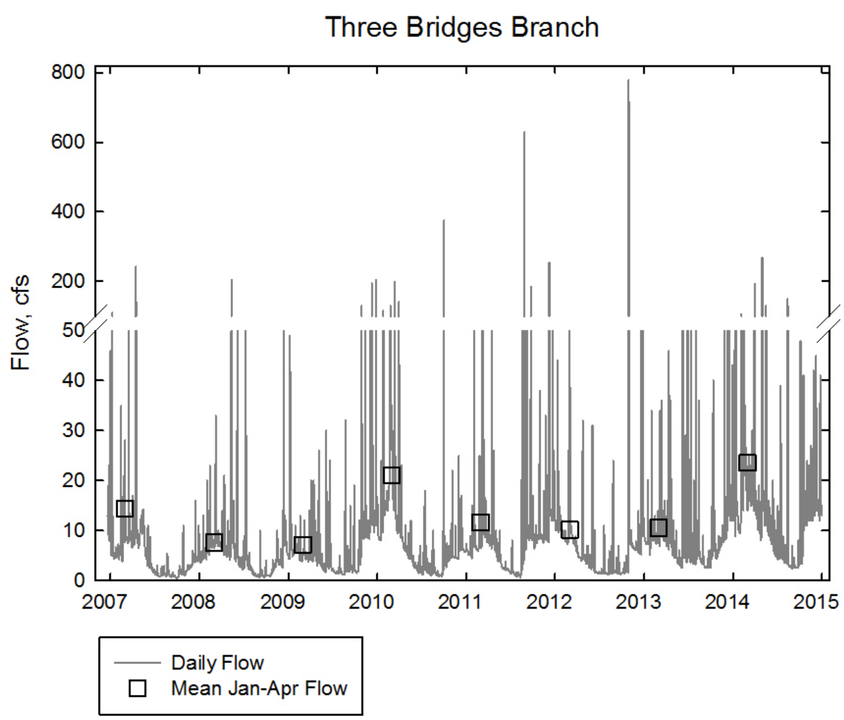


Figure 3-16. Daily time-series (2007-2014) of streamflow at Three Bridges Branch (great line), including the January to April means for each year (open squares). Data are from USGS 2014.

3-3.6.1 Load Changes Versus Needed Load Reductions

The primary success story to date in the Corsica watershed is the reduction in nutrient concentrations in Gravel Run. Continuation of this pattern, and the initiation of similar patterns in the other streams will be instrumental in restoring the Corsica estuary. Boynton et al. (2009) suggested that a 40% reduction in total nitrogen loads would substantially improve both SAV habitat and oxygen concentrations in the Corsica estuary. Unfortunately, without any substantial and spatially widespread load reductions to date, most of this 40% reduction remains to be achieved by watershed management actions.

3-3.6.2 Evidence of Restoration

Considering the previously noted reductions in concentration at Gravel Run, and the widespread reduction in fall (September-November) nutrient concentrations (especially nitrogen), we can document preliminary success in reducing the manageable portion of freshwater inputs, which is the nutrient concentration. Despite these potential successes, nutrient concentrations were unchanged in Old Mill Stream over the 2005-2013 period and overall loads to the estuary were not noticeably reduced. Signs of improvement were apparent, however, in some locations and for some processes within the estuary. The most striking potential improvement is the reduction in respiration and criteria failure that occurred during summer at Sycamore Point after 2007. Because metabolic properties (i.e., the rates of organic matter production and consumption) are the most appropriate indicators of eutrophication (and oligotrophication) we can measure, this reduction in oxygen consumption at Sycamore Point is encouraging. In fact, this decline in criteria failure corresponds with a decline in summer mean chlorophyll-a concentrations at Sycamore Point, which provides at least a correlation to support our conceptual understanding of links between nutrient load→chlorophyll→oxygen depletion. We often seek longer time-series to make more robust connections between management actions on land and in-estuary processes, but at Sycamore Point, this time-series will continue to evolve.

3-4 Recommendations

Based on this relatively comprehensive analysis of nutrient and water-quality dynamics in the Corsica River watershed and estuary, we can make some recommendations for future monitoring, subsequent analyses, and expectations for water quality improvement:

(1) Increase efforts to implement BMPs and reduce nutrient concentrations to ensure future nutrient load declines from all regions of the watershed. Because Old Mill Stream is a large source of nutrients and freshwater to the Corsica estuary, but nutrient concentrations there appear to be more resilient to reduction than at Gravel Run and Three Bridges Branch, this stream and its watershed should be an area of emphasis for BMP implementation.

(2) Continue to expand the cover crop implementation program within the State of Maryland. Our analysis suggests that cover crops may be the primary source of management-induced nutrient concentration declines in streams and recent success in the implementation of cover crop programs indicates that this is an effective tool in the management on nutrients within agricultural systems.

(3) Manage expectations, which need to be realistic. Unfortunately, despite large efforts to reduce nutrient loading to the Corsica River estuary, loads do not appear to have declined since

2005. Despite significant declines in nutrient concentration in Gravel Run, this stream is too small to impact the total nutrient load from the watershed. Sustained and new efforts to implement BMPs, especially cover crops, in the watershed should continue to push the watershed nutrient loads to more substantial reductions.

(4) Improve storm water management in Centreville. A variety of solid efforts have been made to implement BMPs and improve storm water management in Centerville, and new ambitious projects are planned. This storm water is relatively easy to manage (relative to legacy groundwater and agriculture) and will help to reduce TP loading to the estuary, which is largely storm driven.

(5) Continue the water monitoring program in Maryland State waters. Using this analysis as an example, we can clearly document leading indicators of water quality improvements associated with BMP implementation, but we were only able to do this because quality data were available over wide temporal and spatial scales. These scales allowed us to examine seasonally-based patterns in water quality changes and how the magnitude of change was stream- or station-dependent.

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Chapter 4

Predicting Chlorophyll-a in Shallow Tributaries of Chesapeake Bay

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4-1 Introduction

The long-term program to restore water and habitat quality in Chesapeake Bay has entered its 32nd year and while much remains to be done, much has been accomplished. Prominent among these are the continuation of a comprehensive monitoring program with associated analyses of data for water quality and habitat status and trends, the continuing development of more refined landscape and estuarine models of nutrient and sediment loads and water quality and habitat responses, respectively, and the institution of a Total Maximum Daily Load (TMDL) program, the biggest and most complex ever attempted in the USA.

In addition, there have been some significant improvements in water and habitat quality in specific areas of the Bay and tributary rivers where strong management actions have occurred to reduce nutrient loads. For example, reduced WWTP discharges to the Back River, upper Patuxent, and upper Potomac were associated with improved water and habitat conditions (Boynton et al., 2013; Ruhl and Rybicki, 2010). In addition, during a period of low flow and reduced nutrient concentrations a very large SAV bed in the upper mainstem of the Bay recovered and subsequently showed strong signs of resilience in the face of severe stresses associated with tropical storm events (Gurbisz and Kemp, 2014). SAV recovery in other sections of the Bay and tributary rivers has also been documented and associated with nutrient load reductions (Orth et al., 2010). Finally, more subtle changes in mainstem Bay hypoxia have been attributed to reduced nutrient loading (Murphy et al., 2011). Thus, there have been some significant successes in the greater Bay area related to nutrient load modifications.

A great deal of effort has focused on the mainstem Bay in terms of water quality modeling and associated TMDL goals. Somewhat less effort has been expended concerning water quality in the small tributaries in the Maryland portion of the Bay of which there are quite a few with a wide variety of landscape and estuarine characteristics. It seems unlikely that substantial water quality modeling work will be targeted towards these small systems because of the level of effort needed to implement coupled hydrodynamic-water quality models for small systems. There are a few exceptions to this (e.g., Back River; H. Wang, pers.comm.) but most of these systems will not be individually modeled for responses to nutrient load reductions and water quality changes. However, these smaller systems may be the places where responses to load modifications will first appear because they are smaller both in terms of area and volume and because of their proximity to nutrient sources (e.g., Mattawoman Creek; Boynton et al., 2013; Rock Creek; Harris et al., 2015). We ask if there are less complex approaches to linking nutrient load modifications to water quality change. Specifically, we ask if we can relate nutrient loads over multiple annual cycles and in a number of small estuarine systems to chlorophyll-a response to these loads and load changes. In effect we suggest exploring a regression modeling approach that is comparative in the sense of Kemp and Boynton (2012) and can be used to quantitatively better understand the water quality responses of small tributaries to nutrient load changes.

4-1.1 Earlier Results from Lakes and Estuaries

Scientific interest in relatively simple approaches to linking nutrient loads to water quality (chlorophyll-a in most cases) has a long history and some notable successes. Dillon (1975) and Dillon and Rigler (1975) devised regression models relating phosphorus (P) loads to lakes and summer season chlorophyll-a concentrations in the upper mixed layer. They also found that load alone was not sufficient for accurate predictions and found water residence time of the lake to be an important "scaling" variable. Results of these comparative studies were quite stunning with high predictive capabilities. Shortly after these studies were published, Vollenweider (1976) published a more complete synthesis where P loads were related to surface water chlorophyll-a concentration during the ice-free portion of the year as a function of P load with the P load scaled by water residence time and the mean depth of the lake. These results have proved useful in lake management work for many years.

Surprisingly, few comparable relationships have been developed for coastal and marine ecosystems (Boynton et al. 1982; Nixon 1988). Previously we attempted a direct duplication of the Vollenweider (1976) model using average annual surface-water chlorophyll-a concentration as the dependent variable gathered from five major portions of Chesapeake Bay and annual average P loading rate (adjusted for the freshwater fill time and mean depth of the receiving water body) as the independent variable. This selection of variables did not produce either predictive or significant statistical results ($r^2 < 0.10$; $p > 0.10$). We then reasoned that, because algal blooms often accumulate in deep waters, particularly during late winter- spring in Chesapeake Bay, vertically integrated water-column chlorophyll-a (mg m^{-2}) would be a better estimate of algal biomass; however, results were only marginally better. We then substituted nitrogen for phosphorus and results dramatically improved ($r^2 = 0.82$; p<0.01; Fig. 4-1).

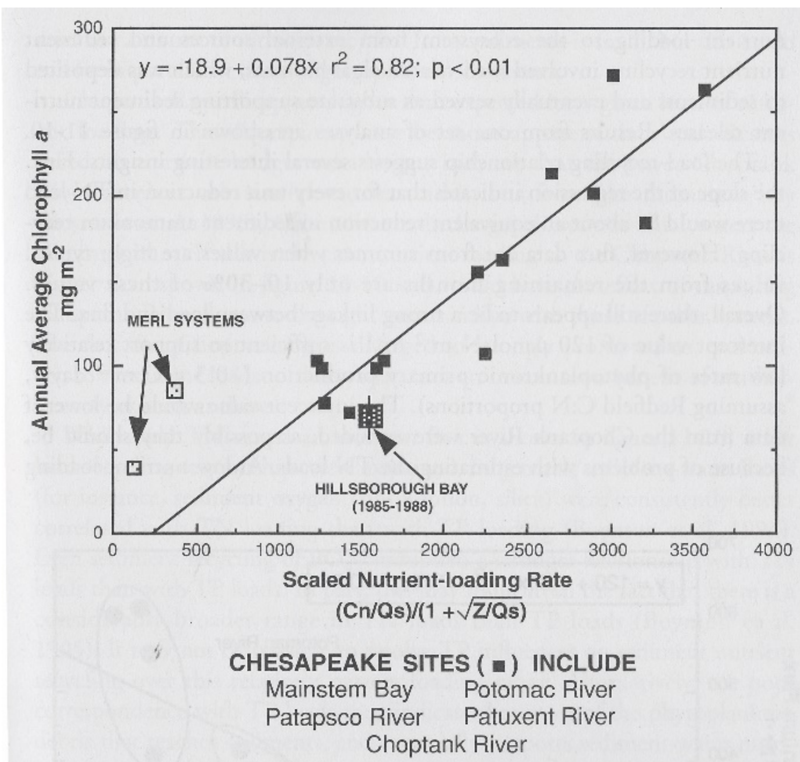

Figure 4-1. A scatter diagram relating average total chlorophyll-a mass to N loading rate. Data are from the 1985-1987 period (Boynton and Kemp 2000). N loading rates were scaled following the method of Vollenweider (1976) where: Cn = N loading rate; Qs = hydraulic fill time; Z = mean depth. MERL = Marine Ecosystems Research Laboratory in Narragansett, RI.

The results support the concept that, for some temperate estuarine systems, phytoplankton biomass levels respond in positive linear relation to nutrient loading rates. Further, there is some indication that different systems respond in a similar fashion when loading rates are scaled for local conditions of depth and flushing rates. It is the intent of the current EPC effort to expand this previous effort involving just a few large portions of Chesapeake Bay to many of the small tributary systems of the Bay. Now that decades of nutrient loading and ecosystem response data are available, we have the opportunity to build multivariate relationships for the shallow-tributaries in Chesapeake Bay. Shallow-water tributaries are of particular interest because the Chesapeake Bay Program Water Quality Modeling System has difficulty in simulating these systems, thus a different set of tools are needed to understand them and manage restoration expectations.

In FY2013, the EPC group performed a comprehensive descriptive analysis of the eutrophication state of 20 shallow estuaries in Chesapeake Bay (Boynton et al., 2013). The data generated by this collation of nutrient loading and water quality data set the stage for a cross-system comparison of relationships between nutrient loading and chlorophyll-a. In FY 2014, the EPC group did an exploratory analysis to generate a broad, cross-system predictive tool that incorporated the effects of nutrient loading and physical features of the systems to estimate chlorophyll-a. Although this analysis was revealing, it needs to be advanced to incorporate a broader set of estuarine features, such as shoreline length, water residence time, regional climate indicators, and others. The value of a predictive tool that incorporates both biological features (e.g., nutrient loading) and physical features (hydrology, climate) is that it allows us to account for the effects of "unmanageable" variability within a particular system in our predictions of loading responses. Understanding responses to load reductions and examining data for meaningful trends is a central concern in the Chesapeake Bay restoration effort.

4-2 Methods

4-2.1 Study Area Descriptions

A total of 20 estuaries were selected for the analyses done in this chapter; however for simplicity we combined the West and Rhode rivers into one estuary, bringing the number of estuaries analyzed to 19 (Table 4-1). When available we chose mesohaline stations from the tributary monitoring program, although 10 of the 19 sites were in tidal fresh or oligohaline environments (Table 4-1, Fig. 4-2). When long-term, fixed-station tributary monitoring stations were unavailable, ConMon and/or DataFlow calibration stations were selected (Table 4-1). Although stations were located in relatively shallow water (mean depth < 10 m), some stations were located in the main channel of a large tributary of Chesapeake Bay, while others were in smaller sub-tributaries with relatively low salinity (Fig. 4-2). Our selection of stations spans a larger latitudinal range in Chesapeake Bay, ranging from the most northern reaches of the Bay to the region south of the Patuxent River estuary mouth (Fig. 4-2).

Table 4-1. A list of estuary names and station codes used in this analysis. Station codes are used by the Chesapeake Bay Program Water Quality Monitoring Program. Abbreviations are used later in the text and in figures to identify particular tributaries. Station names beginning with an "X" indicate a ConMon station.

Estuary	Abbrev.	Stations Used
Tidal Fresh		
Bohemia River	BO	ET2.2
Bush River	BU	WT1.1
Gunpowder River	GU	WT2.1
Mattawoman River	MAT	MAT0016
Northeast River	NO	ET1.1
Piscataway	PI	XFB1986
Oligohaline		
Back River	BA	WT4.1
Middle River	MI	WT3.1
Patapsco River	PAT	WT5.1
Sassafras River	SA	ET3.1
Mesohaline		
Choptank River	CH	ET5.2
Corsica River	CO	XHH3851, XHH4822, XHH5046
Magothy River	MAG	WT6.1
Patuxent River	PAX	RET1.1
Rappahannock River, VA	RA	RET3.2
Severn River	SE	WT7.1
South River	SO	WT8.1
West/Rhode River	WR	WT8.3,WT8.2
Wicomico River	WI	ET7.1

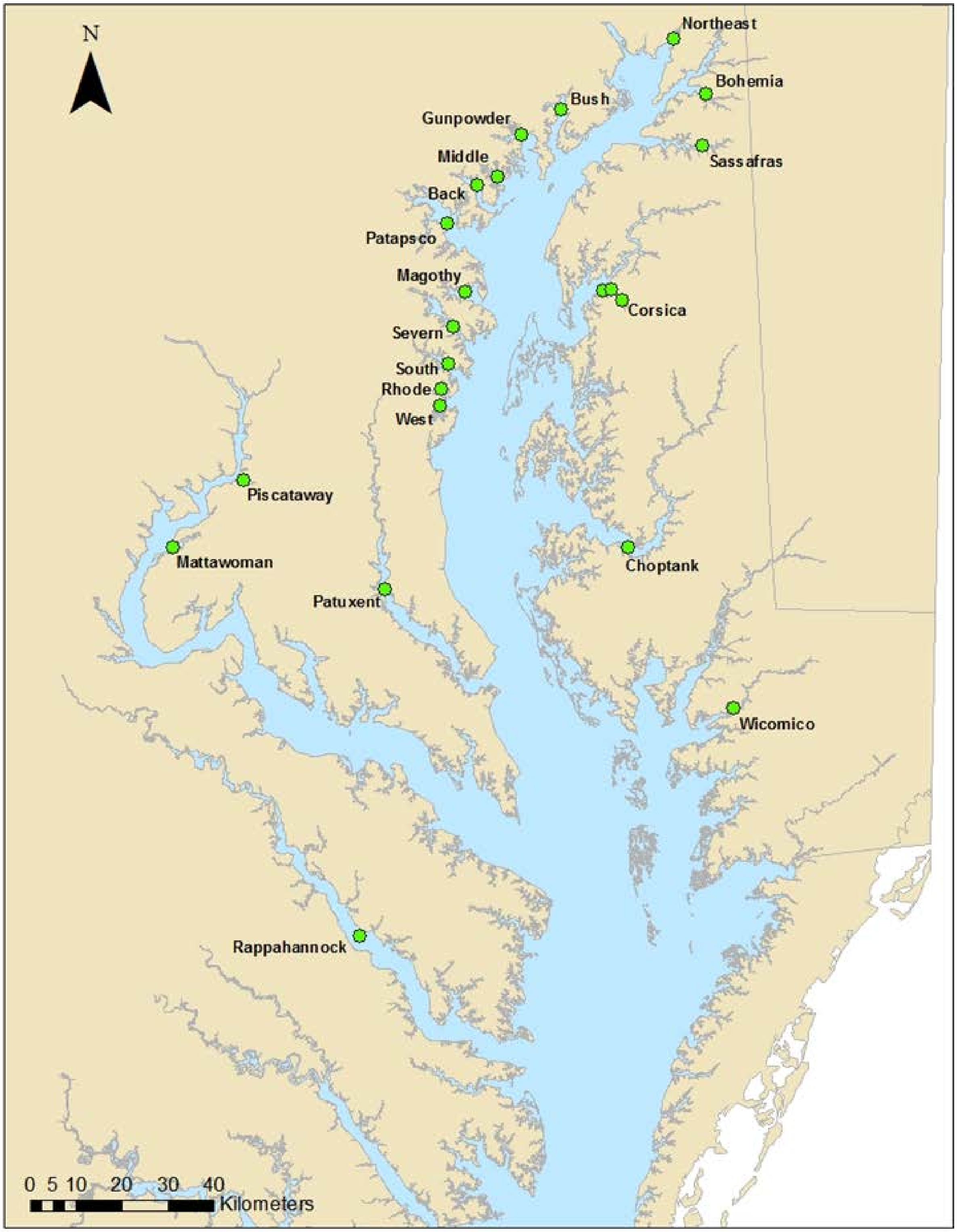

Figure 4-2. A map of Chesapeake Bay showing the location of tributary estuaries included in this analysis. The green dots indicate the general location of Chesapeake Bay Water Quality Monitoring Station data used in this analysis.

4-2.2 Data Sources, Data Manipulations, and Analytical Approaches

Point source and diffuse nutrient loadings data were received from the Chesapeake Bay Program land use model for each estuary based on GIS shapefiles that met our watershed delineations. Water quality data were obtained from the Chesapeake Bay Program CIMS database. We used a previous implementation of the Chesapeake Bay Watershed Model with loads and streamflow available through 2005, so we analyzed data from 1986 through 2005. Additional streamflow data were obtained from the national USGS streamflow database (http://waterdata.usgs.gov/nwis/rt). For each estuary the following parameters were included in our analysis: mean river flow, chlorophyll-a, NH_4, PO_4, NO_{23}, total nitrogen (TN), total phosphorus (TP), dissolved inorganic nitrogen (DIN), dissolved inorganic phosphorus (DIP), salinity, Secchi disk depth, and water temperature. Data were stored in separate Excel files by estuary. For each estuary and water quality parameter, we calculated annual averages, spring (January, February, March, April) averages, summer (June, July, August) averages, and a long term average and standard deviation. These computations were made using values at all sampled depths by the monitoring program. Computations performed on the nutrient loading data were similar to those of the water quality parameters. We calculated annual averages, winter-spring (January-April) averages and a long-term average. Areal loads ($gm^{-2}day^{-1}$) were then calculated using GIS derived surface area values.

A variety of estuarine metrics were analyzed for this chapter (Table 4-2). Basin areas were computed using area values from the watershed shapefiles. We used the river-segments produced for the Chesapeake Bay Program's (USEPA, 2010) Phase 5.3 Watershed Model (USEPA, 2010) to define the watershed boundaries for these analyses. The term "river-segment" refers to the area of land that immediately drains to a river reach. Estuary mouth lengths (Table 4-2) were used to define the estuary boundaries (USGS NHD, 2009). Estuary mouth and smooth shoreline lengths were defined using the editor tool in ArcGIS 10.0 (2012). The zonal statistics tool available in ESRI's ArcGIS 10.0 (2012) spatial analyst toolbox was used to generate estuary volume, average depth, and maximum depth for each estuary boundary. These calculations were based on bathymetric DEM data at 30m raster cell resolution (NOAA, 1998). Surface area and mouth length were summarized using the calculate geometry option within ArcGIS 10.0 (2012) for each estuary boundary. SAV area data were downloaded annually by segment from the Virginia Institute of Marine Science SAV in Chesapeake Bay and Coastal Bays website (http://web.vims.edu/bio/sav/index.html). Data for estuaries that were made up of multiple segments were summed where necessary to obtain a complete annual record for the estuary.

Table 4-2. Summary of physical characteristics of the Chesapeake Bay tributaries included in the modeling analysis.

Estuary	Basin Area	Estuary Volume	Estuary Surface Area	Basin Area: Estuary Area	Basin Area: Estuary Volume	Estuary Average Depth	Estuary Maximum Depth	max depth: avg depth	Estuary Mouth Length	Smooth Shoreline Length	Smooth Shoreline: Mouth	Shoreline Length	Shoreline: Mouth
	m^2x10^6	m^3x10^6	m^2x10^6			m	m		m	m		m	
Middle	33	33	9	4	1	2	3	2	1315	37601	29	69108	53
WestRhode	66	29	15	5	2	2	4	2	4243	34110	8	77063	18
Magothy	94	64	19	5	1	3	10	3	851	30651	36	83684	98
Corsica	97	10	4	22	10	2	5	3	1501	22458	15	37532	25
Bohemia	131	15	10	13	9	2	7	5	1783	35793	20	56087	31
Back	144	25	16	9	6	2	8	5	1443	32878	23	45988	32
South	148	57	19	8	3	3	9	3	2936	48513	17	102875	35
Piscataway	176	3	3	53	67	1	2	3	1199	10963	9	10826	9
Severn	177	109	25	7	2	4	17	4	3319	49876	15	124283	37
Northeast	184	24	15	13	8	2	7	4	2294	20503	9	24316	11
Sassafras	217	82	30	7	3	3	17	6	5541	51045	9	127704	23
Mattawoman	245	9	6	39	27	1	8	6	1607	29572	18	34014	21
Bush	336	48	28	12	7	2	11	6	2513	46909	19	66885	27
Wicomico	561	52	29	19	11	2	12	7	2757	51021	19	148550	54
Gunpowder	1181	63	38	31	19	2	6	4	3392	50842	15	85809	25
Patapsco	1518	451	92	17	3	5	20	4	8026	97541	12	257208	32
Choptank	1951	1027	272	7	2	4	26	7	6246	176557	28	860716	138
Patuxent	2343	404	93	25	6	4	40	9	1094	140940	129	342262	313
Rappahannock	6918	1560	367	19	4	4	24	6	5899	275006	47	1038361	176

4-2.3 Loading Composite Indices and Arrhenius Model

We applied three model formulations to predict chlorophyll-a concentrations in the shallow water dataset. These included the original Vollenweider formulation based on mean depth, flushing time, and phosphorus load, an adaptation of the Vollenweider formulation for estuaries, where nitrogen load replaces phosphorus load (Boynton and Kemp, 2000), and the Van't Hoff Arrhenius formulation that represents the temperature dependence of reaction rates that has been applied to estuaries (Harris and Brush, 2012). The formulas for each of these are included in Table 4-3.

4-2.4 Multi-dimensional Scaling Plots and Cluster Analyses

The dataset generated as part of this analysis lends itself particularly well to a multivariate statistical approach that allows us to consider the complexities of potential explanatory variables in our search for predictive indicators of chlorophyll-a. Multivariate methods use techniques that compare samples and compute similarity coefficients, which can then be visualized in ordination plots and classified into likewise groups using clustering approaches (McGarigal et al., 2000). We initially sought to quantify how similar the explanatory variables were across all stations, so that we might reduce the number of potential explanatory variables used in the analysis. Our approach here was to first normalize the dataset that included both water quality data and estuarine physical features (Table 4-2) and compute a matrix of resemblances between samples based on Euclidean distances. This matrix was then used to generate multi-dimensional scaling (MDS) plots as our preferred ordination technique, ordering the variables or stations in accordance with how similar they were to one another. Superimposed clusters were then applied at a range of similarity levels to the MDS plots to facilitate interpretation of the plots. These methods were applied first to explore similarities between stations, and secondly on the environmental variables themselves. This visualization allowed us to confirm (or question) our assumptions of how either environmental variables or the stations clustered together in a quantitative way. The software program Primer-E (Clarke and Gorley, 2006) was used to carry out the analyses and to generate associated plots. We applied this approach on datasets collapsed into annual averages.

4-2.5 Model Selection

In general, estuarine ecologists exploring water quality data have taken a frequentist statistical perspective, assuming that repeated sampling can generate a measure of the relative frequency and that a “true mean” or estimate of variance exists and is fixed. Bayesian or information theoretic approaches do not have these assumptions, instead they rely on the variance of the sampling data to generate parameters describing the measurement of interest and probabilities. A challenge of applying a frequentist approach to determining whether an empirical model is a good fit to available data is the fact that in a regression analysis model fit increases as additional variables are added to the explanatory term. We sought to apply an Information Theoretic approach to determining which of the three predictive models described in Table 4-2 explained the most information in our chlorophyll-a dataset. The three models were first ranked according to the second-order bias correction, Akaike Information Criteria (AIC), and the adjusted coefficient of multiple determination ($adjr^2$) following the approach of Burnham and Anderson (2002). The adj r^2 is based on the coefficient of determination, r^2, but adjusted for the number of terms in the model.

The AIC is a tool for model selection calculated from the Kullback-Leibler distance between model i and the “true” model that generated the data. The Kullback-Leibler distance is the amount of information lost when using model i to approximate the true model. The best model has the smallest Kullback-Leibler distance and thus the smallest AIC. Akaike weights (w_i) determine the relative support of each candidate model, providing insight into which variables are of interest in predicting chlorophyll-a.

Regression analysis was completed using the R-statistical package (http://www.r-project.org/), and specifically the “leaps” and “cards” libraries. We performed this model selection exercise on the dataset collapsed into both annual averages and summer months (June, July, August) versions of the dataset.

4-3 Results and Discussion

4-3.1 Summary of Shallow Water Stations vs Chlorophyll-a

For deep, phytoplankton-dominated estuaries, strong relationships between external nutrient loading and the biomass and/or production of phytoplankton have been found within (Harding and Perry, 1997) and among (Boynton et al., 1982) ecosystems. These relationships reveal the fundamental linkage between watershed and river nutrient inputs, estuarine nutrient availability, and the relief of nutrient limitation on algal growth. In shallow estuaries, such relationships have been more difficult to discern from the data (Fig. 4-3). One explanation for this weak link is that shallow estuaries tend to be more closely linked in space to freshwater sources, and thus the river flows that deliver nutrients also tend to deliver suspended solids that increase turbidity and also flush algal cells seaward. In concert, these effects should be expected to cause negative relationships between river (and nutrient) inputs and algal biomass. Secondly, shallow estuaries are more likely to have benthic macrophytes and other non-phytoplankton primary producers contribute to ecosystem primary production, and thus compete with phytoplankton for externally-derived nutrients. A plot of the relationship between dissolved inorganic nitrogen loading and summer chlorophyll-a in shallow Chesapeake tributaries and several other shallow ecosystems (Nixon, 2001) illustrates the generally limited relationship between loading and algae in these systems (Fig. 4-3). For example, note the order of magnitude variation in chlorophyll-a at a given DIN load in both the Nixon (2001) and Chesapeake data sets (Fig. 4-3). This feature highlights the fact that at any given station, the level of algal biomass generated for a given nutrient load can vary widely, presumably in response to physical (flushing, depth) or biological (grazing, SAV) features of a particular ecosystem that modulate the estuary's response to external loading.

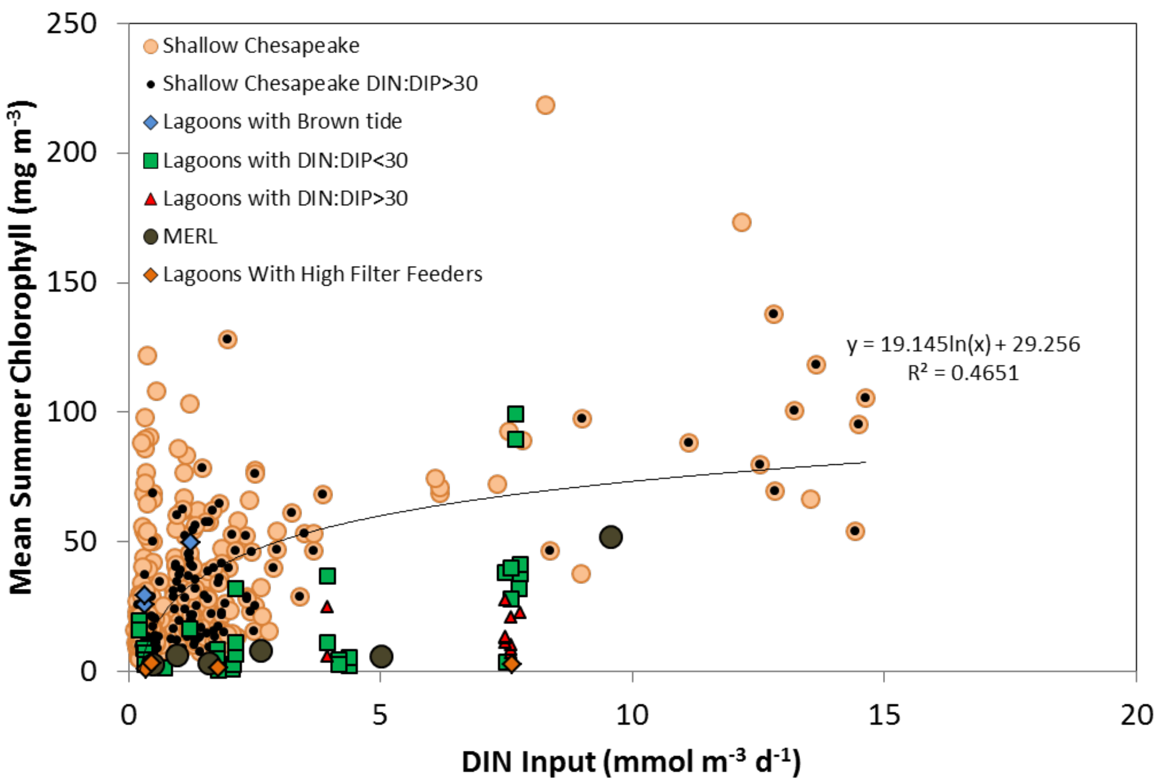

Figure 4-3. Relationship between annual Dissolved Inorganic Nitrogen input and summer chlorophyll-a across 19 shallow Chesapeake tributaries and those shallow systems from Nixon (2001).

Previous cross-system analysis of the relationship between nutrient load and chlorophyll-a (Boynton et al., 2013) in shallow Chesapeake estuaries has revealed that for a subset of locations, links between nutrient load and chlorophyll-a are quite strong. Although this is consistent with our mechanistic understanding of estuaries, where elevated nutrient loads relieve nutrient limitation of phytoplankton and allow high growth rates, the lack of relationship for the other stations indicates that other key processes control phytoplankton biomass. As mentioned above, freshwater inputs can either stimulate phytoplankton biomass by delivering nutrients, or diminish phytoplankton biomass by flushing the estuary faster than phytoplankton can grow to accumulate biomass. A simple regression of annual river flow versus chlorophyll-a illustrates this mechanism clearly, as stations/systems that are in oligohaline or tidal fresh regions (e.g., Back, Sassafras, Bohemia) have reduced chlorophyll-a at high flow, while mesohaline stations (Choptank, South, Patuxent) have positive relationships (Fig. 4-4). In the former case, oligohaline or tidal fresh regions, which tend to have small volumes combined with proximity to freshwater inputs, are flushed under high flow. In contrast, mesohaline stations, which may be deeper and more seaward of freshwater sources, are less well-flushed under high flow and can utilize elevated nutrient availability. Clearly, any predictive tool for chlorophyll-a in shallow water must incorporate the impacts of nutrient loading, depth, and flushing rate.

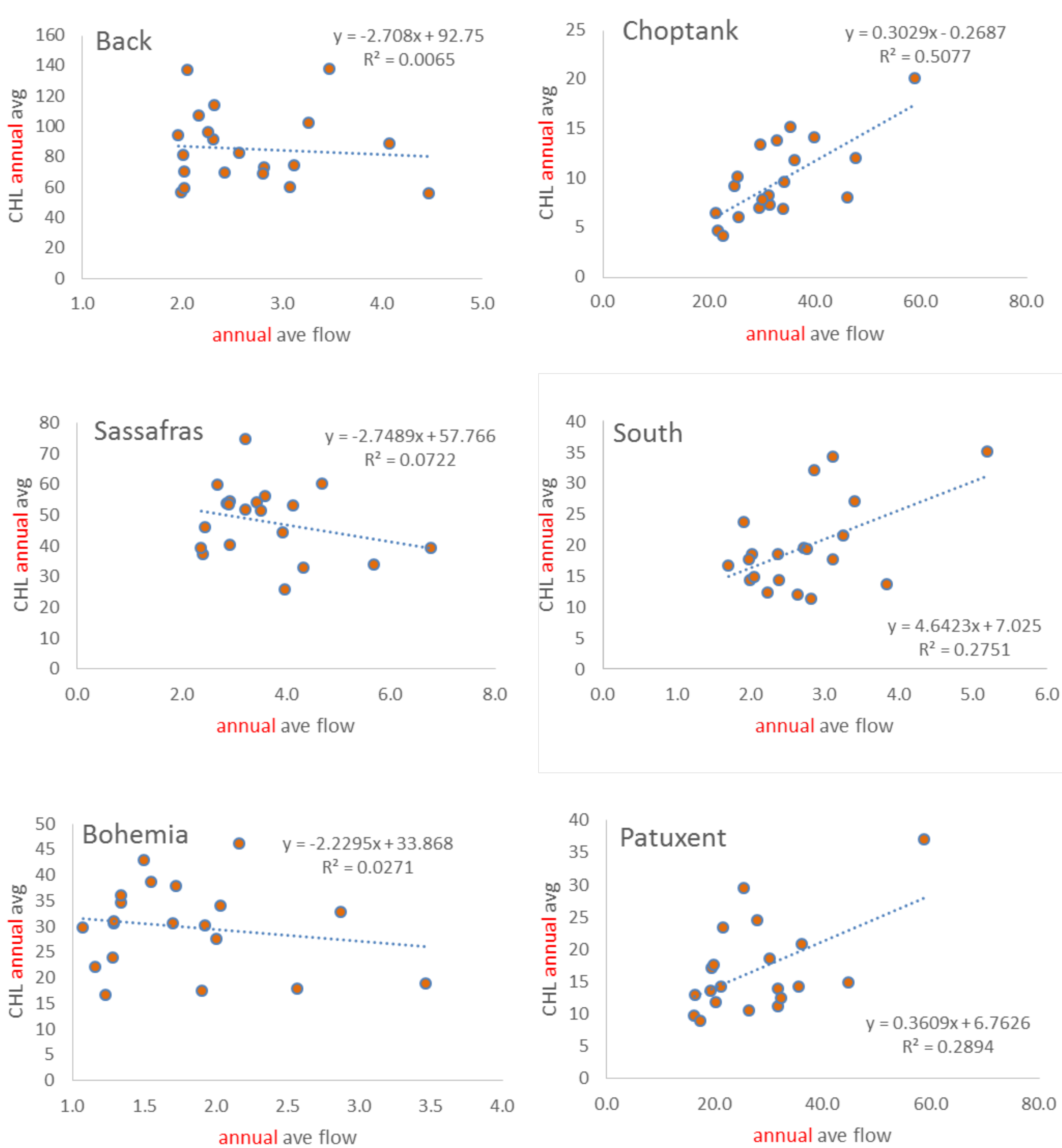

Figure 4-4. Relationship of annul average chlorophyll-a (mg m^{-3}) to annual freshwater inputs (m^3 s^{-1}) in three oligohaline/tidal fresh stations (Back, Sassafras, Bohemia, left) and three mesohaline stations (Choptank, South, Patuxent, right).

4-3.2 Chlorophyll-a Time-Series

Chlorophyll-a time-series for 18 of the 19 stations indicates a variety of temporal changes among the various locations (Fig. 4-5). For example, long-term declines appear to be evident for the Back River, Patapsco River, Mattawoman Creek, Gunpowder River, and the South River, while no clear temporal trends are evident in several of the sites. Yet at other sites, long-term increases are apparent (Patuxent, Choptank). At some sites, chlorophyll-a varies substantially from year to year (Bush River, Bohemia River, Northeast River), while chlorophyll-a variability is muted at others (Middle River, West-Rhode River). Clearly, a variety of factors may disproportionately influence each system, where nutrient loading, geometry, residence time, and salinity vary substantially among these systems. Below, we utilize multivariate tools to discern these forces.

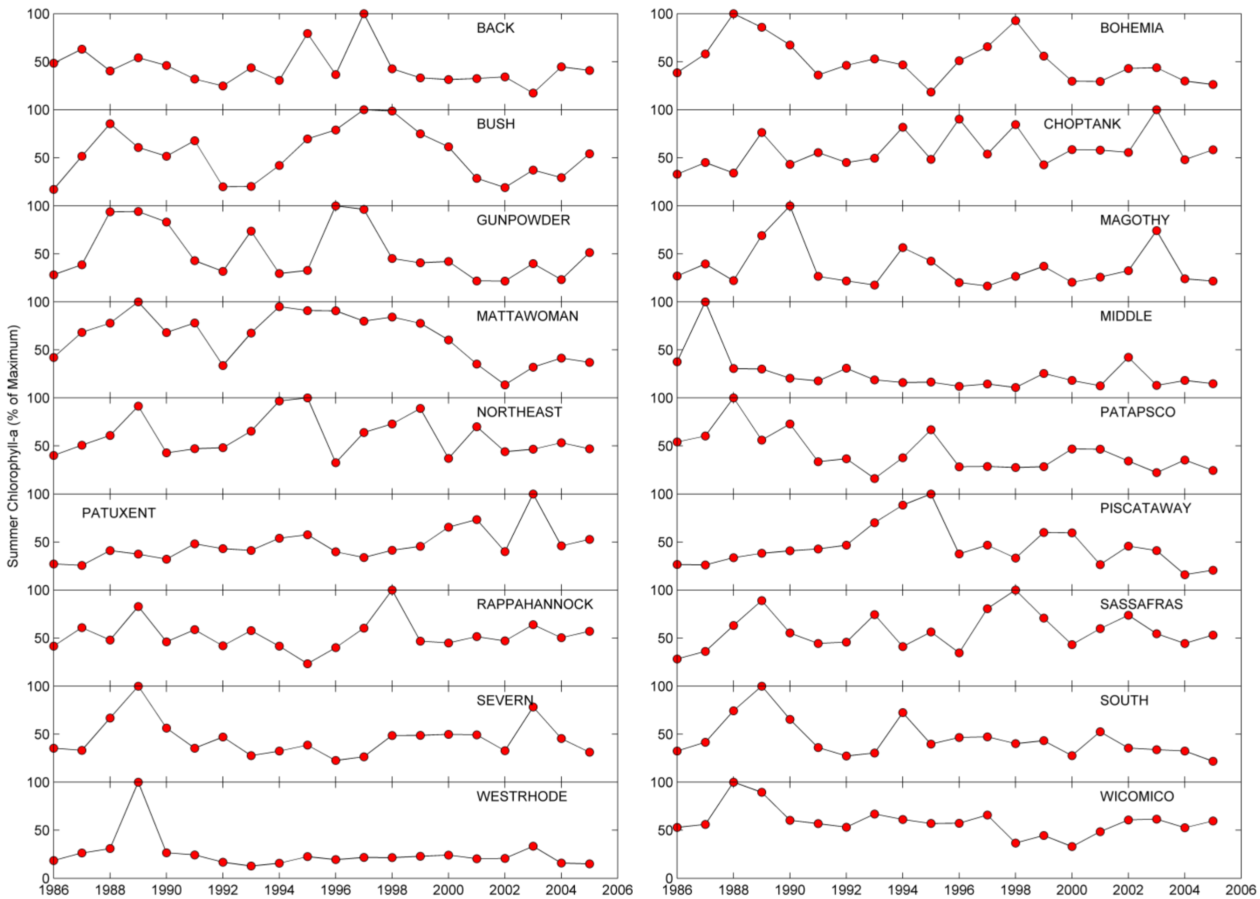

Figure 4-5. Time-Series of chlorophyll-a (expressed as % of summer maxima) at 18 sites in Chesapeake Bay.

4-3.3 Multi-Dimensional Scaling

A first step in our multivariate analyses of the dataset developed in this task was to determine how stations were grouped according to the many environmental variables described in Table 4-2. The cluster analysis resulted in an MDS ordination plot and dendrogram (Fig. 4-6) that illustrate the similarity of particular stations to one another. Stations arranged closer to one another on the plot are more similar, and a 2D stress level of 0.1 or lower provides us with some confidence that this dimensional arrangement of the MDS is truly representative of the resemblances matrix. A second metric of station similarity is illustrated in the dendrogram (bottom panel of Fig. 4-6), where similar stations are positioned next to each other and share common branches. Each of these plots indicate that a large fraction of these stations are relatively similar to each other in terms of nutrient state and physical properties.

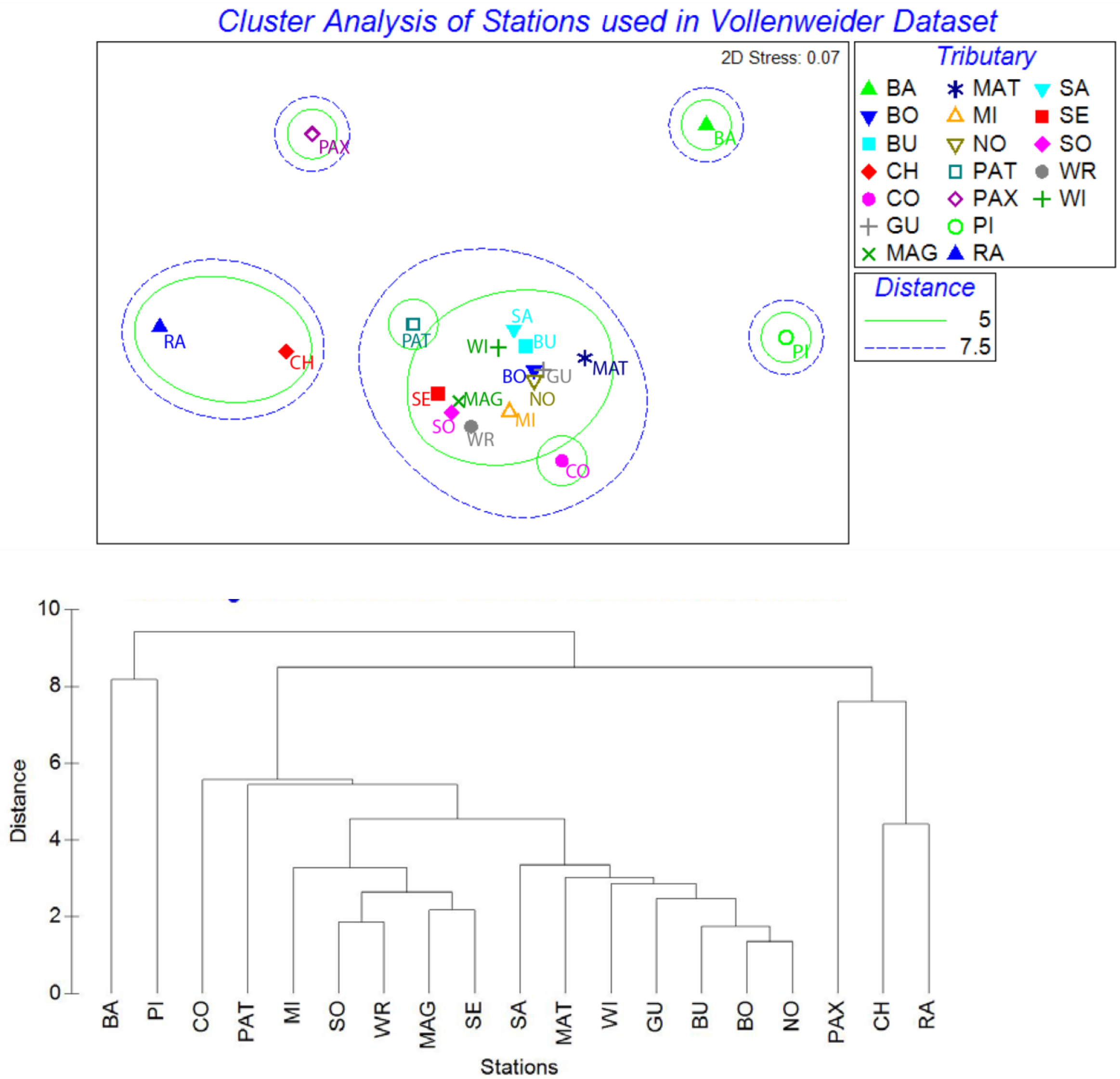

Figure 4-6. Cluster Analysis of Stations. Station abbreviations correspond to those in Table 4-1. Ordination plot pictures MDS 1 plotted against MDS 2. There are no units involved in multi-dimensional scaling.

In this analysis, several key stations also break away from the majority of locations. The Back River (BA) represents an unusually high nutrient loading condition, where in-estuary nutrient levels are extremely high associated with the large sewage treatment plant discharge from this system. In the case of the Patuxent (PAX), Choptank (CH), and Rappahannock (RA) Rivers, these relatively large systems have stations located in deeper, seaward, and mesohaline reaches of the estuary. Prior analyses (Boynton et al., 2013) have indicated that the Piscataway River (PI) station is unusual for a number of reasons, including a large coverage of SAV despite high nutrient loads. Exceptionally high SAV coverage would indicate that the majority of the nutrient in the system is assimilated into rooted macrophytes, and not phytoplankton. Thus such a location would not be appropriate for a phytoplankton model. To help us determine which variables were driving these differences, we completed the same analysis on the complete dataset, but instead performed the ordination on the variables rather than the stations as pictured in Figure 4-7. This analysis also helps us to determine which metrics cluster with our variable of interest; chlorophyll-a.

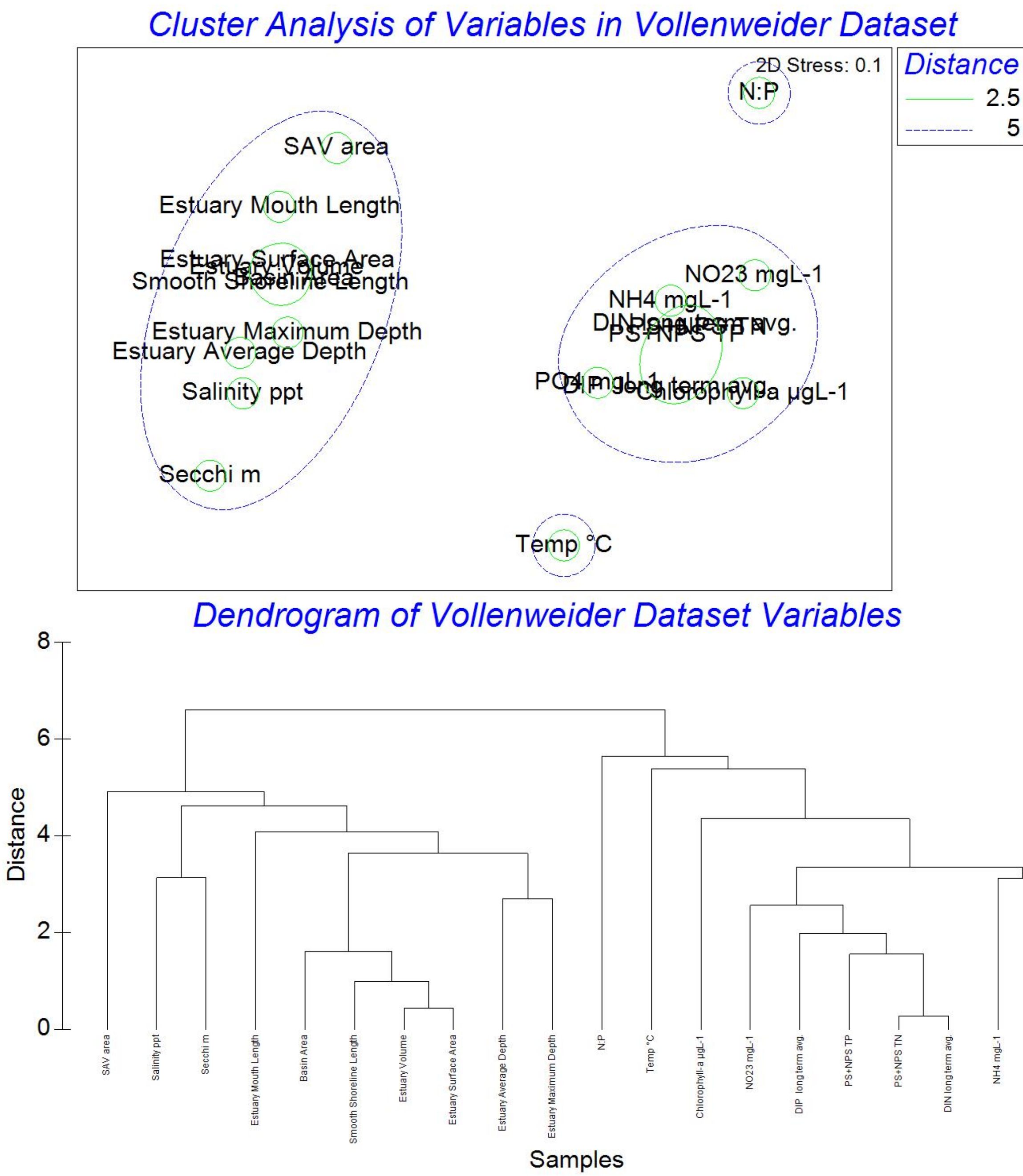

Figure 4-7: Cluster Analysis of Environmental Variables

In general, geomorphic variables such as estuary volume or surface area grouped together, along with salinity, Secchi depth, and SAV area (Fig. 4-7). Nutrient and chlorophyll-a values also clustered together. Neither temperature nor the molar ratio of N to P clustered with the chlorophyll-a variable, however in the dendrogram it is apparent that these indicators are closer to chlorophyll-a than the other cluster. This confirms much of our prior understanding of how these characteristics relate to one another and provides a quantitative test of those assumptions. It is encouraging that the factors we are exploring in this task (nitrogen, phosphorus, temperature) are closely associated with chlorophyll-a in the dataset as a whole.

The close clustering of some of the variables also suggests that it may be possible to collapse these complex datasets into fewer indicator variables for the development of more complex multivariate models. For example, considering only estuary volume instead of all of the other geomorphic metrics or using *in situ* concentrations rather than nutrient loads may well be an efficient way forward. From this analysis we can also confirm from the resemblances matrix generated as part of this analysis that the Piscataway station is an outlier, especially in terms of how SAV and nutrients are related to the other variables. For this reason, we removed the Piscataway station from the remainder of the model testing effort.

4-3.4 Model Selection

The three models explored in this chapter and described fully in Table 4-3 represent various mechanisms hypothesized to control chlorophyll-a concentrations at the system scale. We used a model selection approach to determine whether a classical Vollenweider formulation, based on phosphorus, or the Boynton and Kemp (2000) version, based on nitrogen, might better predict chlorophyll-a values. For temperature, which is hypothesized to be non-linearly related to chlorophyll-a, it is fair to question whether nutrient limitation or temperature effects might have a greater impact and so a third formulation describing temperature effects was also included. Using the AIC as our metric for ranking the various models, we first set out to determine if one of the three formulations (abbreviated here to "*Vollenweider*", "*Van't Hoff*", and "*Boynton*") might better predict chlorophyll-a in a dataset comprised of annually collapsed values and excluding data from the Piscataway station based on results from the previous section.

Table 4-3 reports the results of this first model ranking exercise. Recall that the best model has the lowest AIC value, and the Akaike weights (w_i) determine the relative support of each candidate model. While a second-order bias correction is often applied for small sample sizes to produce a corrected AIC value, AICc, the ratio of sample size to dependent variables for our compiled dataset (n=343) was 114. This is well above the ratio criterion of 40–60 suggested for use of AICc (Anderson, 2008). In this model ranking exercise, the *Boynton* formulation resulted in the lowest AIC value. The AIC value for this second ranked model was 53.21. Burnham and Anderson (2002) suggest that the level of empirical support for a model with a ΔAIC greater than 10 is very low. This same model selection outcome occurred for data collapsed into summer, rather than annual, averages as seen in Table 4-4. The relative support for the other models was 0.

Table 4-3. Annual Chlorophyll-a individual model runs using annual averages without Piscataway *In this and following tables: D=depth, TOT=Turnover Time

Model rank	Independent variables	adj r^2	AIC	Δ AIC	ω_i
1 Boynton	$\frac{[DIN*1000*365/TOT]}{1+\sqrt{(D/TOT)}}$	0.42	814.17	0.00	1.00
2 Vollenweider	$\frac{[TP*1000*365/TOT]}{1+\sqrt{(D/TOT)}}$	0.18	867.38	53.21	0.00
3 Van't Hoff	-E/*k*T	0.00	895.92	81.75	0.00

Table 4-4. Summer Chlorophyll-a individual model runs using annual averages without Piscataway

Model rank	Independent variables	adj r^2	AIC	Δ AIC	ω_i
1 Boynton	$\frac{[DIN*1000*365/TOT]}{1+ sqrt(d/TOT)}$	0.29	948.91	0.00	1.00
2 Vollenweider	$\frac{[TP*1000*365/TOT]}{1+ sqrt(d/TOT)}$	0.14	976.75	27.84	0.00
3 Van't Hoff	-E/*k*T	0.00	998.65	49.74	0.00

While this result helps us to have confidence that nitrogen as normalized to turnover time in the *Boynton* formulation is the best model for use in these systems, this analysis does not help us to evaluate whether a combination of these terms into some composite model might fare even better. To that end, we used the dataset based on annual averages to test the three models on their own, along with every combination of the formulations into composite models (*Boynton+Vollenweider*, or *Boynton + Van't Hoff*, etc.). Because our ratio of independent terms to stations and years sampled is reduced in this exercise to 49, we computed the corrected AICc value. These results are presented in Table 4-5 and provide a more complex picture of what factors might best predict chlorophyll-a concentrations.

Table 4-5. Annual Chlorophyll-a all models using annual averages without Piscataway. * WRB = Boynton, VW = Vollenweider, VH = Van't Hoff.

Model rank	Independent variables	adj r^2	AICc	Δ AICc	ω_i
1	V+VH+WRB	0.45	809.81	0.00	0.49
2	VW +WRB	0.44	811.12	1.30	0.26
3	VH+WRB	0.44	811.70	1.88	0.19
4	WRB	0.42	814.18	4.37	0.06
5	VW+VH	0.20	865.46	55.65	0.00
6	VW	0.18	867.39	57.58	0.00
7	VH	0.00	895.93	86.12	0.00

In this exercise, we see that combing the *Boynton* formulations with both the *Vollenweider* and *Van't Hoff* formulations results in a grouping of models that all predict chlorophyll-a to some degree. The first 4 ranked models all fall within ΔAICc values of less than 10, indicating there is some empirical support for these composite (models 1, 2, 3) or *Boynton* model approach.

In illustrating the performance of the three models in predicting annual average chlorophyll-a, it is clear that Piscataway Creek is an outlier, given extremely low chlorophyll-a despite high nutrient loads (Fig. 4-8). One obvious reason for the difference between Piscataway Creek and the other sites is that this system (and certainly the area where the monitoring station is) is occupied by dense beds of submerged, rooted plants (i.e., SAV). For Piscataway Creek, 3.7% of the estuarine area that is 2 meters deep or less is occupied by SAV, where in contrast, the next highest system is 2.2% (Mattawoman Creek) and the majority of the remaining systems ae less than 1.5%. In removing Piscataway Creek from the analysis, the Boynton and Vollenweider models improve substantially in their ability to reproduce variability in chlorophyll-a (Table 4-5, Fig. 4-8).

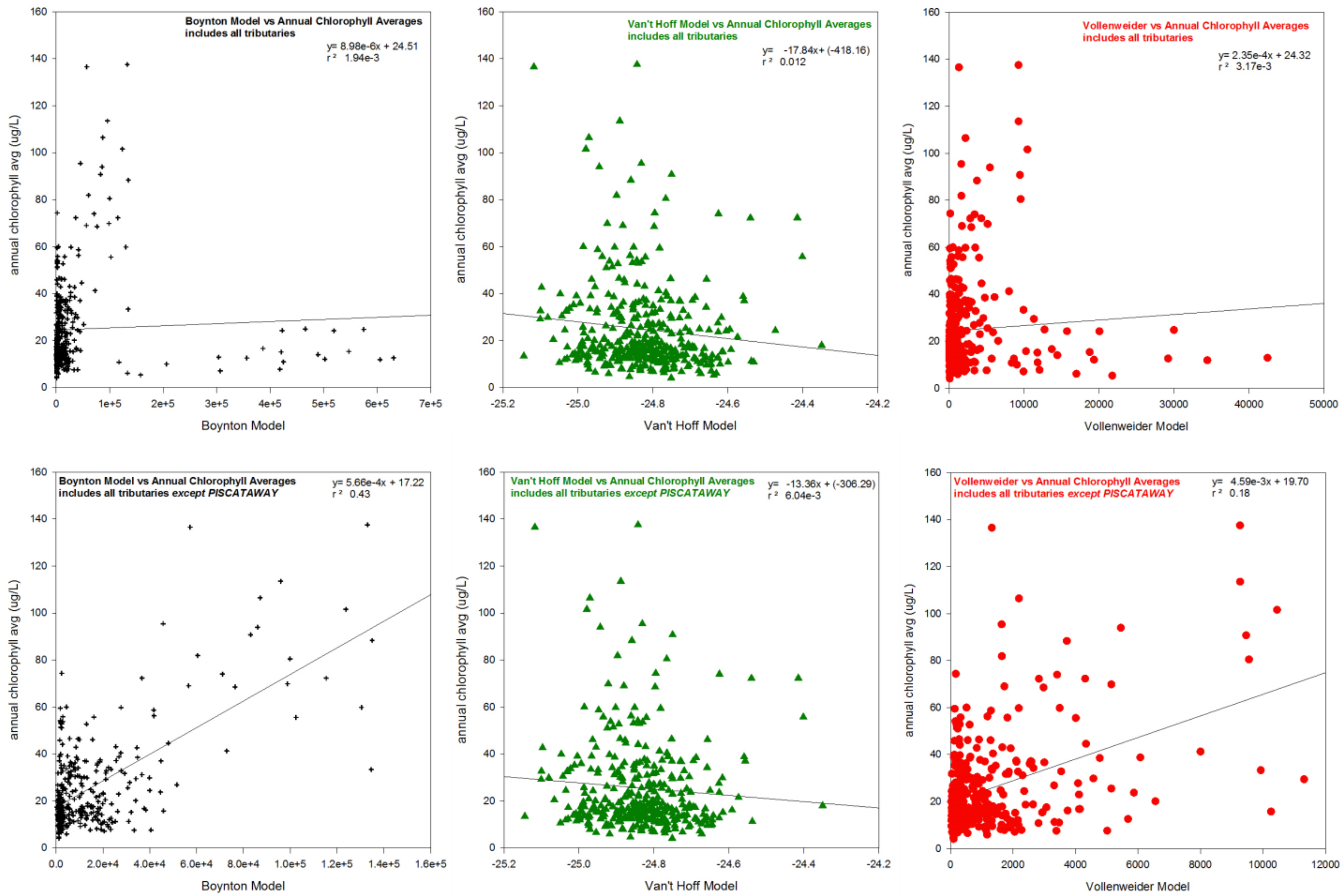

Figure 4-8. Summary of the relationship between each of the three composite models and annual average chlorophyll-a with Piscataway Creek included (top panels) and with Piscataway Creek omitted (bottom panels)

4-3.5 Implications for Shallow Water Chlorophyll and Nutrient Management

The comparative, cross-system analysis presented in this chapter illustrates the value of examining patterns in chlorophyll-a and nutrient loading over a wide-range of environments. In particular, this type of effort helps us to characterize variability in key water-quality metrics at the scale of Chesapeake Bay, as opposed to performing "place-based" analyses in specific segments or tributaries. Chlorophyll-a is an ideal candidate for such an analysis, as it responds strongly to both external forcing and internal cycling and integrates all of the potential controls on variability in water quality.

The objective model-selection tools presented in this chapter generated a highly-predictive model for chlorophyll-a in shallow Chesapeake Bay tributaries that relates phytoplankton biomass to nutrient load, depth, and residence time. Such a tool can be applied to quantify a level of chlorophyll-a to be expected from a given nutrient load in any shallow tributary, and this tool incorporates the impacts of a manageable entity (nutrient load) and an unmanageable entity (residence time). Future work would build on this model to (1) incorporate the impacts of SAV assimilation of nutrient loads, and (2) direct inclusion of nutrient inputs via tidal exchanges from the seaward ends of these tributaries.

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