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Improved estimation of phytoplankton abundance and fine-scale water quality features via simultaneous discrete and semi-continuous surveys

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Abstract

The abundance and distribution of phytoplankton is driven by light and nutrient availability which in turn is controlled by larger-scale regional processes such as climatic variability and global teleconnections. However, such estimates are largely built on evidence gathered from coarse (on the order of kilometers), discrete grab sampling networks where the overall set of measured parameters is limited and whose spatial representativeness is unknown. As a result, abundance estimates can be subject to a high degree of uncertainty and the ability to resolve fine-scale (on the order of meters) water quality features relevant to ecosystem management can be limited.

In the present study, we use a combination of discrete sampling and underway (semi-continuous) flow-through sampling to better constrain estimates of phytoplankton abundance and to better identify the presence, shape, and locations of fine-scale water quality features (boundaries of abrupt change) in a case study set in Florida Bay, USA. We show that phytoplankton abundance is best estimated using a combination of discrete and underway sampling involving simultaneous collection of not only chlorophyll fluorescence but also potential interference materials such as colored dissolved organic matter. Finally, we show that water quality boundaries identified on the basis of underway sampling differ from discretely identified boundaries and are related to climatic variability as well as specific landscape features. These findings have significant implications for algal bloom detection, watershed management, and environmental monitoring both for our case study location and for estuaries in general.

Keywords: water quality, Everglades, cyanobacteria, Florida

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1. Introduction

Phytoplankton abundance plays a critical role in structuring ecosystem processes in subtropical estuaries. For example, unusually high abundance reflects the onset of phytoplankton blooms which can decrease light penetration in the water column causing decreased seagrass growth and benthic productivity (Kelble et al., 2005). Furthermore, phytoplankton abundance is often used as an indirect measure of nutrient loading, eutrophication, and overall ecosystem status (Boyer et al., 2009). As such, it is important to understand the numerous factors that control phytoplankton abundance.

Typically, phytoplankton abundance is assumed to be regulated by light and nutrient availability which in turn is controlled by a variety of regional processes such as advective transport (Dugdale et al., 2012), benthic-pelagic coupling (Zhang and Fischer, 2014; Lawrence et al., 2004), and climatic variability as well as global processes such as teleconnections and atmospheric oscillations (Briceño and Boyer, 2009). However, the evidence for these relationships rests on two features of existing datasets, the accuracy of phytoplankton abundance estimates and the design of monitoring networks from which the data is collected. For example, one of the most common methods of quantitative phytoplankton abundance estimates, which involves measuring chlorophyll fluorescence as a proxy for abundance, is subject to known inaccuracies related to the presence of potential interference materials such as colored dissolved organic matter (Goldman et al., 2013). Furthermore, the distributed nature of most monitoring networks where stations are separated by distances on the order of kilometers means that it is difficult to estimate within-basin spatial variability on the order of meters (Anttila et al., 2008).

The aforementioned issues may not apply in the idealized case where watershed exports are low in potential interference materials and the spatial grain of a particular sampling network is well-aligned with the water quality pattern of interest. However, such idealized cases are likely to be rare. Numerous studies have found that estuaries are commonly subject to high inputs of potential interference materials (e.g. color dissolved organic matter; Du et al., 2010). In addition, long-term (static) sampling networks, which may initially be well-aligned with prevailing water quality patterns, can fall out of alignment either on a temporary basis due to seasonal variation or on a more permanent basis due to alterations in estuary circulation or changes to the upstream watershed. As a result, data collected from grab sampling networks may not be able to resolve water quality features (i.e. locations of abrupt change and hereafter referred to as “water quality boundaries”) either on the basin or sub-basin scales (Anttila et al., 2008; Largier, 1993). Although such boundaries may arise simply from climatic variability or the presence of natural landscape features, they may also arise from individual management actions such as

opening of water control structures (Lane et al., 2007). In an ecological sense, establishing the presence, shape, location, and extent of these boundaries is critical as they are important sites of biogeochemical processing (Largier, 1993). In an applied sense, shifts in these boundaries over time can be a measure of management efficacy in estuaries where alterations in overland freshwater inputs (likely increases) are a key management target.

Here, we present a method to better constrain estimates of phytoplankton abundance and to better identify within-basin variability in such estimates using a combination of discrete sampling and underway (semi-continuous) flow-through sampling. In a case study set in Florida Bay, USA we specifically ask the following questions: Can quantitative estimates of phytoplankton abundance be improved with simultaneous measurement of chlorophyll fluorescence as well as potential interference materials? How do the shape and location of water quality boundaries develop in relation to landscape features and climatic variability? Our hypothesis, which was based on the findings of prior studies using discrete sampling, was that we would find distinct and persistent boundary points between the numerous sub-basins that make up Florida Bay especially at the transition between the central and eastern bay during periods of high watershed export (Figure 1).

2. Methods

2.1. Site Description

Florida Bay is a large, shallow embayment at the southern tip of the Florida peninsula. It is composed of a series of basins that are hydrologically isolated from each other by islands and shallow mud banks. As a result, many of the interior basins that make up the central bay have long (6-12 month) residence times and limited circulation (Lee et al., 2016). The spatial extent of the present study extends from eastern to central Florida Bay and from the upstream coastal lakes and embayments on the northern shore to the open basins that comprise the bay proper (Figure 1).

The Florida Bay estuary is fed by direct precipitation as well as a combination of overland and groundwater flow from Everglades wetlands. Direct precipitation is rare in the dry season from December-May and is concentrated in the wet season from June-November (Figure 2c). In contrast to many estuaries, Florida Bay is characterized by an upside-down” nutrient gradient where nutrients (especially phosphorus) are lower in the estuary headwaters relative to the estuary terminus (Childers et al., 2006).

60 2.2. Underway-discrete sampling

We developed a method to better constrain estimates of phytoplankton abundance (using chlorophyll a as a proxy and referred to as chlorophyll hereafter) and to better identify within-basin variability in such estimates. Our method involves the use of a boat-mounted flow-through collection system (Dataflow; Madden and Day, 1992) whereby a suite of optical probes are operated in tandem with discrete sample collection. While the boat is underway, the Dataflow receives a continuous stream of water from an onboard pump that is routed to a series of sensors operating in flow-through mode. These sensors measure the physical and optical properties of water passing through the system at 6 second intervals (approximately every 40-70 m of boat travel). The primary optical sensor package includes probes to measure colored dissolved organic matter (CDOM), phycocyanin (PC), phycoerythrin (PE), turbidity, and chlorophyll fluorescence (Cyclops-7 Series; Turner Designs; Sunnyvale CA, USA). A second optical sensor package, which operates in tandem, includes probes to measure CDOM and chlorophyll fluorescence (GEOSAI SA de CV). Measurements are georeferenced by an onboard GPS unit with a horizontal accuracy of \pm 250 cm. Each Dataflow survey took place on a quarterly to bi-monthly basis from 2008 - 2015 and was supplemented by a set of concomitant discrete grab samples located in a representative basin or area of distinct water quality (Figure 1a, 1b). These samples were collected from the Dataflow outflow hose while underway and were analyzed in the laboratory for chlorophyll concentration via pigment extraction as well as a suite of organic and inorganic nutrient species (Table 1). Laboratory analyses followed the methods described in Childers et al. (2006).

For each survey, we used multiple linear regression to model the chlorophyll concentration of the underway discrete grab samples as a function of corresponding optical measurements (Seppala and Ylostalo, 2007; Seppälä and Olli, 2008). Initial regressions included all available optical measurements. These “full” models were subject to a model selection procedure where the goodness-of-fit and complexity of candidate models were compared using Akaike information criterion (AIC; Venables and Ripley, 2002). Several models with the lowest AIC values were further investigated to examine normality of residuals and avoid multicollinearity. Also, we checked that coefficients had a logically consistent sign in cases where we had strong prior belief (e.g. the coefficient of chlorophyll fluorescence should be positive). Final models were applied to the full streaming dataset to estimate chlorophyll concentration in areas where underway discrete grab samples were not collected. In order to avoid model extrapolation, calculated values that exceeded the maximum concentration in the discrete sample set were discarded. Due to the presence of many land barriers throughout the study area, the resulting georeferenced datasets were spa-

tially interpolated using Inverse Path Distance Weighting (IPDW) according to the methods described in Stachelek and Madden (2015). IPDW is similar to the more typical Inverse Distance Weighting (IDW) procedure except that distances are "in-water" path distances rather than "as-the-crow-flies" straight line distances. This prevents interpolations from bleeding through land barriers. All statistical analyses
95 and interpolation routines were performed using R, the ipdw package, and the DataflowR package (R Development Core Team, 2015; Stachelek, 2016, 2017c). All code used to generate figures and tables is available from Stachelek (2017a) and all data used in this study are available for download (Madden et al., 2017).

2.3. Water quality boundaries

We considered two approaches for quantifying water quality boundaries. The first approach involved defining fixed linear transects (Dale and Fortin, 2014). The advantage of this approach was that we could calculate detailed information about the shape and range of each boundary. However, the exact location of boundaries is unpredictable so transects were prone to miss boundaries when and if they occurred. As an alternative, we developed a non-fixed approach that calculates the unitless slope" between each pixel
100 and its neighbors. We judged the overall "severity" of boundaries on a qualitative basis by examining the output of interpolated water quality maps and on a quantitative basis by computing the cumulative density of all the slopes for each chlorophyll and salinity surface (each survey). In this way, we avoided developing an arbitrary specification for the threshold that defines a boundary. This non-fixed approach
105 is often used in remote sensing applications to characterize the "hilliness" of a scene (Jordan, 2003). Boundary slopes were calculated using the gdalUtils R package to interface with the Geospatial Data
110 Abstraction Library (Greenberg and Mattiuzzi, 2015; GDAL Development Team, 2017).

2.4. Discrete data collection

We used data from an independent long-term (1993-2015) water quality monitoring program to contrast findings from a typical discrete sampling program with the results from our combined underway-
115 discrete sampling efforts. These data come from a monitoring program of the South Florida Water Management District and are freely available via the DBHYDRO database (Stachelek, 2017b). For visualization purposes, the data was split into geographic regions encompassing three distinct sections of our study area, Biscayne Bay, eastern Florida Bay, and central Florida Bay following Boyer et al. (1999) in the open water portions of Florida Bay (Figure 1c). The area covered by this network is more limited

¹²⁰ than the Dataflow footprint which also includes several saline lakes and semi-enclosed embayments within the wetland zone adjacent to the bay. Data from this longer-term dataset were used as an independent check to verify our underway measurements and interpolated surfaces (See Appendix Table A1).

3. Results

We observed two notable features in the long-term discrete chlorophyll record. First, we observed a declining trend in the central bay (Figure 2a). Average chlorophyll concentration was 2.2 ± 0.05 from 2001 to 2008 but was only 1.3 ± 0.04 from 2008 to 2015. Second, we observed a period of exceptionally high chlorophyll concentrations in 2005 associated with an algal bloom event in Barnes Sound (Rudnick et al., 2006). Following recovery from the 2005 bloom event, chlorophyll concentrations were almost exclusively lower than 2 in all three regions of the open bay (Figure 2b). Exceptions to this threshold occurred following the summer of 2009, which was preceded by a major drought, and following the summer of 2012 when cumulative precipitation was the highest of any year during the study period (151.8 cm versus an annual median of 125.3 cm).

We investigated the incidence of elevated chlorophyll in more detail by examining correlations between chlorophyll and individual nutrient species (Table 1). Chlorophyll was most strongly correlated with total phosphorus (Spearman's $\rho = 0.74$, $p > 0.05$) and particulate phosphorus (Spearman's $\rho = 0.90$, $p > 0.05$). Note that such correlations do not necessarily demonstrate a relationship between phytoplankton abundance and a given nutrient species because of the possibility that high nutrient concentrations do not represent bioavailable nutrients but instead represent cellular bound material within existing phytoplankton cells.

¹⁴⁰ We found that spatially comprehensive estimates of phytoplankton abundance were subject to less uncertainty when estimated on the basis of combined underway-discrete sampling. In particular, there were relatively few surveys where the best model only included chlorophyll fluorescence (Table 2). In general, the performance of these chlorophyll only models was poor relative to their multivariate counterparts with respect to their coefficients of determination and p-value (Table 2). One of the primary reasons for ¹⁴⁵ improved estimates was the fact that underway-discrete sampling included not only chlorophyll fluorescence but also potential interference materials. For example, the variables selected during interpolation model-selection often included phycocyanin and CDOM (Table 2). The selection of phycocyanin as a model variable was not associated with any particular season while CDOM was an important variable only during the dry season surveys (Table 2).

150 In some ways, the spatial distribution of phytoplankton abundance estimated from strictly discrete sampling matched our estimates made on the basis of combined discrete and underway sampling. Both estimates showed a general decreasing west to east chlorophyll gradient and both showed particularly low chlorophyll concentrations in the eastern bay relative to the central bay or Barnes Sound regions (Figure 2, 3, 5). In addition, both estimates showed a similarly sized chlorophyll peak in the central bay in late
155 2012 (Figure 2, 5). However, despite the superficial similarities between the two approaches, there were marked differences in the degree to which they were able to recover within-basin spatial variability (Figure 3, 5). This was evident in the fact that the locations and shapes of water quality boundaries estimated on the basis of underway sampling did not correspond to those that used strictly discrete data (Figure 2, 3, 5). In contrast to the discrete sampling results (with the exception of July and September 2015), our
160 underway-discrete maps did not show distinct water quality boundaries between the central and eastern bay (Figure 5). We did, however, observe consistent and distinct boundaries in both the discrete sampling results and the underway-discrete maps at the transition between the Seven Palm chain-of-lakes (Seven Palm Lake, Monroe Lake, Terrapin Bay) and the central bay (Figure 1, 3, 5).

To some extent, temporal trends in the spatial distribution of phytoplankton abundance over multiple
165 surveys appear to correspond with temporal variations in precipitation (Figure 2b, 2c, 5). Indeed, many of the surveys, which showed elevated chlorophyll concentrations extending over large portions of the study area, were coincident with observations of high precipitation and low salinity (Figure 4, 5). In contrast to these periods of broad chlorophyll increases, the development of localized chlorophyll boundaries did not correspond with relatively wet periods when there was likely to be high watershed export (Figure 2c,
170 6). Instead, they were more prominent during the relatively dry periods, which lagged high watershed export, most notably in 2012 and to a lesser extent in 2009 (Figure 2, 5, 6). The timing of chlorophyll boundary development also contrasted with the timing of salinity boundary development such that salinity boundary development was coincident with periods of high watershed export (Figure 6b).

4. Discussion

175 We have shown that estimates of phytoplankton abundance may be best constrained using a combined underway-discrete sampling approach and that mapping of these estimates can yield important insights into spatial variation on the sub-basin scale. In particular, we found that models, which include many different parameters with potential interference effects such as CDOM, outperformed both discrete sampling approaches and underway-discrete approaches where chlorophyll fluorescence was the sole co-

¹⁸⁰ variate (Table 2). In addition, we found that water quality boundaries identified on the basis of underway sampling differ from discretely identified boundaries and were related to climatic variability as well as specific landscape features (Figure 2-6).

4.1. Phytoplankton abundance

¹⁸⁵ Phytoplankton abundance is typically estimated on the basis of strictly discrete sampling within long-term monitoring networks. In the rare case that abundance is estimated on the basis of underway-discrete sampling chlorophyll fluorescence is often the sole covariate (Lane et al., 2007). In the present study, we found two lines of evidence to suggest that such estimates may be affected by the fact that sampling programs typically do not measure phytopigments or potential interference materials such as colored dissolved organic matter. The first line of evidence was the fact that few of our surveys retained ¹⁹⁰ fluorescence readings from either the primary or secondary Dataflow chlorophyll probes in the “best” model outcome of our variable selection procedure (Table 2). Some of the poor fit of chlorophyll-only fluorescence models may have been due to relatively small per-survey sample sizes or variations in the physiological condition of the phytoplankton community (Goldman et al., 2013). However, we did observe that phycocyanin was often an important fluorescence parameter in these instances. This finding is ¹⁹⁵ broadly consistent with prior observations that algal blooms in Florida Bay are primarily composed of the phycocyanin containing cyanobacteria *Synechococcus* (Phlips et al., 1999; Shangguan et al., 2017). In addition, our observation that phycocyanin and chlorophyll were rarely selected in the same survey suggests that the relative abundance of cyanobacteria and other phytoplankton may be regulated by competitive exclusion (Passarge et al., 2006).

²⁰⁰ The second line of evidence is that CDOM measurements were critical in deriving accurate estimates of phytoplankton abundance (Table 2). Indeed, CDOM is known to affect the performance of optical chlorophyll probes (Du et al., 2010). Contrary to our expectation, we found that CDOM was an important variable only during dry season surveys when watershed exports were likely low. This was unexpected as terrestrial watershed export is known to be a primary source of CDOM (Du et al., 2010). In our case ²⁰⁵ study, the reason that CDOM was selected as an important variable only in the dry season is unknown. One clue may be that CDOM was almost always selected in the same survey as chlorophyll fluorescence (Table 2). If CDOM promotes phytoplankton growth as demonstrated by Traving et al. (2017), this suggests that microbially derived CDOM from local sources may be an important component of dry season nutrient cycling.

210 *4.2. Spatial variability*

Many discrete sampling networks have been continuously operated for multiple decades and have provided great insight into the seasonality and interannual variability associated with phytoplankton abundance across broad (≥ 10 km) geographic scales (Cloern and Jassby, 2010). Our analysis of the long-term discrete chlorophyll record in Florida Bay is broadly consistent with the findings of prior studies 215 that discrete sampling networks are effective at revealing temporal trends in water quality patterns. For example, in our case study, we were able to identify a declining chlorophyll trend in the central bay as well as the development of a severe algal bloom event in 2005 (citation). Furthermore, the coincident sampling of several nutrient species allowed us to examine such variations relative to likely drivers of phytoplankton abundance. Although, correlations between nutrients concentrations and phytoplankton 220 abundance do not necessarily demonstrate a causative relationship, our finding of a strong correlation between chlorophyll and particulate phosphorus is consistent with prior studies (Table 1; Fourqurean et al., 1993). Note that such correlations may simply reflect the presence of cellular bound material within existing phytoplankton cells rather than bioavailable nutrients for phytoplankton growth.

Although discrete sampling networks may be effective tools for examining temporal trends in water 225 quality patterns, they may be less effective for examining spatial variations. One reason is that they typically have a relatively large spatial grain (distance between sampling points) whereby a given interpolation point, which is not coincident with any discrete sampling point, is subject to a high degree of uncertainty (Anttila et al., 2008). Another reason is that the layout of a particular network can be misaligned with the water quality pattern of interest (at a given point in time). Our underway-discrete 230 mapping approach avoided both of these issues by providing a fundamentally different data product than previous efforts involving either strictly discrete estimates or spatial interpolation of discrete sampling network data (Fourqurean et al., 1993). In particular, our estimates of spatial variability had lower uncertainty. This was due in part to the fact that we had a smaller average distance between measurement 235 and interpolation points (Figure 1b). Our underway-discrete sampling was unlikely to be misaligned with any particular water quality feature due to the comprehensive nature of our underway-discrete sampling track (Figure 1b).

An additional benefit of our approach was that it provided high resolution information in areas outside the scope of the discrete sampling network such as the southeastern edge of Barnes Sound and the saline lakes upstream of the central bay (Figure 3, 5). These saline lakes are of great interest in part because 240 they often have high phosphorus concentrations and high phytoplankton abundance despite the fact that

they receive minimal anthropogenic P inputs (Table 1, Figure 7). One possibility is that these lakes receive P inputs from the bay itself during reverse-flow events, storing this P (possibly abiotically via adsorption to particles as well as submerged aquatic vegetation biomass), and releasing this stored P as a function of senescence or disturbance (Rudnick et al., 1999).

²⁴⁵ *4.3. Water quality boundaries*

One of the reasons why we were able to resolve fine-scale water quality boundaries was that our IPDW interpolation approach honors barriers to flow in the landscape (i.e. prevents “bleeding” through islands and peninsulas). We suspect that such boundary difficulties are responsible for the relative rarity of fully 2-dimensional interpolations in complex estuaries (Lane et al., 2007; Roman et al., 2005; Du et al.,
²⁵⁰ 2010). As a result of our approach, we were able to preserve intense water quality gradients among adjacent Florida Bay basins allowing them to be characterized and tracked over time. In particular, our mapping showed that the development of salinity boundaries was strongly associated with wet season precipitation (Figure 4, 6b). In contrast, the development of distinct chlorophyll boundaries was not associated with wet season precipitation when watershed exports are likely to be high. Rather, they
²⁵⁵ were associated with the dry season following these wet periods (Figure 2, 5, 6a). The fact that we observed clear differences between the development of chlorophyll and salinity boundaries suggests that phytoplankton spatial patterns are not simply a result of watershed export but rather a more complex set of non-conservative autochthonous factors such as hydrodynamic circulation, benthic-pelagic coupling, and time lags associated with growth rates and life history (Figure 6; Zhang and Fischer, 2014; Lawrence
²⁶⁰ et al., 2004).

One explanation for our observation that chlorophyll boundaries primarily develop in the dry season is that they are simply a lagged response to prior periods of high watershed exports. However, an alternative explanation is that they develop in response to disturbance caused by periods of extremely low rainfall, high salinity, and low dissolved oxygen conditions (Hall et al., 2016). Such conditions have
²⁶⁵ been implicated as a cause of widespread seagrass die-off in Florida Bay (Borum et al., 2005; Zieman et al., 1999). As seagrass biomass represents one of the largest reservoirs of nutrients in Florida Bay, die-off events have the potential to cause algal blooms by releasing large amounts of nutrients from the benthos to the water column (Fourqurean et al., 2012; Zhang et al., 2004). One such event occurred during the course of the present study (July 2015) with dead seagrass encompassing an area of approximately 9000
²⁷⁰ ha in central Florida Bay (Hall et al., 2016). This event was similar to past die-off events in that it

followed a localized severe drought that resulted in hypersaline conditions followed by die-off (Figure 4; Robblee et al., 1991). The net effects of this event on water column conditions were likely not realized by the conclusion of the present study period. We continue to monitor water column conditions throughout the lifecycle of the die-off in order to expand our understanding of extreme events and their effect on the
275 water quality in Florida Bay.

5. Conclusion

Through the process of combining discrete grab sampling with spatially explicit water quality mapping, we were able to identify several important drivers of phytoplankton abundance in Florida Bay. In particular, we found that prediction of chlorophyll concentration can be enhanced by including measurements of phycocyanin and CDOM fluorescence (Table 2, Figure 5, 8). Our overall underway-discrete mapping approach provided several distinct advantages over a strictly discrete approach. One of the advantages was that we were able to track the location and persistence of water quality features. This approach could prove particularly useful in other estuaries subject to high inputs of potential interference materials (CDOM) which are located in physically complex settings with many sub-basins and barriers
280 to flow. Ultimately, such an approach could be used to improve the design of grab sampling networks, evaluate compliance with water quality standards, or evaluate management efficacy.
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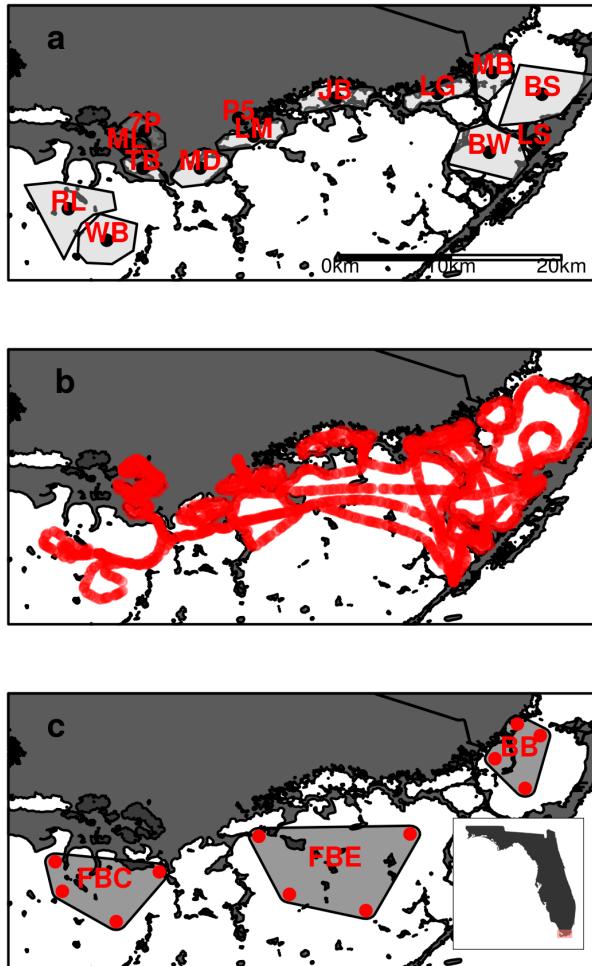


Figure 1: Locations of discrete grab sampling sites within Florida Bay, USA. Polygons represent variability in sampling location over the course of the study period. a) Underway grab sampling network (1993-2015): RL = Rankin Lake, WB = Whipray Basin, TB = Terrapin Bay, ML = Monroe Lake, 7P = Seven Palm Lake, MD = Madeira Bay, LM = Little Madeira Bay, P5 = Pond Five, JB = Joe Bay, LG = Long Sound, BW = Blackwater Sound, LS = Lake Surprise, MB = Manatee Bay, BS = Barnes Sound; b) Representative track line of a Dataflow survey; c) Long-term grab sampling network (2008-2015): BB – Biscayne Bay, FBE – Florida Bay East, FBC = Florida Bay Central.

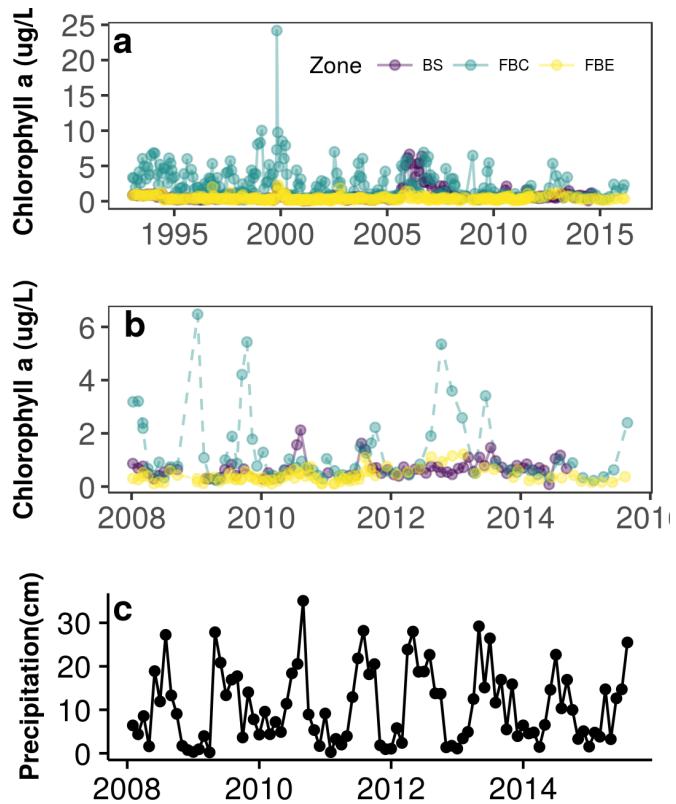


Figure 2: a, b) Time series of average chlorophyll concentration within Florida Bay water quality zones. BS = Barnes Sound, FBC = Florida Bay Central, FBE = Florida Bay East. c) Precipitation during the study period. Precipitation data shown are cumulative monthly totals compositized from three gages in the Florida Bay watershed.

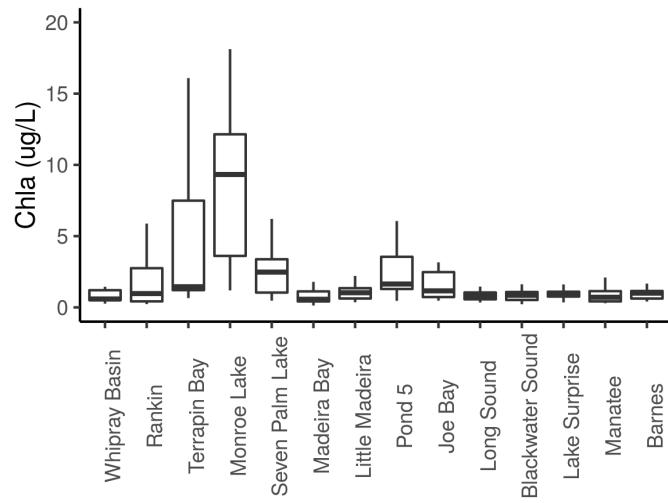


Figure 3: Spatial distribution of chlorophyll concentration in selected Florida Bay basins. Basins are arranged geographically from west to east. The center line of each box is the median of the data, the height of the box represents the interquartile range, and the whiskers represent the fifth and 95th percentiles.

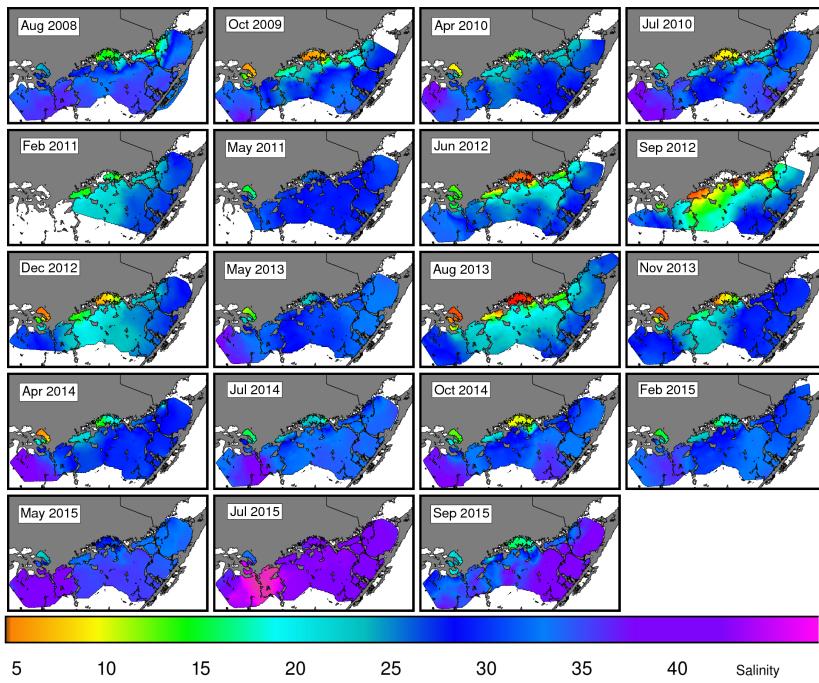


Figure 4: Salinity surfaces for which a valid chlorophyll regression model could be developed. White areas denote areas that were not covered by underway surveys.

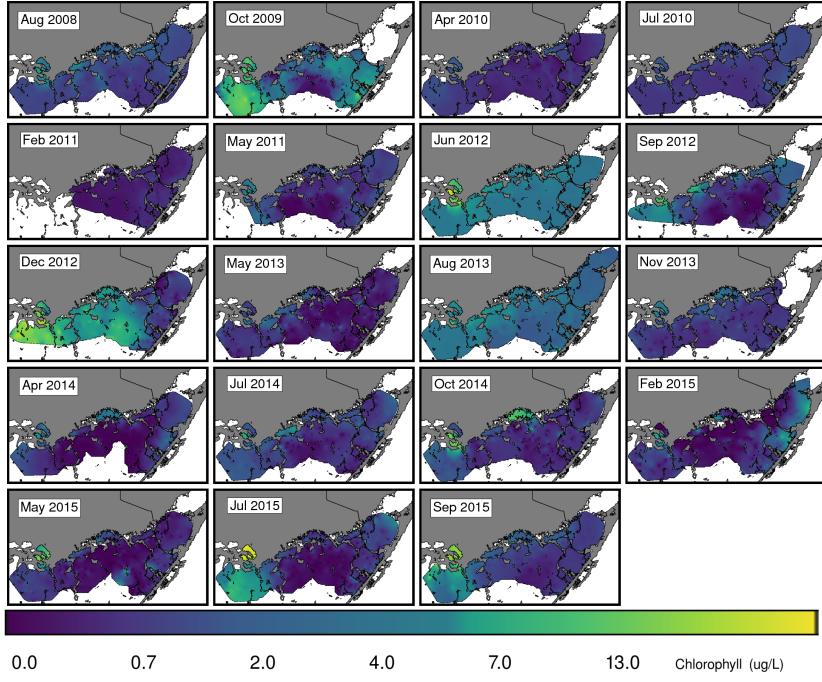


Figure 5: Chlorophyll concentration surfaces calculated using the coefficients in Table 2. Surfaces shown are those for which a valid regression model could be developed. White areas denote areas that were not covered by underway surveys. Note that the color ramp is log-scaled.

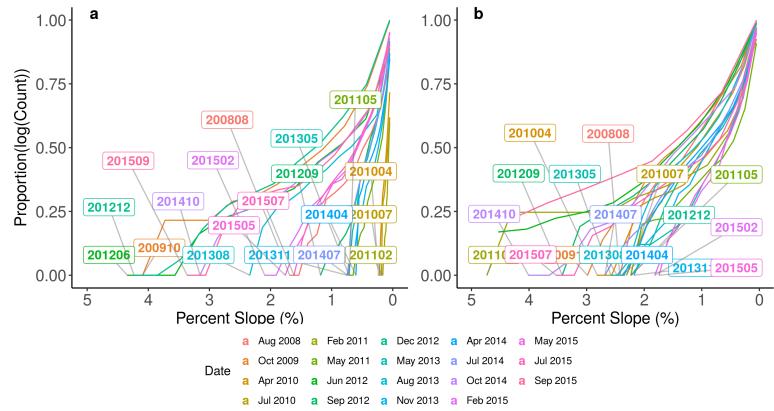


Figure 6: Cumulative distribution of a) chlorophyll and b) salinity boundaries for each survey.

Table 1: Correlation matrix of water quality parameters for selected Florida Bay basins. TP = total phosphorus, TDP = total dissolved phosphorus, PO₄ = ortho-phosphate, TN = total nitrogen, NH₄ = ammonium, NO₃ = nitrate, chla = chlorophyll a, PP = particulate phosphorus. * indicates a significant correlation at P < 0.05. Only complete cases were used in calculations (n = 86).

	TP	TDP	PO ₄	TN	NH ₄	NO ₃	chla
PP	0.68*	0.2	0.34*	0.78*	0.14	-0.11	0.9*
TP		0.65*	0.51*	0.51*	0.16	0.08	0.74*
TDP			0.48*	0.09	0.18	0.3*	0.28*
PO ₄				0.36*	0.16	0.19	0.4*
TN					0.17	-0.12	0.67*
NH ₄						0.55*	0.19
NO ₃							0.02

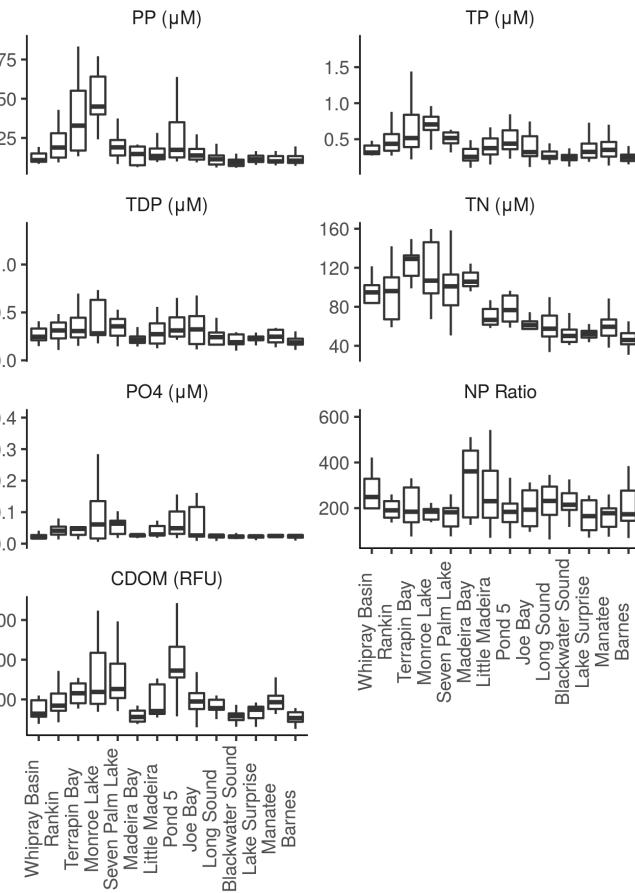


Figure 7: Spatial distribution of discrete water quality parameters in selected Florida Bay basins.

Table 2: Model coefficients for regressions between Dataflow and chlorophyll concentration of discrete grab samples. Potential variables are listed according to whether they were measured as part of the primary or secondary sensor package. CDOM = colored dissolved organic matter, PE = phycoerythrin, PC = phycocyanin. Also given is the coefficient of determination R^2 and p-value of each regression.

Date	Primary			Secondary			intercept	R^2	p	n
	CDOM	chl _a	PE	chl _a	CDOM	PC				
2008-04		27.6258					-4.6263	0.37	0.2	6
2008-08		5.1186					-0.1353	0.90	<0.01	10
2008-12					0.0509		0.0266	0.39	0.19	6
2009-10	-67.1472			0.0495			6.2727	0.97	<0.01	11
2010-02			0.0015	0.0025	-0.0002		-0.1338	0.63	0.5	10
2010-04		7.8275					-0.9164	0.69	<0.01	14
2010-07		3.5643					0.0488	0.45	0.02	13
2011-02				0.0147	-0.0011		0.0012	0.98	<0.01	9
2011-05		12.5233				0.1473	-3.1344	0.90	<0.01	11
2012-06					0.0592		0.2531	0.84	<0.01	12
2012-09		20.2916					-3.4262	0.84	<0.01	10
2012-12				0.0003	0.1430		-1.2135	0.97	<0.01	11
2013-05					0.2594		-2.7694	0.96	<0.01	14
2013-08					0.1580		-0.2626	0.68	<0.01	15
2013-11					0.1864		-1.4612	0.93	<0.01	14
2014-04			0.0217				-1.3616	0.97	<0.01	14
2014-07			0.0048	0.0019		0.1469	-2.6215	0.91	<0.01	14
2014-10			-0.0011		-0.0005	0.2580	-2.1036	0.99	<0.01	14
2015-02				0.0121	-0.0005	0.0485	-0.9664	0.94	<0.01	15
2015-05					0.2731		-3.0247	0.74	<0.01	14
2015-07					0.3283		-3.4682	0.97	<0.01	14
2015-09					0.1184		-0.8047	0.68	<0.01	14