

SAN FRANCISCO BAY NUTRIENT MANAGEMENT STRATEGY

Exploring Trends in San Francisco Bay Water Quality Indicators, 1990-2019

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1. INTRODUCTION

Located at the land-sea interface, estuaries are transition zones where the mixing of water, solutes, and biota between upstream freshwater systems and the downstream ocean drive physical and biogeochemical processes that shape water quality and biological communities. Conditions in estuarine habitats are influenced by multiple factors, including strong physical forcings (e.g., freshwater flows, tides, exchange with the coastal ocean, climatic cycles) and anthropogenic stressors (e.g., contaminant loads, flow and land-use alterations, introduced species) (Cloern and Jassby 2012). As a result, water quality conditions in estuaries can be highly variable over space and a range of timescales (diurnal, tidal, seasonal, interannual, decadal).

Understanding how these drivers influence water quality is important for placing current conditions in context and anticipating how conditions may respond to new anthropogenic impacts, shifts in major environmental forcings (e.g., Pacific Decadal Oscillation, El Niño Southern Oscillation, North Pacific Gyre Oscillation), or management actions aimed at mitigating current impacts. Moreover, as climate change and human-produced stressors continue to affect estuaries worldwide, detecting changing conditions and identifying the underlying drivers of those changes will be an important component of effective resource management (Lindenmayer et al. 2012). In order to detect changes in dynamic systems like estuaries, long-term monitoring data are needed, including sufficiently intensive data collection over relevant spatial and temporal scales. While condition assessments often rely heavily on water quality ‘status’ (i.e., current conditions), investigating and quantifying temporal trends in water quality indicators can yield important information about a system’s behavior and trajectory; for example, the direction in which a water quality indicator is moving (better, worse), rate of change, and covariation between a priority indicator and other environmental data. Detecting trends in environmental data can be challenging due to the intra- and inter-annual variability inherent in natural systems, and may require longer observational records in order to confidently detect a trend. The exploration of water quality status and trends at different time scales and spatial variability may also yield insights into mechanisms driving system responses, including short- and long-term drivers of condition (Foley et al. 2015) or spatial variability in the relative importance of key mechanisms.

San Francisco Bay (SFB), the U.S. Pacific Coast’s largest estuarine system, is a heavily urbanized estuary that receives high anthropogenic inputs of nitrogen (N) and phosphorus (P) (Novick and Senn 2014; Senn and Novick 2014; Cloern et al. 2020). The majority of SFB’s nutrient loads enter the system via the discharge of treated wastewater effluent by 40 publicly-owned treatment works (POTWs) that service the Bay Area’s 7.6 million people

(Novick and Senn 2014). Despite SFB's nutrient-enriched status, however, research and long-term monitoring data extending back to the 1970s indicated that SFB has been relatively insensitive to its high nutrient levels and generally has not experienced the impacts common to many other nutrient-enriched estuaries (Senn and Novick 2014). SFB's 'resistance' to high-nutrients arises from multiple factors, including: high suspended sediment concentrations (decreasing light delivery to phytoplankton); strong tides (thoroughly mixing the water column, which further limits available to phytoplankton, and also replenishes oxygen levels in deeper waters); and dense populations of filter-feeding clams in some regions of SFB that maintain phytoplankton at relatively low levels (e.g., Cloern 1996; SFEI 2015).

However, studies conducted over the last 20 years indicate there have been substantial changes to some water quality indicators, raising concerns that SFB's resistance to elevated nutrients may be waning (e.g., Cloern et al. 2007; Senn and Novick 2014; Sutula et al. 2017; Peacock et al. 2018). Cloern et al. (2007) documented a 2-3 fold increase in fall chlorophyll-a (chl-a) concentrations and gross primary production (GPP) in South Bay between the mid-1990s and 2005. Subsequent studies have noted the frequent detections of harmful algae and associated phycotoxins in deep subtidal habitats (Sutula et al. 2017; Peacock et al., 2018; SFEI 2023), and low dissolved oxygen and high respiration rates in tidal slough habitats (SFEI 2015; SFEI 2021; Roberts et al. 2022). The highly-impactful harmful algae bloom in August 2022 (*Heterosigma akashiwo*) (SFEI 2025) provides the clearest indication to date of changing conditions in SFB.

This report analyses long-term data records for chl-a, GPP, and dissolved oxygen (DO) in SFB with the goal of characterizing changes, or trends, in water quality. Motivated by and building on the prior studies that evaluated conditions through 2005 (Cloern et al. 2007), this project aims to further characterize and interpret space-time variability in water quality indicators in SFB by: 1) Extending the analysis of summer-fall chl-a and GPP data (Aug-Oct) and annual GPP through 2019 to assess how conditions evolved over the subsequent ~15 years, including identifying eras over which statistically-significant changes occurred; 2) apply similar approaches to examine long-term variability in DO concentration; 3) evaluate how changes varied spatially (direction, rate, magnitude, duration of change) among subembayments by analyzing data at representative stations and by expanding the geographic scope to include Central Bay and Lower South Bay.

2. METHODS

2.1 DATA

Water quality data were collected by the US Geological Survey San Francisco Bay Water Quality Project (Cloern and Schraga 2016; Schraga and Cloern 2017). Sample collection, processing, and laboratory analyses are detailed elsewhere (Schraga and Cloern 2017), and summarized briefly here. Samples were collected during biweekly to monthly cruises aboard the *R/V Polaris* and *R/V Peterson*, at 37 fixed stations along a 145 km transect following SFB's deep channel from Lower South Bay to the lower Sacramento River and analyzed for a range of water quality parameters, including chlorophyll-a, dissolved oxygen, suspended sediment, nutrients (dissolved inorganic nitrate and phosphate), salinity, and temperature. For this analysis, we focused on stations 18-34, from Central Bay to Lower South Bay (Figure 1).

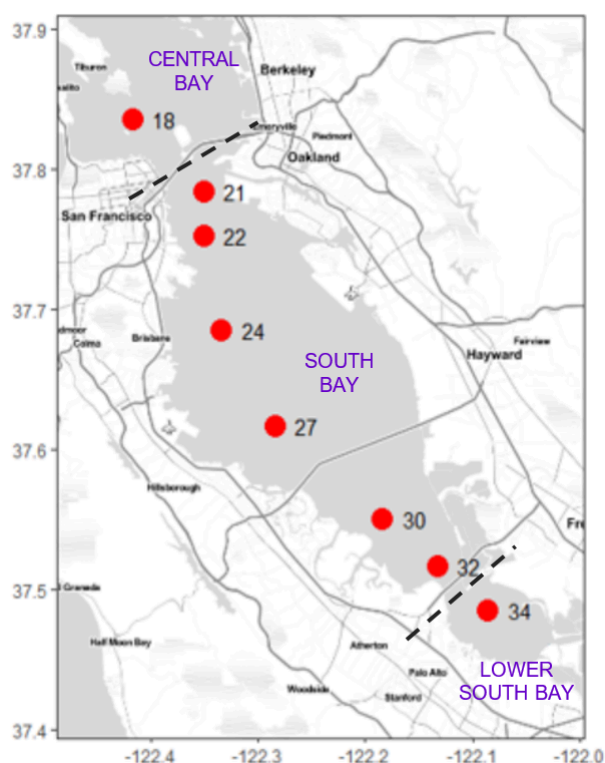


Figure 1. Subset of water quality monitoring stations occupied by the USGS long-term monitoring in San Francisco Bay that are used in this report: Central Bay (18), South Bay (21, 22, 24, 27, 30, 32), and Lower South Bay (34) are analyzed in this report.

2.2 DATA ANALYSIS

For this study, we focused on the analysis of three water quality indicators: chlorophyll-a concentration, as a measure of phytoplankton biomass (chl-a, mg/L; near-surface, depth of 1-2 m); gross primary production (GPP_{index} ; $mg\ C\ m^{-2}\ d^{-1}$), a calculated index estimating

phytoplankton production rate; and dissolved oxygen concentration (DO, mg/L; averaged over the full water column depth).

GPP_{index} was calculated using a relationship developed for SFB (Cole and Cloern 1987; Cloern et al. 2007):

$$GPP = \frac{4.6 * \Psi * [ChlA] * PAR}{K_{att}}$$

where:

Ψ light utilization efficiency ($0.82 \frac{mg\ C}{mg\ Chla\ (mol\ m^{-2})}$; Cloern et al. 2007);

[ChlA] chl-a concentration, discrete samples, mean over the surface 3m ($\mu g\ L^{-1}$);

PAR daily mean photosynthetically active radiation ($mol\ photons\ m^{-2}\ d^{-1}$). Long term daily-average PAR values for the region were used (Cloern et al. 2007);

K_{att} light attenuation coefficient, measured in the water column during cruises; when K_{att} data were unavailable, K_{att} was calculated using a relationship developed for K_{att} : SSC from the same dataset.

The water quality parameters chl-a, GPP, and DO were examined over the years 1990-2019, an era that maximized overlap in data availability across the three parameters and stations (chl-a and GPP data were available for the entire period; DO was available for 1993-2019). We evaluated conditions on a seasonal basis and explored how conditions changed over time during those seasons. The months of August-October were the primary seasonal focus, selected to overlap with seasonal-windows used in prior studies (e.g., August-December, Cloern et al. 2007). We also explored conditions during February-April, the late-winter/early-spring period when phytoplankton biomass levels generally reach their annual-maximum values in South Bay (e.g., Cloern et al. 1985; Alpine and Cloern 1988; Huzzey et al. 1990; Cloern 1996). For GPP, annual values were also explored because annual GPP is a commonly used indicator for evaluating the trophic status of water bodies (Cloern et al. 1985; Duarte and Regaudie-de-Gioux 2009).

Although the work presented here primarily focused on chl-a, GPP, and DO, early results from the analysis of dissolved inorganic nitrogen (DIN) concentrations from cruises and analysis of high frequency suspended sediment concentration data at the Dumbarton Bridge (USGS, CA Water Science Center; [link](#)) are also highlighted. For DIN analyses, data from 2005-2019 were used because 2005 marks when DIN measurements began to be consistently collected (1-2 times per month, at a consistent set of stations).

For each station and parameter we: 1) used the R package [wqtrends](#) (developed during Phase II of this project, Beck et al. 2022) to fit GAMs to the measured data; 2) extracted

each year's mean value and confidence interval for a specified season from the GAM-fit; 3) computed the slope, or change in condition over $\Delta\tau$, and its statistical significance (i.e., significantly different from zero at the $p < 0.05$ level) over a specified rolling trend window ($\Delta\tau$, years) using an approach that takes into account the uncertainties (confidence intervals) of the seasonal means. In general, trends were evaluated using a 10-year rolling window, with the year noted being the ending year (i.e., right-justified).

3. RESULTS AND DISCUSSION

3.1 CHLOROPHYLL-*a*

Chlorophyll-*a* levels in SFB follow a well-documented seasonal cycle of peak concentrations occurring between February-April during spring blooms and lower levels ($\text{chl-}a \sim 3\text{-}5 \mu\text{g/L}$) over the rest of the year (e.g., Cloern et al. 1985; Huzzey et al. 1990; Cloern 1996). The GAM fits capture this seasonal cycle along with the between-year variations in concentrations (Figure A.1; $r^2 = 0.69\text{-}0.78$). The GAM fits were used to estimate each year's seasonal-mean chl-*a* for August-October ($\text{chl}_{\text{AugOct}}$), which were then analyzed for changes over time using a right-justified rolling window of $\Delta\tau = 10 \text{ y}$ (Figure 2).

At stations s21 through s32, significant $\text{chl}_{\text{AugOct}}$ increases were detected as early as 1999-2002, with significant positive increases continuing over the eight subsequent ten-year windows (Figure 2). While $\text{chl}_{\text{AugOct}}$ also increased in Central Bay (s18) and Lower South Bay (s34), changes in those regions did not register as significant until 2008 and 2009, respectively. The timing and magnitudes of $\text{chl}_{\text{AugOct}}$ changes detected through 2005 at South Bay stations (s21, s24, s27, s30, s32) agree closely with the subembayment-average increases documented by Cloern et al. (2007), in terms of their both timing and magnitude.

Through extending the time-series through 2019, and by evaluating conditions at individual stations as opposed to subembayment averages, we find that the trajectories of $\text{chl}_{\text{AugOct}}$ differed substantially across subregions of South Bay. By the mid- to late-2000s, $\text{chl}_{\text{AugOct}}$ levels plateaued over a large swath of South and Lower Bays (s27-s34), before decreasing during the 2010s. Significant negative trends were first detectable in the mid-2010s, with the most pronounced decreases observed at the furthest south stations (s30-s34) where $\text{chl}_{\text{AugOct}}$ concentrations approached pre-1995 levels by the late-2010s. By contrast, $\text{chl}_{\text{AugOct}}$ levels at the northernmost sites (s18, s21, s22) plateaued several years later (~ 2010) than those to the south, and remained elevated through 2019 (i.e., no statistically-significant decreases). The $\text{chl}_{\text{AugOct}}$ responses at s24 and s27 can be reasonably characterized as hybrids of stations to the south and north, decreasing slightly between 2010-2019 but remaining above the early-1990s baseline. A summary and figure of chl-*a* concentrations in Feb-Apr ($\text{chl}_{\text{FebApr}}$) are included in Appendix B.

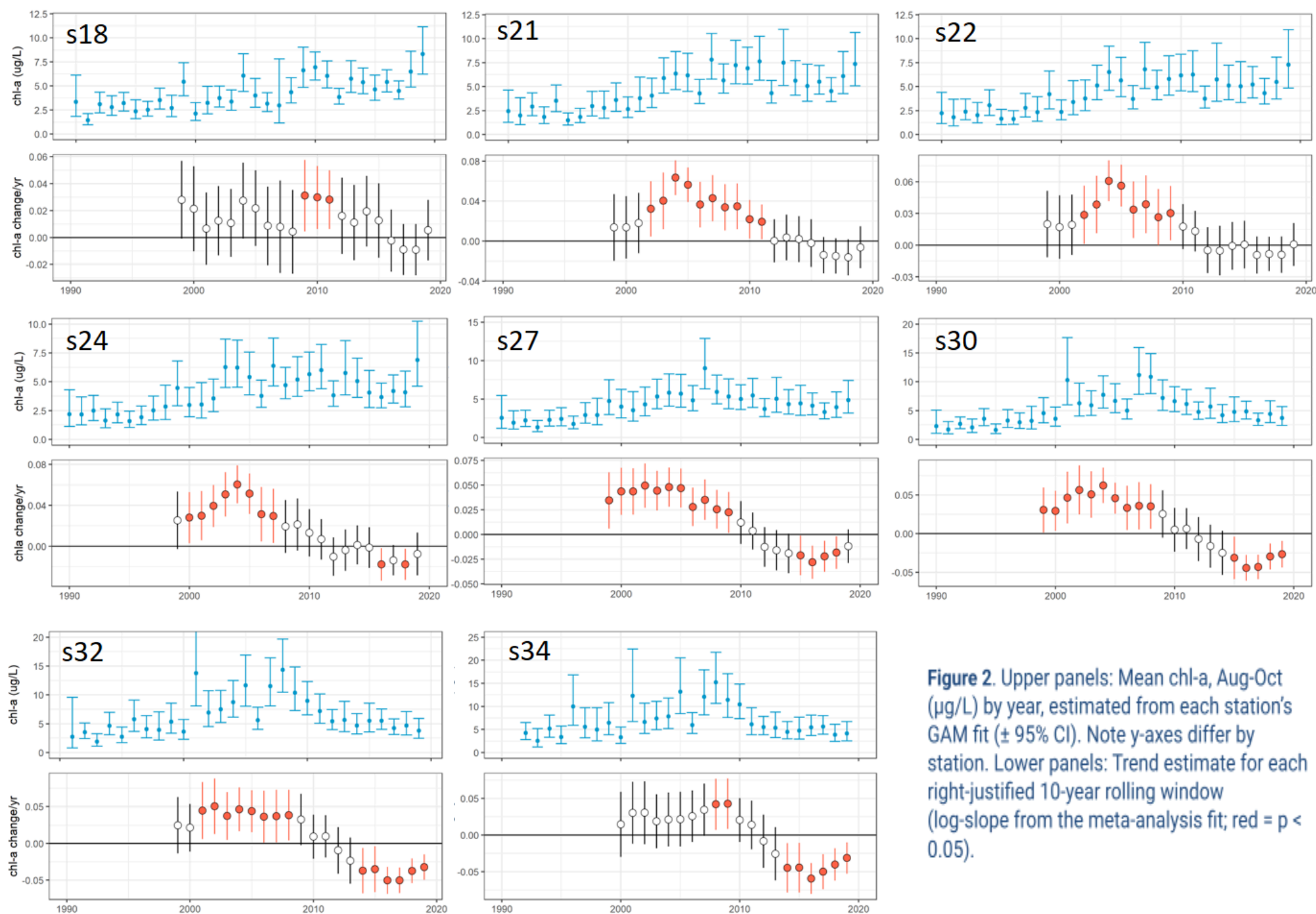


Figure 2. Upper panels: Mean chl-a, Aug-Oct ($\mu\text{g/L}$) by year, estimated from each station's GAM fit ($\pm$ 95% CI). Note y-axes differ by station. Lower panels: Trend estimate for each right-justified 10-year rolling window (log-slope from the meta-analysis fit; red = $p < 0.05$).

3.2 GROSS PRIMARY PRODUCTIVITY

The seasonal cycles and interannual variability in GPP are also well-represented by the GAM fits (Figure A.2; $r^2 = 0.76-0.87$). Following the same approach as above for chl-a, the mean and confidence intervals for GPP during August through October (GPP_{AugOct}) and annually (Jan-Dec, GPP_{annual}) were extracted from the GAM for each station and year for the period of 1990-2019 and trends were evaluated using a rolling $\Delta\tau = 10$ y trend window.

Overall, temporal changes in mean GPP for August through October, GPP_{AugOct} followed similar patterns as those described above for chl_{AugOct} including significantly higher rates between 2005-2010 compared to those in the early-1990s across South Bay and Central Bay stations (s18-s32; Figure 3). These similarities are not surprising because GPP_{index} is proportional to chl-a concentration; however, the other variables used to calculate GPP (e.g., light attenuation coefficient) can also be highly influential. The onset and duration of statistically significant increases in GPP_{AugOct} tended to align with those of chl_{AugOct} with significant increases at s18 and s21 lagging by several years those at southern stations. GPP_{AugOct} at stations 30-34 increased over the early 2000s, plateaued through the late 2000s, and began decreasing significantly post-2010 (significant negative trends 2014-2019), with GPP_{AugOct} nearly returning to early-1990s rates. GPP_{AugOct} at Central Bay (s18) and northern South Bay stations (s21, s22) climbed to values that were 3-times GPP rates at those locations in the early-1990s. GPP_{AugOct} at s18-s22 plateaued by ~2010, and, unlike at stations to the south, remained 2-3 times greater than their early-1990s baselines through 2019. Finally, the responses at s24 and s27 were intermediate between those of their northern and southern neighbors. The increases in GPP_{AugOct} detected at stations 21-32 between 1990-2005 are consistent with the changes to subembayment-average GPP estimates of Cloern et al. (2007), analogous to the observation above pertaining to chl-a.

GPP_{annual} serves as an estimate of phytoplankton primary production over the full year. To a first approximation, GPP_{annual} followed similar time-space patterns as described above for GPP_{AugOct} (Figure 4). At stations s18, s21, and s22, GPP_{annual} estimates climbed between 2005-2010 to values that were 2-3x baseline estimates in the early 1990s. Although GPP_{annual} decreased modestly (nonsignificant) at those locations between 2010-2015, toward the end of this record (2018-2019) it remained approximately 2-fold higher than early-1990 annual productivity. The GPP_{annual} increases at s18-s21 between 2000-2010 from approximately 400 to 800 mg C m⁻² d⁻¹ translate to a doubling of annual gross phytoplankton production in the region of Central Bay and northern-South Bay over 10 years. Central Bay's (s18) GPP_{annual} in the early 1990s (~300 mg C m⁻² d⁻¹, ~100 g C m⁻² y⁻¹) placed its trophic status on the boundary between oligotrophic and mesotrophic. In 2018-2019, GPP_{annual} in Central Bay was on the boundary between mesotrophic and eutrophic (~825 mg C m⁻² d⁻¹, 300 g C m⁻² d⁻¹).

As noted above for chl-a, through extending the time-series through 2019 and evaluating GPP at individual stations, we find that the trajectories of GPP_{AugOct} and GPP_{annual} differed substantially across subregions of South Bay and Central Bay. The decreases in GPP_{annual} (and GPP_{AugOct}) at southern stations (South Bay: s27-s32; LSB: s34) beginning around 2010-2011, with rates approaching early-1990s levels by 2019, differ markedly from conditions in Central Bay (s18) where GPP_{AugOct} and GPP_{annual} remained elevated through 2019. The spatially-differing responses post-2010 suggest that different factors or mechanisms were driving ecologically-meaningful changes in phytoplankton productivity and among regions. A summary and figure of GPP during Feb-Apr (GPP_{FebApr}) are included in Appendix B.

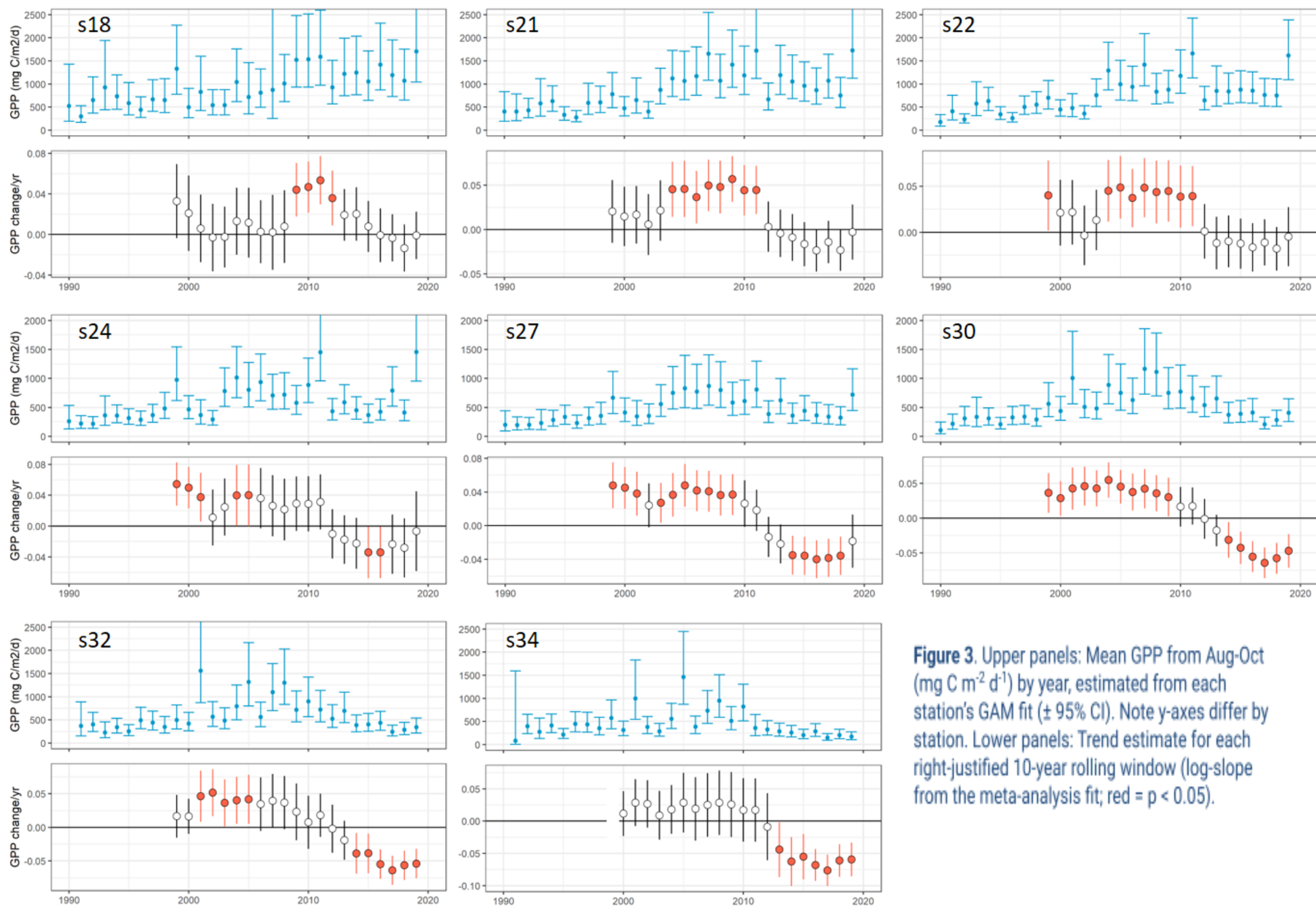


Figure 3. Upper panels: Mean GPP from Aug-Oct ($\text{mg C m}^{-2} \text{d}^{-1}$) by year, estimated from each station's GAM fit ($\pm 95\%$ CI). Note y-axes differ by station. Lower panels: Trend estimate for each right-justified 10-year rolling window (log-slope from the meta-analysis fit; red = $p < 0.05$).

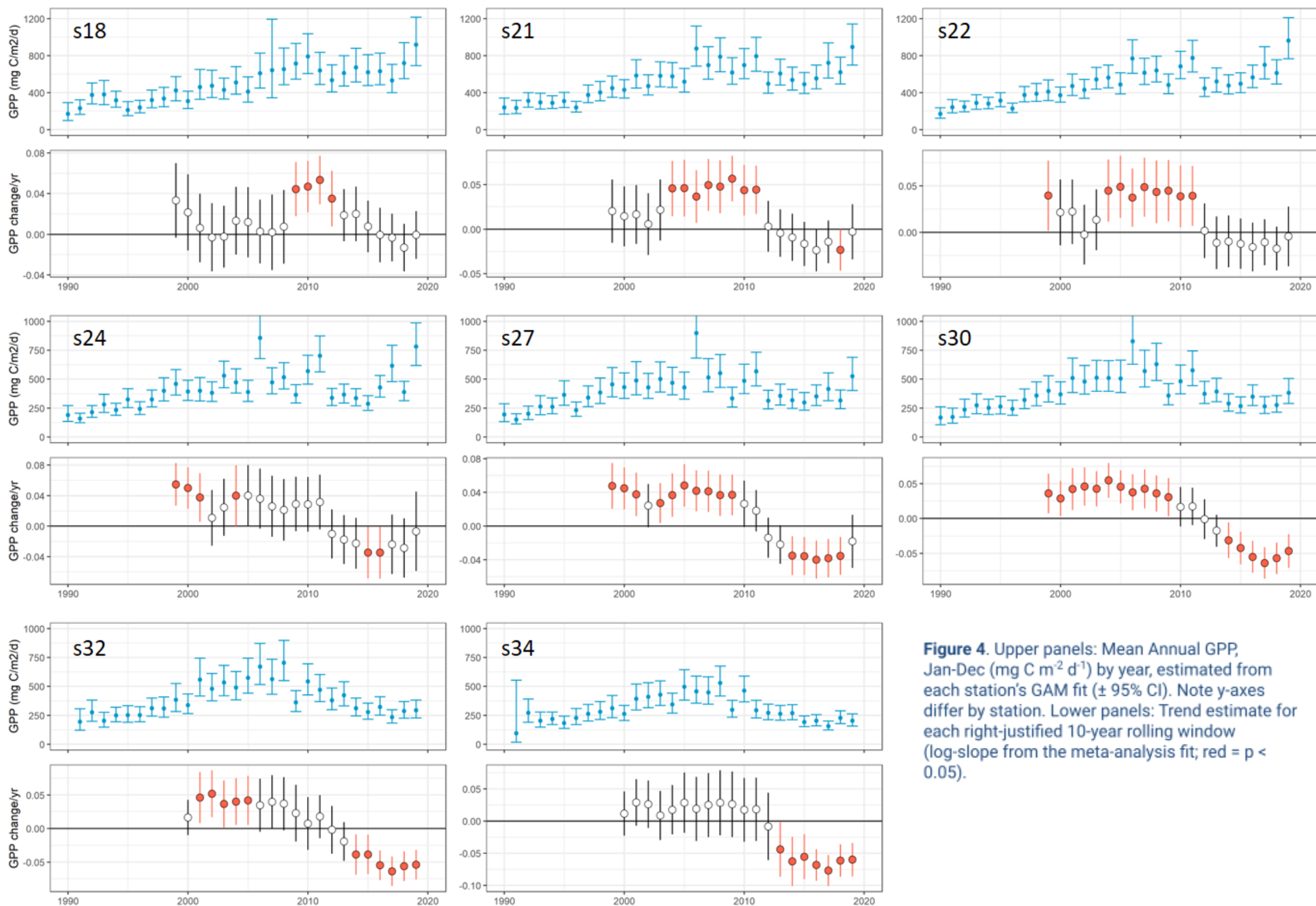


Figure 4. Upper panels: Mean Annual GPP, Jan-Dec (mg C m⁻² d⁻¹) by year, estimated from each station's GAM fit ($\pm$ 95% CI). Note y-axes differ by station. Lower panels: Trend estimate for each right-justified 10-year rolling window (log-slope from the meta-analysis fit; red = $p < 0.05$).

3.3 DISSOLVED OXYGEN

The GAM fits captured the strong seasonality and interannual variability of DO concentrations. The observational data suggest that DO in channel habitats extending from Central Bay to far South Bay (s18-s32) rarely dropped below the SFB Basin Plan standard of 5 mg/L between 1993-2019. In Lower South Bay (station 34), conditions with DO < 5 mg/L were occasionally observed.

Using a window of $\Delta\tau = 10$ y, only one statistically significant change was detected across all stations over the 27-year record (s34, 2014; Figure 5). However, there are multiple consecutive 10-year windows with negative, but not significant, DO_{AugOct} slopes at most stations. In Section 3.4 we explore whether some of those decreases would be significant if a different $\Delta\tau$ were used.

Biogeochemical processes and time-varying oceanographic and hydrologic forcings have the potential to complicate the detection or interpretation of changes in DO. For example, phytoplankton produce oxygen during photosynthesis and windows of high phytoplankton production can substantially increase DO. Such responses could perturb DO sufficiently to increase within-season variability and interannual variability, making the detection of gradual long-term changes difficult to discern. In addition, recently upwelled coastal water contains relatively low concentrations of DO. When these dense (cold, salty) water masses periodically move into SFB, the low-DO waters may decrease depth-averaged DO levels. Lastly, years with high freshwater flows can lead to short-lived (days) periods when the water column becomes vertically stratified, leading to enhanced DO production in surface waters (due to increased phytoplankton production) along with decreased DO concentration in subsurface waters due to respiration, without opportunity for reaeration through exchange with the atmosphere. Because of these complex physical and biogeochemical factors, we focused the analysis of DO data on August-October. However, a figure (Figure B.3) and summary of DO concentrations in Feb-Apr (DO_{FebApr}) are included in Appendix B.

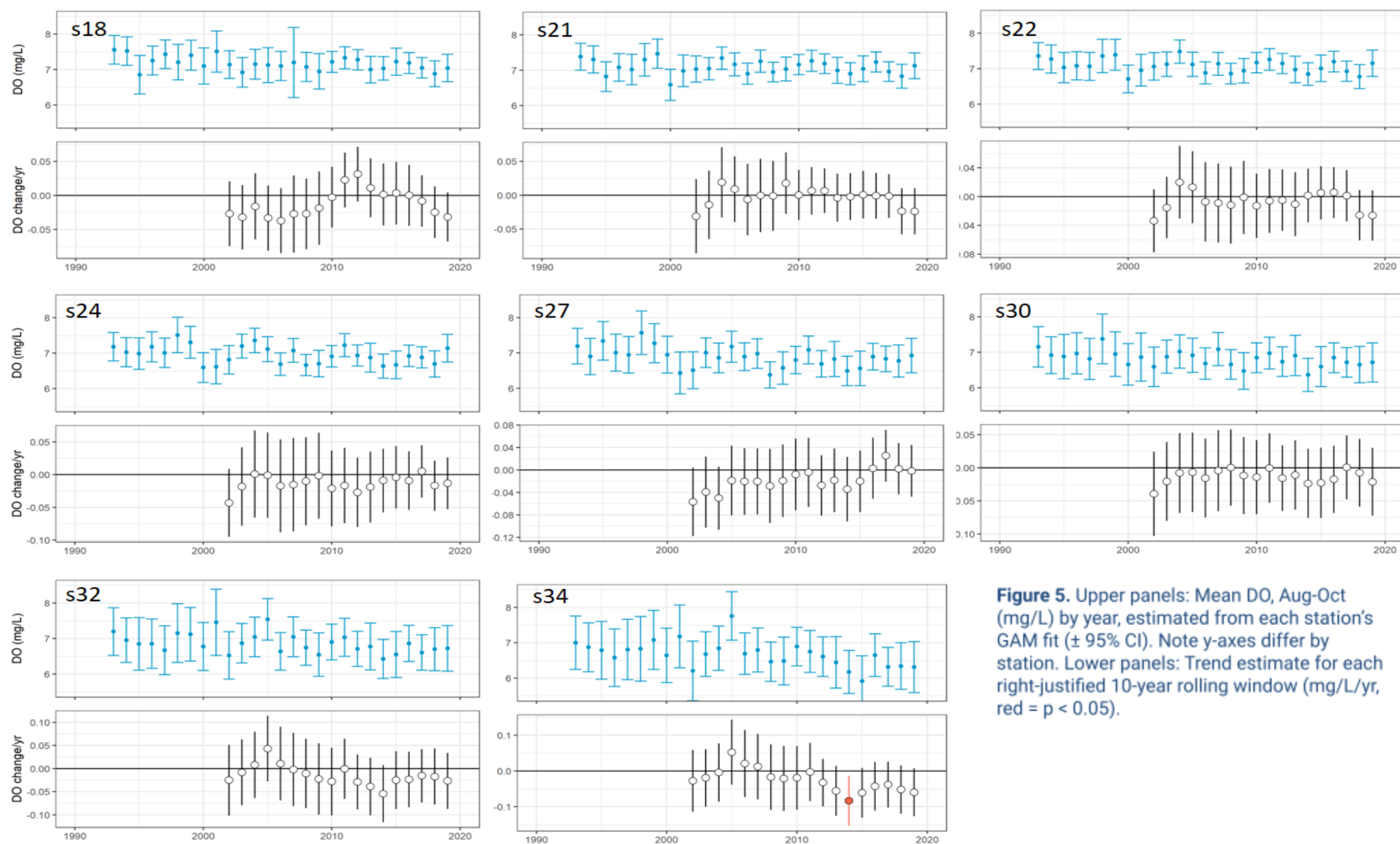


Figure 5. Upper panels: Mean DO, Aug-Oct (mg/L) by year, estimated from each station's GAM fit ($\pm$ 95% CI). Note y-axes differ by station. Lower panels: Trend estimate for each right-justified 10-year rolling window (mg/L/yr, red = $p < 0.05$).

3.4 CONTINUING WORK

Upcoming rounds of work exploring SFB water quality trends will explore the influence of the trend window size on detection of significance changes and on investigating trends in other water quality parameters. Early results for examples are presented below.

TREND TIME-WINDOWS

The best or most relevant timescale for evaluating trends in SFB water quality indicators may vary depending on the management question or management decisions being considered, the specific indicator, and the underlying mechanisms driving changes. For example, trends over a 5-year period may be appropriate for detecting relatively fast changes that trigger additional monitoring. Windows longer than 10 years may be needed to detect trends in water quality parameters that exhibit substantial natural variability (i.e. low signal to noise ratio), or when indicators are strongly influenced by large-scale climate processes (e.g., Pacific Decadal Oscillation, El Niño Southern Oscillation).

For the trend analyses presented in Sections 3.1-3.3, we used $\Delta\tau = 10$ y as a default, and characterized changes over the length of the time series (approximately 30 years). Stepping the 10-year window forward one year at a time (rolling window) allowed us to evaluate how the trend magnitude, or rate of change, varied over time, and to identify both positive and negative changes over 10-year windows, within the longer 30-year record. Trends in environmental parameters are also commonly assessed by analyzing data over the full record (e.g., Greening et al. 2014, Harding et al. 2016). For comparison, we also used the GAM and mixed-effects and meta-analysis approach to assess trends for chl-a and GPP (1990-2019) and DO (1993-2019) using a single, longer $\Delta\tau$ that extended over the full record ($\Delta\tau = 30$ y and 27 y, respectively). Using the longer time windows, the analysis identified statistically significant increases in chl_{AugOct} and GPP_{AugOct} at stations s18-s30, but no significant changes at s32 or s34; and statistically significant decreases in DO_{AugOct} at s27 and s34, but no changes at other stations (Table 1).

Table 1. Trends in seasonal means for chl-a ($\mu\text{g L}^{-1}$), GPP ($\text{mg C m}^{-2} \text{d}^{-1}$), and DO (mg L^{-1}). The rows for 10 yr-rolling are summaries of the results from Sections 3.1-3: for each station, indicating end-years for which statistically significant trends ($p < 0.05$) were detected over the preceding $\Delta\tau = 10$ y (red: positive trend; blue: negative trend). Trends were also assessed using a single window for the full record: chl-a and GPP, 1990-2019 ($\Delta\tau = 30$ y); DO, 1993-2019 ($\Delta\tau = 27$ y). For the full record trend evaluations, the p-values of significant trends are denoted as * $p < 0.05$; ** $p < 0.01$.

		s18	s21	s24	s27	s30	s32	s34
chl-a ($\mu\text{g L}^{-1}$)	10yr-rolling	+	2009-2011	2002-2011	2000-2008	1999-2009	1999-2008	2001-2008
		-		2016, 2018	2015-2018	2015-2019	2014-2019	2014-2019
	Full Record 1990-2019		**	**	**	**		
GPP ($\text{mg C m}^{-2} \text{d}^{-1}$)	10yr-rolling	+	2009-2012	2004-2011	1999-2001, 2004	1999-2001, 2003-2009	1999-2009	2001-2005
		-			2015-2016	2014-2018	2014-2019	2013-2019

Full Record 1990-2019			**	**	**	**	*		
DO (mg/L)	10yr-rolling	+							
		-							2014
	Full Record 1993-2019					*			*

The trend window used may be important for characterizing changes in SFB DO concentrations. While the majority of the 10-year-window slopes for $\text{DO}_{\text{AugOct}}$ concentrations were negative (Figure 5), in almost all cases the slopes were not significantly different from zero. To explore the influence of trend window length on trends estimates and significance, we reanalyzed the $\text{DO}_{\text{AugOct}}$ data using a range of $\Delta\tau$ values for 1993-2019. Figure 6 summarizes the results of the analysis for station s27, with each box indicating the magnitude, sign (+,-) and significance for $\text{DO}_{\text{AugOct}}$ slopes for combinations of $\Delta\tau$ (y-axis: 8-27 years) and end-date (x-axis: 2000-2019). With trend windows ≤ 13 years, $\text{DO}_{\text{AugOct}}$ changes were rarely significant (2 of 95 combinations). For longer windows, $\Delta\tau = 14$ -27 years, significant $\text{DO}_{\text{AugOct}}$ changes were detected in more than 35% of the combinations (35/98), particularly for years ending around 2008-2010 and 2014-2016. Similar analyses were conducted for stations s18 (Figure C.1) and s24 (Figure C.2). Follow-up studies will include work exploring approaches or criteria for identifying the most suitable trend window(s) for DO and other parameters.

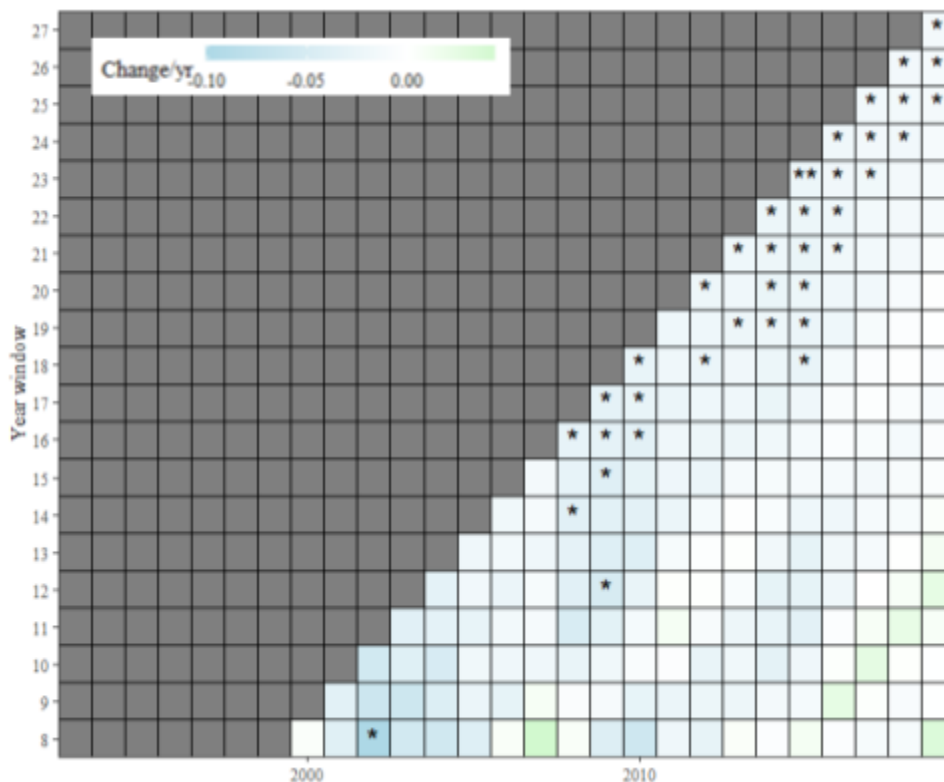


Figure 6. Station s27 dissolved oxygen (DO, mg/L) trends at for the seasonal window Aug-Oct (DO_{AugOct}), across a range of values for $\Delta\tau$ (trend window) and ending year. **y-axis:** $\Delta\tau$ ranging from 8 to 27 years. **x-axis:** ending year (right-justified), 2000-2019. Changes in DO_{AugOct} were statistically significant for the combinations of $\Delta\tau$ and end-year indicated by * ($p < 0.05$) or ** ($p < 0.005$). Slope magnitude and sign (+,-) indicated by color. Similar plots for s18 and s24 in Appendix C.

INVESTIGATING WATER QUALITY TRENDS

Work is underway investigating trends in additional water quality parameters, including suspended sediment and dissolved inorganic nitrogen, which are summarized below.

Suspended sediment and turbidity

The underlying mechanisms or causes that contributed to the large changes in chl_{AugOct} , GPP_{AugOct} , and GPP_{annual} in Central Bay and South Bay (Figures 2, 3, 4) are important to understand, independently and in combination with nutrient concentration. A primary hypothesis invoked for explaining the chl_{AugOct} and GPP_{AugOct} increases between the mid-1990s and 2005 was a substantial decrease in filter-feeding clams in South Bay, leading to decreased benthic grazing, resulting in an increased standing stock of phytoplankton, indirectly measured as chl-a and GPP (Cloern et al. 2007). Cloern and colleagues also hypothesized that suspended sediment is one of the dominant controls on phytoplankton production in San Francisco Bay, with a strong negative correlation between suspended particulate matter and phytoplankton productivity (Cloern and Jassby 2012; Cloern et al. 2017).

Our initial analyses exploring suspended sediment concentration (SSC) and light attenuation coefficient (K_D) estimates from biweekly to monthly cruises suggested that higher frequency data may be needed to capture long-term SSC and K_D trends (and/or that the tendency of cruises to start in Lower South Bay at high tides may bias the estimates). We therefore shifted to exploring the long-term high-frequency (15 min) SSC data collected at the Dumbarton Bridge (DMB; just south of s32). Prior studies had observed that SSC concentrations decreased Bay-wide beginning in the late-1990s (Schoellhamer 2010), including at the DMB (Schoellhamer et al., 2015). We applied the GAM-mixed-meta analysis pipeline used for analyzing cruise data to analyze the August-October high-frequency SSC data at DMB (Figure 7). To a first approximation, the timing of SSC decreases at DMB (Figure 7) appears to coincide with the timing of the early 2000s increases in $\text{chl}_{\text{AugOct}}$ and

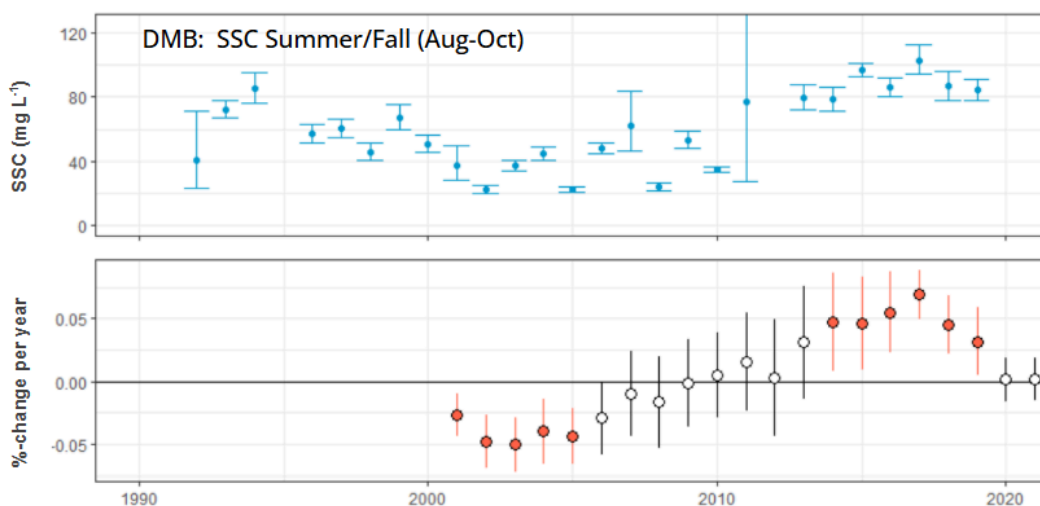


Figure 7. Upper panels: Average SSC at Dumbarton Bridge (DMB), based on 15 min in-situ sensor data, estimated from GAM fit ($\pm$ 95% CI). Lower panels: Trend estimate for each right-justified 10-year rolling window (mg/L/yr, red = $p < 0.05$). Note: Substantial data gaps during the months of Aug-Oct may affect data reliability and warrant further exploration.

$\text{GPP}_{\text{AugOct}}$ at southern South Bay and Lower South Bay sites (Figures 2 and 3; s27-s34). Moreover, the apparent $\text{SSC}_{\text{AugOct}}$ increases over the early 2010s coincides with the timing of decreasing $\text{chl}_{\text{AugOct}}$ and $\text{GPP}_{\text{AugOct}}$ decreases at those same locations (Figures 2 and 3). Work is underway to identify datasets that can offer similar information about long-term variability in Aug-Oct turbidity in northern South Bay and Central Bay to evaluate the potential for changes in SSC to explain the temporal and spatial variability in chl-a and GPP responses in South Bay and Central Bay. It is important to also note that there are substantial gaps in the DMB high-frequency SSC data due to sensor fouling during summer months; the potential influence of these gaps on Aug-Oct estimates needs to be evaluated.

Dissolved Inorganic Nitrogen

Our analyses of long-term trends in DIN concentrations have thus far focused on the months of September to October (Figure 8) to avoid seasonal windows when substantial phytoplankton blooms commonly occur that can introduce large changes in ambient DIN concentrations (e.g., spring). For this analysis, we also shifted to using a 14-year window to test whether significant increases in $\text{DIN}_{\text{SepOct}}$ were detectable between 2005-2019, a time period over which combined DIN loads from the Bay Area's five largest POTWs increased by approximately 30% (Figure 9).

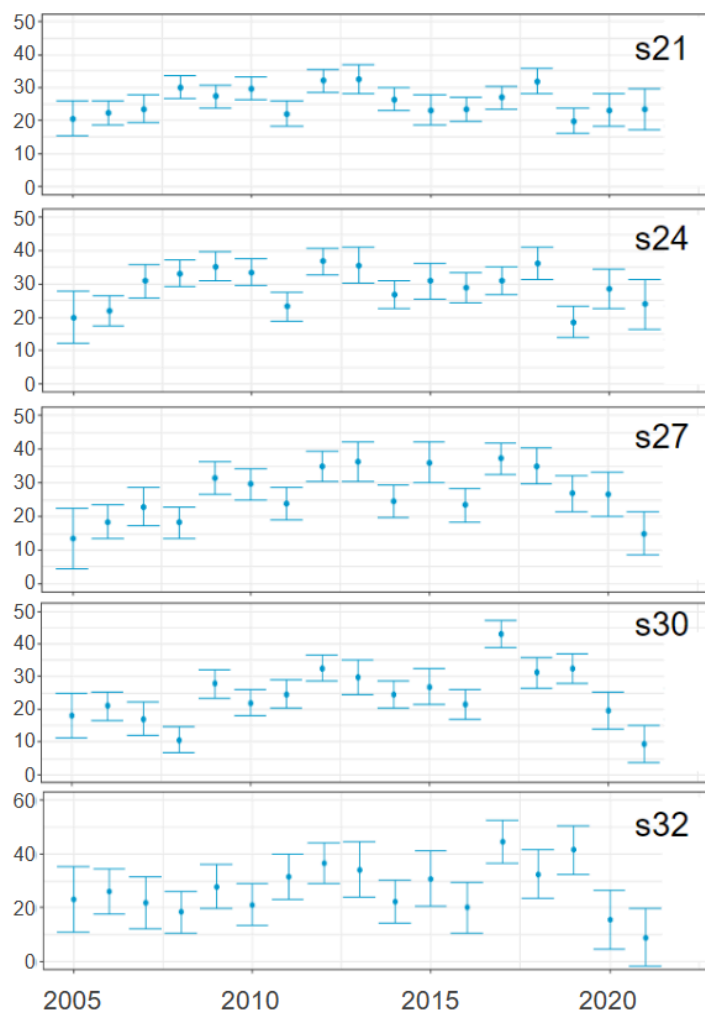


Figure 8. Mean DIN, Sep-Oct ($\mu\text{mol/L}$) by year from 2005-2021, estimated from each station's GAM fit ($\pm$ 95% CI). Note y-axes differ by station. Using a trend window of $\Delta\tau = 14$ years, there were no significant trends in $\text{DIN}_{\text{SepOct}}$ between 2005-2019 ($p < 0.05$). The slope of $\text{DIN}_{\text{SepOct}}$ between 2005-2019 at stations s21 and s24 was not significantly different from zero. The $\text{DIN}_{\text{SepOct}}$ decreases from 2018-2021 were also significant ($p < 0.05$) at stations s27, s30, and s32, using a trend window of $\Delta\tau = 4$ years.

Statistically significant increases in $\text{DIN}_{\text{SepOct}}$ were observed at stations s27-s32 over this time period (Figure 8), with an average slope of +1 $\mu\text{mole/yr}$. The $\text{DIN}_{\text{SepOct}}$ slopes between 2005-2019 at s21 and s24 were not significantly different from zero. Stations s21 and s24 are in substantially deeper waters, meaning changes in DIN delivery to these areas would have been diluted over a much larger volume of water, and changes may have been more difficult to detect relative to natural variability.

Between 2018-2021, $\text{DIN}_{\text{SepOct}}$ decreased significantly between at s27-s32 (using $\Delta\tau = 4$ years), which coincided with a steep decrease in DIN loads from the five largest POTWs (Figure 8). The variations in $\text{DIN}_{\text{SepOct}}$ concentrations need to be interpreted with caution, because those concentrations can also be strongly influenced by interannual differences in seasonal GPP during these months or earlier in the summer.

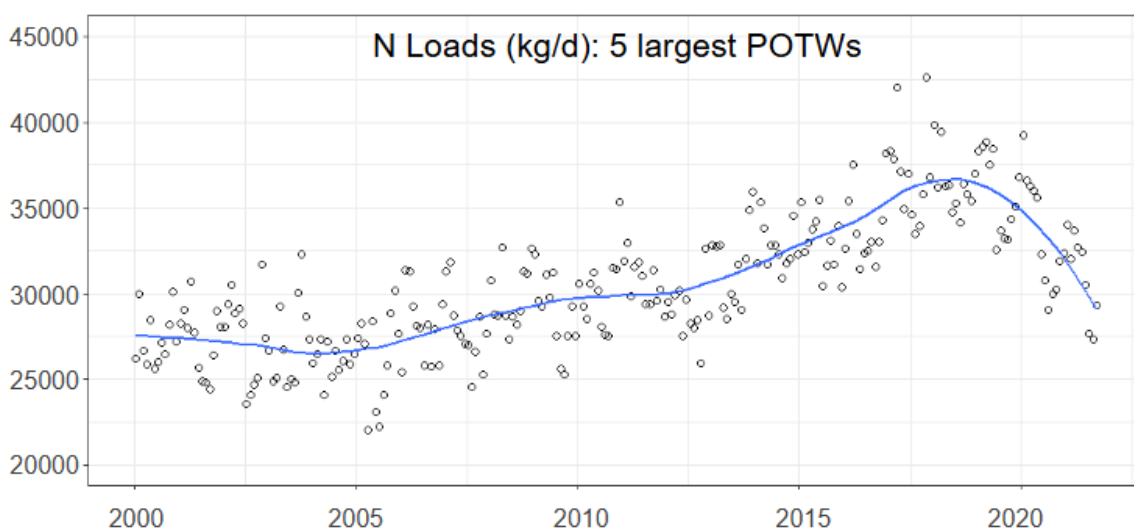


Figure 9. Combined DIN loads (kg/d) from the Bay Area’s five largest POTWs. The blue curve is a GAM smoother with a relatively small number of knots to register annual or multi-year variability (as opposed to seasonal).

5. SUMMARY and CONTINUING WORK

Key observations from this work include:

- Central, South, and Lower South Bays experienced statistically-significant increases in $\text{chl}_{\text{AugOct}}$, $\text{GPP}_{\text{AugOct}}$ and $\text{GPP}_{\text{annual}}$ beginning in the 1990s. $\text{GPP}_{\text{annual}}$ reached productivity rates in the mid to late 2000s that were 2-3 times higher than those in the early-1990s.
- At the southernmost stations (s30-s34), $\text{chl}_{\text{AugOct}}$, $\text{GPP}_{\text{AugOct}}$ and $\text{GPP}_{\text{annual}}$ decreased significantly between 2010-2019 comparable to early-1990 values. During that same time period, those parameters did not decrease significantly in Central Bay and northern South Bay (s21). Responses at stations s24-s27 were hybrids of the responses in the regions to their north and south. The spatially-varying responses post-2010 suggest that different factors or mechanisms were driving ecologically-meaningful changes in phytoplankton biomass and productivity within adjacent regions of SFB.
- When using a 10-year to investigate variations in $\text{DO}_{\text{AugOct}}$, significant trends were rarely observed. However, significant decreases were detected at several stations (s24, s27, s18) when trends were evaluated over longer windows.

Understanding the interplay between the multiple water quality indicators, how changes in one part of the system may affect another, and the mechanisms driving changes throughout the system are important next steps for this work. The GAM and mixed-meta approaches used here to describe trends over time by season and subembayment have expanded our understanding of how the system is changing, but they do not provide us with indications of why. Understanding the “why” will help us to refine our methods, as well as identify how these analyses can be most useful in a management context. There are many mechanisms that may be driving the patterns we are seeing in the water quality indicators reported here, including climate oscillations, local weather patterns, hydrodynamics, and ecological conditions. In addition, there are likely connections between the indicators—potentially with lags in their relationship—that will be important to explore, including light attenuation and GPP, as well as chl-a and DO. The next step for this project is to explore those connections and quantitatively identify which mechanisms are driving the trends we have observed in the system, how those mechanisms play out in time and space, and how the system may respond to changes in those drivers in the future.

We anticipate this work being used to inform the revision of indicator metrics in the next phase of the Open Bay Assessment Framework 2.0. The analyses presented here highlight the importance of considering trends at management-relevant time and spatial scales. Because the time scales most relevant for management purposes may depend on the mechanisms driving change, future analyses will include an exploration of appropriate time scales for evaluating trend metrics. In addition, water quality indicators may be used for different purposes. For example, light attenuation may be a good leading indicator because it affects chl-a and GPP, while DO may be best used as a lagging indicator because it is

typically affected by other post-bloom processes in the system (e.g., primary productivity, grazing pressure, and bacterial decomposition).

Future reports will build on the work presented here with a refined approach that is based on input from expert advisors, indicators and metrics developed as part of the Assessment Framework 2.0 effort, and the management needs of the NMS.

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APPENDIX A

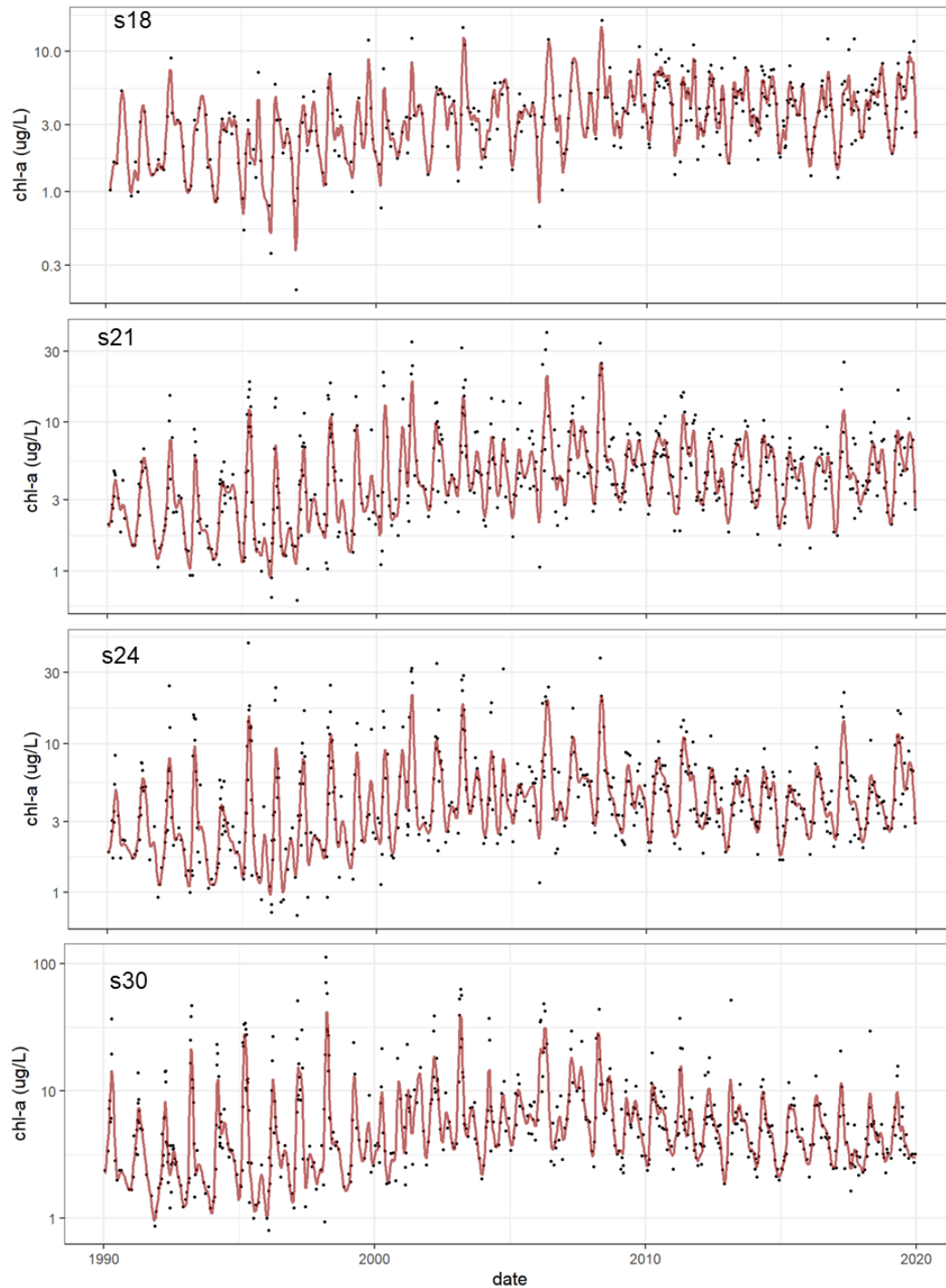


Figure A.1. GAM fits (solid line) for chl-a concentration (ug/L) at a subset of stations from Central Bay (s18) and South Bay (s21-30). The points represent observational data. Note y-axes differ by station.

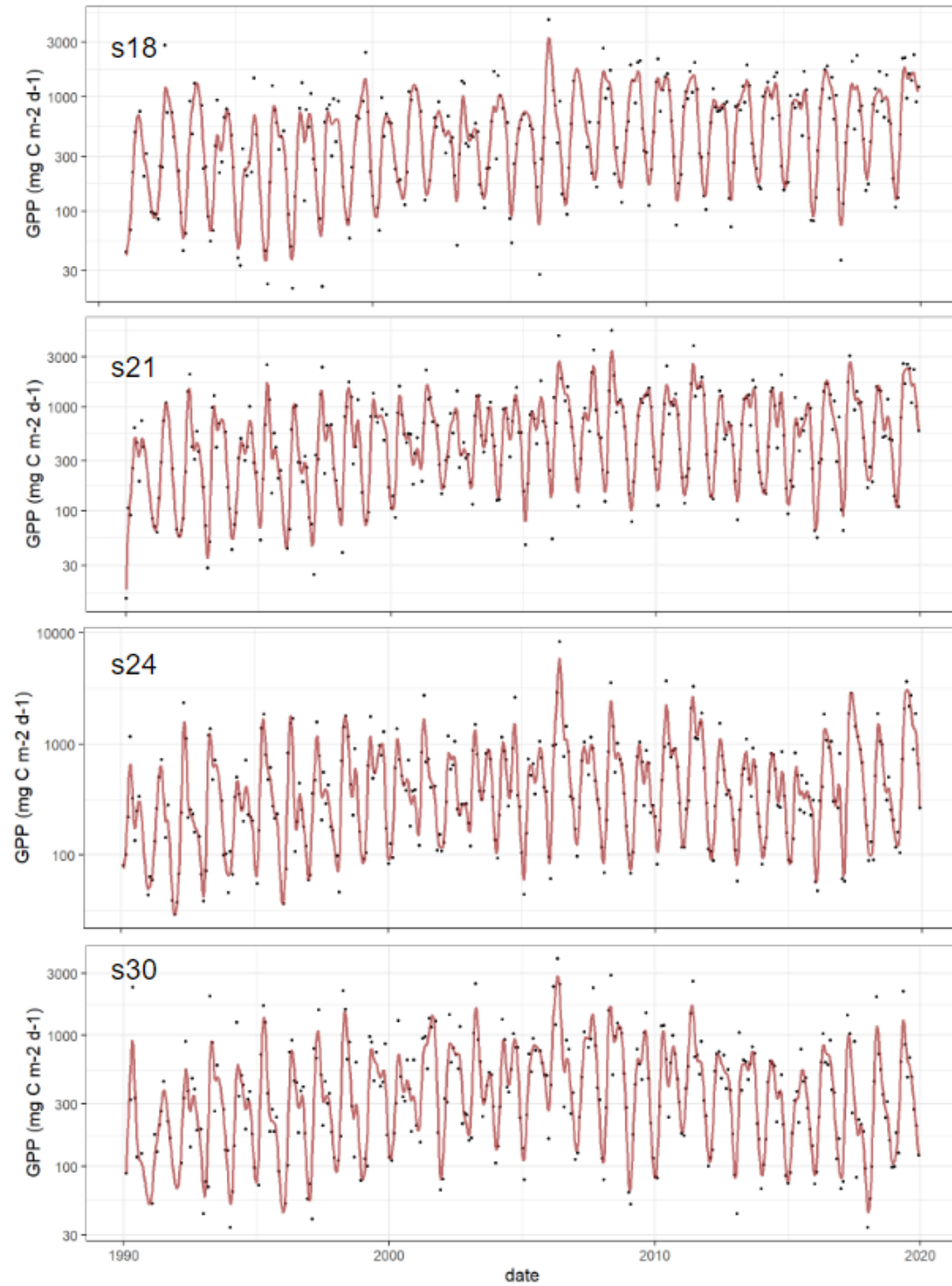


Figure A.2 GAM fits (solid line) for GPP ($\text{mg C m}^{-2} \text{d}^{-1}$) at a subset of stations from Central Bay (s18) and South Bay (s21-30). Points represent calculated GPP for individual dates based on observational data. Note y-axes differ by station.

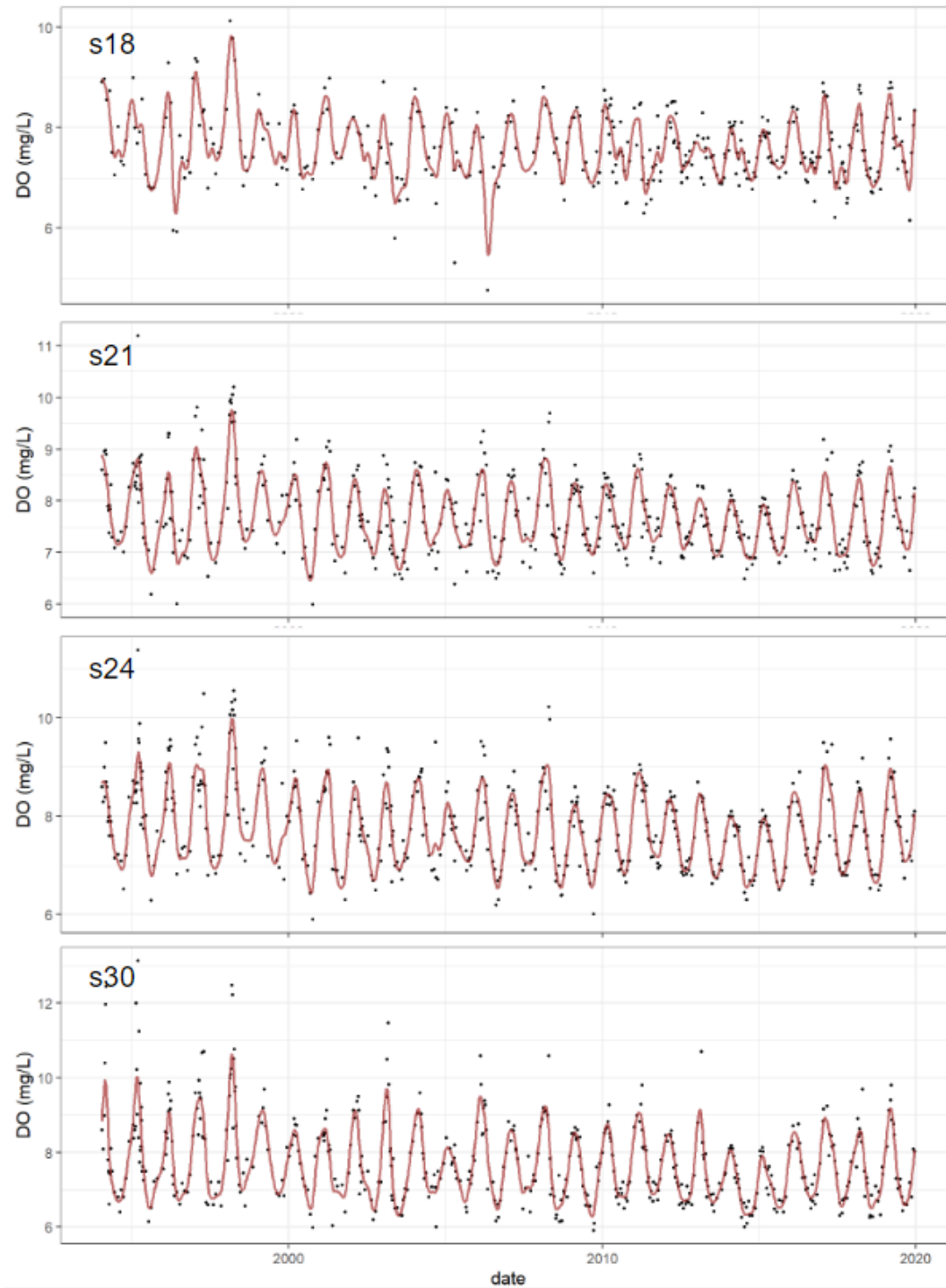


Figure A.3. GAM fits (solid line) for DO (mg/L) at a subset of stations in Central Bay (s18) and South Bay (s21-30). Points represent depth-averaged DO (mg/L) for individual dates, calculated from DO depth profiles. Note y-axes differ by station.

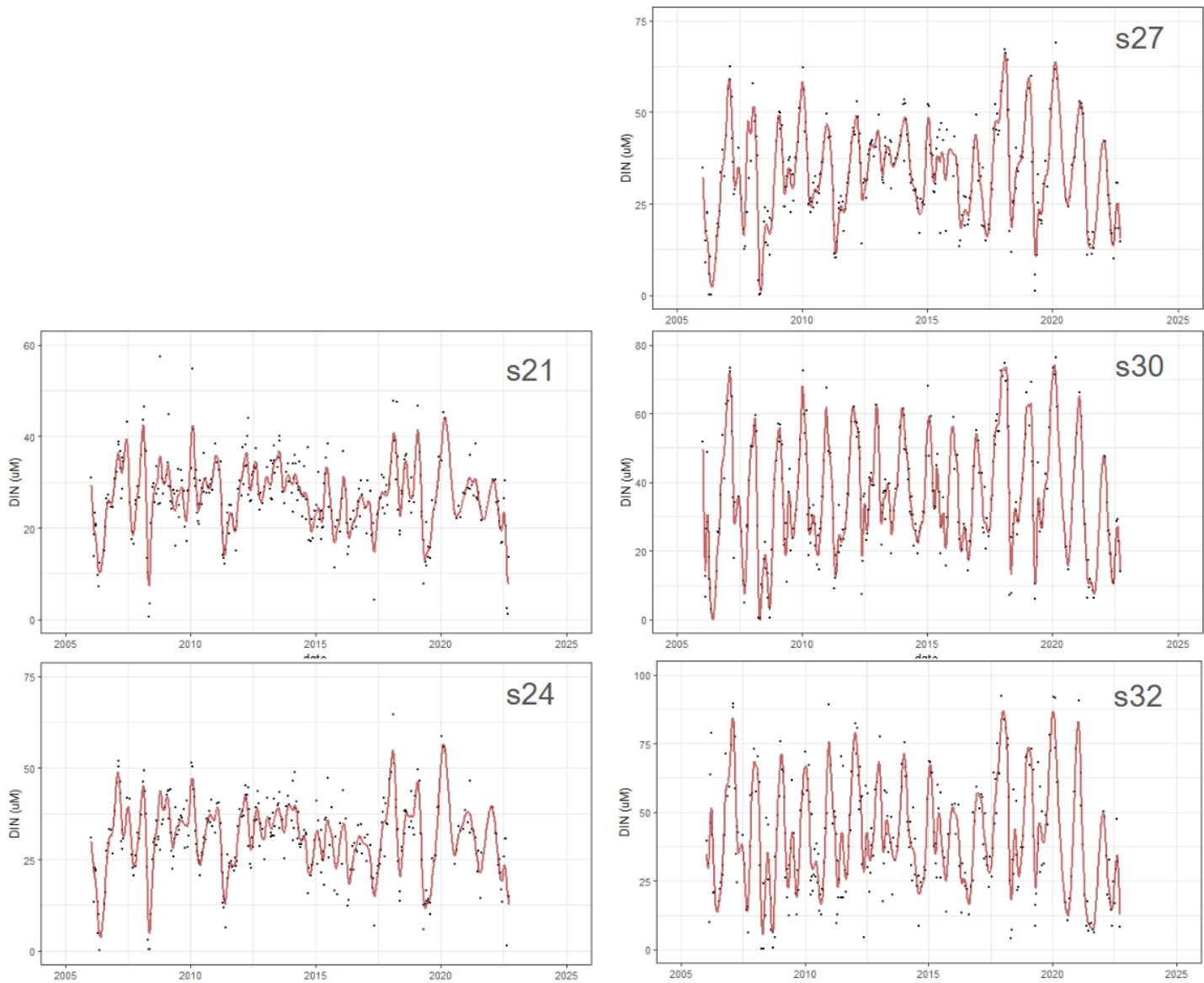


Figure A.4. GAM fits (solid line) for dissolved inorganic nitrogen (DIN, $\mu\text{mol/L}$) at stations from South Bay. Points represent DIN concentration in surface grab samples for individual dates. Note y-axes differ by station.

APPENDIX B

CHL, February-April (spring)

The space-time patterns for Feb-Apr chl-a ($\text{chl}_{\text{FebApr}}$) trends differed substantially from Aug-Oct trends (Figure B.1). Between 1990-2010, $\text{chl}_{\text{FebApr}}$ increased significantly at the four northernmost stations (s18-s24) over multiple rolling 10-year windows, while no significant changes were detected at the four southernmost stations (s27-s34). Over the remainder of the record, $\text{chl}_{\text{FebApr}}$ levels at s21-s30 approached their early-1990s levels. In Central Bay (s18), however, $\text{chl}_{\text{FebApr}}$ remained elevated through 2019. Although $\text{chl}_{\text{FebApr}}$ at s32 and s34 varied substantially among years, there were few windows over which changes were significant.

GPP, February-April (spring)

$\text{GPP}_{\text{FebApr}}$ variations also followed patterns similar to $\text{chl}_{\text{FebApr}}$ (Figure B.2). The high 2003 and 2006 $\text{GPP}_{\text{FebApr}}$ at s27-s34 failing to trigger any significant trends may be because the mixed-effect analysis discounted those years because of their large confidence intervals. By contrast, multiple consecutive years with significant $\text{GPP}_{\text{FebApr}}$ increases were detected at s18-s22 between 1999-2008, with s18 $\text{GPP}_{\text{FebApr}}$ remaining ~2x greater baseline through 2019. While s27-s34 returned baseline levels by ~2010, $\text{GPP}_{\text{FebApr}}$ at s21-s24 remained moderately elevated through 2019.

DO, February-April (spring)

The analysis of $\text{DO}_{\text{Feb-Apr}}$ detected at least one statistically-significant negative trend at each station (Figure B.3). Interpreting the interannual variability and changes in $\text{DO}_{\text{Feb-Apr}}$ is made complicated by the fact that Feb-Apr is a time period when phytoplankton blooms commonly occur, which produce O_2 , and therefore lower DO concentrations during some years may be a function of lower productivity (less O_2 produced) rather than higher rates of oxygen consumption.

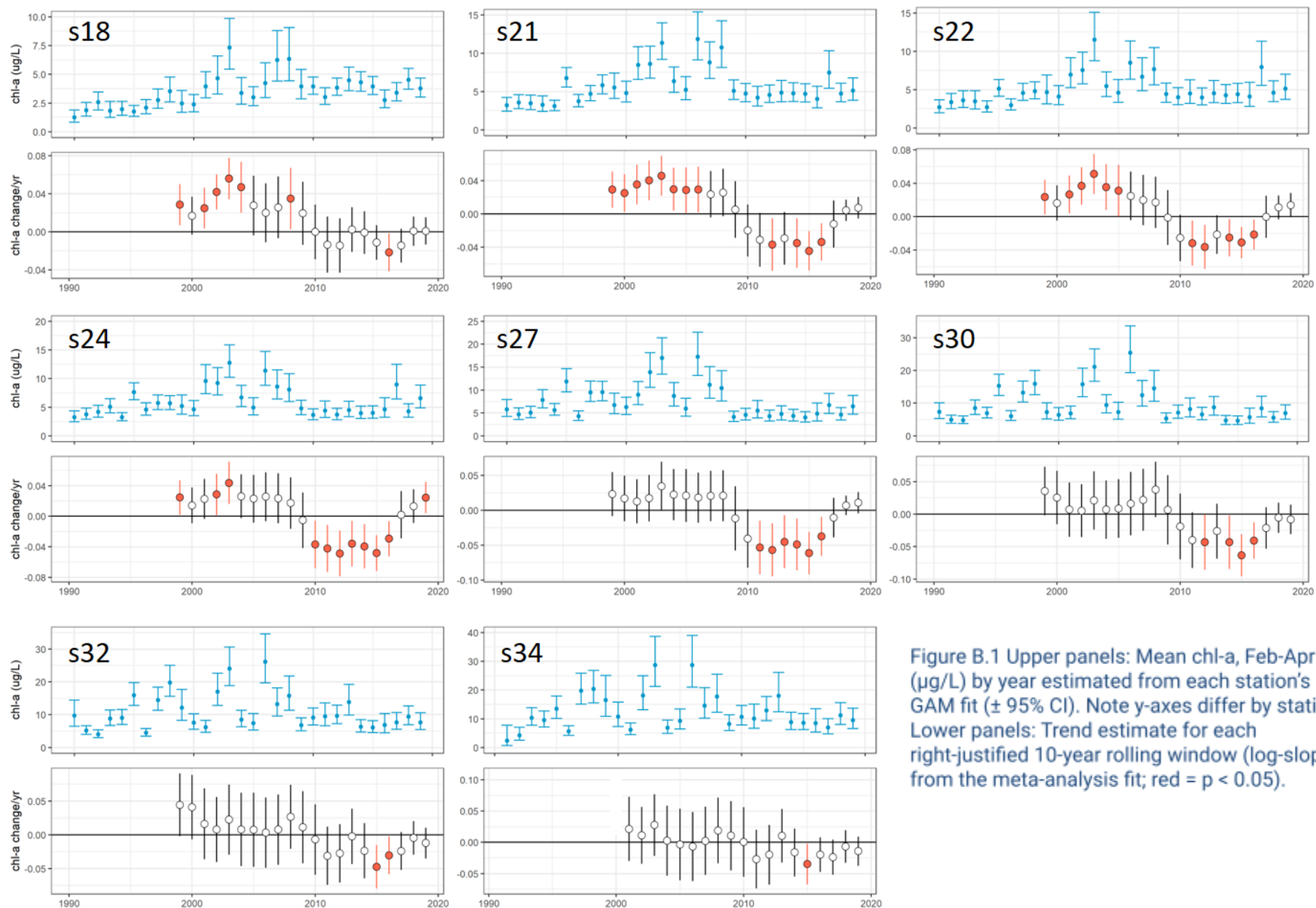
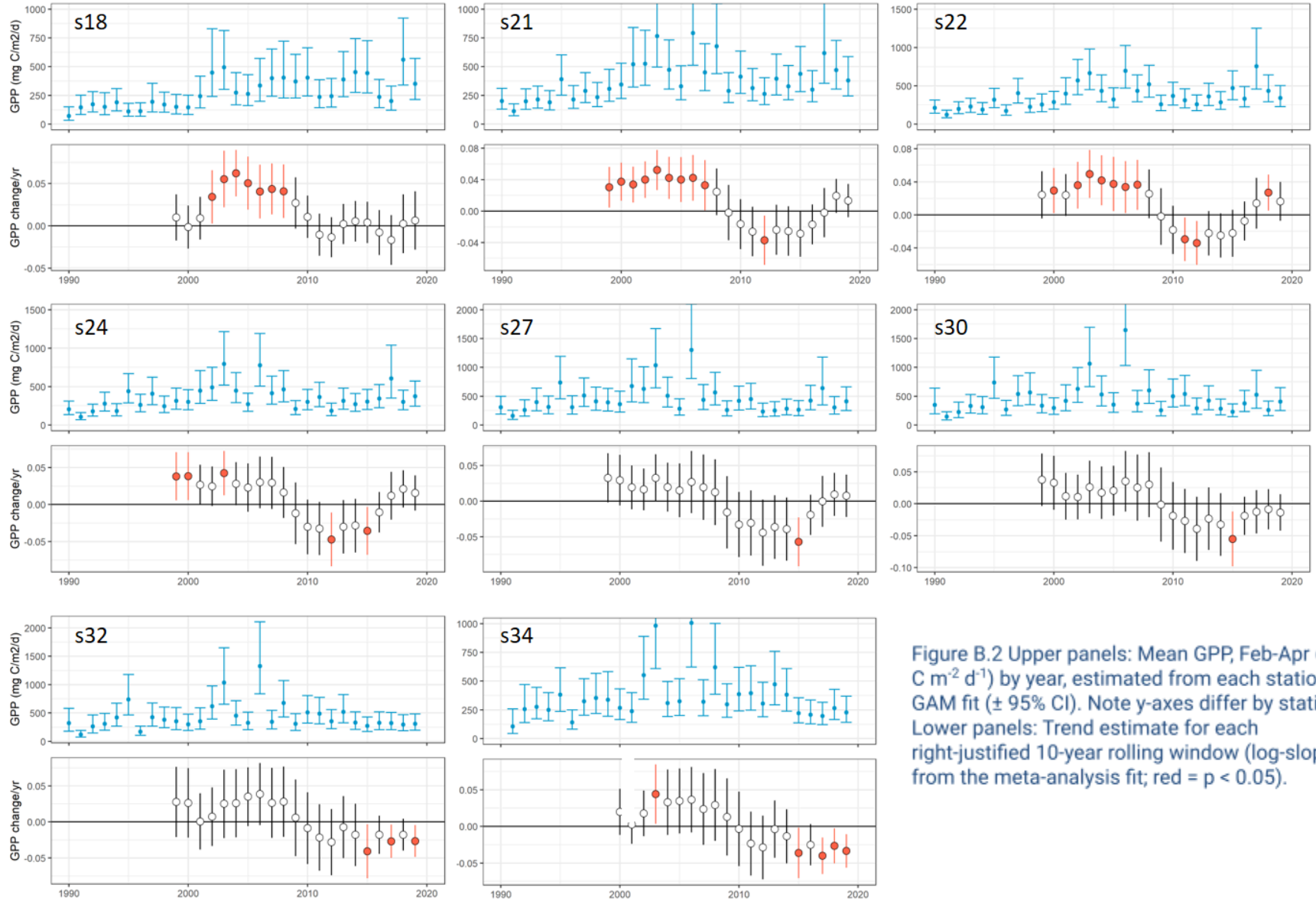


Figure B.1 Upper panels: Mean chl-a, Feb-Apr ($\mu\text{g/L}$) by year estimated from each station's GAM fit ($\pm$ 95% CI). Note y-axes differ by station. Lower panels: Trend estimate for each right-justified 10-year rolling window (log-slope from the meta-analysis fit; red = $p < 0.05$).



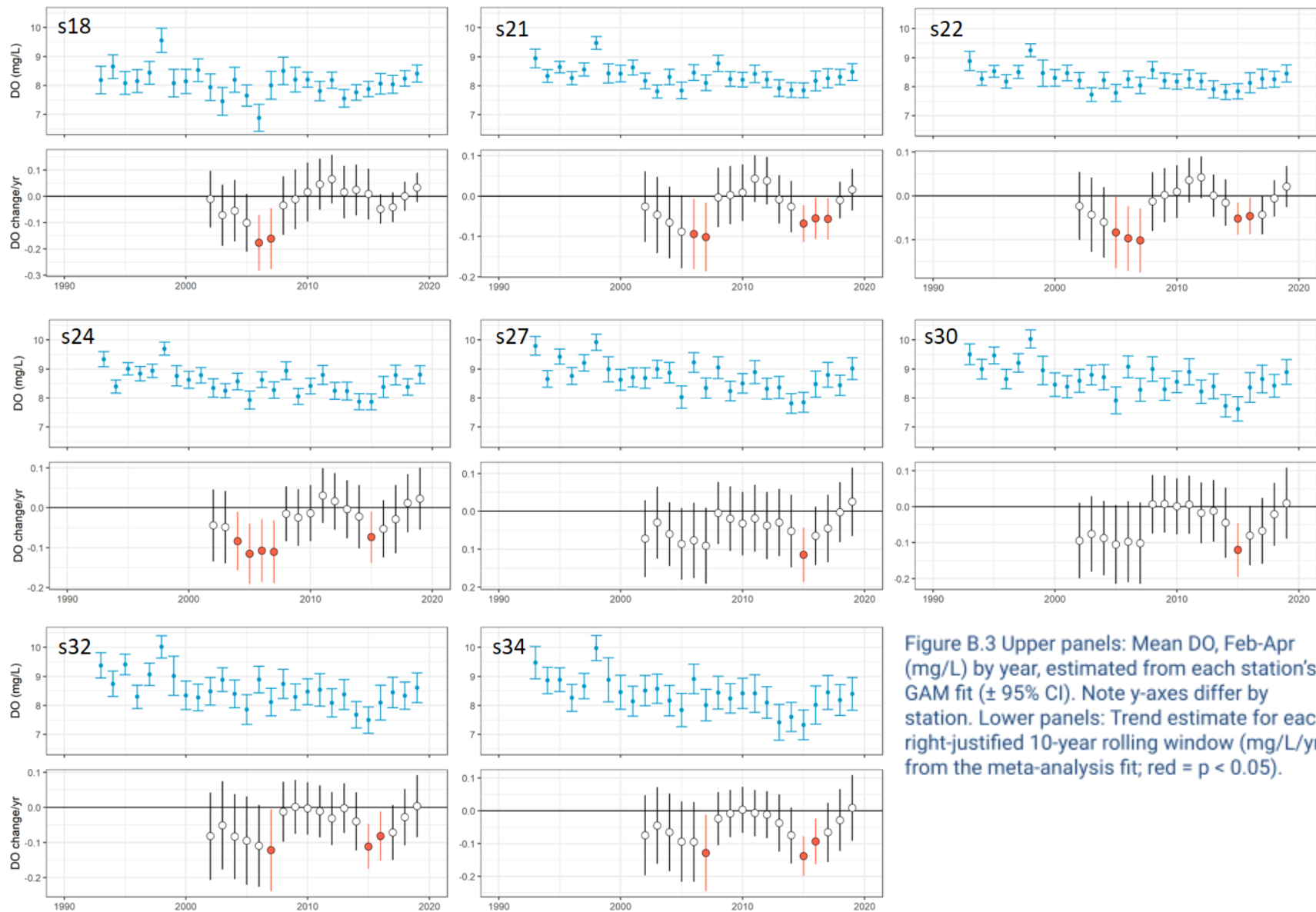


Figure B.3 Upper panels: Mean DO, Feb-Apr (mg/L) by year, estimated from each station's GAM fit ($\pm 95\%$ CI). Note y-axes differ by station. Lower panels: Trend estimate for each right-justified 10-year rolling window (mg/L/yr, from the meta-analysis fit; red = $p < 0.05$).

APPENDIX C

Annual slopes for seasonal average trends: Aug 1-Oct 31

Estimates based on right window

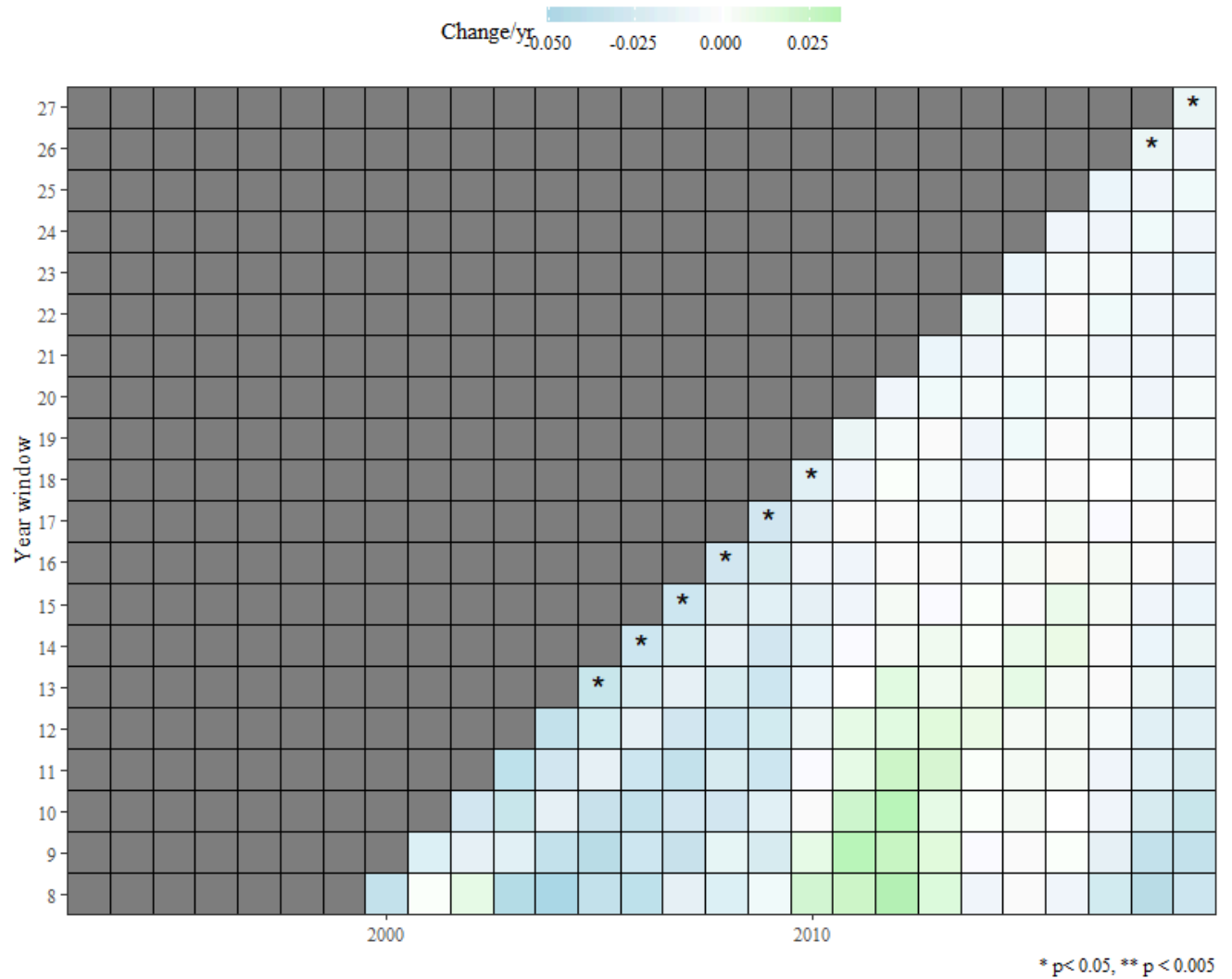


Figure C.1. Station s18 dissolved oxygen (DO, mg/L) trends at for the seasonal window Aug-Oct (DO_{AugOct}), across a range values for $\Delta\tau$ (trend window) and ending year. **y-axis:** $\Delta\tau$ ranging from 8 to 27 years. **x-axis:** ending year (right-justified), 2000-2019. Changes in DO_{AugOct} were statistically significant for the combinations of $\Delta\tau$ and end-year indicated by * ($p < 0.05$) or ** ($p < 0.005$). Slope magnitude and sign (+,-) indicated by color.

Annual slopes for seasonal average trends: Aug 1-Oct 31

Estimates based on right window

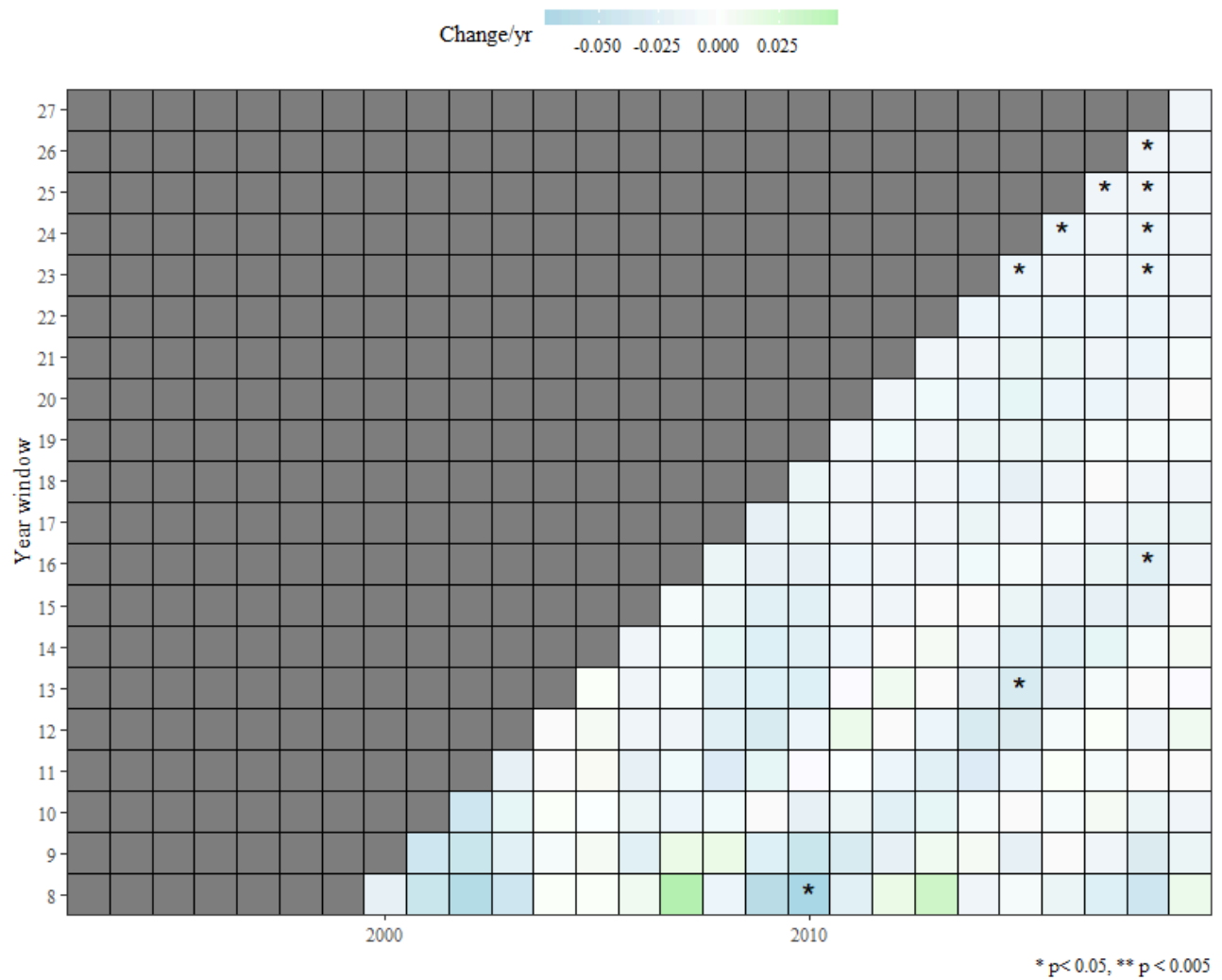


Figure C.2. Station s24 dissolved oxygen (DO, mg/L) trends at for the seasonal window Aug-Oct (DO_{AugOct}), across a range values for $\Delta\tau$ (trend window) and ending year. **y-axis:** $\Delta\tau$ ranging from 8 to 27 years. **x-axis:** ending year (right-justified), 2000-2019. Changes in DO_{AugOct} were statistically significant for the combinations of $\Delta\tau$ and end-year indicated by * ($p < 0.05$) or ** ($p < 0.005$). Slope magnitude and sign (+,-) indicated by color.