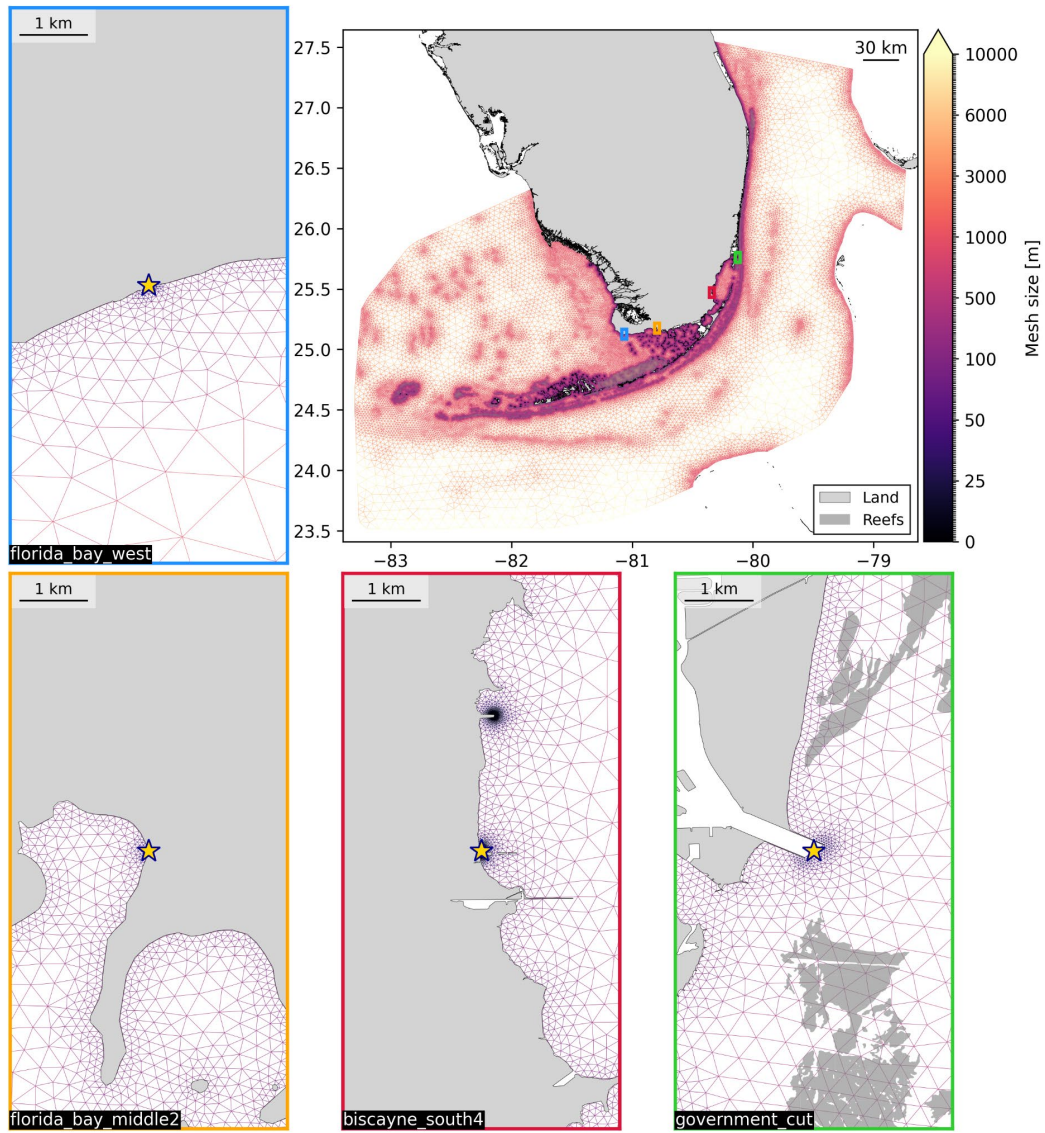


Terrestrial watershed connections to water quality on Florida's Coral Reef.



Terrestrial watershed connections to water quality on Florida's Coral Reef.

Draft Final Report

Prepared By:

Gareth J. Williams¹, Emmanuel Hanert², Louis Rycx Lamme d'Huisnacht², David Whitall³, Jeffrey A. Maynard⁴, and Brian K. Walker⁵

¹School of Ocean Sciences, Bangor University, LL59 5AB, UK; ²UCLouvain, Earth and Life Institute, Louvain-la-Neuve, Belgium; ³Coastal Ocean Assessments Stressors and Trends (COAST) LLC, 3300 E Broad St, Richmond, VA 23223; ⁴SymbioSeas, 1114 Merchant Lane, Carolina Beach, NC, 28428; ⁵Halmos College of Arts and Science, Nova Southeastern University, 8000 N. Ocean Drive, Dania Beach, FL 33004; walkerb@nova.edu

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UCLouvain



Management Summary (300 words or less)

This study identified hydrographic connections between inland water sources in south Florida and coral reefs and investigated the environmental drivers associated with nutrient measurements at water quality monitoring stations between 2018 and 2024. The most significant outcomes were: 1) exposure of analytes to reefs depends on location: exposure is northward of their adjacent inlet on the east coast and more localized in southern embayments, 2) reducing nutrient loads at Government Cut would have the largest single source downstream effect, 3) WQ samples are affected by co-varying factors of sample program, sample location, depth, season, and the amounts of recent rainfall, wind, and nearby inlet outflow, 4) analyzing WQ data requires the control of these variables through modeling, 5) analyte concentrations on the east coast increased until 2022 and have plateaued coinciding with recent fertilizer restrictions and drought conditions, 6) WQ sample program was the single most influential predictor indicating monitoring program must be a factor in analyses containing multiple programs, 7) significance between land-based drivers and WQ decreased with distance from source indicating that Florida's mainland is not the main source of nutrients throughout the Keys.

This study provides crucial insights into the hydrographic dynamics affecting coral reefs in South Florida. Identifying the relationship between nutrient sources and WQ sample sites lays the groundwork for effective management actions to mitigate impacts and promote reef resilience. These findings highlight the importance of managing inland water quality to protect coral reefs. The model provides a detailed understanding of how nutrients from inland sources are transported to reefs, offering valuable insights for targeted intervention strategies. Efforts are currently underway to refine the models and use the modeled nutrient data, compiled environmental data, and reef monitoring data to conduct machine learning models of the relationships between factors relating to reef health. This will provide a deeper understanding of the factors affecting reef health and the ability to target high impact mitigative actions and restoration strategies.

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List of Acronyms

BRT	Boosted Regression Tree
CREMP	Coral Reef Evaluation and Monitoring Project
DTCREMP	Dry Tortugas Coral Reef Evaluation and Monitoring Project
DEP	Florida Department of Environmental Protection
DERM	Miami-Dade County Environmental Resources Management
ECMWF	European Centre for Medium-Range Weather Forecasts
FCR	Florida's Coral Reef
FL	Florida
FWC	Florida Fish and Wildlife Conservation Commission
GMSH	3D finite element mesh generator
HYCOM	Hybrid Coordinate Ocean Model
ICA	Inlet Contributing Area
IEA	Inlet Exposure Area
KJCAP	Kristin Jacobs Coral Aquatic Preserve
MDL	Method Detection Limit
NCEI	National Centers for Environmental Information
NOAA	National Oceanic and Atmospheric Administration
NSU	Nova Southeastern University
SCTLD	stony coral tissue loss disease
SECREMP	Southeast Florida Coral Reef Evaluation and Monitoring Project
SERC	Southeast Environmental Research Center
SLIM	Second-generation Louvain-la-Neuve Ice-ocean Model
TSS	Total Suspended Solids
WIN	Watershed Information Network
WQ	Water quality

Acknowledgements

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Executive Summary

Reduced water quality (WQ), (e.g. excessive nutrients) is widely suspected to contribute to the decline of Florida's Coral Reef (FCR). This study identified hydrographic connections between inland water sources in south Florida and coral reefs and investigated the environmental drivers associated with nutrient measurements at water quality monitoring stations between 2018 and 2024. The most significant outcomes were: 1) exposure of analytes to reefs depends on location: exposure is northward of their adjacent inlet on the east coast and more localized in southern embayments, 2) reducing nutrient loads at Government Cut would have the largest single source downstream effect, 3) WQ samples are affected by co-varying factors of sample program, sample location, depth, season, and the amounts of recent rainfall, wind, and nearby inlet outflow, 4) analyzing WQ data requires the control of these variables through modeling, 5) analyte concentrations on the east coast increased until 2022 and have plateaued coinciding with recent fertilizer restrictions and drought conditions, 6) WQ sample program was the single most influential predictor indicating monitoring program must be a factor in analyses containing multiple programs, 7) significance between land-based drivers and WQ decreased with distance from source indicating that Florida's mainland is not the main source of nutrients throughout the Keys.

The model domain continuously spanned the entire FCR, from the Dry Tortugas to the northern KJCAP, over a six-year period (September 2018 – August 2024) now representing a wider range of circulation regimes than the comparatively uniform setting of the KJCAP. The simulations revealed two contrasting dispersal regimes that bracket conditions across the FCR. In areas under the direct influence of the Florida Current, the residual flow was strong and directionally persistent, producing anisotropic, far-reaching plumes: analytes were advected over tens of kilometers, predominantly downstream (northward), and reefs were exposed not only to their adjacent inlet but also to inlets located further south. Government Cut and Baker's Haulover exemplified this behavior, exerting an influence well beyond their immediate vicinity. In contrast, in the tidally and wind-driven environments of Biscayne Bay, the Keys, and Florida Bay, residual flows were weak and the circulation was largely oscillatory. The fate of land-based analytes in these areas was governed by local tidal flow, wind forcing, and the degree of physical enclosure rather than by along-shelf advection.

Nearshore water quality was governed first by when a sample was collected and second by where, but neither signal was visible in the raw data. Season emerged as the leading or near-leading predictor for most analytes, with spatial position close behind. In the KJCAP, the modeled seasonal trajectories of the seven analytes sorted into three shapes: a rise to a peak with a tentative recent decline (nitrate and silicate); a rise to an elevated asymptote (nitrite, orthophosphate, and total phosphorus); and an oscillation with no trend (total suspended solids and turbidity). The most striking feature is that four nutrient analytes, spanning different chemistries, leveled off or, for nitrate, begin to decline across the most recent seasons. The reasons for the decreasing nutrients seen in the KJCAP are not known, but there have been many efforts to mitigate water quality in south Florida coinciding with the same timeframe and south Florida is in a severe drought and has had a total rain deficit. A two-season decline is not a confirmed reversal, and continued monitoring and analyses are needed to establish a persistent pattern.

Aggregated multi-agency databases offer unmatched spatial and temporal coverage, but our results show they cannot be used to infer broad-scale water-quality patterns unless the contributing agency is modeled explicitly. Sampling agency was the single most influential predictor in four of the seven analyte models, exceeding 60% of relative influence in two of them. In those analytes, most of the variation reflects differences in how agencies sample and analyze rather than differences in the water itself. This is a transferable lesson for any regional synthesis that pools heterogeneous monitoring sources.

The explanatory power of the models declined in a clear gradient from the KJCAP, through DERM and WIN, to SERC, where cross-validated deviance explained fell to 15 - 44 percent, the lowest in the synthesis. This gradient aligned with both distance from the mainland and whether the spatial framework was informed by hydrographic modeling exposure. The KJCAP models, built on a coordinated program with hydrographically defined exposure areas, were the most predictive, whereas the SERC models, drawn from a broad and heterogeneous Keys-wide network, were the weakest. The extended hydrographic modeling southward into the Keys and Florida Bay from this project provided exposure data that can be used in subsequent analyses to refine the geographic analyses that should raise their explanatory power. The KJCAP was highly linked to the nutrient sources along the east coast as the land-based water comes out of the inlets and hugs the coast. The DERM data were also in very close proximity to the nutrient source. The WIN and SERC datasets contained sites throughout the Keys and out into open ocean. These sites were very far from the land-based nutrient sources in this study coming from Florida's mainland. The weaker relationships indicate that Florida's mainland is not the main source of nutrients throughout the Keys and that to get a more accurate terrestrial connection to nutrients at monitoring stations in the Keys, more localized source data need to be used in the modeling.

This study provides crucial insights into the hydrographic dynamics affecting coral reefs in South Florida. Identifying the relationship between nutrient sources and WQ sample sites lays the groundwork for effective management actions to mitigate impacts and promote reef resilience. These findings highlight the importance of managing inland water quality to protect coral reefs. The model provides a detailed understanding of how nutrients from inland sources are transported to reefs, offering valuable insights for targeted intervention strategies. Efforts are currently underway to refine the models and use the modeled nutrient data, compiled environmental data, and reef monitoring data to conduct machine learning models of the relationships between factors relating to reef health. This will provide a deeper understanding of the factors affecting reef health and the ability to target high impact mitigative actions and restoration strategies.

1. INTRODUCTION

Reduced water quality (WQ), (e.g. excessive nutrients) is widely suspected to contribute to the decline of Florida's Coral Reef (FCR). Nutrient impacts on corals depend on both the concentration of pollutants and the balance of carbon, nitrogen, phosphorous, and iron (C:N:P:Fe) [1]. Studies show that maintaining a specific phosphate-to-nitrogen ratio is essential for stable coral photosymbiosis [2]. Corals naturally thrive in nutrient-poor waters through tightly regulated symbiosis with their photosynthetic endosymbionts. When nutrient levels rise or become imbalanced, this partnership breaks down, leading to coral bleaching and tissue loss diseases [1, 3, 4]. Nitrogen and phosphorous enrichment are strongly associated with coral disease through several mechanisms [1]. Elevated nitrogen, especially from human sources such as nitrate [1, 5, 6], can disrupt the coral-symbiont relationship [4, 7, 8]. Nitrate assimilation increases oxidative stress, promotes excessive symbiont growth, and causes phosphate limitation in the symbionts [1]. In addition, anthropogenic nitrogen may enhance viral activity in corals, weakening coral hosts and driving a virus-mediated cycle of reef decline [1].

Most of the FCR occurs within 5 km from shore [9], making it highly vulnerable to coastal human activities. These impacts include terrestrial runoff, river discharge, sewage outflow, beach restoration, dredging, and shipping. Watershed-based pollution – such as excess nutrients, sediments, and contaminants – often reaches reefs through run-off after rainfall events. Measuring these terrestrial inputs can be challenging. South Florida's hydrology is highly modified by urban flood control systems and agricultural drainage canals. These engineered waterways can deliver large volumes of freshwater to nearshore ecosystems during planned releases. Such discharges often carry pollutants [10] and cause rapid changes in salinity, turbidity, sedimentation, and siltation. Long-term datasets exist for inland canal flow, rainfall, and coastal water quality at reef sites. These data allow researchers to examine links between inlet discharges and nutrient enrichment of nearshore reefs. Quantifying these connections is critical for managing reef health amid multiple stressors, identifying sources to improve WQ, and improving the success of coral restoration.

Historically, linking WQ data to coral reef decline on FCR has been difficult. Much of the challenge stems from being unable to identify the drivers of WQ variability, infrequent water sampling (e.g. monthly, quarterly), and the dynamic nature of WQ and reef conditions [11, 12]. Our team recently adopted a new approach to better connect WQ patterns with reef health metrics (Fig. 1). First, we combined historical rainfall and inland canal flow data across multiple timeframes for each WQ site and sampling event. Using a statistical modeling framework, we quantified the contribution of terrestrial water to observed WQ variation [13] (Fig. 1A). Next, we developed a high-resolution hydrographic model that incorporates ocean circulation, wind forcing, inland flow, and in situ WQ data. This model simulates continuous nutrient loads from coastal inlets to the nearshore reefs over a five-year period [14] (Fig. 1B). We then summarized the modeled nutrient data at each reef site across different timeframes. Finally, we used a second statistical model to examine how modeled nutrients and environmental variables relate to coral disease dynamics [15] (Fig. 1C).

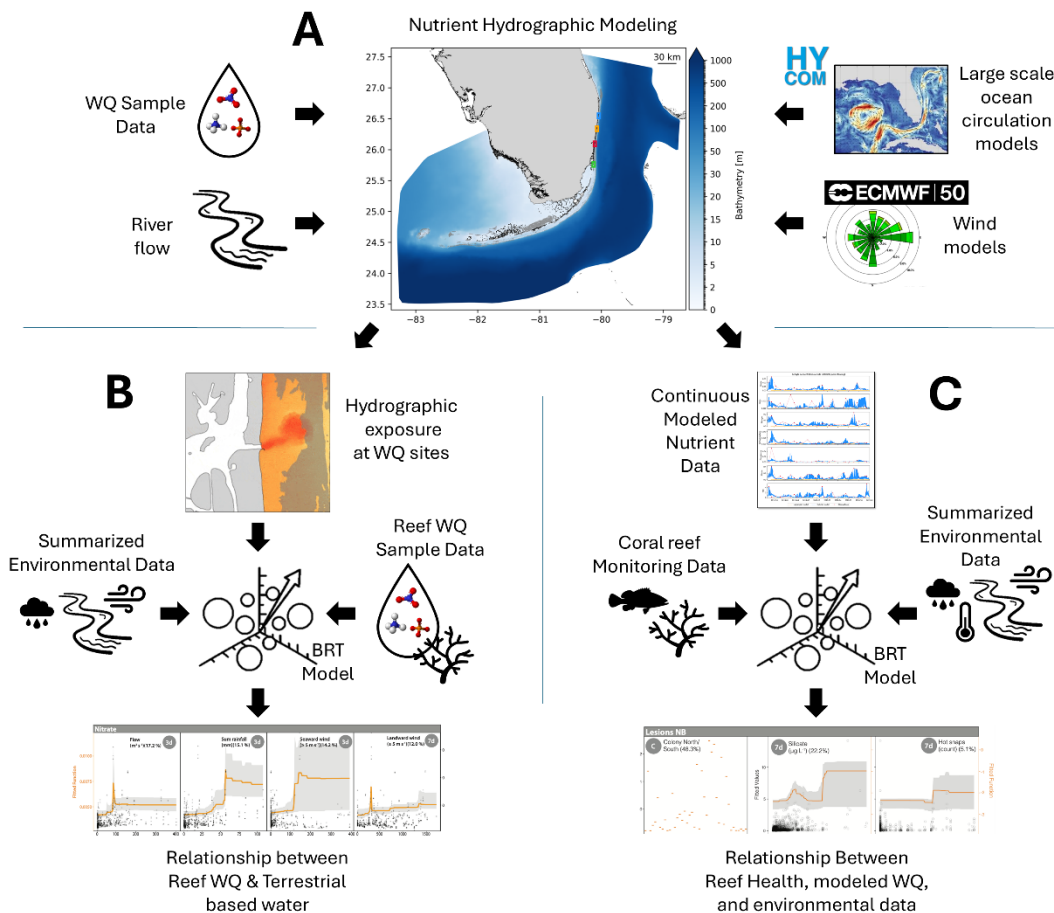


Figure 1. Illustration of the workflow for relating continuous modeled nutrient data and environmental data to reef health.

Our previous DEP work (C3D88F) accomplished these goals in the Kristin Jacobs Coral Aquatic Preserve (KJCAP), focusing on four inlets in Miami-Dade and Broward counties. This work demonstrated that our modelling approach identifies relationships between reef health metrics and terrestrial runoff (Fig. 1A). We found that rainfall, inlet flow, and wind are major drivers of water quality patterns on the reef. These factors strongly influence certain analytes: for example, they explain 55% of nitrate and 79% of orthophosphate variation [13]. In earlier EPA-supported work (Award no. 02D21722), we also detected significant links between terrestrial water sources and stony coral tissue loss disease (SCTLD). Mean inland rainfall and inlet flow were key factors explaining temporal variation in SCTLD incidence and prevalence [16]. The hydrographic model generated continuous estimates of nutrient exposure from terrestrial sources (Fig. 1B). Results showed highly irregular circulation patterns driven by tides, mesoscale eddies, and seafloor topography. Seasonal shifts in flow rates and analyte loads further shaped these patterns [14]. Inland water plumes had higher analyte concentrations during the wet season and typically extended north of each inlet, with some southern spread. Government Cut and Baker's Haulover discharged the highest pollutant loads, creating large, nutrient-rich plumes that affected areas far beyond their sources. On average, 71.7% of silicate (indicator of land-based water) reaching reef sites originated from Government Cut, indicating that reducing loads there could yield the most benefits to the reef. This work highlighted the

urgent need to manage land-sea connections [17] to reduce disease-related coral mortality along populated coastal reefs.

Here, we report out on our 2025-26 DEP-funded work (C5C983) which expanded our hydrographic and statistical modeling approach to the entire reef system, including Dry Tortugas, Florida Keys, Florida Bay, and Biscayne Bay (September 2018 – December 2024).

2. METHODS

2.1. Task 2: Compile relevant regional environmental data (inlet flow, temperature, rainfall, wind) from 2018 – 2024

Historical regional environmental data (inlet flow, temperature, rainfall, wind) across the FCR were compiled from 2018 – 2024 for the analyses. Figure 2 illustrates the location of the monitoring stations by data type throughout the FL Keys and southern KJCAP used in this study. Figure 3 illustrates the location of the monitoring stations by data type throughout the northern KJCAP used in this study.

2.1.1. *Spatial predictors*

Every Boosted Regression Tree (BRT) model included a categorical spatial predictor. Its purpose was to capture underlying drivers of variations in water quality not explained by our estimates of flow, rainfall, and wind. The way this spatial term was defined differed between programs. For the KJCAP, it was hydrographically informed, based on inlet exposure areas (IEAs; Figure 4). For Dade County Environmental Resources Management (DERM), Watershed Information Network (WIN), and Southeast Environmental Research Center (SERC) analyses, it was instead a set of spatial divisions based purely on geography, which we refer to as spatial polygons (Figures 5 to 7).

Each KJCAP water-quality site was assigned to an IEA by spatially joining its coordinates to the IEA polygon within which it fell. The IEA polygons are an extension and adaptation of the inlet contributing areas developed for Whitall et al. [13], expanded northward to cover the full KJCAP extent. Critically, the IEAs for the KJCAP were informed by the hydrographic modeling reported in Walker et al. [15]. That modeling characterized the prevailing northward flow of water from the Government Cut, Baker’s Haulover, Port Everglades, and Hillsboro inlets along this coast. We extended this logic further north all the way to Jupiter inlet. This northward extension lies beyond the area covered by the Walker et al. [15] hydrographic modeling. We therefore defined its northernmost unit conservatively, combining the Jupiter and St. Lucie inlets into a single exposure area. Water moves predominantly northward from both inlets, and the area lacks hydrographic data fine enough to partition nearshore sites between them. Once the sites clustered around the inlet mouths had been excluded, only one monitoring site remained north of the St. Lucie inlet, with three just to its immediate south. Because flow is predominantly northward, those three southern sites are more likely influenced by the Jupiter inlet. Pooling the two inlets into one exposure area was therefore the most logical approach. This combination was applied consistently to the assignment of water-quality sites to IEAs and the aggregation of inlet-flow data. The resulting nine KJCAP IEAs define the categorical spatial

predictor used in the KJCAP BRT models. These IEAs are Jupiter, Lake Worth, Boynton, Boca, Hillsboro, Port Everglades, Baker's Haulover, Government Cut, and Biscayne.

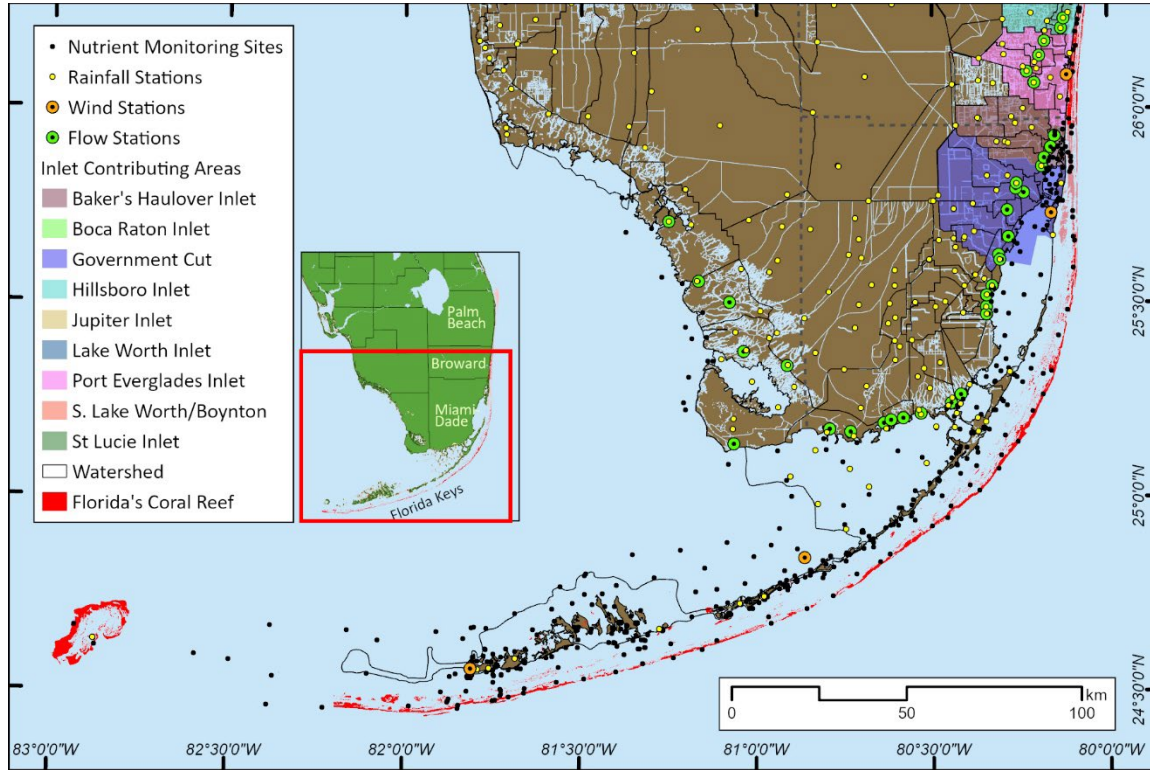


Figure 2. Map of the southern project area depicting the Inlet Contributing Areas, watersheds, DBHydro flow stations, rainfall and wind stations, water quality monitoring sites and the FCR.

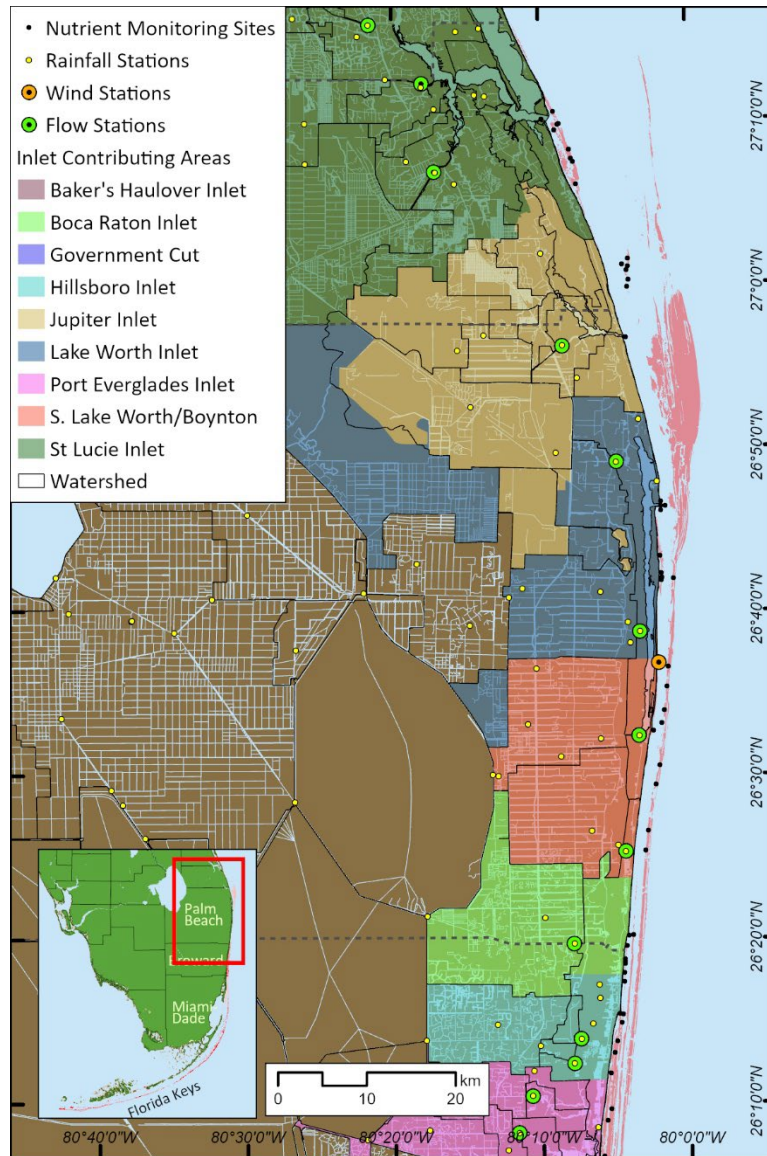


Figure 3. Map of the northern project area depicting the Inlet Contributing Areas, watersheds, DBHydro flow stations, rainfall and wind stations, water quality monitoring sites and the FCR.

For DERM, WIN, and SERC, the spatial predictor was instead a set of geographic polygons. These polygons are spatial units, not inlet-outflow exposure areas, and were not derived from hydrographic modeling. Their role was to absorb residual spatial structure in water quality not captured by the other predictors. Each site was assigned to the polygon within which it fell. The DERM sites span five polygons across Biscayne Bay and the upper Keys (Figure 5). The WIN sites span nine polygons across the Florida Keys and Florida Bay (Figure 6). The SERC sites span eight polygons across the same region (Figure 7). Each polygon set and its member sites are described in the corresponding results section.

2.1.2. Inlet outflow, rainfall, and wind

Inlet outflow, rainfall, and wind data were assembled at daily resolution for the full study period (November 2018 to April 2025; the SERC record ends in December 2024) (Appendix 3). The effects of freshwater outflow, rainfall, and wind propagate to coastal coral reefs on lagged time scales [17]. We therefore computed each environmental predictor over a series of temporal windows. These windows extended back 1, 3, 7, 14, 30, 60, and 90 days prior to each water-quality sampling date. This choice balances short-term (1 to 7 days) and longer-term (30 to 90 days) drivers. It also remains within the boundaries of the wet and dry seasonal cycle [13].

Flow data were drawn from the South Florida Water Management District’s DBHydro database (<https://www.sfwmd.gov/science-data/dbhydro>), restricted to canal-and-structure gauges flagged active for the November 2018 to April 2025 study window. Within each spatial unit, we identified the most-downstream non-nested DBHydro flow stations (*sensu* [13]). Their daily-volume outputs were converted from cubic feet per second to cubic meters per second and summed to give a single daily outflow time series ($\text{m}^3 \text{s}^{-1}$) for that unit. This series was then summed over each of the temporal windows defined above. Each water-quality observation was intersected with a single spatial unit, and the resulting daily-outflow predictors were assigned to every analyte sampled at that site on that date. Consistent with the combined Jupiter IEA used for the KJCAP, the three St. Lucie DBHydro flow stations (S48, S49, S80) were aggregated into the Jupiter IEA outflow series. The number of contributing DBHydro gauges per dataset depended on which spatial units that dataset’s monitoring sites occupied: 28 gauges for the KJCAP (the 25 native to the nine KJCAP IEAs plus the three St. Lucie gauges folded into Jupiter), 24 for WIN, 23 for DERM, and 23 for SERC — drawing on 52 unique active DBHydro flow stations across the four datasets. The full list of stations used, grouped by IEA and spatial polygon, is provided in Appendix 1.

Rainfall data were drawn from the U.S. National Oceanic and Atmospheric Administration’s National Centers for Environmental Information (NCEI; <https://www.ncei.noaa.gov/products/precipitation>). Daily precipitation records were obtained for each NCEI station within a bounding box covering the study region (23.0° to 28.0° N, 83.0° to 80.0° W) whose published metadata indicated activity at or before 1 January 2018 and at or after 1 October 2025. For every water-quality monitoring site, the five geodesically nearest qualifying stations were identified, and the daily-precipitation coverage of each candidate station was computed as the proportion of in-range days with a record. Any station with zero usable records was excluded. The per-site “best” station was then selected by weighting data quality slightly less than proximity, so that a closer station with a small data gap was preferred over a substantially more distant station of marginally better coverage. Daily rainfall for the selected station was then summed, averaged, and characterized by its standard deviation over the same temporal windows defined for flow and wind. Across the four datasets, 15 NCEI stations contributed to the KJCAP, 13 to WIN, 6 to DERM, and 11 to SERC — drawing on 29 unique stations in total.

Wind data were drawn from NOAA’s National Data Buoy Center (NDBC; <https://www.ndbc.noaa.gov/>), consisting of 6-minute average wind speed and direction. After screening every coastal NDBC station in the study region for temporal completeness across the November 2018 to April 2025 study window, five buoys retained a continuous record across the period and were used for the analysis: KYWF1 (Key West), LONF1 (Long Key), VAKF1

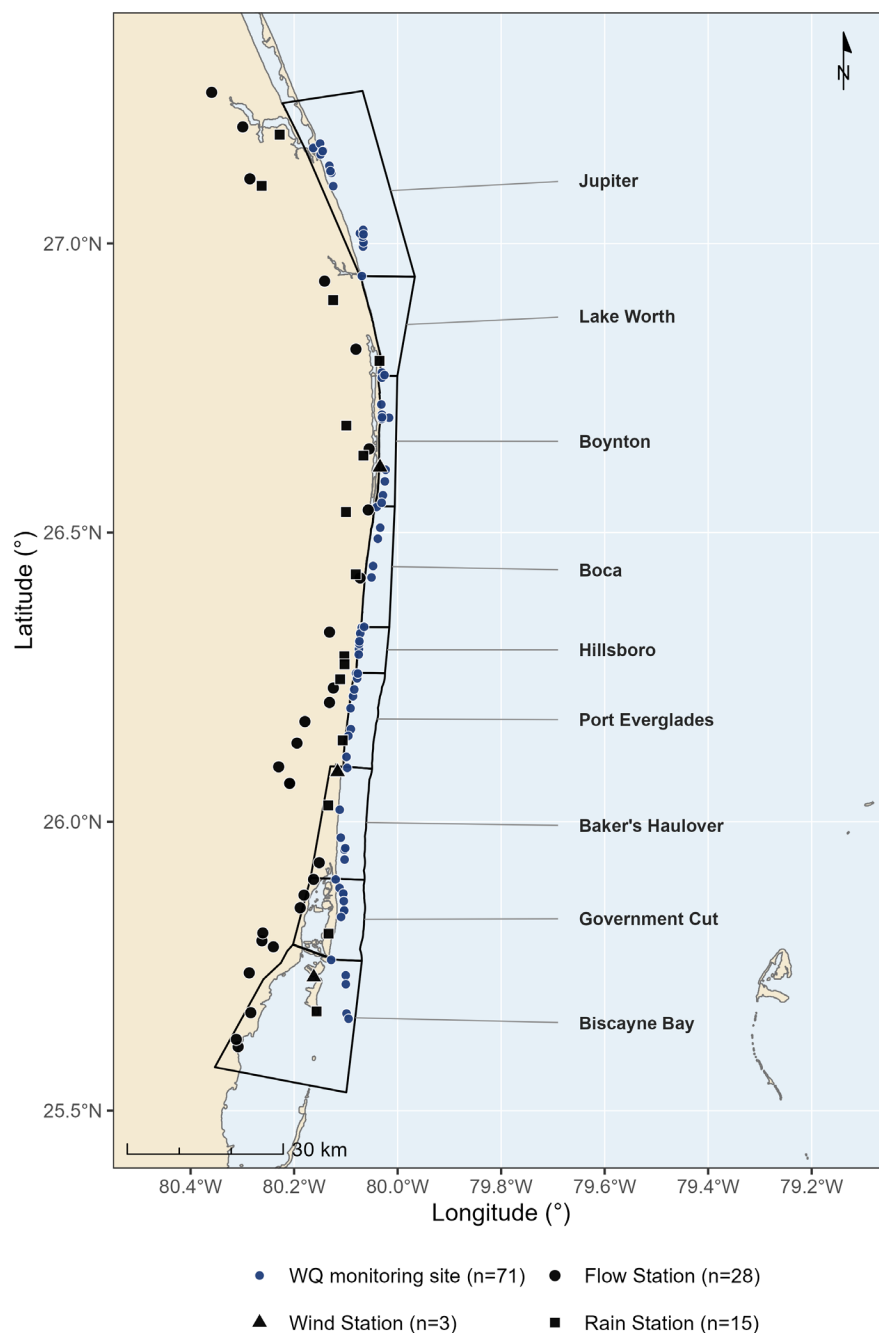


Figure 4. Water-quality monitoring sites and meteorological and hydrological stations across the nine inlet exposure areas (IEAs) of the KJCAP, southeast Florida, ordered from Jupiter Inlet in the north ($\sim 27.25^\circ$ N) to Biscayne Bay in the south ($\sim 25.50^\circ$ N). Black-outlined polygons show the spatial extent of each IEA, labeled from north to south: Jupiter, Lake Worth, Boynton, Boca Raton (hereafter “Boca”), Hillsboro, Port Everglades, Baker’s Haulover, Government Cut, and Biscayne Bay (hereafter “Biscayne”). Symbols mark the 71 water-quality monitoring sites used in the present analysis, together with the DBHydro flow stations, wind stations, and rainfall stations from which the environmental predictors were derived (see legend for counts). Coordinates are in decimal degrees, WGS 84 datum.

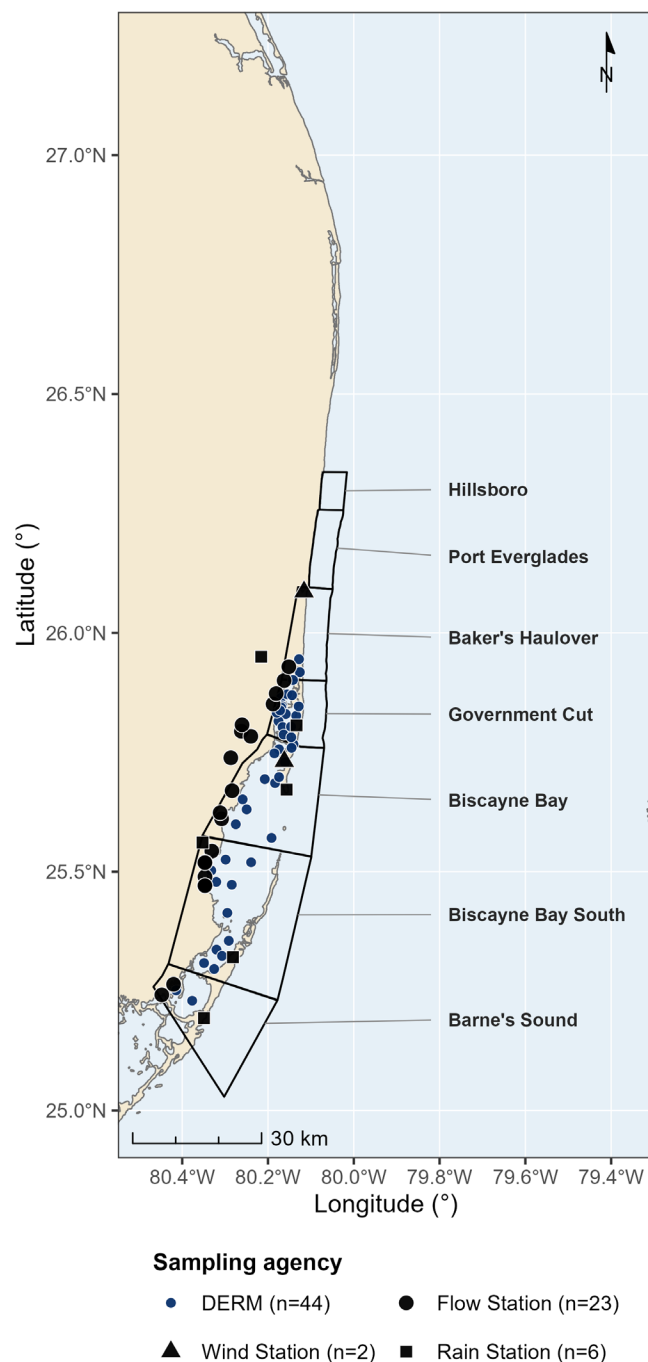


Figure 5. DERM water-quality monitoring sites and the meteorological and hydrological stations supplying the environmental predictors. Filled circles mark the 44 DERM monitoring sites used in the present analysis, which fall within five spatial polygons labeled from north to south: Baker's Haulover, Government Cut, Biscayne Bay, Biscayne Bay-South, and Barne's Sound. The Hillsboro and Port Everglades polygons immediately to the north are also outlined for regional context and contain no DERM monitoring sites. Flow, wind, and rainfall stations are shown with the symbols given in the legend. Coordinates are in decimal degrees, WGS 84 datum.

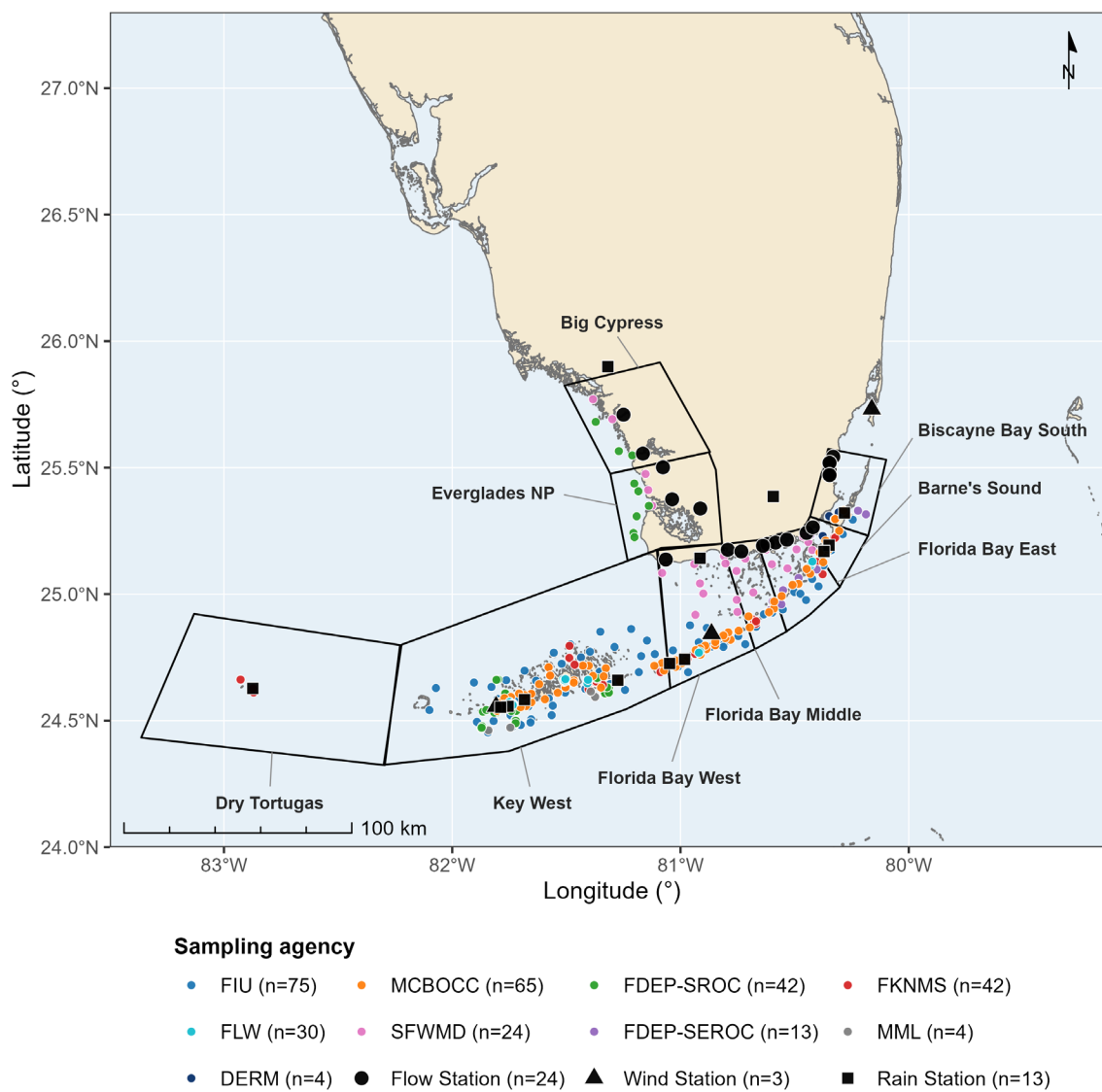


Figure 6. WIN water-quality monitoring sites across the Florida Keys and Florida Bay, colored by the sampling agency that collected each site's data, together with the nine spatial polygons used in the BRT models (black outlines): Big Cypress, Everglades National Park, Biscayne Bay-South, Barne's Sound, the eastern, middle, and western basins of Florida Bay, Key West, and the Dry Tortugas. Flow, wind, and rainfall stations supplying the environmental predictors are also shown (see legend for counts). Coordinates are in decimal degrees, WGS 84 datum. The sampling-agency site counts in the map legend sum to 299, four above the 295 unique WIN sites reported in the text and Table 9. This reflects a small number of sites sampled by more than one agency. FIU, Florida International University; FLW, Florida Lakewatch, DERM, Division of Environmental Resources Management; MCBOCC, Monroe County Board of County Commissioners; SFWMD, South Florida Water Management District; FDEP-SROC, Florida Department of Environmental Protection South Regional Operations Center; FDEP-SEROC, FDEP Southeast Regional Operations Center; FKNMS, Florida Keys National Marine Sanctuary; MML, Mote Marine Laboratory.

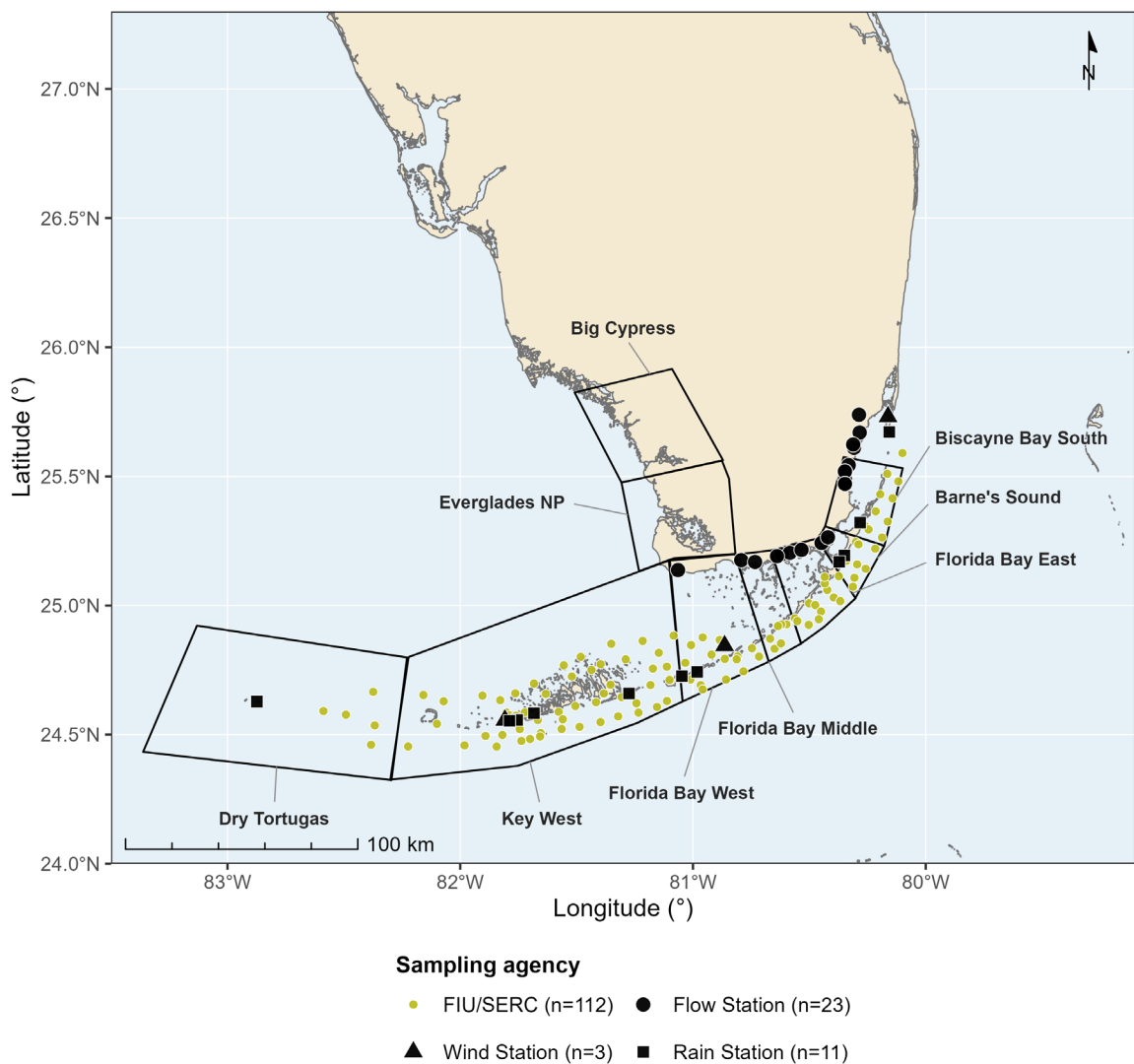


Figure 7. SERC water-quality monitoring sites across the Florida Keys and Florida Bay. Filled circles mark the 112 SERC monitoring sites used in the present analysis. Black-outlined polygons show the regional Keys polygons used for spatial reference, labeled Big Cypress, Everglades National Park, Dry Tortugas, Key West, the western, middle, and eastern basins of Florida Bay, Barne's Sound, and Biscayne Bay-South. Flow, wind, and rainfall stations supplying the environmental predictors are also shown (see legend for counts). Coordinates are in decimal degrees, WGS 84 datum. FIU, Florida International University; SERC, Southeast Environmental Research Center.

(Virginia Key), PEGF1 (Port Everglades), and LKWF1 (Lake Worth). The five buoys distributed across the four water-quality datasets as follows: three buoys for the KJCAP (LKWF1, PEGF1, VAKF1), three for WIN (KYWF1, LONF1, VAKF1), two for DERM (PEGF1, VAKF1), and three for SERC (KYWF1, LONF1, VAKF1). Each water-quality monitoring site was attributed to its geodesically closest buoy of the five, so that each nutrient observation drew its wind covariates from the buoy most representative of the local wind regime at that site. From these records we counted the number of 6-minute observations exceeding 5 m

s⁻¹, defining a high-wind event, and partitioned the counts by direction into landward (azimuth 0 to 179 degrees) and seaward (180 to 359 degrees) sectors so that on-shore and off-shore forcing could be distinguished. These counts were then summed over the same temporal windows as flow and rainfall.

2.1.3. Additional predictors

Each model also included several non-meteorological predictors. These were sample depth (m), the spatial IEA/polygon term described above, Season, Water Year, and Tourism. Season was a binary wet-versus-dry indicator. Water Year is the 12-month period from the start of the wet season in May through the following April. Tourism is a binary Peak-versus-Off-peak indicator for the December-to-April tourist high season. These five predictors were included for all four programs. Each WIN model additionally included sampling agency, a categorical predictor with one level per contributing agency. The agencies do not all use the same laboratory to process their samples. The sampling-agency term therefore also captures any effect of differing laboratory methods. Together, these predictors aimed to capture spatial and temporal effects not represented by inlet outflow, rainfall, and wind.

2.1.4. In situ temperature data

Separately from the predictor datasets described above, we synthesized a large body of in situ temperature data from across the study region. These data were collected with HOBO[®] Pro temperature loggers deployed throughout southeast Florida and the Florida Keys. The logger deployments were conducted by the Coral Reef Evaluation and Monitoring Project (CREMP), the Dry Tortugas CREMP (DTCREMP), and the Southeast CREMP (SECREMP) monitoring programs. The full set of logger locations is mapped in Appendix 4. The temperature logger data were compiled and reviewed, but not used as predictors in the statistical models reported here.

2.2. Task 3: Synthesize water quality monitoring data for both regions from 2018 – 2024

2.2.1. Water-quality data and method detection limit adjustment

This report draws on water-quality data from four independent monitoring programs in the nearshore waters of southeast Florida and the Florida Keys. The programs differ in spatial coverage, sampling design, and the suite of analytes measured. Each data set was cleaned, adjusted, and each analyte modeled separately, using the common framework described below.

The four programs measured overlapping but non-identical sets of water-quality analytes. Several of the programs also measure other variables, but we used the Kristin Jacobs Coral Aquatic Preserve (KJCAP) as the baseline and focused on the analytes from the other programs that most closely matched it. The KJCAP program measured seven: nitrate, nitrite, orthophosphate, total phosphorus, silicate, total suspended solids (TSS), and turbidity. The Department of Environmental Resources Management (DERM) program measured five: nitrate-nitrite, nitrogen-total, orthophosphate, total phosphorus, and turbidity. The Watershed Information Network (WIN) Florida Keys dataset included seven: nitrate-nitrite, nitrite, nitrogen-total, orthophosphate, total phosphorus, silica, and TSS. The Southeast Environmental

Research Center (SERC) network measured seven: nitrate, nitrite, nitrogen-total, total phosphorus, salinity, silica, and turbidity.

The KJCAP data come from the joint NOAA and FDEP nearshore monitoring program first described in Whitall et al. [12]. Across the KJCAP, water samples were collected at the depth of the reef using Niskin bottles, at a median depth of 6.5 m (range 0.5 to 28.5 m). Sampling was timed for the ebbing tide whenever possible, at least 2 to 3 hours after the peak high tide. All sampling equipment was rinsed with deionized water and then with site water between sites. Field equipment blanks were collected at a minimum of one per day and one per 20 samples. The KJCAP analytes were determined via standard analytical methods. Full sampling and laboratory protocols are described in Whitall et al. [12] and Whitall & Bricker [18]. The KJCAP monitoring sites are mapped in Figure 2.

The DERM, WIN, and SERC datasets were contributed by their respective programs as compiled water-quality records. The DERM program is operated by Miami-Dade County. It conducts monthly surface-water sampling at 87 designated stations spanning Biscayne Bay, adjacent canals, and its tidal tributaries. For this analysis we excluded the canal samples and focused on the sampling within Biscayne Bay. All DERM samples used here were collected at a fixed depth of 0.5 m. The WIN dataset is an FDEP repository that aggregates records from many independent monitoring agencies across the Florida Keys. The SERC network, led by Florida International University, has long monitored water quality across the Florida Keys and Florida Bay. Unlike the DERM data, the WIN and SERC datasets span variable sampling depths. WIN depths had a median of 0.66 m (range 0.1 to 32.8 m) and SERC a median of 4.46 m (range 0.0 to 39.6 m). Sample depth was therefore retained as a model predictor (see below). The DERM, WIN, and SERC monitoring sites are mapped in Figures 3 to 5.

We used the Flynn [19] method to account for analyte observations that fell below the laboratory method detection limit (MDL). This adjustment was applied to the KJCAP, DERM, and SERC datasets. The WIN data were obtained from the FDEP repository with MDL adjustments already applied. We then $\log_{10}$ -transformed the Flynn-adjusted data to better normalize their distributions prior to BRT modeling using a Gaussian response. Salinity, measured only by SERC, was modeled on its natural scale. We followed a modified version of the Flynn [19] methodology. The method maximizes the normality of a sample distribution after a best-guess substitution for values below the MDL. The starting value for the iterative calculations was set to half the reported MDL for each analyte. Where an analyte had several different MDLs over the period of record, we used the mean of those MDLs as the starting point. The Flynn adjustments were performed using a custom R routine developed by this project team that computes the Shapiro weights used in Flynn [19].

We further adapted the Flynn [19] approach to account for the time-series nature of our data. As implemented, the Flynn approach estimates below-MDL values by placing them along the x-axis of a normal distribution built from the above-MDL values. It moves from low to increasingly higher values, in the order in which the data are received. If observations are supplied in time order, the estimated below-MDL values therefore creep upward across the time series. This produces a spurious upward trend when temporal patterns in analyte concentrations are later visualized. To remove this artifact, we permuted the order of the dataset prior to MDL

adjustment, stratified by sampling station (sensu Walker et al. [15]). This randomized time when estimating below-MDL values within each station. It also preserved any underlying spatial gradients in nutrient concentrations, and their joint relationship to inlet outflow, rainfall, and wind. We applied this time-series adaptation to the three datasets we adjusted ourselves (KJCAP, DERM, and SERC). The resulting distributions of MDL-adjusted, $\log_{10}$ -transformed concentrations are shown for each program in Figures 15, 24, 31, and 40.

2.3. Task 4: Build hydrographic flow model for the entire FCR frame, quantify the probability of source water in any given location, and quantify nutrient load estimates across space and time

In the present project, the simulation domain now covers the entire Florida Coral Reef (FCR), continuously stretching from the Dry Tortugas to the northern Kristin Jacobs Coral Aquatic Preserve (KJCAP, see Figure 8), and the simulation period has been extended from three to six years (September 2018 to August 2024). The advection–diffusion transport model has been configured to simulate analyte dispersal from 10 individual wastewater inlets (9 located along the east coast of Florida and 1 on the west coast of Florida Bay), as well as from 4 inlet groups (4 inlets on the west coast of Florida, 5 on the southeast coast, 3 in the south of Biscayne Bay, and 3 in the north of Biscayne Bay). For the east-coast inlets, six analytes were considered (nitrate–nitrite, orthophosphate, total P, total N, TSS, and silicate); for the west-coast inlets, four analytes were considered (nitrate–nitrite, orthophosphate, total P, and total N). In total, 74 individual analyte transport equations were solved across the entire FCR domain. The methodological steps described in Tasks 4a-c below have been applied to this expanded configuration.

2.3.1. Task 4a: Simulating ocean dynamics from Sep. 2021 to Aug. 2024

We simulated the ocean circulation along Florida’s coastline with the multiscale ocean model SLIM, which has already been extensively applied and validated in Florida’s coastal waters [20–22]. Here, we considered an area of interest that covers the entire FCR, and between 23.5°N and 27.5°N, and between 79°W and 83°W (Figure 8). The 25 considered inlets were included in the area of interest as open boundaries through which water flow and analytes could enter in the model domain. SLIM uses an unstructured mesh whose resolution can be locally increased to accurately represent fine-scale flow features, such as those produced near the inlets and over the nearshore and offshore coral reefs. The mesh was generated with Gmsh [23] using the Python package seamsh. The model resolution reached 5 m around the inlets, 100 m along the coastlines, 200 m over the coral reefs, and a few km further offshore, in the Florida Straits (Figure 9). The model bathymetry was obtained by combining data from NCEI Coastal Relief Model (3 arcseconds) and NCEI Continuously Updated Digital Elevation Model (1/9 arcseconds). Reef polygons were extracted from the Unified Reef Map [24]. The model was forced with winds from ECMWF-ERA5, large-scale currents (including tides) from HYCOM-GoM and processed DBHydro flow rates at the inlet boundaries. The model was run between September 1, 2018, and September 1, 2024, with hourly exports of the simulated sea surface elevation and currents.

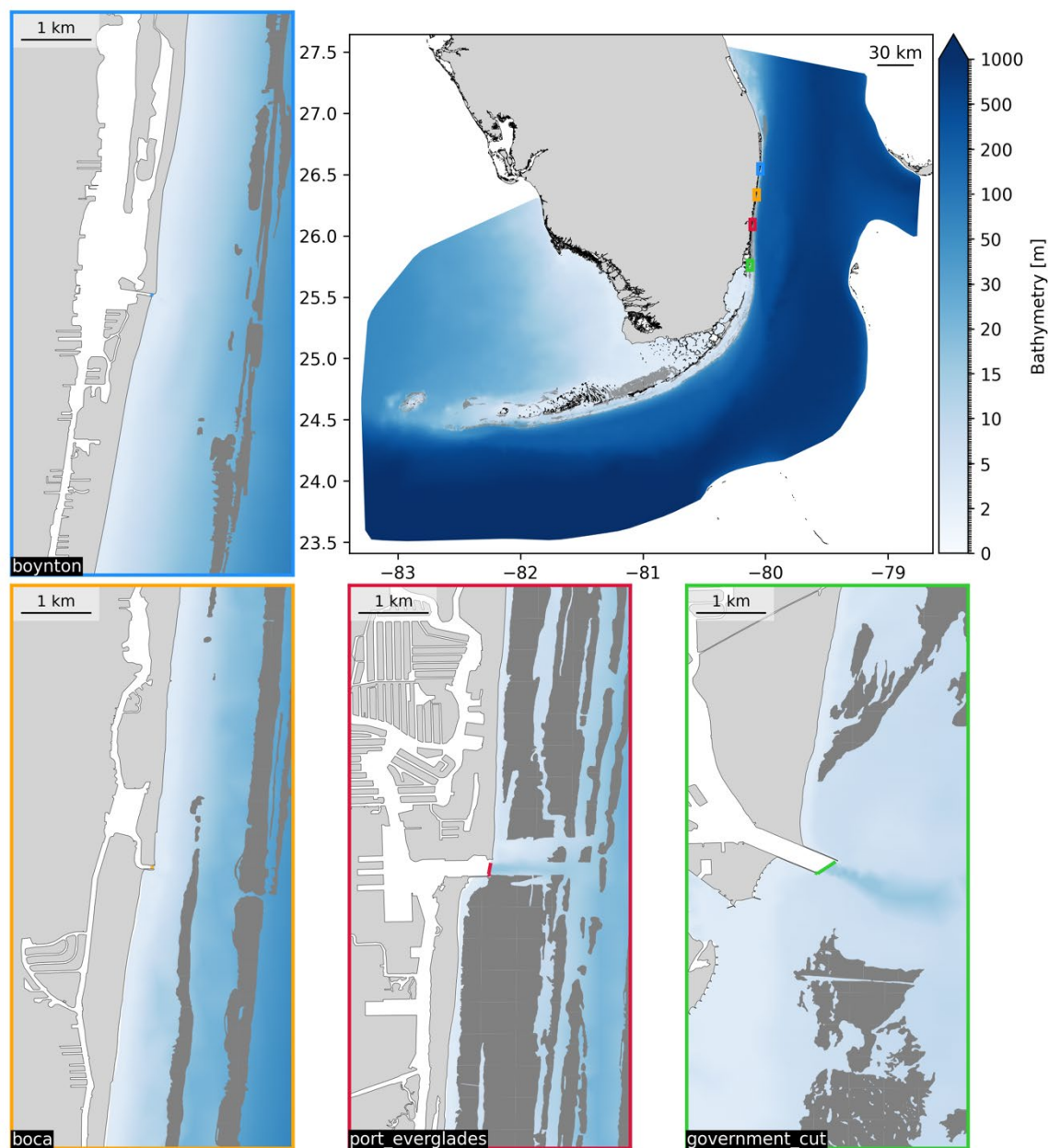


Figure 8. Model domain with the bathymetry and close-up views on four inlets on the east coast of Florida. The inlet open boundaries where flow rates and analyte loads were imposed are highlighted with thick colored lines. The land is shown in light grey and reef polygons in dark grey.

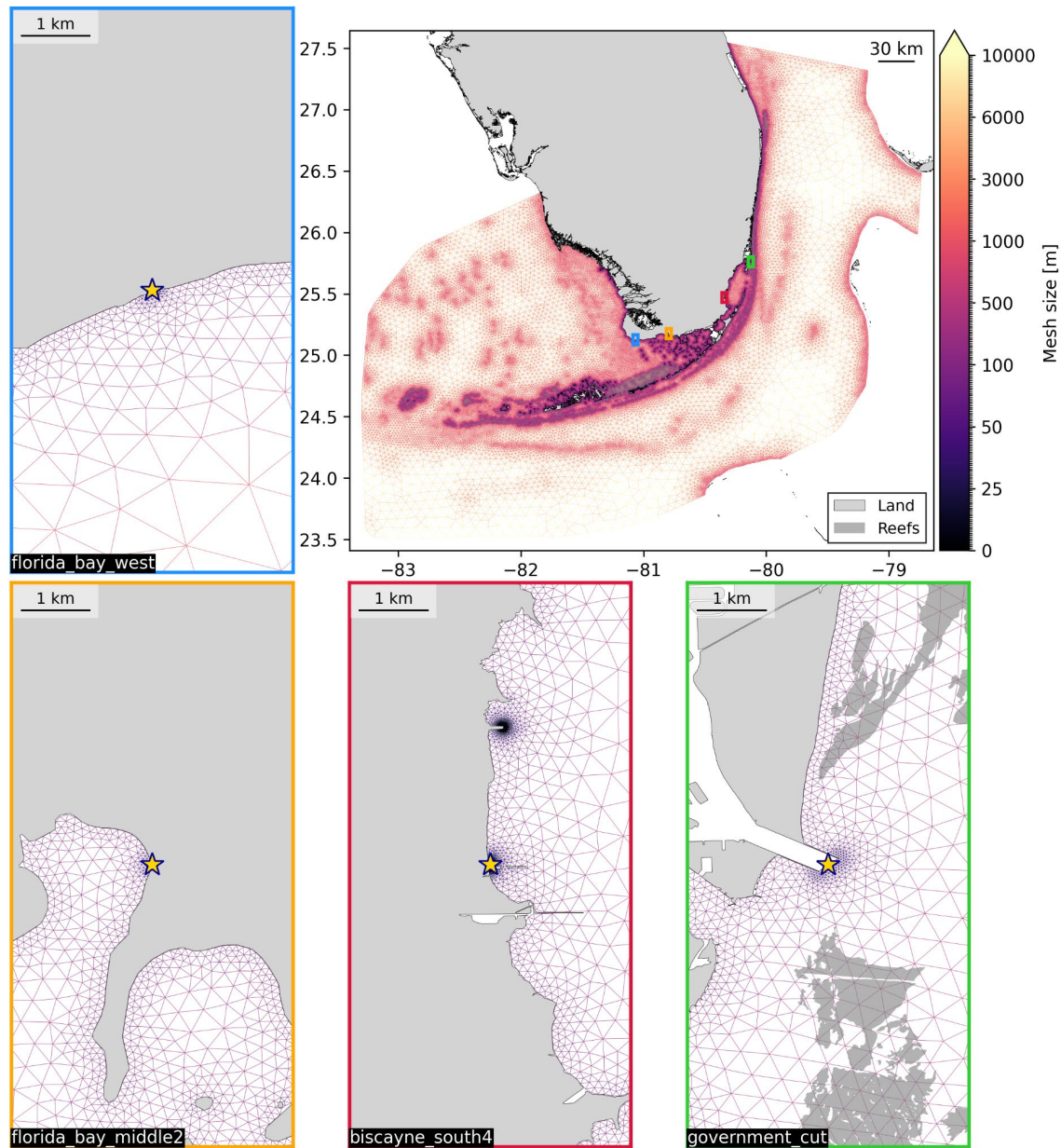


Figure 9. Same as Fig. 8 but with the model mesh. The resolution reaches 5 m around the inlets, 100 m along the coastlines, 200 m over the coral reefs, and a few km further offshore, in the Florida Straits.

2.3.2. Task 4b: Simulating plumes from the main river inlets, from the Keys to the northern KJCAP

We used the modeled currents to simulate the dispersal of inland wastewater plumes from the 25 inlets, including 10 individual inlets (9 located along the east coast of Florida and 1 on the west coast of Florida Bay), as well as 4 inlet groups (4 inlets on the west coast of Florida, 5 on the southeast coast, 3 in the south of Biscayne Bay, and 3 in the north of Biscayne Bay). Our inland water dispersal model employs a Eulerian approach, solving an advection-diffusion equation for each of the analyte concentrations released from each of the inlets, resulting in a

total of 74 equations (9 inlets x 6 analytes per inlet plus 5 inlets x 4 analytes per inlet). For the east-coast inlets, the six analytes considered were nitrate–nitrite, orthophosphate, total P, total N, TSS, and silicate. For the other inlets, the four analytes considered were nitrate–nitrite, orthophosphate, total P, and total N. We assumed that the initial concentration of each analyte within the domain is zero, with the only sources being the 25 inlets considered in this study.

In our previous study [15], each analyte was treated as a passive, non-reactive tracer undergoing no decay in the water column due to biological uptake (e.g. for dissolved nutrients) or gravitational settling (e.g. for total suspended solids). However, this conservative assumption led to unrealistically large analyte concentrations in poorly flushed areas such as Biscayne Bay and parts of the Florida Keys, where local water residence times can exceed several months and analytes tend to accumulate near the inlets. To address this, we introduced a first-order decay term $-\lambda C$ in the advection-diffusion equation, where C is the analyte concentration and $\lambda = 1/\tau$ is the decay rate expressed as the inverse of a characteristic e-folding timescale τ . This linear decay parameterizes the net effect of multiple removal processes — including biological uptake by phytoplankton, microbial remineralization, particle scavenging and gravitational settling — without resolving the underlying biogeochemical cycling explicitly.

We adopted a uniform decay timescale of $\tau = 7$ days for all analytes except dissolved silicate, for which we used $\tau = 21$ days. The 7-day timescale for dissolved inorganic nitrogen species (nitrate-nitrite, total nitrogen), total phosphorus (orthophosphate, total phosphorus) and total suspended solids is consistent with reported nutrient turnover times in warm, shallow coastal waters. In subtropical and tropical environments, phytoplankton uptake of dissolved inorganic nitrogen and phosphorus operates on timescales of a few days to two weeks, driven by sustained light availability and warm temperatures that promote year-round biological activity [25]. For TSS, gravitational settling in shallow shelf waters typically removes the bulk of suspended particles within a comparable timeframe, particularly after flocculation in saline waters increases effective settling velocities [26]. A longer timescale of $\tau = 21$ days was assigned to dissolved silicate because its biological removal is restricted to diatoms — specifically for the construction of their siliceous frustules — rather than the full phytoplankton community [27, 28]. In the oligotrophic waters off southeast Florida, where the phytoplankton community is dominated by picophytoplankton (*Prochlorococcus*, *Synechococcus*) that do not utilize silicic acid, the biological uptake capacity for silicate is inherently limited. It should be noted that the selected decay timescales represent effective removal rates calibrated to produce realistic near-field concentrations when compared with available water quality observations, rather than direct measurements of individual biogeochemical process rates.

Among the analytes considered, dissolved silicate is particularly informative because, unlike nutrients such as nitrogen and phosphorus that are largely associated with anthropogenic activities, it is primarily derived from the weathering and erosion of terrestrial materials. Background silicate concentrations in Florida coastal waters are relatively low, approximately $0.025 \text{ mg Si L}^{-1}$ [29], whereas concentrations in inlet-associated plumes from Government Cut or Port Everglades commonly exceed 1 mg Si L^{-1} due to the transport of silica-rich freshwater from inland catchments. Because a wide range of anthropogenic contaminants are transported along the same hydrodynamic pathways from land to the coastal ocean, the spatial footprint of the silicate plume provides a useful first-order proxy for the dispersal of land-based pollutants

more broadly. Biological removal of silicate is comparatively limited over the short transport timescales considered here, as it is primarily consumed by diatoms [30]. Consequently, only partial silicate uptake is expected during the 2–6 day transit from the inlets to the reefs, making dissolved silicate a robust tracer for assessing the influence of land-based inputs on reef environments.

The simulated concentrations were validated against monthly water quality measurements from the reef water quality monitoring sites. Due to the disparity in temporal resolution (hourly vs monthly) and the water quality measurement uncertainty, this validation was performed by comparing the distributions of the observed and simulated concentrations at the monitoring sites. We computed the first and third quartiles of the distributions of the observed and daily resampled simulated concentrations. We then defined three concentration levels: low below the first quartile, high above the third quartile, medium otherwise. We then defined an accuracy score by computing the proportion of simulated concentration levels matching the observed concentration levels. This score was first computed using the predicted concentration level at the date of the observation. We then used a tolerance of at most 2.5 days between the observed and simulated concentration levels. Simulated concentration peaks occurring within 2.5 days before or after the date of the observed peaks were then considered correct.

2.3.3. Task 4c: Estimating nearshore coral reef water exposure

The 74 simulated concentrations were also computed over reef polygons to estimate coral reef exposure to the analytes released at each of the inlets. Reef polygons were extracted from the coral and hardbottom layer of the Unified Reef Map [24] and intersected with a 500 m × 500 m grid. The resulting heat maps highlight reefs most exposed to inland water plumes and indicate the seasonal variability of this exposure.

2.4. Task 5: Run analyses to determine how the predicted nutrient loads differ from the in-situ water quality monitoring data

The validation methodology described below is applied to the expanded modelling configuration outlined under Task 4 (entire FCR domain, 10 individual inlets plus 4 inlet groups, September 2018 – August 2024). Modelled hourly concentrations are aggregated to the temporal resolution of the in-situ measurements following several resampling strategies; accuracy scores are then computed by comparing the distributions of modelled and observed concentration levels at the FDEP/NOAA, SERC, WIN, and DERM monitoring stations.

2.5. Task 6: Build statistical models to quantify the effects of changes in inlet flow, rainfall and wind on water quality in both regions

2.5.1. Boosted regression tree modeling

Prior to model fitting, all continuous predictor variables were screened for pairwise collinearity. We computed pairwise Pearson correlations across all flow, rainfall, and landward and seaward wind windows. One predictor from each pair correlated at $r \geq 0.8$ was excluded. Correlations were rounded down to one decimal place, so the highest correlation retained was $r = 0.84$. Where the rule offered a choice, we retained short (3- or 7-day), medium (30-day), or long (90-day) windows over the other windows. Where several of these still remained, we prioritized the 7-, 30-, and 90-day windows. This screening was applied independently to each of the four

programs. It removed 10 predictors for the KJCAP, 8 for DERM, 10 for WIN, and 11 for SERC. The full list of removed predictors for each program is given in Appendix 2.

We modeled variation in each water-quality analyte separately for each of the four programs, using a boosted regression tree (BRT) framework. This followed Whittall et al. [13] and Walker et al. [15]. BRTs are an additive non-linear regression approach. They fit a sequence of decision trees in a forward stage-wise manner, with each new tree fitted to the residuals of the prior ensemble [31]. BRTs suit these data because they accommodate non-linear responses, predictor interactions, they can incorporate a mix of continuous and categorical predictors, they are robust to any temporal autocorrelation in the water-quality response variable [13], and they do not require *a priori* specification of the model form. Models were built using the *gbm.step* routine in the *dismo* package [32]. They were visualized using the *ggBRT* package [33]. Both were run in R 4.2.0 [34], with a Gaussian response distribution.

Our parameter choices followed our previous work on this system [13, 15]. We set the bag fraction to 0.8, the learning rate to 0.001, and the tree complexity to 5. These settings were used for every analyte model. We then ran a sensitivity test for each model that reduced the bag fraction from 0.8 to 0.5. This confirmed that model performance was not being driven by overtraining. The sensitivity results are reported in the model-performance tables in the Results. A 10-fold cross-validation approach was used to assess out-of-sample model performance. The cross-validated percentage deviance explained (cv% explained) was our primary model performance metric.

For each BRT, we calculated the relative influence of every predictor. Relative influence is based on the number of times a predictor is selected for splitting. Each split is weighted by the squared improvement it contributes to the model, and the values are averaged across all trees [35]. We then visualized the conditional relationship between each predictor and the response using partial dependency plots. The 95% confidence intervals were computed from 100 bootstrapped replicates [36]. Each partial dependency plot isolates the marginal effect of one predictor on the modeled response. The remaining predictors are held at their respective means when this marginal effect is computed.

3. RESULTS

3.1. Task 2: Compile relevant regional environmental data (inlet flow, temperature, rainfall, wind) from 2018 – 2024

Inlet outflow at the KJCAP monitoring sites increased from north to south and was consistently higher in the wet season than the dry season (Figure 10). The southern inlets dominated: at the 30-day window, the median wet-season outflow reached about 820 m³ s⁻¹ at Government Cut and 390 at Biscayne Bay, against near-zero medians at Jupiter. The wet-season median exceeded the dry-season median at essentially every inlet exposure area, often by a factor of two to three; Hillsboro, for example, rose from about 57 in the dry season to 228 in the wet season over the 30-day window. The distributions were strongly right-skewed and broadened with window length, indicating that sites experienced occasional large multi-week flow pulses on top of a low baseline. Occasional negative values, which denote net landward or return flow, were most evident at the 7-day window.

Rainfall showed a strong wet/dry seasonality and was remarkably consistent among the four programs (Figure 11). Across all programs the wet-season median was roughly three times the dry-season median; at the 30-day window, wet-season medians clustered between about 144 and 173 mm, against dry-season medians of about 45 to 51 mm. The four programs were nearly interchangeable in both the magnitude and the shape of their rainfall distributions, reflecting their shared regional climate and the common NCEI station network. The distributions were right-skewed, with a long tail of high-rainfall periods that lengthened at the 30- and 90-day windows.

Wind, summarized as the frequency of high-wind events, reversed the seasonal direction seen for flow and rainfall: high-wind events were more frequent in the dry season than the wet season at every program (Figure 12), consistent with the passage of winter cold fronts. Landward events far outnumbered seaward events in every program and window; at the 30-day window, for example, KJCAP sites recorded a dry-season median of about 2,745 landward events against about 666 seaward. The seasonal contrast was sharper for seaward events, which fell steeply from the dry to the wet season (KJCAP, about 666 down to 175; SERC, about 238 down to 55), whereas landward events declined more modestly. The programs also differed in absolute exposure, reflecting the different buoys assigned to their sites: KJCAP sites experienced the most high-wind events, followed by DERM and SERC, while WIN sites recorded the fewest.

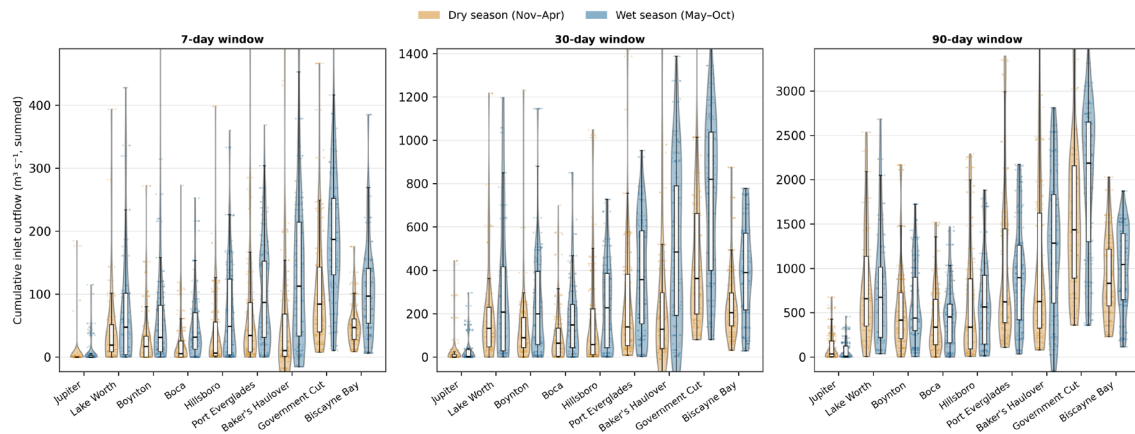


Figure 10. Inlet outflow conditions across the KJCAP monitoring sites, by inlet exposure area (IEA) and season. Values are the DBHydro daily inlet outflow summed over each window (7, 30, and 90 days; cubic meters per second). Dry-season (amber) and wet-season (blue) distributions are shown separately for each IEA, with IEAs ordered from north (Jupiter) to south (Biscayne Bay). Outflow increases southward and is higher in the wet season. Negative values denote net landward or return flow. Note the difference in y-axis scales across the figure panels.

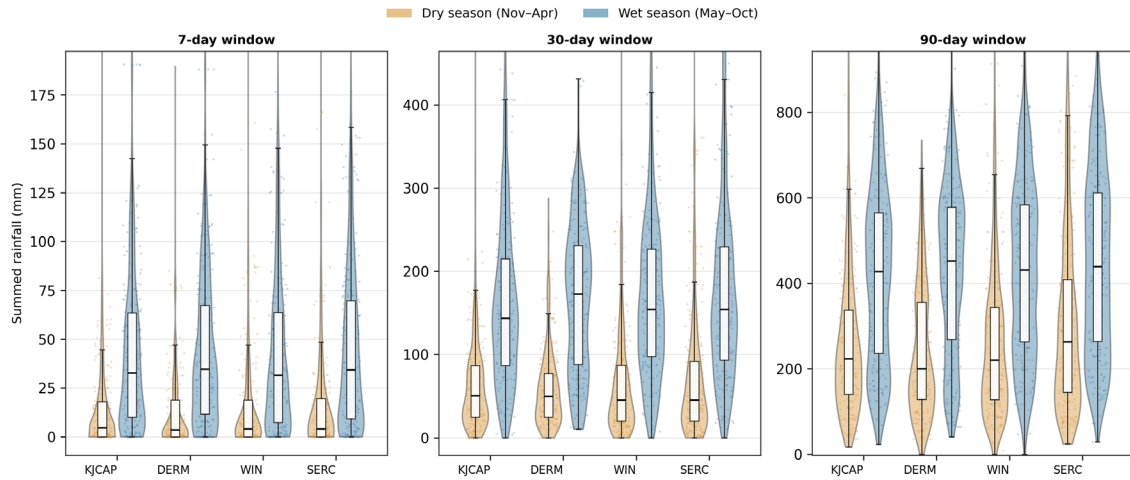


Figure 11. Rainfall conditions across the water-quality monitoring sites, by program and season. Values are the daily NCEI precipitation at each site's selected station, summed over each window (7, 30, and 90 days; millimeters). Wet-season totals are about three times dry-season totals, and the distributions are broadly interchangeable among the four programs, reflecting the shared wet and dry seasonal cycle of the region.

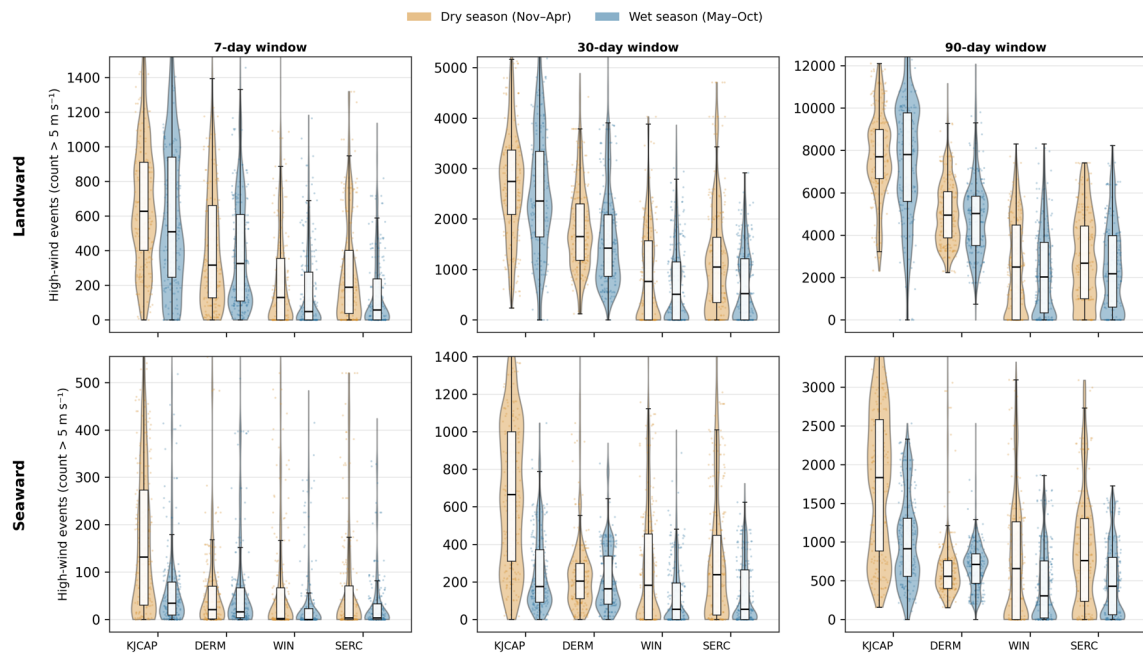


Figure 12. Wind conditions across the water-quality monitoring sites, by program, direction, and season. Values are the number of high-wind events, defined as 6-minute NDBC buoy observations exceeding 5 meters per second, counted over each window (7, 30, and 90 days); landward events (top row) and seaward events (bottom row) are shown separately. High-wind events are more frequent in the dry season, opposite to the seasonality of flow and rainfall, and landward events outnumber seaward events. KJCAP sites experienced the most high-wind events, followed by DERM and SERC, with WIN the fewest, reflecting the different buoys assigned to each program.

3.2. Task 3: Synthesize water quality monitoring data for both regions from 2018 – 2024

The water quality data from all four programs (KJCAP, DERM, WIN, and SERC) showed variations in concentrations across space and time. These are summarized for each monitoring program throughout Section 3.5 and by season in Appendix 3. Viewed as raw concentrations, the water-quality analytes show comparatively modest and inconsistent seasonality (Figures 13 and 14). Of the 25 analyte-by-program combinations, only about half ran higher in the wet season, and most wet-dry differences were small, typically under 0.2 log10 units, which is less than a 1.6-fold change. The clearest and most consistent wet-season signal was silica, which rose in the wet season across the KJCAP, WIN, and SERC sites (about +0.11 to +0.20 dex). KJCAP nitrate and nitrite were also higher in the wet season (about +0.12 and +0.15 dex). In the other direction, several total phosphorus measures and turbidity tended to run slightly higher in the dry season, and KJCAP orthophosphate showed the largest dry-season elevation (about -0.16 dex). Salinity at the SERC sites was essentially aseasonal, near 36 in both seasons.

The figures also expose differences among programs measuring nominally the same analyte. Total nitrogen, for example, was markedly lower at the SERC sites than at the DERM and WIN sites, and the orthophosphate and total phosphorus distributions shift noticeably from one program to the next. Because the programs differ in their sites, laboratories, and, for WIN, their contributing agencies, these between-program offsets cannot be read straightforwardly as real spatial gradients, a caution developed further in the cross-region synthesis section of this report (section 3.5.6).

Most importantly, these raw patterns should be read with care, because they make no attempt to separate season itself from the environmental conditions that co-vary with it. As the environmental-conditions figures show, inlet outflow and rainfall peak in the wet season while high-wind events peak in the dry season, so a raw wet-versus-dry contrast for an analyte bundle together the effects of season, flow, rainfall, and wind, along with depth and spatial position. A higher wet-season silica or nitrate concentration, for instance, cannot be attributed to season itself without accounting for the simultaneous rise in inlet outflow and rainfall. Disentangling these correlated drivers is exactly what the boosted regression tree models in this report are designed to do: by estimating each predictor's partial effect while holding the others constant, they convert these ambiguous raw contrasts into interpretable, driver-specific responses. The raw distributions shown here are therefore best treated as a descriptive starting point that motivates, rather than substitutes for, the modeled analyses that follow.

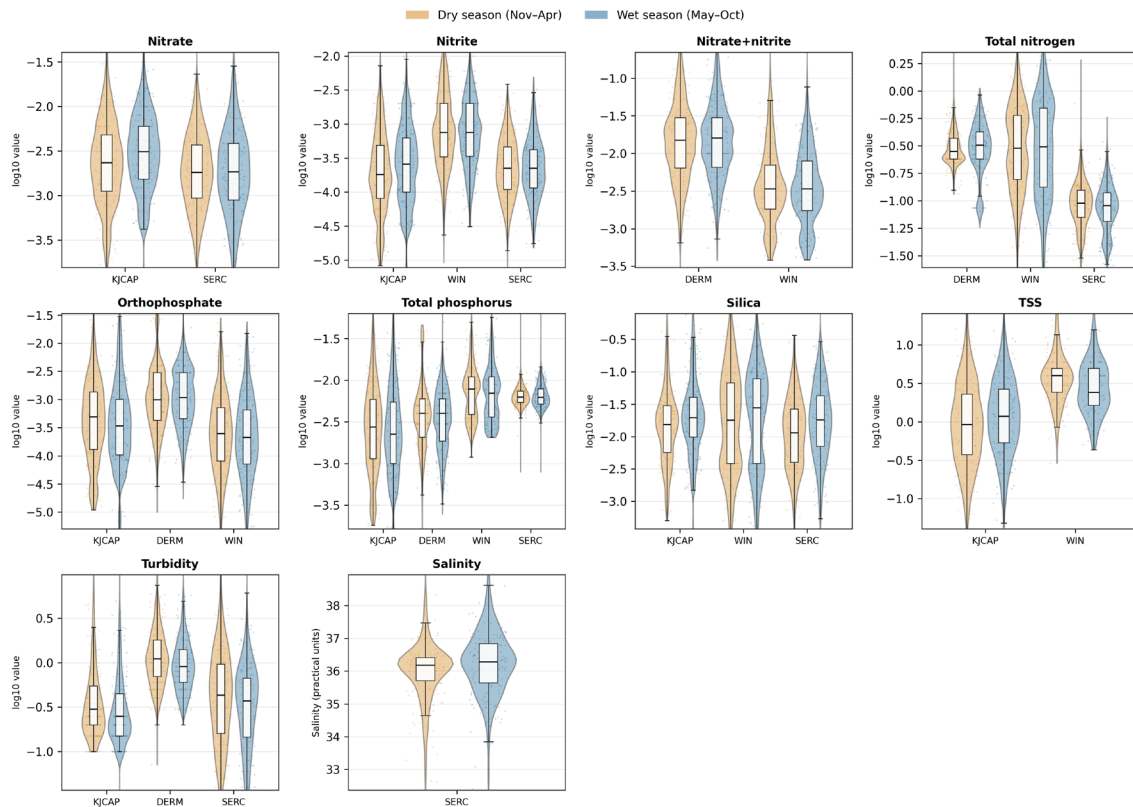


Figure 13. Raw water-quality analyte concentrations at the modeled monitoring sites, by program and season. Each panel shows one analyte; dry-season (amber) and wet-season (blue) distributions are shown for each program that measured it. Values are Flynn (MDL-adjusted) concentrations on a log10 scale (milligrams per liter, except turbidity in NTU); salinity (SERC only) is on its natural scale. These are observed concentrations and are not adjusted for flow, rainfall, wind, depth, or spatial position.

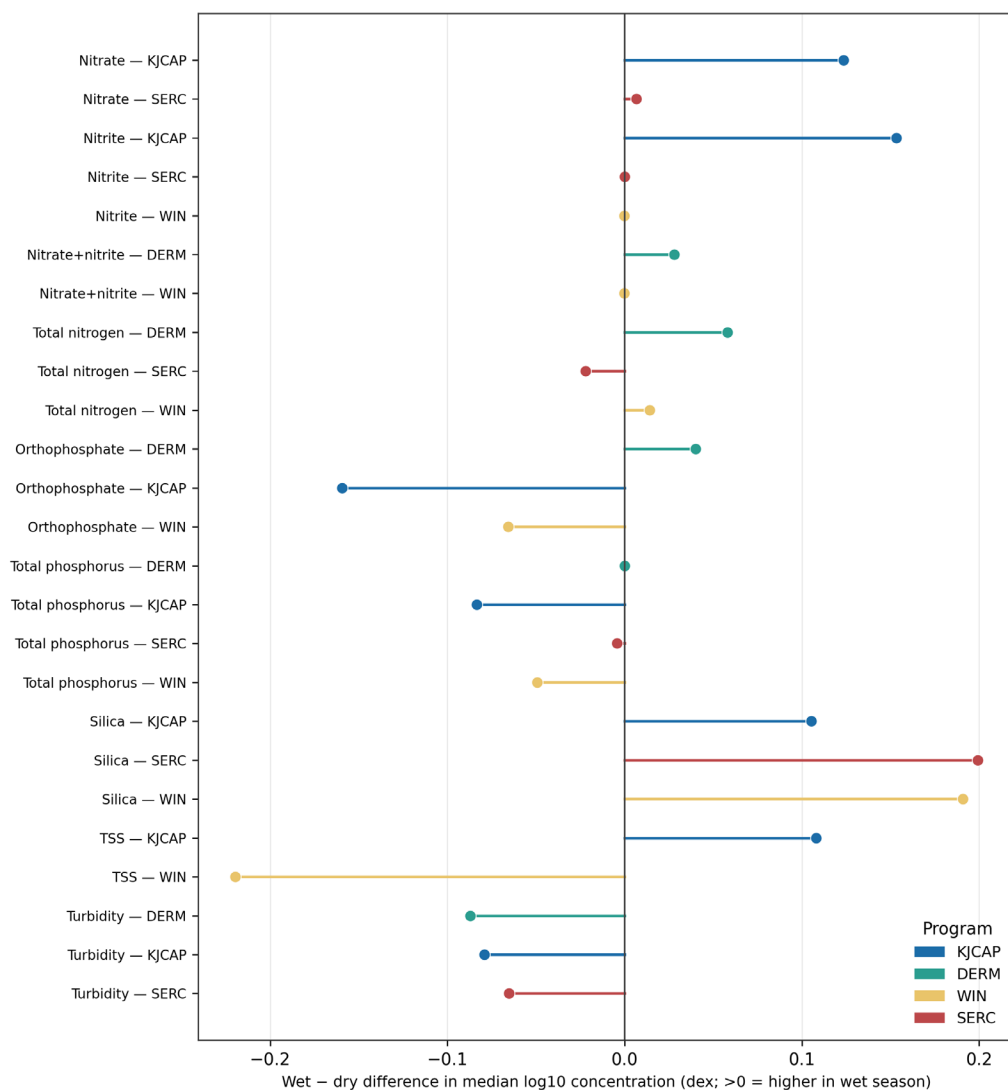


Figure 14. Seasonal contrast in raw analyte concentrations, by analyte and program. Each point is the wet-season minus dry-season difference in median log₁₀ concentration (dex); values above zero indicate higher concentrations in the wet season. Differences are generally small and inconsistent in sign across analytes and programs. Salinity is omitted (natural scale). As with Figure 13, these contrasts are unadjusted and conflate season with the co-varying environmental drivers.

3.3. Task 4: Build hydrographic flow model for the entire FCR frame, quantify the probability of source water in any given location, and quantify nutrient load estimates across space and time

Across the new six-year simulation (September 2018 – August 2024), ocean circulation was reproduced over the full domain from the Dry Tortugas to the northern KJCAP. From these currents, we derived dispersal plume fields and reef-exposure indicators for each of the 10

individual inlets and 4 inlet groups, covering the six analytes considered (six for the east-coast inlets and four for the west-coast Florida Bay inlets) for a total of 74 analyte transport simulations. For each analyte–inlet combination, monthly dispersal plume maps and reef-exposure heatmaps were exported in GIS format; time series of analyte concentrations were further computed at every monitored coral reef site, separately for each contributing inlet or inlet group, providing a continuous temporal record of reef exposure throughout the simulation period.

3.3.1. Task 4a: Simulating ocean dynamics from Sep. 2018 to Aug. 2024

The simulated ocean circulation across FCR shows different dynamics between the sub-regions of the domain. Along the southeast Florida coast — from the upper Keys through the KJCAP and up to the northernmost FCR — the circulation is predominantly northward under the influence of the Florida Current (Figure 15). This northward flow is modulated by tidal currents, which introduce oscillatory dynamics that can locally alter and occasionally reverse the flow direction, and by the passage of (sub)mesoscale baroclinic eddies that induce meandering of the Florida Current and can further influence its trajectory. In the Florida Keys, the circulation is largely controlled by tidal exchange between the Atlantic Ocean and Florida Bay through the passes separating the islands, producing strong reversing currents on each tidal cycle. Within Florida Bay, the shallow bathymetry and partial enclosure by the Keys give rise to a low-energy, wind- and tide-driven circulation, with limited exchange with the surrounding ocean. In the northern part of Biscayne Bay, exchange is dominated by the narrow inlets (incl. Government Cut and Baker's Haulover), whereas in the central and southern Bay it occurs across the much broader, shallow opening between Key Biscayne and the upper Keys. Further offshore, the reef tract remains strongly influenced by the Florida Current. In the Dry Tortugas region, the simulated circulation is shaped by the Loop Current and its shed mesoscale eddies, leading to variable flow conditions and episodic intrusions of warm offshore waters onto the reef tract. Across all sub-regions, the ocean currents interact with the coral reefs: their shallower depths and higher rugosity, compared with the surrounding sandy seabed, tend to slow down and deflect the flow. The ocean circulation model outputs have been validated against observations from stations distributed across the entire FCR domain (see Figure 16 for an illustration in February 2019).

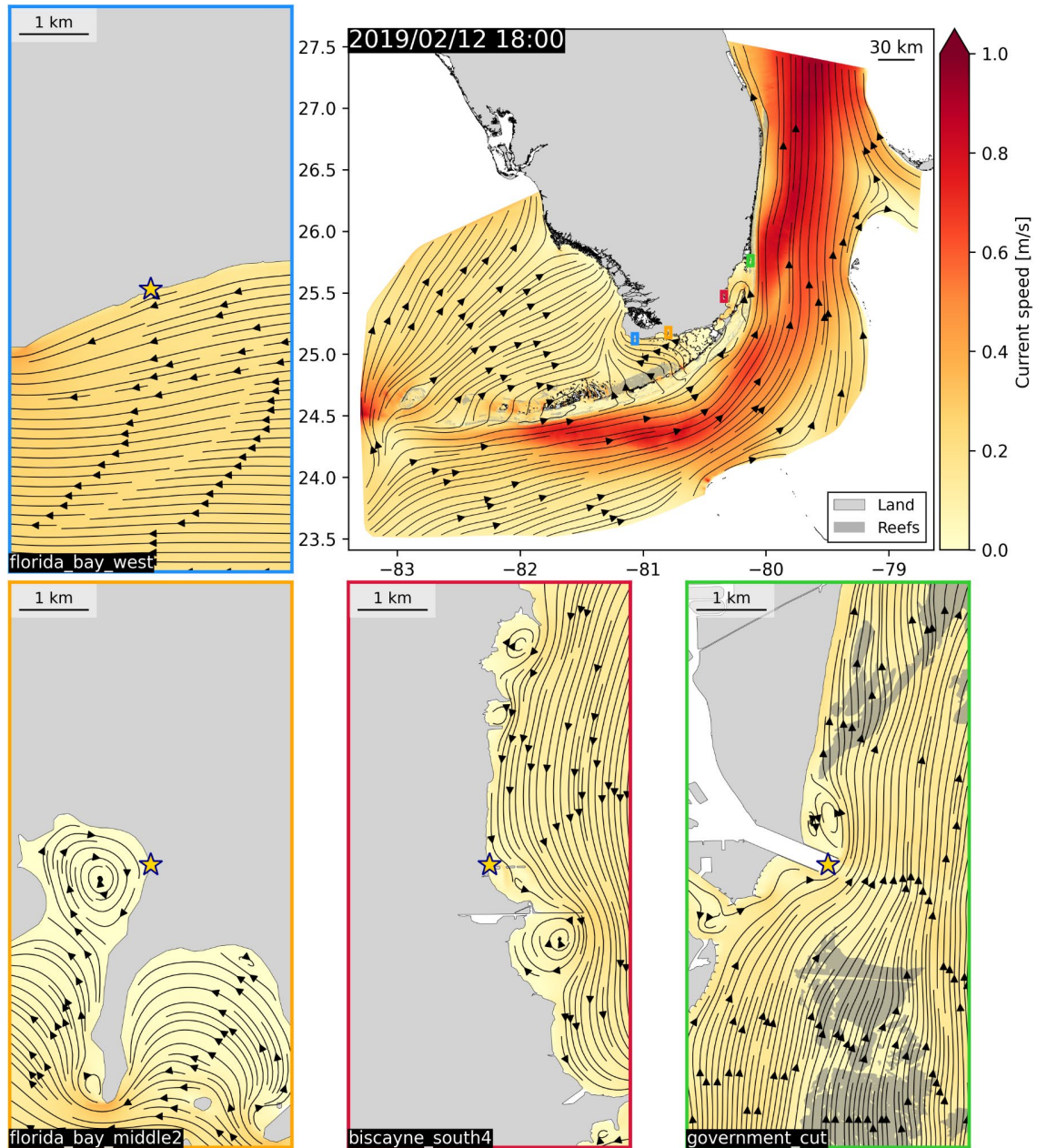


Figure 15. Snapshot of the simulated instantaneous currents over the entire FCR on Sept. 2nd, 2019 at 18:00 UTC with a close-up views on some of the inlets considered in this study. This illustrates the small-scale circulation patterns, such as recirculation eddies, that the model can represent.

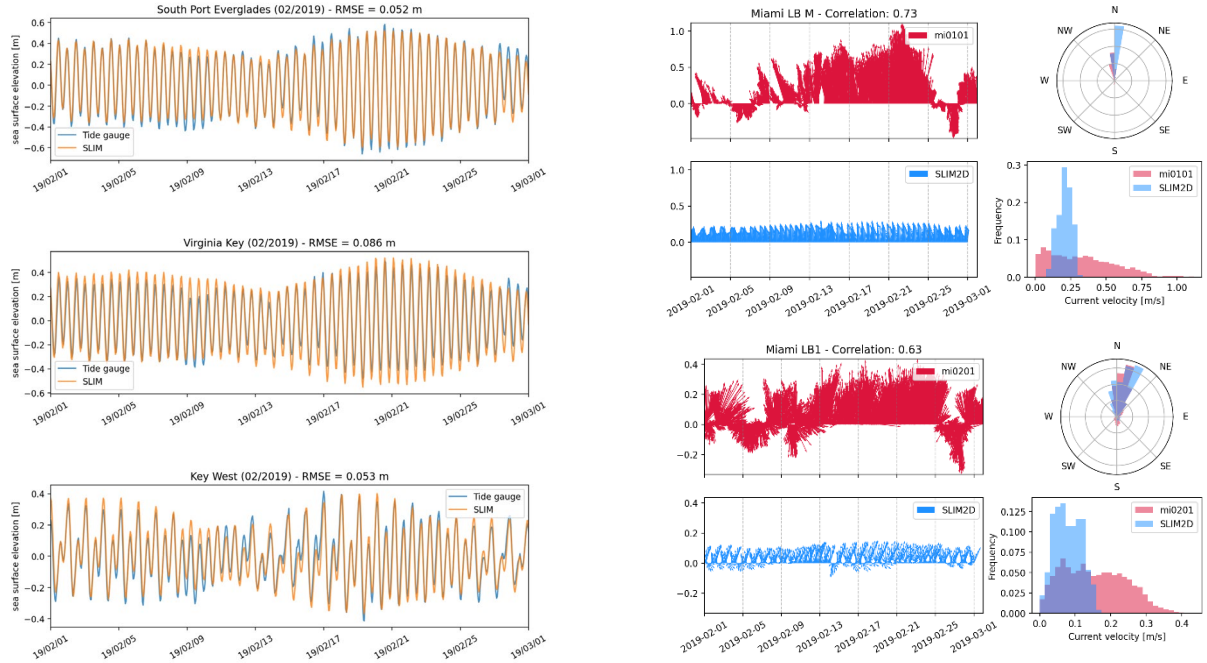


Figure 16. Validation of the simulated sea surface elevation and currents velocity at different stations across our study area three stations within the area of interest in February 2019. Similar validations were performed throughout the project period.

3.3.2. Task 4b: Simulating plumes from the main river inlets, from the Keys to the northern KJCAP

The simulated plume dynamics differ markedly between the sub-regions of the FCR, reflecting the contrasting flow regimes outlined in Section 3.3.1. Along the energetic eastern coast, between the upper Keys and the northern KJCAP, the inlet plumes are advected and rapidly diluted by the Florida Current. Plumes released from the east-coast inlets (e.g. Government Cut, Baker's Haulover, Port Everglades) typically extend tens of kilometers downstream (predominantly northward, with a non-negligible southern footprint produced by tidal reversals and eddy meanders) and are partially flushed offshore as the current meanders and entrains nearshore water. In contrast, in the more sheltered embayments, such as Florida Bay, the inner Florida Keys, and the central and southern Biscayne Bay, the much weaker currents and longer water residence times confine the plumes to comparatively localized areas around their source inlets. Within these sheltered waters, the plumes oscillate with the tidal cycle but show only modest net advection, so that the analytes remain concentrated within a few kilometers of the inlets. The 7-day (and 21-day for silicate) effective decay timescales introduced in the model are most influential in these poorly flushed sub-regions, where they prevent the unrealistic accumulation of analytes seen under a purely conservative tracer assumption and allow the plumes to settle to a steady, locally bounded extent. As an illustration, Figure 17 shows the mean nitrate-nitrite concentration in April 2024 originating from all 25 inlets and highlights the strong contrast between the broad, north-stretching plumes along the eastern coast and the more localized footprints in Florida Bay and the inner Keys.

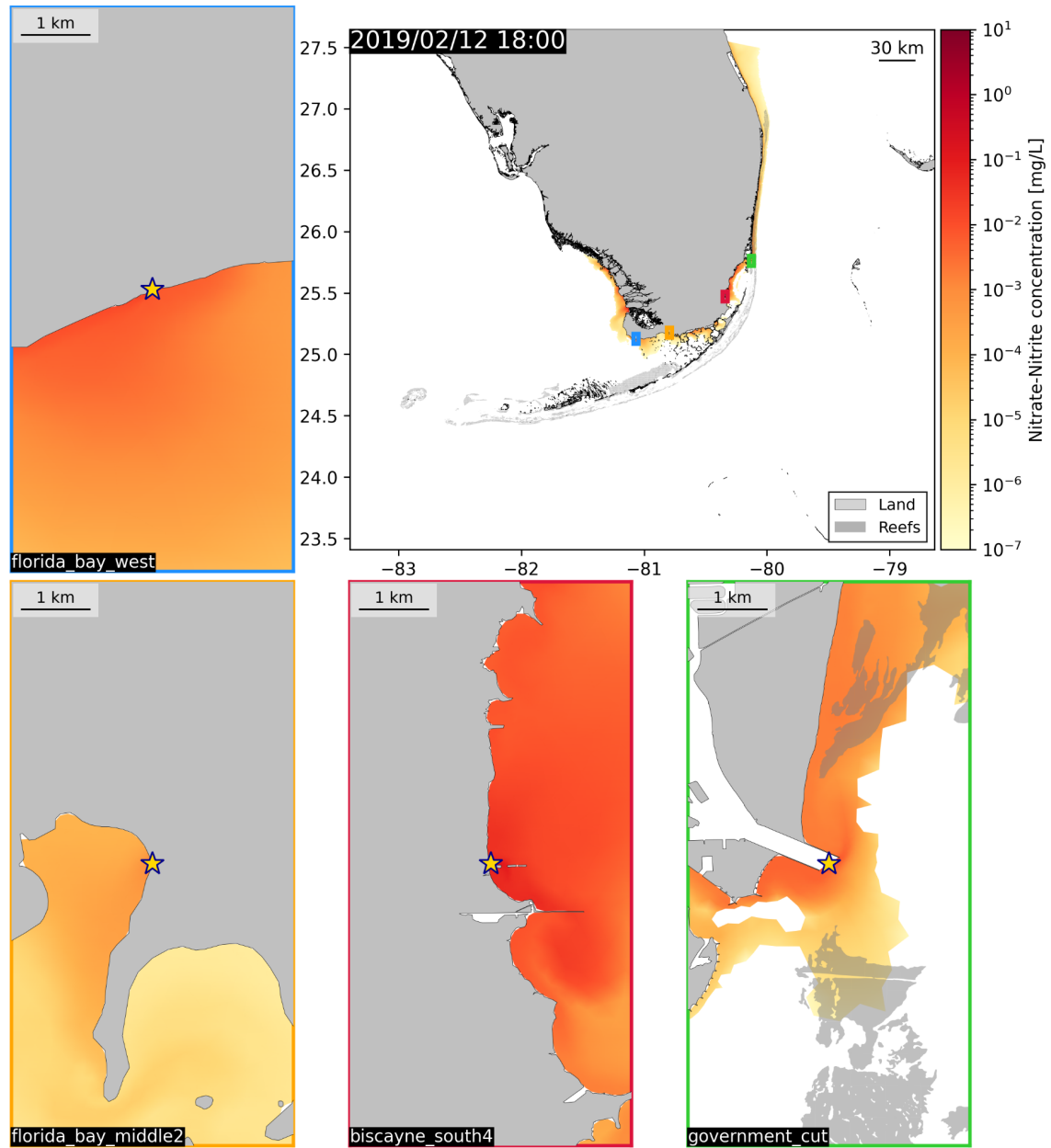


Figure 17. Same as Fig. 15 but for the instantaneous nitrate-nitrite concentration, which is released from the 25 inlets considered in this study.

3.3.3. *Task 4c: Estimating nearshore coral reef water exposure*

The contrasting plume dynamics described above translate directly into very different reef-exposure patterns across the FCR. Along the eastern coast, reefs offshore of the major inlets sit within the dominant northward plume corridor and consequently experience the largest integrated exposure to inlet-derived analytes. Because the Florida Current rapidly advects the plumes downstream, the exposure footprint of each east-coast inlet typically extends well to the north of the inlet itself, while still producing a smaller but persistent southern signature through tidal reversals and eddy meanders. In the more sheltered sub-regions, like Florida Bay, the inner Florida Keys and the central and southern Biscayne Bay, reef exposure is more spatially concentrated: the reefs closest to a given inlet receive the bulk of its exposure, with relatively rapid attenuation of the signal with distance from the source. Within these embayments, reefs further away from the inlets are largely buffered from direct inlet inputs, but the longer water residence times mean that even modest discharges can sustain elevated exposure locally. Figure 18 illustrates these contrasts for total phosphorus in April 2024: reefs along the central and northern KJCAP show the largest exposure, decaying gradually northward of each inlet, while reefs in Florida Bay and the inner Keys show more discrete, inlet-centered hotspots.

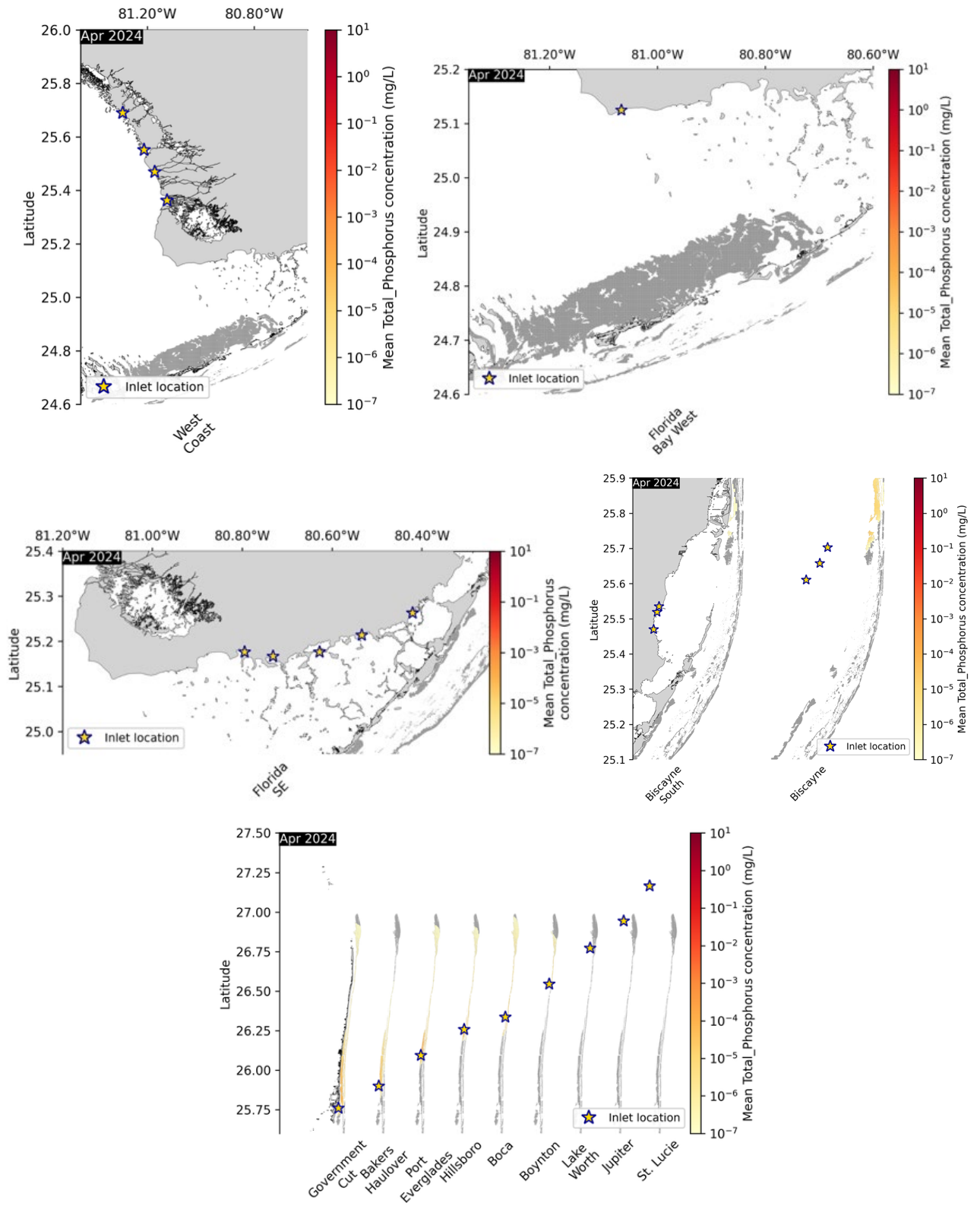


Figure 18. Illustration of coral reefs exposure to total phosphorus in April 2024.

3.3.4. Task 4d: Identifying the analyte(s) and inland source responsible for disease occurrence

We derived complete time series of analyte concentrations on reefs where disease signs were observed. These time series were derived from the analyte dispersal simulations initiated at each inlet and cover the entire 6-year simulated period. They indicated the concentration of all analytes over the reef site for each of the four considered inlets. As an illustration, we show the time series of the concentrations of the 6 considered analytes for eastern coast inlets at reef site LC-005 (Figure 19). This site is located north of Port Everglades and was mostly impacted by Government Cut, Baker's Haulover and Port Everglades. It's interesting to note the decrease in the contribution of Government Cut's inlet, from being the main source of analytes at the reef site in 2018 to a much more minor source from mid-2019. This is related to a sharp reduction of analyte concentrations at the inlet. Figure 20 summarizes the contribution of each of the inlets closest to the monitored reefs during the 10 days before disease observations. We did this analysis for each of the analytes and here only show results for nitrite-nitrate.

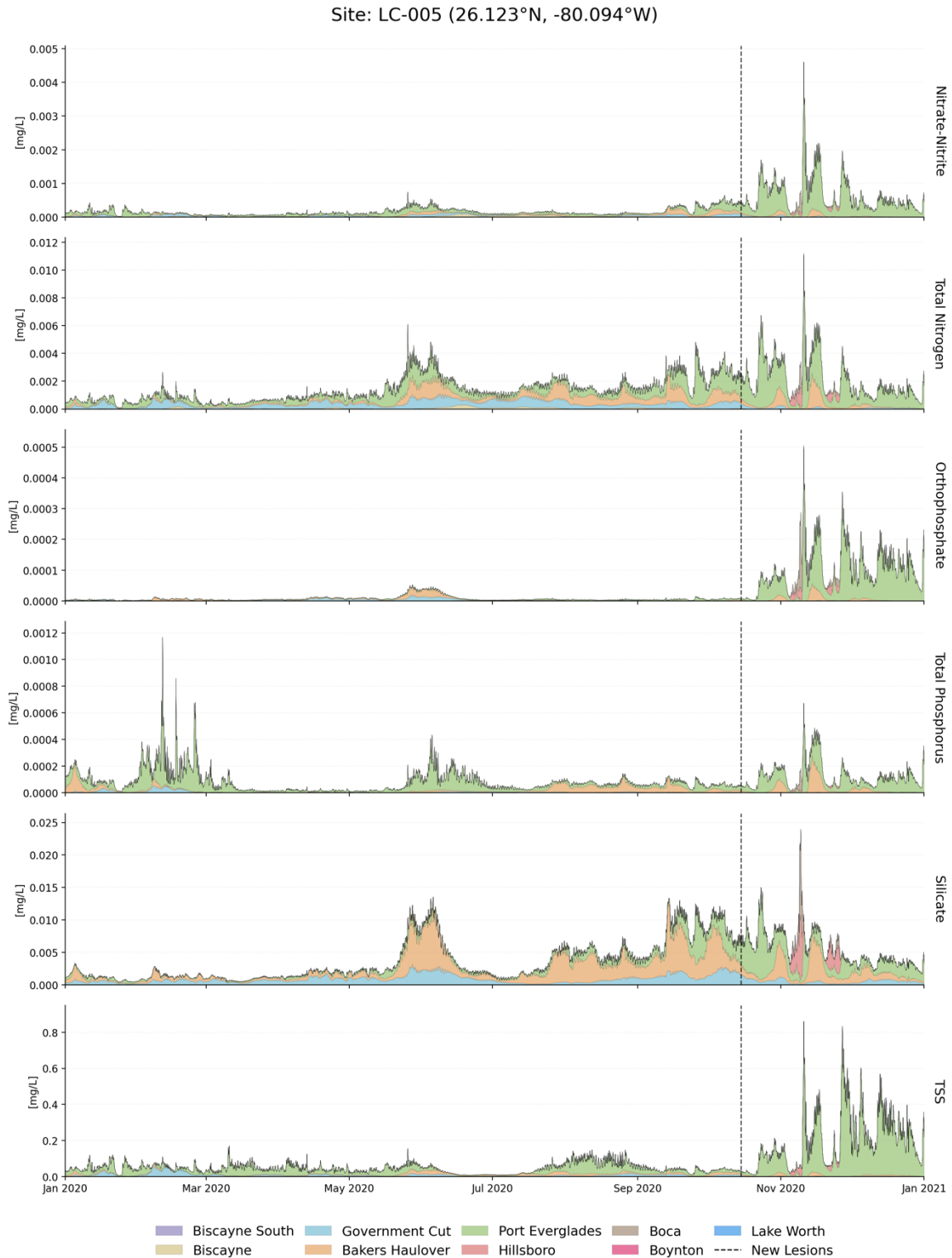


Figure 19. Time series of the contribution of the eastern coast inlets to the modeled analyte concentrations over reef site LC-005 over the six-year project duration. Dotted lines correspond to the observation dates of new lesions.

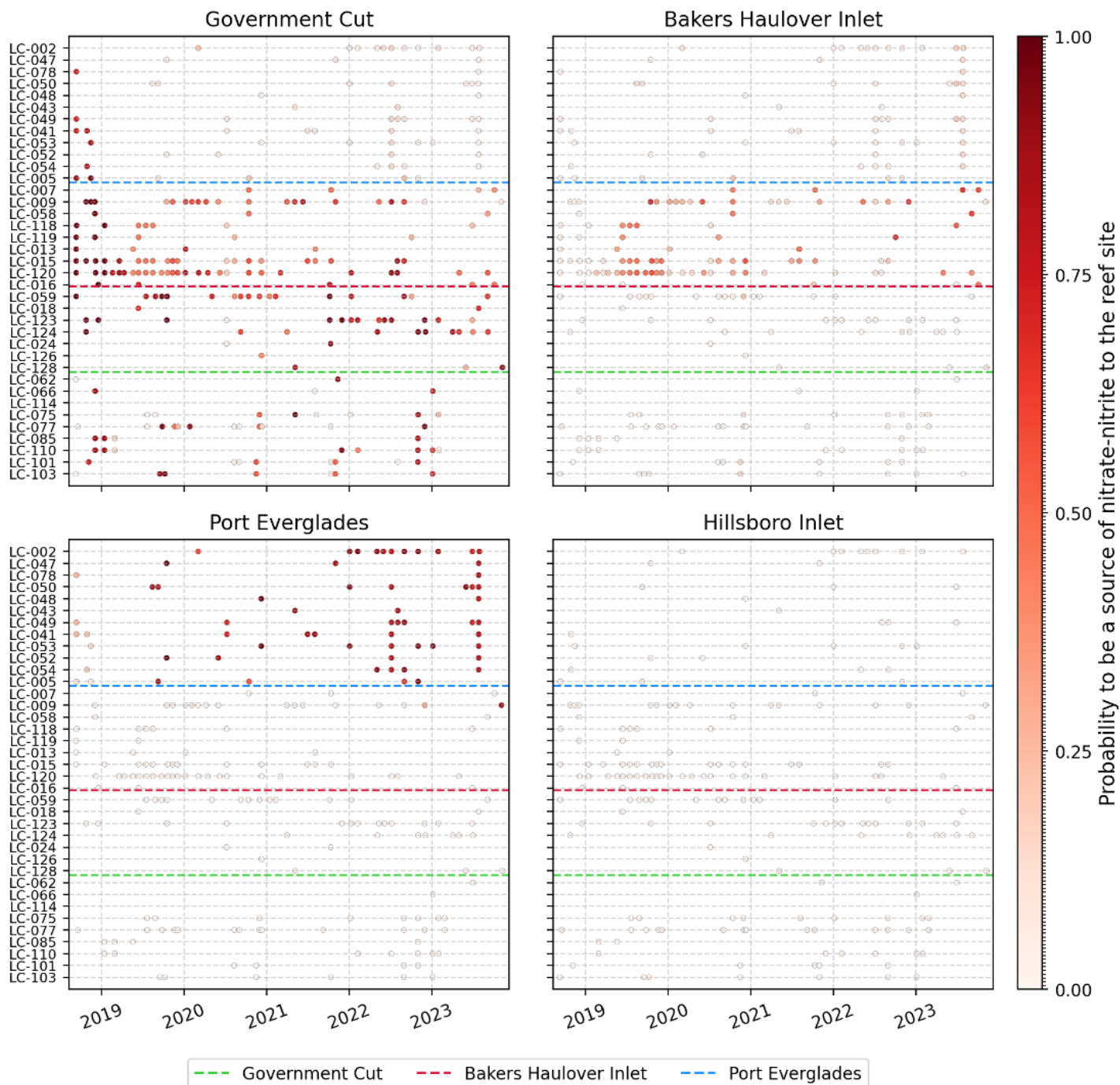


Figure 20. Probability for the Government Cut, Bakers Haulover, Port Everglade and Hillsboro inlets to be a source of nitrate-nitrite that reached the reef monitoring sites during the 10 days preceding the observation of new SCTLD lesions in 2018-2024. The sites on the y-axis are ordered from south to north, the points correspond to the dates and locations of observation of new lesions and their color indicate the probability for particles to originate from the different inlets. The latitudes of the different inlets are indicated by colored dashed lines.

3.4. Task 5: Run analyses to determine how the predicted nutrient loads differ from the in-situ water quality monitoring data

We further validated the simulated analyte concentrations against measurements at the different DBHydro monitoring stations (Figure 21). The model performs best near the inlets, where boundary conditions from DBHydro were imposed. At these sites, accuracy scores of up to 90% were found. The accuracy scores decreased with increasing distance from the inlets. On average, the simulated concentration levels matched 47% of the observed nitrate-nitrite concentration levels when no lag was allowed. The same analysis was performed for all the other analytes. The lowest accuracy scores were found in the Keys at the northernmost and southernmost monitoring sites, which are quite distant from the inlets, in regions also probably impacted by sources of analytes that were not included in the model. Allowing for a lag of at most 2.5 days between the simulated and observed concentrations slightly increased the model performance. It shifted the distribution of the accuracy scores to the right and increased the mean accuracy score from 47% to 66%.

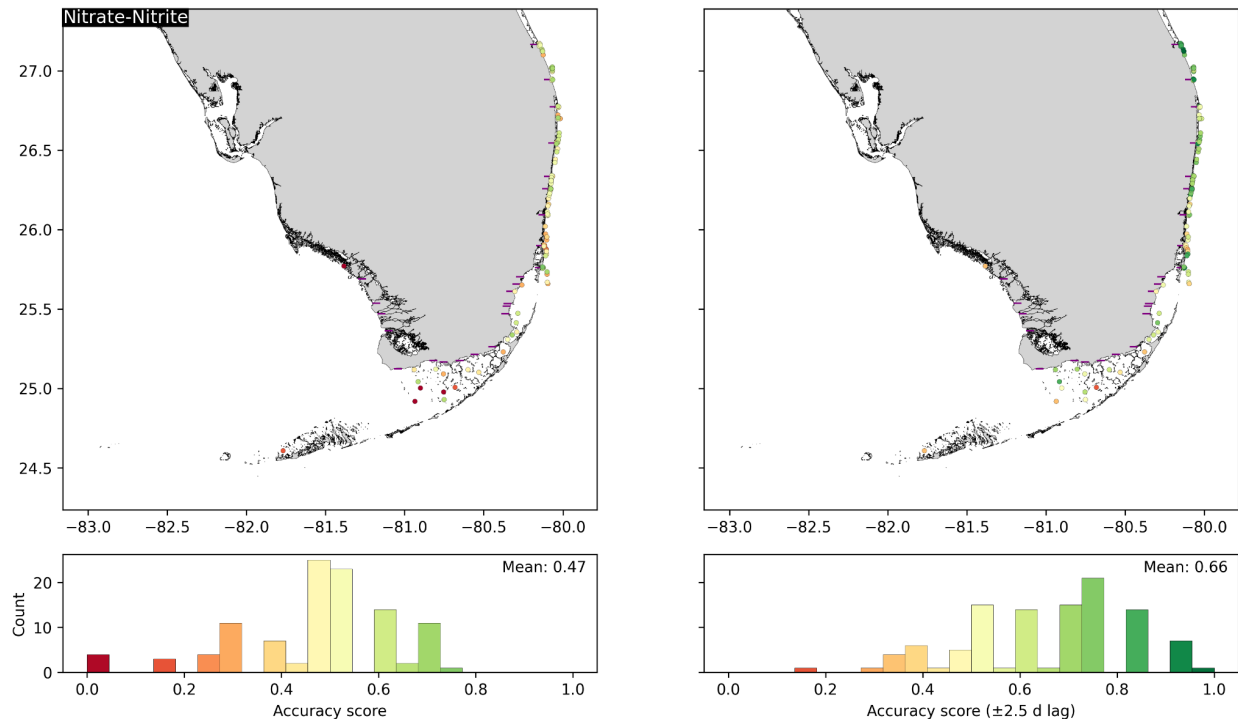


Figure 21. Validation of the simulated nitrate-nitrite concentration against measurements at monitoring stations. Three concentration levels (low, medium, high) were defined based on the first and third quartiles of the distributions of the observed and simulated concentrations. The accuracy score gives the fraction of simulated concentration levels matching the measured levels with no lag allowed (left), or with a tolerance of at most 2.5 days between the simulated and measured concentration peaks (right). The model performance decreases with increasing distance from the inlets. Allowing a lag between the measured and simulated concentrations slightly improves the accuracy score.

3.5. Task 6: Build statistical models to quantify the effects of changes in inlet flow, rainfall and wind on water quality in both regions

3.5.1. *Kristin Jacobs Coral Aquatic Preserve (KJCAP)*

3.5.1.1. Monitoring network and spatial coverage

Our analyses for the KJCAP drew on a substantially expanded water-quality monitoring network. This network was larger than the dataset used by Walker et al.[15] and Whitall et al. [13], in both geographic and temporal extent. The expanded network comprised 71 unique monitoring sites distributed along the southeast Florida coast. These ran from Jupiter Inlet in the north ($\sim 27.25^\circ$ N) to Biscayne Bay in the south ($\sim 25.50^\circ$ N). This spans a total north-to-south distance of approximately 200 km along Florida's Coral Reef (Figure 4). These 71 sites contributed 38,333 individual water-quality observations over the period November 2018 to April 2025. The observations span the seven analytes considered in this analysis: nitrate, nitrite, orthophosphate, total phosphorus, silicate, total suspended solids (TSS), and turbidity.

Every monitoring site fell within an IEA polygon, providing complete spatial coverage of the monitoring network across the study region (Figure 4). Prior to analysis, we purposely excluded 27 nutrient-monitoring sites located in immediate proximity to nine major coastal inlets. These comprised three sites per inlet, sampled at the northern, southern, and seaward sides. Such sites would otherwise have introduced an inlet-mouth signal that did not reflect on-reef water quality. Sampling effort across the remaining 71 sites was unevenly distributed among IEAs. Site counts ranged from three sites in Lake Worth to 16 sites in Jupiter. Observation counts ranged from 1,617 in Lake Worth to 8,606 in Jupiter (Figure 22). The remaining IEAs each contributed between roughly 2,700 and 6,000 observations. The northern IEAs (Jupiter, Boynton) and Port Everglades together accounted for $\sim 50\%$ of the total observations in the dataset. This reflects both denser site coverage and longer monitoring records at those locations.

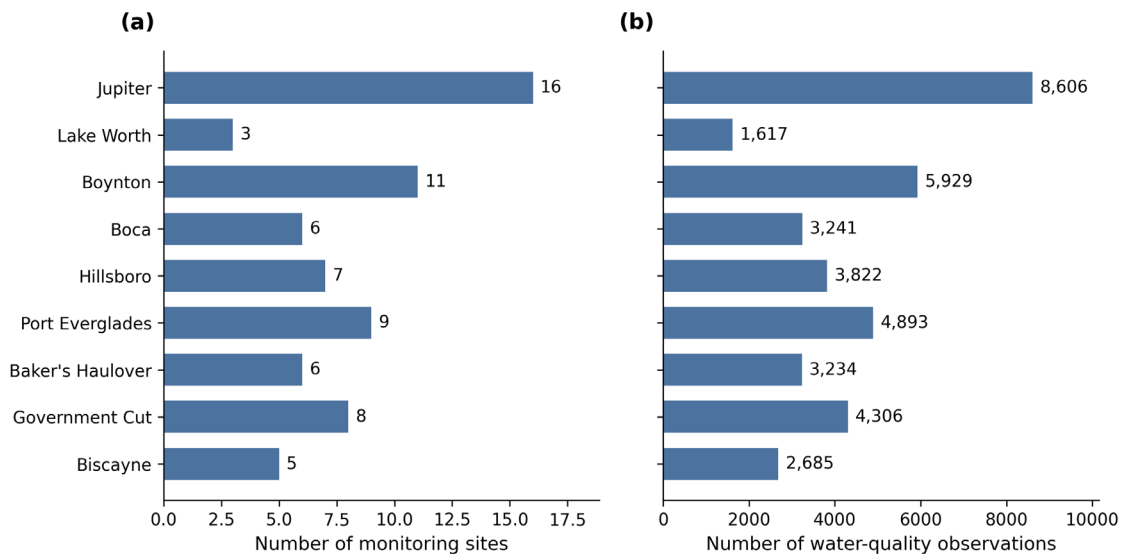


Figure 22. Spatial coverage of water-quality monitoring effort by IEA within the KJCAP, ordered from north (top) to south (bottom). Panel (a) shows the number of unique monitoring sites in each IEA. Panel (b) shows the total number of water-quality observations contributed by each IEA across the seven analytes considered in this analysis. Numeric values are printed at the end of each bar.

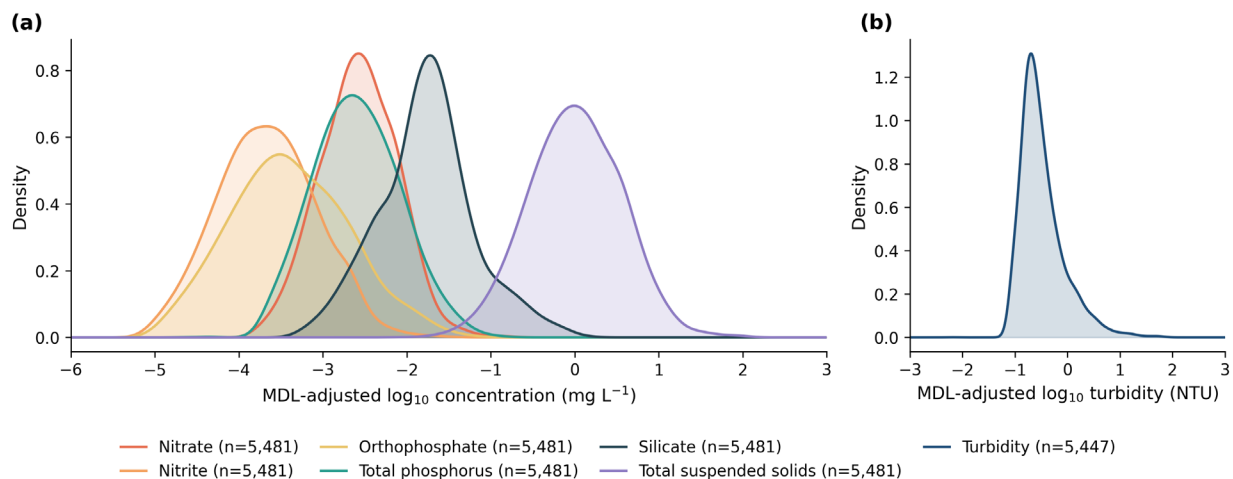


Figure 23. Variations in the method detection limit (MDL) adjusted $\log_{10}$ concentration of the seven on-reef water-quality analytes measured across the KJCAP from November 2018 to April 2025. Density curves are kernel density estimates derived from all observations available for each analyte ($n = 5,481$ for each of nitrate, nitrite, orthophosphate, total phosphorus, silicate, and TSS; $n = 5,447$ for turbidity). Panel (a) shows the six analytes measured in mg L⁻¹; panel (b) shows turbidity, measured in NTU and displayed separately because of its different measurement units. These distributions represent the response variables in our boosted regression tree (BRT) models. MDL corrections follow the Flynn-adjustment method (see Methods).

3.5.1.2. Modeling spatial and temporal variations in water-quality analytes

After data cleaning, 5,481 paired observations were available for nitrate, nitrite, orthophosphate, total phosphorus, silicate, and TSS, and 5,447 paired observations were available for turbidity. The MDL-adjusted log-concentrations of these seven analytes (the response variables in our BRT models) showed substantial variation both among analytes and within each analyte across space and time (Figure 23).

Across the seven analytes, our BRTs explained between 50.7% (TSS) and 78.5% (turbidity) of the variation in the training data. They explained between 39.4% (TSS) and 72.4% (turbidity) of the cross-validated variation (Table 1). Reducing the bag fraction from 0.8 to 0.5 changed each of these metrics by no more than ~1 percentage point. Model performance was therefore largely insensitive to the resampling fraction.

The predictors responsible for explaining each analyte's patterns of underlying variation differed among the seven analytes (Table 2; Figure A59). Season was the single most influential predictor for five of the seven analytes (nitrate, nitrite, orthophosphate, total phosphorus, and TSS), contributing between 20.6% (TSS) and 32.1% (orthophosphate) to overall model performance. For silicate and turbidity, inlet exposure area (IEA) instead ranked first, although for silicate it led season only marginally (23.4% versus 22.9%). IEA ranked first or second for every analyte except nitrite, where it ranked third behind season and Water Year. Depth was a strong third-ranked predictor for the analytes whose distributions were most clearly tied to the water column

(orthophosphate, total phosphorus, silicate, TSS), and ranked second for turbidity. We unpack the seasonal patterns more fully in a later subsection. Here we focus on what each analyte's top predictors collectively indicate about its dominant spatial and meteorological drivers. Partial dependency response plots for each analyte are shown in Figures 24 to 30.

3.5.1.3. Nitrate

Variations in *nitrate* concentrations were predominantly explained by season, IEA, and a series of wind and inlet-flow metrics (Table 2; Figure 24). Modeled nitrate concentrations rose through the early years of the time series to a peak around the 2022 wet season, held within a narrow band through 2024, and traced a tentative decline across the two most recent seasons (2025 wet and 2025 dry). Across the modeled IEA categories, concentrations were broadly similar, with a modest depression at the northernmost IEA (Jupiter). Higher counts of landward high-wind events, both 3 and 60 days prior, were each associated with modest increases in modeled nitrate concentrations. Higher inlet outflow in the 7 days prior to sampling had a similar effect. In each case the increase plateaued at high values of the predictor.

3.5.1.4. Nitrite

Variations in *nitrite* concentrations were also predominantly explained by season, water year, IEA, and inlet flow (Table 2; Figure 25). Modeled nitrite concentrations showed a particularly strong directional increase over the time series, rising progressively from approximately $-4.02 \log \text{mg L}^{-1}$ in the 2019 dry season to -3.39 by the 2023 dry season, and then holding within a narrower -3.34 to -3.50 band through 2025. Water year provided an additional $\sim 11\%$ of relative influence beyond season, absorbing the residual year-to-year drift not captured by season; the partial-dependence response on water year rose monotonically from 2019 to 2025. Across IEAs, nitrite concentrations were broadly similar, with Jupiter trending modestly higher than the other IEAs. Higher inlet outflow in the 7 days prior to sampling was associated with increasing modeled nitrite concentrations that plateaued at higher flows.

3.5.1.5. Orthophosphate

Variations in *orthophosphate* concentrations were predominantly explained by season, IEA, depth, and seaward wind (Table 2; Figure 26). Season was the strongest seasonal signal of any KJCAP analyte at 32.1% relative influence. Modeled orthophosphate concentrations increased steeply through the first three years, then held within a remarkably narrow band of about -3.07 to -3.16 from the 2022 dry season onward, with the 2024 dry season as the record peak. Across IEAs, Jupiter exhibited notably higher modeled concentrations than the other modeled IEA categories, which were broadly similar to one another. Depth was a strong negative driver: modeled orthophosphate concentrations decreased steeply over the upper ~ 10 m of the water column and plateaued at deeper depths. Higher counts of seaward high-wind events in the 30 days prior to sampling were associated with a modest upward shift in modeled orthophosphate, although the partial-dependence response was shallow.

3.5.1.6. Total Phosphorus

Variations in total phosphorus concentrations were predominantly explained by season, IEA, depth, and landward wind (Table 2; Figure 27). Modeled total phosphorus concentrations rose more modestly across the time series than orthophosphate or nitrite, but still showed clear elevation in the late record, with the 2025 dry season the highest in the time series. Across IEAs, Jupiter

again stood out with the highest modeled concentrations, with the other IEAs showing broadly similar concentrations. Depth was a moderately strong negative driver: modeled total phosphorus concentrations decreased over the upper ~10 m of the water column before plateauing. Higher counts of landward high-wind events in the 7 days prior to sampling were associated with modest increases in modeled total phosphorus concentrations.

3.5.1.7. Silicate

Variations in *silicate* concentrations were predominantly explained by IEA, season, depth, and cumulative rainfall (Table 2; Figure 28). Modeled silicate concentrations rose steadily from 2019 to a peak around the 2024 dry season, then fell back across the two most recent seasons. This rise-then-decline is distinct from the asymptotic responses of the co-occurring KJCAP nutrient analytes. Among the IEAs, Jupiter exhibited the highest modeled silicate concentrations. Values declined progressively southward through Lake Worth and Boynton before leveling off across the more southern IEAs. Depth was a strong negative driver: modeled silicate concentrations dropped steeply over the upper ~10 m of the water column and plateaued at deeper depths. Cumulative rainfall summed over the 60 days prior to sampling was positively associated with modeled silicate concentrations, with the response rising over the lower range of rainfall values before plateauing.

3.5.1.8. Total suspended solids (TSS)

Variations in *total suspended solids (TSS)* concentrations were predominantly explained by season, IEA, depth, and seaward wind (Table 2; Figure 29). Modeled TSS concentrations oscillated within a narrow band of approximately -0.12 to +0.22 log units across the time series, with no directional trend; the highest model-adjusted value fell on the earliest season (2019 dry) rather than during the recent monitoring years. Across IEAs, Jupiter exhibited the highest modeled TSS values, with the other IEAs showing broadly similar concentrations. Depth was a moderately strong negative driver, with modeled TSS concentrations declining across the upper ~10 m of the water column before plateauing. The confidence ribbon widened markedly at the deepest portion of the depth gradient (Figure 29c), reflecting sparser data at depth. The partial dependency on the number of seaward high-wind events in the 30 days prior to sampling was relatively flat. It showed only a small uptick at the highest wind-event counts (Figure 29d). However, this uptick coincides with very sparse data at the upper end of the predictor range and is therefore associated with high model uncertainty.

3.5.1.9. Turbidity

In contrast to the six analytes above, variations in *turbidity* were dominated by spatial, rather than seasonal, controls (Table 2; Figure 30). Inlet exposure area was the single most influential predictor, contributing 30.4% to overall model performance, with depth contributing a further 23.8% and season demoted to a third-ranked role at 13.5%. Modeled turbidity values were highest at Jupiter and declined progressively southward, mirroring the pattern seen for several of the nutrient analytes but more pronounced. Depth was the strongest negative driver of any analyte-by-predictor pairing in the analysis. Modeled turbidity declined steeply across the upper ~10 m of the water column and continued to decrease at greater depths. This pattern suggests a strong near-surface attenuation effect. The seasonal signal in turbidity was correspondingly weak, oscillating within a narrow band of approximately -0.59 to -0.29 on the log axis without any directional trend across the time series. Higher counts of landward high-wind events in the 7 days prior to sampling were associated with modest increases in modeled turbidity. Notably, the turbidity model also

achieved the highest training and cross-validated performance of the seven analytes (78.5% and 72.4%, respectively; Table 1). This is consistent with turbidity's variation being captured largely by two highly informative spatial predictors.

Table 1. Boosted regression tree (BRT) model performance statistics for seven water-quality analytes monitored across the KJCAP from November 2018 to April 2025. cv, cross-validated. cvPercentage explained (the cross-validated percentage of the deviance in the response variable explained by the model) is the metric used to assess model performance. It is shown in bold for each sensitivity run. The lower block (bag fraction = 0.5) reports a sensitivity run in which the proportion of training data used at each iteration was reduced from the default 0.8. TSS, total suspended solids.

	Nitrate	Nitrite	Orthophosphate	Total Phosphorus	Silicate	TSS	Turbidity
<i>Model parameters</i>							
Number of observations	5481	5481	5481	5481	5481	5481	5447
Tree complexity	5	5	5	5	5	5	5
Learning rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Bag fraction	0.8	0.8	0.8	0.8	0.8	0.8	0.8
Number of trees	37400	28750	21400	23750	30450	22100	26150
<i>Model performance (bag fraction = 0.8)</i>							
Percentage explained (%)	67.0	74.5	68.5	56.4	73.2	50.7	78.5
cvPercentage explained (%)	55.0	65.4	60.1	44.9	64.5	39.4	72.4
<i>Model performance (bag fraction = 0.5)</i>							
Percentage explained (%)	66.1	74.0	68.3	56.4	72.7	50.5	77.9
cvPercentage explained (%)	54.3	65.0	59.8	44.5	64.3	39.0	72.0

Table 2. Top predictors of variation in each water-quality analyte across the KJCAP, ranked by relative influence (%) in the corresponding boosted regression tree (BRT) model, with their cumulative influence. For each analyte we report the top four predictors, or enough to reach a cumulative relative influence of at least 50%, whichever yields more rows. Values in parentheses give the temporal window in days prior to sampling (see Methods). TSS, total suspended solids.

Analyte	Predictor	Relative influence (%)	Cumulative influence (%)
<i>Nitrate</i>	Season	28.3	28.3
	Inlet exposure area	9.1	37.4
	Landward wind (3 d)	5.4	42.8
	Landward wind (60 d)	4.7	47.5
	Flow (7 d)	4.5	52.0
<i>Nitrite</i>	Season	28.7	28.7
	Water Year	11.0	39.7
	Inlet exposure area	7.6	47.3
	Flow (7 d)	5.5	52.8
<i>Orthophosphate</i>	Season	32.1	32.1
	Inlet exposure area	20.2	52.3
	Depth	15.7	68.0
	Seaward wind (30 d)	2.9	70.9
<i>Total Phosphorus</i>	Season	24.3	24.3
	Inlet exposure area	18.6	42.9
	Depth	10.7	53.6
	Landward wind (7 d)	4.6	58.2
<i>Silicate</i>	Inlet exposure area	23.4	23.4
	Season	22.9	46.3
	Depth	14.3	60.6
	Rainfall (60 d)	7.3	67.9
<i>TSS</i>	Season	20.6	20.6
	Inlet exposure area	19.3	39.9
	Depth	11.4	51.3
	Seaward wind (30 d)	5.0	56.3
<i>Turbidity</i>	Inlet exposure area	30.4	30.4
	Depth	23.8	54.2
	Season	13.5	67.7
	Landward wind (7 d)	3.7	71.4

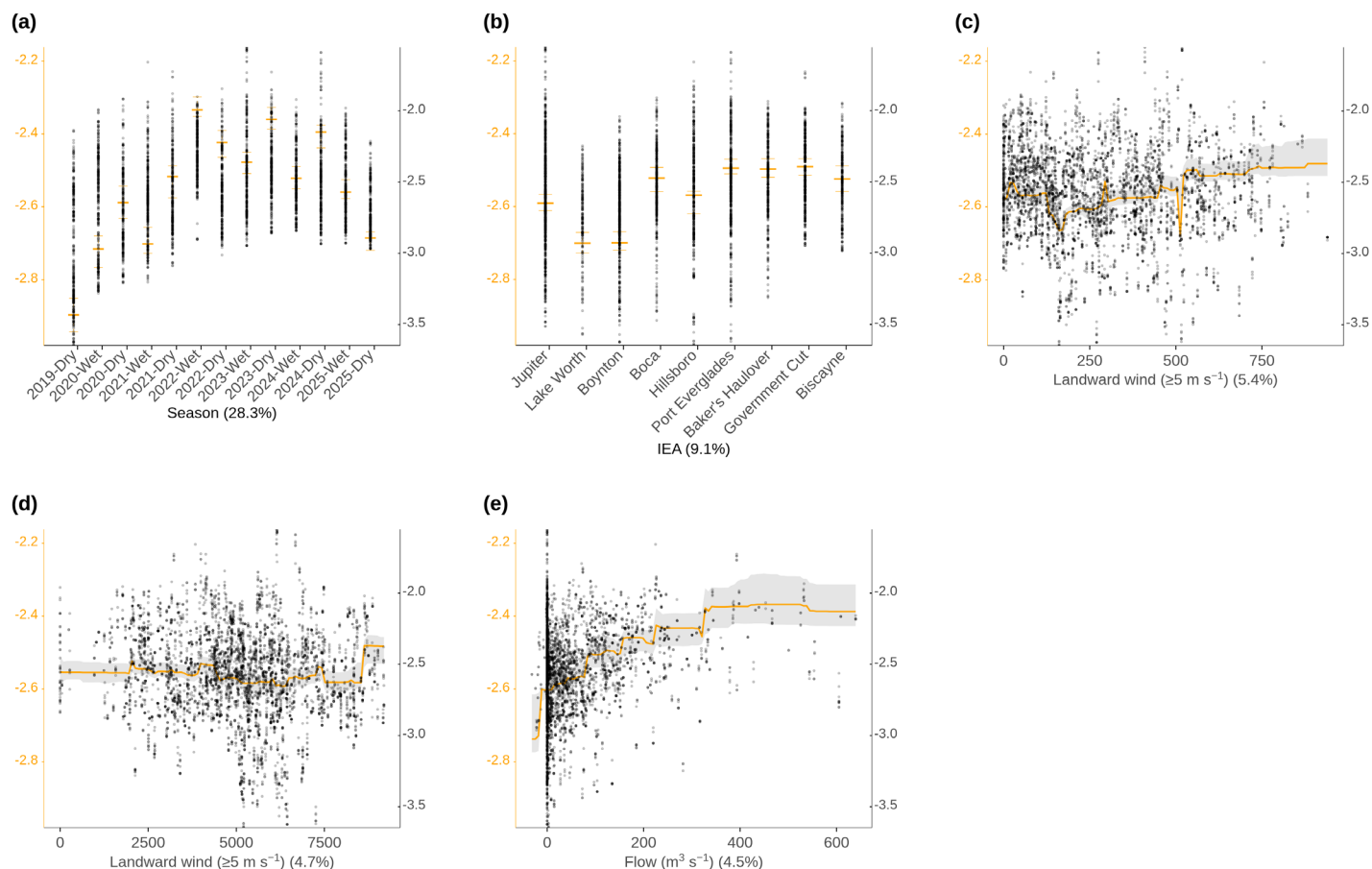


Figure 24. Nitrate, KJCAP. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrate concentration to gradients in season (a), inlet exposure area (b), the number of landward high-wind events counted over the 3 days and 60 days prior to sampling (c and d, respectively), and inlet outflow summed over the 7 days prior to sampling (e) across the Kristin Jacobs Coral Aquatic Preserve (Nov 2018 – Apr 2025; $n = 5,481$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and IEA predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{ mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis (see Table 2 for relative influences across the full set of top predictors). High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period. IEA, inlet exposure area.

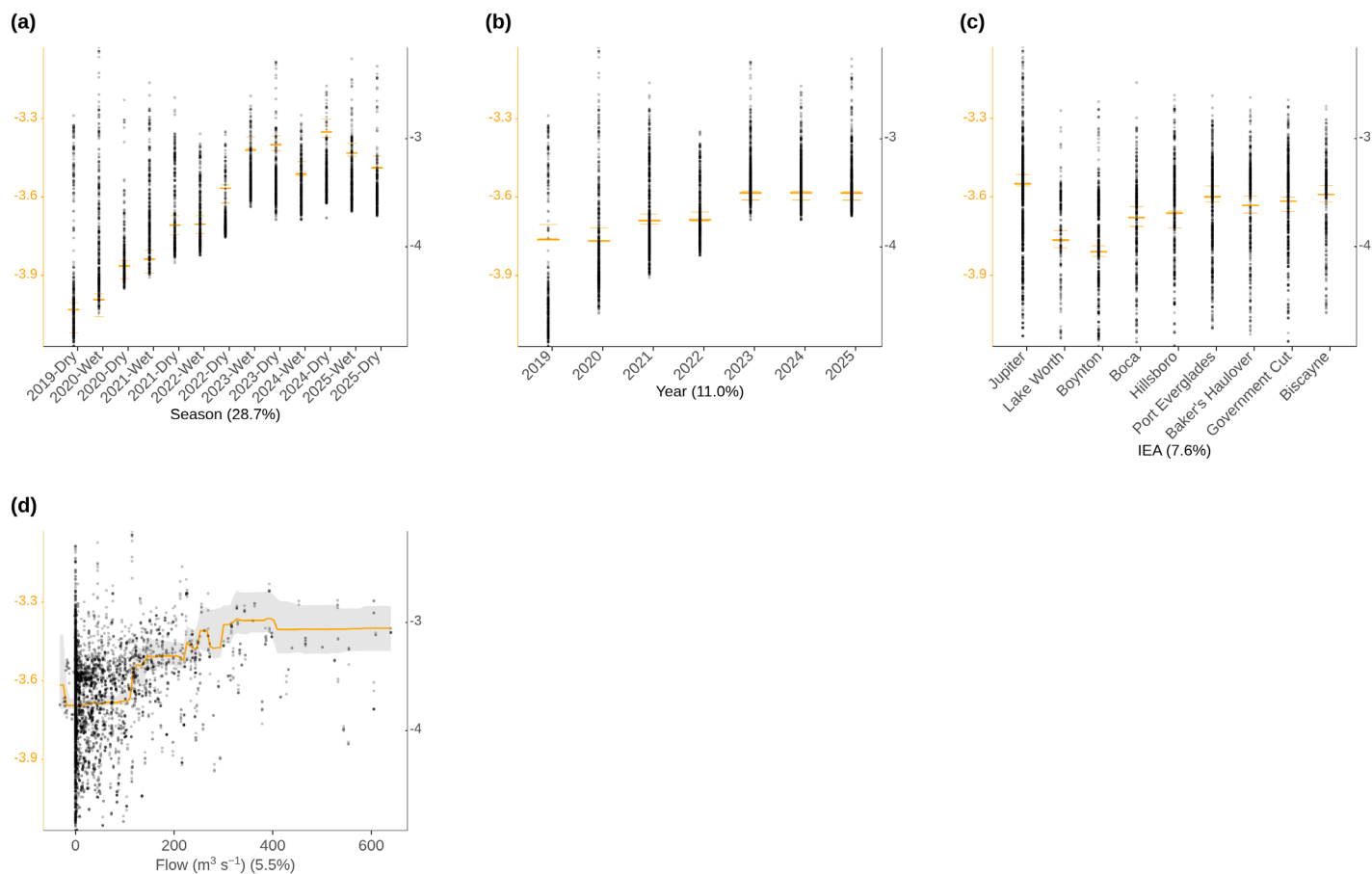


Figure 25. Nitrite, KJCAP. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrite concentration to gradients in season (a), inlet exposure area (b), inlet outflow summed over the 7 days prior to sampling (c), and the number of landward high-wind events counted over the 3 days prior to sampling (d) across the Kristin Jacobs Coral Aquatic Preserve (Nov 2018 – Apr 2025; $n = 5,481$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and IEA predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{ mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis (see Table 2 for relative influences across the full set of top predictors). High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period. IEA: inlet exposure area.

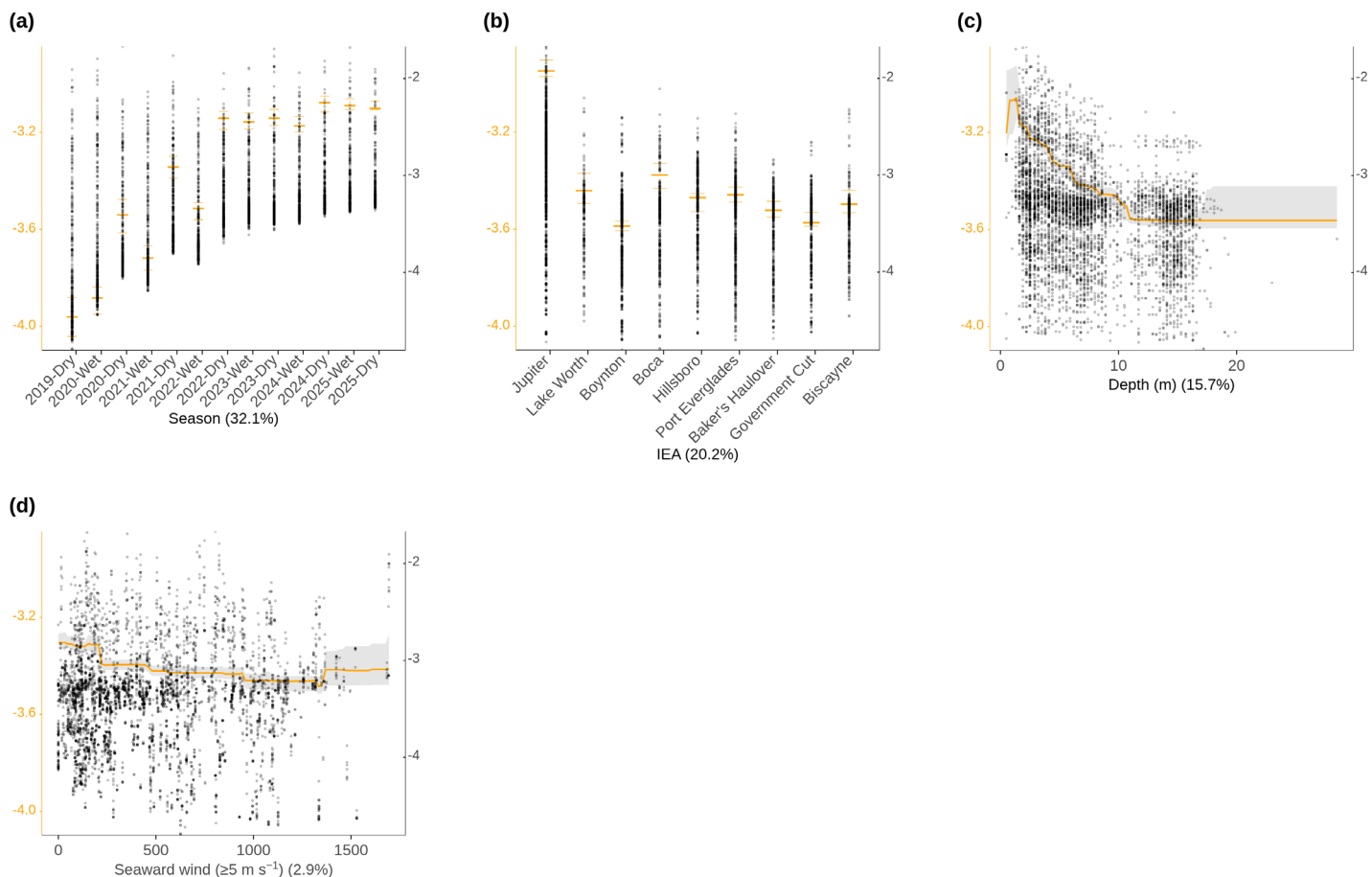


Figure 26. Orthophosphate, KJCAP. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed orthophosphate concentration to gradients in season (a), inlet exposure area (b), depth (c), and Water Year (d) across the Kristin Jacobs Coral Aquatic Preserve (Nov 2018 – Apr 2025; $n = 5,481$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and IEA predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis (see Table 2 for relative influences across the full set of top predictors). IEA: inlet exposure area.

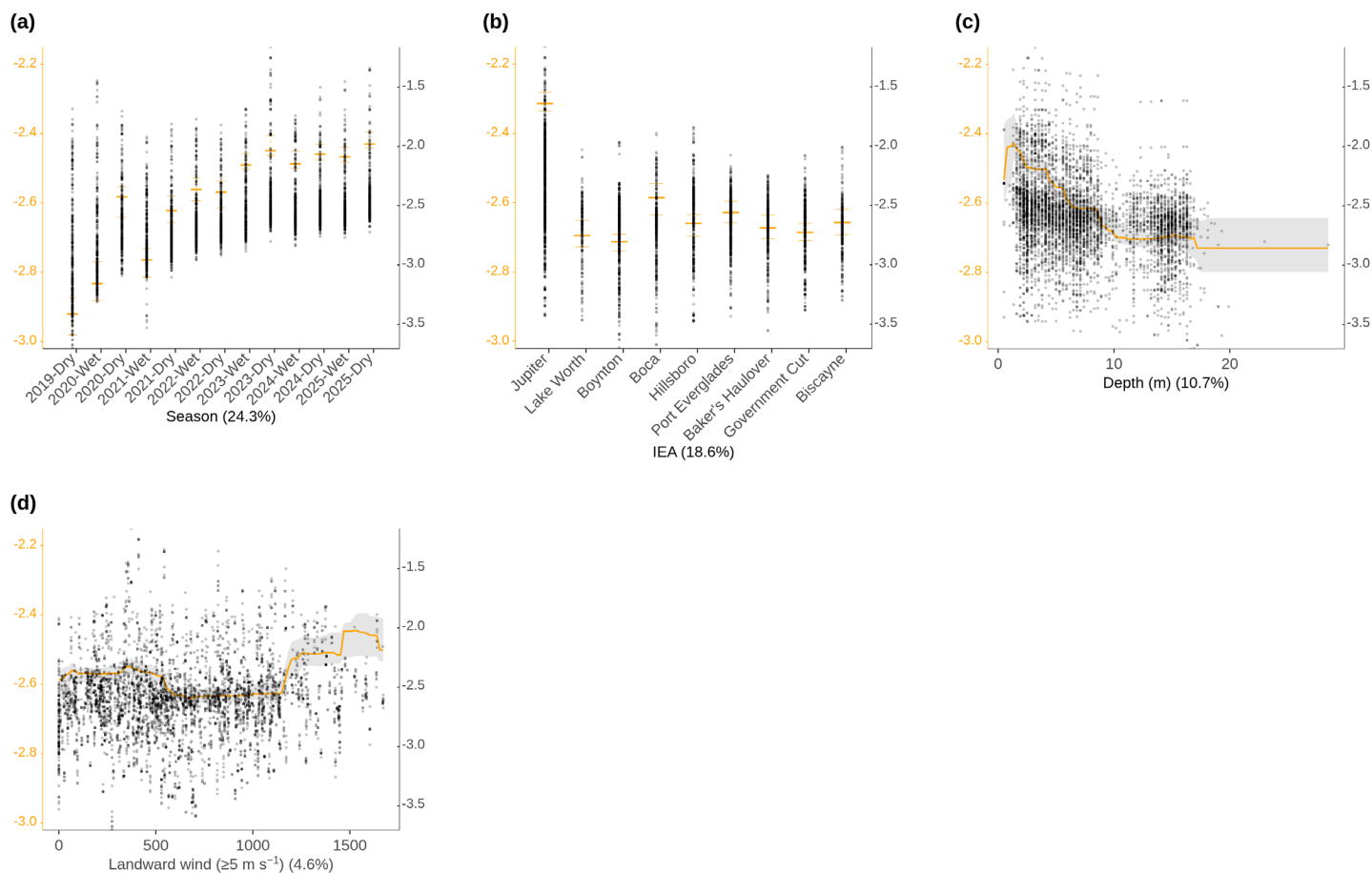


Figure 27. Total phosphorus, KJCAP. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed total phosphorus concentration to gradients in season (a), inlet exposure area (b), depth (c), and the number of landward high-wind events counted over the 7 days prior to sampling (d) across the Kristin Jacobs Coral Aquatic Preserve (Nov 2018 – Apr 2025; $n = 5,481$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and IEA predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{ mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis (see Table 2 for relative influences across the full set of top predictors). High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period. IEA, inlet exposure area.

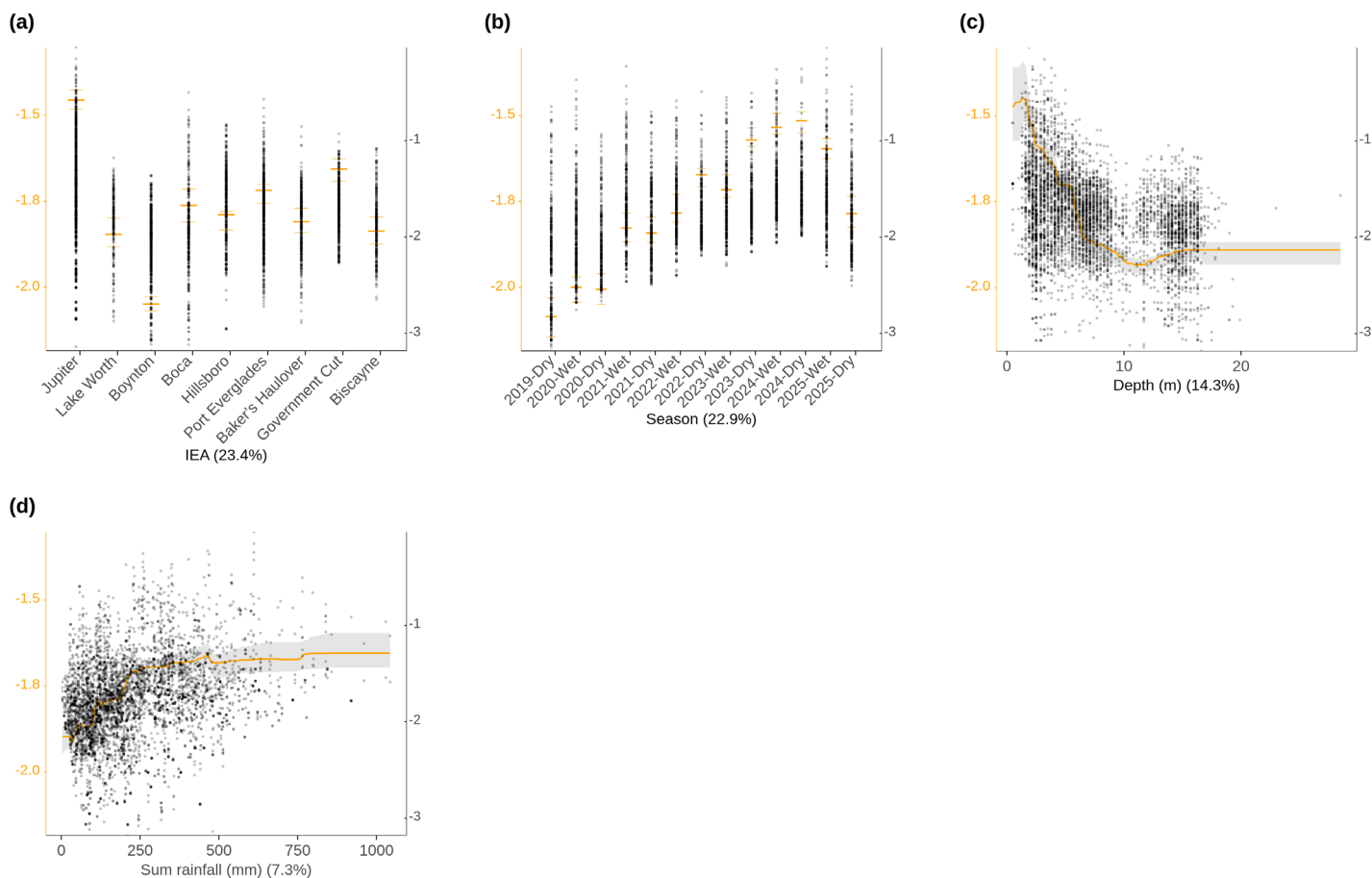


Figure 28. Silicate, KJCAP. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed silicate concentration to gradients in season (a), inlet exposure area (b), depth (c), and cumulative rainfall summed over the 60 days prior to sampling (d) across the Kristin Jacobs Coral Aquatic Preserve (Nov 2018 – Apr 2025; $n = 5,481$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and IEA predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{ mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis (see Table 2 for relative influences across the full set of top predictors). IEA, inlet exposure area.

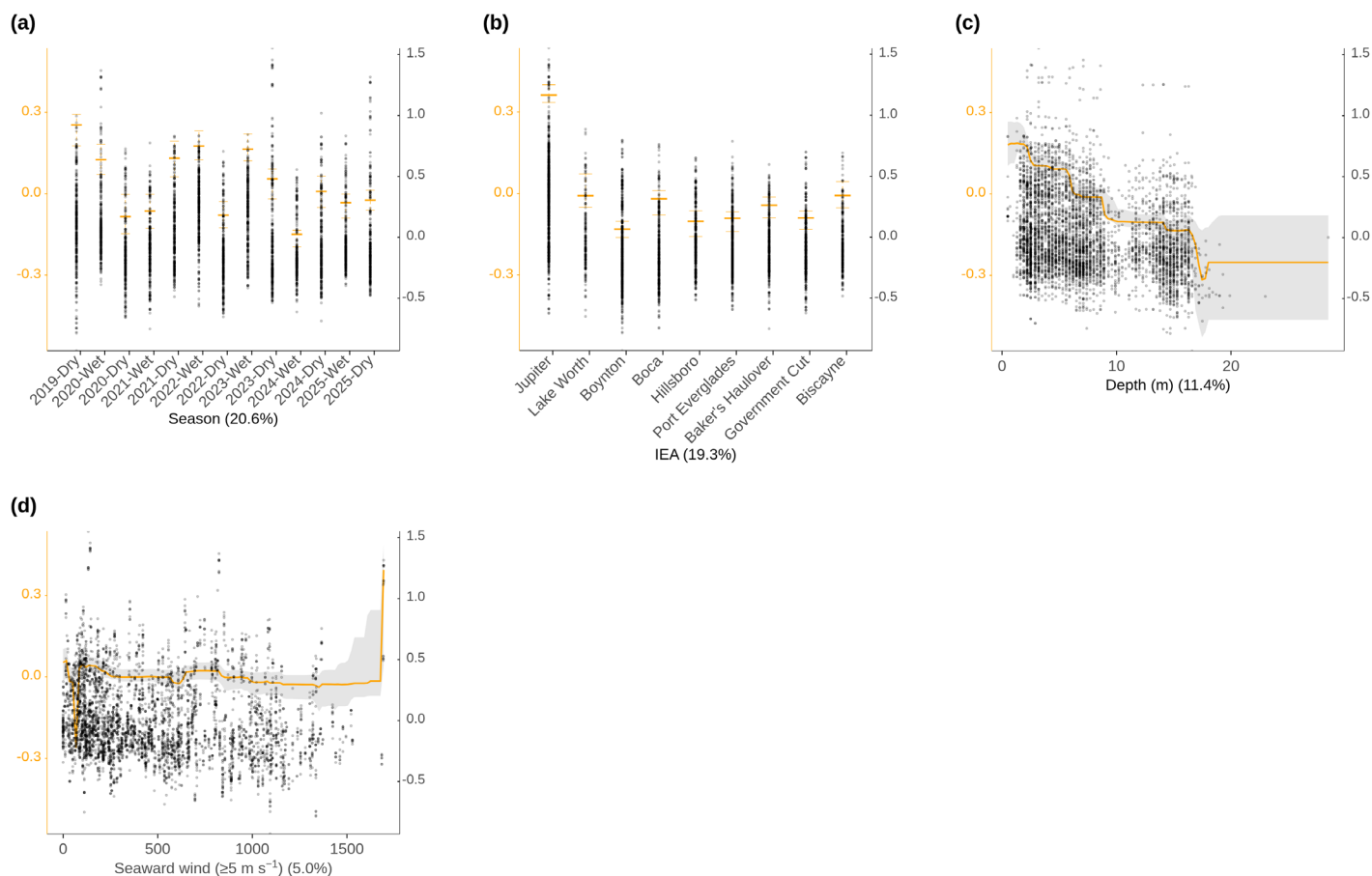


Figure 29. Total Suspended Solids, KJCAP. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed TSS concentration to gradients in season (a), inlet exposure area (b), depth (c), and the number of seaward high-wind events counted over the 30 days prior to sampling (d) across the Kristin Jacobs Coral Aquatic Preserve (Nov 2018 – Apr 2025; $n = 5,481$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and IEA predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log mg L^{-1} , corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis (see Table 2 for relative influences across the full set of top predictors). High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period. IEA: inlet exposure area.

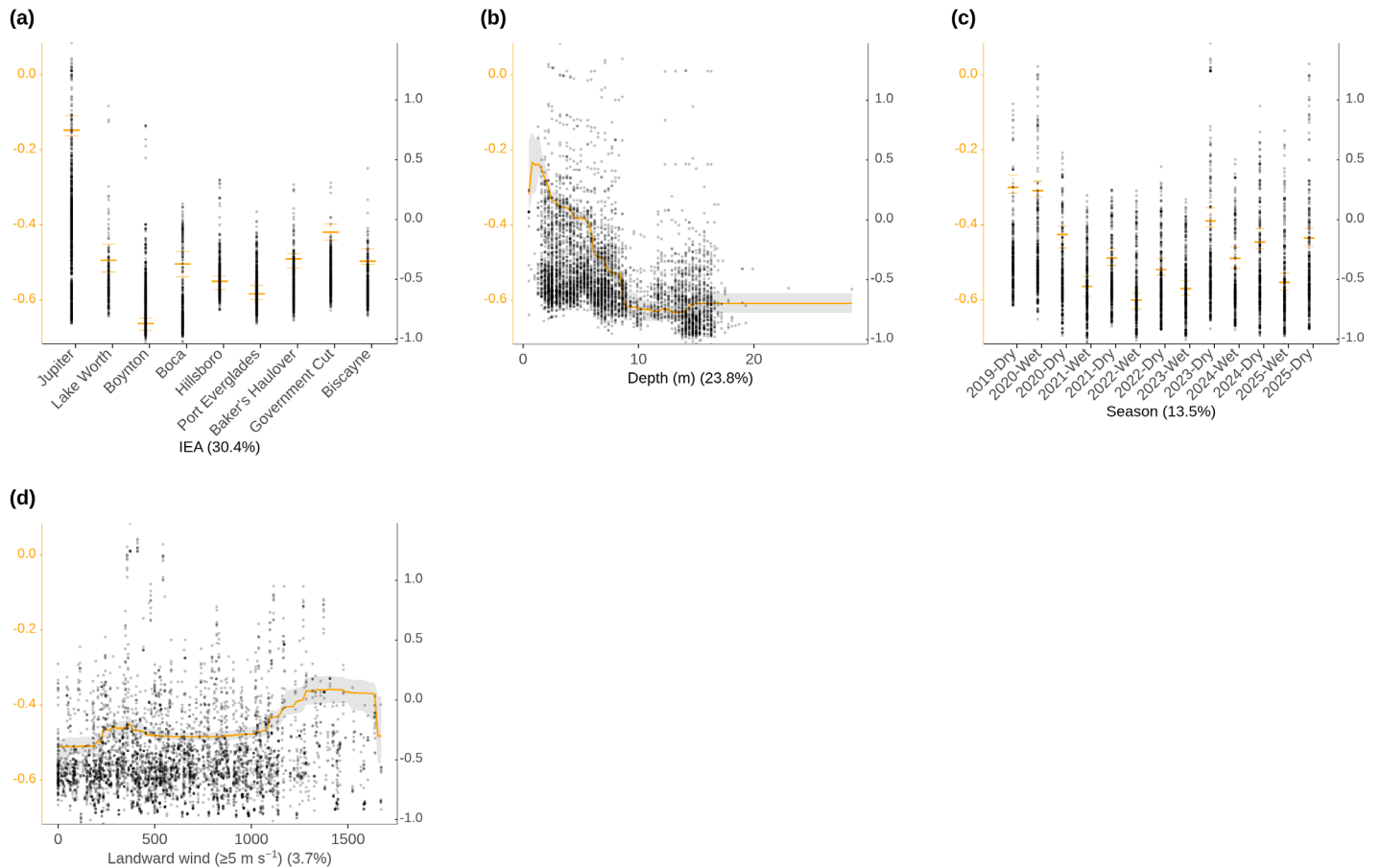


Figure 30. Turbidity, KJCAP. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed turbidity concentration to gradients in inlet exposure area (a), depth (b), season (c), and the number of landward high-wind events counted over the 7 days prior to sampling (d) across the Kristin Jacobs Coral Aquatic Preserve (Nov 2018 – Apr 2025; $n = 5,447$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and IEA predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log NTU, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis (see Table 2 for relative influences across the full set of top predictors). High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period. IEA, inlet exposure area.

3.5.2. *Miami-Dade Department of Environmental Resources Management (DERM)*

3.5.2.1. Monitoring network and spatial coverage

The DERM water-quality dataset was contributed by the Miami-Dade County Department of Environmental Resources Management (DERM). The DERM long-term monitoring program samples nearshore and bay waters across Biscayne Bay and the upper Florida Keys. After data cleaning and site filtering, the DERM dataset comprised 44 unique monitoring sites (Figure 5). These contributed 12,504 individual water-quality observations over the period November 2018 to April 2025. The observations span five analytes: nitrate-nitrite, nitrogen-total, orthophosphate, total phosphorus, and turbidity.

Each DERM monitoring site was assigned to one of five spatial polygons spanning Biscayne Bay and the upper Keys. Ordered from north to south, these are Baker's Haulover, Government Cut, Biscayne Bay, Biscayne Bay-South, and Barne's Sound (Figure 5). Unlike the KJCAP inlet exposure areas, these polygons are not derived from hydrographic modeling of inlet outflow. Instead, they are spatial units included in the BRT models as a single categorical predictor. They are intended to absorb underlying spatial structure in water quality not captured by the flow, rainfall, and wind predictors. We refer to these spatial units as **polygons** throughout the text. Sampling effort was uneven across the polygons. Site counts ranged from two sites in both Baker's Haulover and Barne's Sound to 17 sites in Government Cut. Observation counts ranged from 661 in Barne's Sound to 4,750 in Government Cut (Figure 31). Government Cut and the two Biscayne Bay polygons together accounted for most of the dataset.

3.5.2.2. Modeling spatial and temporal variations in water-quality analytes

We modeled the five DERM analytes using the same boosted regression tree (BRT) framework, candidate predictor set, and collinearity screening described in the Methods. The spatial polygons replaced the KJCAP inlet exposure area as the categorical spatial predictor. The method detection limit-corrected (Flynn-adjusted) log-concentrations of the five analytes spanned a broad range, both among analytes and within each analyte across space and time (Figure 32).

Across the five analytes, the DERM BRTs explained between 47.3% (turbidity) and 74.0% (total phosphorus) of the variation in the training data. They explained between 37.3% (turbidity) and 66.9% (total phosphorus) of the cross-validated variation (Table 3). As for the KJCAP, reducing the bag fraction from 0.8 to 0.5 changed each performance metric by no more than ~1 percentage point. Model performance was therefore largely insensitive to the resampling fraction.

The predictors explaining each analyte's variation differed across the five DERM analytes (Table 4; Figure A60). The spatial polygon was the single most influential predictor for nitrogen-total, total phosphorus, and turbidity. Season ranked first for orthophosphate. Flow summed over the 7 days prior to sampling ranked first for nitrate-nitrite. In the KJCAP, season was the leading predictor for most analytes. In contrast, the DERM models point to a stronger relative role for persistent spatial structure and for freshwater flow. Partial dependency response plots for each analyte are shown in Figures 33 to 37.

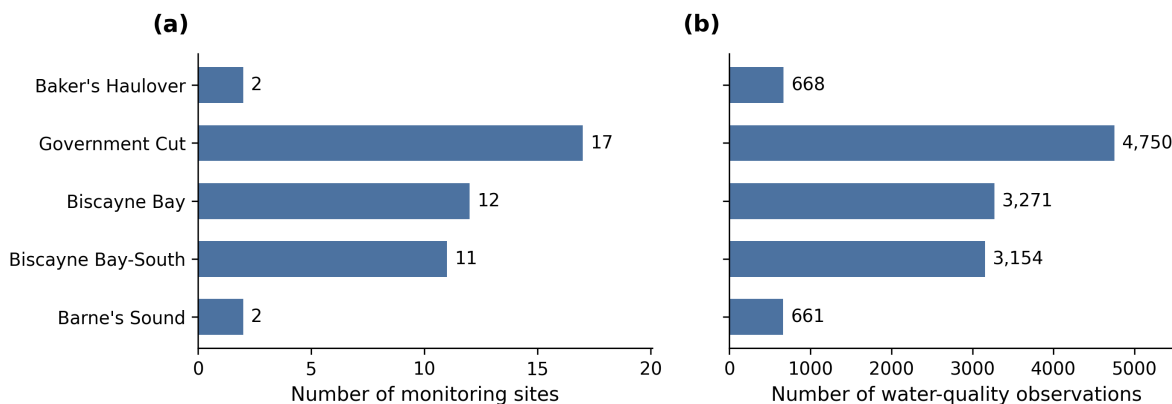


Figure 31. Spatial coverage of DERM water-quality monitoring effort by spatial polygon, ordered from north (top) to south (bottom). Panel (a) shows the number of unique monitoring sites in each polygon; panel (b) shows the total number of water-quality observations contributed by each polygon across the five analytes considered in this analysis. Numeric values are printed at the end of each bar.

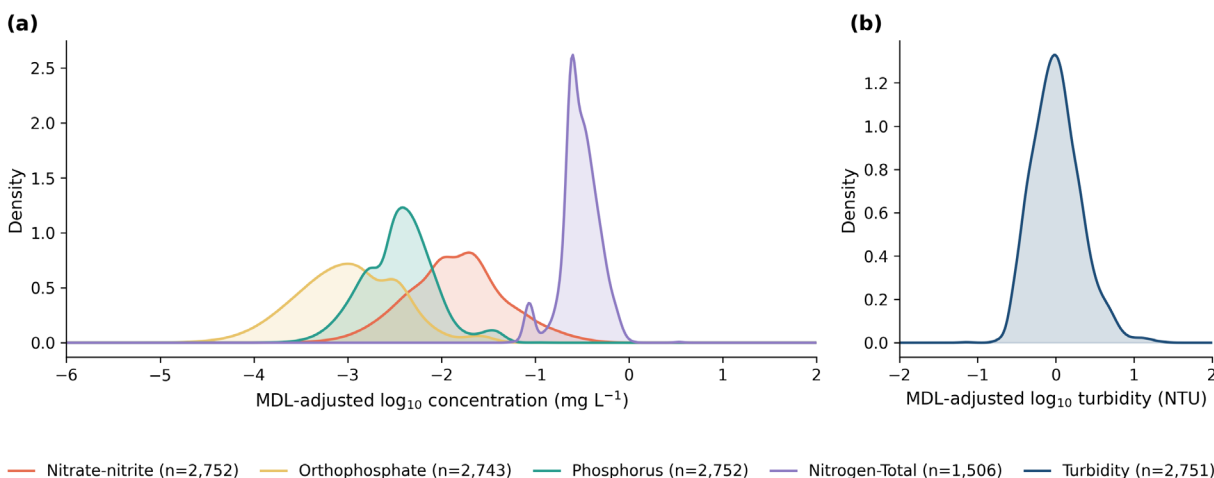


Figure 32. Variations in the method detection limit (MDL) adjusted $\log_{10}$ concentration of the five DERM water-quality analytes, November 2018 to April 2025. Density curves are kernel density estimates derived from all observations available for each analyte. Panel (a) shows the four analytes measured in mg L^{-1} ; panel (b) shows turbidity, measured in NTU and displayed separately because of its different measurement units. MDL corrections follow the Flynn-adjustment method (see Methods).

Table 3. Boosted regression tree (BRT) model performance statistics for the five water-quality analytes monitored by DERM from November 2018 to April 2025. cv, cross-validated. cvPercentage explained (the cross-validated percentage of the deviance in the response variable explained by the model) is the metric used to assess model performance. It is shown in bold for each sensitivity run. The lower block (bag fraction = 0.5) reports a sensitivity run in which the proportion of training data used at each iteration was reduced from the default 0.8.

	Nitrate-nitrite	Nitrogen-total	Ortho-phosphate	Total Phosphorus	Turbidity
<i>Model parameters</i>					
Number of observations	2752	1506	2743	2752	2751
Tree complexity	5	5	5	5	5
Learning rate	0.001	0.001	0.001	0.001	0.001
Bag fraction	0.8	0.8	0.8	0.8	0.8
Number of trees	14550	8700	24400	12750	9000
<i>Model performance (bag fraction = 0.8)</i>					
Percentage explained (%)	55.0	60.1	64.7	74.0	47.3
cvPercentage explained (%)	41.6	46.8	43.3	66.9	37.3
<i>Model performance (bag fraction = 0.5)</i>					
Percentage explained (%)	54.5	59.6	64.2	73.8	47.4
cvPercentage explained (%)	41.8	46.6	43.1	66.9	37.3

Table 4. Predictors of variation in each DERM water-quality analyte, ranked by relative influence (%) in the corresponding boosted regression tree (BRT) model, with their cumulative influence. The predictors listed for each analyte are those retained as influential and visualized in its partial dependency plots (Figures 33 to 37). Values in parentheses give the temporal window in days prior to sampling (see Methods).

Analyte	Predictor	Relative influence (%)	Cumulative influence (%)
<i>Nitrate-nitrite</i>	Flow (7 d)	19.8	19.8
	Season	14.4	34.2
	Spatial polygon	11.9	46.1
	Flow (30 d)	8.0	54.1
<i>Nitrogen-total</i>	Spatial polygon	18.8	18.8
	Season	16.7	35.5
	Flow (7 d)	9.5	45.0
	Flow (30 d)	6.1	51.1
<i>Orthophosphate</i>	Season	16.2	16.2
	Spatial polygon	8.5	24.7
	Seaward wind (90 d)	8.3	33.0
	Rainfall (90 d)	7.8	40.8
	Flow (90 d)	6.0	46.8
<i>Total Phosphorus</i>	Spatial polygon	36.2	36.2
	Season	24.1	60.3
<i>Turbidity</i>	Spatial polygon	34.1	34.1
	Season	17.4	51.5
	Landward wind (3 d)	12.9	64.4

3.5.2.3. Nitrate-nitrite

Variations in *nitrate-nitrite* concentrations were predominantly explained by flow, season, and the spatial polygon (Table 4; Figure 33). Flow summed over the 7 days prior to sampling was the single most influential predictor: modeled nitrate-nitrite rose steeply with increasing flow before plateauing at higher flows (Figure 33a). Flow over the longer 30-day window showed a similar positive relationship. Modeled concentrations also varied seasonally and among the spatial polygons, although both signals were weaker than the flow response. Together, these four predictors accounted for 54.1% of the explained variation.

3.5.2.4. Nitrogen-total

Variations in *nitrogen-total* concentrations were predominantly explained by the spatial polygon, season, and flow (Table 4; Figure 34). The spatial polygon was the single most influential predictor: modeled nitrogen-total was highest in Barne's Sound and declined through the more northern polygons (Figure 34a). Modeled concentrations increased with flow over both the 7-day and 30-day windows. The seasonal signal was comparable in influence to the spatial signal. The four retained predictors together accounted for 51.1% of the explained variation.

3.5.2.5. Orthophosphate

Variations in *orthophosphate* concentrations were comparatively diffuse, with no single dominant predictor (Table 4; Figure 35). Season ranked first, followed by the spatial polygon, the count of seaward high-wind events over the 90 days prior to sampling, cumulative rainfall over the same window, and flow. Each of these five predictors contributed less than 17% of the explained variation, and together they accounted for 46.8%. Modeled orthophosphate increased with cumulative rainfall and declined at the highest counts of seaward high-wind events.

3.5.2.6. Total Phosphorus

Variations in total phosphorus concentrations were explained almost entirely by two predictors: the spatial polygon and season (Table 4; Figure 36). The spatial polygon was strongly dominant, alone accounting for 36.2% of the explained variation. Modeled total phosphorus was markedly higher in the Government Cut and Baker's Haulover polygons than in the Biscayne Bay polygons (Figure 36a). Season contributed a further 24.1%, giving a cumulative influence of 60.3%, the highest two-predictor total of any DERM analyte.

3.5.2.7. Turbidity

As for the KJCAP, variations in *turbidity* were dominated by spatial controls (Table 4; Figure 37). The spatial polygon was the single most influential predictor, contributing 34.1% to overall model performance, with modeled turbidity highest in the Government Cut polygon. Season contributed a further 17.4%. Higher counts of landward high-wind events in the 3 days prior to sampling were associated with a clear increase in modeled turbidity (Figure 37c). The three retained predictors together accounted for 64.4% of the explained variation.

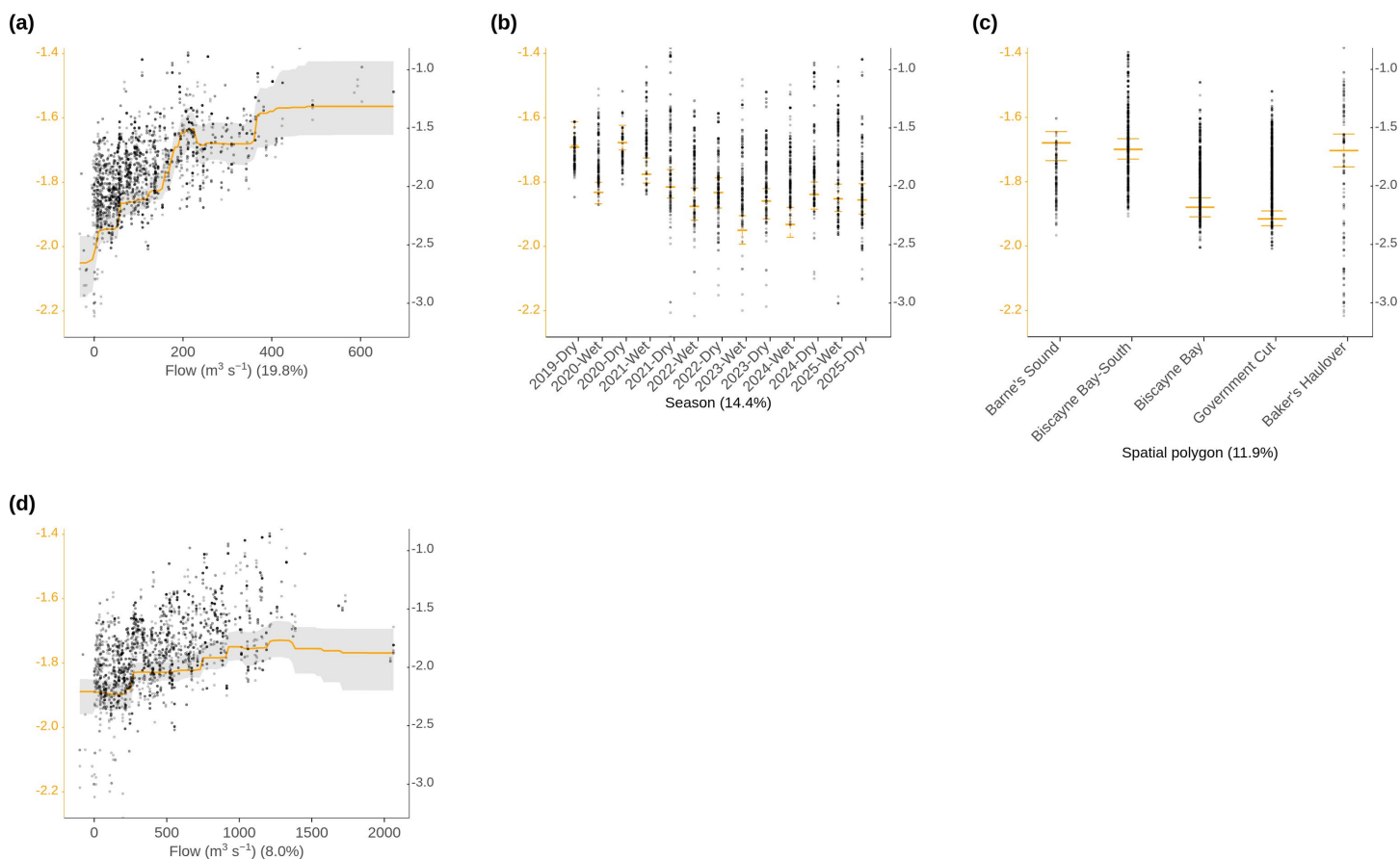


Figure 33. Nitrate-Nitrite, DERM. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrate-nitrite concentration to gradients in flow summed over the 7-day and 30-day windows prior to sampling (a and b, respectively), season (c), and the spatial polygon (d) across the DERM monitoring domain (Nov 2018 to Apr 2025; $n = 2,752$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

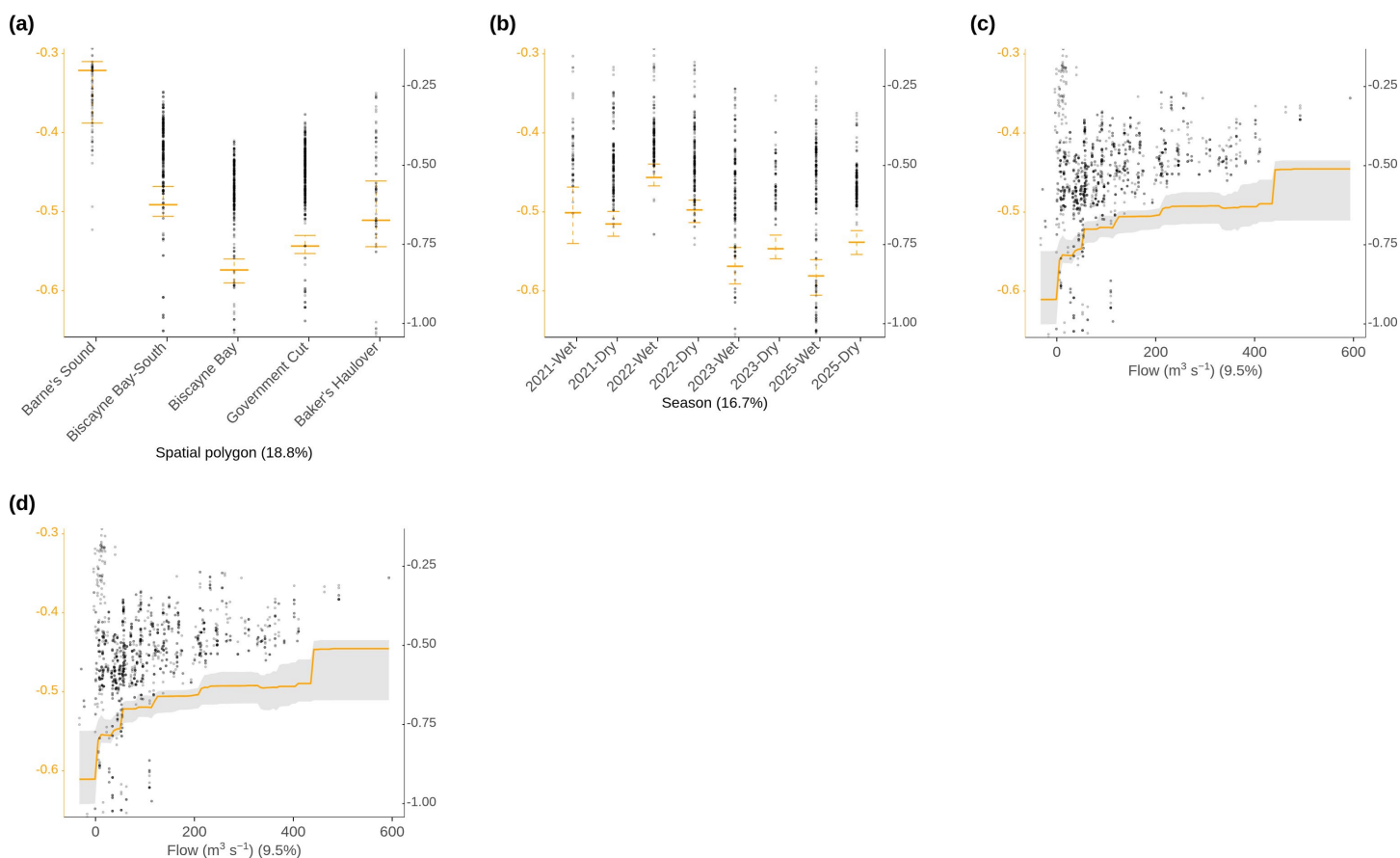


Figure 34. Nitrogen-total, DERM. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrogen-total concentration to gradients in the spatial polygon (a), season (b), and flow summed over the 7-day and 30-day windows prior to sampling (c and d, respectively) across the DERM monitoring domain (Nov 2018 to Apr 2025; $n = 1,506$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

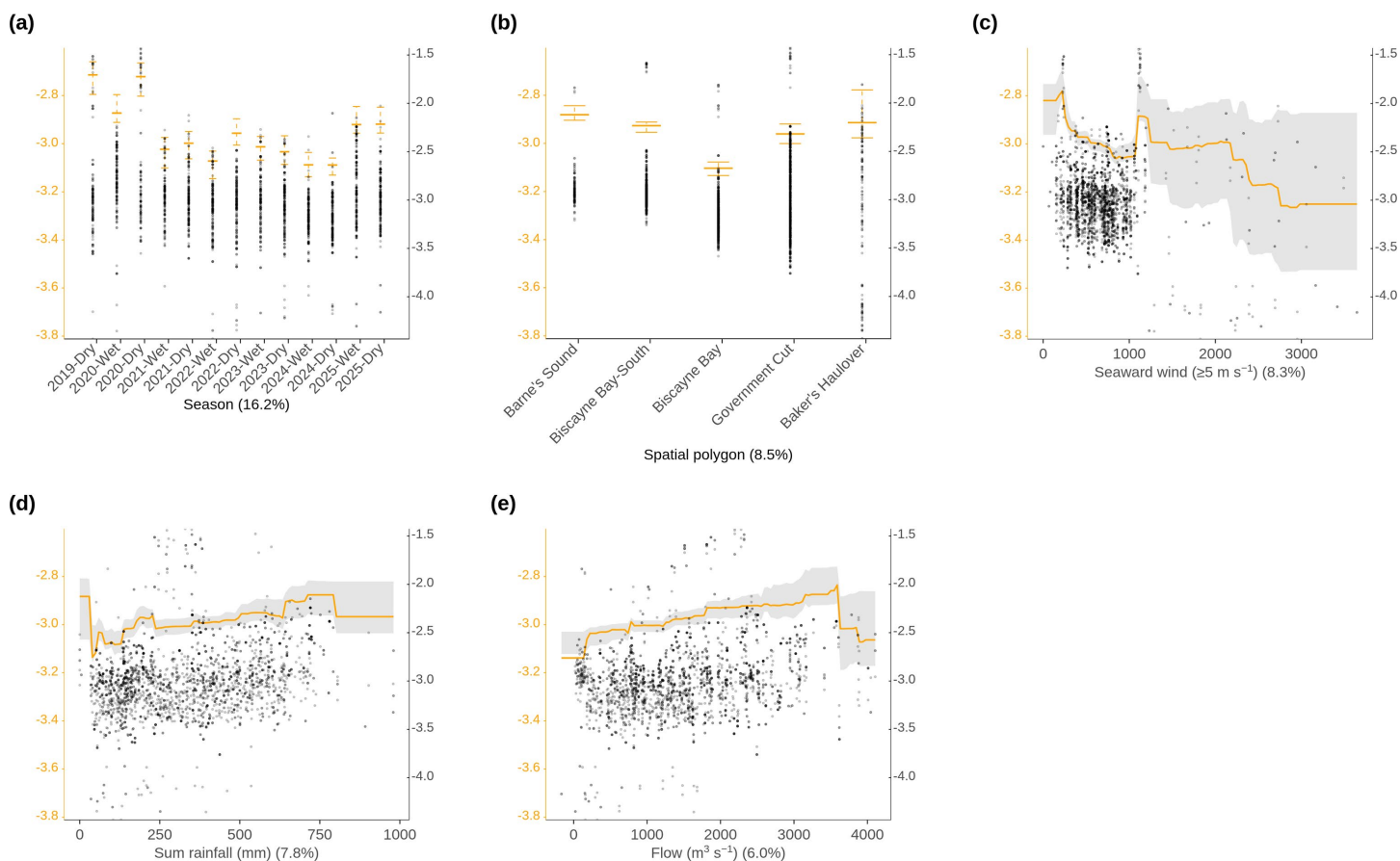


Figure 35. Orthophosphate, DERM. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed orthophosphate concentration to gradients in season (a), the spatial polygon (b), the number of seaward high-wind events (c) and cumulative rainfall over the 90 days prior to sampling (d), and flow (e) across the DERM monitoring domain (Nov 2018 to Apr 2025; $n = 2,743$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{ mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period.

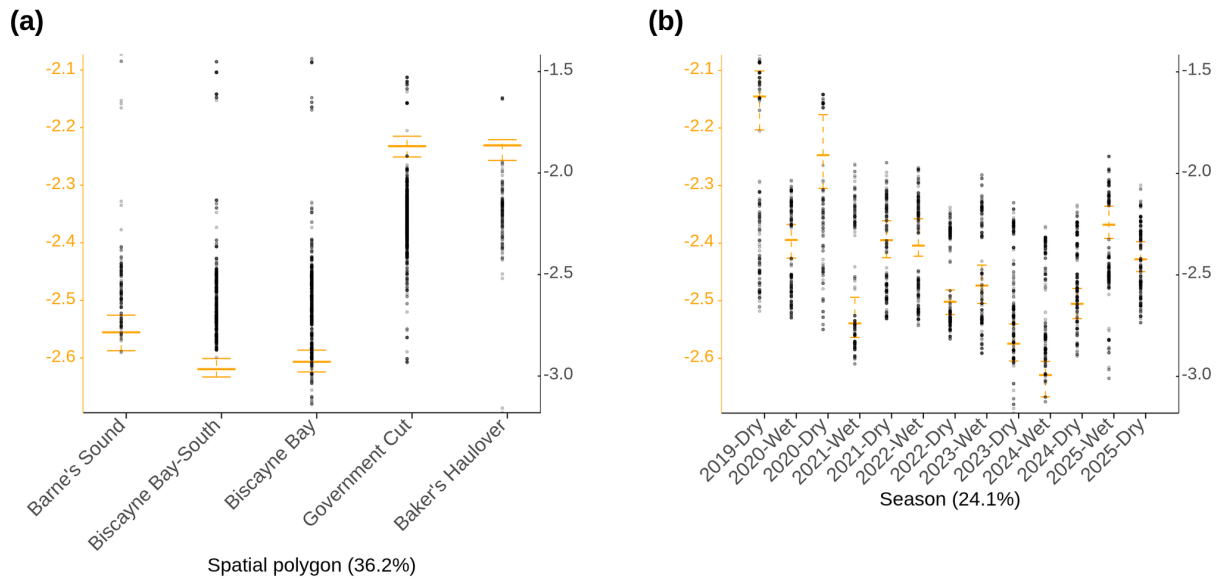


Figure 36. Total phosphorus, DERM. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed total phosphorus concentration to gradients in the spatial polygon (a) and season (b) across the DERM monitoring domain (Nov 2018 to Apr 2025; $n = 2,752$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log mg L⁻¹, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

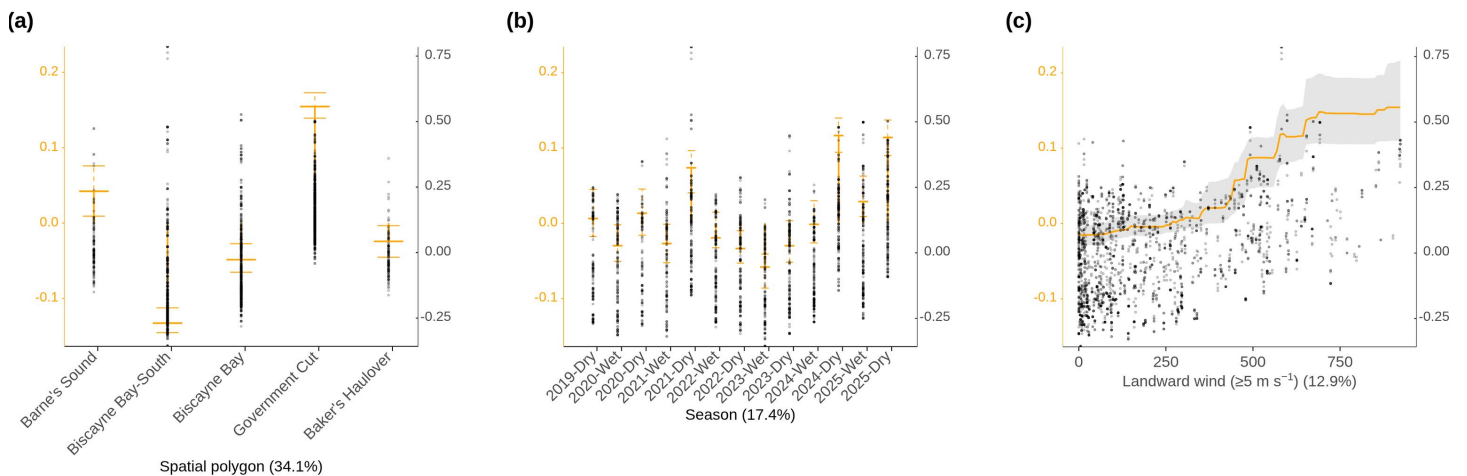


Figure 37. Turbidity, DERM. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed turbidity concentration to gradients in the spatial polygon (a), season (b), and the number of landward high-wind events counted over the 3 days prior to sampling (c) across the DERM monitoring domain (Nov 2018 to Apr 2025; $n = 2,751$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the

left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log NTU, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period.

3.5.3. Watershed Information Network (WIN)

3.5.3.1. Monitoring network and spatial coverage

The Florida Department of Environmental Protection's Watershed Information Network (WIN) is a statewide repository that aggregates water-quality data collected by many independent monitoring programs. For this analysis we drew on the WIN records for the Florida Keys and the surrounding waters of Florida Bay. After data cleaning and site filtering, the WIN Keys dataset comprised 295 unique monitoring sites. These contributed 19,848 individual water-quality observations over the period November 2018 to April 2025. The observations span seven analytes: nitrate-nitrite, nitrite, nitrogen-total, orthophosphate, total phosphorus, silica, and total suspended solids (TSS).

The WIN Keys dataset is unusual among the data sources considered in this report. Its monitoring sites were sampled by nine different agencies and programs (Figure 6). These include Florida International University, the South Florida Water Management District, Florida LAKEWATCH, Monroe County, Mote Marine Laboratory, and several Florida DEP and Florida Keys National Marine Sanctuary programs. Florida International University and the South Florida Water Management District together contributed roughly 70% of all observations. Because different agencies use different sampling designs, equipment, laboratories, and target sites, we included the sampling agency as a categorical predictor in every WIN BRT model.

Each WIN site was assigned to one of nine spatial polygons spanning the Florida Keys and Florida Bay (Figure 6). These polygons are Big Cypress, Everglades National Park, Biscayne Bay-South, Barne's Sound, the eastern, middle, and western basins of Florida Bay, Key West, and the Dry Tortugas. As in the DERM analysis, these polygons are spatial units rather than inlet-outflow exposure areas. They were included to absorb residual spatial structure not captured by the other predictors. Sampling effort was highly uneven. The Key West polygon alone contained 152 of the 295 sites and 7,526 of the 19,848 observations. The Dry Tortugas contributed only three sites and 64 observations (Figure 38).

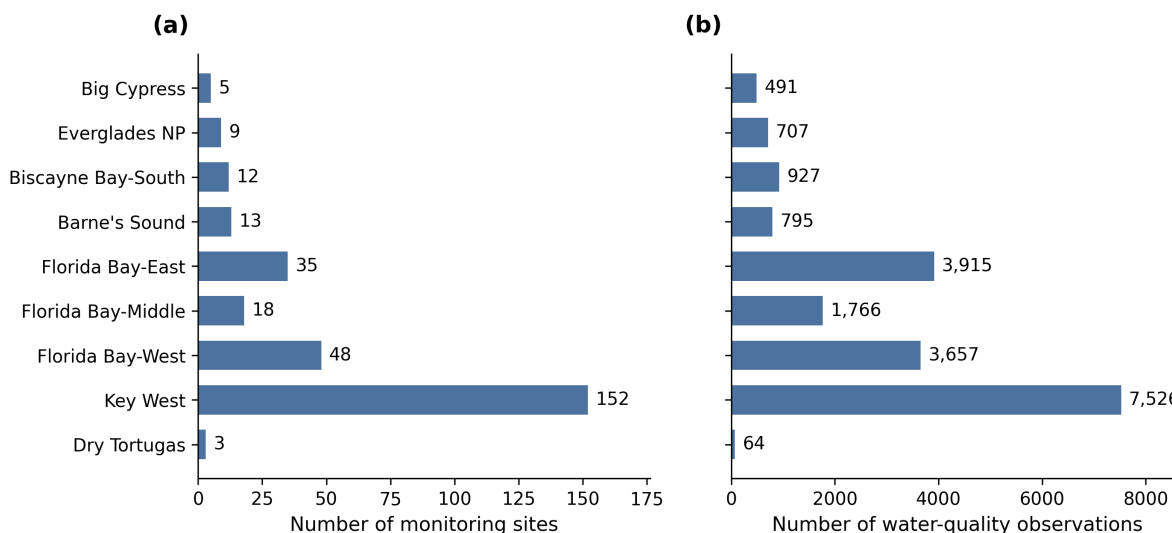


Figure 38. Spatial coverage of WIN water-quality monitoring effort by spatial polygon, ordered from north (top) to south (bottom). Panel (a) shows the number of unique monitoring sites in each polygon; panel (b) shows the total number of water-quality observations contributed by each polygon across the seven analytes considered in this analysis. Numeric values are printed at the end of each bar.

3.5.3.2. Modeling spatial and temporal variations in water-quality analytes

We modeled the seven WIN analytes using the same boosted regression tree (BRT) framework, candidate predictor set, and collinearity screening described in the Methods. In addition to the spatial polygon, season, depth, flow, rainfall, and wind predictors, each WIN model included sampling agency as a categorical predictor with nine levels, one per contributing agency. On the partial dependency plots, the sampling-agency panel orders the nine agencies along the x-axis by ascending sample size, so that sampling effort increases from left to right. The MDL-adjusted (Flynn-adjusted) log-concentrations of the seven analytes spanned a broad range, both among analytes and within each analyte (Figure 39).

Across the seven analytes, the WIN BRTs explained between 53.0% (nitrate-nitrite) and 84.8% (nitrogen-total) of the variation in the training data. They explained between 31.2% (TSS) and 80.0% (nitrogen-total) of the cross-validated variation (Table 5). Reducing the bag fraction from 0.8 to 0.5 changed each performance metric by no more than ~1 percentage point. The exception was the cross-validated performance of TSS, which fell by ~3 points. TSS had by far the smallest sample ($n = 253$).

The predictors explaining each analyte's variation differed markedly across the seven WIN analytes (Table 6; Figure A61). Most strikingly, sampling agency was the single most influential predictor for four of the seven analytes. This was overwhelmingly so for nitrogen-total, where it alone accounted for 66.0% of the explained variation. It was also the leading predictor for orthophosphate (64.7%), total phosphorus (37.3%), and nitrate-nitrite (33.1%). The spatial polygon ranked first for silica, depth for nitrite, and season for TSS. Partial dependency response plots for each analyte are shown in Figures 40 to 46.

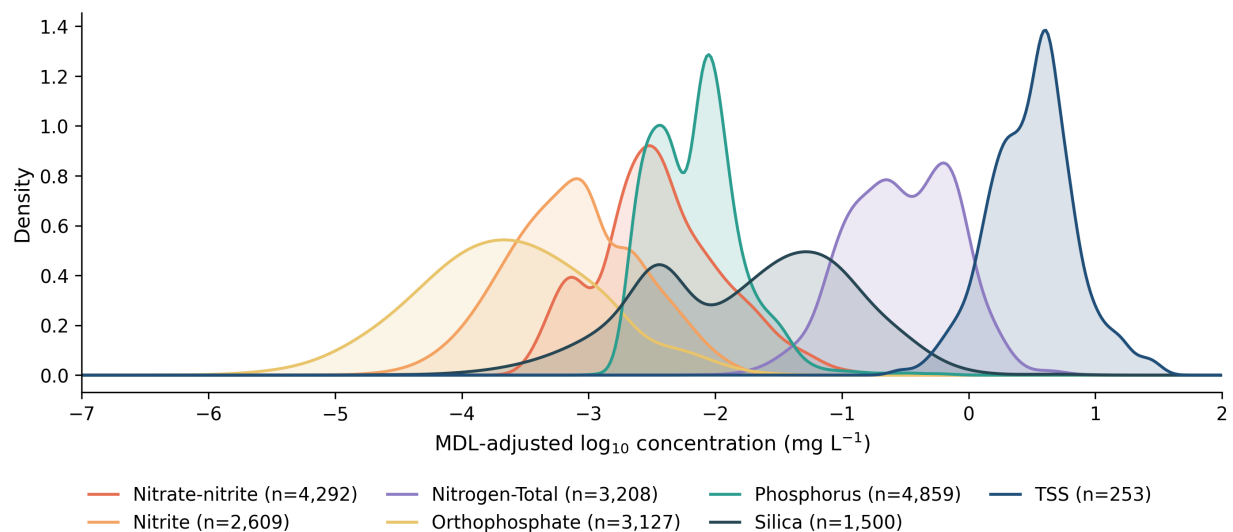


Figure 39. Variations in the method detection limit (MDL) adjusted $\log_{10}$ concentration of the seven WIN water-quality analytes, November 2018 to April 2025. Density curves are kernel density estimates derived from all observations available for each analyte; all seven analytes are reported in mg L^{-1} and are shown on a single panel. MDL corrections follow the Flynn-adjustment method (see Methods).

Table 5. Boosted regression tree (BRT) model performance statistics for the seven water-quality analytes drawn from the WIN database for the Florida Keys, November 2018 to April 2025. cv, cross-validated; cvPercentage explained is the metric used to assess model performance, and is shown in bold for each sensitivity run. The lower block (bag fraction = 0.5) reports a sensitivity run in which the proportion of training data used at each iteration was reduced from the default 0.8.

	Nitrate-Nitrite	Nitrite	Nitrogen-total	Ortho-phosphate	Total Phosphorus	Silica	TSS
<i>Model parameters</i>							
Number of observations	4292	2609	3208	3127	4859	1500	253
Tree complexity	5	5	5	5	5	5	5
Learning rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Bag fraction	0.8	0.8	0.8	0.8	0.8	0.8	0.8
Number of trees	16250	10700	18050	8150	20900	11900	6000
<i>Model performance (bag fraction = 0.8)</i>							
Percentage explained (%)	53.0	59.0	84.8	80.0	71.8	70.8	70.7
cvPercentage explained (%)	41.6	47.2	80.0	75.1	63.4	57.2	31.2
<i>Model performance (bag fraction = 0.5)</i>							
Percentage explained (%)	52.9	58.1	84.7	79.1	71.2	70.5	70.5
cvPercentage explained (%)	41.9	47.1	79.8	74.6	62.9	56.4	28.4

Table 6. Predictors of variation in each WIN water-quality analyte, ranked by relative influence (%) in the corresponding boosted regression tree (BRT) model, with their cumulative influence. The predictors listed for each analyte are those retained as influential and visualized in its partial dependency plots (Figures 40 to 46). Values in parentheses give the temporal window in days prior to sampling (see Methods).

Analyte	Predictor	Relative influence (%)	Cumulative influence (%)
<i>Nitrate-nitrite</i>	Sampling agency	33.1	33.1
	Spatial polygon	12.2	45.3
	Season	9.8	55.1
	Flow (90 d)	7.4	62.5
	Depth	7.0	69.5
<i>Nitrite</i>	Depth	32.6	32.6
	Spatial polygon	22.5	55.1
	Season	9.3	64.4
	Flow (30 d)	6.9	71.3
<i>Nitrogen-total</i>	Sampling agency	66.0	66.0
	Depth	9.8	75.8
	Rainfall (3 d)	5.9	81.7
	Season	5.8	87.5
<i>Orthophosphate</i>	Sampling agency	64.7	64.7
	Spatial polygon	20.3	85.0
	Depth	4.0	89.0
	Flow (30 d)	2.2	91.2
<i>Total Phosphorus</i>	Sampling agency	37.3	37.3
	Spatial polygon	27.2	64.5
	Season	10.6	75.1
	Water Year	3.0	78.1
<i>Silica</i>	Spatial polygon	30.8	30.8
	Depth	23.5	54.3
	Season	10.5	64.8
	Rainfall (7 d)	5.0	69.8
	Rainfall (3 d)	4.2	74.0
<i>TSS</i>	Season	20.0	20.0
	Landward wind (90 d)	14.0	34.0
	Rainfall (7 d)	9.0	43.0
	Spatial polygon	7.5	50.5
	Rainfall (90 d)	6.2	56.7

The prominence of sampling agency in the WIN models warrants careful interpretation. Because each agency tends to monitor a distinct set of sites, the sampling-agency predictor and the spatial-polygon predictor are partly confounded. An apparent agency effect may reflect real geographic differences in water quality among the areas an agency happens to sample. It may instead reflect genuine methodological differences among agencies, in sampling design, equipment, or laboratory analysis. It may also reflect some combination of the two. The BRT framework cannot fully separate these contributions, and the very large agency influence on the nitrogen and total phosphorus analytes suggests that the confounding effect is substantial.

This has a clear practical implication for the use of aggregated, multi-agency databases such as WIN. Pooling records from many programs greatly increases spatial and temporal coverage. However, our results indicate that the resulting dataset cannot be used to interpret broad-scale spatial patterns in water quality at face value. Where agency and geography are confounded, a map of pooled concentrations may track which agency sampled where as much as any underlying water quality gradient. Analyses of WIN-type datasets should therefore retain sampling agency as an explicit term, and treat large-area spatial inferences cautiously unless agency effects have been accounted for.

3.5.3.3. Nitrate-nitrite

Variations in *nitrate-nitrite* concentrations were led by sampling agency, followed by the spatial polygon, season, flow, and depth (Table 6; Figure 33). Sampling agency alone accounted for 33.1% of the explained variation, and the spatial polygon a further 12.2%. As noted above, these two terms are partly confounded and should not be read as wholly independent. Modeled nitrate-nitrite increased with flow summed over the 90 days prior to sampling and showed a modest seasonal signal. Together the five retained predictors accounted for 69.5% of the explained variation.

3.5.3.4. Nitrite

Variations in *nitrite* concentrations were predominantly explained by depth and the spatial polygon (Table 6; Figure 34). Sampling agency was not among the influential predictors, in contrast to most other WIN analytes. Depth was the single strongest driver: modeled nitrite declined steeply over the upper few metres of the water column. The spatial polygon contributed a further 22.5%, with weaker contributions from season and flow. The four retained predictors together accounted for 71.3% of the explained variation.

3.5.3.5. Nitrogen-total

Variations in *nitrogen-total* concentrations were dominated by sampling agency to a degree seen for no other analyte in this report. It alone accounted for 66.0% of the explained variation (Table 6; Figure 35). No other predictor exceeded 10%, with depth, recent rainfall, and season each contributing modestly. Such overwhelming dependence on the agency term means the nitrogen-total model is best read as a statement about between-program differences rather than environmental gradients. Any spatial interpretation of WIN total-nitrogen data should be treated with particular caution.

3.5.3.6. Orthophosphate

Variations in *orthophosphate* concentrations were also dominated by sampling agency (64.7%), with the spatial polygon second (20.3%) (Table 6; Figure 36). Together these two partly confounded categorical terms accounted for 85.0% of the explained variation, leaving depth and flow with only minor roles. As for nitrogen-total, the strong agency signal limits how far the orthophosphate model can be used to infer genuine spatial patterns.

3.5.3.7. Total Phosphorus

Variations in total phosphorus concentrations were explained by sampling agency (37.3%) and the spatial polygon (27.2%), with a smaller seasonal contribution (Table 6; Figure 37). The agency and polygon terms were more evenly balanced than for orthophosphate or nitrogen-total, but together still dominated the model. Modeled total phosphorus showed a modest seasonal signal and little systematic trend across water years.

3.5.3.8. Silica

Variations in *silica* concentrations were predominantly explained by the spatial polygon and depth (Table 6; Figure 38). Unlike the nitrogen and total phosphorus analytes, sampling agency was not influential, so the silica model carries a clearer spatial signal. Modeled silica varied strongly among polygons and declined with depth. Season and cumulative rainfall over the 3-day and 7-day windows made smaller contributions. The five retained predictors together accounted for 74.0% of the explained variation.

3.5.3.9. Total suspended solids (TSS)

Variations in *total suspended solids (TSS)* concentrations were the most evenly distributed across predictors of any WIN analyte, with season ranking first at only 20.0% (Table 6; Figure 39). Counts of landward high-wind events over the 90 days prior to sampling, cumulative rainfall, and the spatial polygon each made comparable contributions. Sampling agency was not influential. The TSS model should nonetheless be interpreted cautiously. With only 253 observations, it had by far the smallest sample of any model in this report. It also had the weakest cross-validated performance (31.2%; Table 5).

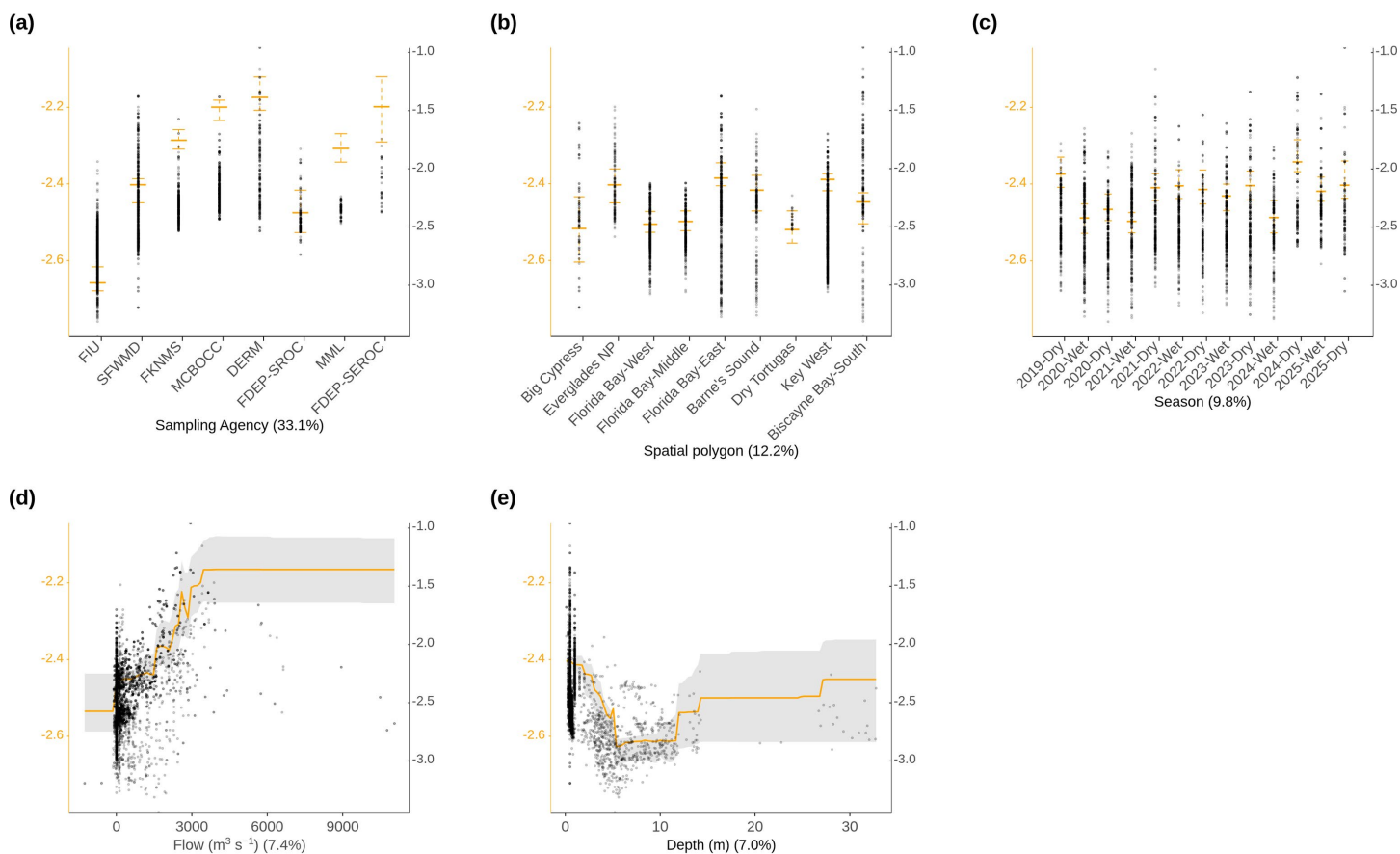


Figure 40. Nitrate-Nitrite, WIN. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrate-nitrite concentration to gradients in sampling agency (a), the spatial polygon (b), season (c), flow summed over the 90 days prior to sampling (d), and depth (e) across the WIN Florida Keys monitoring domain (Nov 2018 to Apr 2025; $n = 4,292$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for categorical predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. In the sampling-agency panel, the nine contributing agencies are ordered along the x-axis by ascending sample size (left, fewest samples; right, most).

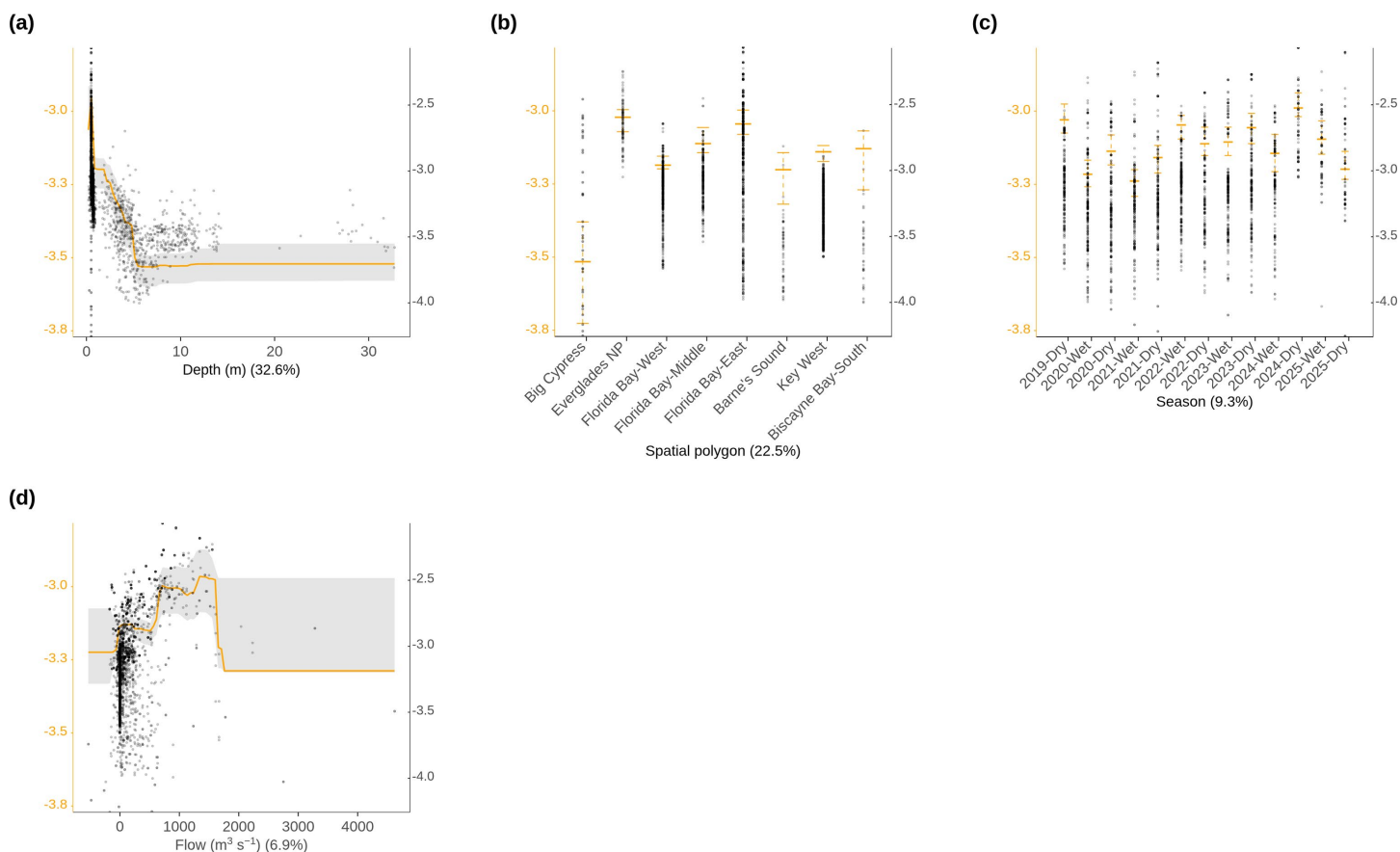


Figure 41. Nitrite, WIN. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrite concentration to gradients in depth (a), the spatial polygon (b), season (c), and flow summed over the 30 days prior to sampling (d) across the WIN Florida Keys monitoring domain (Nov 2018 to Apr 2025; $n = 2,609$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for categorical predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

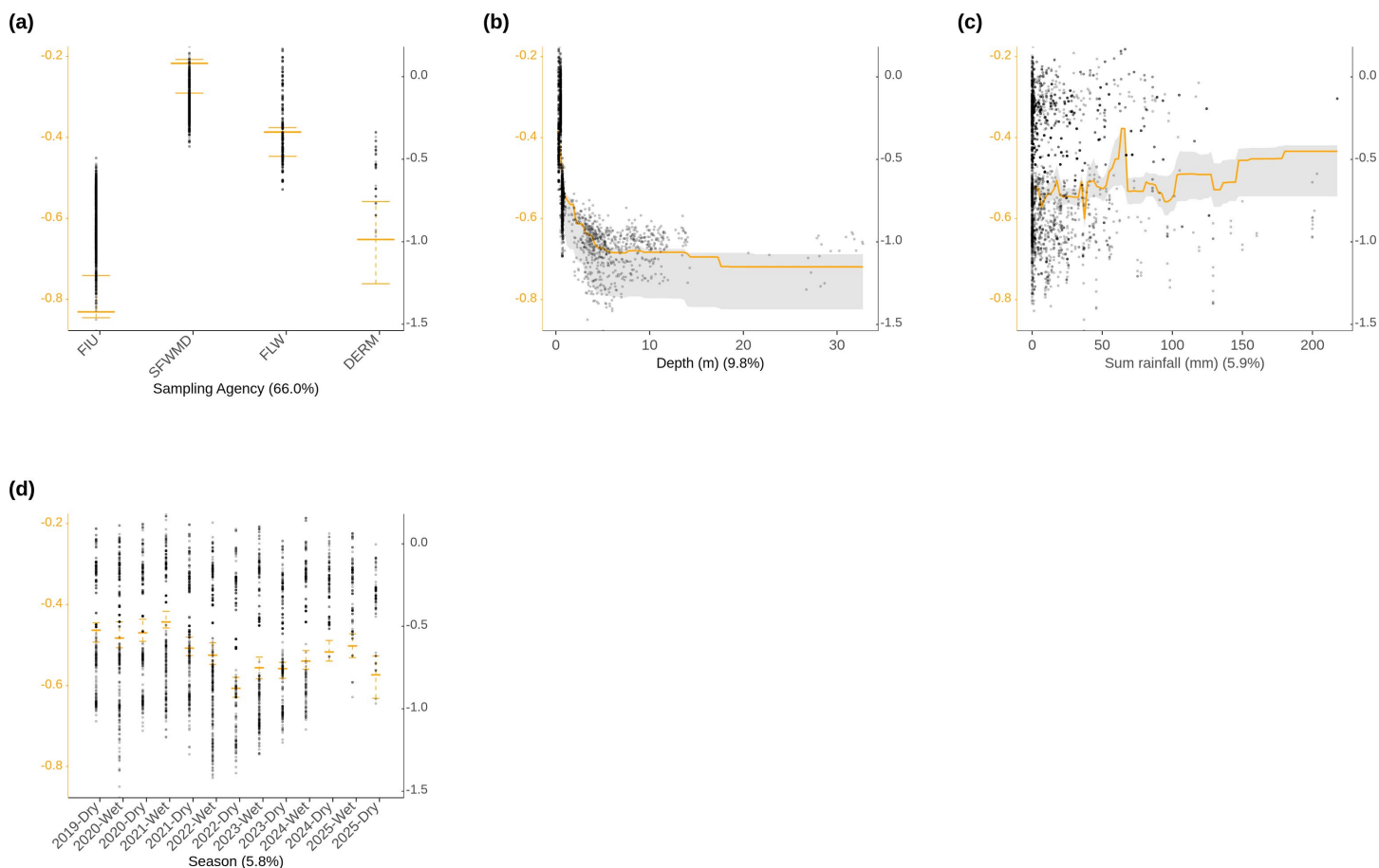


Figure 42. Nitrogen-total, WIN. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrogen-total concentration to gradients in sampling agency (a), depth (b), cumulative rainfall over the 3 days prior to sampling (c), and season (d) across the WIN Florida Keys monitoring domain (Nov 2018 to Apr 2025; $n = 3,208$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for categorical predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{ mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. In the sampling-agency panel, the nine contributing agencies are ordered along the x-axis by ascending sample size (left, fewest samples; right, most).

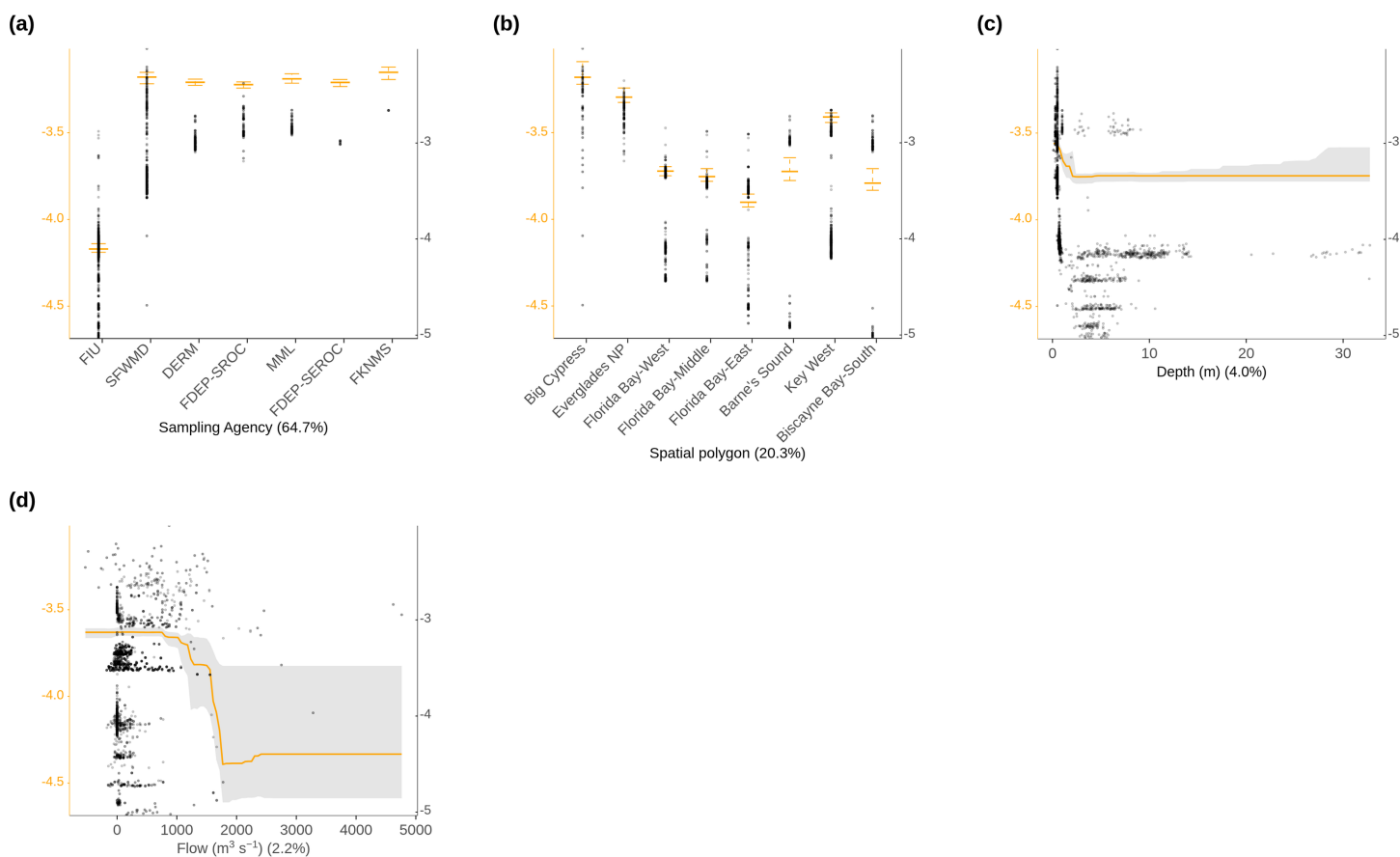


Figure 43. Orthophosphate, WIN. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed orthophosphate concentration to gradients in sampling agency (a), the spatial polygon (b), depth (c), and flow summed over the 30 days prior to sampling (d) across the WIN Florida Keys monitoring domain (Nov 2018 to Apr 2025; $n = 3,127$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for categorical predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{ mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. In the sampling-agency panel, the nine contributing agencies are ordered along the x-axis by ascending sample size (left, fewest samples; right, most).

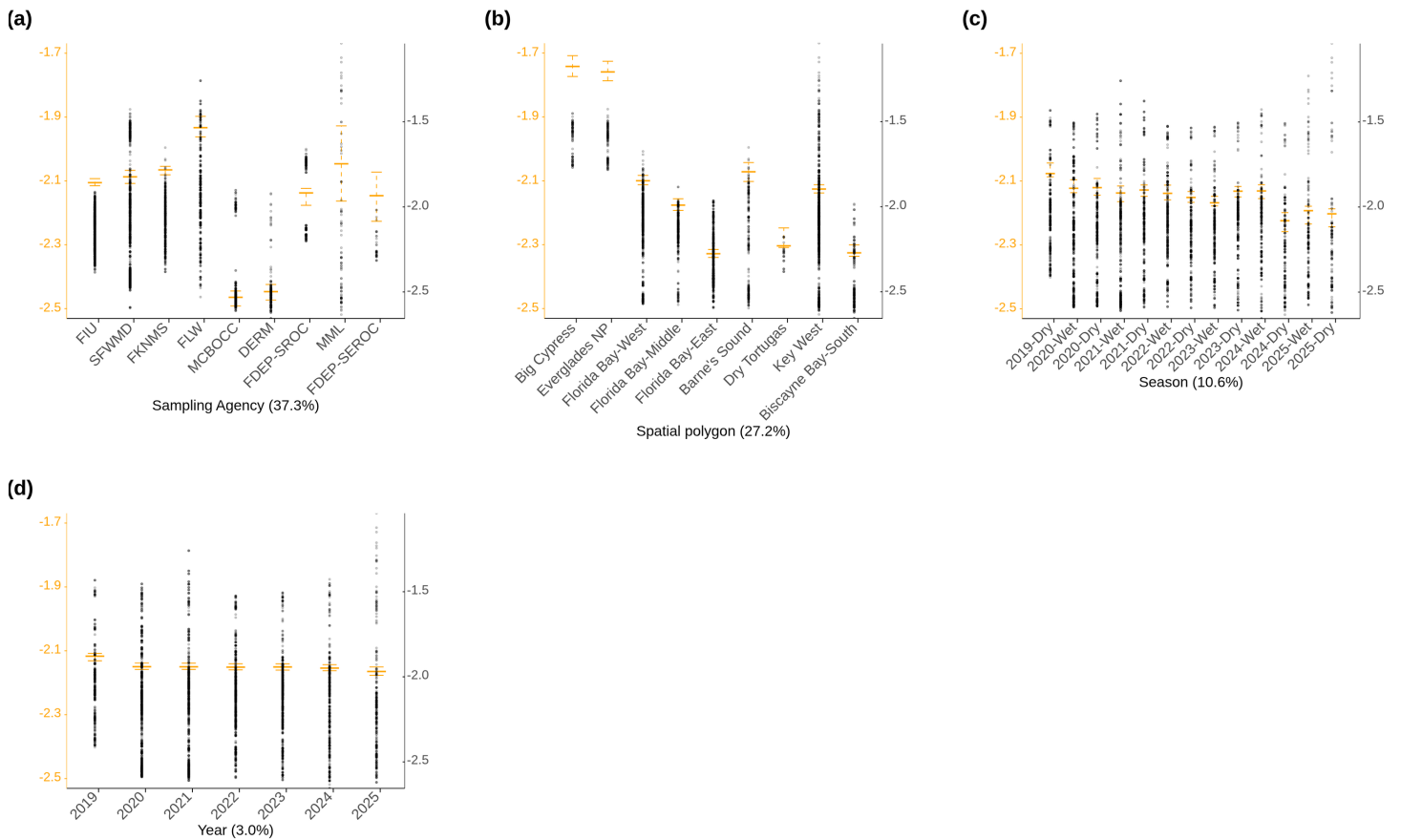


Figure 44. Total phosphorus, WIN. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed total phosphorus concentration to gradients in sampling agency (a), the spatial polygon (b), season (c), and water year (d) across the WIN Florida Keys monitoring domain (Nov 2018 to Apr 2025; $n = 4,859$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for categorical predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. In the sampling-agency panel, the nine contributing agencies are ordered along the x-axis by ascending sample size (left, fewest samples; right, most).

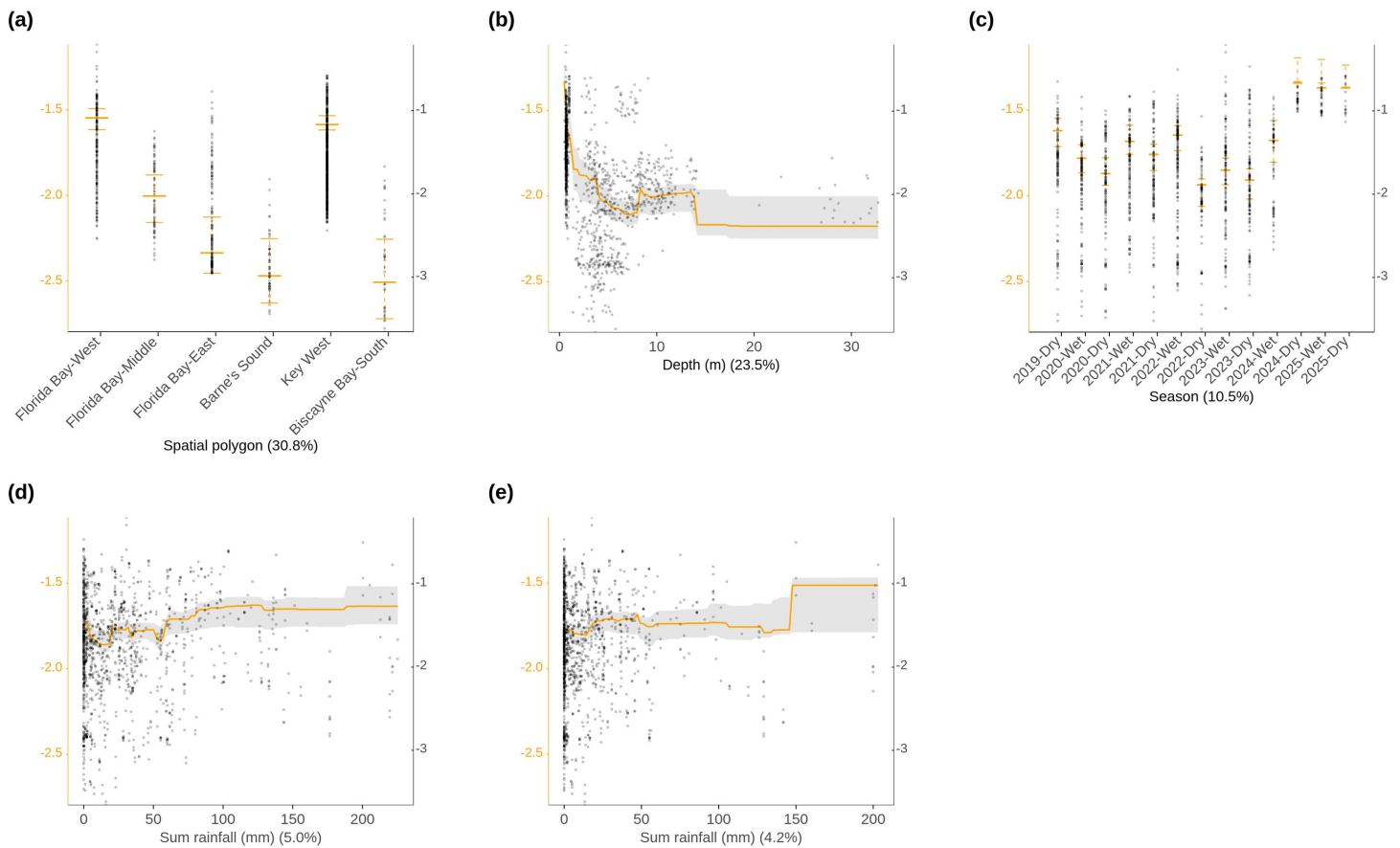


Figure 45. Silica, WIN. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed silica concentration to gradients in the spatial polygon (a), depth (b), season (c), and cumulative rainfall over the 7-day and 3-day windows prior to sampling (d and e, respectively) across the WIN Florida Keys monitoring domain (Nov 2018 to Apr 2025; $n = 1,500$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for categorical predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log mg L^{-1} , corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

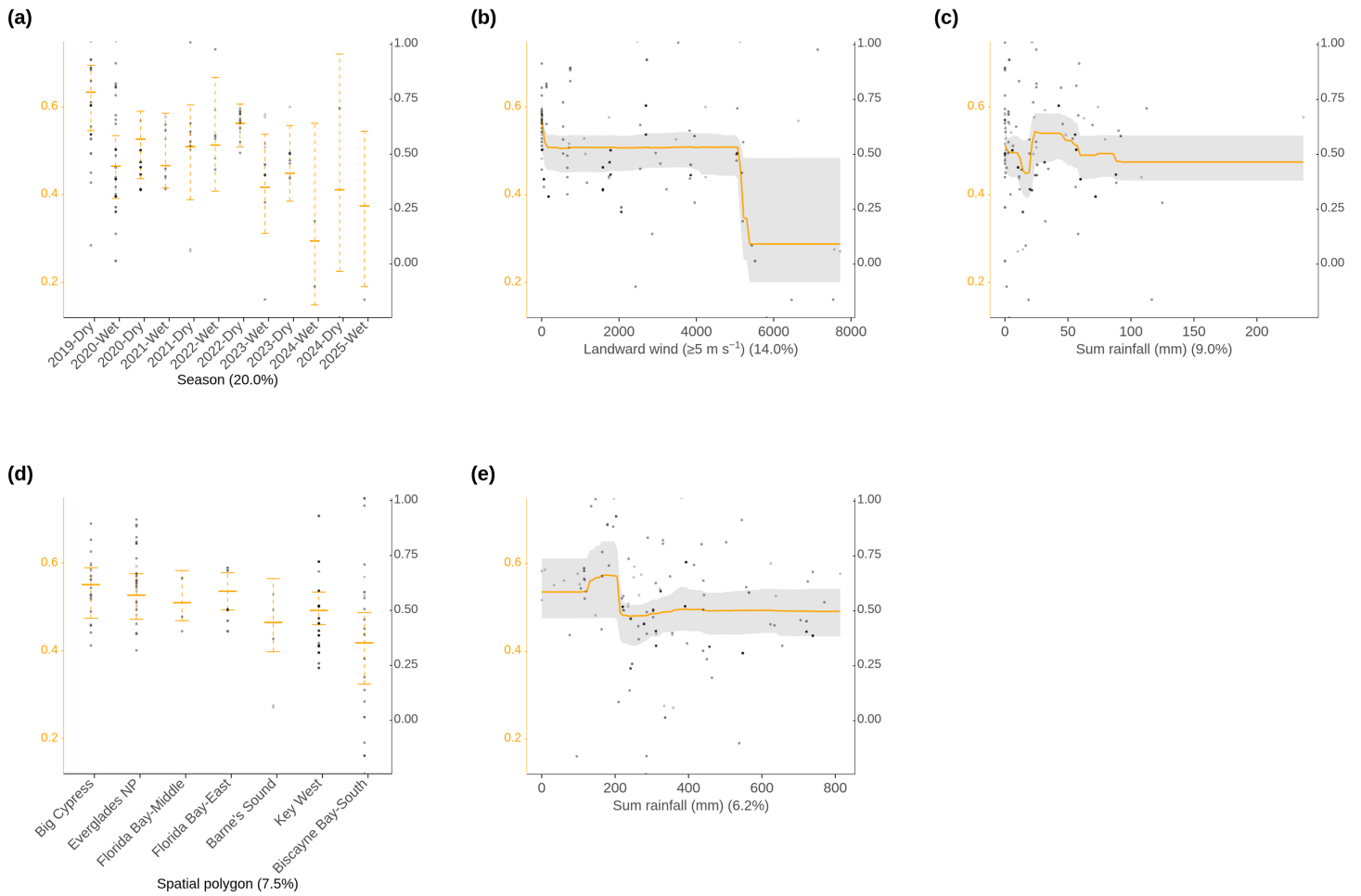


Figure 46. Total Suspended Solids, WIN. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed TSS concentration to gradients in season (a), the number of landward high-wind events counted over the 90 days prior to sampling (b), cumulative rainfall (c), and the spatial polygon (d) across the WIN Florida Keys monitoring domain (Nov 2018 to Apr 2025; $n = 253$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for categorical predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log mg L^{-1} , corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period.

3.5.4. Southeast Environmental Research Center (SERC)

3.5.4.1. Monitoring network and spatial coverage

The SERC water-quality dataset was contributed by the Southeast Environmental Research Center, which has operated a long-term water-quality monitoring network across the Florida Keys and Florida Bay. After data cleaning and a trimming of the time series, the SERC dataset comprised 112 unique monitoring sites. These contributed 12,564 individual water-quality observations over the period November 2018 to December 2024. The observations span seven analytes: nitrate, nitrite, nitrogen-total, total phosphorus, salinity, silica, and turbidity. The SERC record was trimmed to end in December 2024, slightly shorter than the period used for the other three data sources.

Each SERC site was assigned to one of eight spatial polygons spanning the Florida Keys and Florida Bay (Figure 7). These polygons are Biscayne Bay, Biscayne Bay-South, Barne's Sound, the eastern, middle, and western basins of Florida Bay, Key West, and the Dry Tortugas. As in the DERM and WIN analyses, these polygons are spatial units rather than inlet-outflow exposure areas. They were included to absorb residual spatial structure. Sampling effort was uneven: the Key West polygon contained 54 of the 112 sites and 5,385 of the 12,564 observations, while Biscayne Bay contributed a single site (Figure 47).

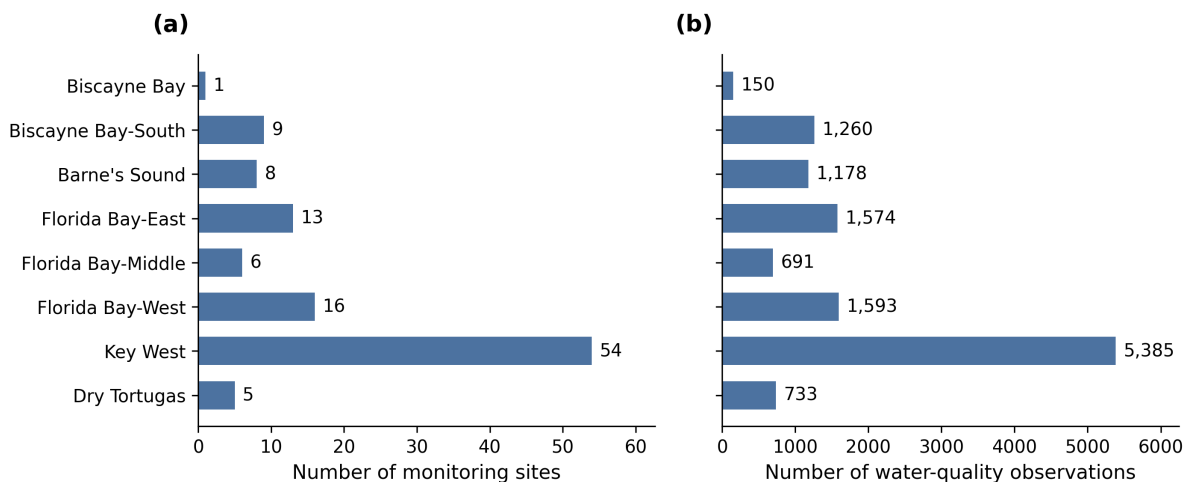


Figure 47. Spatial coverage of SERC water-quality monitoring effort by spatial polygon, ordered from north (top) to south (bottom). Panel (a) shows the number of unique monitoring sites in each polygon; panel (b) shows the total number of water-quality observations contributed by each polygon across the seven analytes considered in this analysis. Numeric values are printed at the end of each bar.

3.5.4.2. Modeling spatial and temporal variations in water-quality analytes

We modeled the seven SERC analytes using the same boosted regression tree (BRT) framework, candidate predictor set, and collinearity screening described in the Methods. The spatial polygon served as the categorical spatial predictor. The five nutrient analytes and turbidity were modeled as MDL-adjusted (Flynn-adjusted) log₁₀ values, whereas salinity was modeled on its natural measurement scale. Because salinity and turbidity are

measured on scales different from the five nutrient analytes, the three groups are shown on separate panels (Figure 48).

Across the seven analytes, the SERC BRTs explained between 34.2% (nitrite) and 64.0% (nitrogen-total) of the variation in the training data. They explained between 15.4% (nitrite) and 44.2% (nitrogen-total) of the cross-validated variation (Table 7). SERC model performance was lower than for the other three data sources. Several models, notably those for nitrate, nitrite, and silica, explained less than a quarter of the cross-validated variation. Their predictor rankings should therefore be read with corresponding caution. Reducing the bag fraction from 0.8 to 0.5 changed cross-validated performance by no more than ~1 percentage point for every analyte.

The predictors explaining each analyte's variation were broadly consistent across the seven SERC analytes (Table 8; Figure A62). Season was the single most influential predictor for five of the seven analytes (nitrate, nitrogen-total, total phosphorus, salinity, and silica), and depth ranked first for nitrite and turbidity. The spatial polygon, preceding rainfall, and flow made smaller and more variable contributions. Relative to the KJCAP, DERM, and WIN models, the SERC models leaned more heavily on season and depth and less on persistent spatial structure. Partial dependency response plots for each analyte are shown in Figures 49 to 55.

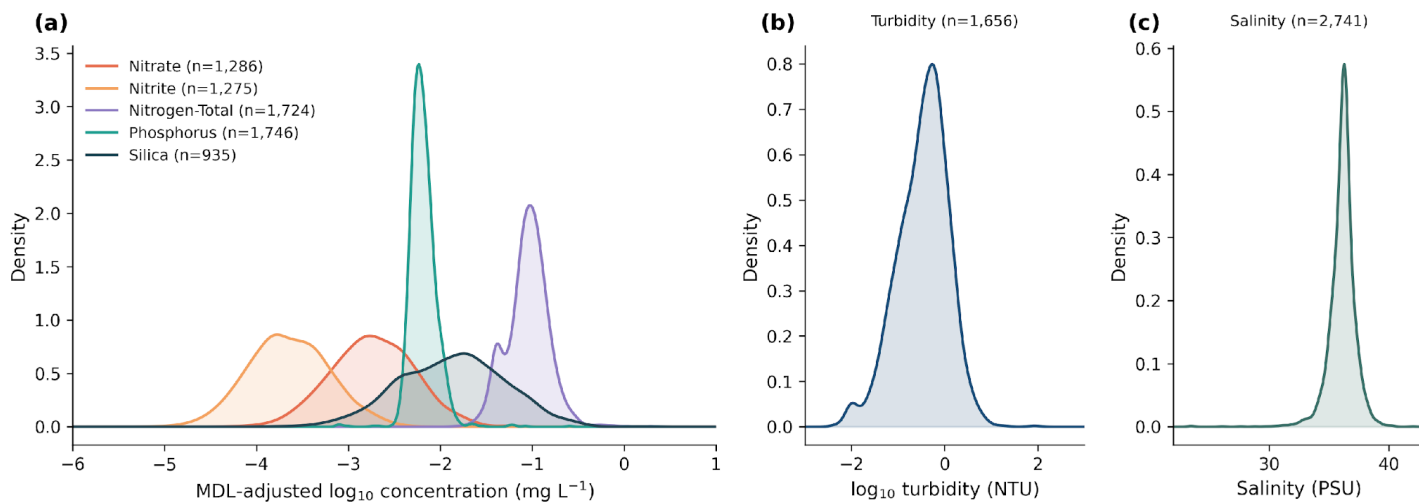


Figure 48. Density distributions of the seven SERC analytes, November 2018 to December 2024. Density curves are kernel density estimates derived from all observations available for each analyte. Panel (a) shows the method detection limit (MDL) adjusted $\log_{10}$ values of the five nutrient analytes (mg L^{-1}); panel (b) shows MDL-adjusted $\log_{10}$ turbidity (NTU); and panel (c) shows salinity on its natural measurement scale. The three groups are displayed on separate panels because they are measured on different scales. MDL corrections follow the Flynn-adjustment method (see Methods).

Table 7. Boosted regression tree (BRT) model performance statistics for the seven water-quality analytes monitored by SERC from November 2018 to December 2024. cv, cross-validated; cvPercentage explained is the metric used to assess model performance, and is shown in bold for each sensitivity run. The lower block (bag fraction = 0.5) reports a sensitivity run in which the proportion of training data used at each iteration was reduced from the default 0.8.

	Nitrate	Nitrite	Nitrogen-total	Total Phosphorus	Salinity	Silica	Turbidity
<i>Model parameters</i>							
Number of observations	1286	1275	1724	1746	2741	934	1656
Tree complexity	5	5	5	5	5	5	5
Learning rate	0.001	0.001	0.001	0.001	0.001	0.001	0.001
Bag fraction	0.8	0.8	0.8	0.8	0.8	0.8	0.8
Number of trees	5250	5500	12100	5500	11450	4600	12600
<i>Model performance (bag fraction = 0.8)</i>							
Percentage explained (%)	35.1	34.2	64.0	42.8	59.6	41.4	56.7
cvPercentage explained (%)	16.1	15.4	44.2	27.6	40.5	22.2	34.8
<i>Model performance (bag fraction = 0.5)</i>							
Percentage explained (%)	37.2	33.2	63.3	41.2	61.7	43.1	57.5
cvPercentage explained (%)	17.0	15.6	44.8	26.8	41.0	21.5	35.4

Table 8. Predictors of variation in each SERC water-quality analyte, ranked by relative influence (%) in the corresponding boosted regression tree (BRT) model, with their cumulative influence. The predictors listed for each analyte are those retained as influential and visualized in its partial dependency plots (Figures 49 to 55). Values in parentheses give the temporal window in days prior to sampling (see Methods).

Analyte	Predictor	Relative influence (%)	Cumulative influence (%)
<i>Nitrate</i>	Season	30.5	30.5
	Rainfall (90 d)	12.2	42.7
	Depth	12.0	54.7
<i>Nitrite</i>	Depth	25.2	25.2
	Season	15.9	41.1
	Spatial polygon	8.1	49.2
	Rainfall (7 d)	7.6	56.8
<i>Nitrogen-total</i>	Season	31.1	31.1
	Rainfall (90 d)	8.9	40.0
	Depth	8.5	48.5
	Flow (7 d)	5.8	54.3
<i>Total Phosphorus</i>	Season	43.6	43.6
	Depth	7.2	50.8
<i>Salinity</i>	Season	23.9	23.9
	Depth	19.3	43.2
	Rainfall (14 d)	7.3	50.5
<i>Silica</i>	Season	25.1	25.1
	Spatial polygon	22.1	47.2
	Depth	19.6	66.8
<i>Turbidity</i>	Depth	17.8	17.8
	Spatial polygon	17.4	35.2
	Season	17.0	52.2
	Landward wind (1 d)	5.8	58.0

3.5.4.3. Nitrate

Variations in *nitrate* concentrations were explained mainly by season, with smaller contributions from cumulative rainfall over the 90 days prior to sampling and depth (Table 8; Figure 49). Modeled nitrate increased with preceding rainfall. The nitrate model was among the weakest in this report, explaining only 16.1% of the cross-validated variation (Table 7), so these rankings should be interpreted cautiously.

3.5.4.4. Nitrite

Variations in *nitrite* concentrations were led by depth, followed by season, the spatial polygon, and recent rainfall (Table 8; Figure 50). Modeled nitrite declined with depth. With the lowest cross-validated performance of any model in this report (15.4%; Table 7), the nitrite model explains little of the observed variation, and its predictor rankings are correspondingly uncertain.

3.5.4.5. Nitrogen-total

Variations in *nitrogen-total* concentrations were predominantly explained by season, with cumulative rainfall, depth, and preceding flow making smaller contributions (Table 8; Figure 51). The nitrogen-total model was the strongest of the SERC set, explaining 44.2% of the cross-validated variation (Table 7).

3.5.4.6. Total Phosphorus

Variations in total phosphorus concentrations were explained almost entirely by season, which alone accounted for 43.6% of the explained variation, with depth a distant second (Table 8; Figure 52). The strong, near-singular seasonal signal is consistent with the marked total phosphorus seasonality seen in the other data sources.

3.5.4.7. Salinity

Variations in *salinity* were explained by season and depth in roughly equal measure. A smaller contribution came from cumulative rainfall over the 14 days prior to sampling (Table 8; Figure 53). Modeled salinity declined with preceding rainfall, consistent with freshwater dilution following wet periods.

3.5.4.8. Silica

Variations in *silica* concentrations were explained by season, the spatial polygon, and depth, each contributing roughly a fifth of the explained variation (Table 8; Figure 54). The comparatively even split among these three predictors, together with low cross-validated performance (22.2%; Table 7), indicates no single dominant driver.

3.5.4.9. Turbidity

Variations in *turbidity* were the most evenly distributed across predictors of any SERC analyte, with depth, the spatial polygon, and season each contributing close to 17% (Table 8; Figure 55). Counts of landward high-wind events in the day before sampling made a smaller contribution. Modeled turbidity declined with depth.

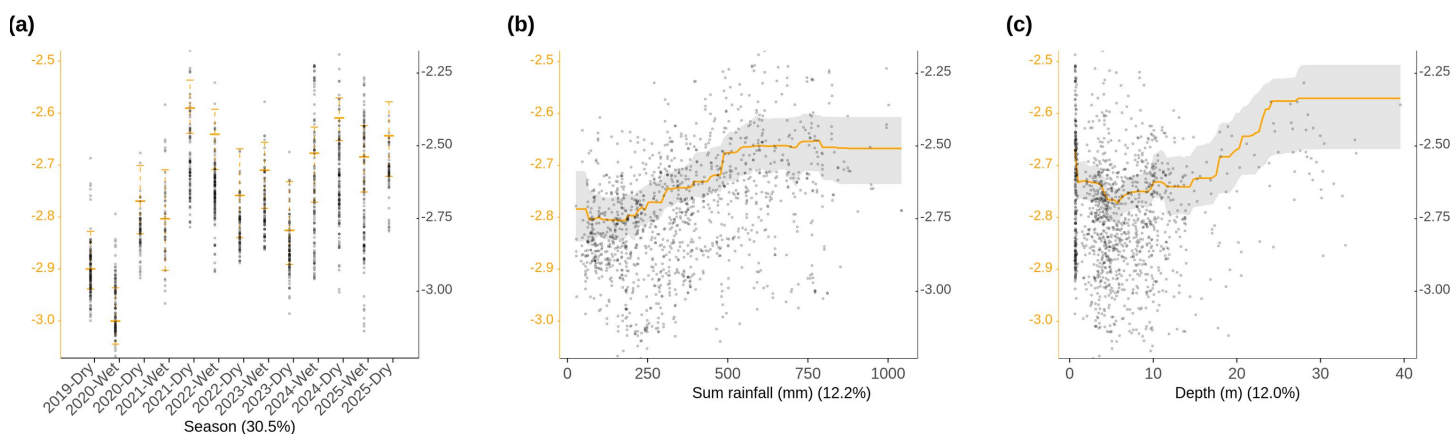


Figure 49. Nitrate, SERC. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrate concentration to gradients in season (a), cumulative rainfall over the 90 days prior to sampling (b), and depth (c) across the SERC monitoring domain (Nov 2018 to Dec 2024; $n = 1,286$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

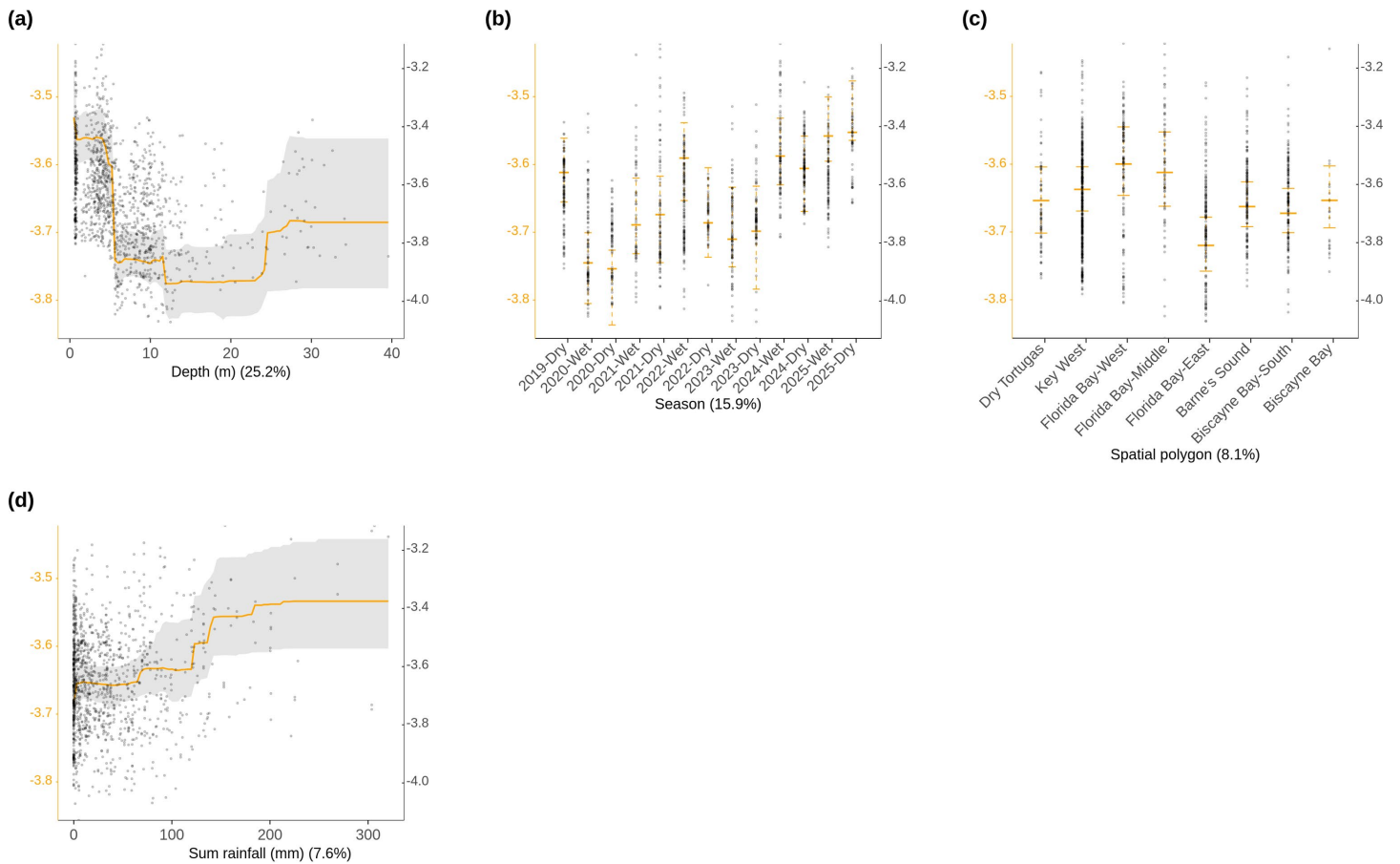


Figure 50. Nitrite, SERC. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrite concentration to gradients in depth (a), season (b), the spatial polygon (c), and cumulative rainfall over the 7 days prior to sampling (d) across the SERC monitoring domain (Nov 2018 to Dec 2024; $n = 1,275$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log mg L⁻¹, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

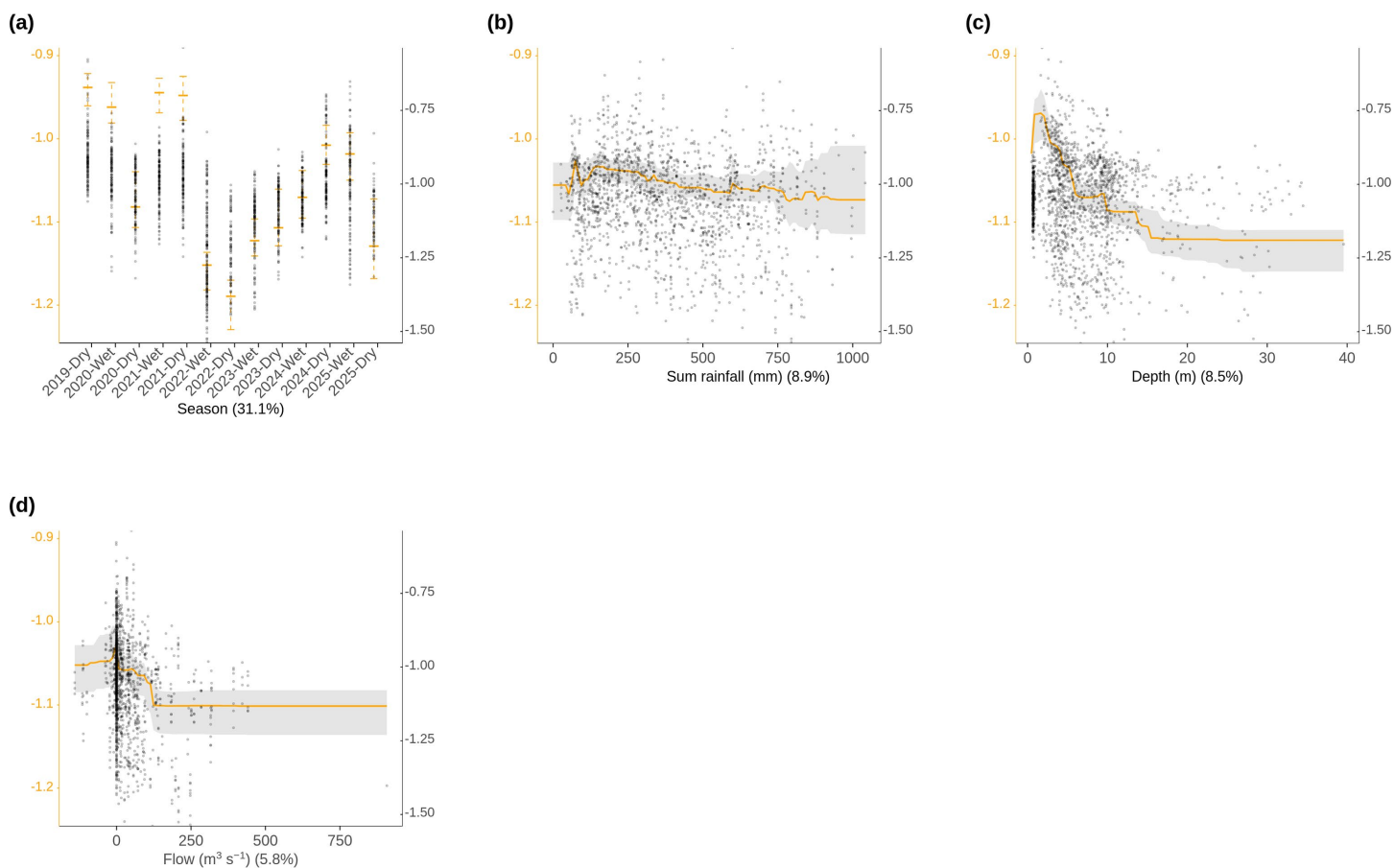


Figure 51. Nitrogen-total, SERC. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed nitrogen-total concentration to gradients in season (a), cumulative rainfall over the 90 days prior to sampling (b), depth (c), and flow summed over the 7 days prior to sampling (d) across the SERC monitoring domain (Nov 2018 to Dec 2024; $n = 1,724$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

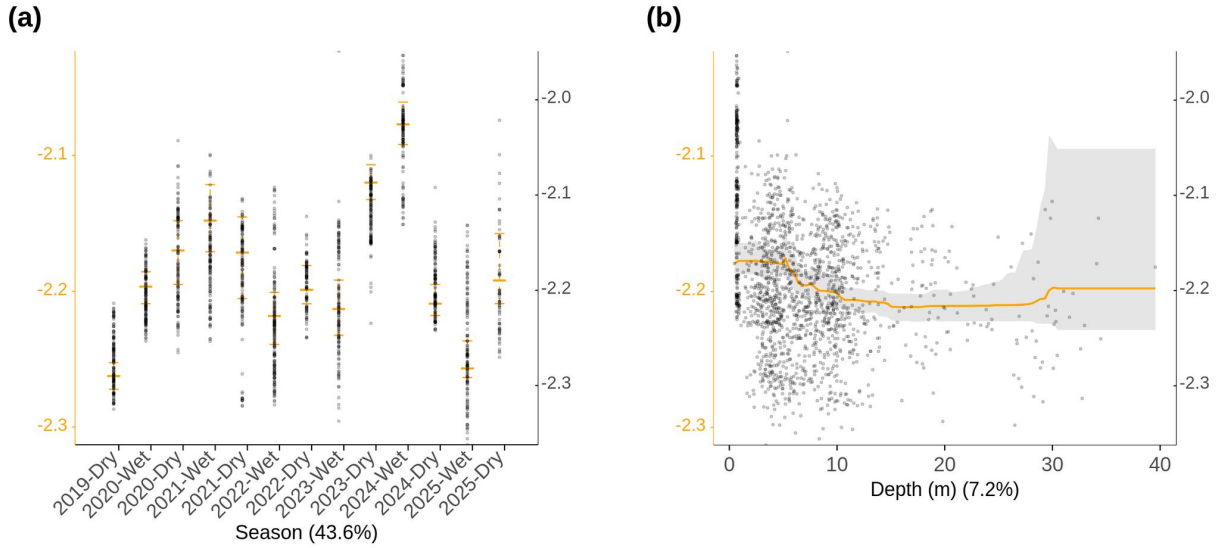


Figure 52. Total phosphorus, SERC. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed total phosphorus concentration to gradients in season (a) and depth (b) across the SERC monitoring domain (Nov 2018 to Dec 2024; $n = 1,746$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in $\log \text{mg L}^{-1}$, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

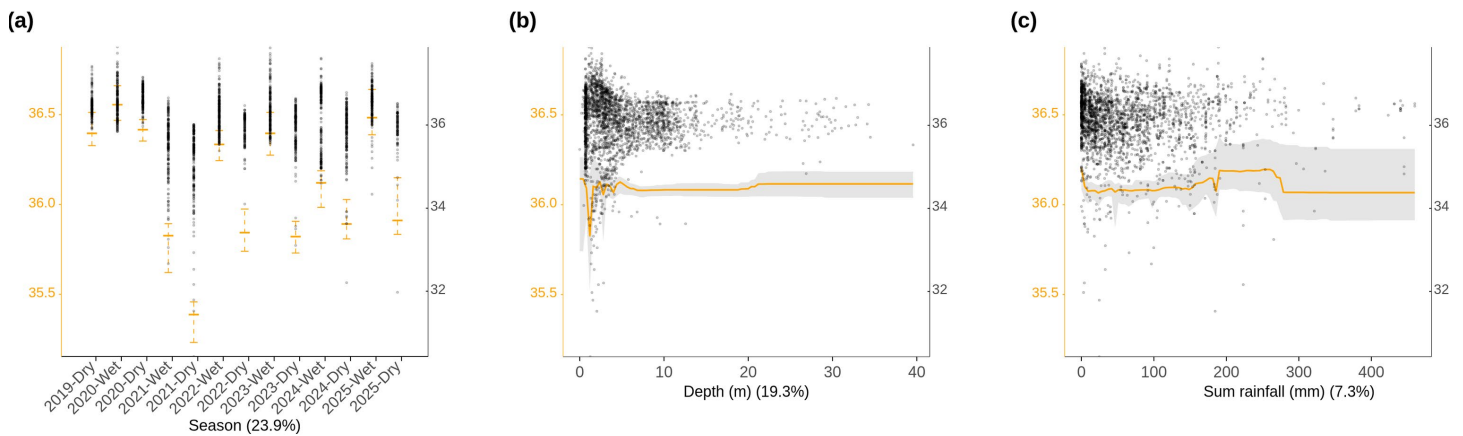


Figure 53. Salinity, SERC. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in salinity to gradients in season (a), depth (b), and cumulative rainfall over the 14 days prior to sampling (c) across the SERC monitoring domain (Nov 2018 to Dec 2024; $n = 2,741$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in salinity units, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

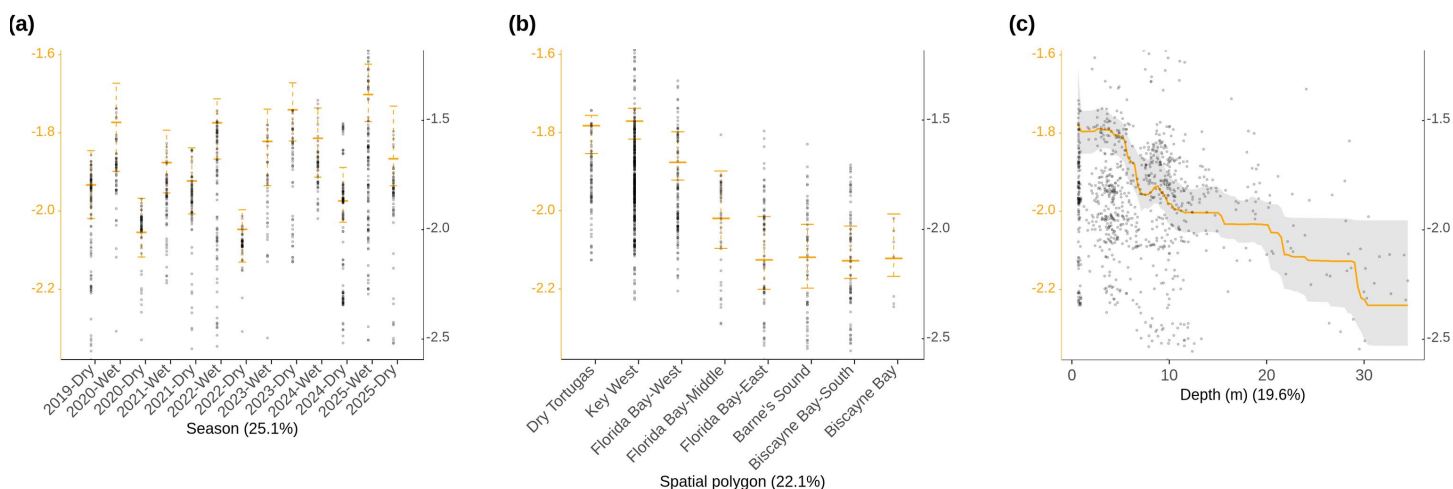


Figure 54. Silica, SERC. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed silica concentration to gradients in season (a), the spatial polygon (b), and depth (c) across the SERC monitoring domain (Nov 2018 to Dec 2024; $n = 934$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log mg L^{-1} , corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis.

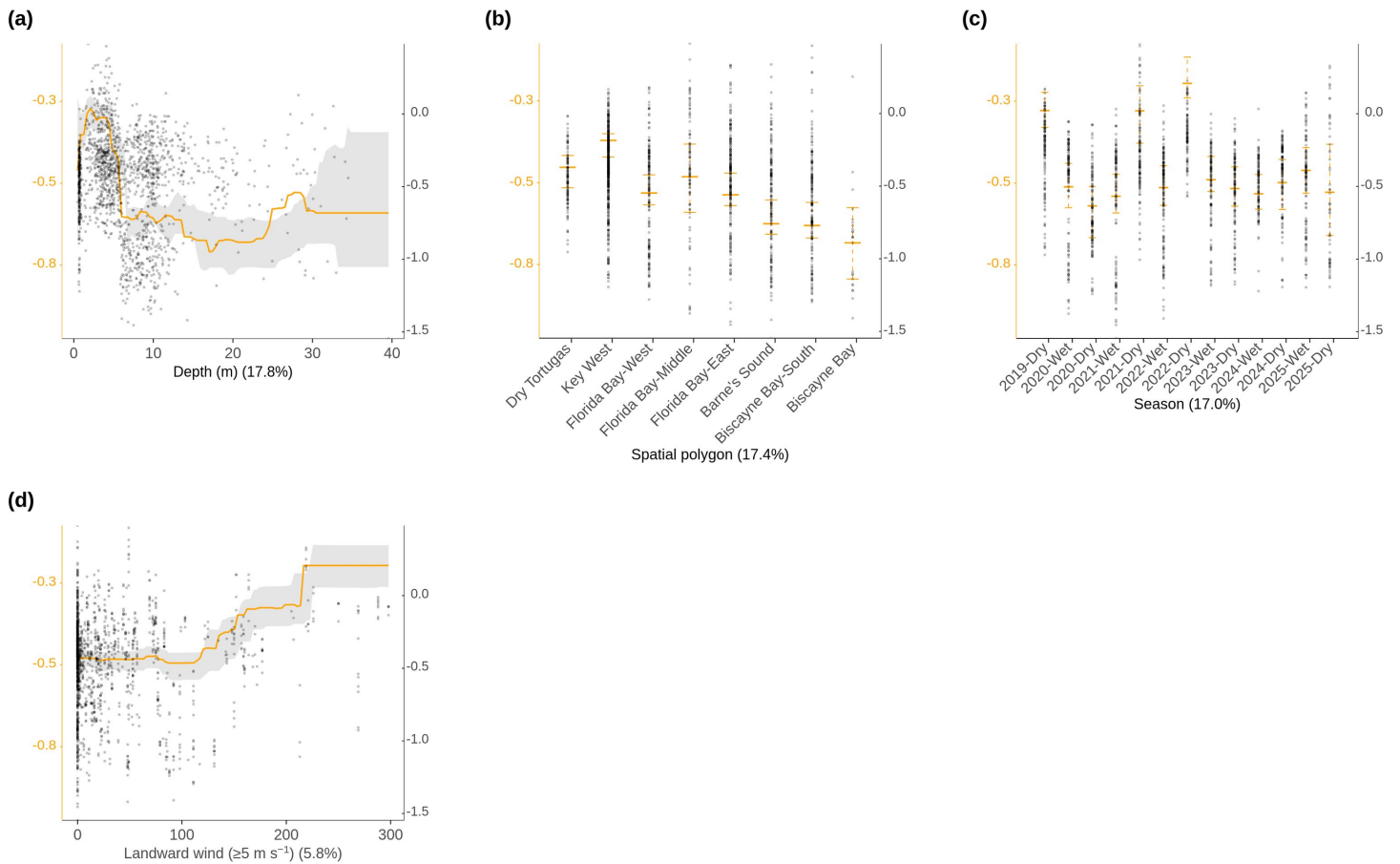


Figure 55. Turbidity, SERC. Partial dependency response plots from a boosted regression tree (BRT) model relating changes in log-transformed turbidity to gradients in depth (a), the spatial polygon (b), season (c), and the number of landward high-wind events counted over the day prior to sampling (d) across the SERC monitoring domain (Nov 2018 to Dec 2024; $n = 1,656$). Solid orange lines represent the BRT fitted function for continuous predictors (with the 95% confidence interval, i.e., model uncertainty, shown as the grey ribbon and corresponding to the left-hand y-axis); for the categorical season and spatial-polygon predictors, the thick orange line marks the fitted-function median and the thin orange lines mark the interquartile range. Points represent the underlying raw observations (in log NTU, corresponding to the right-hand y-axis). The relative influence of each predictor on overall model performance is shown in parentheses below each panel's x-axis. High-wind metrics count the number of high-wind events (wind exceeding 5 m s^{-1} in the indicated direction) summed over the indicated time period.

3.5.5. *Seasonal patterns in water-quality analytes*

The boosted regression tree (BRT) analyses above identified season as a leading predictor of water quality for most analytes across all four data sources. This section examines that seasonal structure directly, analyte by analyte. Observations were grouped into water-year seasons, each running from the start of the wet season in May. The resulting series spans the 2019 dry season through the 2025 dry season for the KJCAP, DERM, and WIN records. It ends in the 2024 calendar year for the shorter SERC record.

Each analyte is summarized with two figures in the main text: a seasonal and temporal panel and an overall-median spatial map. The seasonal panel shows raw measured values, method detection limit (MDL) adjusted (Flynn-corrected) values, and a model-adjusted seasonal partial effect. The model-adjusted view isolates the effect of season after the co-varying contributions of preceding flow, rainfall, and wind have been removed by the BRT. It is the clearest expression of each analyte's underlying seasonal trajectory. The relative influence of season in the corresponding BRT model is reported alongside as a measure of how strongly season shaped each analyte. Supporting density distributions and per-season spatial composites are provided in Appendix 3.

3.5.5.1. Kristin Jacobs Coral Aquatic Preserve (KJCAP)

Across the seven KJCAP analytes the model-adjusted seasonal trajectories separate into three broad types. The first is multi-year rises that level into an asymptote (nitrite, orthophosphate, total phosphorus). The second is a rise followed by a tentative recent decline (nitrate, silicate). The third is oscillatory signals with no directional trend (total suspended solids, turbidity).

Nitrate

Model-adjusted nitrate followed a three-phase trajectory over the monitoring period (Figure 56c). A rising phase carried the season-level median up from approximately $-2.89 \log \text{ mg L}^{-1}$ in the 2019 dry season to a peak near -2.33 around the 2022 wet season, a rise of about $0.56 \log$ units. A peak-band phase followed, with medians for the 2022 dry through 2024 dry seasons fluctuating within a relatively narrow -2.35 to -2.51 band. The two most recent seasons then traced a tentative decline, with the 2025 dry season falling to -2.68 , approaching levels last seen in the 2020 dry season. Whether this is a sustained reversal or an episodic fluctuation cannot be resolved from the present record, but it is the most notable downward movement in the model-adjusted nitrate trajectory to date. Season carried a relative influence of 28.3% in the nitrate BRT. This structured trajectory is largely invisible in the raw and Flynn-corrected linear-scale data (Figure 56a, b), where wet-versus-dry differences were inconsistent across years.

The pooled distribution of Flynn-corrected nitrate was broadly unimodal on the log scale, spanning roughly three orders of magnitude (Figure A8). The per-season composite map resolved clear IEA-level structure (Figure A9). The southern Baker's Haulover and Government Cut IEAs carried higher site-level medians than the northern Jupiter and Lake Worth IEAs in most seasons. This north-versus-south contrast appeared in nearly every

season panel and is consistent with differing terrestrial connectivity among the inlets. The composite also tracked the model-adjusted trajectory. Elevated medians in the 2022 wet and 2023 dry seasons were evident across several IEAs at once, matching the levelling phase. The tentative late-record decline was also broadly visible, with several IEAs showing lower medians in 2025 than at the 2022 to 2023 peak. The overall-median map integrates the rise, the plateau, and the recent decline, so it represents a period average rather than the current state (Figure 57).

Nitrite

Model-adjusted nitrite rose steeply and then levelled (Figure 58c). The season-level median climbed from approximately $-4.02 \log \text{mg L}^{-1}$ in the 2019 dry season to -3.39 by the 2023 dry season, an increase of about 0.63 log units across nine successive seasons. From the 2024 wet season onward the median held within a narrower -3.34 to -3.50 band across four consecutive seasons, with the 2024 dry season as the record peak and the two most recent seasons (2025 wet, 2025 dry) sitting 0.08 to 0.14 log units below that peak. The pattern is best described as a rise into a peak-band: nitrite rose substantially through the early years and has since stabilized at an elevated baseline, with no indication so far of a sustained decline. Season carried a relative influence of 28.7%. The rise is compressed against the detection limit in the raw and Flynn-corrected data (Figure 58a, b). There, values cluster near zero before a visible network-wide shift between the 2022 dry and 2023 wet seasons.

The pooled density spanned roughly four orders of magnitude, with most mass between 10^{-4} and 10^{-3}mg L^{-1} (Figure A10). The per-season composite map showed a clear network-wide temporal shift (Figure A11). Through the early period, from the 2019 dry season to the 2022 dry season, site-level medians sat at the low end of the scale across all IEAs. From the 2023 wet season onward they shifted toward higher values across essentially every IEA at once. This synchronous step matches the rise into the elevated asymptote. Within the post-2023 elevated state, the Baker's Haulover, Government Cut, and Hillsboro IEAs carried higher medians than the northern Lake Worth and Jupiter IEAs. The overall-median map blends the early near-detection period with the elevated post-2023 state, so it sits below the network's current condition (Figure 57).

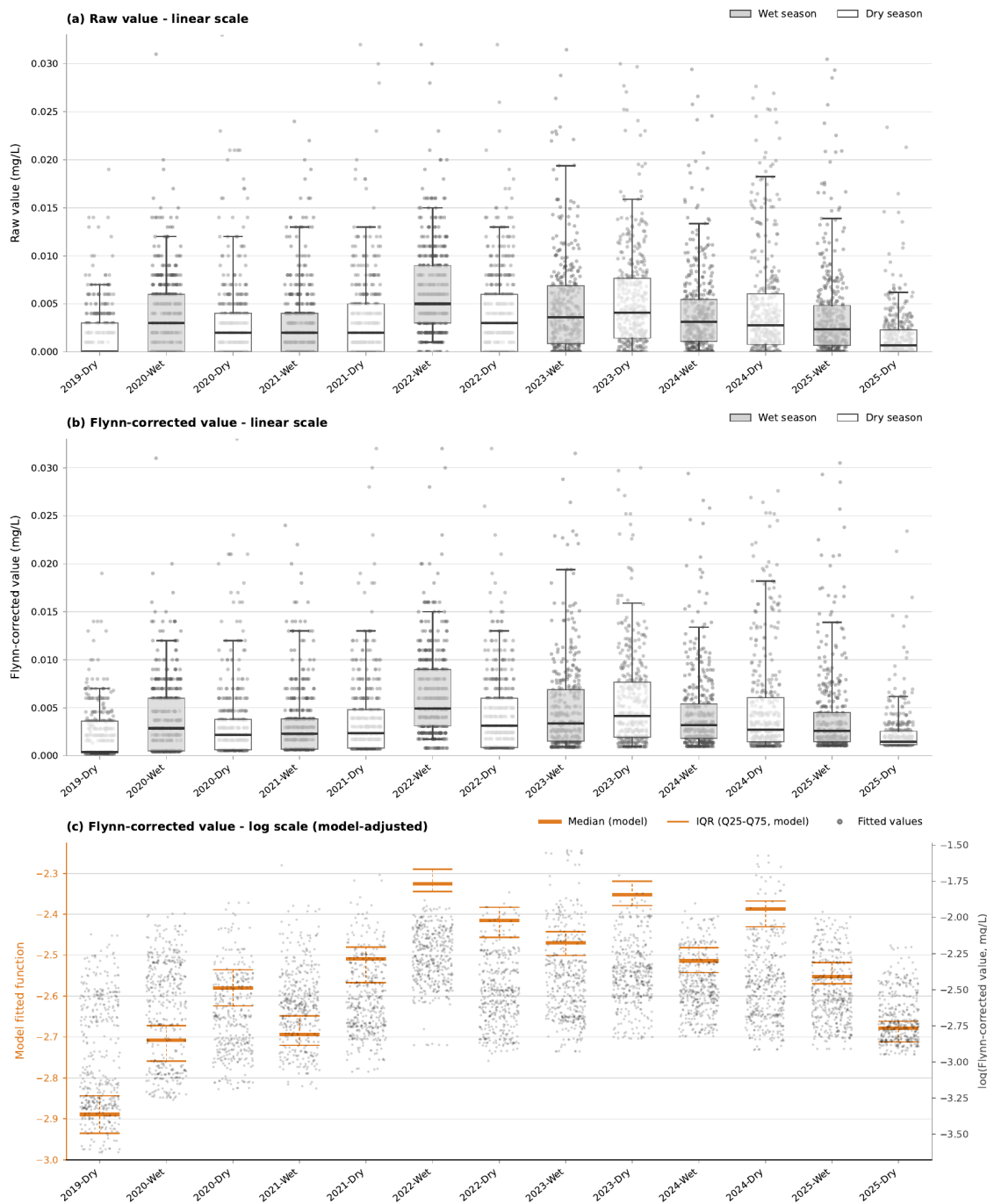


Figure 56. Nitrate, KJCAP. Seasonal and temporal patterns at the KJCAP monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

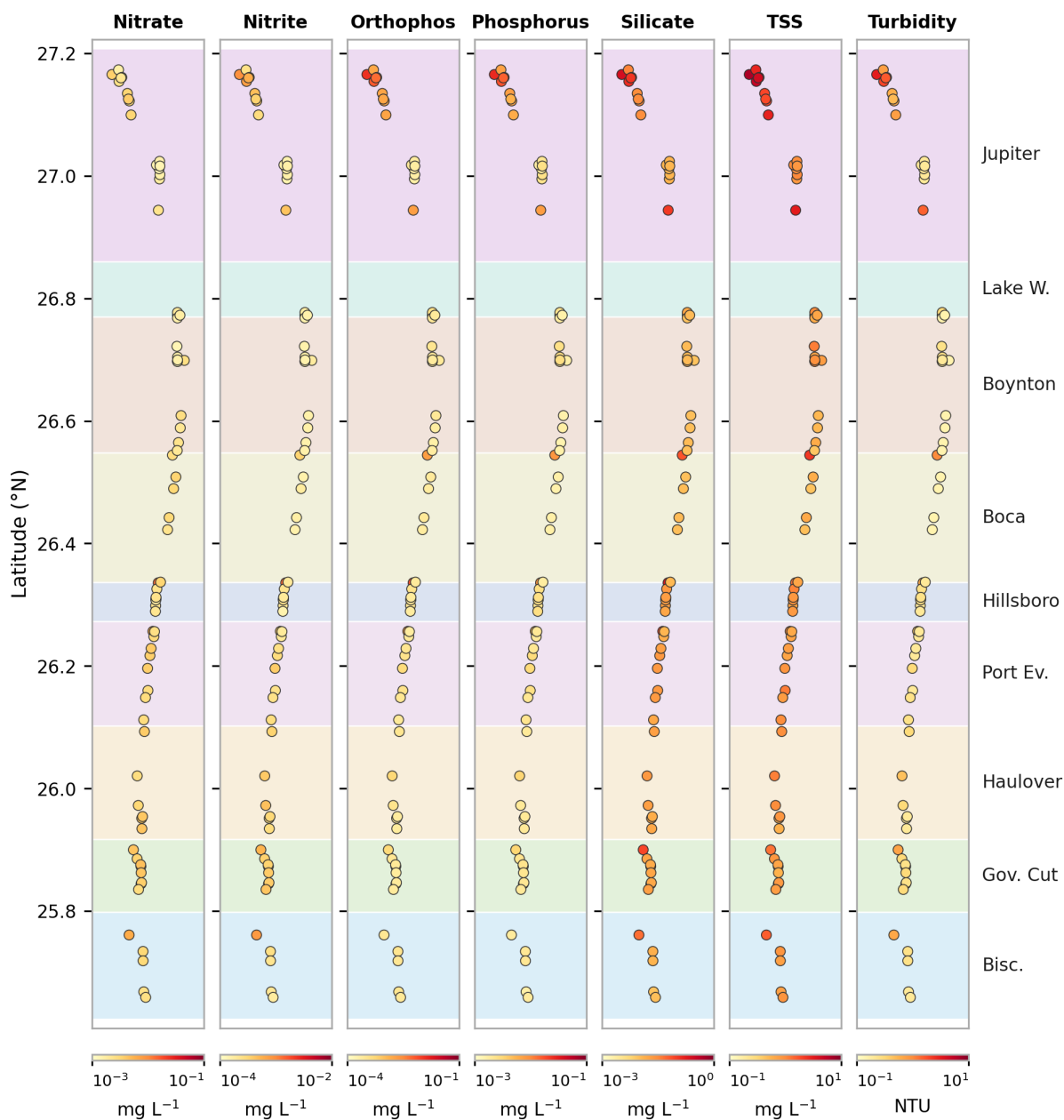


Figure 57. Overall median values per monitoring site across the KJCAP monitoring network for the full monitoring period (November 2018 to April 2025). Panels show, from left to right, Nitrate, Nitrite, Orthophosphate (Orthophos), Total Phosphorus, Silicate, Total Suspended Solids (TSS), and Turbidity; each panel uses a logarithmic, panel-specific color scale. Shaded background bands denote the nine inlet exposure areas (IEAs), labelled in abbreviated form at the right of the figure. From north to south, these are Jupiter, Lake Worth, Boynton, Boca, Hillsboro, Port Everglades, Baker's Haulover, Government Cut, and Biscayne. Coordinates are in decimal degrees, WGS 84 datum. Smaller grey circles mark monitoring sites with no recorded data for that analyte.

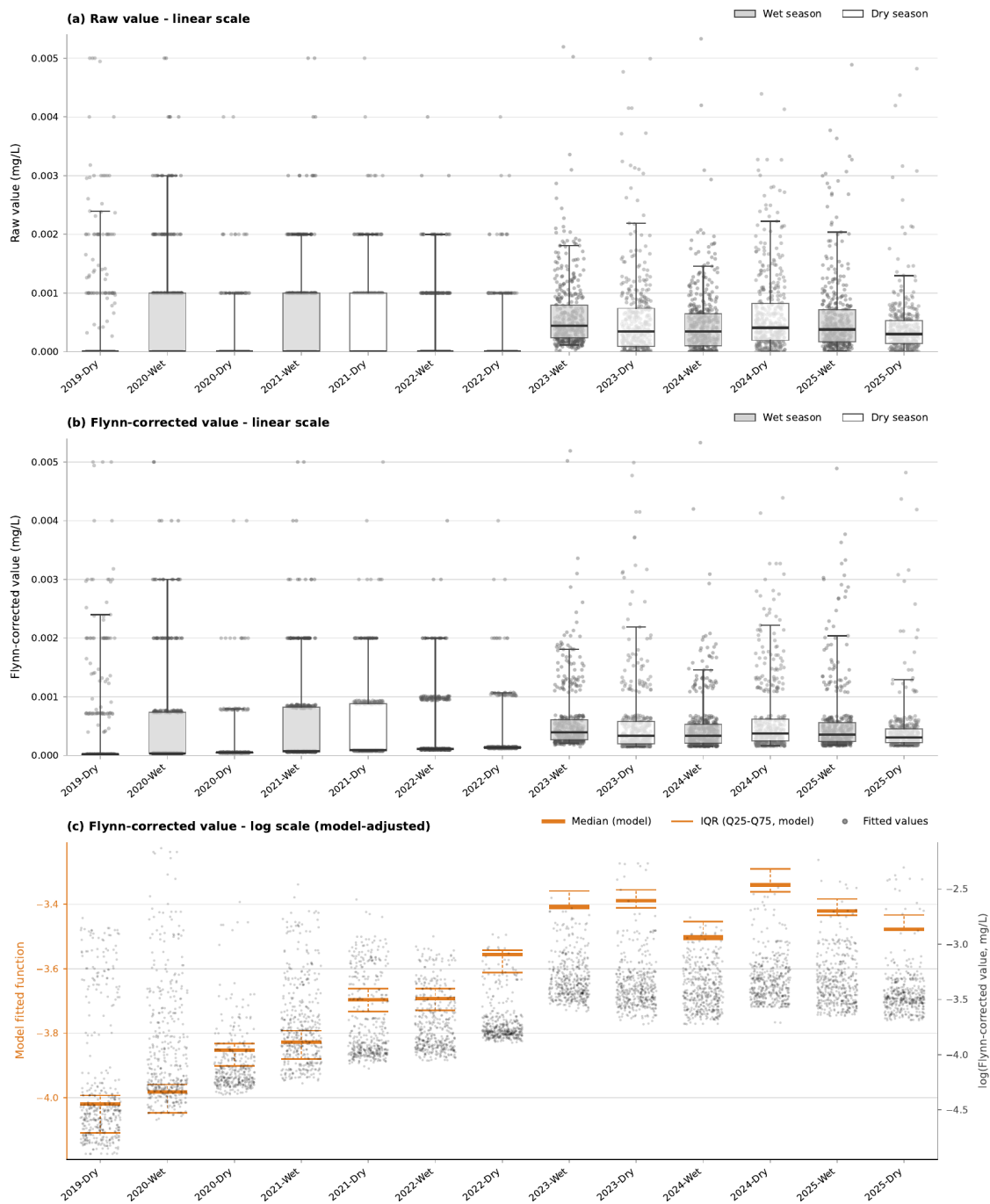


Figure 58. Nitrite, KJCAP. Seasonal and temporal patterns at the KJCAP monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Orthophosphate

Model-adjusted orthophosphate followed a two-phase rise-then-asymptote (Figure 52c). The season-level median rose from approximately $-3.95 \log \text{mg L}^{-1}$ in the 2019 dry season to -3.13 by the 2022 dry season, an increase of about 0.82 log units. It then held within a remarkably narrow -3.07 to -3.16 band across the seven seasons from the 2022 dry season to the 2025 dry season, with the 2024 dry season carrying the record peak. Season carried a relative influence of 32.1%, the highest of any KJCAP analyte. The per-season density curves continue to walk rightward even after the model-adjusted partial effect has stabilized (Figure A12). This indicates that the continued rightward movement in the observed data reflects co-varying environmental drivers rather than a continued underlying increase.

The pooled density was broadly unimodal across roughly three orders of magnitude, with a subtle high-concentration hump contributed by an elevated cluster of Jupiter sites (Figure A12). The per-season composite map combined a persistent spatial signal with a network-wide temporal step (Figure A13). Through the early seasons, to the 2022 wet season, site-level medians sat low across all IEAs, with isolated darker sites in the northern Jupiter IEA. From the 2022 dry season onward medians stepped up across essentially every IEA at once. Within the elevated post-2022 state, the Jupiter, Biscayne, and Hillsboro IEAs carried consistently higher medians than the central Boca and Boynton IEAs. The overall-median map is weighted toward the elevated post-2022 state, which covers seven of the thirteen seasons, but still sits below the current condition (Figure 57).

Total Phosphorus

Model-adjusted total phosphorus rose and is now levelling (Figure 60c). The season-level median increased from approximately $-2.91 \log \text{mg L}^{-1}$ in the 2019 dry season to -2.48 by the 2023 wet season, a gain of about 0.43 log units across eight seasons. The six seasons through the 2025 dry season then sat in a tight -2.42 to -2.48 band. The year-on-year movement has clearly slowed, but the most recent season is also the highest in the record, so a confirmed plateau cannot yet be asserted. The pattern is best described as an emerging asymptote. Season carried a relative influence of 24.3%.

The pooled density spanned about three orders of magnitude, with a subtle secondary hump traced to the elevated Jupiter sites (Figure A14). Total phosphorus showed the strongest spatial structure of the KJCAP nutrient analytes. The per-season composite map combined a fixed north-south gradient with a network-wide rise (Figure A15). The northern Jupiter IEA carried the highest site-level medians in every season, with the darkest sites in the dataset, reflecting a localized high-loading source. Across the rest of the network, medians rose visibly from the 2019 to 2022 seasons into the 2023 to 2025 seasons. Within the elevated late record, the Hillsboro and Boca IEAs ranked next-highest after Jupiter. The overall-median map blends the persistent Jupiter signal with the network-wide rise, so it sits slightly below the current state (Figure 57).

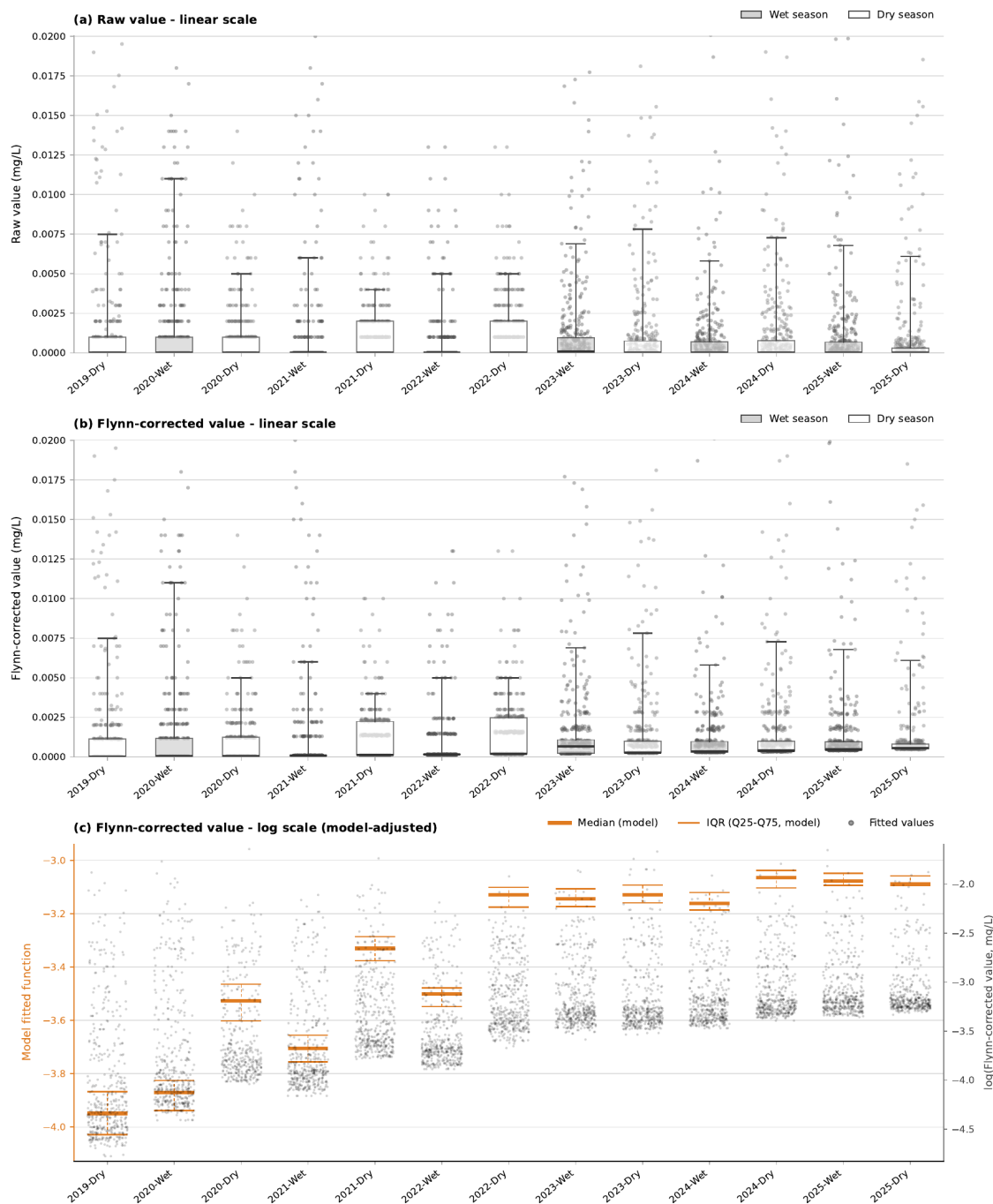


Figure 59. Orthophosphate, KJCAP. Seasonal and temporal patterns at the KJCAP monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

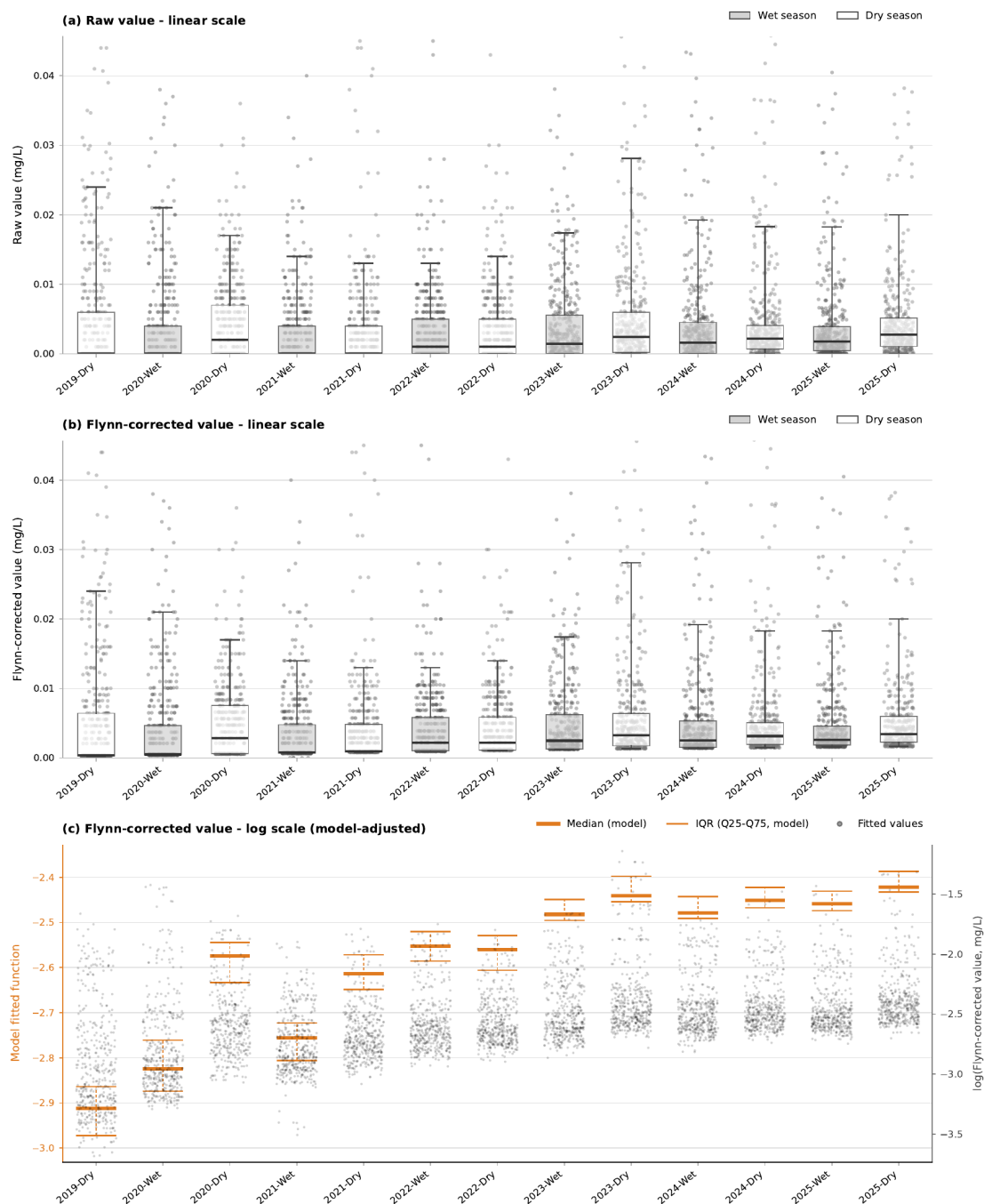


Figure 60. Total phosphorus, KJCAP. Seasonal and temporal patterns at the KJCAP monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Silicate

Model-adjusted silicate rose and then declined (Figure 61c). The season-level median climbed steadily from approximately $-2.08 \log \text{mg L}^{-1}$ in the 2019 dry season to a peak of -1.51 by the 2024 dry season, a gain of about 0.57 log units across eleven seasons. From that peak the median fell to -1.59 in the 2025 wet season and -1.78 in the 2025 dry season, a decline of roughly 0.27 log units that returned silicate to about its 2022 wet level. This rise-then-decline is distinct from the asymptotic responses of the co-occurring KJCAP nutrient analytes. It is consistent with a biological steady state, in which diatom uptake progressively draws down silica as concentrations rise. The decline spans only the two most recent seasons, so caution is warranted before treating it as a sustained reversal. Season carried a relative influence of 22.9%.

The pooled density was unimodal across roughly four orders of magnitude (Figure A16). The per-season composite map showed a network-wide rise and recent decline over persistent spatial heterogeneity (Figure A17). The earliest seasons, through the 2020 dry season, were predominantly light-coloured across all IEAs. From the 2021 wet season the panels darkened sharply and network-wide, reaching their most pervasive dark colouring at the 2024 dry season. The 2025 wet and dry panels then lightened again across many IEAs, most clearly in the central and southern parts of the network. The northern Jupiter IEA carried consistently higher and more variable medians than the rest of the network, though by a smaller margin than for total phosphorus or orthophosphate. The overall-median map sits between the 2024 peak and the lower 2025 state (Figure 57).

Total suspended solids

Total suspended solids showed no directional seasonal trajectory (Figure 62c). The model-adjusted season-level median oscillated within a narrow band of approximately -0.12 to $+0.22 \log$ units across all thirteen seasons. This total span is roughly half that of the KJCAP nutrient analytes. The highest value fell on the earliest season rather than during the recent monitoring years. A subtle wet-above, dry-below alternation is visible in 2020 to 2023 before breaking down from 2024 onward. This oscillatory behavior, without cumulative structure, is consistent with episodic physical forcing such as resuspension events, storm-driven loading, and wind-induced mixing rather than the loading-and-equilibration dynamics of the nutrient analytes. Season carried a relative influence of 20.6%.

The pooled density was broadly unimodal, with a mode near 1 mg L^{-1} and a right shoulder set by the consistently elevated Jupiter IEA (Figure A18). The per-season composite map showed persistent spatial heterogeneity without a directional temporal shift (Figure A19). The northern Jupiter IEA held the darkest sites in nearly every season panel. The remaining IEAs carried lower medians in a relatively flat distribution. The 2019 dry season panel was the darkest network-wide and the 2024 wet season the lightest, but dark and light panels were interleaved rather than ordered by date. This interleaving is consistent with episodic physical forcing rather than a cumulative trend. Because the signal oscillates rather than trends, the overall-median map is a genuine period average and a reasonable approximation of the current state (Figure 57).

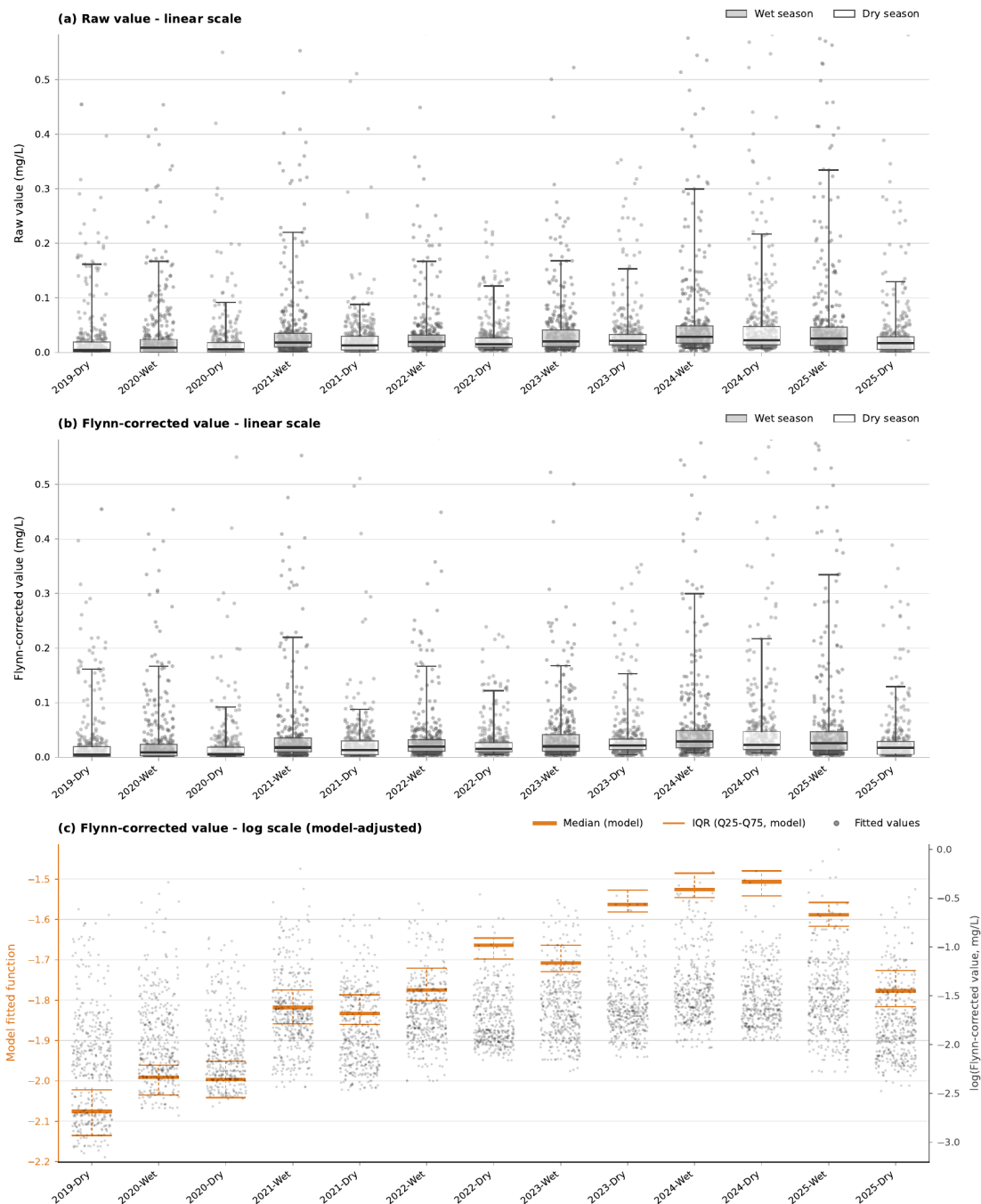


Figure 61. Silicate, KJCAP. Seasonal and temporal patterns at the KJCAP monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

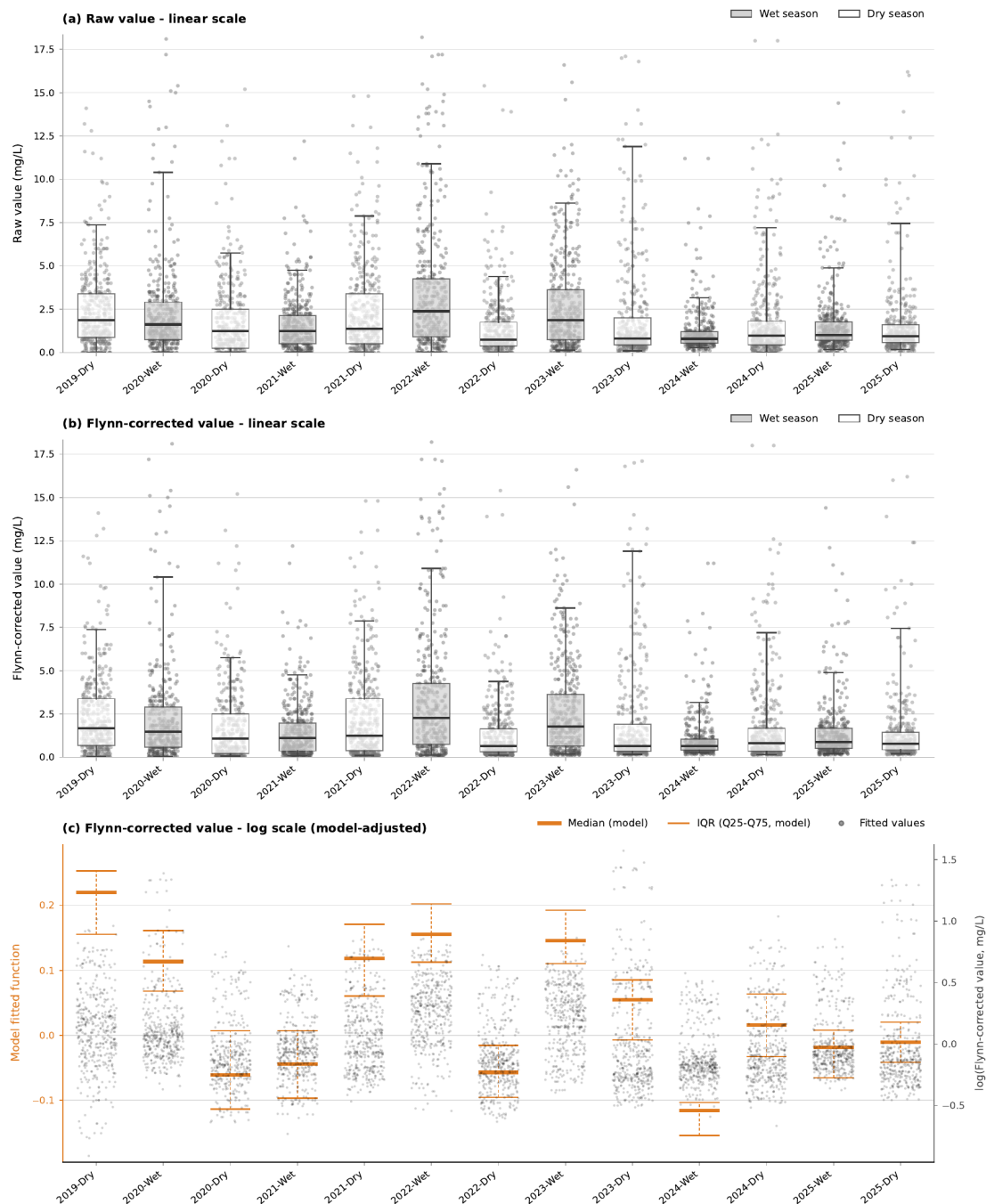


Figure 62. Total Suspended Solids, KJCAP. Seasonal and temporal patterns at the KJCAP monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Turbidity

Turbidity showed no structured rise, asymptote, or decline (Figure 63c). The model-adjusted seasonal partial effect oscillated within a narrow band between approximately -0.59 and -0.29 on the log axis, with every season-level median below zero. Within this oscillation a modest wet-versus-dry contrast emerged. The mean of the wet-season medians (-0.51) sat below the mean of the dry-season medians (-0.42). The wet-season median fell below the dry-season median in four of the five complete year-pairs. Season carried a relative influence of 13.5%, the lowest of any KJCAP analyte. That weakness is itself diagnostic. It confirms that turbidity is dominated by episodic physical forcing rather than a seasonally structured biogeochemical process.

The pooled density was unimodal and strongly right-skewed, with a mode near 0.2 NTU and a right shoulder set by the elevated Jupiter IEA (Figure A20). The per-season composite map was dominated by a single high-turbidity region (Figure A21). The Jupiter IEA held the darkest sites in essentially every season panel, separated from the rest of the network by about 0.4 log units. Below Jupiter, the remaining IEAs showed no consistent inter-IEA gradient and clustered within a narrow band. This Jupiter-versus-rest contrast was fixed across seasons, with no network-wide synchronous shift from one panel to the next. The pattern most plausibly reflects sediment loading and reduced ocean exchange in the Loxahatchee River and Jupiter Inlet system. Because the trajectory is oscillatory and stationary in time, the overall-median map approximates the current state (Figure 57).

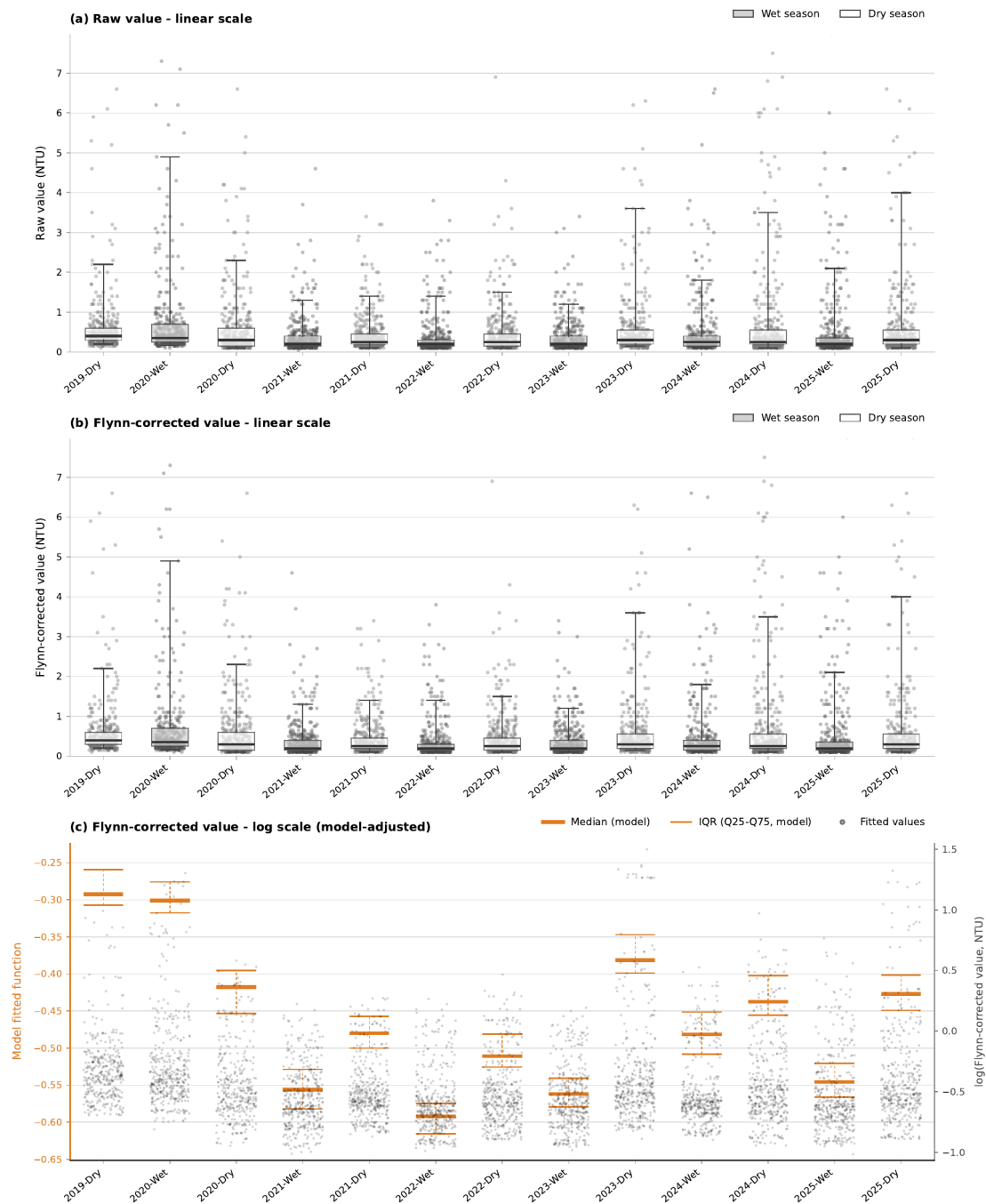


Figure 63. Turbidity, KJCAP. Seasonal and temporal patterns at the KJCAP monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (NTU); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

3.5.5.2. Miami-Dade Department of Environmental Resources Management (DERM)

The five DERM analytes show seasonal trajectories that contrast with the KJCAP rises. The two nitrogen analytes decline to a lower plateau, the two phosphorus analytes decline and then partially rebound in 2025, and turbidity oscillates without a directional trend.

Nitrate-nitrite

Model-adjusted nitrate-nitrite followed a two-phase decline-then-plateau, the mirror image of the rises seen for the KJCAP nutrient analytes (Figure 64c). An elevated initial phase spanned the 2019 dry season through the 2021 wet season, with season-level medians between approximately -1.68 and $-1.82 \log \text{ mg L}^{-1}$. After a step down through the 2021 dry and 2022 wet seasons, the medians settled onto a lower plateau from the 2022 dry season onward. They held within -1.82 to -1.94 across eight consecutive seasons. The total decline was about 0.25 to 0.27 log units, and no further drift is evident in 2025, consistent with a system that has settled at a new, lower baseline. Season carried a relative influence of 14.4%, ranking second behind 7-day preceding flow; this is a moderate effect, substantially weaker than season's dominant role for the KJCAP nitrogen species.

The pooled density was broadly unimodal across roughly 3.5 orders of magnitude (Figure A22). The per-season composite map showed modest, distributed spatial heterogeneity not dominated by any single polygon (Figure A23). The five spatial polygons fell within a tight 0.010 to 0.020 mg L^{-1} band, and the highest-median sites were scattered across several polygons rather than concentrated in one. Against this weak gradient the composite tracked the model-adjusted decline. The elevated initial phase, through the 2021 wet season, carried more orange and red sites, particularly along the southern Biscayne Bay-South band. The lower plateau from the 2022 dry season onward showed mostly yellow and pale-orange sites across all five polygons. The step-down was synchronous across polygons, so the pattern is best read as a network-wide temporal decline rather than a fixed gradient. Because the trajectory is decline-then-plateau, the overall-median map sits above the current state, and the late-record panels give a better picture of present concentrations (Figure 65).

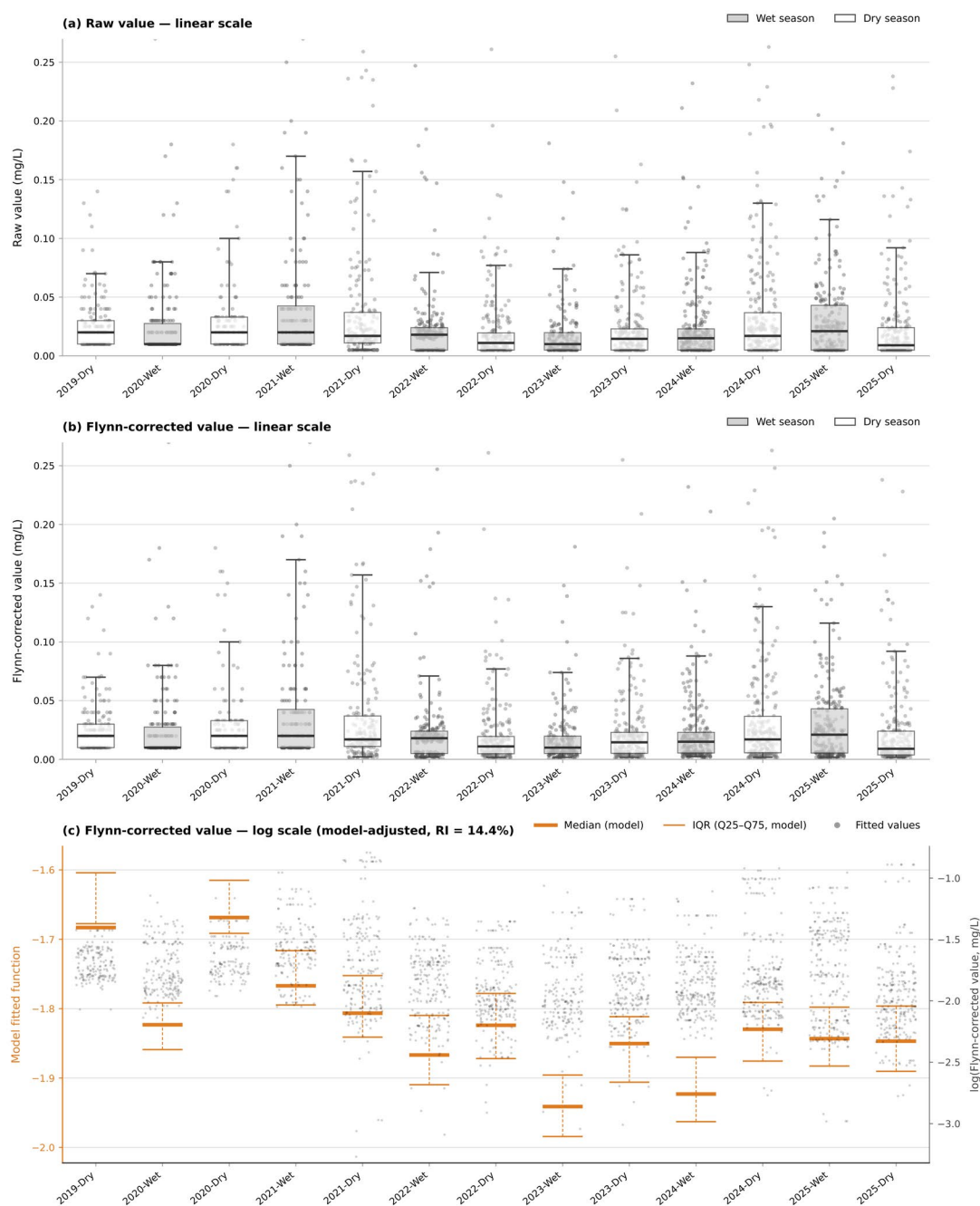


Figure 64. Nitrate-Nitrite, DERM. Seasonal and temporal patterns at the DERM Biscayne Bay monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

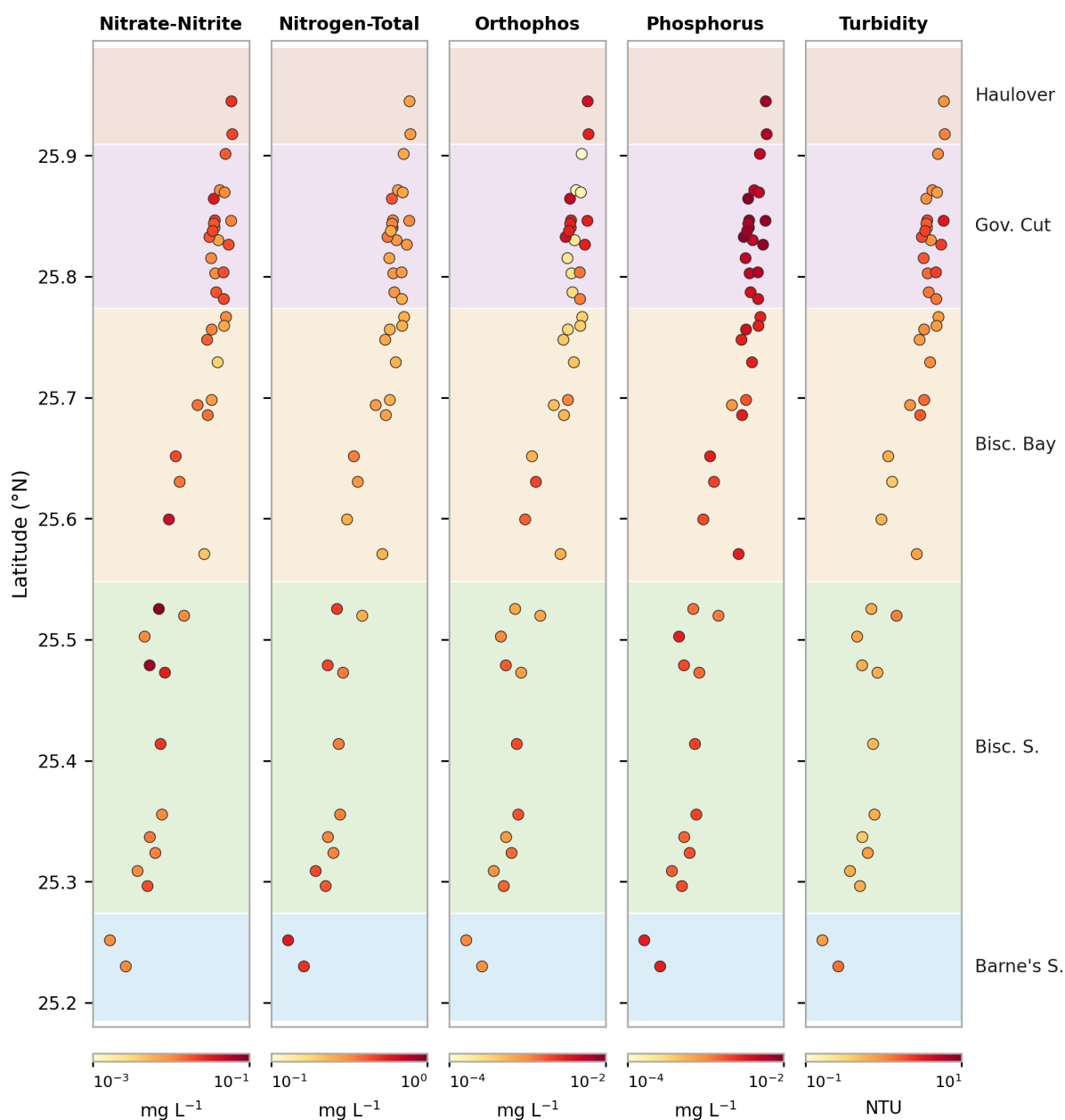


Figure 65. Overall median values per monitoring site across the DERM Biscayne Bay monitoring network for the full monitoring period (November 2018 to April 2025). Panels show, from left to right, Nitrate-Nitrite, nitrogen-total, Orthophosphate (Orthophos), total phosphorus, and Turbidity; each panel uses a logarithmic, panel-specific color scale. Shaded background bands denote the five DERM spatial polygons, labelled in abbreviated form at the right of the figure. From north to south, these are Baker's Haulover, Government Cut, Biscayne Bay, Biscayne Bay-South, and Barne's Sound. Coordinates are in decimal degrees, WGS 84 datum. Smaller grey circles mark monitoring sites with no recorded data for that analyte.

Nitrogen-total

Model-adjusted nitrogen-total followed the same two-phase decline-then-plateau as DERM nitrate-nitrite, although compressed into a shorter record (Figure 66c). An elevated initial phase spanned the 2021 wet season through the 2022 dry season, with season-level medians of approximately -0.45 to -0.51 log mg L⁻¹. After a step down, a lower plateau ran from the 2023 wet season through the 2025 dry season within a -0.54 to -0.58 band. The total decline was only about 0.07 log units, far smaller than the 0.25 log-unit decline for nitrate-nitrite at the same network. Season carried a relative influence of 16.7%, ranking second behind the spatial polygon.

The pooled density was broadly unimodal, with a primary mode near 0.25 mg L⁻¹ (Figure A24). The per-season composite map showed persistent regional heterogeneity dominated by the southernmost polygon, Barne's Sound (Figure A25). The two Barne's Sound sites appeared as dark, high-median points in every season, sitting about 0.27 log units above the rest of the network. The southern Biscayne Bay-South sites ranked next, while the three northern polygons clustered more tightly at lower values. This south-to-north gradient persisted throughout the record. Overlaid on it, the composite tracked the model-adjusted decline: the 2021 and 2022 panels carried more orange and red sites than the 2023 to 2025 panels. The step-down was synchronous across polygons while the Barne's Sound hot spot persisted. Because the trajectory is decline-then-plateau, the overall-median map sits above the current state (Figure 65).

Orthophosphate

Model-adjusted orthophosphate followed a three-phase trajectory distinctive among the DERM analytes (Figure 67c). An elevated initial phase spanned the 2019 dry season through the 2020 dry season, with season-level medians of approximately -2.70 to -2.86 log mg L⁻¹. A deep plateau followed across the eight seasons from the 2021 wet season to the 2024 dry season, within -2.94 to -3.08 . A partial rebound then lifted the 2025 medians back to approximately -2.91 , about halfway to the early-record level. The decline was about 0.26 log units and the rebound about 0.11 log units. Season carried a relative influence of 16.2%, the first-ranked predictor in the orthophosphate model and the only DERM analyte for which season led.

The pooled density was broadly unimodal across about 3.6 orders of magnitude (Figure A26). The per-season composite map showed the strongest spatial structure of the DERM analytes, with two polygons elevated and depleted in opposite directions (Figure A27). The northern Baker's Haulover and Government Cut polygons held the darkest sites in every season, with Baker's Haulover about 0.48 log units above the rest of the network. The central Biscayne Bay polygon was depleted by about 0.40 log units. This northern enrichment is consistent with terrestrial nutrient inputs from urbanized Miami-Dade catchments. Overlaid on the fixed pattern, the composite tracked the three-phase trajectory. Dark-red sites were most widespread in the 2020 wet season. They gave way to a yellow plateau through 2024, then returned to orange and red in 2025, most clearly in the northern cluster. The overall-median map integrates all three phases, so it sits between the deep-plateau and recent states (Figure 65).

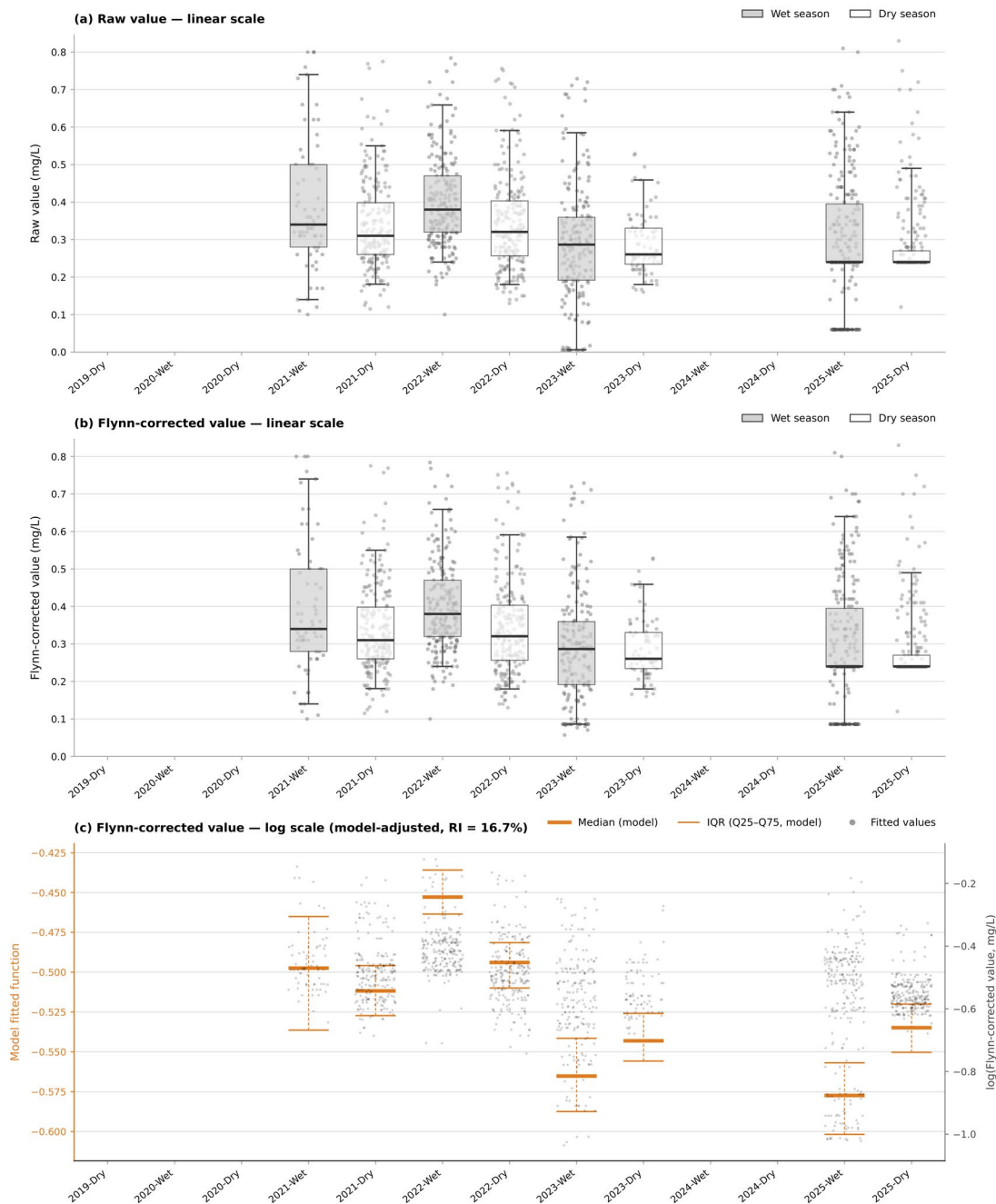


Figure 66. Nitrogen-total, DERM. Seasonal and temporal patterns at the DERM Biscayne Bay monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

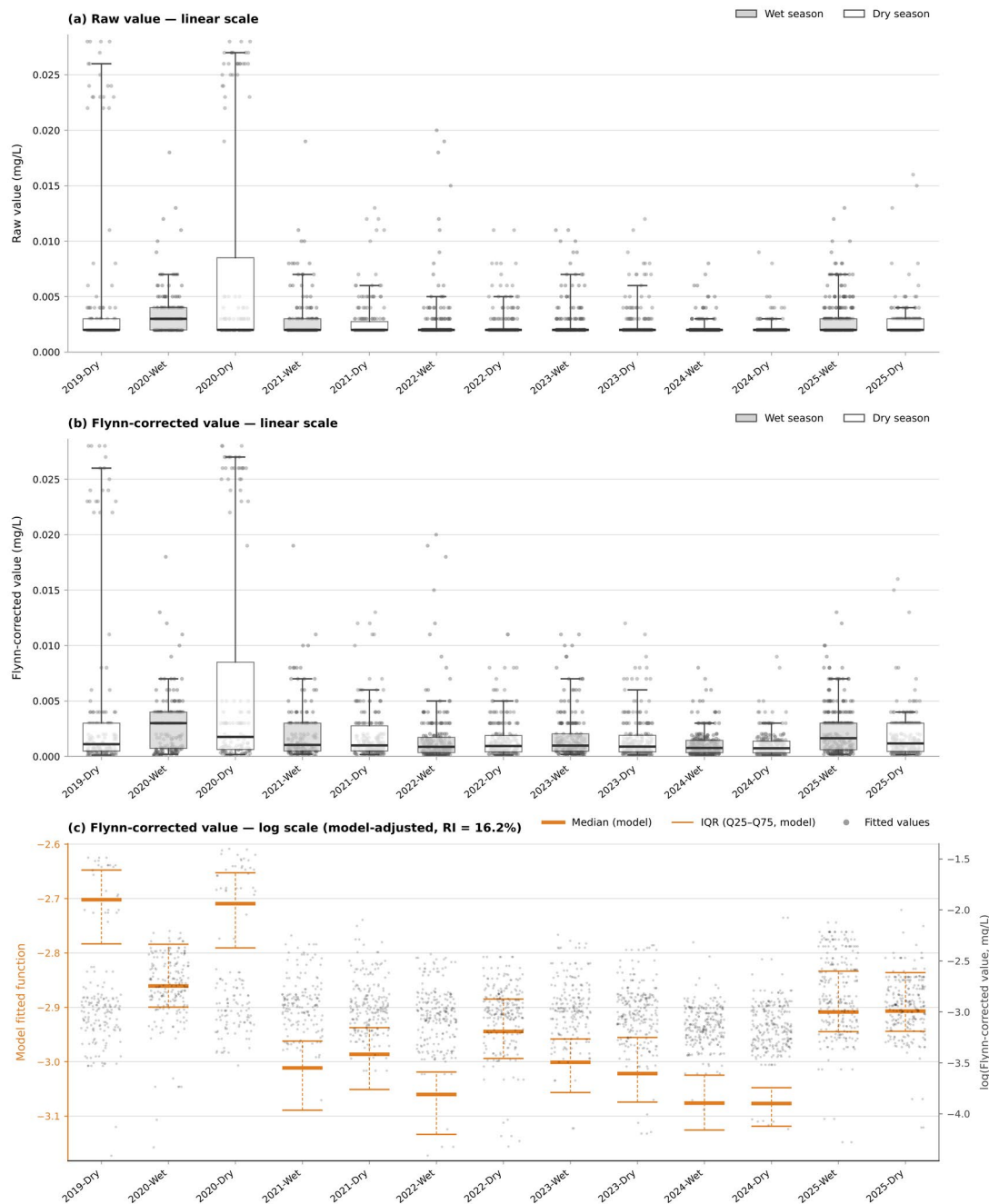


Figure 67. Orthophosphate, DERM. Seasonal and temporal patterns at the DERM Biscayne Bay monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Total Phosphorus

Model-adjusted total phosphorus closely paralleled DERM orthophosphate, following the same three-phase decline-plateau-rebound (Figure 68c). An elevated initial phase spanned the 2019 dry season through the 2020 dry season, with season-level medians of approximately -2.14 to -2.39 log mg L⁻¹. A lower plateau followed across the eight seasons to the 2024 dry season, within -2.39 to -2.62 , and the 2025 medians rebounded to about -2.36 to -2.42 . The decline of about 0.24 log units and the rebound of about 0.11 log units match orthophosphate almost exactly, suggesting both analytes respond to the same underlying forcing. Season carried a relative influence of 24.1%, the highest of any DERM analyte and the closest of the DERM analytes to KJCAP-like behavior, although the spatial polygon remained the leading predictor.

The pooled density was broadly unimodal across about 2.9 orders of magnitude, with a mode near 4 µg L⁻¹ (Figure A28). The per-season composite map showed a strong, persistent northern hot zone centred on the Government Cut polygon (Figure A29). Government Cut held the darkest sites in every season, about 0.30 log units above the rest of the network. The southern Biscayne Bay-South polygon was depleted by a similar margin. This north-to-south gradient is consistent with terrestrial nutrient inputs entering through the Government Cut shipping channel. Overlaid on it, the composite tracked the three-phase trajectory. Dark-red sites were most widespread in the 2019 dry season, gave way to a yellow plateau through 2024, and returned in 2025, most strongly in Government Cut. The overall-median map integrates all three phases (Figure 65).

Turbidity

Turbidity oscillated without a directional trajectory, in contrast to the structured trajectories of the DERM nutrient analytes (Figure 69c). Most model-adjusted season-level medians sat within 0.05 log units of the partial-effect baseline. The total range was only about 0.175 log units, less than half that of any DERM nutrient analyte. A consistent dry-above-wet contrast was present. The mean of the dry-season medians sat about 0.055 log units above the mean of the wet-season medians. The dry-season median exceeded the wet-season median in five of the six complete year-pairs. This is the inverse of the wet-high signal for nitrate-nitrite at the same network and is consistent with dry-season conditions favoring sediment resuspension. Two late-record dry seasons, 2024 and 2025, stand out as localized spikes. Season carried a relative influence of 17.4%, ranking second.

The pooled density was broadly unimodal across about 2.5 orders of magnitude, with a mode near 1 NTU (Figure A30). The per-season composite map was dominated by a persistent Government Cut hot zone (Figure A31). The mid-bay sites in and near the shipping channel appeared as the darkest points in every season, about 0.24 log units above the rest of the network. The southern Biscayne Bay-South polygon was depleted by a similar margin. The season panels were otherwise broadly similar to one another, with no progression from early to late. The 2024 and 2025 dry seasons were the darkest panels overall, and the elevation in those seasons concentrated at the already-high Government Cut sites. This pattern most plausibly reflects periodic dredging, ship-wake resuspension, and storm-driven sediment mobilization. Because turbidity oscillates rather than trends, the overall-median map represents a stable long-term spatial signature.

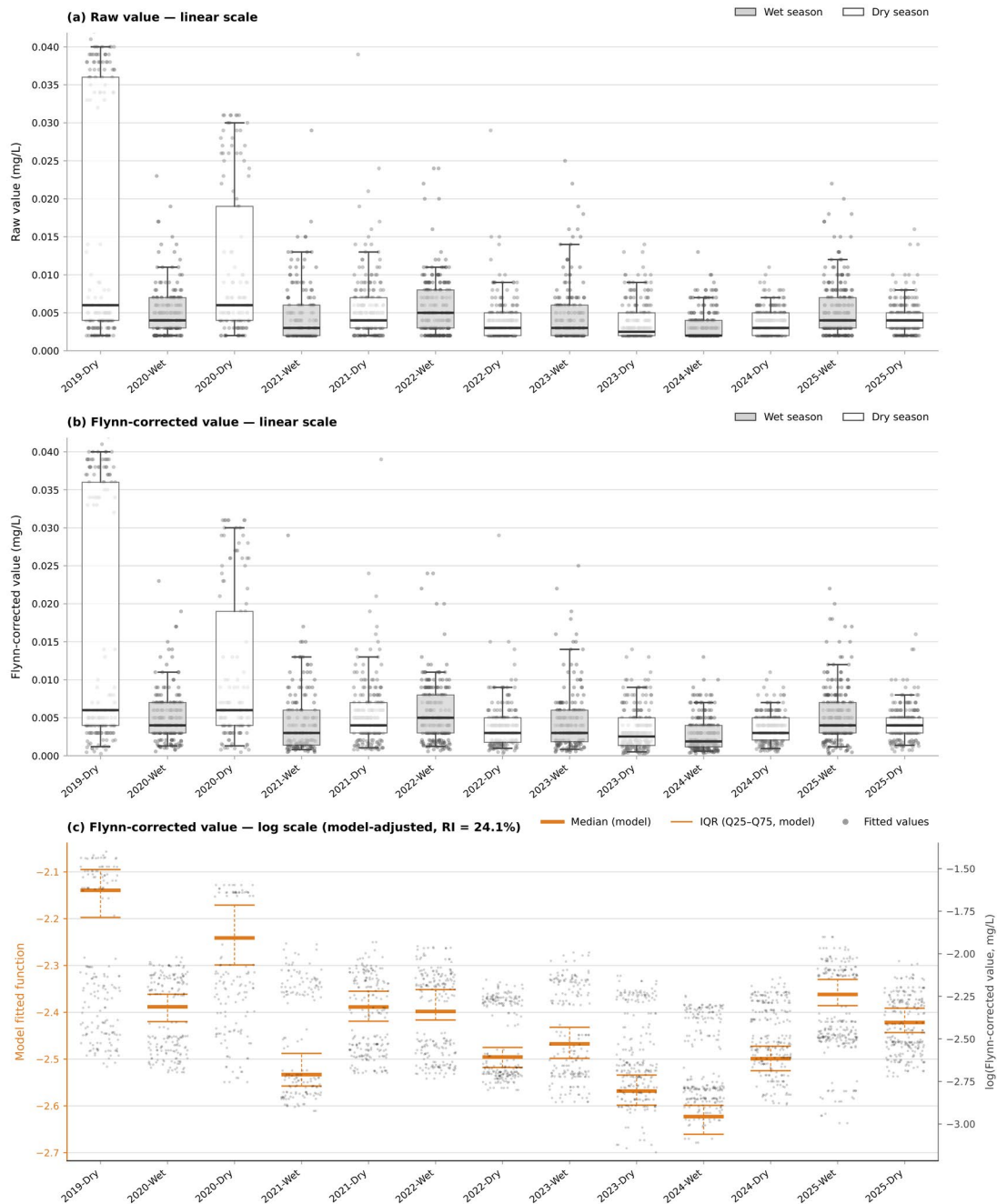


Figure 68. Total phosphorus, DERM. Seasonal and temporal patterns at the DERM Biscayne Bay monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes

wet seasons.

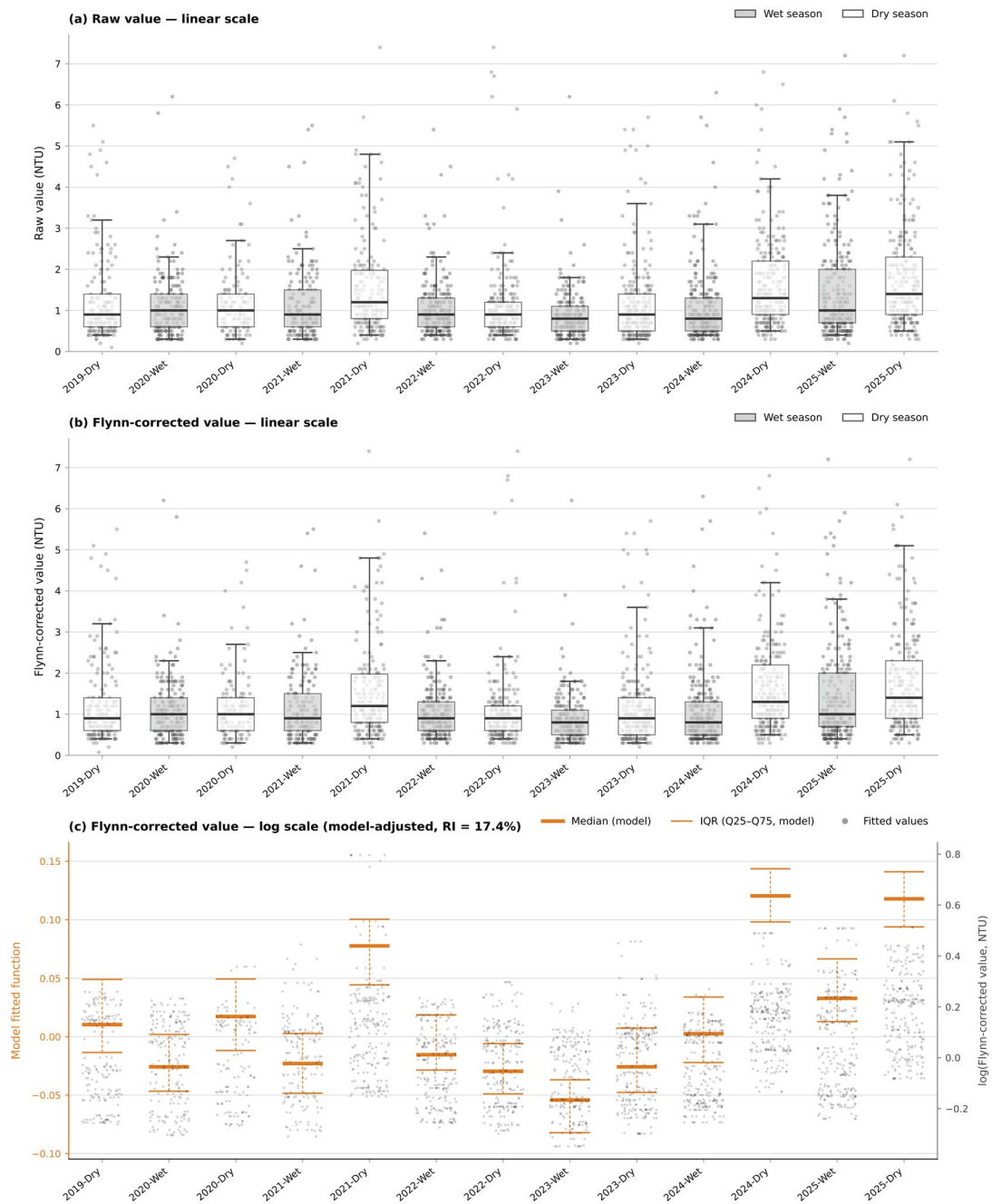


Figure 69. Turbidity, DERM. Seasonal and temporal patterns at the DERM Biscayne Bay monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (NTU); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

3.5.5.3. Watershed Information Network (WIN)

Seasonal structure is weak across the WIN analytes. Season carried a low relative influence in every WIN model, and the model-adjusted trajectories are correspondingly flat or only gently sloped. Two analytes, silica and total suspended solids, show larger late-record movements, but both coincide with a sharp contraction in sampling effort and are interpreted with caution.

The WIN seasonal subsection covers six of the seven WIN analytes. Orthophosphate is not examined here because season carried a relative influence of only 1.6% in the WIN orthophosphate BRT, too low for a meaningful seasonal trajectory.

Nitrate-nitrite

Model-adjusted nitrate-nitrite showed a flat seasonal trajectory (Figure 70c). The season-level medians oscillated within a narrow band of roughly 0.003 to 0.005 mg L⁻¹, with no sustained rise, decline, or phased structure. The medians sat near the lower end of this band for most of the record. A single uptick followed at the 2024 dry season, the highest value in the series. A modest drop followed in 2025. Season carried a relative influence of 9.8%, a weak effect far below that seen for the equivalent nitrogen species at the KJCAP and DERM networks.

The pooled distribution was broadly unimodal across roughly three orders of magnitude, with about half of all observations originally below detection (Figure A32). The per-season composite map resolved a clear and stable spatial structure (Figure A33). The highest site-level medians sat in the inland Everglades polygons, Big Cypress and Everglades NP, and along the eastern arc from Florida Bay-East through Barne's Sound to Biscayne Bay-South. Site medians in these areas reached roughly 0.02 to 0.03 mg L⁻¹ across most seasons. The Lower and Middle Keys sites within the Key West polygon, together with Florida Bay-West, carried generally lower medians near 0.001 to 0.005 mg L⁻¹. This east-and-inland-versus-west gradient appeared in every season panel and changed little across the record. The most striking feature of the composite was a coverage change rather than a concentration change. From the 2024 dry season onward the number of active sites contracted sharply, and the Key West polygon dropped almost entirely out of coverage by 2025. The overall-median map integrates this persistent gradient, and given the flat seasonal trajectory it represents the network's stable spatial signature rather than a directional trend (Figure 71).

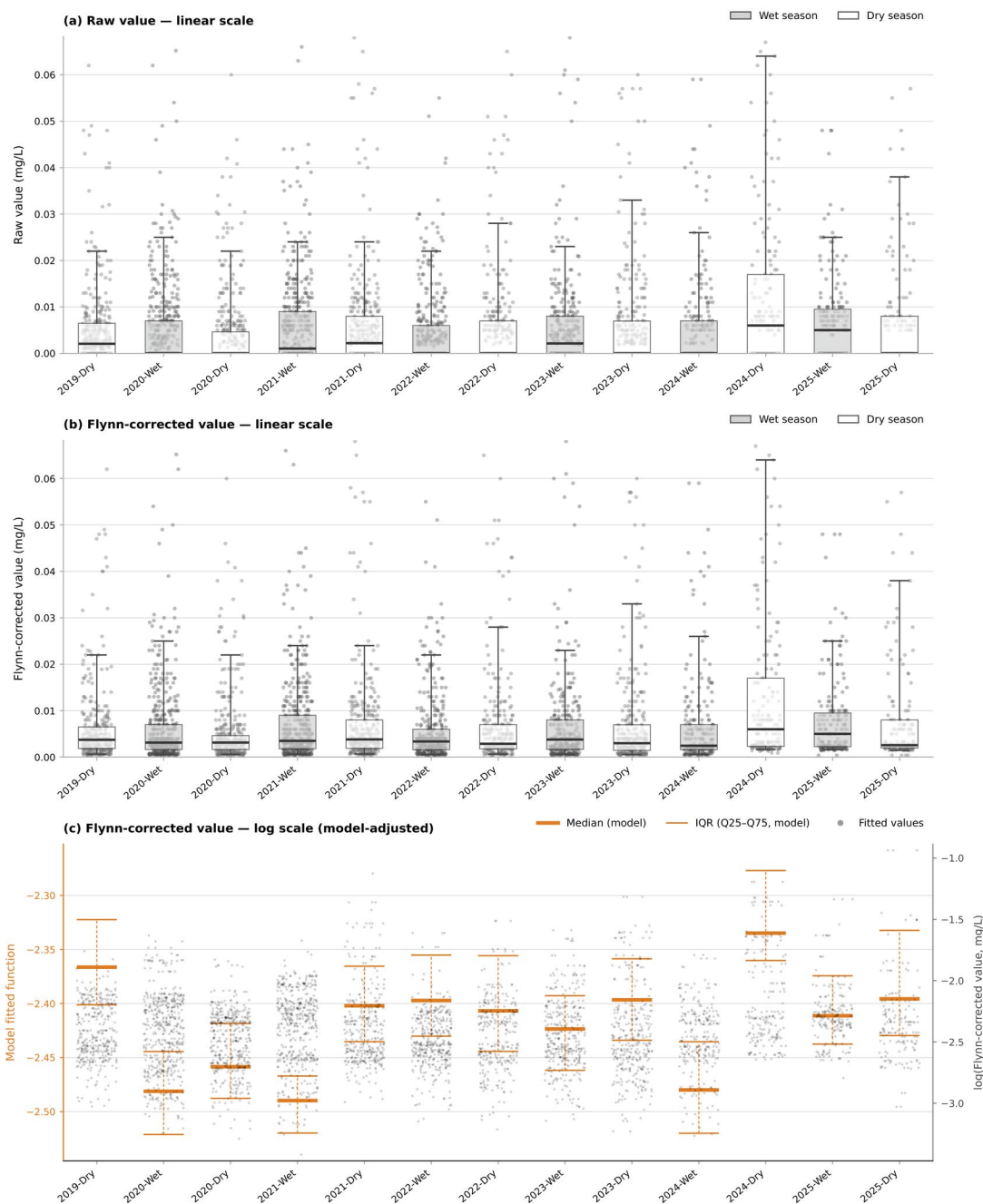


Figure 70. Nitrate-Nitrite, WIN. Seasonal and temporal patterns at the WIN monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

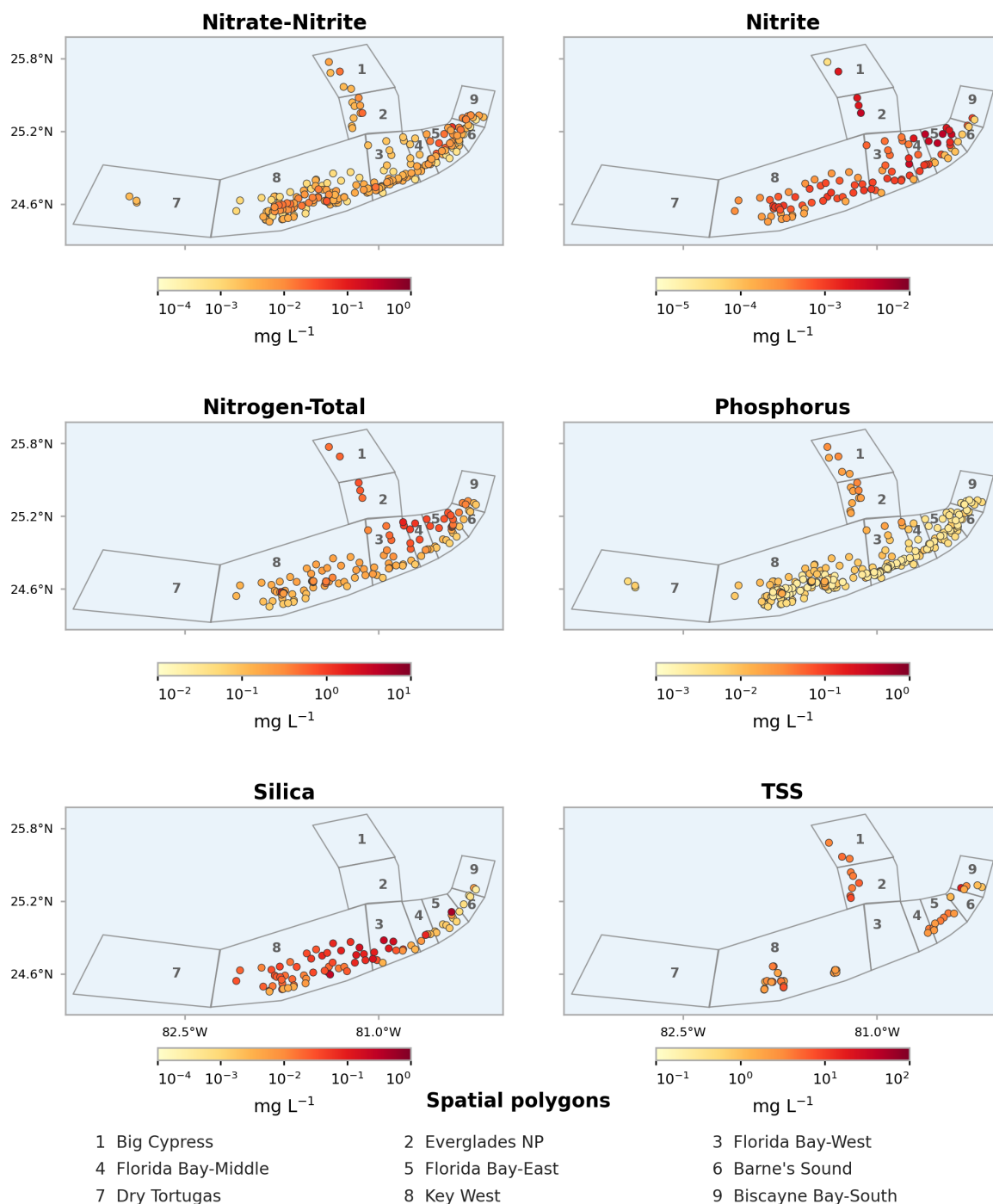


Figure 71. Overall median values per monitoring site across the WIN monitoring network for the full monitoring period (November 2018 to April 2025). Panels show, in reading order, Nitrate-Nitrite, Nitrite, nitrogen-total, total phosphorus, Silica, and Total Suspended Solids (TSS); each panel uses a logarithmic, panel-specific color scale. Numbered grey outlines denote the nine WIN spatial polygons, identified in the key below the panels. Polygons 1 to 5 are Big Cypress, Everglades National Park, Florida Bay-West, Florida Bay-Middle, and Florida Bay-East. Polygons 6 to 9 are Barne's Sound, Dry Tortugas, Key West, and Biscayne Bay-South. Coordinates are in decimal degrees, WGS 84 datum.

Nitrite

Model-adjusted nitrite showed a flat seasonal trajectory (Figure 72c). The season-level medians oscillated within a very narrow band of approximately 0.0006 to 0.0011 mg L⁻¹. This span was only about a quarter of a log unit, with no sustained rise, decline, or phased structure. The medians sat near the lower end of the band in the early-record wet seasons. They drifted modestly upward through the middle of the record. They reached their highest value in the 2024 dry season, before returning to the lower band by 2025. Season carried a relative influence of 9.3%, a weak effect.

The pooled density was dominated by a single mode near 10⁻³ mg L⁻¹, set by the network's detection-limit landscape (Figure A34). The per-season composite map resolved a clear east-and-inland-versus-west gradient (Figure A35). The highest site-level medians sat in the inland Everglades polygons and along the eastern arc through Florida Bay-Middle, Florida Bay-East, Barne's Sound, and Biscayne Bay-South. Site medians in those areas reached roughly 0.002 to 0.006 mg L⁻¹. The Florida Bay-West and Key West polygons carried generally lower medians. The Dry Tortugas polygon was entirely without data, as nitrite was never sampled there. This gradient appeared in every season panel and changed little across the record. From the 2024 dry season onward the number of active sites contracted sharply, and the Key West polygon and most of the Lower Keys dropped out of coverage. The overall-median map represents stable spatial heterogeneity rather than a directional temporal trend (Figure 71).

Nitrogen-total

Model-adjusted nitrogen-total showed a modest early-to-mid-record step-down (Figure 73c). The season-level medians spanned only about 0.17 log units. They sat in a higher band of roughly 0.32 to 0.37 mg L⁻¹ for the four earliest seasons. They then stepped down by about a tenth of a log unit from the 2021 dry season. They remained in a lower band of roughly 0.25 to 0.32 mg L⁻¹ through the rest of the record. This early-high, later-lower pattern is the clearest seasonal feature in the WIN nitrogen analytes, but its magnitude is small. Season carried a relative influence of 5.8%, the weakest of any WIN analyte.

Total nitrogen sat well above the network's detection limits, with only 2.7% of observations originally below detection, so the pooled density showed no detection-limit shoulder (Figure A36). The per-season composite map resolved a clear east-and-inland-versus-west gradient (Figure A37). The highest site-level medians sat in the inland Everglades polygons and along the eastern arc through Florida Bay-Middle, Florida Bay-East, Barne's Sound, and Biscayne Bay-South. Site medians in those areas commonly reached 0.5 to 1.0 mg L⁻¹. The Florida Bay-West and Key West polygons carried generally lower medians near 0.1 to 0.3 mg L⁻¹. The Dry Tortugas polygon was entirely without data. This gradient was the dominant feature of every season panel and held consistent through the record. The composite also showed the late-record contraction in sampling effort, with active site counts dropping from roughly 280 to near 100 from the 2024 dry season. The overall-median map represents the persistent spatial signature of total nitrogen rather than a temporal trend (Figure 71).

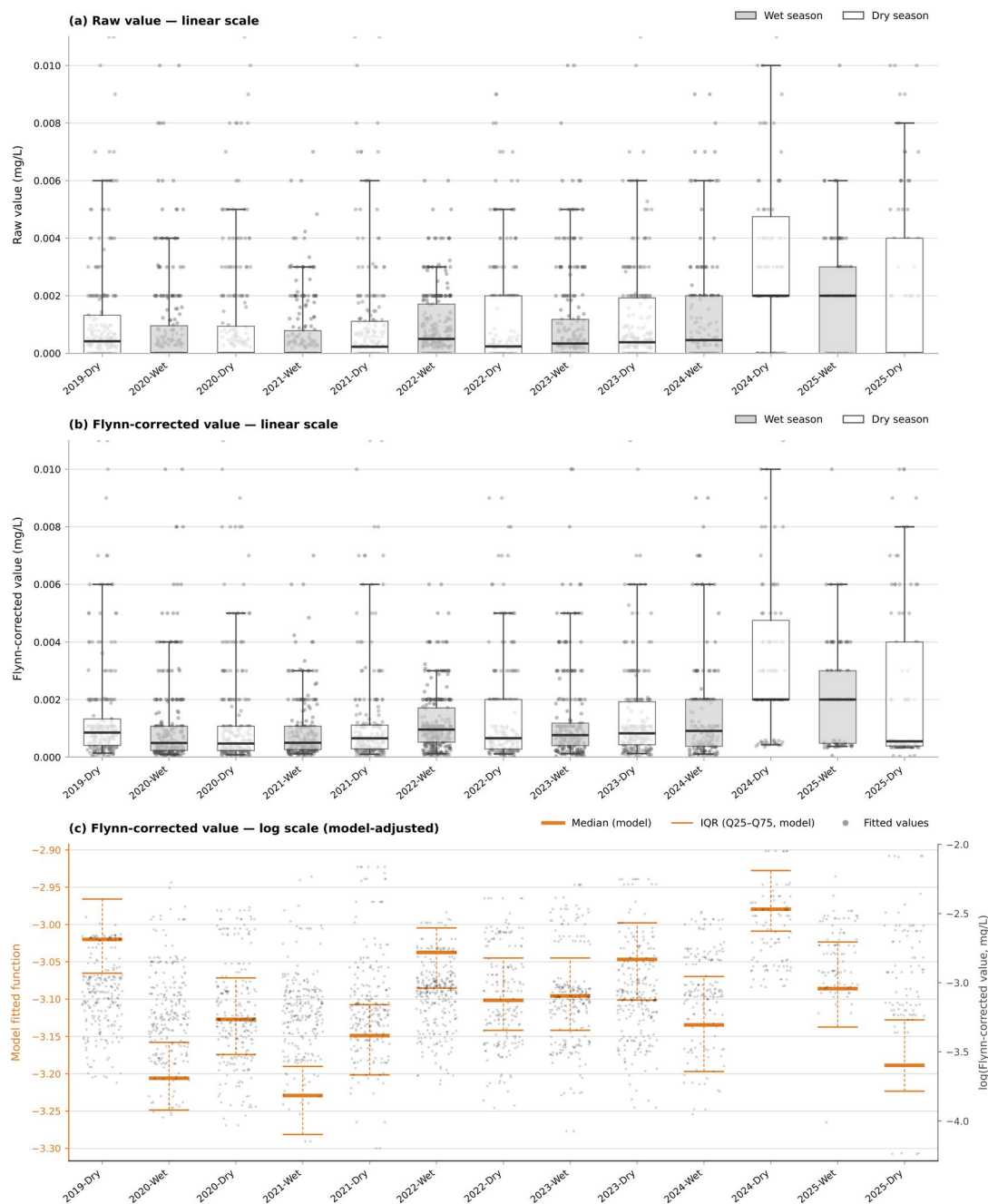


Figure 72. Nitrite, WIN. Seasonal and temporal patterns at the WIN monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

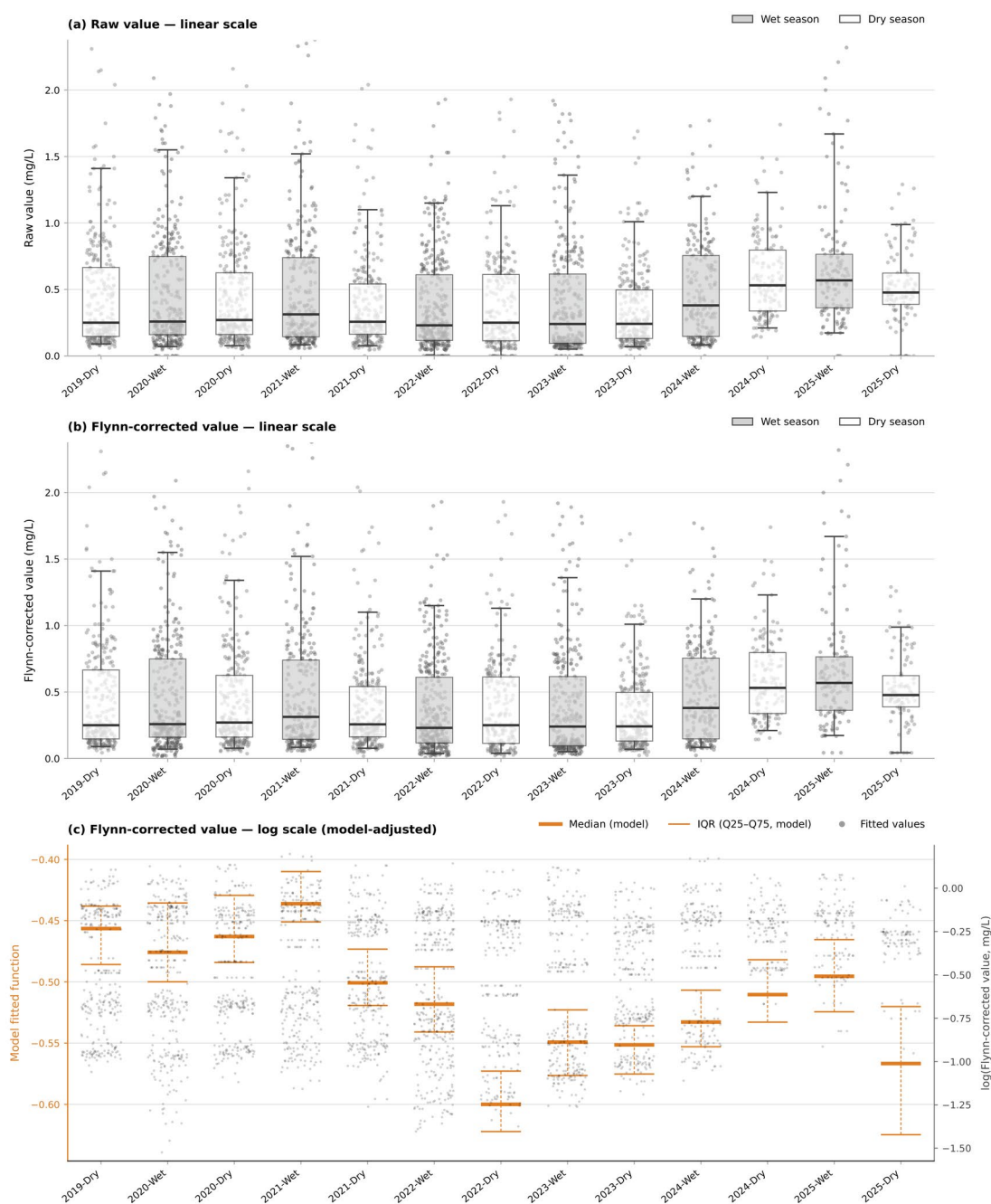


Figure 73. Nitrogen-total, WIN. Seasonal and temporal patterns at the WIN monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Total Phosphorus

Model-adjusted total phosphorus showed a gentle, continuous decline (Figure 74c). The season-level medians spanned only about 0.15 log units. They sat highest in the 2019 dry season at roughly 0.0086 mg L⁻¹. They drifted downward through the record to about 0.0061 to 0.0065 mg L⁻¹ in the last three seasons. This is a reduction of roughly a quarter to a third in absolute terms. The shift was gradual and continuous rather than abrupt. Season carried a relative influence of 10.6%, a weak effect.

The pooled density was unimodal across roughly two orders of magnitude, with the below-detection observations redistributed smoothly into the lower tail (Figure A38). The per-season composite map resolved a spatial structure distinct from the WIN nitrogen species (Figure A39). The highest site-level medians were concentrated in the inland Everglades polygons, Big Cypress and Everglades NP, reaching roughly 0.02 to 0.03 mg L⁻¹. Florida Bay, the southeast coastal arc through Barne's Sound and Biscayne Bay-South, the Key West polygon, and the Dry Tortugas all carried lower medians near 0.003 to 0.01 mg L⁻¹. This inland-versus-coastal pattern is consistent with the oligotrophic character of the Florida Keys and Florida Bay. The gradient was the dominant feature of every season panel and held consistent through the record. The composite also showed the late-record contraction in sampling effort, with active site counts falling from roughly 400 toward 160. The overall-median map represents the persistent spatial signature, with the inland Everglades clearly elevated above the coastal and Keys regions (Figure 71).

Silica

Model-adjusted silica showed the most pronounced trajectory of any WIN analyte, but one that must be read with caution (Figure 75c). From the 2019 dry season through the 2024 wet season the season-level medians oscillated within a band of roughly 0.012 to 0.025 mg L⁻¹ with no directional drift. Beginning at the 2024 dry season the medians stepped up sharply to approximately 0.044 to 0.047 mg L⁻¹ and held there through 2025. However, the step-up coincides exactly with a collapse in sampling effort. The three step-up seasons carry only 34, 41, and 17 observations, against roughly 95 to 200 earlier. The step-up may therefore reflect a change in which sites were sampled rather than a network-scale change in silica. Silica monitoring effectively ceased in December 2024. Season carried a relative influence of 10.5%, a weak effect even with the visually striking step.

The pooled density spanned roughly two orders of magnitude, with a lower-tail shoulder set by the below-detection observations (Figure A40). Silica was sampled only in the coastal and Keys polygons; Big Cypress, Everglades NP, and the Dry Tortugas carried no data and rendered grey on every panel (Figure A41). Within the monitored area the dominant signal was a within-Key West gradient. The Lower and Middle Keys sites carried the highest medians, roughly 0.05 to 0.3 mg L⁻¹. Florida Bay, Barne's Sound, and Biscayne Bay-South carried generally lower medians. This Keys-versus-Bay gradient held consistent through the seasons with substantial sampling. The late record showed a dramatic loss of coverage, with only 34, 41, and 17 observations in the final three seasons. Because those seasons contribute little weight, the overall-median map is dominated by the earlier, more heavily sampled record (Figure 71).

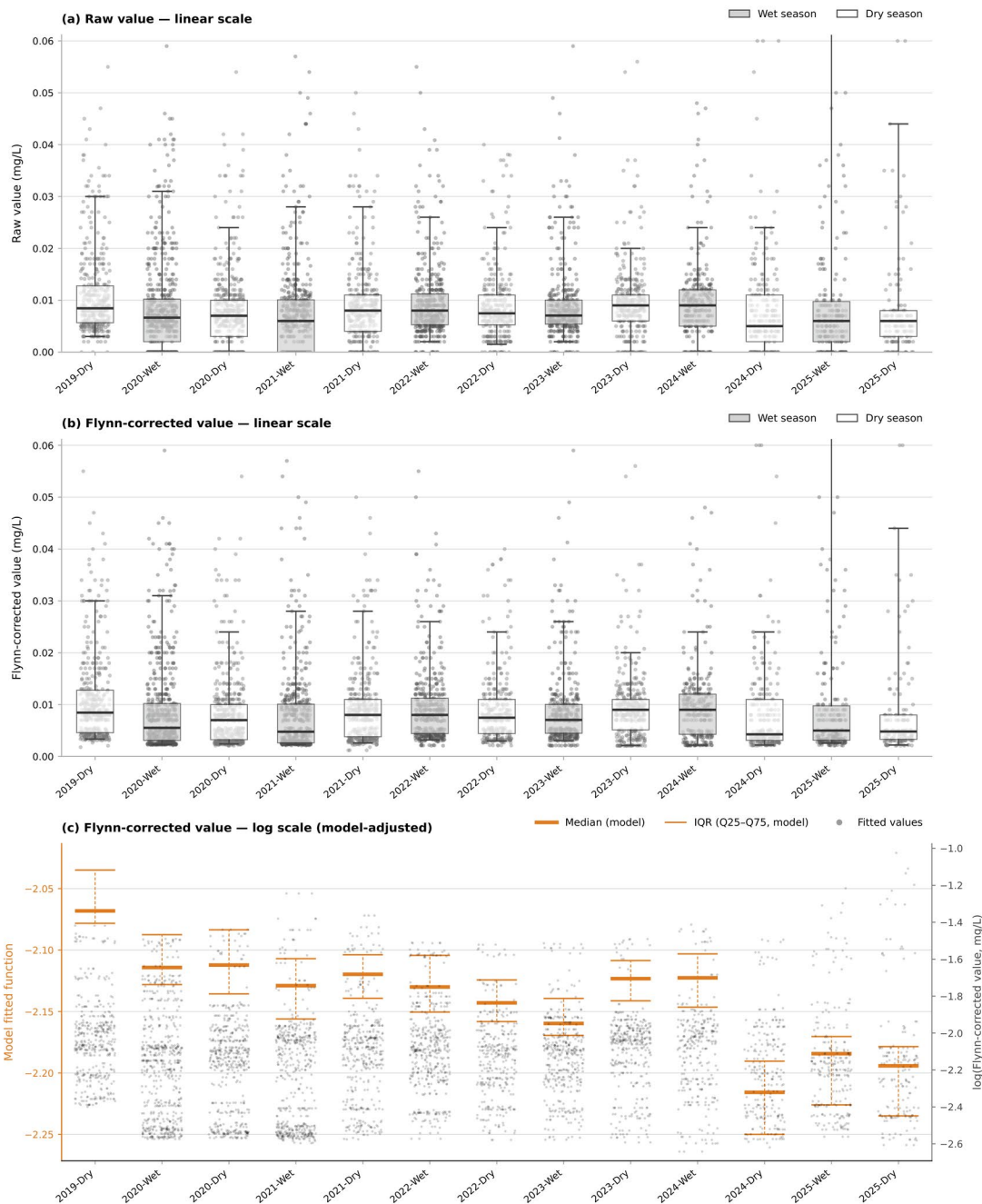


Figure 74. Total phosphorus, WIN. Seasonal and temporal patterns at the WIN monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

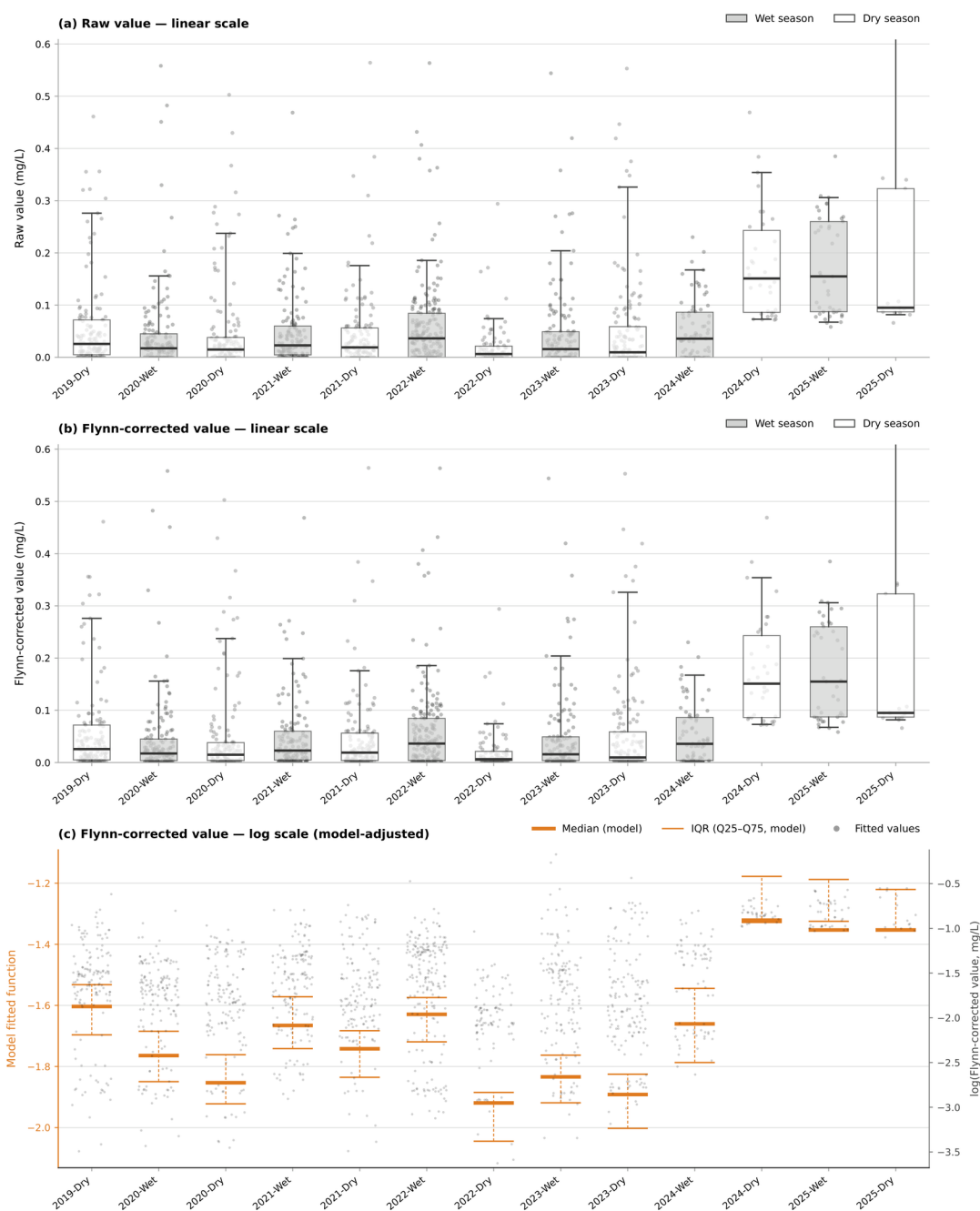


Figure 75. Silica, WIN. Seasonal and temporal patterns at the WIN monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Total suspended solids

Model-adjusted total suspended solids showed a gentle declining trajectory, but on a severely contracting sample (Figure 76c). The season-level medians sat highest in the 2019 dry season at about 4.4 mg L⁻¹. They drifted down through the record. They reached their lowest values from the 2024 wet season onward, a total span of roughly half a log unit. Season carried a relative influence of 20.0%, by far the largest value of any WIN analyte and the only WIN analyte for which season was the dominant model driver. This combination must be read with care. The last sampled seasons carry only two to four observations each. The late-record medians are therefore imprecisely estimated rather than reliable indicators of network-scale change.

The pooled density spanned roughly one and a half orders of magnitude, with most mass between 1 and 10 mg L⁻¹ (Figure A42). Total suspended solids was the sparsest WIN analyte, sampled at only 54 of the 295 canonical sites. The per-season composite covered only seven of the nine polygons, with Florida Bay-West and the Dry Tortugas carrying no data (Figure A43). The higher site-level medians sat in the inland Everglades polygons, with scattered higher sites in the Lower Keys and the eastern Florida Bay arc. The composite is dominated by a rapid contraction in sampling effort. The 2019 and 2020 panels carried coloured sites across most monitored polygons, but from the 2021 wet season only 11 to 22 sites were active per season. The 2024 and 2025 panels carried just two to four sites each, and the 2025 dry season was unsampled. Because the early seasons carry most of the sample weight, the overall-median map reflects the 2019 to 2020 record (Figure 71).

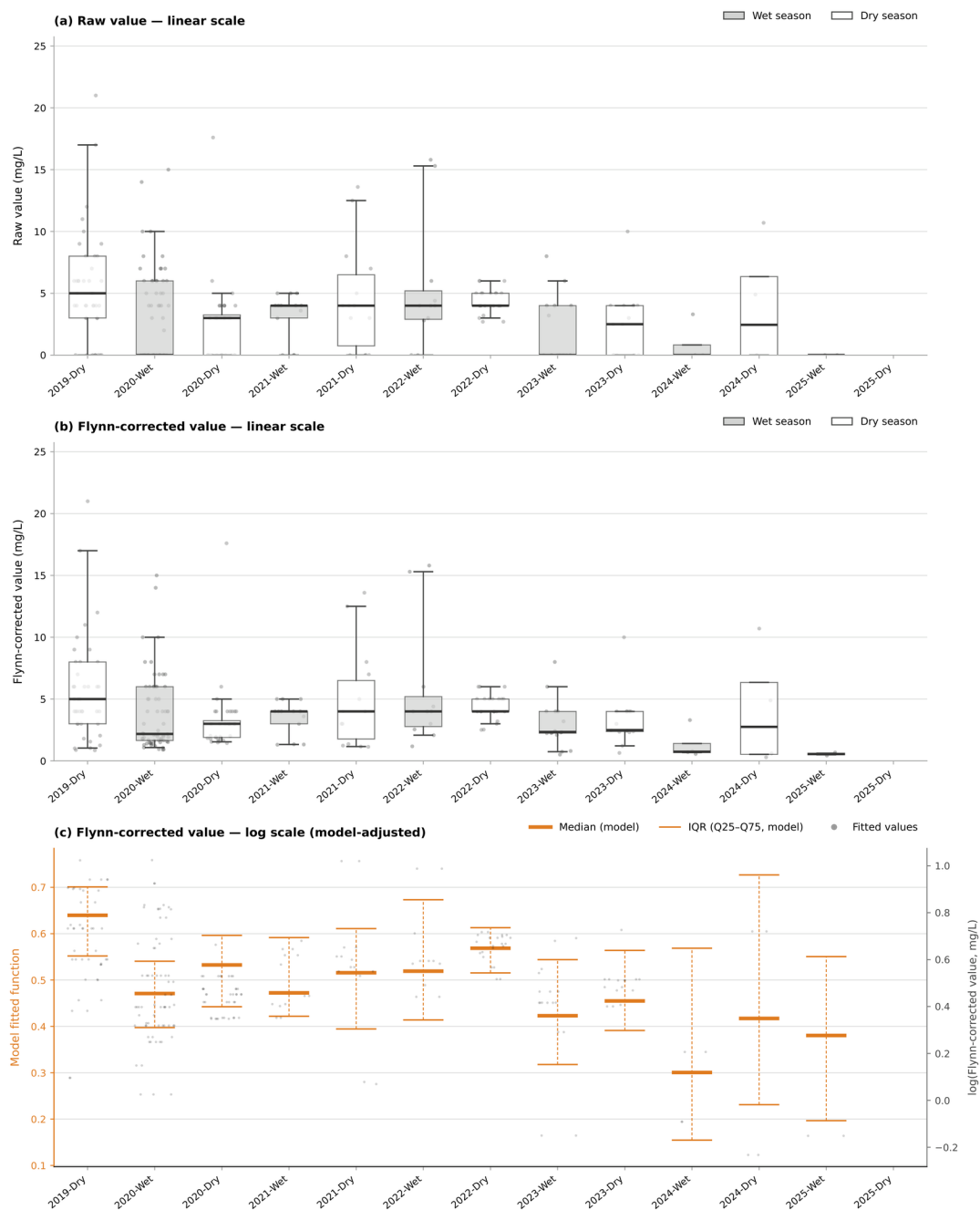


Figure 76. Total Suspended Solids, WIN. Seasonal and temporal patterns at the WIN monitoring network, by water-year season (November 2018 to April 2025). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

3.5.5.4. Southeast Environmental Research Center (SERC)

The SERC analytes carry the strongest seasonal signals of the four data sources. Season was the leading BRT predictor for five of the seven analytes. The model-adjusted trajectories include a nitrate step-up, a nitrogen-total V-shape, a salinity freshening event, and a silica wet-versus-dry alternation.

Nitrate

Model-adjusted nitrate followed a two-regime step-up (Figure 77c). The three earliest seasons sat in a lower band near 0.001 to 0.0017 mg L⁻¹. The season-level median then stepped up at the 2021 dry season to a higher plateau near 0.002 to 0.0025 mg L⁻¹. This plateau held through the end of the record, with brief returns toward the lower band at the 2022 and 2023 dry seasons. The total movement was about 0.4 log units and the 2021 dry-season step-up was the single clearest feature. Season carried a relative influence of 30.5%, the largest contribution among nitrate's predictors. This is more pronounced than the seasonal effects seen for nitrogen species in the other Keys networks. The cross-validated fit of the nitrate model was low, however, so the ranking should be read with corresponding caution.

The pooled density was broadly unimodal, with about 44% of observations originally below detection redistributed smoothly into the lower tail (Figure A44). The per-season composite map resolved a clear west-to-east gradient (Figure A45). The Dry Tortugas, Key West, and Florida Bay-West polygons in the west carried the lowest site-level medians. Values rose eastward through Florida Bay to the highest medians in the eastern coastal arc, from Florida Bay-East through Biscayne Bay-South. This gradient appeared in every season panel and held consistent through the record. The composite also tracked the model-adjusted step-up. The three earliest seasons carried more yellow sites, and panels from the 2021 dry season onward darkened across all polygons. Sampling coverage was consistent across seasons, with no late-record contraction. The overall-median map combines the persistent west-to-east gradient with the directional late-record rise (Figure 77).

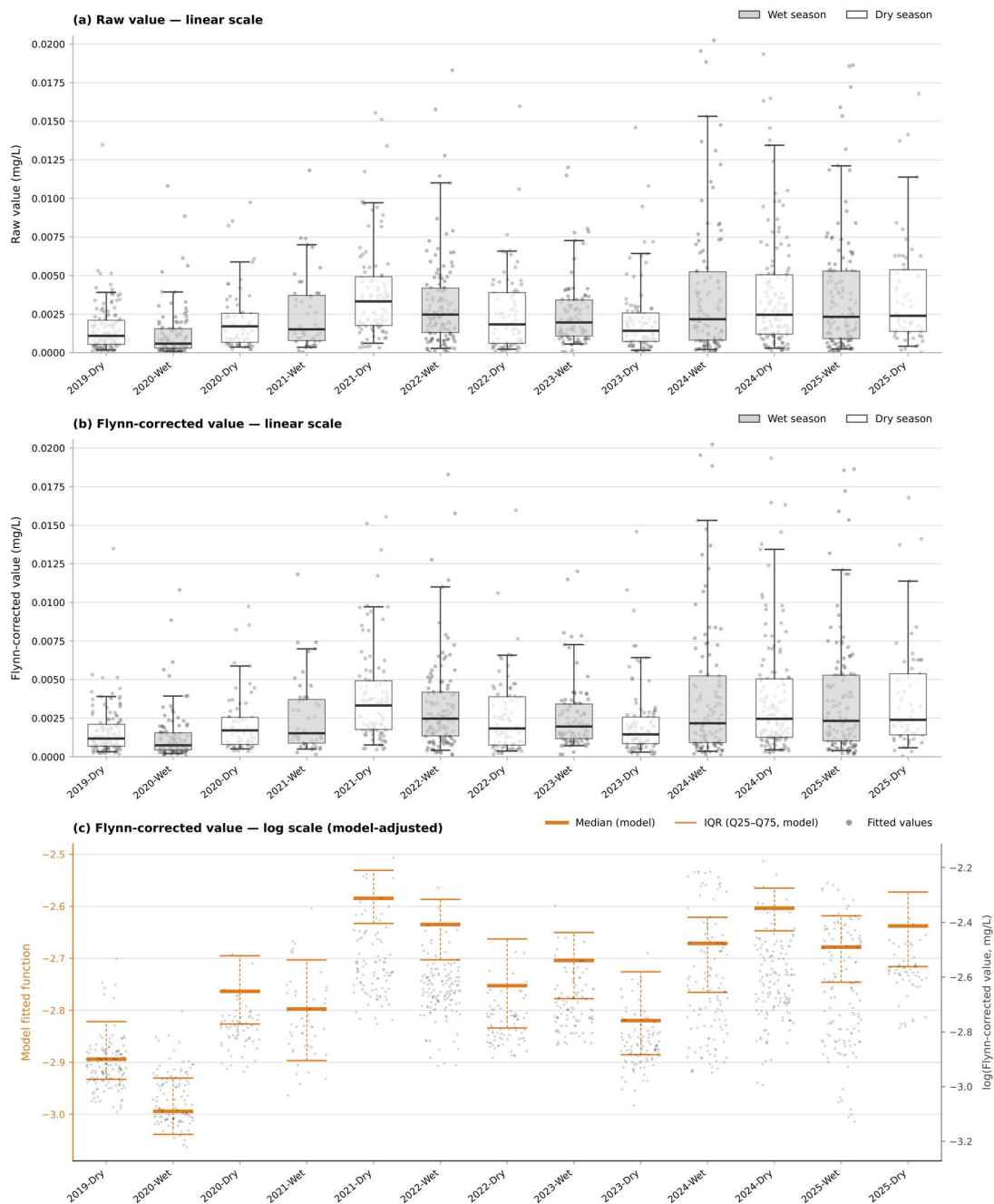


Figure 77. Nitrate, SERC. Seasonal and temporal patterns at the SERC monitoring network, by water-year season (November 2018 to December 2024). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

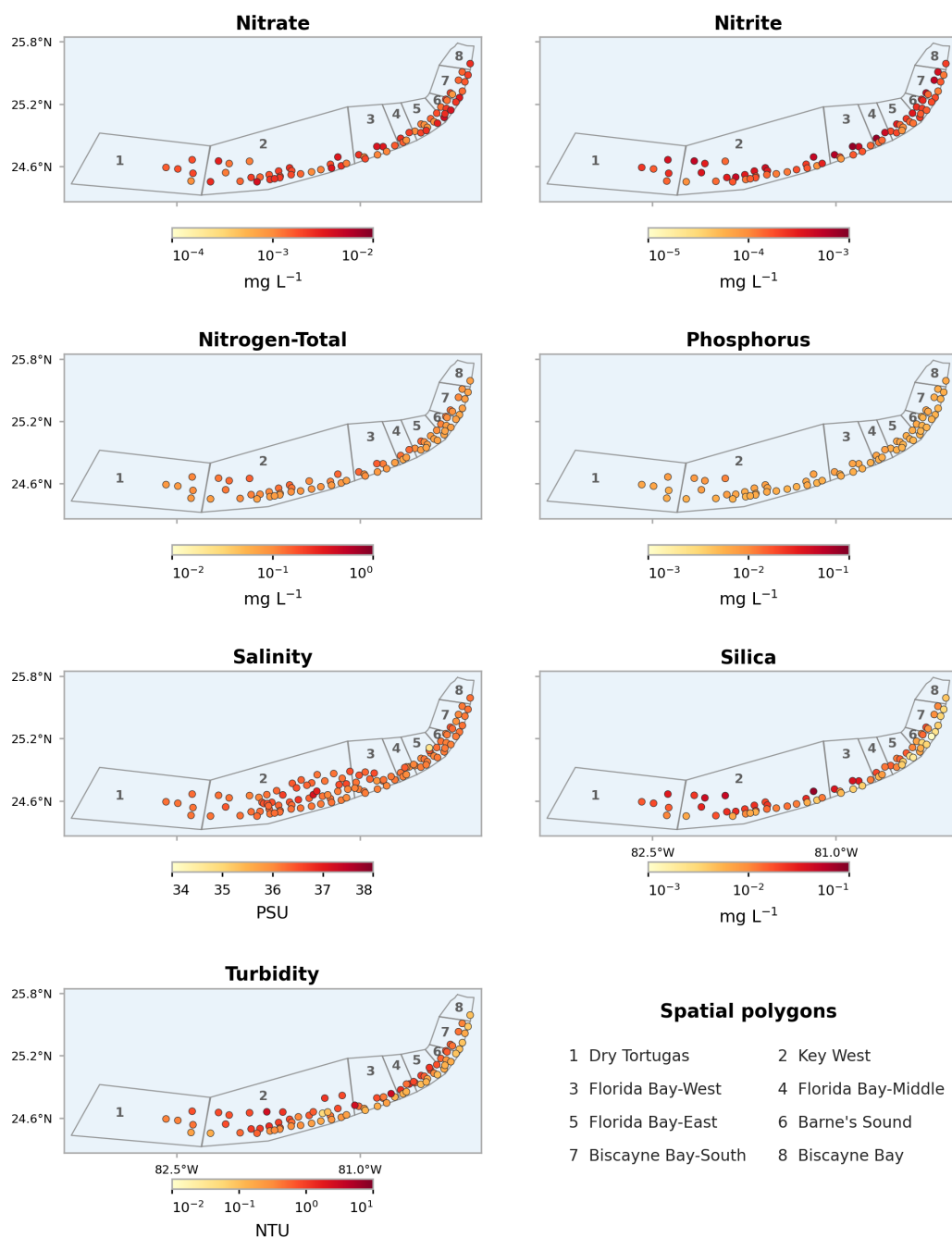


Figure 78. Overall median values per monitoring site across the SERC monitoring network for the full monitoring period (November 2018 to December 2024). Panels show, in reading order, Nitrate, Nitrite, nitrogen-total, total phosphorus, Salinity, Silica, and Turbidity; each panel uses a panel-specific color scale, logarithmic for all analytes except salinity, which is shown on a linear scale. Numbered grey outlines denote the eight SERC spatial polygons, identified in the key below the panels. Polygons 1 to 4 are Dry Tortugas, Key West, Florida Bay-West, and Florida Bay-Middle. Polygons 5 to 8 are Florida Bay-East, Barne's Sound, Biscayne Bay-South, and Biscayne Bay. Coordinates are in decimal degrees, WGS 84 datum.

Nitrite

Model-adjusted nitrite followed a three-regime trajectory (Figure 79c). An elevated initial season in 2019 was followed by a deep trough in 2020. A flat middle plateau followed, from the 2021 wet season to the 2023 dry season, near 0.00020 to 0.00021 mg L⁻¹. A clear late-record step-up then ran from the 2024 wet season onward, peaking in 2025. The total span was about 0.20 log units and the late-record step-up was the clearest feature. Season carried a relative influence of 15.9%, the second-ranked predictor behind depth, placing nitrite's seasonal effect in the substantive range for SERC though below that of SERC nitrate.

The pooled density was broadly symmetric on the log scale, with very low censoring; only 0.8% of observations sat at the detection limit (Figure A46). The per-season composite map showed modest spatial structure, with a polygon-to-polygon spread of only about 0.24 log units (Figure A47). There was no strong west-to-east or coastal gradient; the spatial signal was fine-grained, site-level heterogeneity rather than a coherent network-scale gradient. The dominant pattern in the composite was temporal. The eastern coastal polygons, Barne's Sound, Biscayne Bay-South, and Biscayne Bay, together with Florida Bay-Middle, reddened progressively across the record. The Lower and Middle Keys within the Key West polygon stayed cooler throughout, so the late-record rise was concentrated in the eastern coastal polygons. The overall-median map sits between the flat mid-record plateau and the elevated 2024 to 2025 state (Figure 78).

Nitrogen-total

Model-adjusted nitrogen-total traced a pronounced V-shape (Figure 80c). An elevated initial band, from the 2019 dry season through the 2021 dry season, held near 0.11 to 0.12 mg L⁻¹. A deep trough in the 2022 wet and dry seasons then fell to roughly 0.065 to 0.071 mg L⁻¹. This was the most pronounced single-year drop of any SERC analyte. A gradual recovery through the 2023 to 2025 wet seasons reached about 0.10 mg L⁻¹ before a sharp drop to 0.075 mg L⁻¹ in the 2025 dry season. The total span was about 0.25 log units. Season carried a relative influence of 31.1%, the largest contribution among the predictors and essentially matching SERC nitrate. Here, however, it acts on a far better-fitting model. The 2022 regime shift is therefore a real, well-identified seasonal effect.

The pooled density was unimodal, with a left shoulder near 0.04 mg L⁻¹ traced to the 2022 trough seasons (Figure A48). The per-season composite map was notably uniform in space, with a polygon-to-polygon spread of only about 0.14 log units, the tightest of any SERC analyte (Figure A49). There was no clear west-to-east gradient; site-level heterogeneity dominated any inter-polygon signal. The dominant pattern in the composite was therefore temporal. The 2019 to 2021 panels carried widespread orange and red sites along the eastern coastal arc and through Florida Bay. The 2022 wet and dry panels cooled sharply, with most sites dropping to yellow network-wide. The 2023 to 2025 panels then re-warmed progressively, without fully regaining the early-record state. The overall-median map is weighted toward the elevated early record, which occupied seven of the thirteen seasons, so it understates the depth of the 2022 trough (Figure 78).

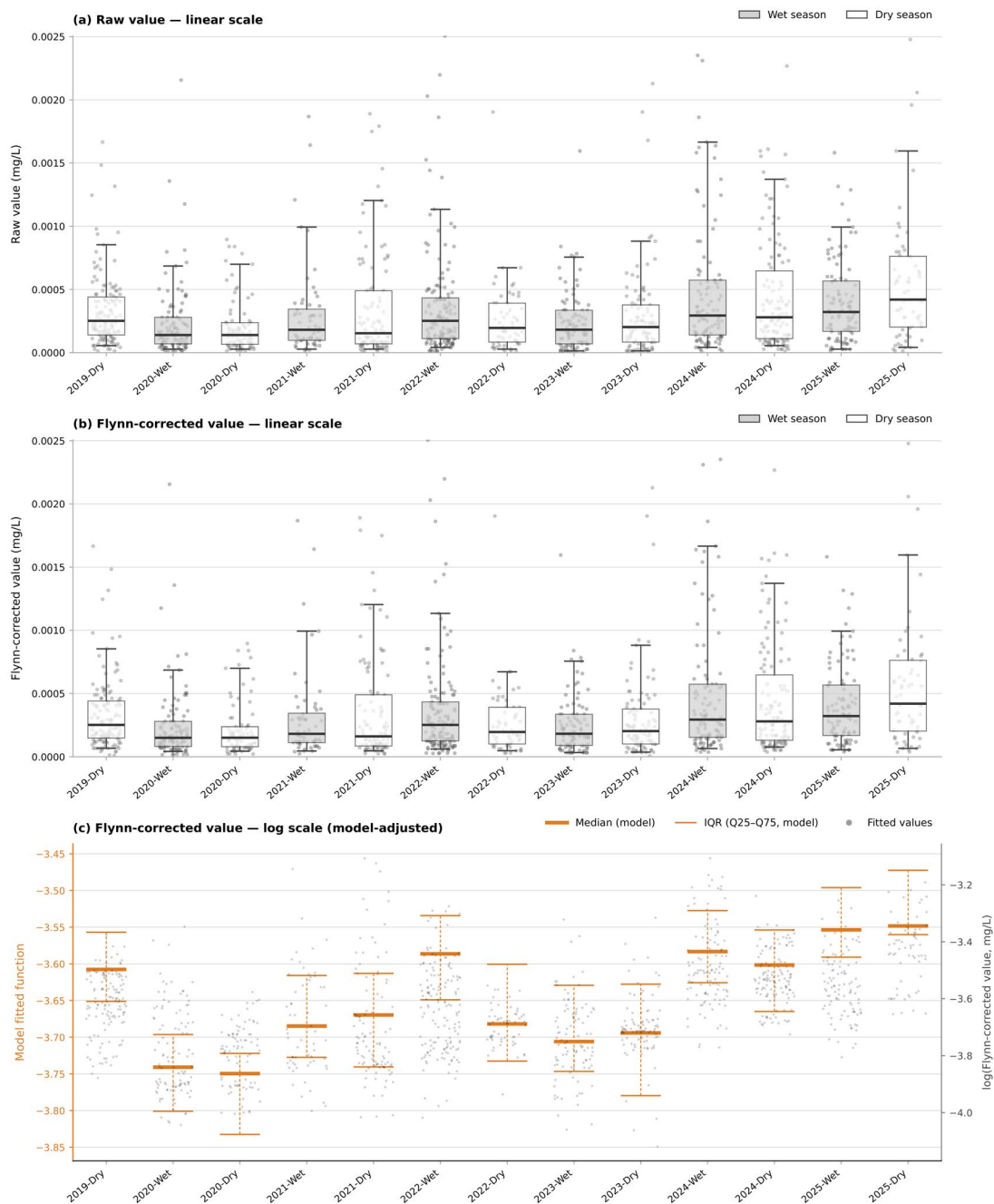


Figure 79. Nitrite, SERC. Seasonal and temporal patterns at the SERC monitoring network, by water-year season (November 2018 to December 2024). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

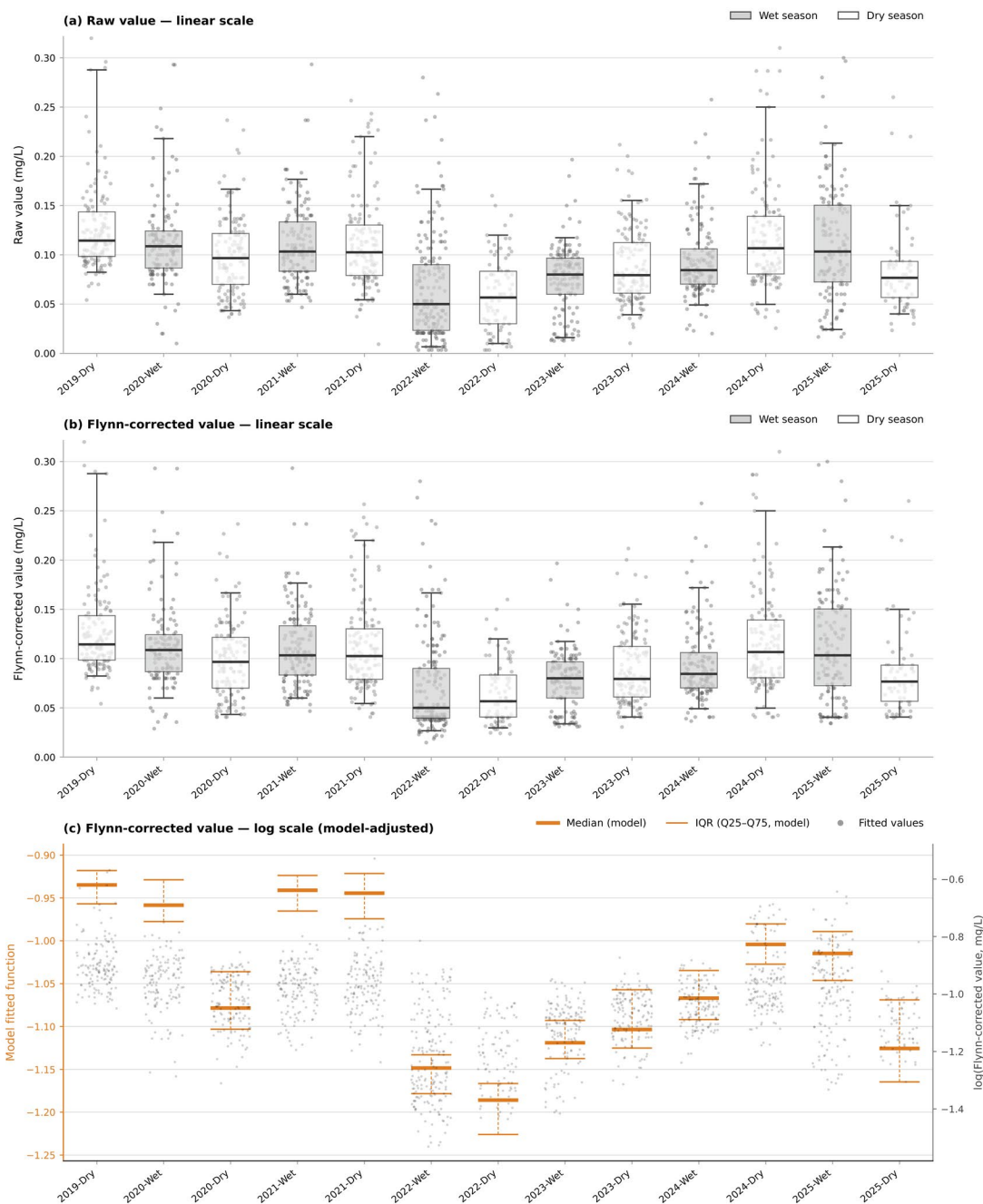


Figure 80. Nitrogen-total, SERC. Seasonal and temporal patterns at the SERC monitoring network, by water-year season (November 2018 to December 2024). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Total Phosphorus

Model-adjusted total phosphorus followed a coherent but small-magnitude trajectory (Figure 81c). The season-level median was lowest in the 2019 dry season. It rose through 2020 and 2021 to a mid-band near 0.0068 to 0.0072 mg L⁻¹. It dipped gently through 2022 and 2023, then reached a single-season peak at the 2024 wet season, the record high. It then dropped back to mid-range values in 2025. The total span was only about 0.19 log units. Season carried a relative influence of 43.6%, the largest single contribution by a wide margin. This is the highest seasonal relative influence of any SERC analyte. The effect is therefore well-identified, though modest in absolute magnitude.

Total Phosphorus was completely uncensored, with no observations at the detection limit, and the pooled density was symmetric and narrowly concentrated (Figure A50). The per-season composite map showed essentially no network-scale spatial structure (Figure A51). The polygon-to-polygon spread of medians was only about 0.084 log units, the tightest of any SERC analyte. The composite read as near-uniform pale yellow across all seasons and all polygons, with only a few red sites marking the extreme outliers. The model-adjusted 2024 wet-season peak was visible only as a slight, network-wide intensification of tone. Nearly all of the visible colour heterogeneity was site-level rather than polygon-level. Together, the near-absent spatial structure and the strong seasonal influence are telling. They point to a network in which total phosphorus is controlled by basin-wide temporal forcing, most likely seasonal hydrology, acting near-uniformly across all eight polygons (Figure 78).

Salinity

Model-adjusted salinity traced a three-phase freshening trajectory (Figure 82b). An elevated marine baseline in 2019 and 2020 held near 36.4 to 36.6 practical salinity units. A sharp drop into 2021 followed. The 2021 dry season reached 35.40 units, the lowest model median of the record. A partial recovery from 2022 onward followed, with dry seasons consistently lower than the corresponding wet seasons, indicating a residual freshening signature that persists through the late record. The total swing was 1.17 units. Season carried a relative influence of 23.9%, the leading predictor. The salinity model was among the best-fitting of the SERC analytes. The 2021 freshening is therefore a well-identified, network-scale event rather than a noise excursion. Salinity was modeled on its natural measurement scale, not log-transformed.

The pooled distribution was sharply unimodal, with most mass within a single 35 to 37 unit window and a thin left tail from a few freshwater-influenced inner-bay sites (Figure A52). The per-season composite map was notably uniform in space, with a polygon-to-polygon spread of only about 0.19 practical salinity units (Figure A53). The dominant pattern in the composite was therefore temporal. The 2019 and 2020 panels carried the most dark, high-salinity sites, consistent with a sustained dry, marine period. The 2021 panels cooled markedly, and the 2021 dry season showed the broadest band of low-salinity sites in the record. The 2022 to 2025 panels recovered partially, with dry seasons remaining visibly fresher than the adjacent wet seasons. Salinity serves as the network's physical reference variable, and the 2021 freshening seen here is the most likely driver of the corresponding 2021 excursions in the SERC chemistry analytes (Figure 78).

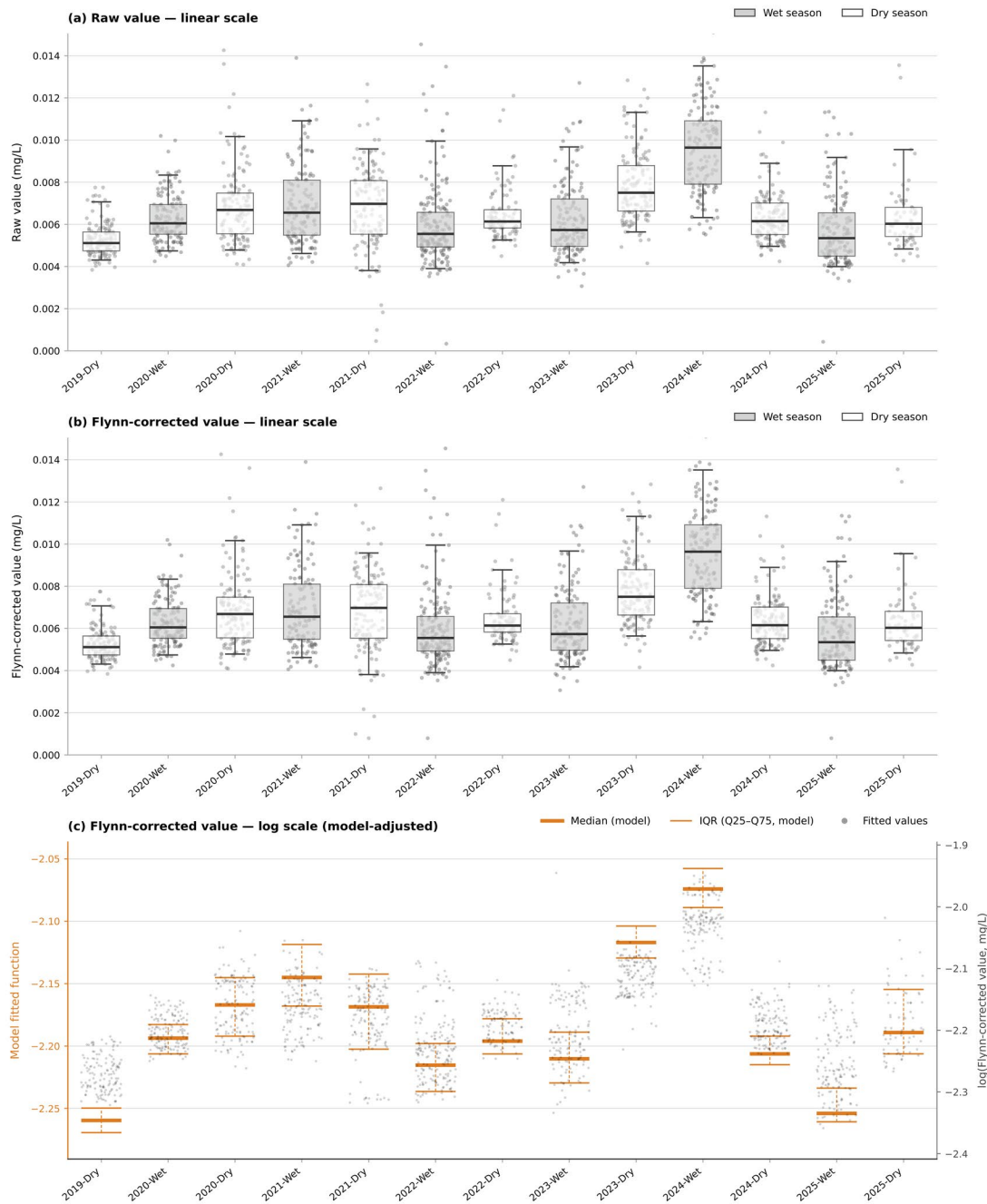


Figure 81. Total phosphorus, SERC. Seasonal and temporal patterns at the SERC monitoring network, by water-year season (November 2018 to December 2024). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-

varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

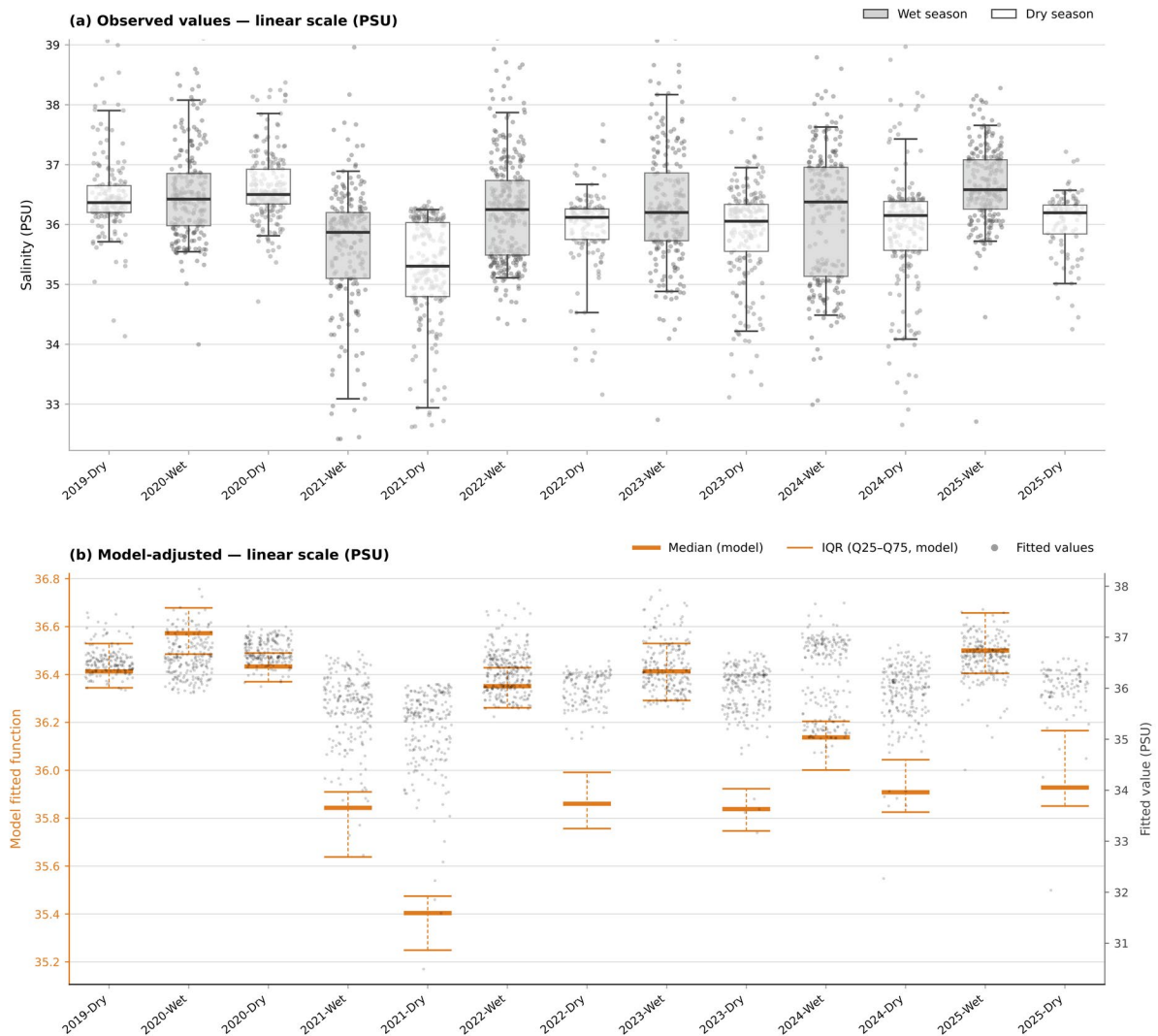


Figure 82. Salinity, SERC. Seasonal and temporal patterns at the SERC monitoring network, by water-year season (November 2018 to December 2024). Panel (a) shows observed values on a linear scale (practical salinity units); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (b) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

Silica

Model-adjusted silica was dominated by a wet-versus-dry alternation rather than a long-term trend (Figure 83c). Wet-season medians sat consistently above the adjacent dry-season medians. The trajectory spanned about 0.35 log units. It ran from a record low near 0.009 mg L⁻¹ in the 2020 dry season to a record high near 0.020 mg L⁻¹ in the 2025 wet season. Two dry seasons, 2023 and 2025, broke the pattern by sitting at the upper end of the range, possibly reflecting coverage-driven sampling differences. Season carried a relative influence of 25.1%, the leading predictor, with the spatial polygon and depth close behind, an unusually distributed influence pattern.

The pooled density was visibly bimodal, with the two modes set by geography rather than time (Figure A54). The per-season composite map showed the strongest spatial gradient of any SERC analyte (Figure A55). The polygon-to-polygon spread of medians reached about 0.65 log units, running monotonically west-high to east-low. The western Key West and Dry Tortugas polygons read as dark red on every panel. The Florida Bay polygons sat in the middle, and the Biscayne Bay polygons and Barne's Sound read as pale yellow. The model-adjusted wet-versus-dry alternation was also visible, with wet panels showing more red in the western polygons than the adjacent dry panels. The gradient is consistent with silica being controlled primarily by water-source mixing across the network. The overall-median map sits between the wet-season and dry-season network states (Figure 78).

Turbidity

Model-adjusted turbidity was characterized by elevated dry-season peaks (Figure 84b). Three dry seasons, 2019, 2021, and 2022, formed the three highest model medians of the record, ranging from 0.54 to 0.65 NTU. The wet seasons sat uniformly low near 0.29 to 0.35 NTU. The late dry seasons returned to that low band. The trajectory spanned about 0.37 log units, with the 2022 dry season the standout high. Season carried a relative influence of 17.0%, the third-ranked predictor behind depth and the spatial polygon, an unusually even three-way split.

The pooled density was bimodal, with the two modes set by geography, as for silica (Figure A56). The per-season composite map showed the widest spatial gradient of any SERC analyte, exceeding even that of silica (Figure A57). The polygon-to-polygon spread of medians reached about 0.78 log units, running west-high to east-low. The Key West polygon and the Florida Bay polygons carried the highest medians, near 0.4 to 0.6 NTU. The eastern Barne's Sound, Biscayne Bay-South, and Biscayne Bay polygons carried the lowest, near 0.1 to 0.3 NTU. The model-adjusted dry-season peaks were also visible, with the 2019, 2021, and 2022 dry panels showing more red across Florida Bay and Key West than the wet panels. Because seven of the thirteen seasons are wet, the overall-median map is weighted toward the lower wet-season state (Figure 78).

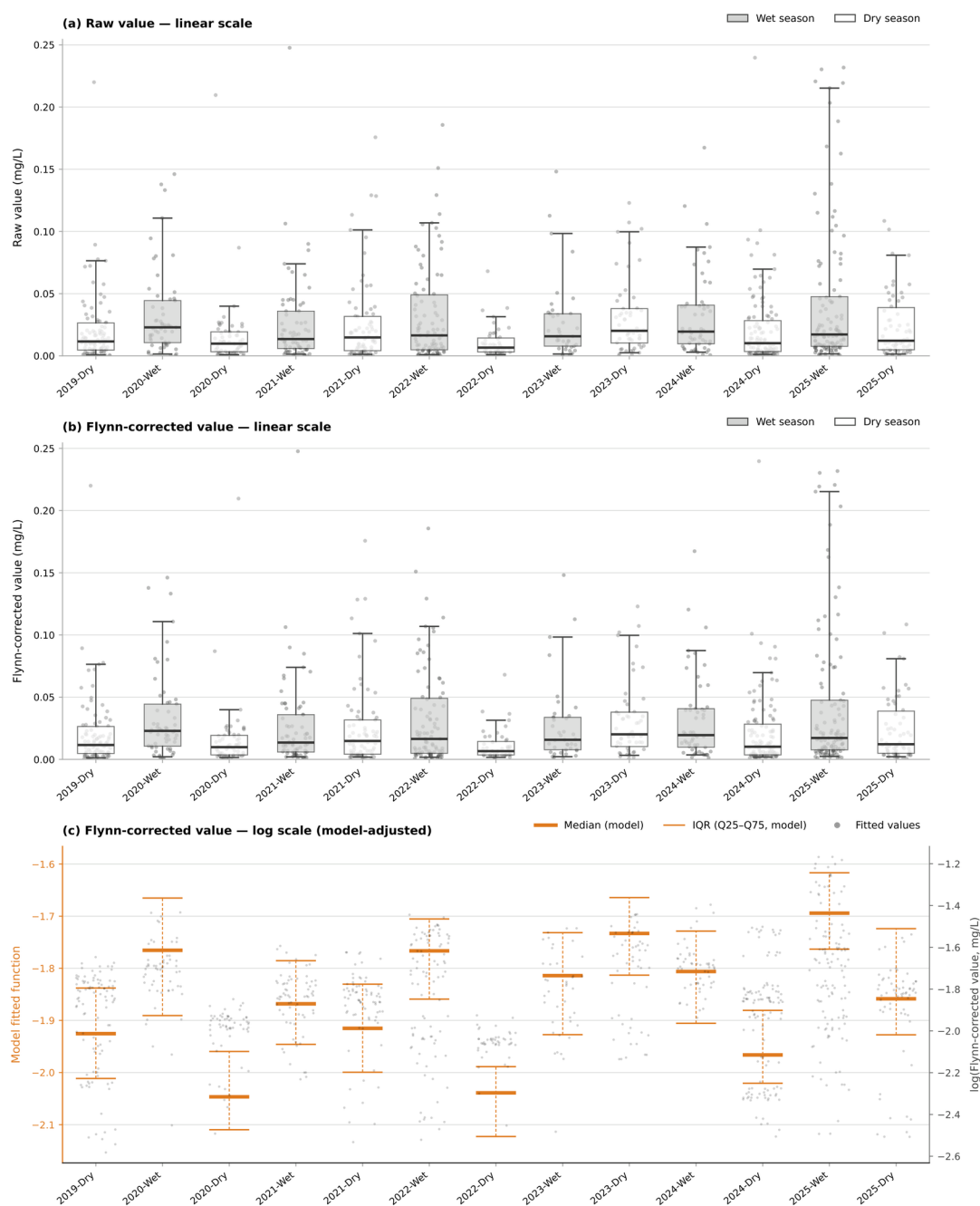


Figure 83. Silica, SERC. Seasonal and temporal patterns at the SERC monitoring network, by water-year season (November 2018 to December 2024). Panels (a) and (b) show raw measured values and method detection limit (MDL) adjusted (Flynn-corrected) values respectively, on a linear scale (mg L^{-1}); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (c) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

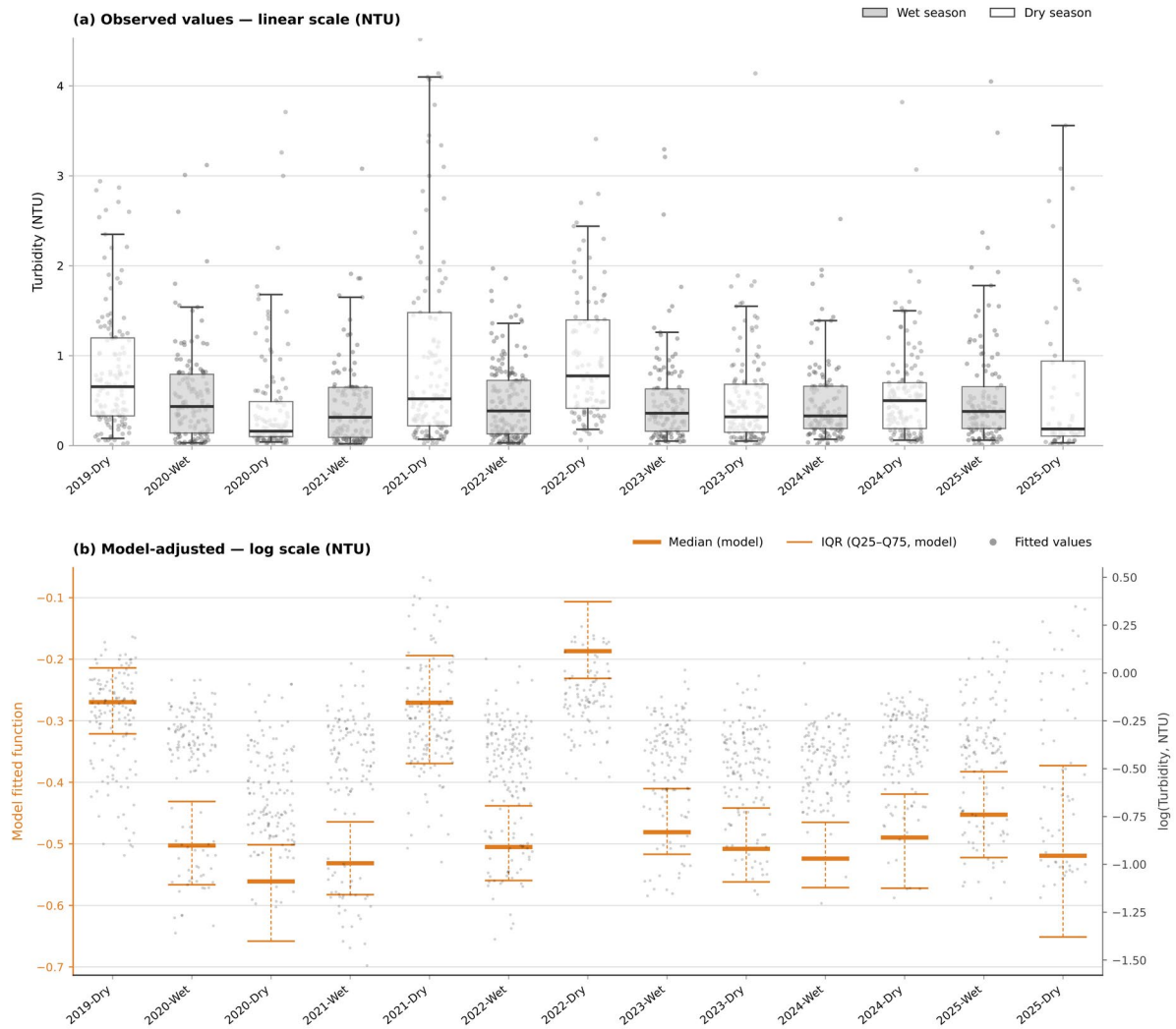


Figure 84. Turbidity, SERC. Seasonal and temporal patterns at the SERC monitoring network, by water-year season (November 2018 to December 2024). Panel (a) shows observed values on a linear scale (NTU); box plots show the median, the interquartile range, and 5th to 95th percentile whiskers, with individual observations jittered behind. Panel (b) shows the model-adjusted seasonal partial effect from the boosted regression tree (BRT) model, that is, the effect of season after the contributions of co-varying environmental drivers have been removed; the thick line marks the season-level median and the thin lines the interquartile range. Light shading denotes wet seasons.

3.5.6. Cross-region synthesis

Taken together, the four data sources provide a near-continuous picture of nearshore water quality along southeast Florida and the Florida Keys. This picture extends from Jupiter Inlet in the north to the Dry Tortugas in the southwest. They comprise 522 monitoring sites and more than 83,000 individual water-quality observations, each modeled within a common boosted regression tree framework. The principal features of the four datasets are compared in Table 9, and several patterns recur across all of them.

Table 9. Comparison of the four water-quality data sources analyzed in this report. cv deviance explained gives the range of cross-validated percentage deviance explained across each source's analyte models (bag fraction = 0.8). Leading predictor(s) summarizes the predictors that most often ranked first across analytes.

Data source	Analytes (n)	Sites (n)	Observations (n)	Spatial framework	cv deviance explained (%)	Leading predictor(s)
KJCAP	7	71	38,333	Nine inlet exposure areas (hydrographically defined)	39–72	Season (5 of 7 analytes); inlet exposure area
DERM	5	44	12,504	Five spatial polygons	37–67	Spatial polygon; season
WIN	7	295	19,848	Nine spatial polygons; nine sampling agencies	31–80	Sampling agency (4 of 7 analytes)
SERC	7	112	12,564	Eight spatial polygons	15–44	Season (5 of 7 analytes); depth

The most consistent finding was the important effect of season. Season was the single most influential predictor for most analytes in the KJCAP and SERC datasets, and ranked among the top predictors in every dataset and for nearly every analyte. The clearest exception was WIN, where sampling agency displaced season for the nitrogen and phosphorus analytes. The strength and shape of these seasonal signals are examined analyte by analyte in the seasonal patterns section above.

Spatial structure was the second recurring theme. The inlet exposure area (KJCAP) or spatial polygon (DERM, WIN, SERC) ranked first or second for most analytes in every dataset. This confirms that where a sample was collected mattered as much as when. An important distinction, however, is that the KJCAP inlet exposure areas are hydrographically grounded, informed by modeled inlet outflow. The DERM, WIN, and SERC polygons, by contrast, are spatial catch-all units included to absorb residual structure. Spatial signal in the three Keys datasets should therefore be read as descriptive rather than mechanistic. Depth was a further consistent contributor, particularly for the analytes most closely tied to the water column (orthophosphate, silica, and turbidity). Preceding flow, rainfall, and wind generally played secondary roles.

The WIN analysis surfaced a caution that applies well beyond this report. Because WIN aggregates data from many independent monitoring agencies, and because sampling agency was the dominant predictor for several analytes, agency and geography are

substantially confounded in that dataset. Aggregated multi-agency databases offer unmatched spatial and temporal coverage, but our results show that they cannot be used to infer broad-scale spatial water-quality patterns without explicitly modeling the contributing agency.

Finally, model performance declined across the four data sources. Cross-validated deviance explained fell from the KJCAP (39 to 72%) through DERM (37 to 67%) and WIN (31 to 80%) to SERC (15 to 44%). The KJCAP models, built on a single coherent monitoring program and hydrographically defined exposure areas, were the most predictive. The SERC models, drawn from a more heterogeneous Keys-wide network, were the least predictive. WIN occupied an intermediate position, although its strongest model, for nitrogen-total, owed much of its performance to the sampling-agency term rather than to environmental gradients.

3.6. Future work needed

Several avenues for future work follow directly from the analyses presented here. The most concrete concerns the spatial predictors. For the DERM, WIN, and SERC datasets, the spatial term was a set of geographic polygons rather than hydrographically informed exposure areas. The hydrographic model that underpins the KJCAP inlet exposure areas is currently being updated. A future project could use the updated model to redefine the DERM, WIN, and SERC polygons as hydrographically informed exposure areas. That change would place all four programs on a common, mechanistically grounded spatial footing.

The same updated hydrography could also refine the KJCAP exposure areas themselves. In particular, the Jupiter and St. Lucie inlets were pooled here for want of finer hydrographic data. Better-resolved flow fields would allow this northern unit to be partitioned, if the data support it.

A second priority is the agency and geography confounding in the WIN dataset. Sampling agency was the dominant predictor for several WIN analytes, and it cannot be cleanly separated from spatial structure. Targeted inter-agency comparisons, or a laboratory inter-calibration exercise, would help to quantify how much of the agency signal is methodological rather than environmental.

A third opportunity is the in situ temperature record. We synthesized a large body of HOBO temperature logger data, but did not use it in the statistical models. Incorporating temperature as a candidate predictor in a future iteration could test whether thermal stress co-varies with the water-quality drivers identified here.

Finally, model performance varied considerably among programs, and was weakest for the heterogeneous SERC network. Extending the time series as monitoring continues would strengthen every model, and the SERC models in particular. A combined Florida Keys analysis, integrating the WIN, DERM, and SERC networks, would also help to place the Keys-wide patterns in a single spatial framework.

4. DISCUSSION

Hydrographic modeling

A central difference between the present work and our previous study [15] was the spatial scope of the simulation. The model domain now continuously spans the entire FCR, from the Dry Tortugas to the northern KJCAP, over a six-year period (September 2018 – August 2024). This expansion is not merely a matter of covering more area. It forces the model to represent a wider range of circulation regimes than the comparatively uniform setting of the previous project. The northeastern KJCAP portion of the domain was dominated by the Florida Current and is characterized by an energetic, persistent, and largely unidirectional flow that efficiently flushes inlet-derived analytes away from their source and transports them predominantly northward along the shelf. By extending the domain southward and westward, we now also resolve sheltered, low-energy environments, such as in Biscayne Bay, in the Florida Keys, and Florida Bay, whose dynamics are fundamentally different.

The simulations revealed two contrasting dispersal regimes that bracket conditions across the FCR. In areas under the direct influence of the Florida Current, the residual flow was strong and directionally persistent, producing anisotropic, far-reaching plumes: analytes were advected over tens of kilometers, predominantly downstream (northward), and reefs were exposed not only to their adjacent inlet but also to inlets located further south. Government Cut and Baker's Haulover exemplified this behavior, exerting an influence well beyond their immediate vicinity. In contrast, in the tidally and wind-driven environments of Biscayne Bay, the Keys, and Florida Bay, residual flows were weak and the circulation was largely oscillatory [37]. Here the dispersal patterns were more isotropic and spatially confined: plumes disperse less, retain higher near-field concentrations, and have a smaller footprint. These areas were effectively decoupled from the energetic offshore transport of the Florida Current, so the fate of land-based analytes was governed by local tidal flow, wind forcing, and the degree of physical enclosure rather than by along-shelf advection.

The contrast between these regimes has a direct methodological consequence. In the previous KJCAP study, the strong and persistent flushing of the Florida Current kept simulated concentrations realistic even when analytes were treated as effectively conservative over the short reef transit times. Over the full FCR, this assumption breaks down in the weakly flushed, semi-enclosed areas. Without a removal mechanism, the limited exchange in Biscayne Bay, the Keys, and Florida Bay caused analytes to accumulate to unrealistically high concentrations. We therefore introduced an explicit first-order decay term in the transport equations, with an effective removal timescale of seven days for the dissolved nitrogen and phosphorus species and for total suspended solids [25, 26], and a longer timescale of twenty-one days for dissolved silicate, reflecting its more restricted (diatom-limited) biological uptake [27, 28]. It should be emphasized that these timescales are effective, calibrated parameters chosen to reproduce realistic near-field concentrations against the available water-quality observations, rather than direct measurements of individual biogeochemical rates. The longer silicate timescale, combined with its predominantly terrestrial origin and low marine background, is what makes silicate a robust first-order tracer of land-based inputs reaching the reef tract.

Distinguishing hydrographic regimes matters for how the model results should be interpreted and strategies for water quality management. Where the Florida Current dominates (east coast), the strong along-shelf connectivity results in reef's exposure set by the aggregate of upstream sources. Therefore, reducing loads at a single large southern inlet, like Government Cut, can lower analyte concentrations across many downstream reefs. In bays, where residual flows are weak, plumes remain relatively close to their source. Therefore, reducing loads at single locations are more spatially contained and have less of a broadscale downstream benefit. This regime dependence also helps explain the spatial structure of the modeled exposure fields, including the persistent north–south asymmetry around Government Cut and the more confined plumes within the bays, and it should be kept in mind when relating modeled exposure to the observed water-quality and reef-condition patterns.

Although the model performed well and validated satisfactorily against observations distributed across the FCR domain, several limitations should be acknowledged. First, once released into the coastal ocean, the analytes undergo complex biogeochemical reactions (nutrient cycling and speciation transformations, biological uptake and regeneration, and benthic exchange, including uptake by the extensive seagrass beds south of Government Cut) that the current model does not explicitly represent. Our first-order decay formulation captures the net effect of these processes only in a bulk, calibrated sense, and the fixed timescales cannot reproduce spatial or seasonal variability in reactivity. Second, the circulation was computed with a two-dimensional, depth-averaged barotropic model. While this configuration permitted the very high horizontal resolution needed near the inlets and over the reefs, depth-averaging suppressed the vertical structure of the flow and tends to reduce its variability, in particular the meandering and (sub)mesoscale eddy activity associated with the Florida Current [38, 39]. Coupling to HYCOM partly offsets this shortcoming, but the simulated flow, while directionally consistent with observations, remains somewhat too weak and lacks some of the observed variability. These limitations are most consequential precisely where the flow is energetic and three-dimensional, and they place bounds on the accuracy of the far-field, along-shelf transport estimates.

The clearest avenue for improvement is to move from the present two-dimensional barotropic configuration to a three-dimensional baroclinic model, while preserving the high horizontal resolution in the nearshore areas of interest. A baroclinic formulation would resolve vertical density structure and stratification, represent buoyant freshwater plume dynamics more faithfully, and recover much of the eddy-driven variability and flow strength that depth-averaging currently damps, hence directly addressing the principal source of error identified above. A natural complementary step would be to replace the bulk decay term with a more mechanistic representation of the dominant biogeochemical and benthic processes, so that analyte removal responds to local conditions rather than a fixed timescale. Together, these developments would strengthen confidence in both the magnitude and the spatial reach of modeled reef exposure, and would extend the framework's usefulness for evaluating management scenarios across the full diversity of FCR environments.

Drivers of nearshore water quality

Across all four monitoring programs, the boosted regression tree models converged on a consistent message: **nearshore water quality in this region is governed first by when a sample is collected and second by where, but neither signal is visible in the raw data.** A measured nutrient sample reflects season together with the rainfall, wind, and inlet outflow of the preceding days to weeks, the depth of the sample, and its spatial position, all of which co-vary. Raw concentrations therefore conflate these drivers, and a simple wet-versus-dry contrast cannot be attributed to season alone. The modeling technique used herein isolated the marginal effect of each predictor while holding the others constant. This accommodated the interpretation of the highly variable ambiguous raw data into interpretable, driver-specific responses. Season emerged as the leading or near-leading predictor for most analytes, with spatial position close behind, and the partial effects discussed below should be read as the temporal and spatial signals that survive once the correlated environmental drivers were removed.

In the KJCAP, the modeled seasonal trajectories of the seven analytes sorted into three shapes: a rise to a peak with a tentative recent decline (nitrate and silicate); a rise to an elevated asymptote (nitrite, orthophosphate, and total phosphorus); and an oscillation with no trend (total suspended solids and turbidity). The most striking feature is that four nutrient analytes, spanning different chemistries, leveled off or, for nitrate, begin to decline across the most recent seasons (Figure 85). The most plausible interpretation of several analytes moving in the same direction at the same time is a reduction in upstream nutrient loading on the nearshore reefs. Two further lines of evidence strengthen this interpretation. First, the analytes that were not driven by land-based loading, turbidity and total suspended solids, showed no such leveling. Spatial position (inlet exposure area) and depth dominated their influences, contributing about 30% and 24% of turbidity model influence (versus 14% for season). Second, silicate showed a clear late-period decline of about 0.27 log units across the two 2025 seasons, after rising about 0.57 log units since 2019. This outcome would be consistent with silicate-limited diatoms drawing down an elevated supply and providing a biological corroboration of reduced inputs.

The reasons for the decreasing nutrients seen in the KJCAP are not known. There have been many efforts to mitigate water quality in south Florida for several years. Notably since 2021, many local ordinances have been created to limit the use and types of fertilizers near water sources to reduce runoff into the ocean. These ordinances coincide with the timing of the plateauing analytes. This could be a sign that WQ mitigation efforts are helping. However, south Florida is in a severe drought and has had a total rain deficit for several years. Although the model accounts for rain and flow in some locations, it may not be accounting for all drought effects. We won't know how this is affecting the WQ offshore until rainfall returns to more normal conditions. A two-season decline is not a confirmed reversal, and continued monitoring is needed to establish whether the pattern persists.

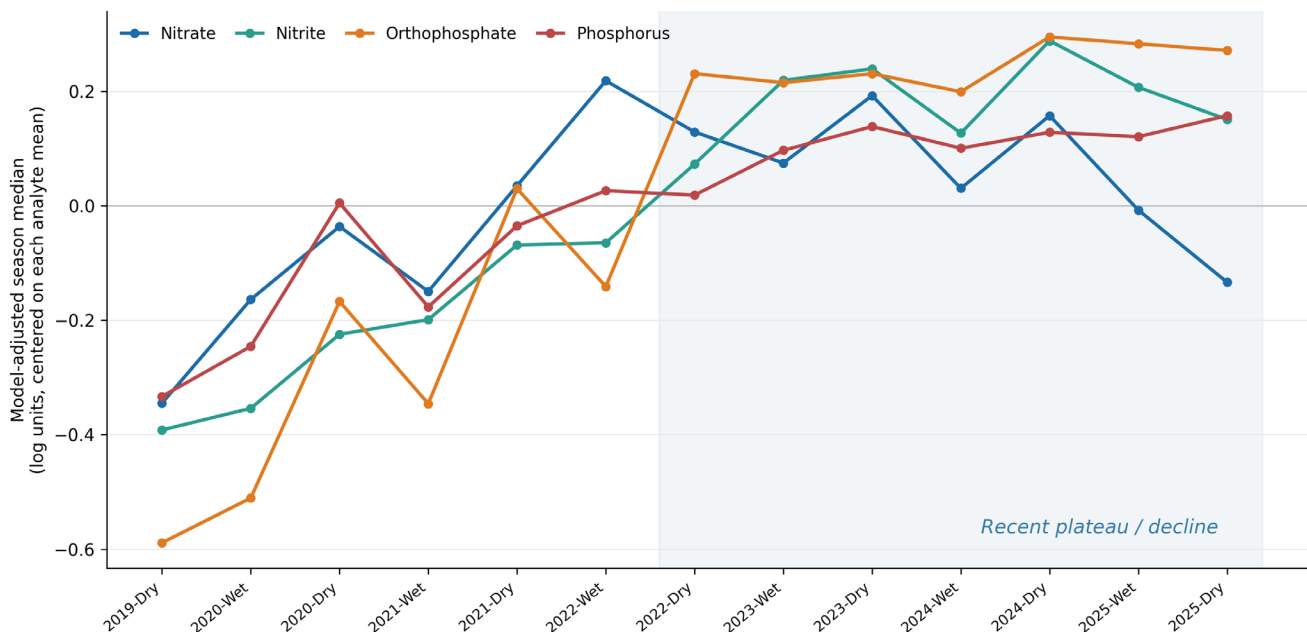


Figure 85. Model-adjusted seasonal trajectories of the four KJCAP nutrient analytes, November 2018 to April 2025. Each line is the boosted regression tree model-adjusted season-level median for one analyte (nitrate, nitrite, orthophosphate, and total phosphorus), centered on that analyte's own mean so the shapes are directly comparable; values are in log units. After rising through the early years, all four analytes level off across the recent seasons (shaded), and nitrate begins a tentative decline. Because several analytes of differing chemistry move together, the pattern is difficult to attribute to measurement drift and is consistent with reduced upstream nutrient loading reaching the nearshore reef. The medians are partial effects, estimated with rainfall, wind, inlet outflow, depth, and spatial position held constant.

Spatial structure was the second recurring theme, but its meaning depended entirely on the framework beneath it. In the KJCAP, the nine inlet exposure areas were hydrographically derived, informed by modeled inlet outflow, so their influence was interpretable mechanistically. Therefore, the model data at each site was summarized according to its dominant hydrographic model exposure. The Jupiter inlet exposure area (pooled with St. Lucie River inlet) carried the highest overall medians for total phosphorus and turbidity and elevated values for orthophosphate, silicate, and total suspended solids, while the remaining areas sat in a more uniform background. This concentration was plausibly inlet-driven, reflecting sediment loading from the Loxahatchee and St. Lucie rivers and reduced ocean exchange relative to the open-coast inlets to the south. Because the hydrographic modeling was conducted concurrent to the WQ modeling, there was no hydrographic exposure information to inform the sample site data summaries south of the KJCAP. Therefore, the DERM, WIN, and SERC analyses were conducted in more arbitrary geographic polygons associated to the nearest coastal locations. Not having been linked to hydrographic exposure, their analyses are more geographically descriptive rather than mechanistic.

The DERM models add an instructive cross-region contrast. In Biscayne Bay, the nitrogen and phosphorus trajectories declined and then plateaued, a near mirror image of the KJCAP rises. A coastal network still rising and an already-elevated embayment recovering may sit at different points on the same arc, but the opposing directions caution against generalizing any single program's temporal signal to the region as a whole.

The WIN analysis surfaced a caution that extends well beyond this report. Because WIN aggregated data from nine independent agencies and laboratories, **sampling agency was the single most influential predictor in four of the seven analyte models, exceeding 60% of relative influence in two of them.** In those analytes, most of the variation reflects differences in how agencies sample and analyze rather than differences in the water itself. The genuine gradients in space, depth, season, and flow only became visible once the agency term was included and partialled out. The consequence is easy to overlook in a performance ranking: the WIN models that rank highest do so largely because of the agency term, not because of environmental signal (Figure 86). Aggregated multi-agency databases offer unmatched spatial and temporal coverage, but our results show they cannot be used to infer broad-scale water-quality patterns unless the contributing agency is modeled explicitly. This is a transferable lesson for any regional synthesis that pools heterogeneous monitoring sources.

Finally, the explanatory power of the models declined in a clear gradient from the KJCAP, through DERM and WIN, to SERC, where cross-validated deviance explained fell to 15 - 44 percent, the lowest in the synthesis. This gradient tracks both distance from the mainland and, importantly, whether the spatial framework is mechanistic or merely descriptive. The KJCAP models, built on a coordinated program with hydrographically defined exposure areas, were the most predictive, whereas the SERC models, drawn from a broad and heterogeneous Keys-wide network, were the weakest. WIN appears strong only until the sampling-agency contribution is set aside, after which its nutrient model performances fall sharply (Figure 86). The most direct route to improvement is therefore to place the other programs on the same mechanistic footing. The extended hydrographic modeling southward into the Keys and Florida Bay from this project provided exposure data that can be used in subsequent analyses to refine the geographic analyses that should raise their explanatory power.

Another reason for the explanatory power of the models declining in a clear gradient from the KJCAP, through DERM and WIN, to SERC is their distance from the nutrient sources. The KJCAP is highly linked to the nutrient sources along the east coast as the land-based water comes out of the inlets and hugs the coast. The DERM data were also in very close proximity to the nutrient source. The WIN and SERC datasets contained sites throughout the Keys and out into open ocean. These sites were very far from the land-based nutrient sources in this study coming from Florida's mainland. The weaker relationships indicate that Florida's mainland is not the main source of nutrients throughout the Keys and that to get a more accurate terrestrial connection to nutrients at monitoring stations in the Keys, more localized source data need to be used in the modeling.

The natural next step is to integrate these modeled water-quality datasets with the in-water reef data on corals, algae, and fish, so that the drivers identified here can be linked directly to reef condition and persistence. This is a goal of our 2026-27 efforts for DEP while updating the models to include hydrographic exposures.

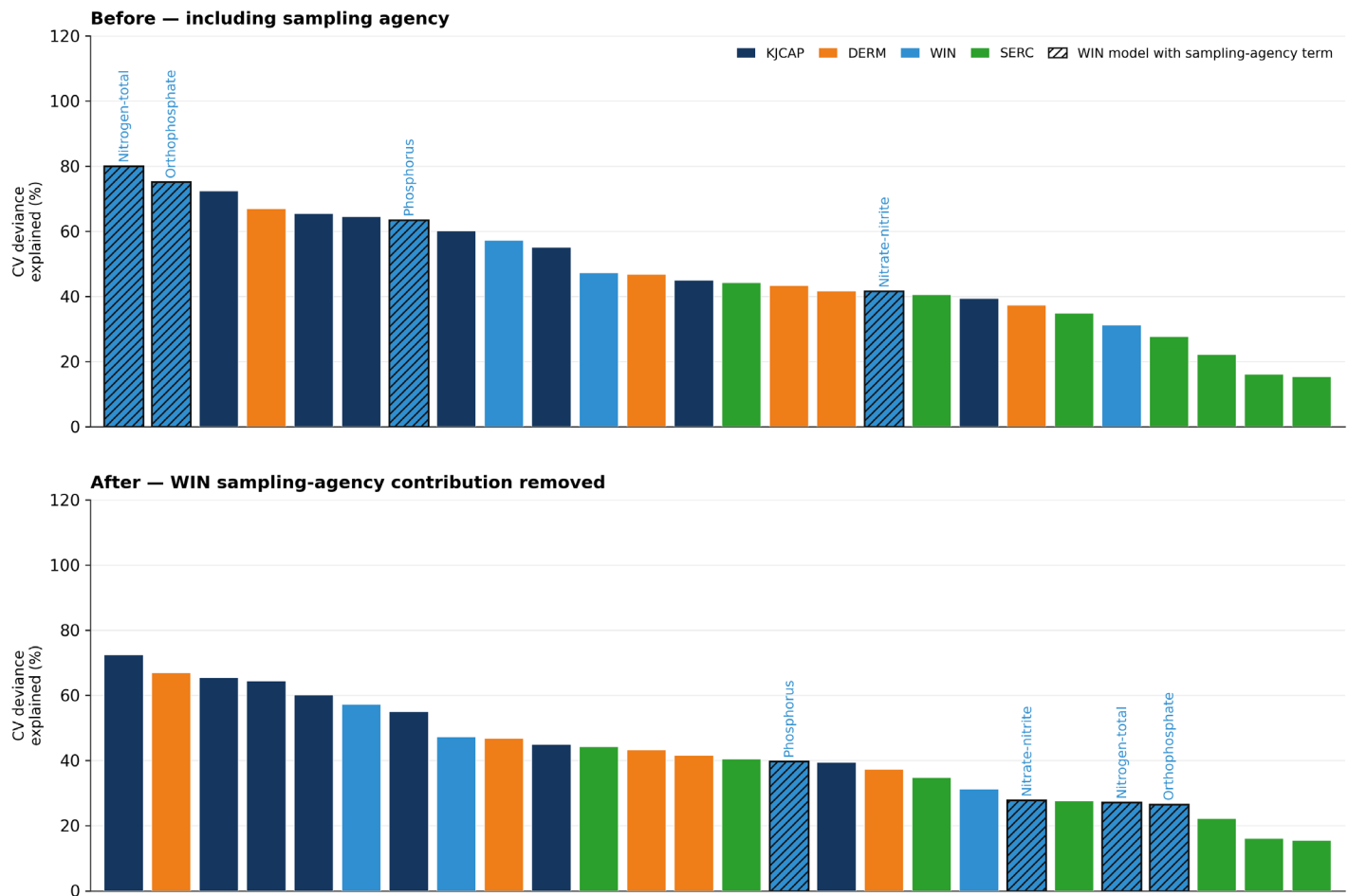


Figure 86. Cross-validated deviance explained by the 26 analyte models, ranked high to low and colored by program, before (top panel) and after (bottom panel) removing the WIN sampling-agency contribution. In the top panel the models are ranked on their original deviance; the two highest, both WIN (nitrogen-total and orthophosphate), owe most of that performance to the sampling-agency term. Hatched bars mark the four WIN models in which sampling agency was a leading predictor. In the bottom panel each of those WIN models is scaled by one minus its sampling-agency relative influence and the models are re-ranked; the connecting lines track the four WIN models. Nitrogen-total and orthophosphate fall from first and second to near the bottom of the ranking (positions 22 and 23), and WIN no longer dominates. This is a first-order illustration that scales model deviance by relative influence rather than refitting the models; sampling agency was not among the leading predictors for the remaining WIN analytes (nitrite, silica, and total suspended solids), which are unchanged.

5. MANAGEMENT RECOMMENDATIONS

Standardize water quality monitoring data across programs. Aggregated multi-agency databases offer unmatched spatial and temporal coverage, but our results show they cannot be used to infer broad-scale water-quality patterns unless the contributing agency is modeled explicitly. Our work required that program data be analyzed separately. Management should work towards standardization of water quality collections and chemical analyses to make them more compatible for regional analyses.

Integrating coral reef monitoring data and developing predictive statistical models

We recommend integrating various coral reef monitoring program data and the BCG into predictive statistical models to quantify the relationship between each reef health indicator and changes in WQ and other local environmental conditions, identifying the local conditions that either promote reef persistence or exacerbate decline. These results will deliver actionable management targets for local conditions that maximize reef resilience and restoration success.

Identify and quantify water quality mitigation actions responsible for water quality improvements. There have been many efforts to mitigate water quality in south Florida for several years. Notably since 2021, many local ordinances have been created to limit the use and types of fertilizers near water sources to reduce runoff into the ocean. These ordinances coincide with the timing of the plateauing analytes. This could be a sign that WQ mitigation efforts are helping. Management should coordinate with Miami-Dade County Biscayne Bay Reasonable Assurance Plan to identify past, present, and future projects capable of reducing loads into the coastal waterways.

Continued annual temporal trend analysis. Repeating the statistical modeling of WQ analytes to land-based water sources annually will provide yearly rates of changes for each WQ parameter. This gives an understanding whether WQ mitigation improvements are having effects on the reefs. The timing of the observed changes can be compared to known implementation periods of mitigation activities to evaluate their effectiveness in improving reef WQ.

Upgrade to three-dimensional hydrodynamic model application and validation. We recommend upgrading to the full 3D model configuration to explicitly resolve vertical dynamics, temperature, and salinity variations. The horizontal resolution will reach approximately 100 m across reef areas. Model validation should be conducted using NOAA current-meter and temperature records collected at multiple FCR locations, including iconic reef sites.

Expand model spatial framework. We recommend to spatially expand the model up to include the Caloosahatchee, a major source of Lake Okeechobee water coming from the W FL shelf, and modeling sources in the FL Keys.

Incorporate the EPA-funded Halo-Zone data to identify common WQ sources connecting nearshore and offshore water in the Florida Keys. We recommend to

integrate the EPA-funded Halo-Zone dataset, which provides observations of water quality along nearshore-to-reef transects in the Florida Keys, and the broader South Florida Ecosystem Restoration (SFER) oceanographic monitoring dataset, which conducts cruises approximately every 6 weeks, making the same measurements across the Florida Keys National Marine Sanctuary and adjacent waters. Together, these complementary datasets can be used to evaluate modeled transport pathways and nutrient plume dynamics by comparing simulated tracer dispersal from coastal sources with observed gradients along the transects, improving representation of nearshore-offshore connectivity influencing Florida's Coral Reef.

Update Data Assembly and Integration for another statistical analysis that includes 2023 and 2025. The year 2025 was a drought year for South Florida during which extensive bleaching occurred on the FCR. Extending the dataset captures two bleaching events (2023 and 2025): one during normal rainfall and one during drought. This addition will strengthen future analyses of how terrestrial and environmental conditions influence nutrient levels at offshore WQ stations and their relationship to coral bleaching.

Create spatiotemporal WQ exposure maps to identify upland targets that maximize mitigation effectiveness. We recommend simulating WQ stress by coupling the hydrodynamic model with transport models to track seven analytes: nitrite, nitrate, total nitrogen, orthophosphate, total phosphorus, silicate, and total suspended solids (TSS). These analytes can be continuously released from the major wastewater inlets along the FCR and transported by ocean currents and traced to its specific inlet source to precisely identify the origin of reef exposure.

Incorporate high-resolution heat exposure to identify microrefugia during thermal stress events to inform an adaptive approach to restoration prioritization. We recommend simulating temperatures at reef depth, capturing subsurface processes such as upwelling, stratification, and along-reef jets. These processes influence cumulative heat exposure but are undetectable by satellite sea surface temperature products. The resulting thermal stress metric will have a spatial resolution of approximately 100 m, offering far greater detail than the 5-km NOAA Coral Reef Watch dataset.

Apply machine learning models based on *in situ* WQ data to detect WQ improvement benefits on the reef. We recommend building statistical models to quantify relationships between environmental drivers and WQ variables. Results will be used to generate *safe-operating-space* thresholds that define environmental conditions supporting optimal reef water quality.

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6. APPENDIX

APPENDIX 1. DBHYDRO FLOW STATIONS USED IN THE ANALYSES

The following active South Florida Water Management District (SFWMD) DBHydro flow stations contributed to the daily outflow time series used as candidate predictors in the BRT models. Stations are listed moving in approximate north-to-south, by inlet exposure area (IEA) for the KJCAP, and by spatial polygons further south. Across the KJCAP, 28 stations (S49 down to S123) were aggregated into the 9 IEAs used in the KJCAP BRT models. The 3 St. Lucie flow stations were pooled into the Jupiter IEA. Stations south of Biscayne Bay were used in the WIN, SERC, and DERM analyses (see Results).

Table A1. Active SFWMD DBHydro flow stations used in the present analyses, listed by inlet exposure area (IEA) in approximate north-to-south order. Stations are listed by spatial polygon for Biscayne Bay and the Florida Keys. For the KJCAP, the three St. Lucie flow stations were pooled into the Jupiter IEA (see Methods).

Station	County	IEA / Spatial polygon
S49_S	ST LUCIE	<i>St. Lucie</i>
S48_S	MARTIN	
S80_S	MARTIN	
S46_S	PALM BEACH	<i>Jupiter</i>
S44_S	PALM BEACH	<i>Lake Worth</i>
S155_S	PALM BEACH	
S41_S	PALM BEACH	<i>Boynton</i>
S40_S	PALM BEACH	
G56_S	BROWARD	<i>Boca</i>
G57_S	BROWARD	<i>Hillsboro</i>
S37A_S	BROWARD	
S36_S	BROWARD	<i>Port Everglades</i>
S33_S	BROWARD	
G54_S	BROWARD	
S13_S	BROWARD	
S13_P	BROWARD	
S13TEMP_P	BROWARD	
S29_S	MIAMI-DADE	<i>Baker's Haulover</i>
G58_C	MIAMI-DADE	
S28_S	MIAMI-DADE	
S27_S	MIAMI-DADE	<i>Government Cut</i>
S26_S	MIAMI-DADE	
S25B_S	MIAMI-DADE	
S25_C	MIAMI-DADE	
G93	MIAMI-DADE	<i>Biscayne</i>
S22_S	MIAMI-DADE	
S700_P	MIAMI-DADE	
S123_S	MIAMI-DADE	

Station	County	IEA / Spatial polygon
S21_S	MIAMI-DADE	<i>Biscayne Bay-South</i>
S703_P	MIAMI-DADE	
S21A_S	MIAMI-DADE	
S705_C	MIAMI-DADE	
S705_P	MIAMI-DADE	
S20G_S	MIAMI-DADE	
S709_C	MIAMI-DADE	
S709_P	MIAMI-DADE	
S709TEMP_P	MIAMI-DADE	
S20F_S	MIAMI-DADE	
02290888	MONROE	<i>Big Cypress</i>
02290918	MONROE	
02290878	MONROE	<i>Everglades NP</i>
SHARKRIVBG	MONROE	
022908205	MONROE	
MANBAYCK	MIAMI-DADE	<i>Barne's Sound</i>
HIGHWAY_CR	MIAMI-DADE	
TROUT CR_B	MIAMI-DADE	<i>Florida Bay-East</i>
MUD_CRKM	MIAMI-DADE	
EASTCK	MIAMI-DADE	
TAYLORS3	MIAMI-DADE	
ALLIGARF	MIAMI-DADE	<i>Florida Bay-Middle</i>
MCCORMICK	MIAMI-DADE	
EASTSIDE	MONROE	<i>Florida Bay-West</i>

APPENDIX 2. PREDICTORS REMOVED DURING COLLINEARITY SCREENING

This appendix lists the candidate environmental predictors removed from each program's boosted regression tree models during the pairwise collinearity screening described in the Methods. A predictor was removed when it correlated at $r \geq 0.8$ with a predictor that was retained. The screening was applied independently to each of the four programs.

Table A2. Candidate environmental predictors removed from each program's boosted regression tree models during pairwise collinearity screening (see Methods). A predictor was removed when it correlated at $r \geq 0.8$ with a predictor that was retained. Values give the temporal window, in days prior to sampling, of each removed predictor.

Predictor	KJCAP	DERM	WIN	SERC
Inlet outflow	1, 3, 14, 60, 90	1, 3, 14, 60	1, 3, 14, 60	1, 3, 14, 30, 60
Cumulative rainfall	90	60	60	60
Landward high-wind events	14, 90	1, 60	1, 3, 14, 60	3, 14, 60
Seaward high-wind events	60, 90	60	60	14, 60
Total predictors removed	10	8	10	11

APPENDIX 3. SEASONAL SUPPORTING FIGURES

This appendix provides the supporting seasonal figures for each analyte: the distribution of values, shown pooled and by water-year season, and the per-season spatial composite. These complement the seasonal and temporal panels and the overall-median maps presented in the Seasonal patterns section.

KJCAP: Nitrate

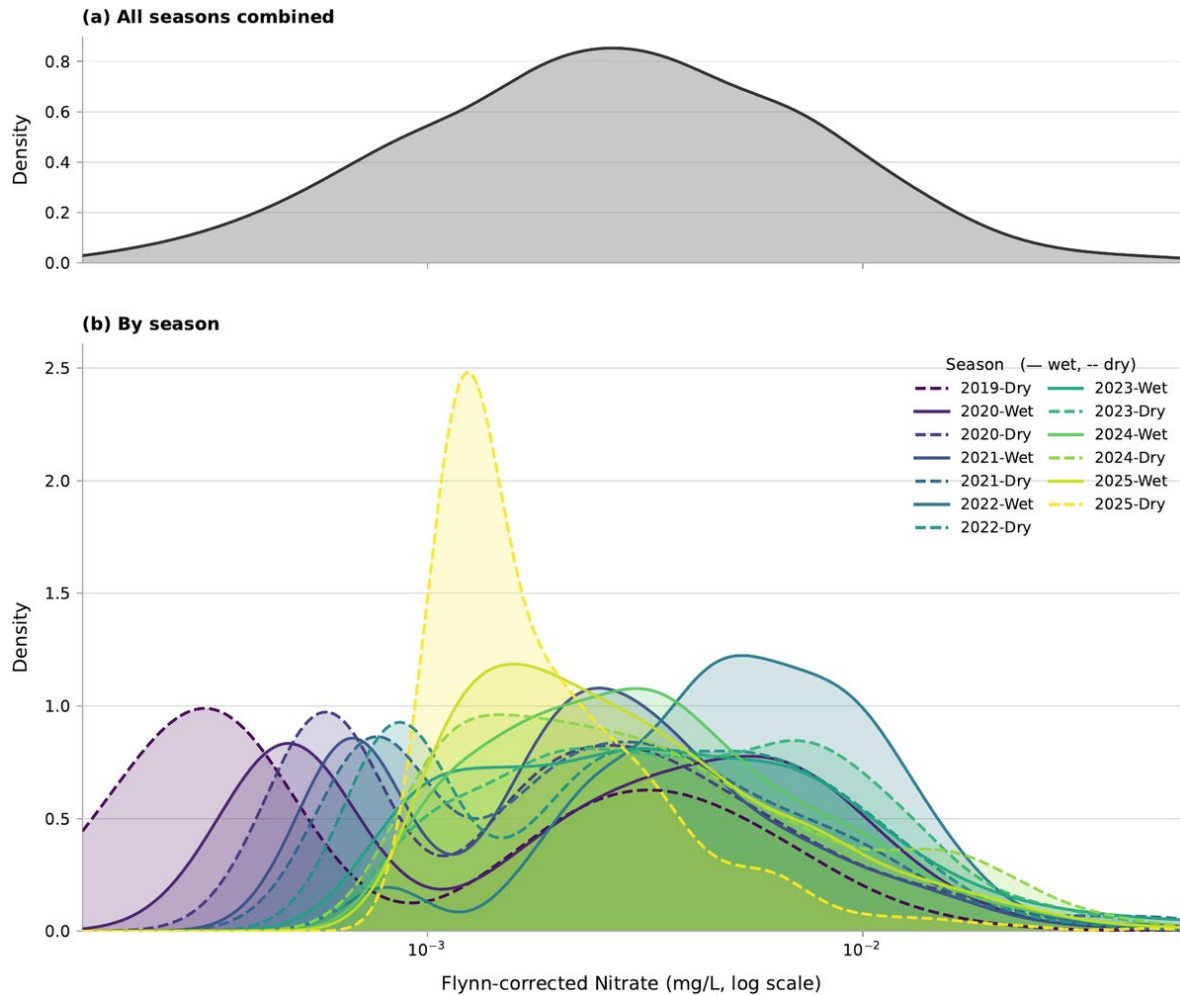


Figure A8. Nitrate, KJCAP. Distribution of values at the KJCAP monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

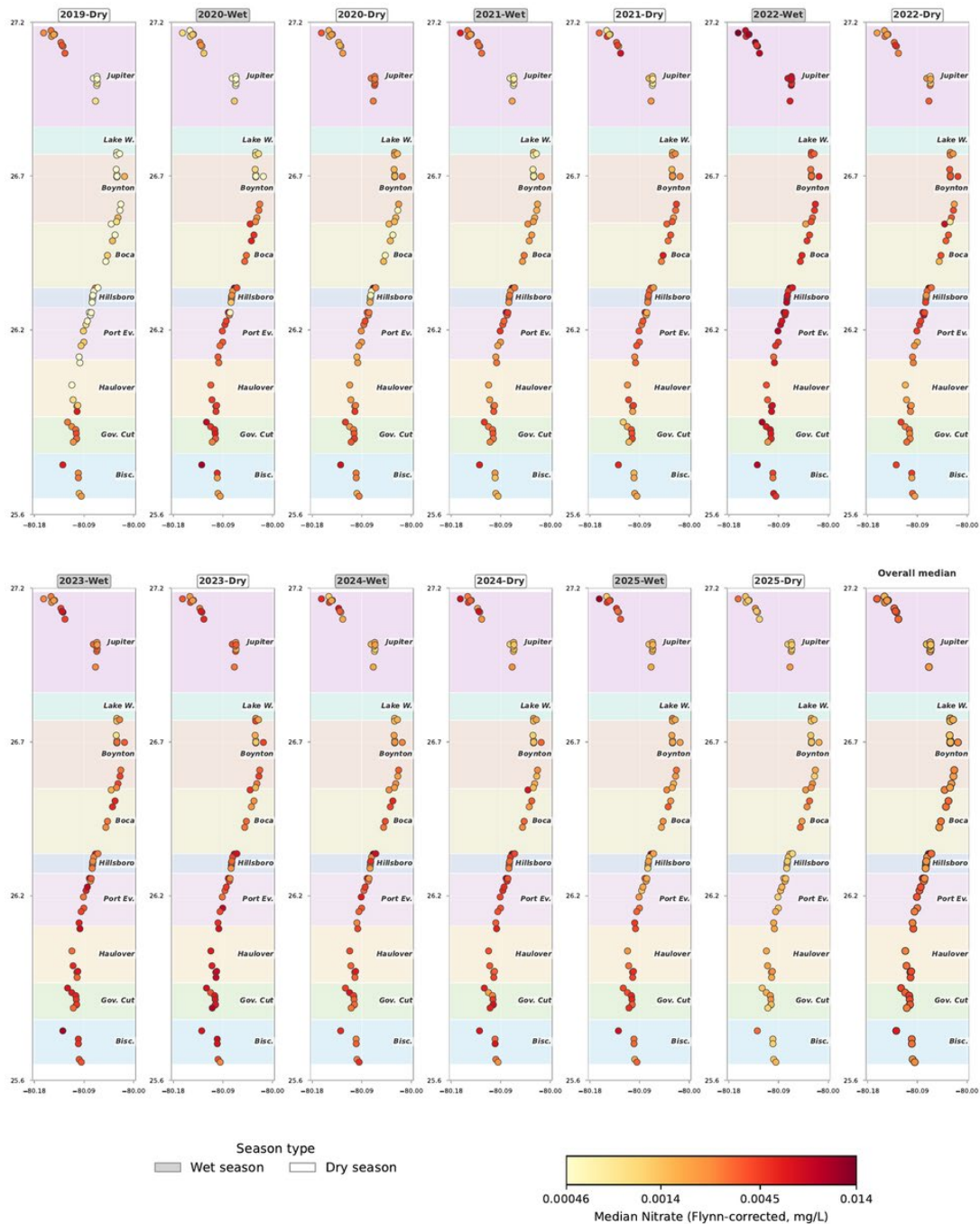


Figure A9. Nitrate, KJCAP. Per-season spatial distribution of the median across the KJCAP monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

KJCAP: Nitrite

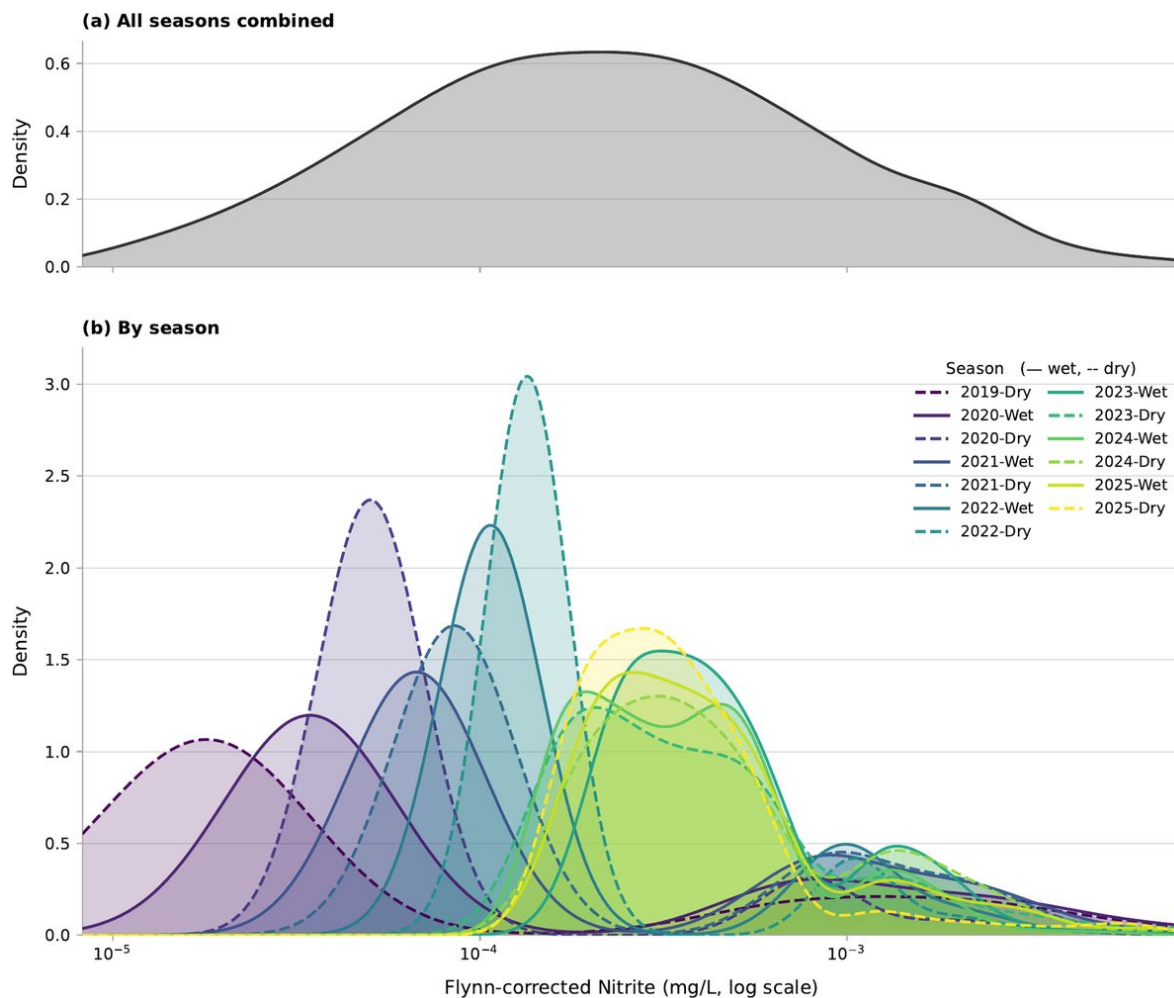


Figure A10. Nitrite, KJCAP. Distribution of values at the KJCAP monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

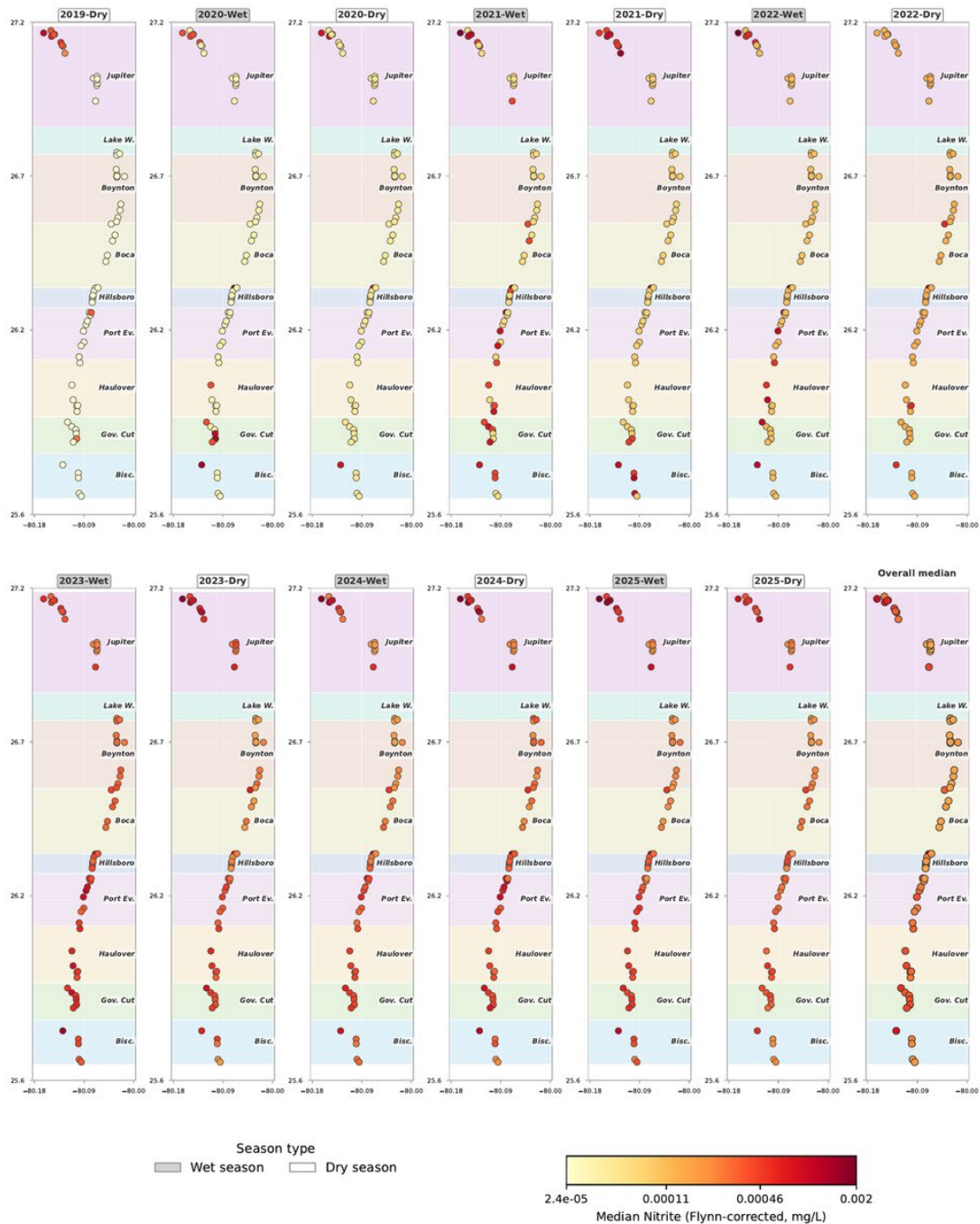


Figure A11. Nitrite, KJCAP. Per-season spatial distribution of the median across the KJCAP monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

KJCAP: Orthophosphate

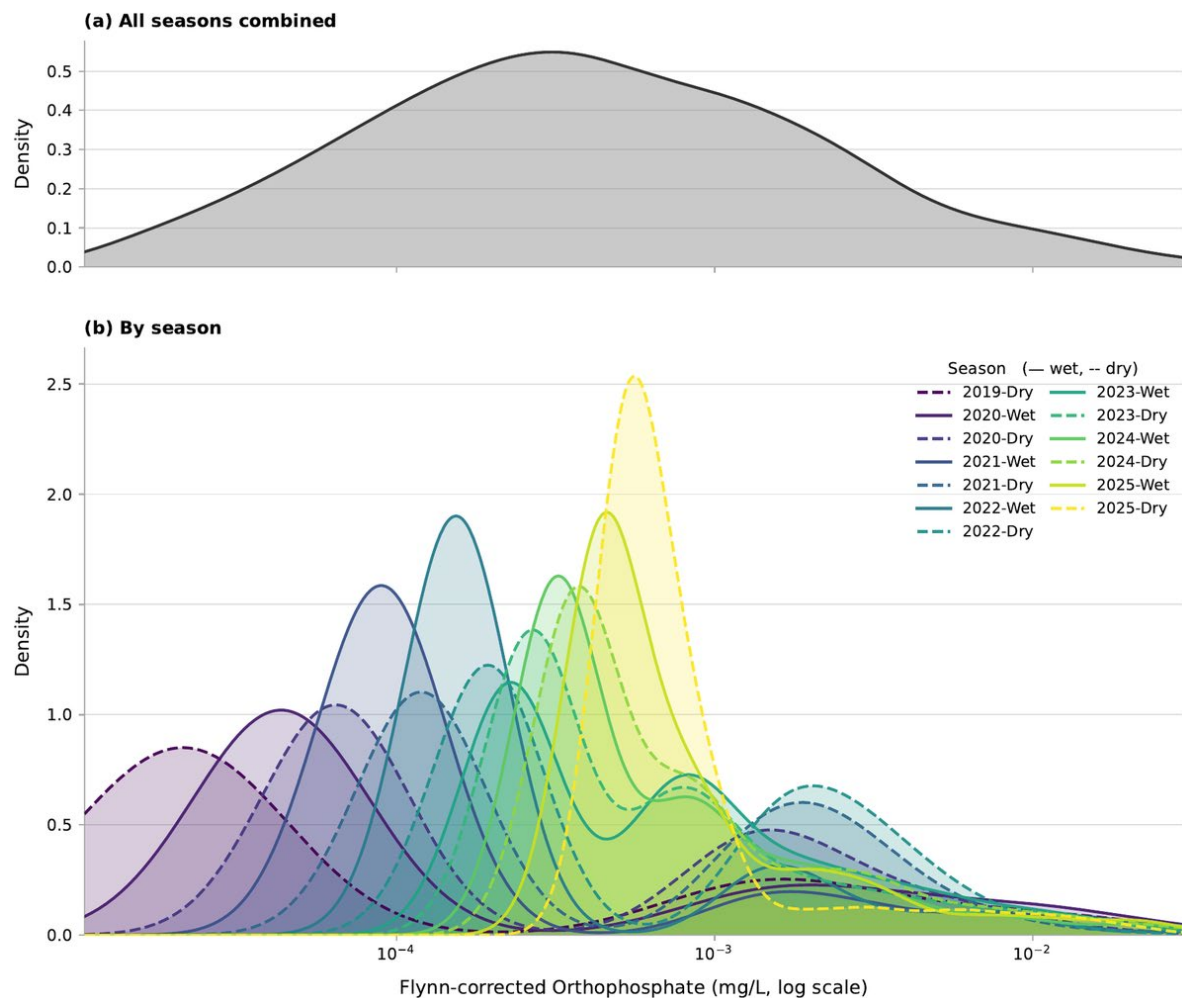


Figure A12. Orthophosphate, KJCAP. Distribution of values at the KJCAP monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

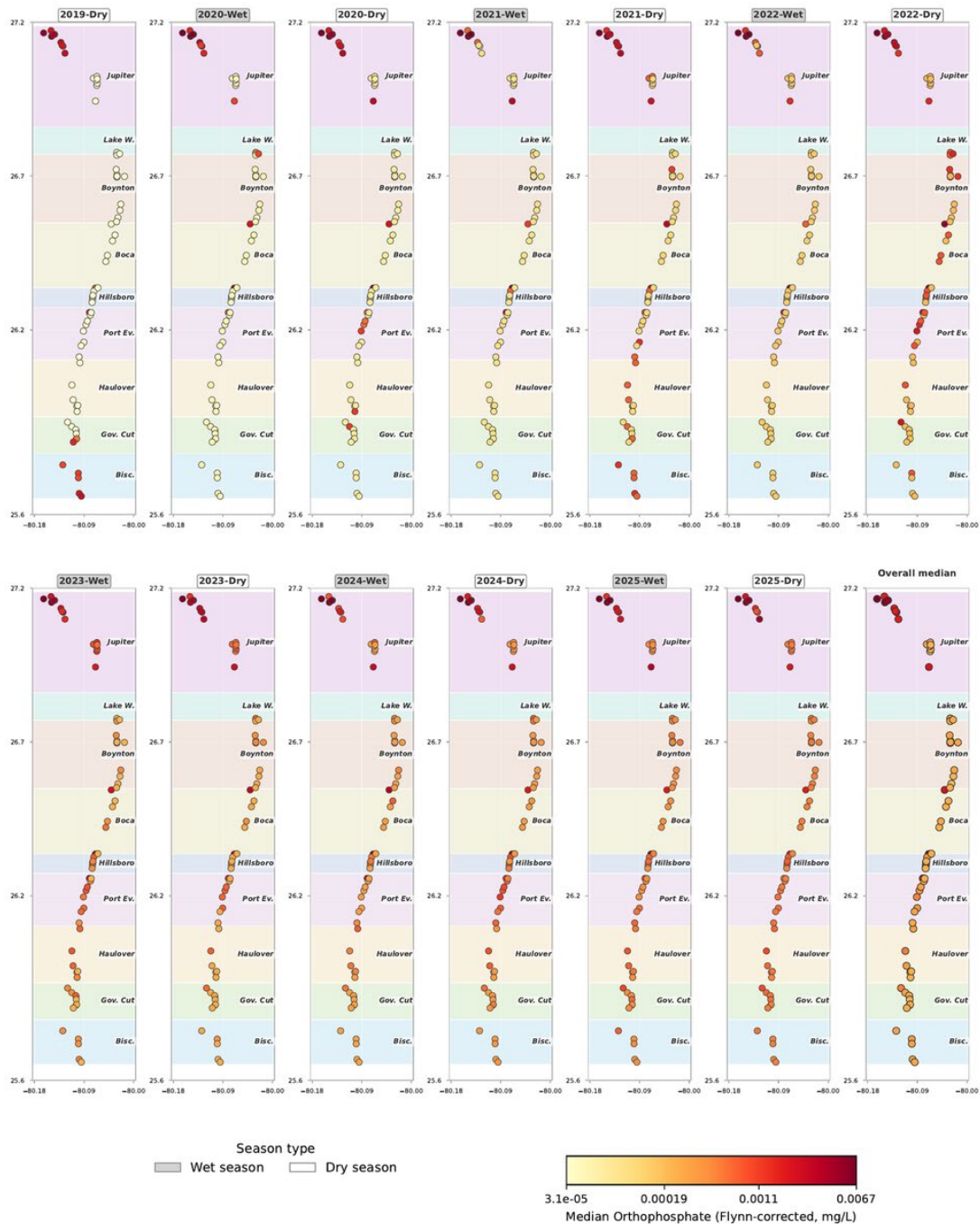


Figure A13. Orthophosphate, KJCAP. Per-season spatial distribution of the median across the KJCAP monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

KJCAP: Total Phosphorus

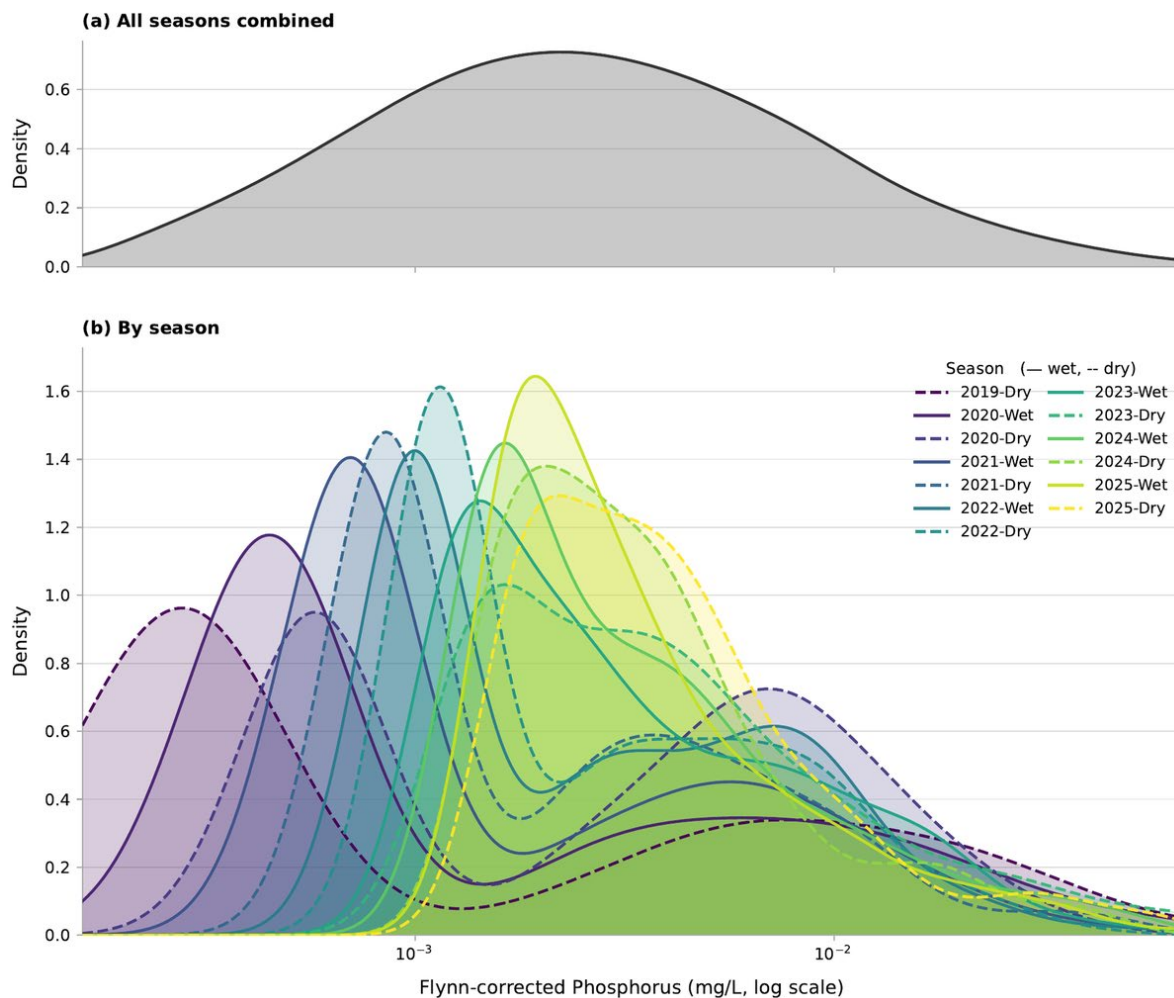


Figure A14. Total phosphorus, KJCAP. Distribution of values at the KJCAP monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

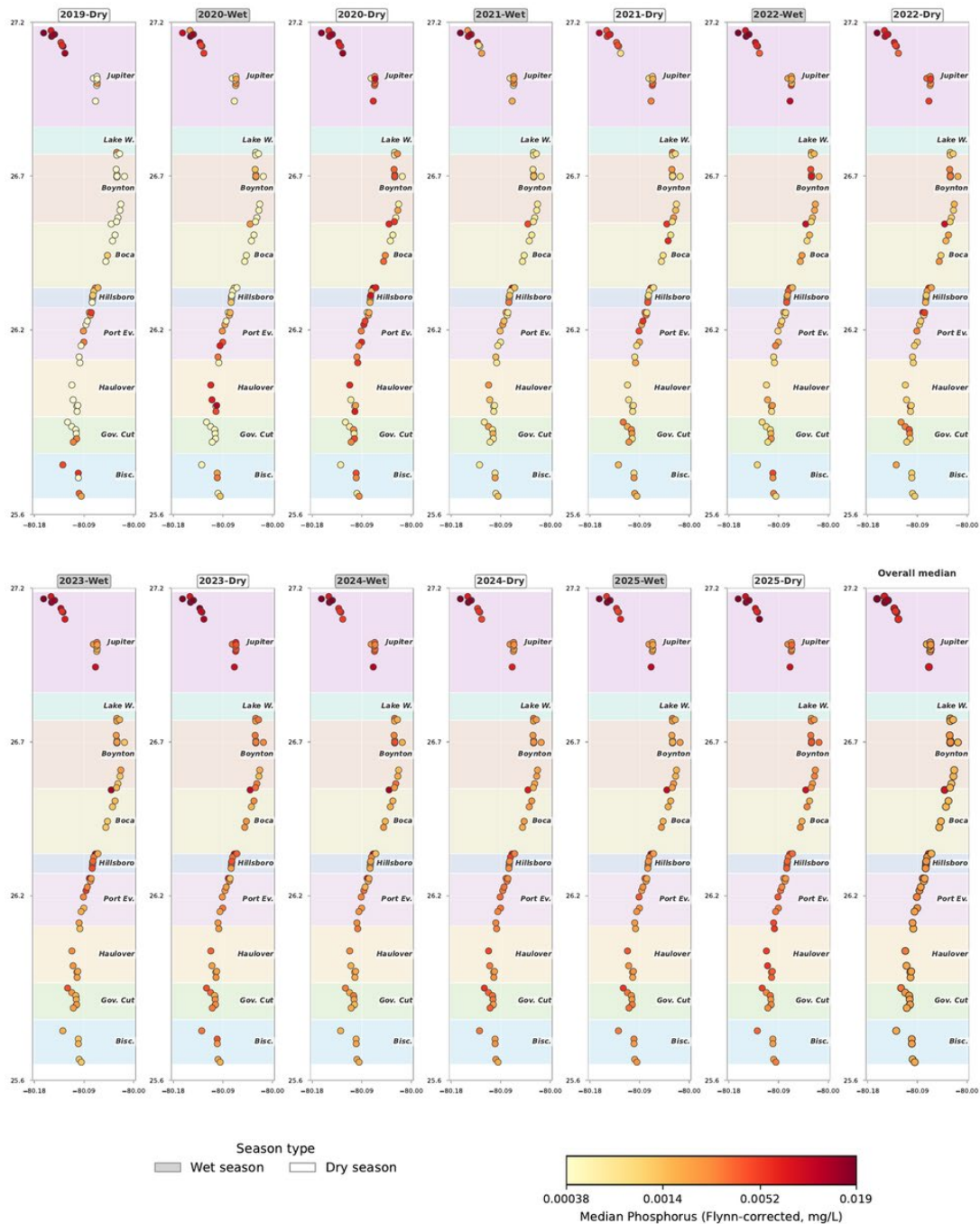


Figure A15. Total phosphorus, KJCAP. Per-season spatial distribution of the median across the KJCAP monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

KJCAP: Silicate

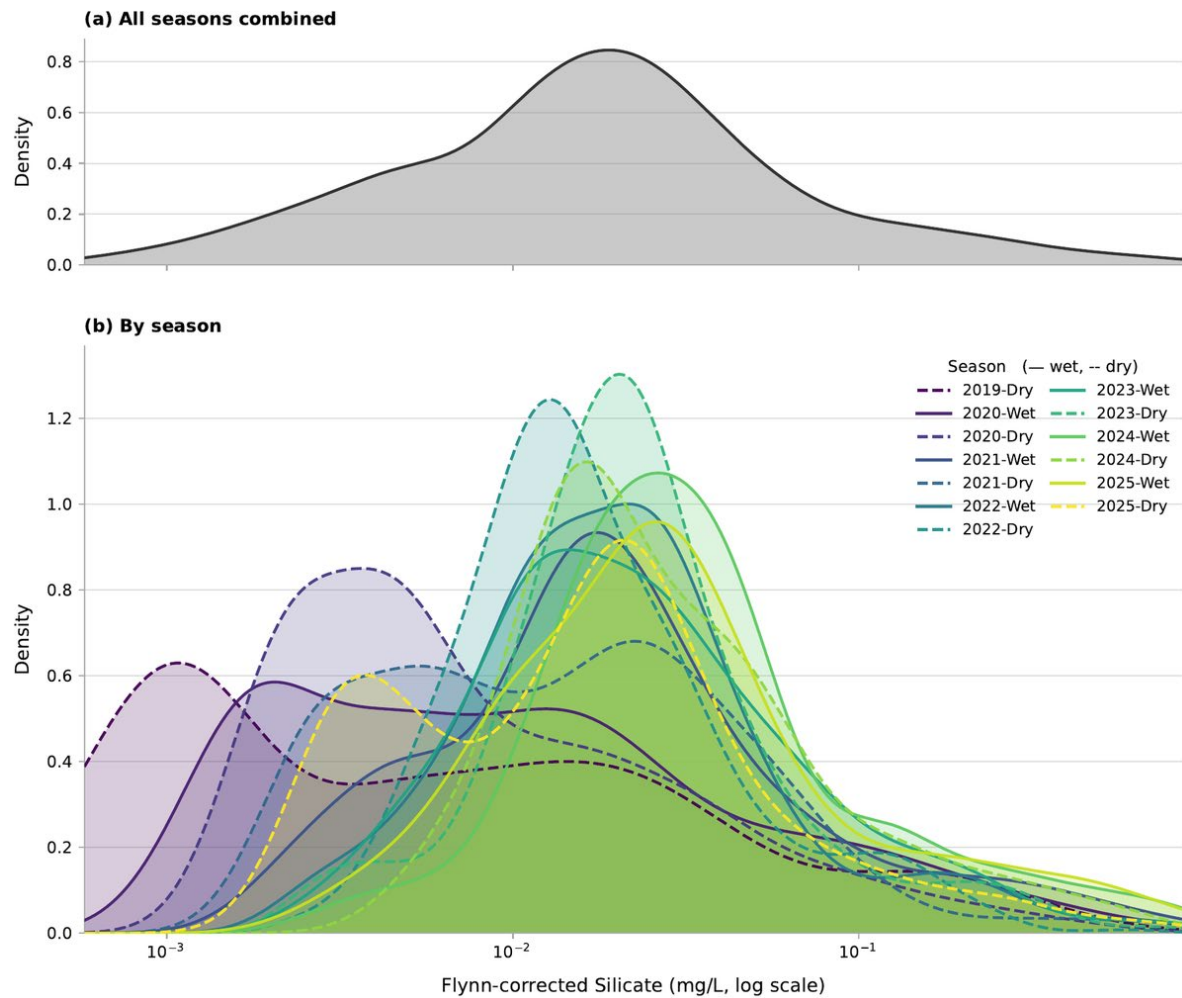


Figure A16. Silicate, KJCAP. Distribution of values at the KJCAP monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

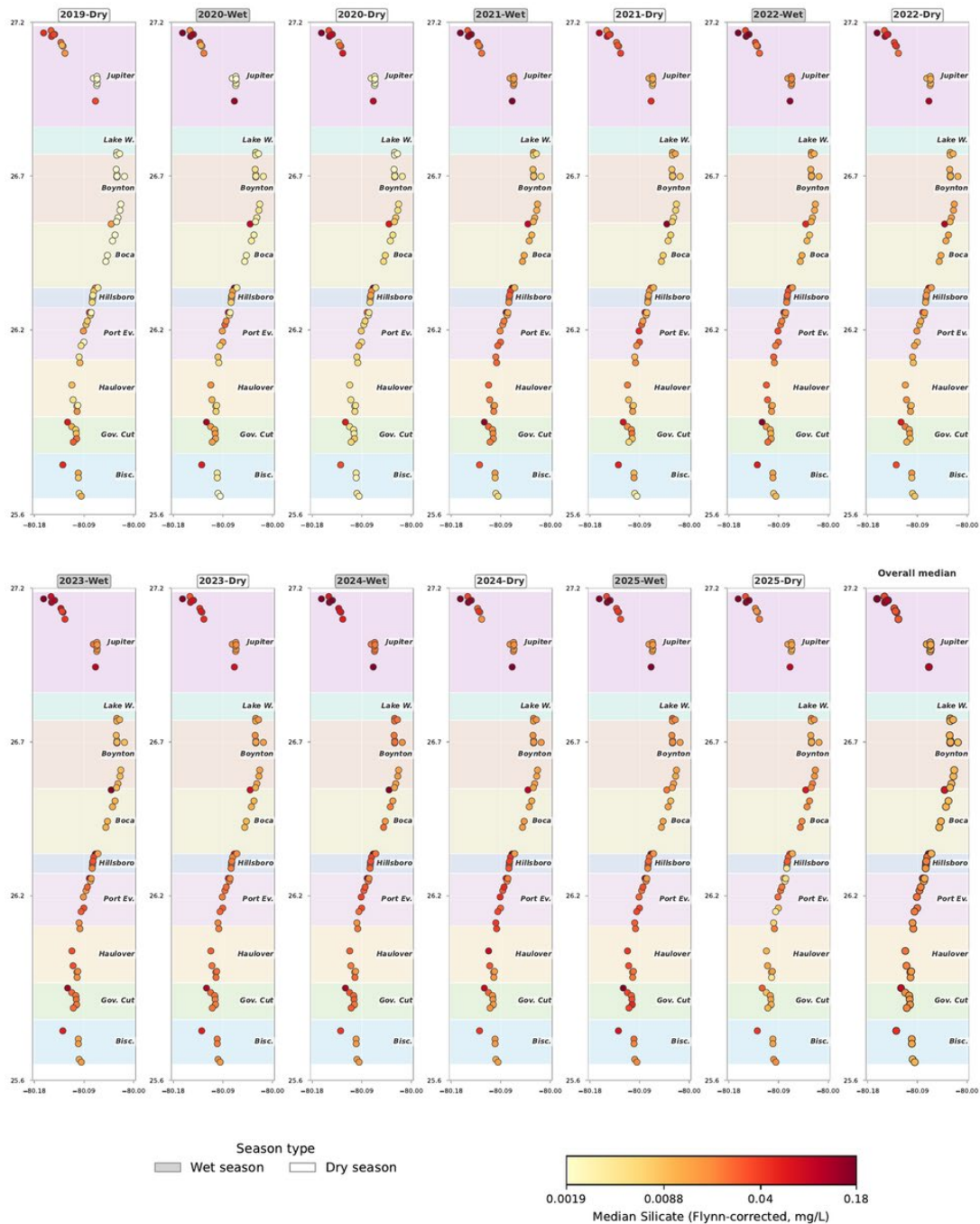


Figure A17. Silicate, KJCAP. Per-season spatial distribution of the median across the KJCAP monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

KJCAP: Total suspended solids

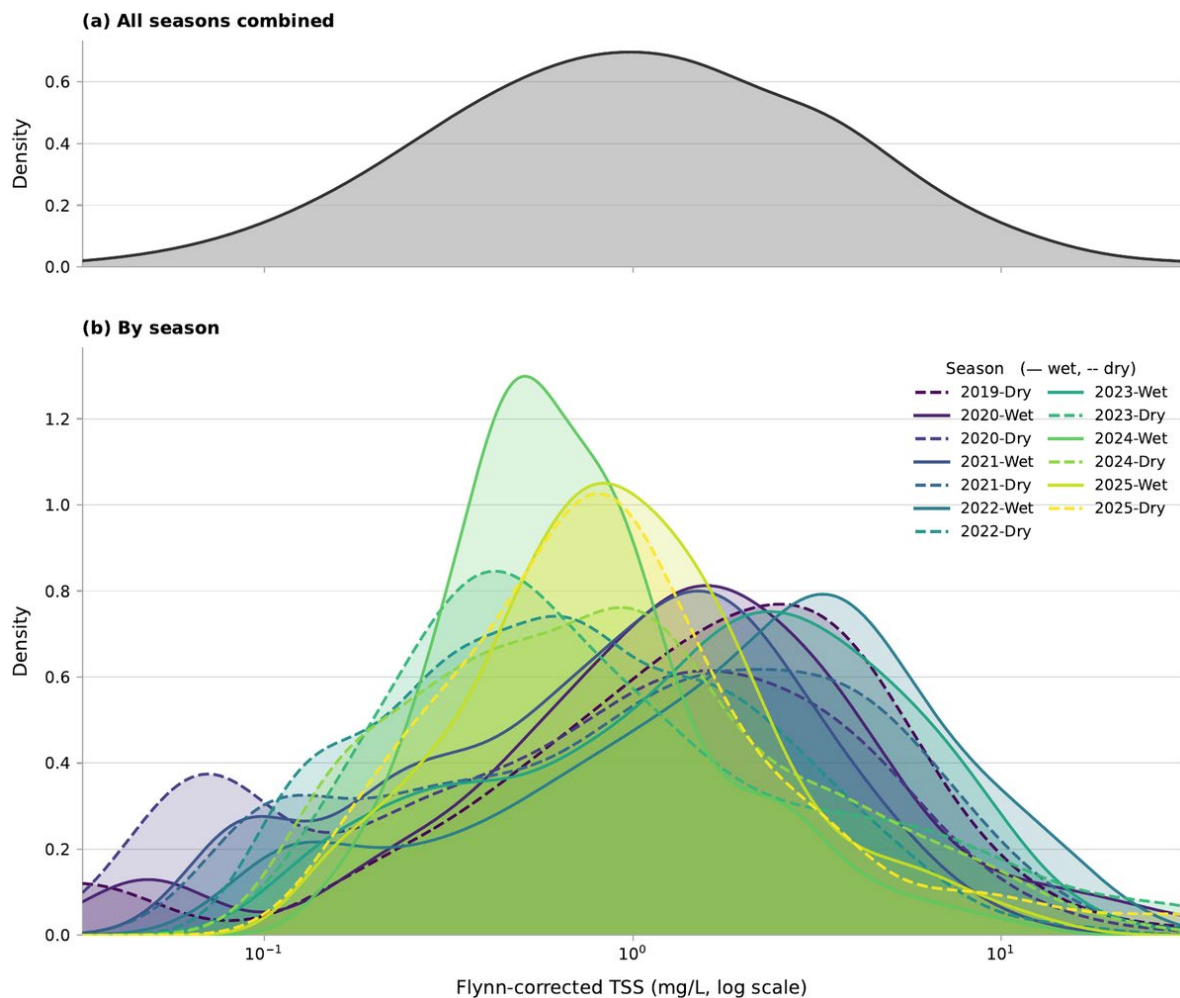


Figure A18. Total Suspended Solids, KJCAP. Distribution of values at the KJCAP monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

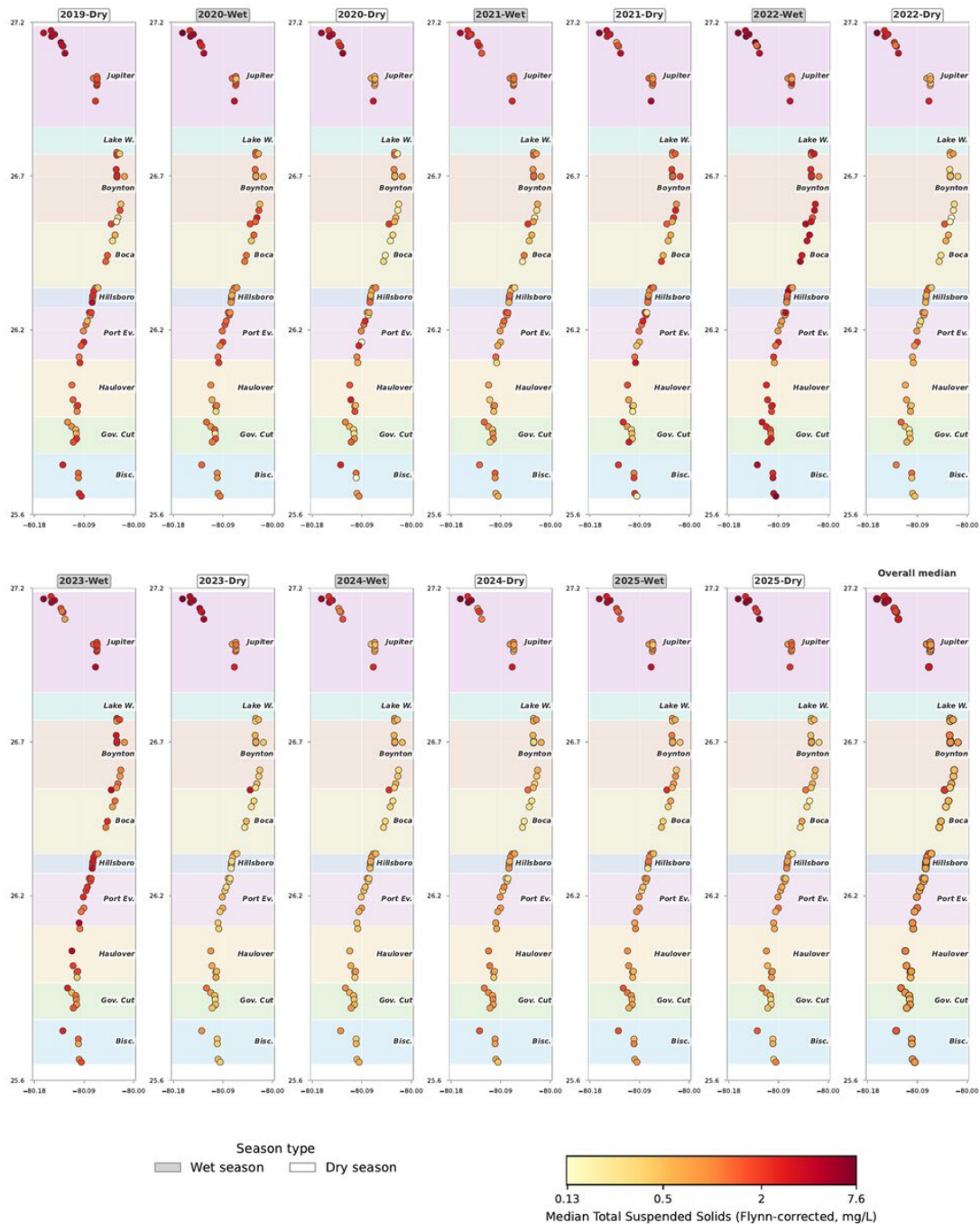


Figure A19. Total Suspended Solids, KJCAP. Per-season spatial distribution of the median across the KJCAP monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

KJCAP: Turbidity

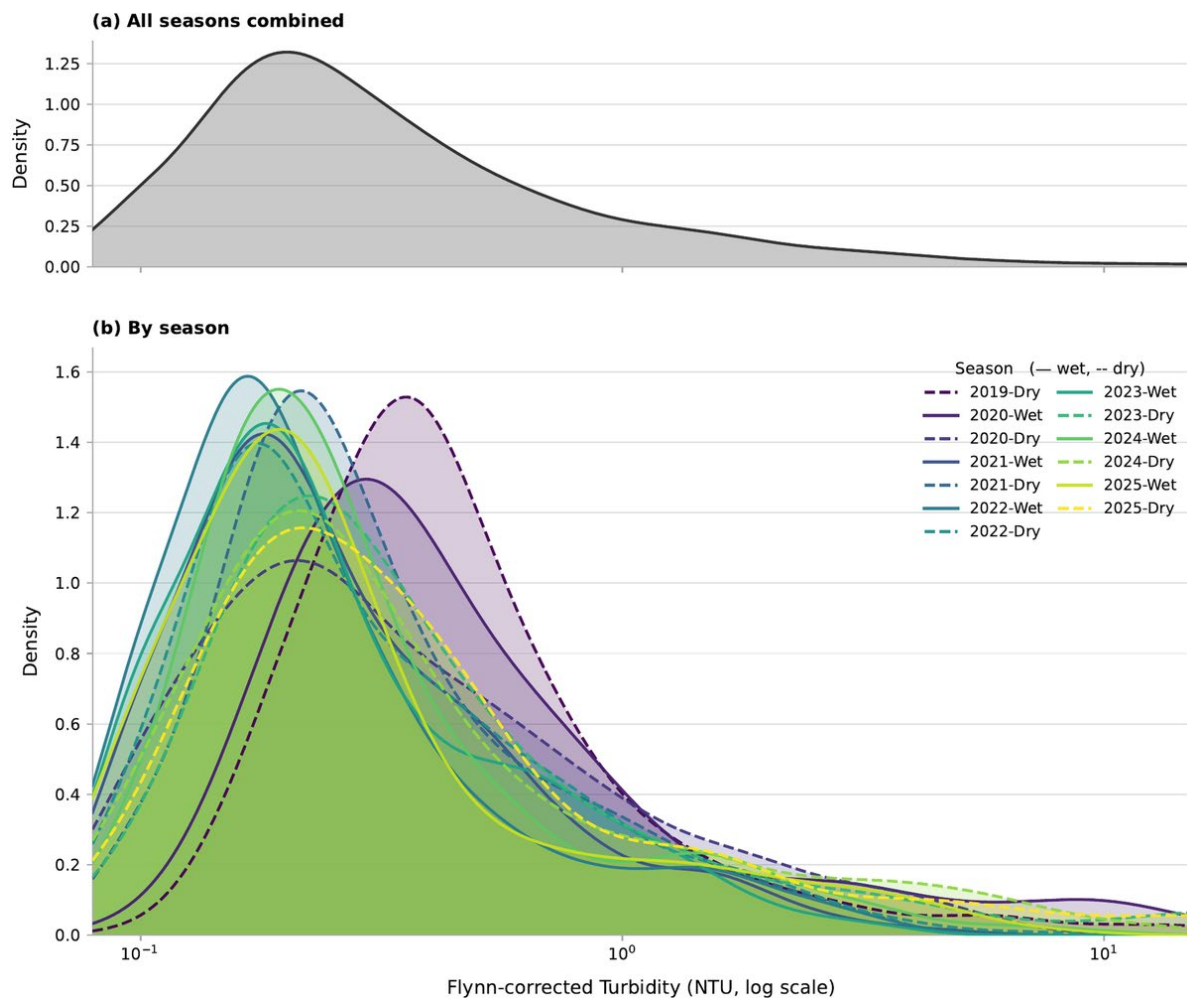


Figure A20. Turbidity, KJCAP. Distribution of values at the KJCAP monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

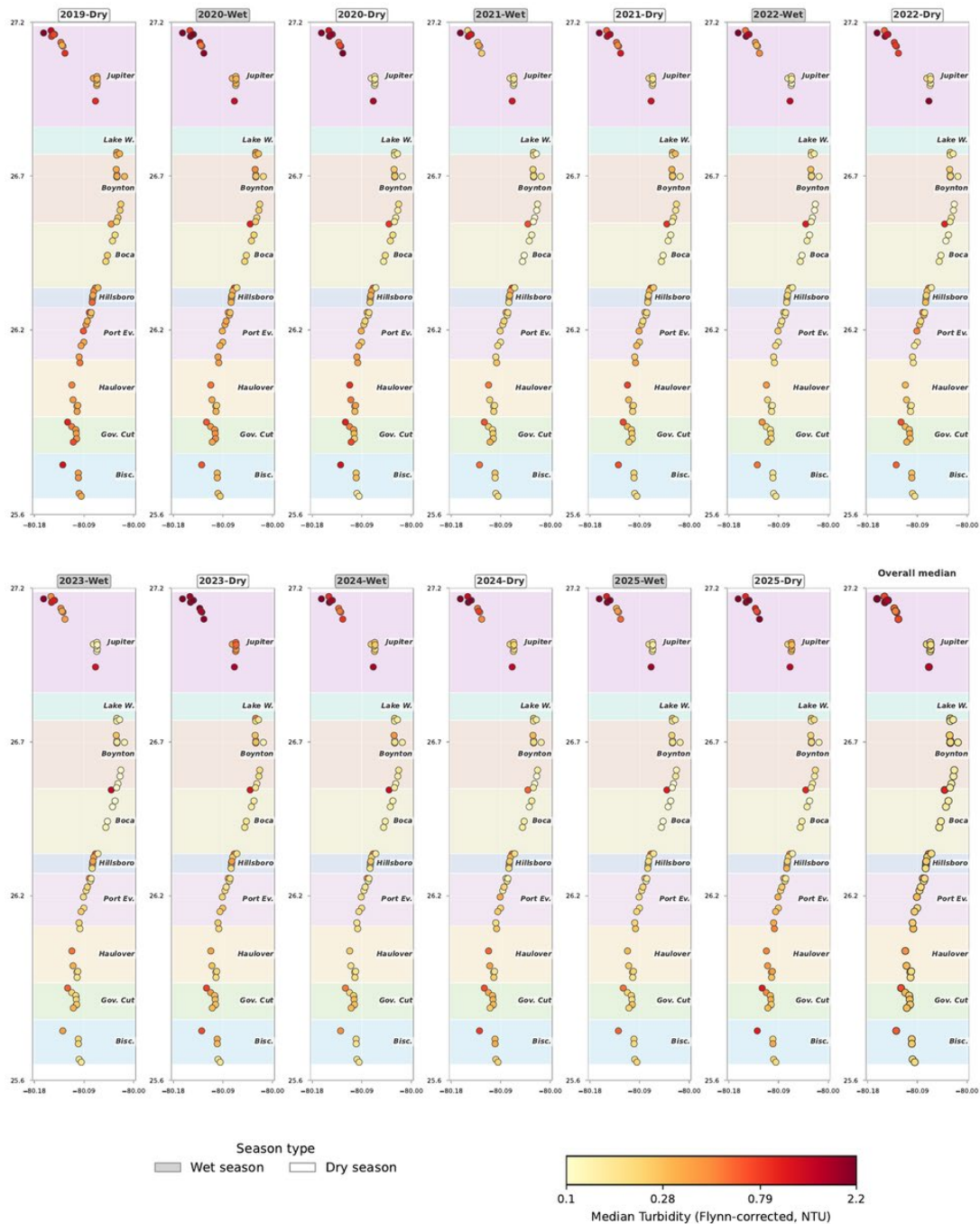


Figure A21. Turbidity, KJCAP. Per-season spatial distribution of the median across the KJCAP monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

DERM: Nitrate-nitrite

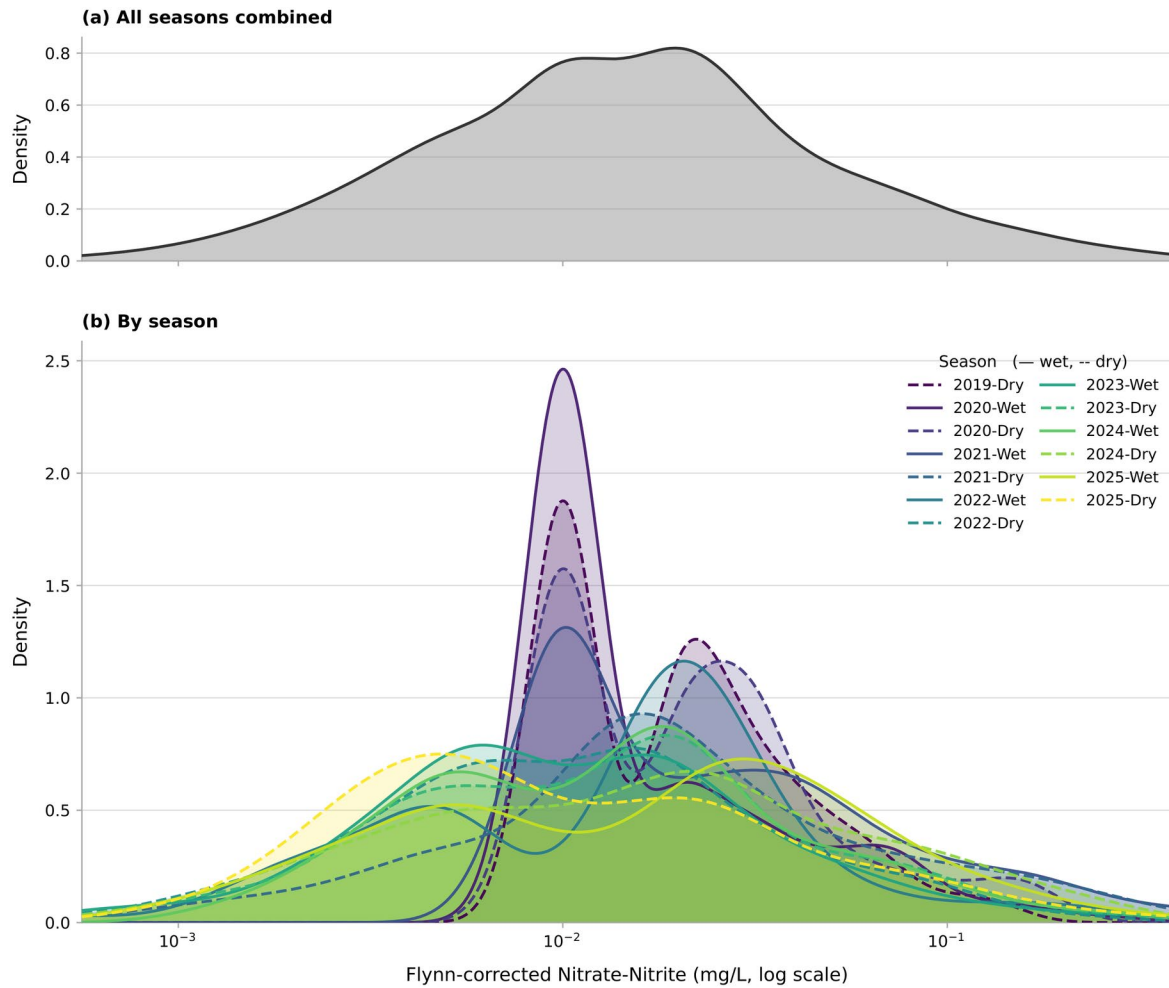


Figure A22. Nitrate-Nitrite, DERM. Distribution of values at the DERM Biscayne Bay monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

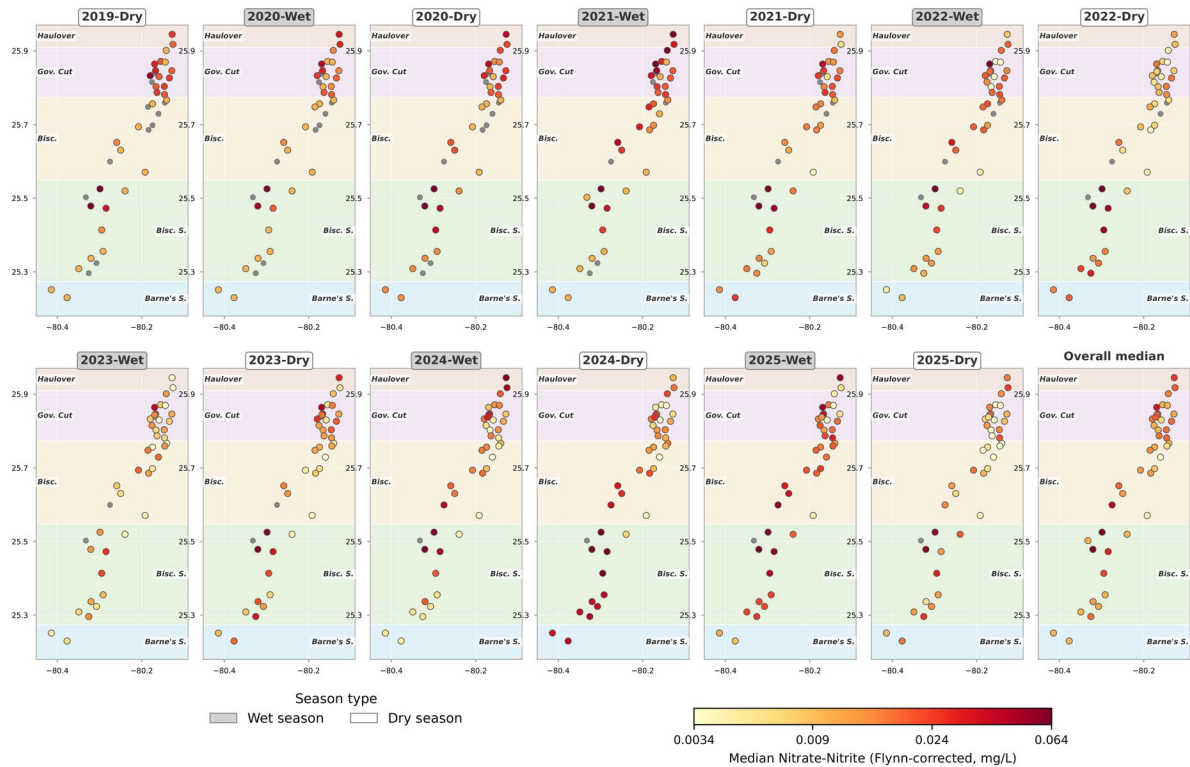


Figure A23. Nitrate-Nitrite, DERM. Per-season spatial distribution of the median across the DERM Biscayne Bay monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

DERM: Nitrogen-total

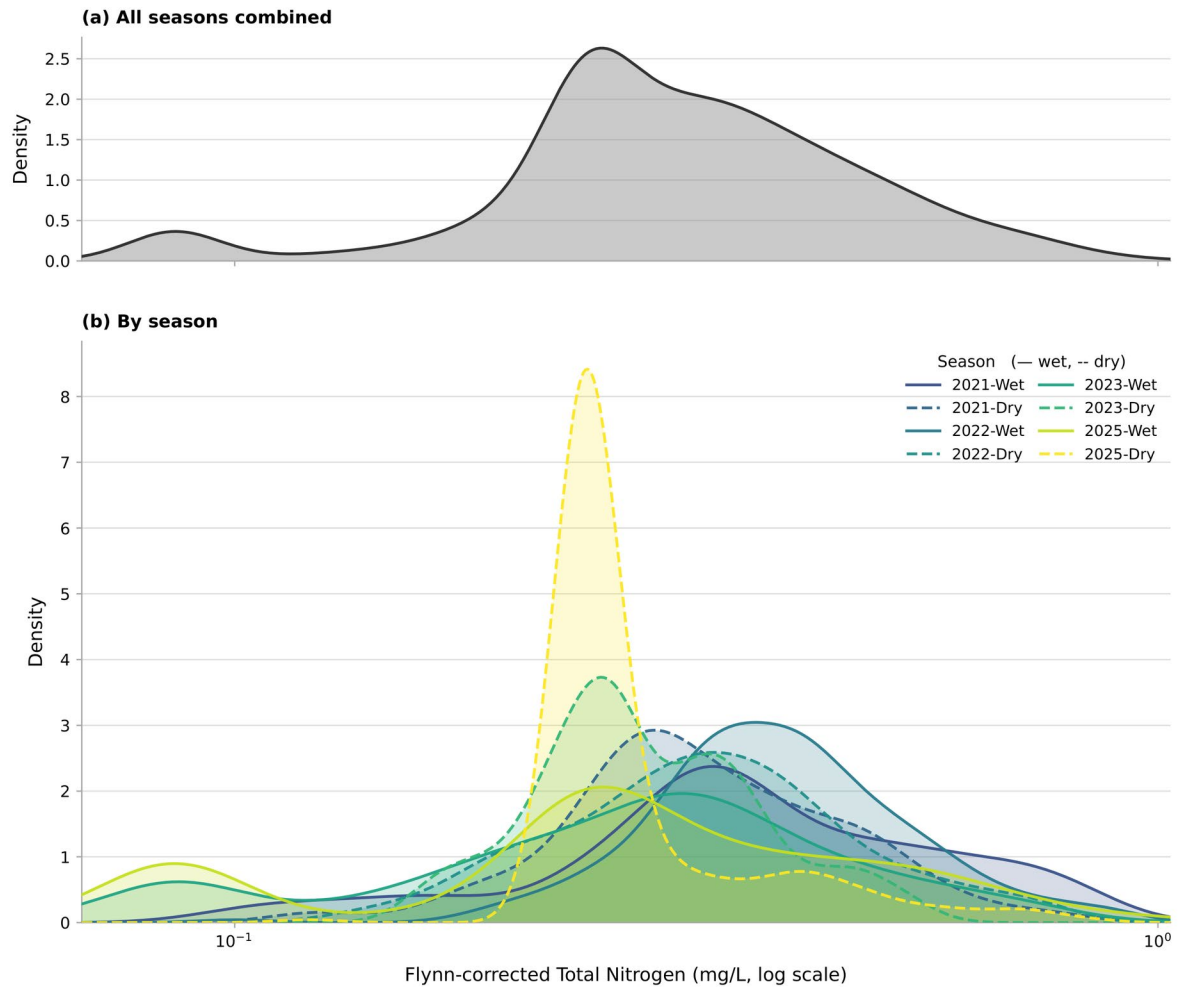


Figure A24. Nitrogen-total, DERM. Distribution of values at the DERM Biscayne Bay monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

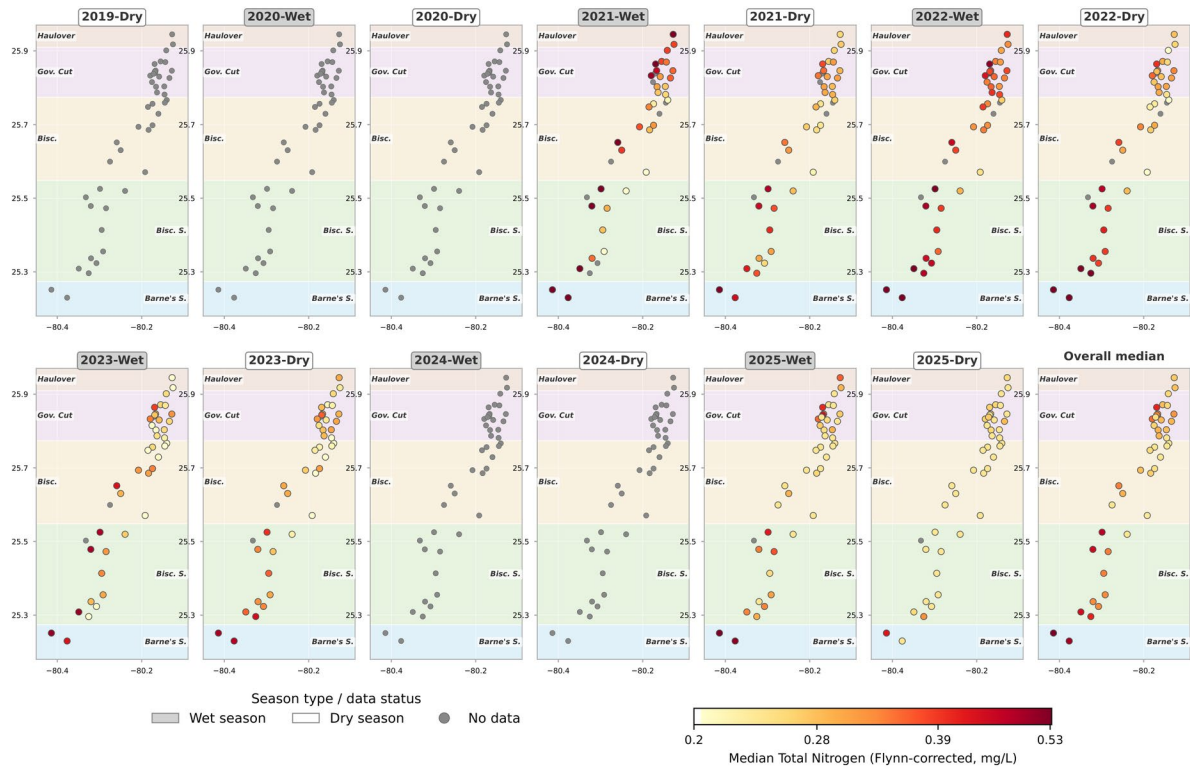


Figure A25. Nitrogen-total, DERM. Per-season spatial distribution of the median across the DERM Biscayne Bay monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

DERM: Orthophosphate

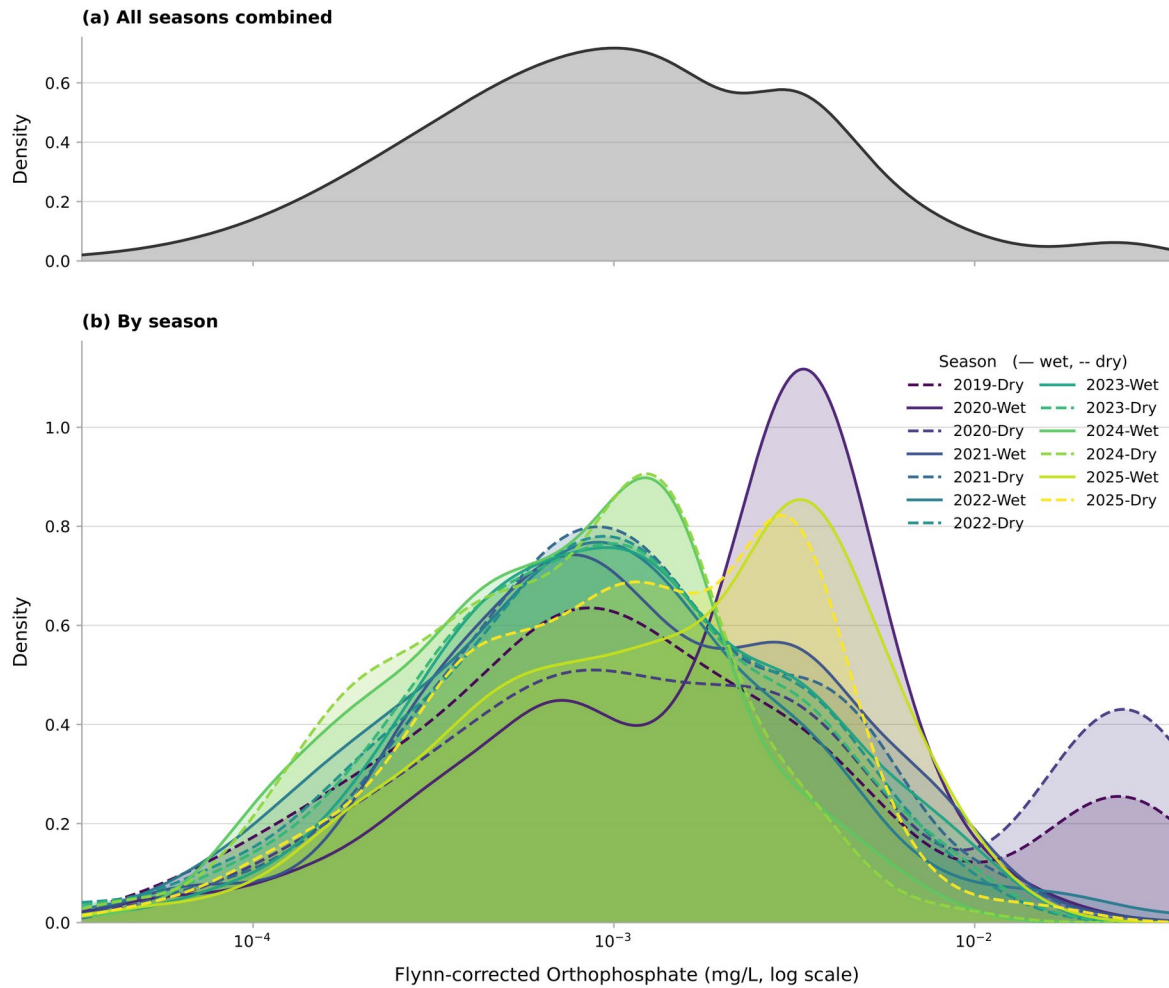


Figure A26. Orthophosphate, DERM. Distribution of values at the DERM Biscayne Bay monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

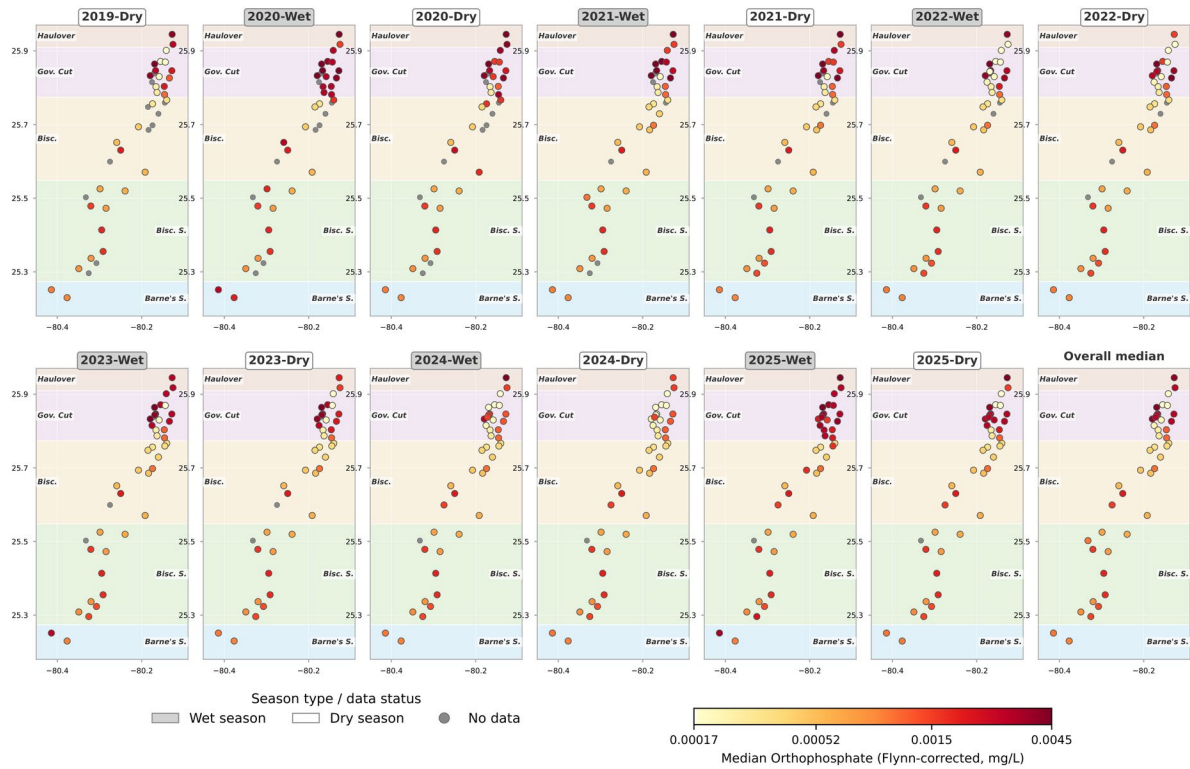


Figure A27. Orthophosphate, DERM. Per-season spatial distribution of the median across the DERM Biscayne Bay monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

DERM: Total Phosphorus

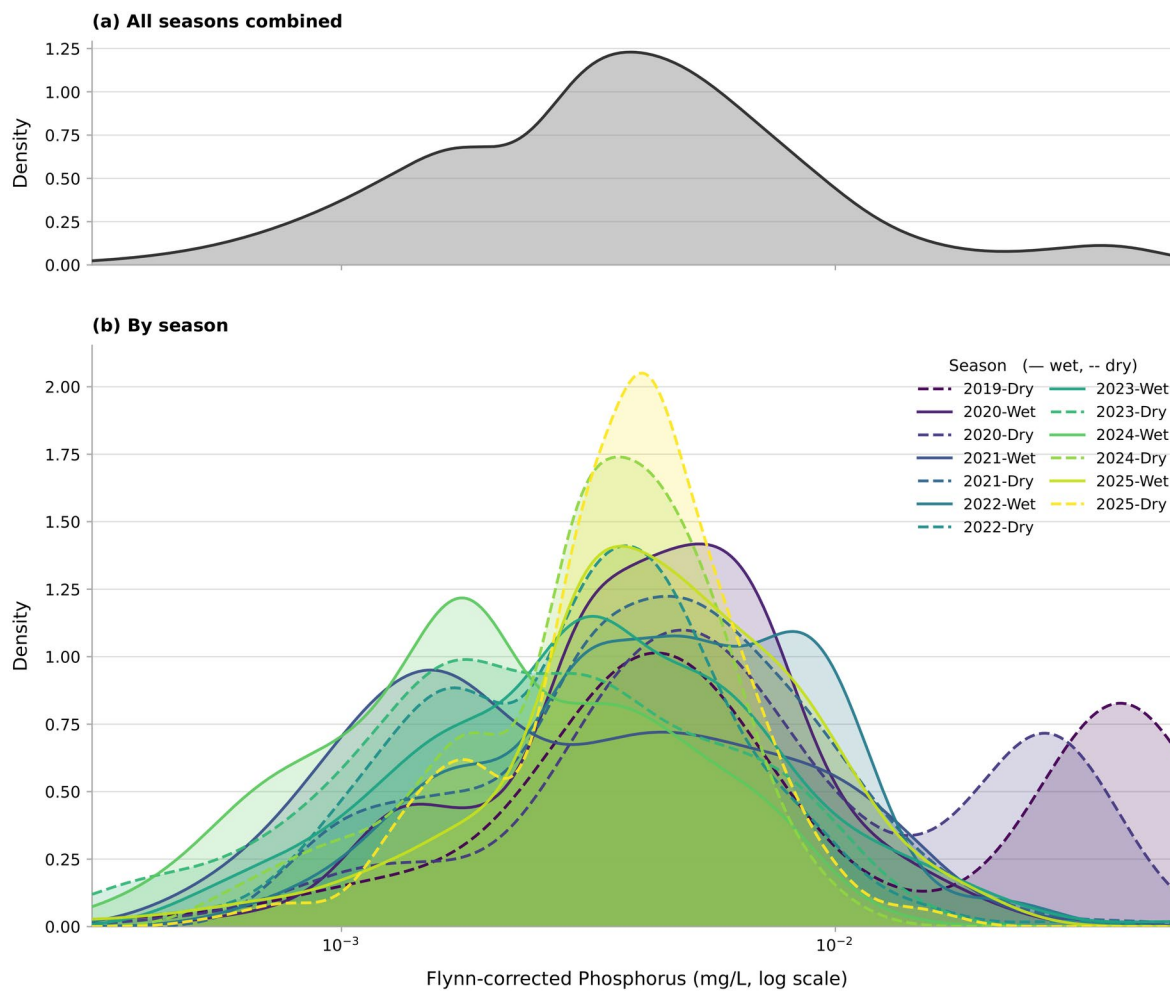


Figure A28. Total phosphorus, DERM. Distribution of values at the DERM Biscayne Bay monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

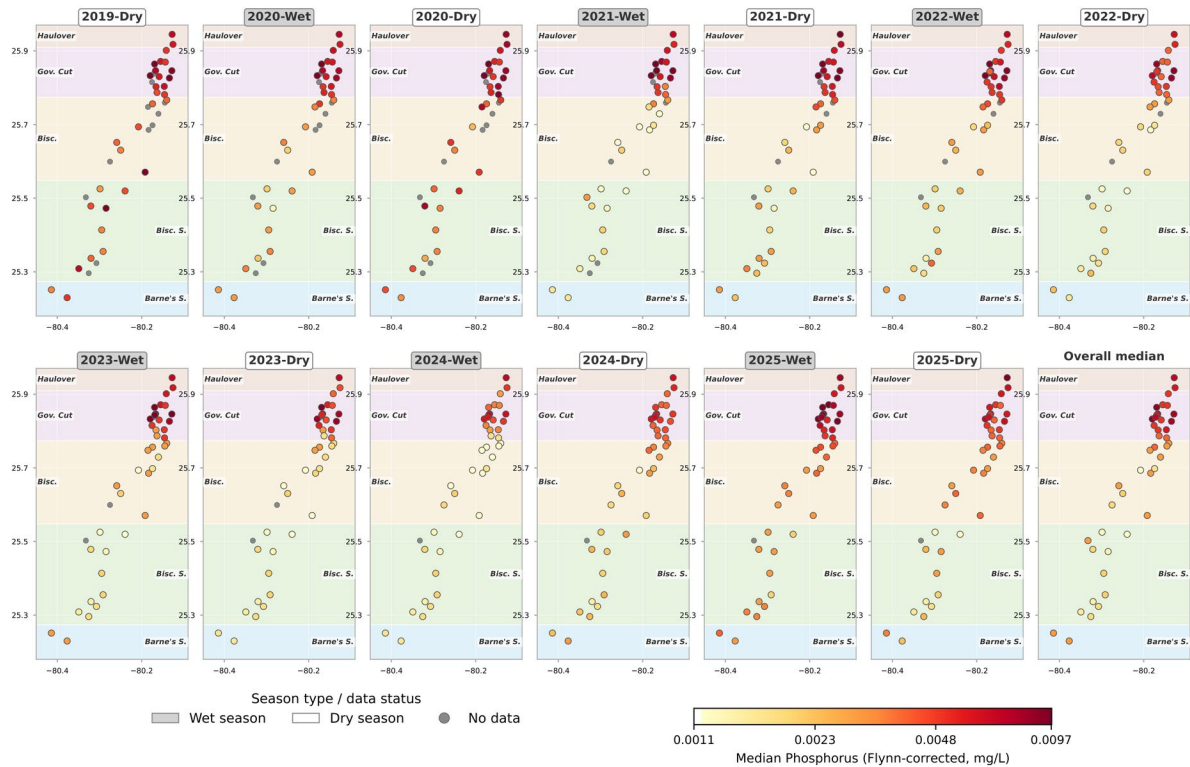


Figure A29. Total phosphorus, DERM. Per-season spatial distribution of the median across the DERM Biscayne Bay monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

DERM: Turbidity

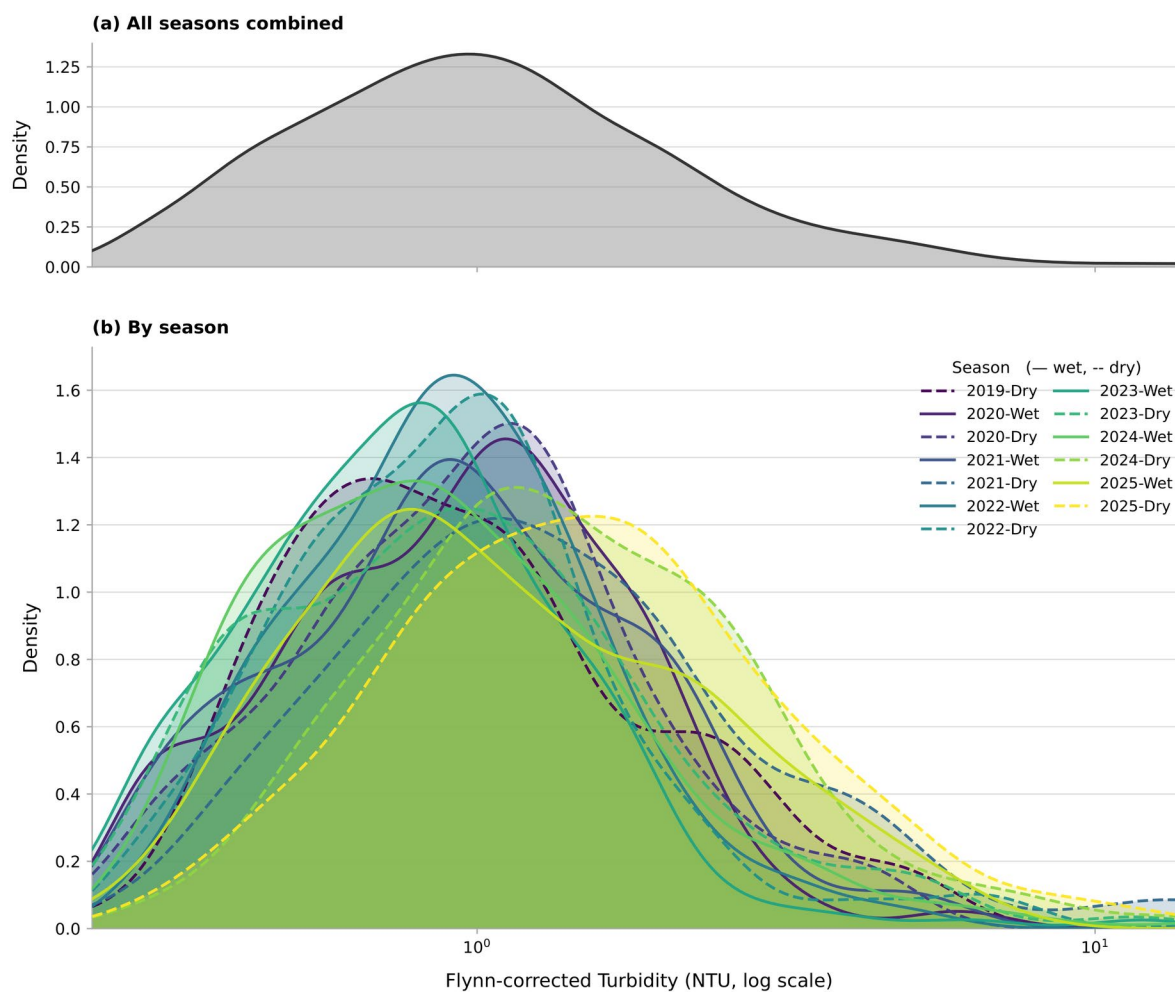


Figure A30. Turbidity, DERM. Distribution of values at the DERM Biscayne Bay monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

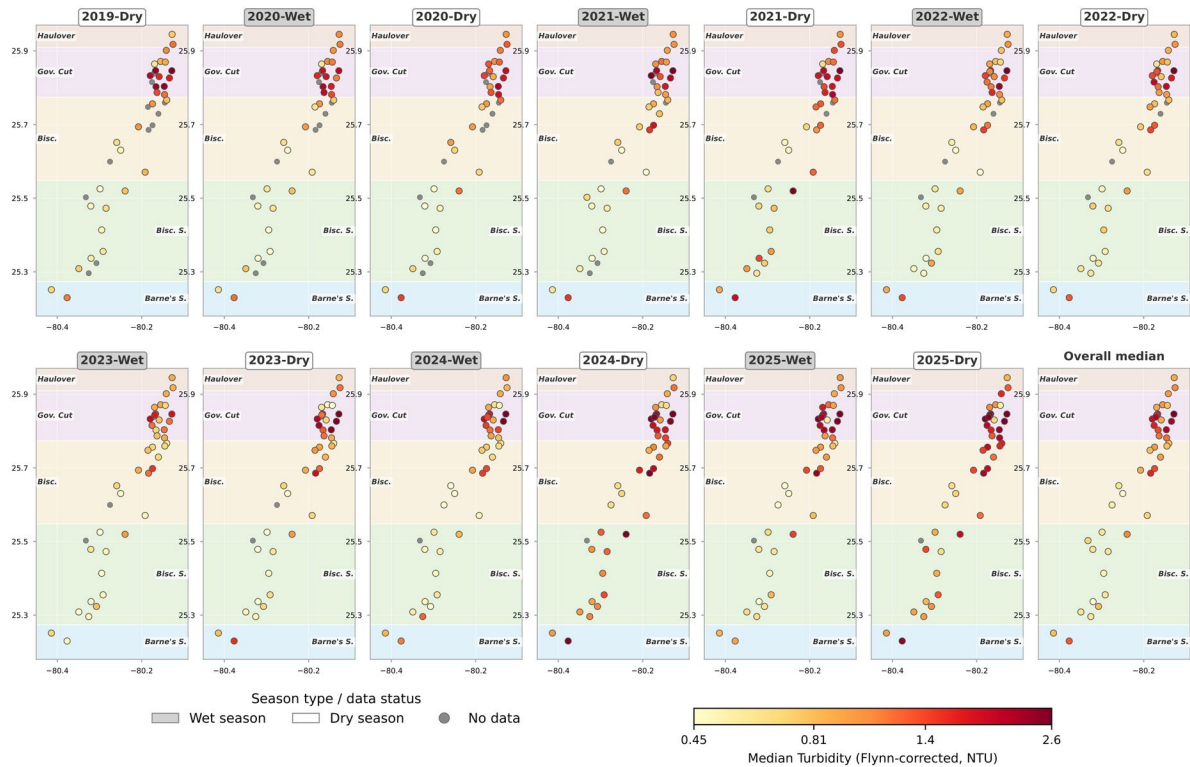


Figure A31. Turbidity, DERM. Per-season spatial distribution of the median across the DERM Biscayne Bay monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

WIN: Nitrate-nitrite

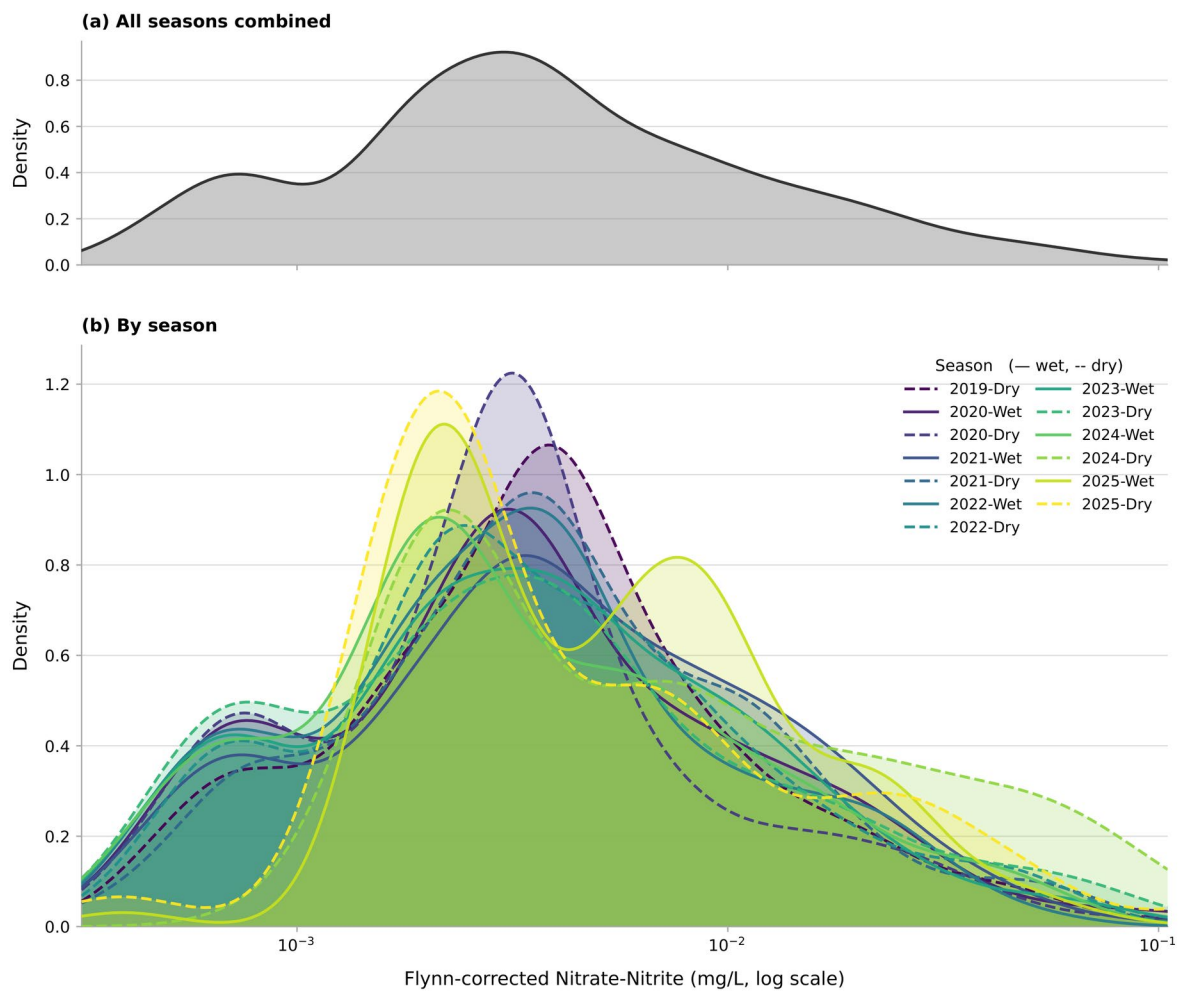


Figure A32. Nitrate-Nitrite, WIN. Distribution of values at the WIN monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

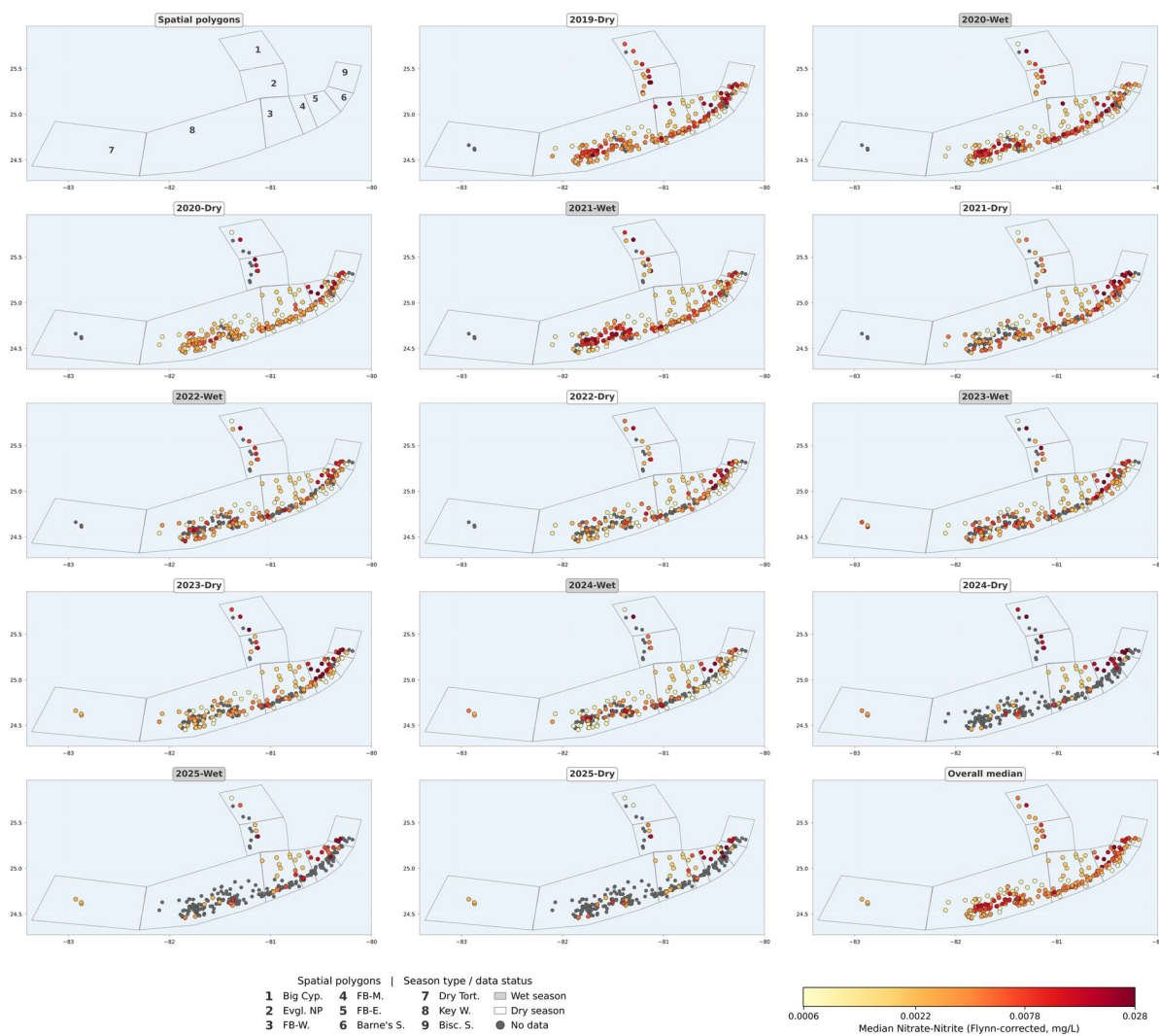


Figure A33. Nitrate-Nitrite, WIN. Per-season spatial distribution of the median across the WIN monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

WIN: Nitrite

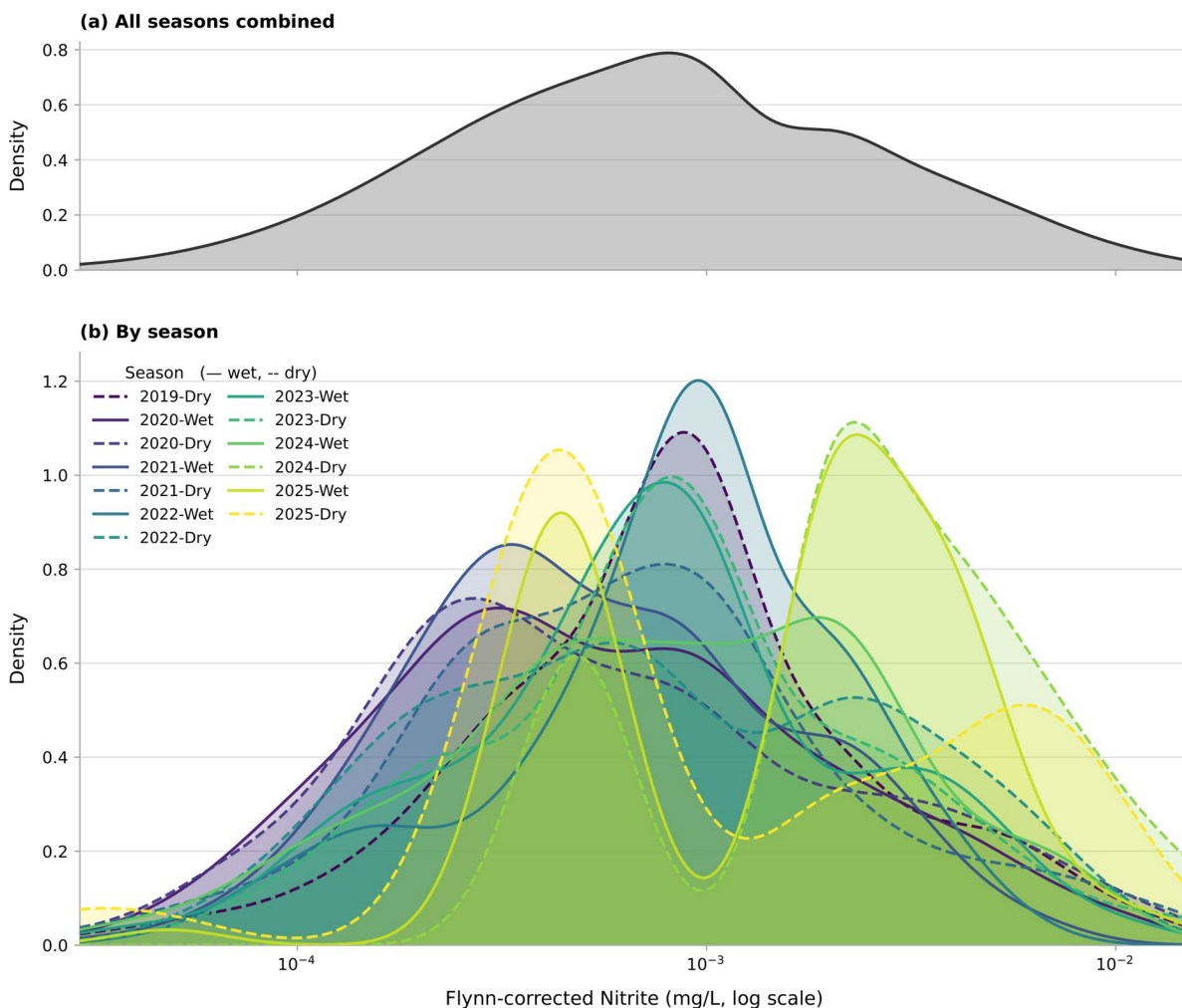


Figure A34. Nitrite, WIN. Distribution of values at the WIN monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

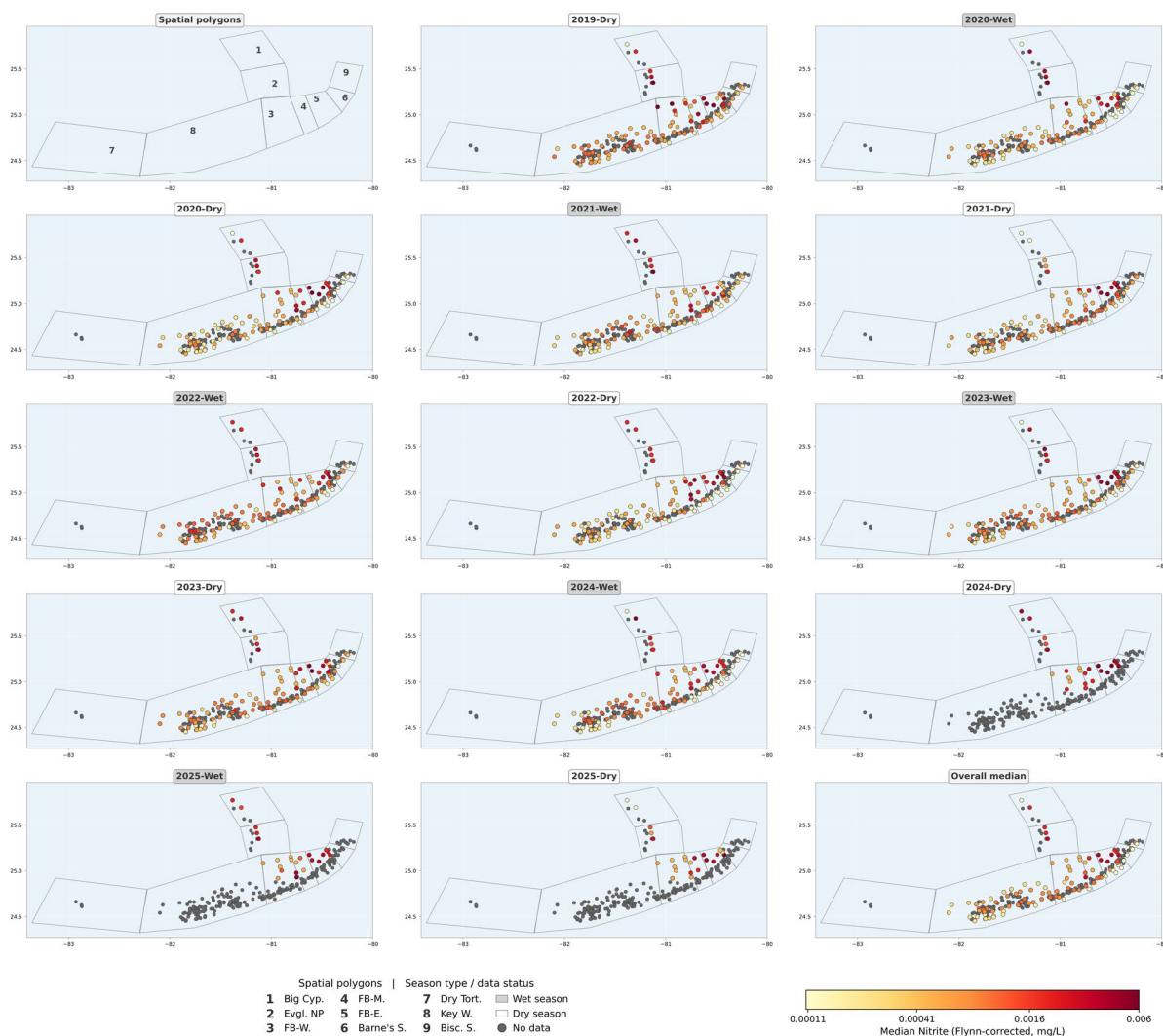


Figure A35. Nitrite, WIN. Per-season spatial distribution of the median across the WIN monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

WIN: Nitrogen-total

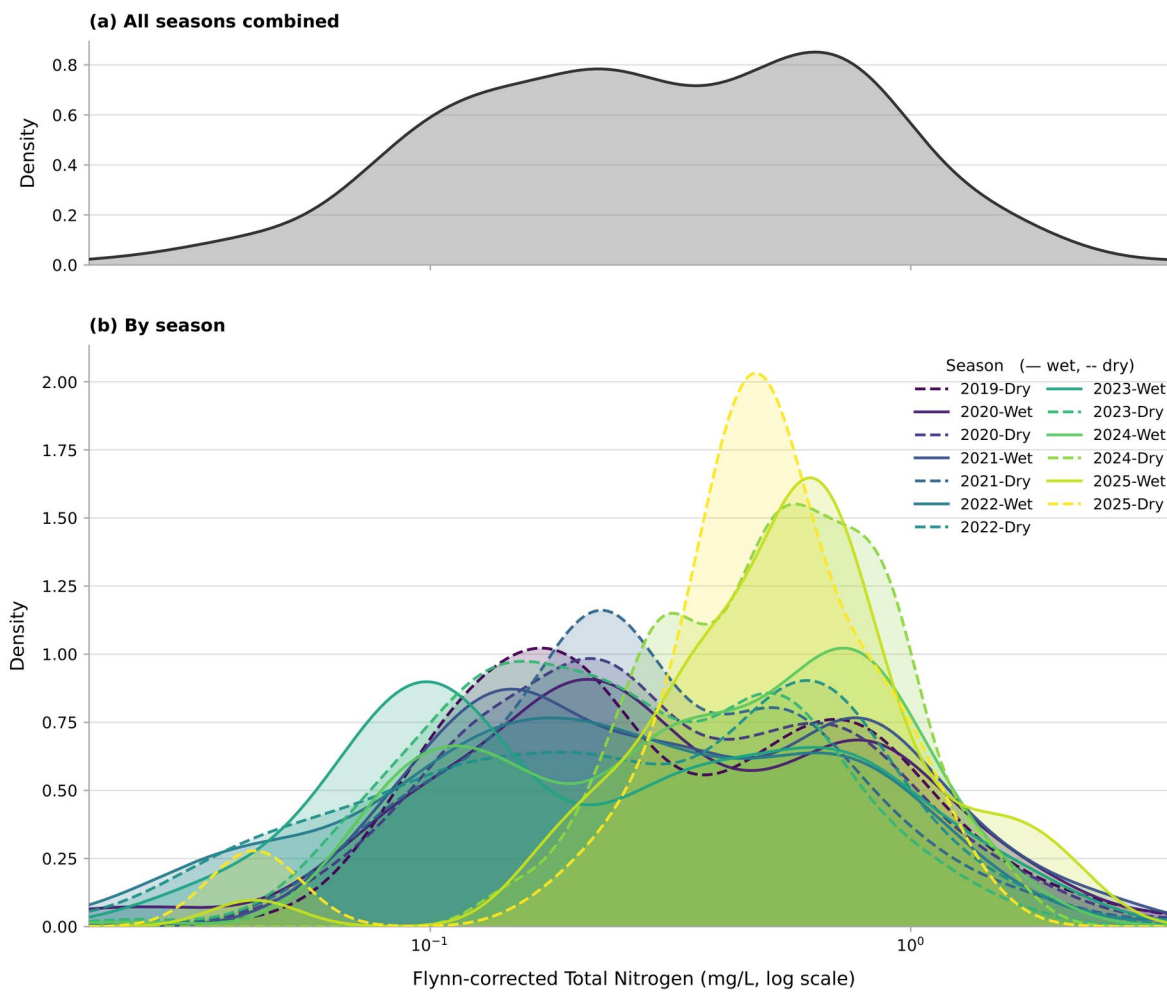


Figure A36. Nitrogen-total, WIN. Distribution of values at the WIN monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

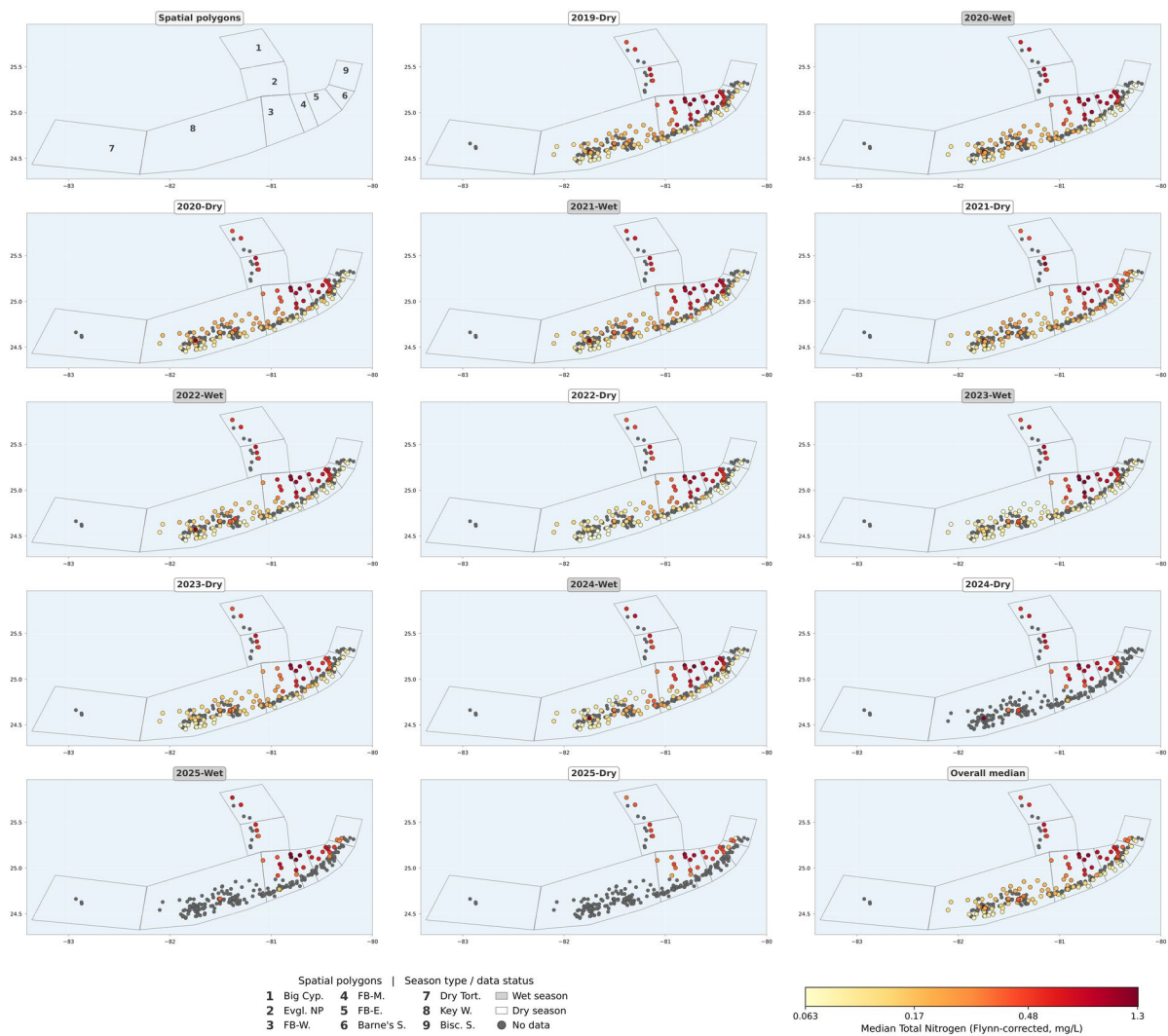


Figure A37. Nitrogen-total, WIN. Per-season spatial distribution of the median across the WIN monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

WIN: Total Phosphorus

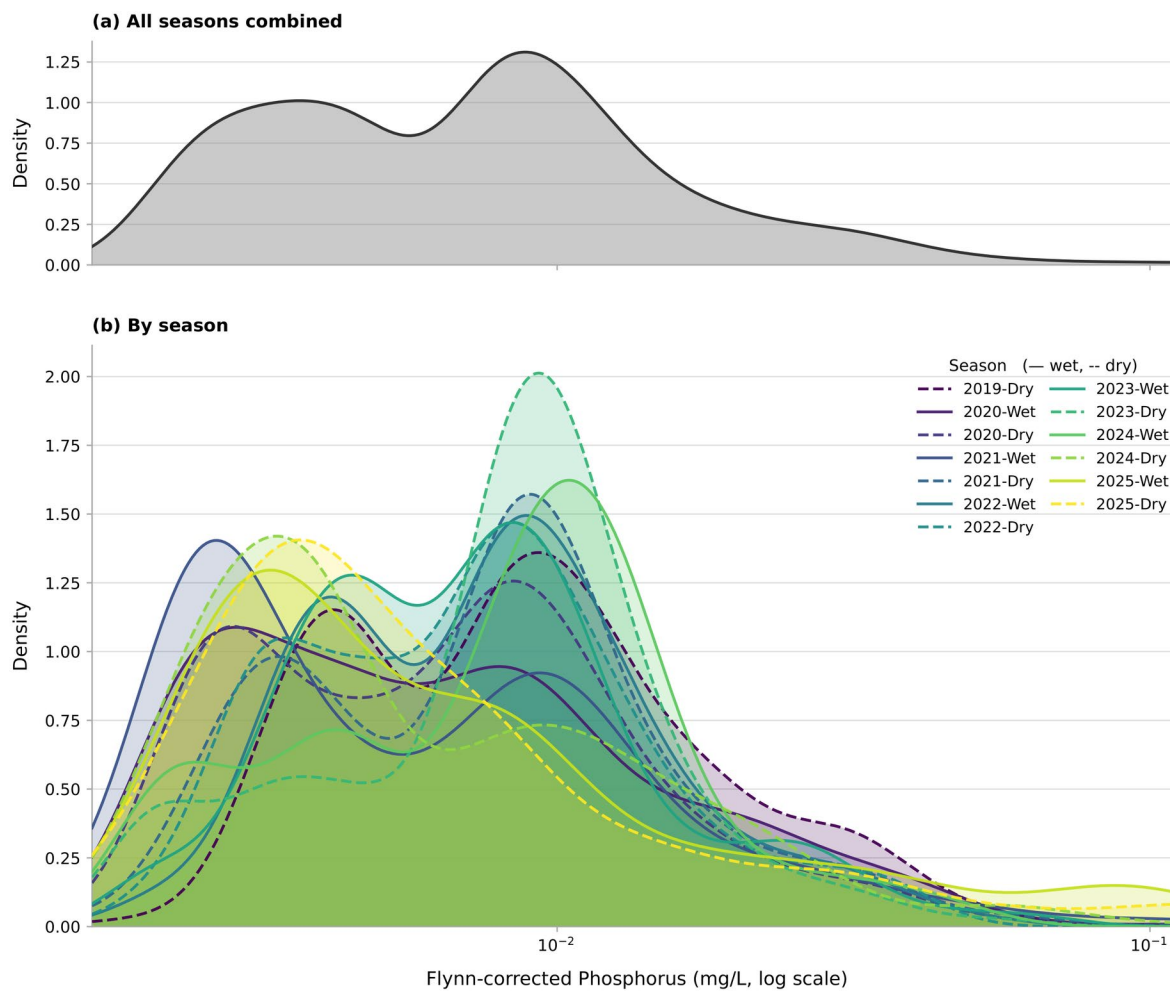


Figure A38. Total phosphorus, WIN. Distribution of values at the WIN monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

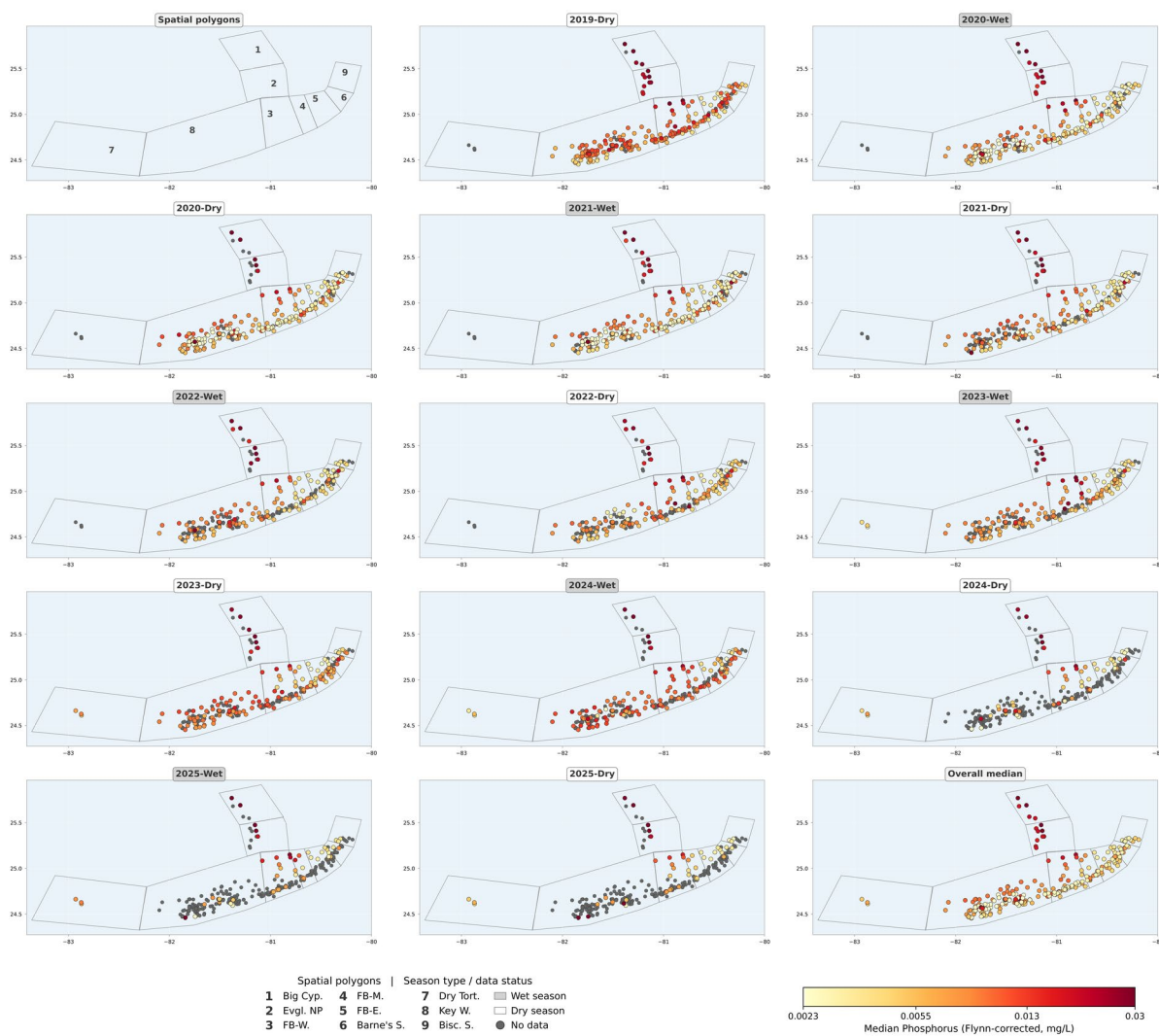


Figure A39. Total phosphorus, WIN. Per-season spatial distribution of the median across the WIN monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

WIN: Silica

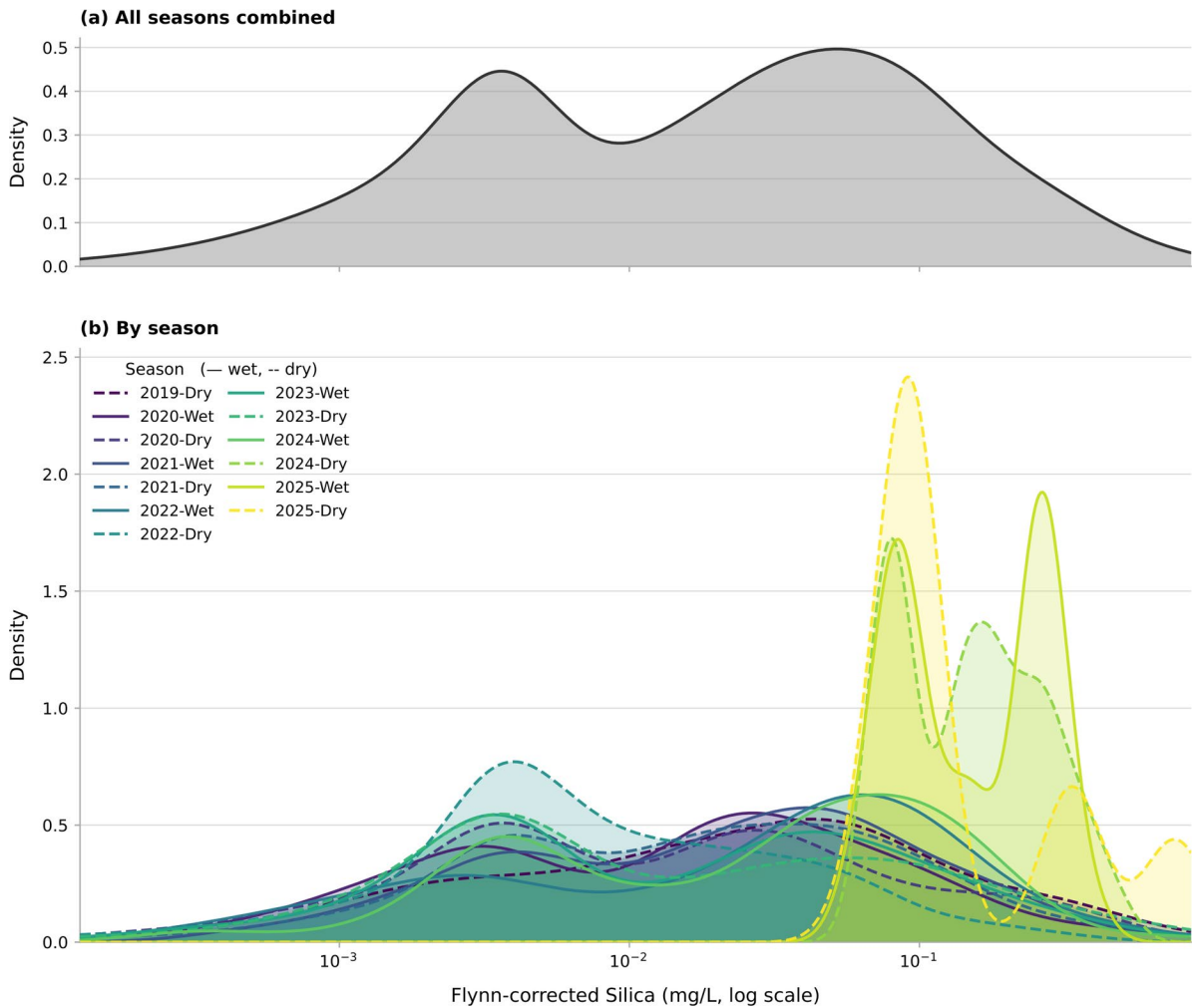


Figure A40. Silica, WIN. Distribution of values at the WIN monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

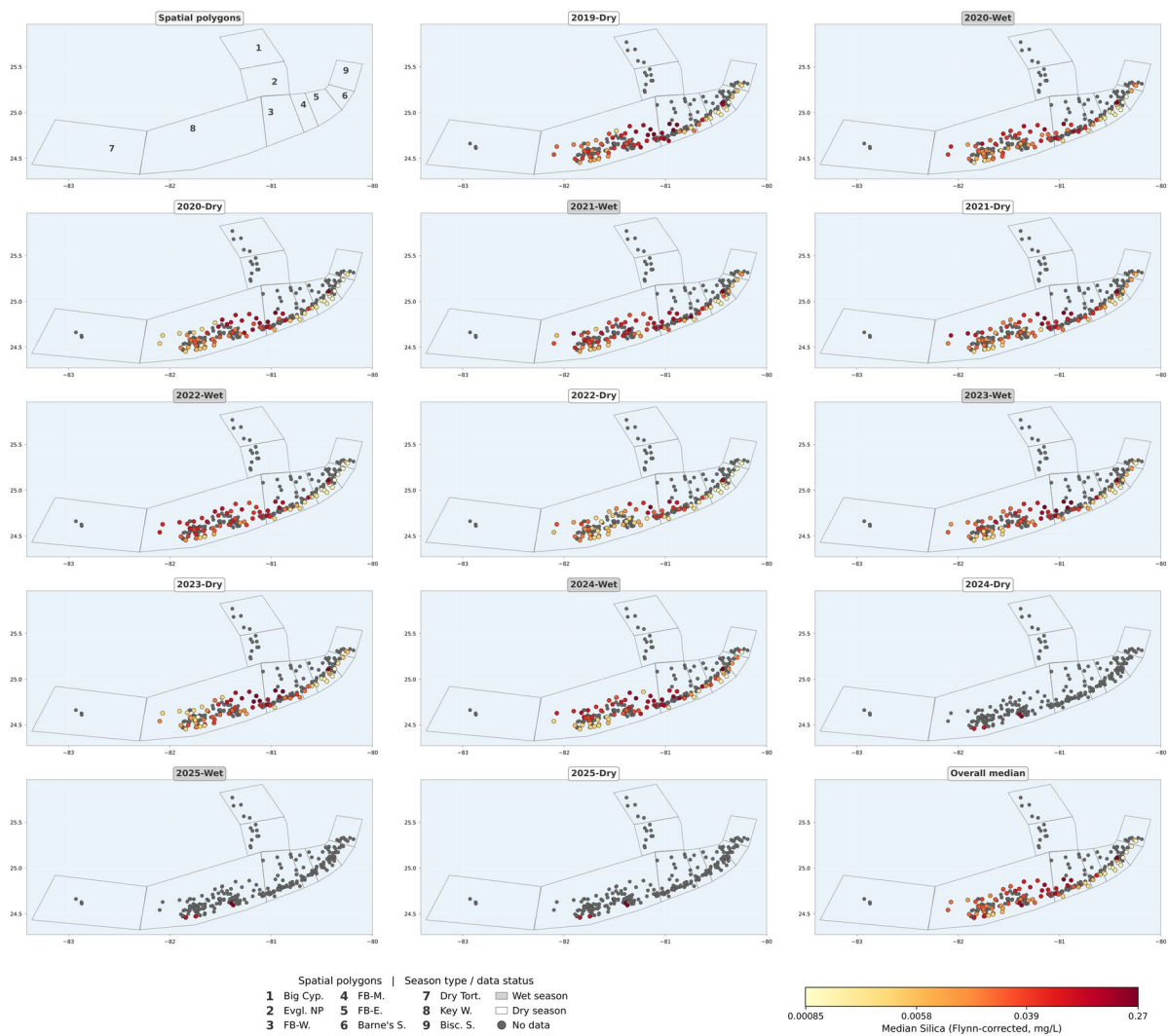


Figure A41. Silica, WIN. Per-season spatial distribution of the median across the WIN monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

WIN: Total suspended solids

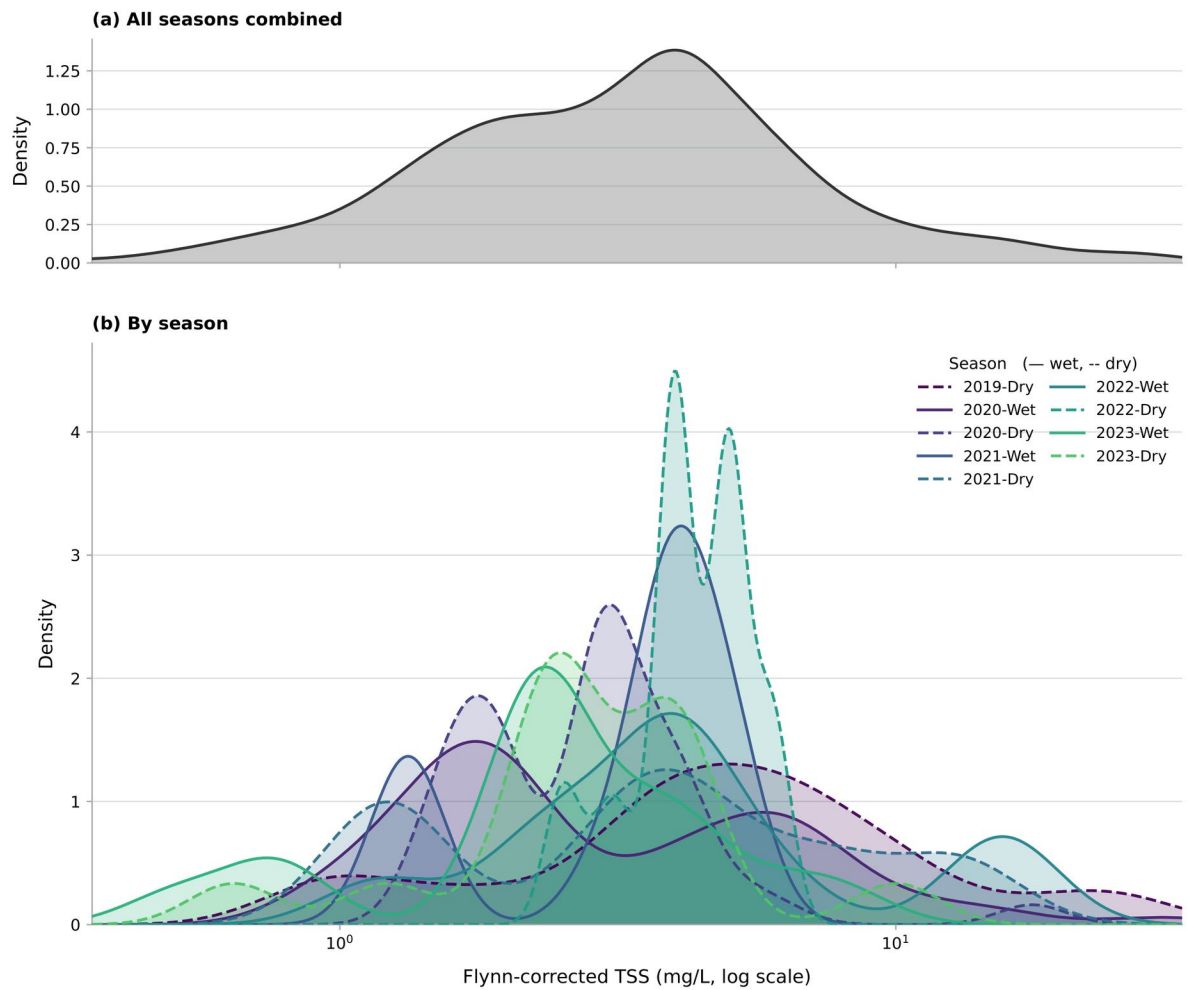


Figure A42. Total Suspended Solids, WIN. Distribution of values at the WIN monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

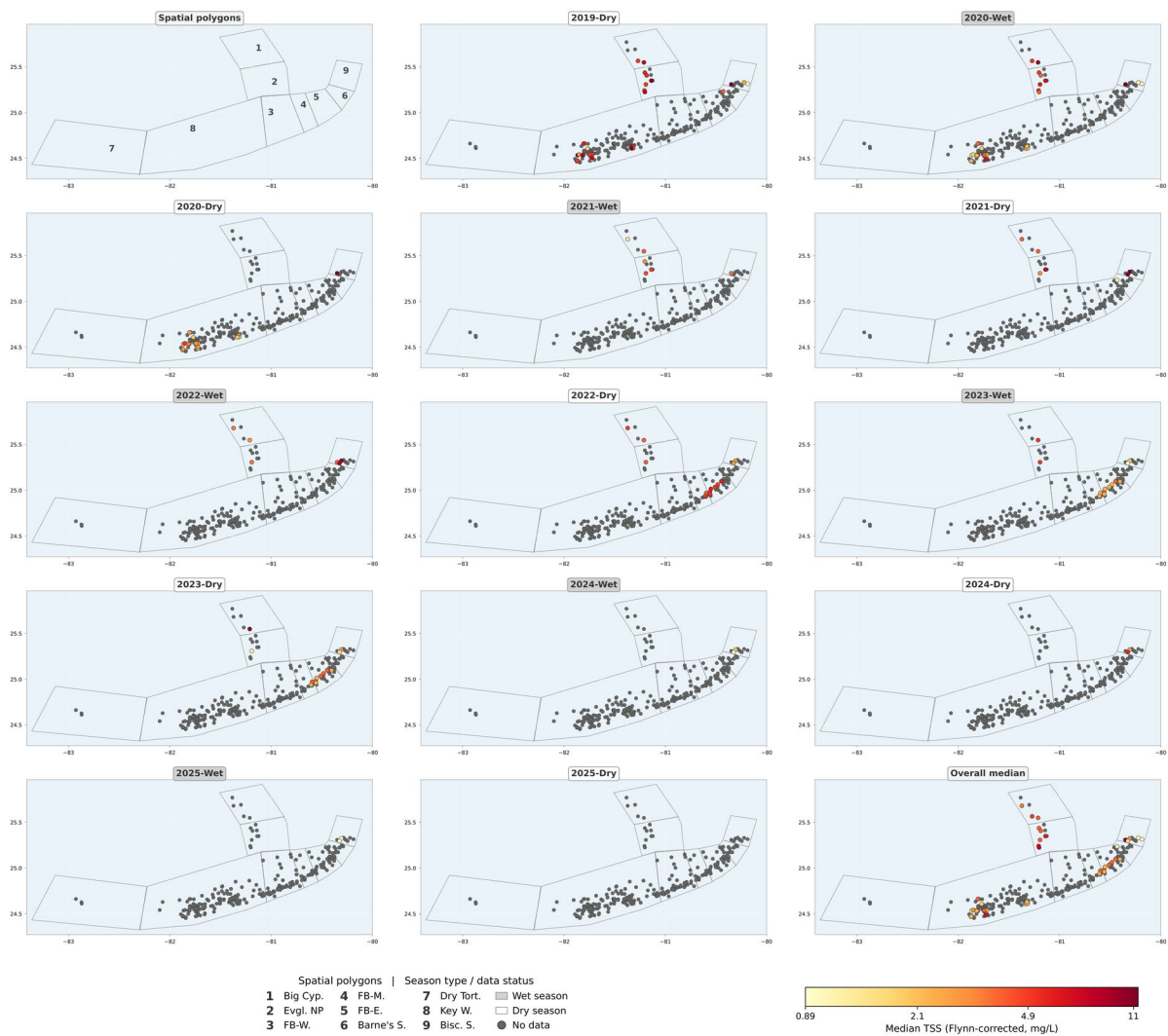


Figure A43. Total Suspended Solids, WIN. Per-season spatial distribution of the median across the WIN monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

SERC: Nitrate

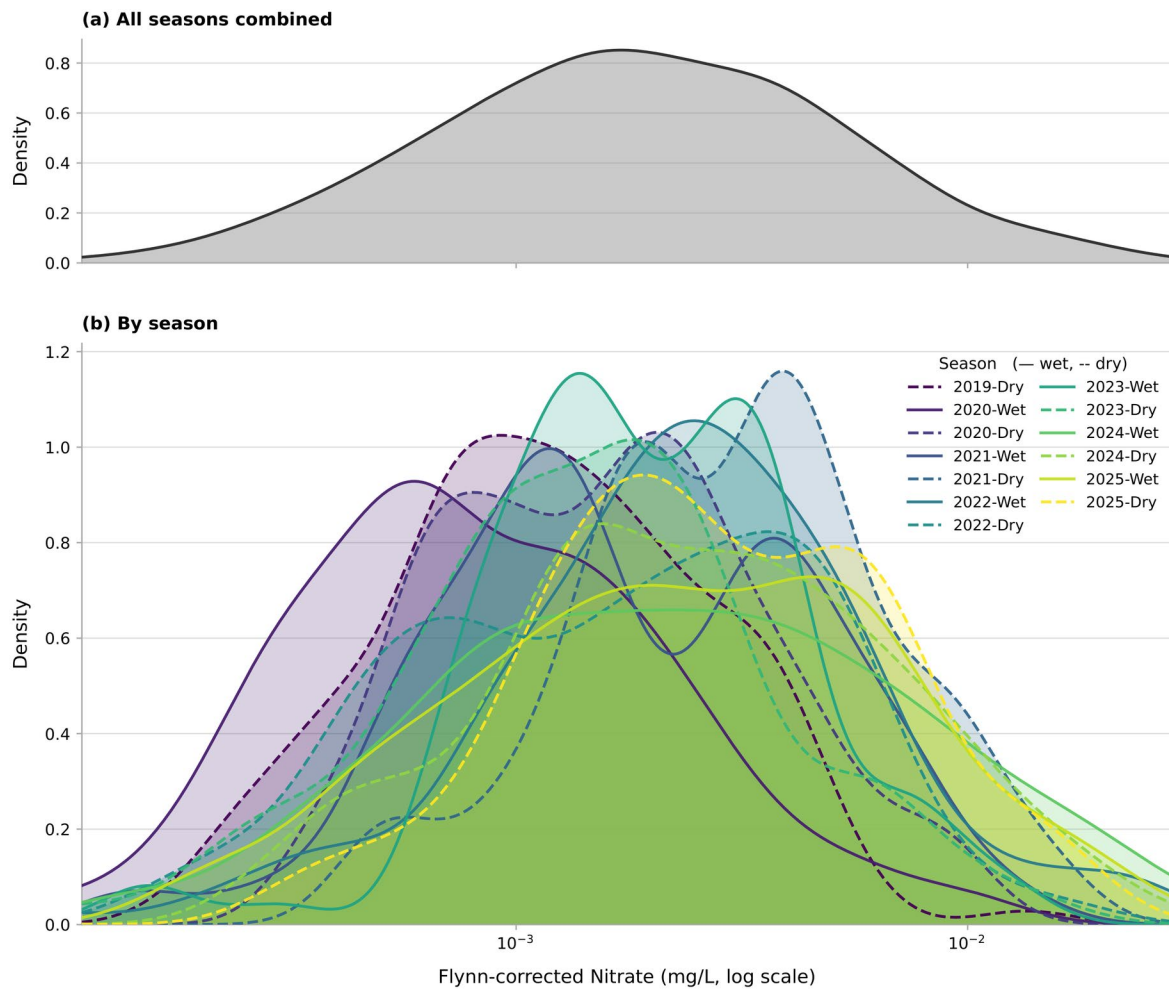


Figure A44. Nitrate, SERC. Distribution of values at the SERC monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

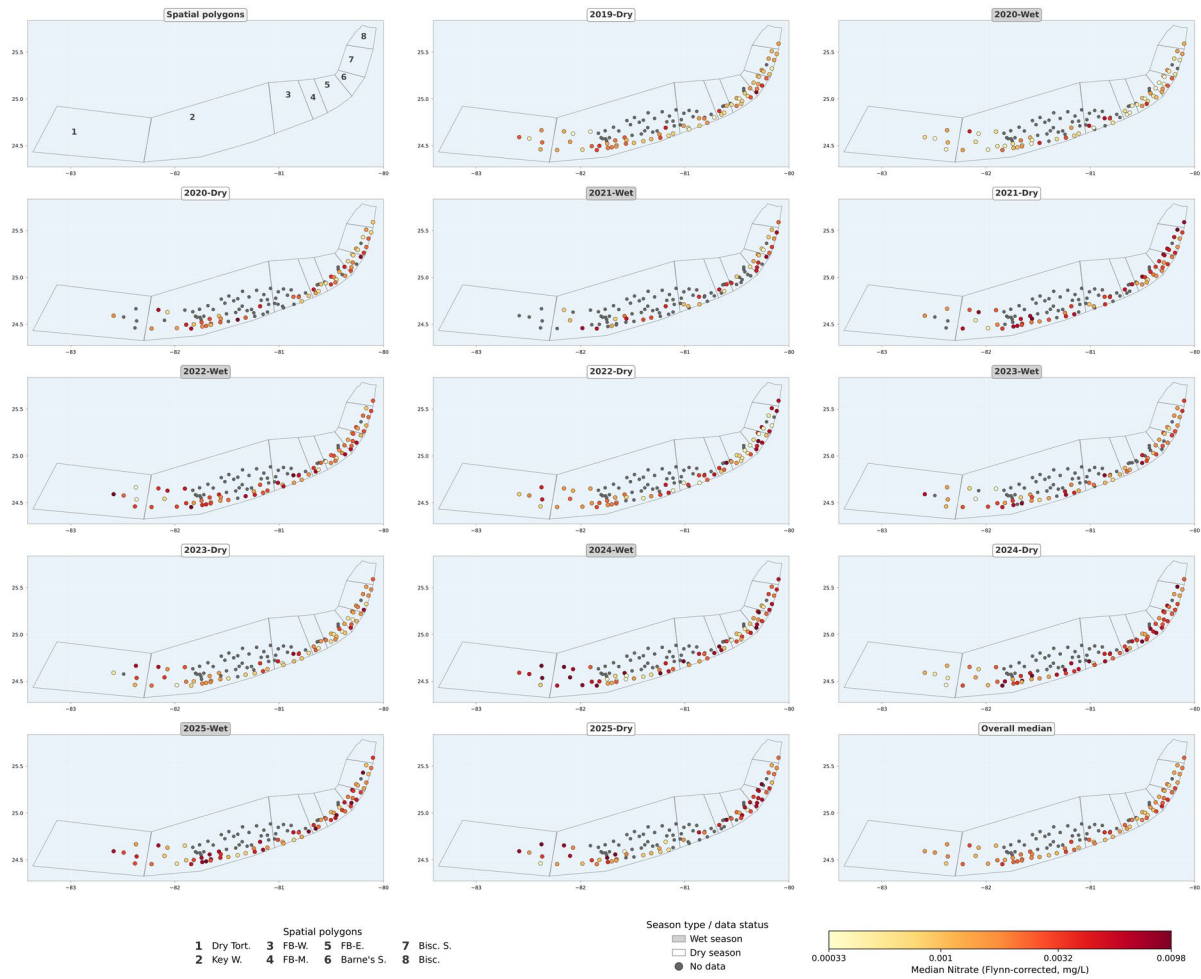


Figure A45. Nitrate, SERC. Per-season spatial distribution of the median across the SERC monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

SERC: Nitrite

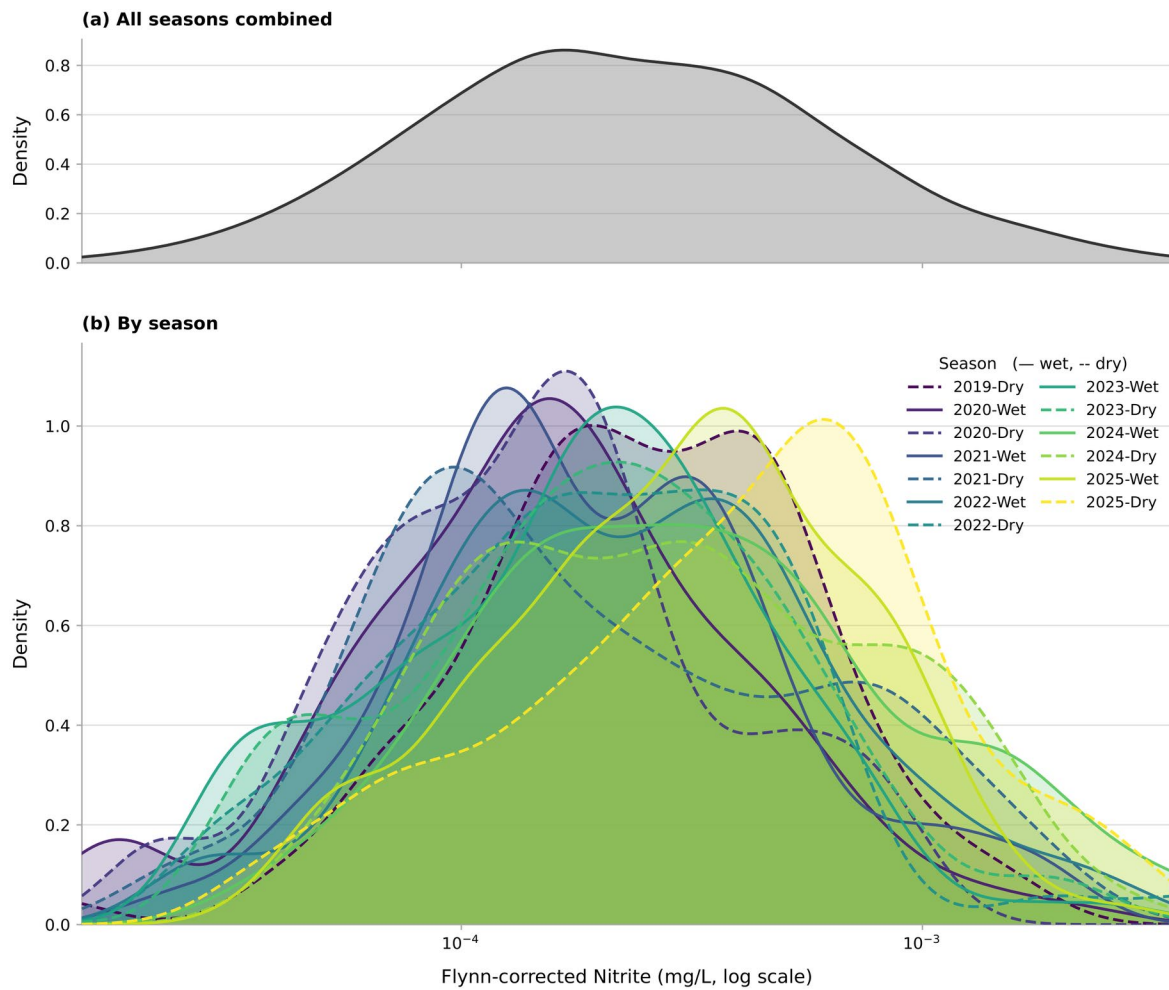


Figure A46. Nitrite, SERC. Distribution of values at the SERC monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

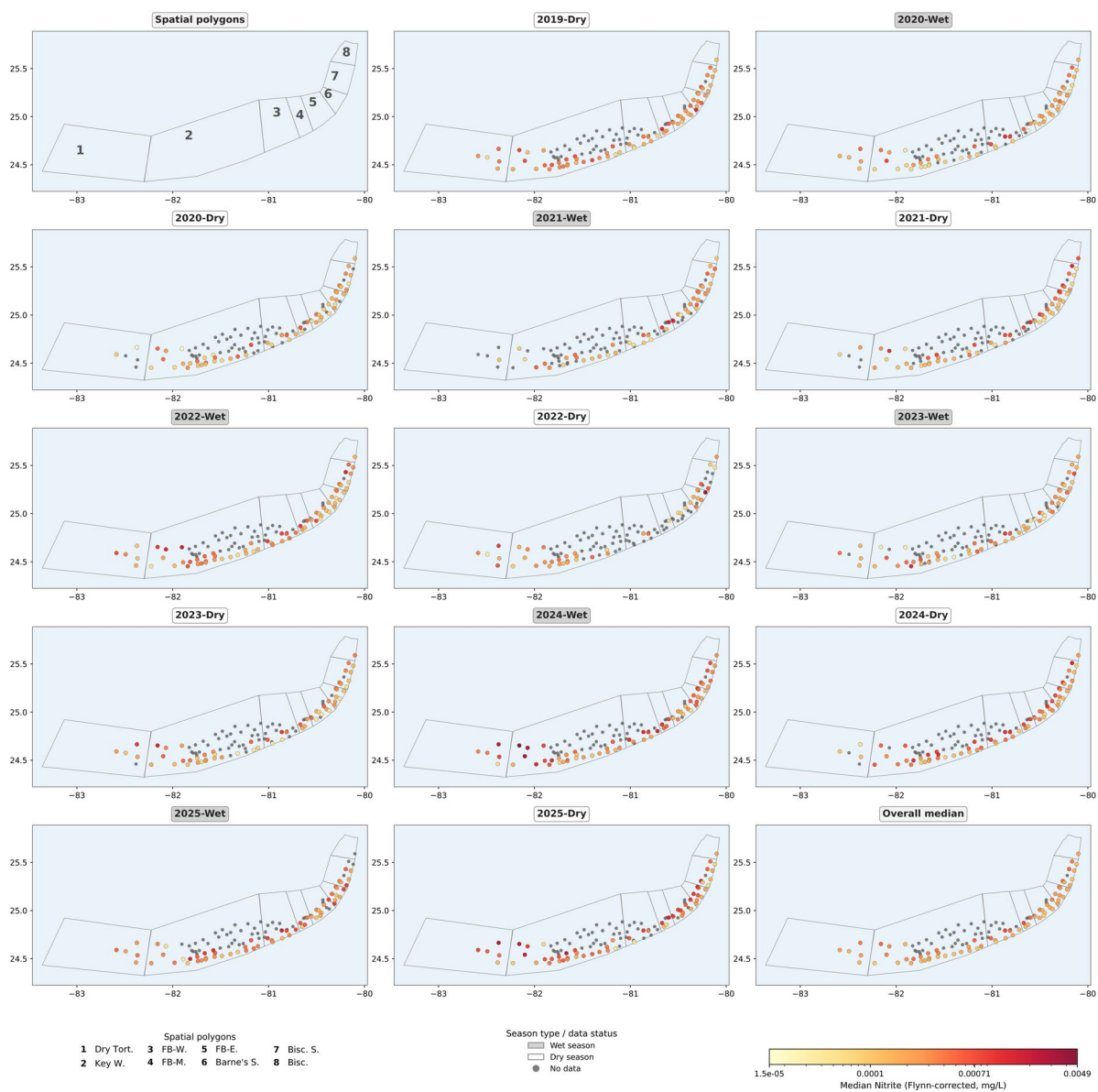


Figure A47. Nitrite, SERC. Per-season spatial distribution of the median across the SERC monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

SERC: Nitrogen-total

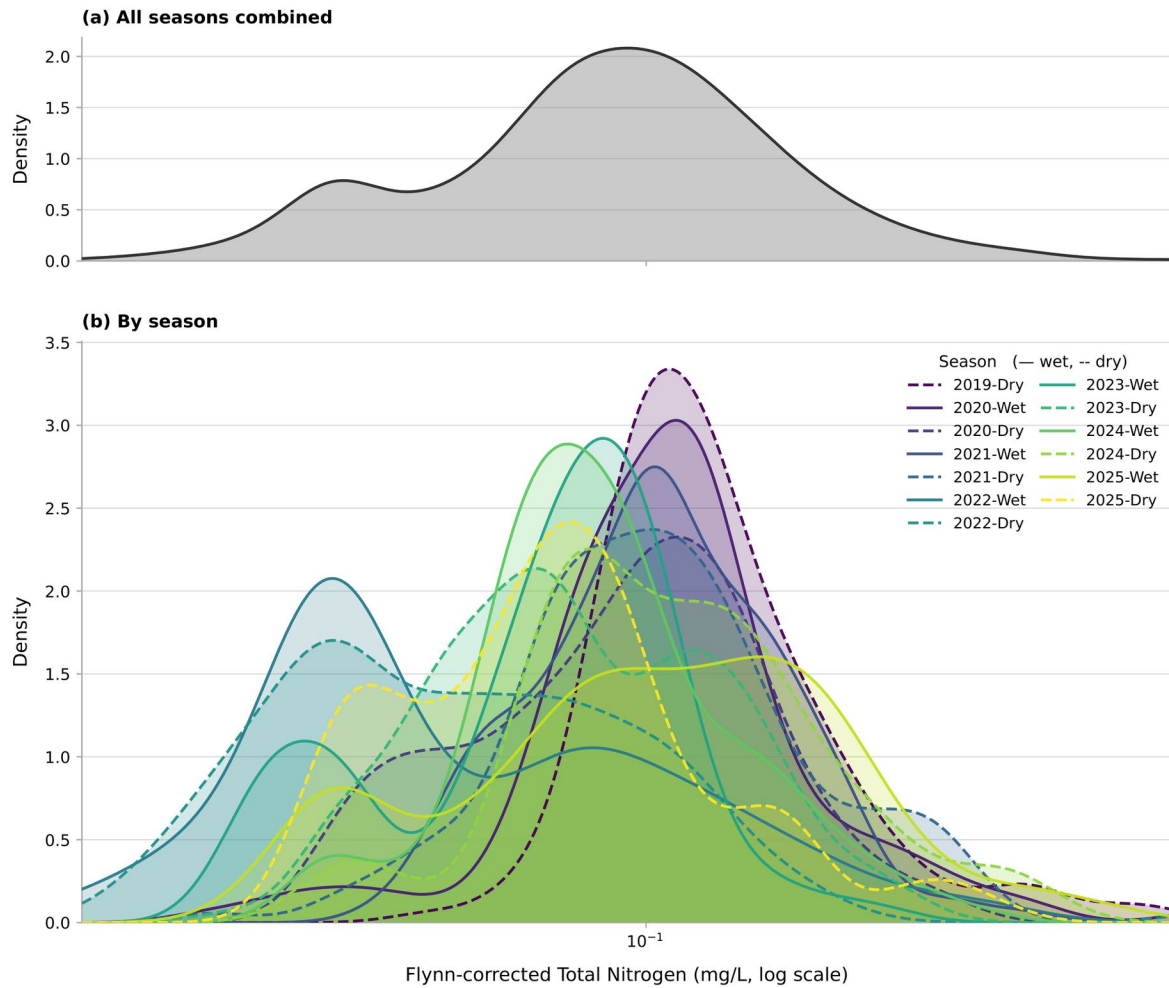


Figure A48. Nitrogen-total, SERC. Distribution of values at the SERC monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

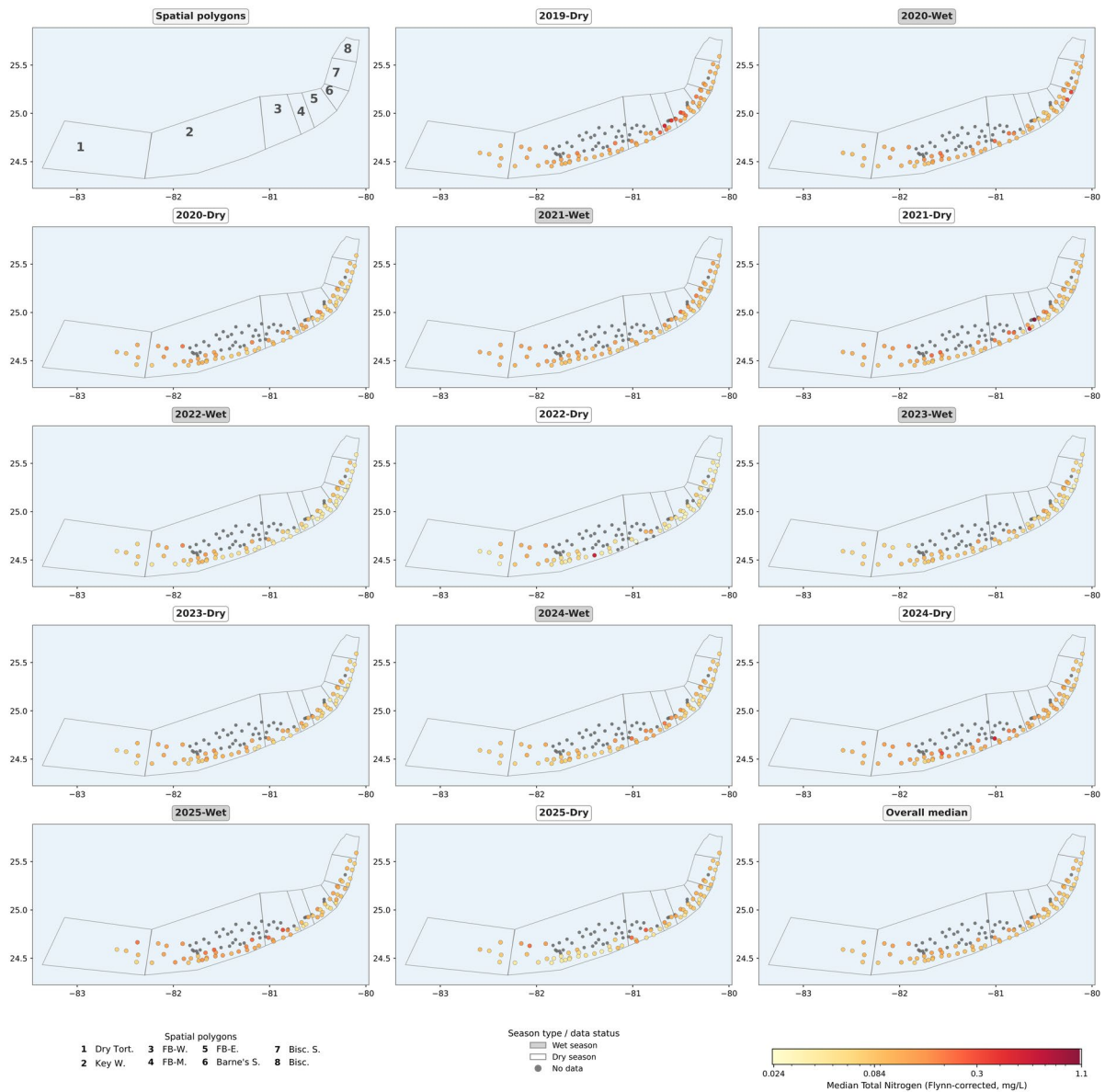


Figure A49. Nitrogen-total, SERC. Per-season spatial distribution of the median across the SERC monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

SERC: Total Phosphorus

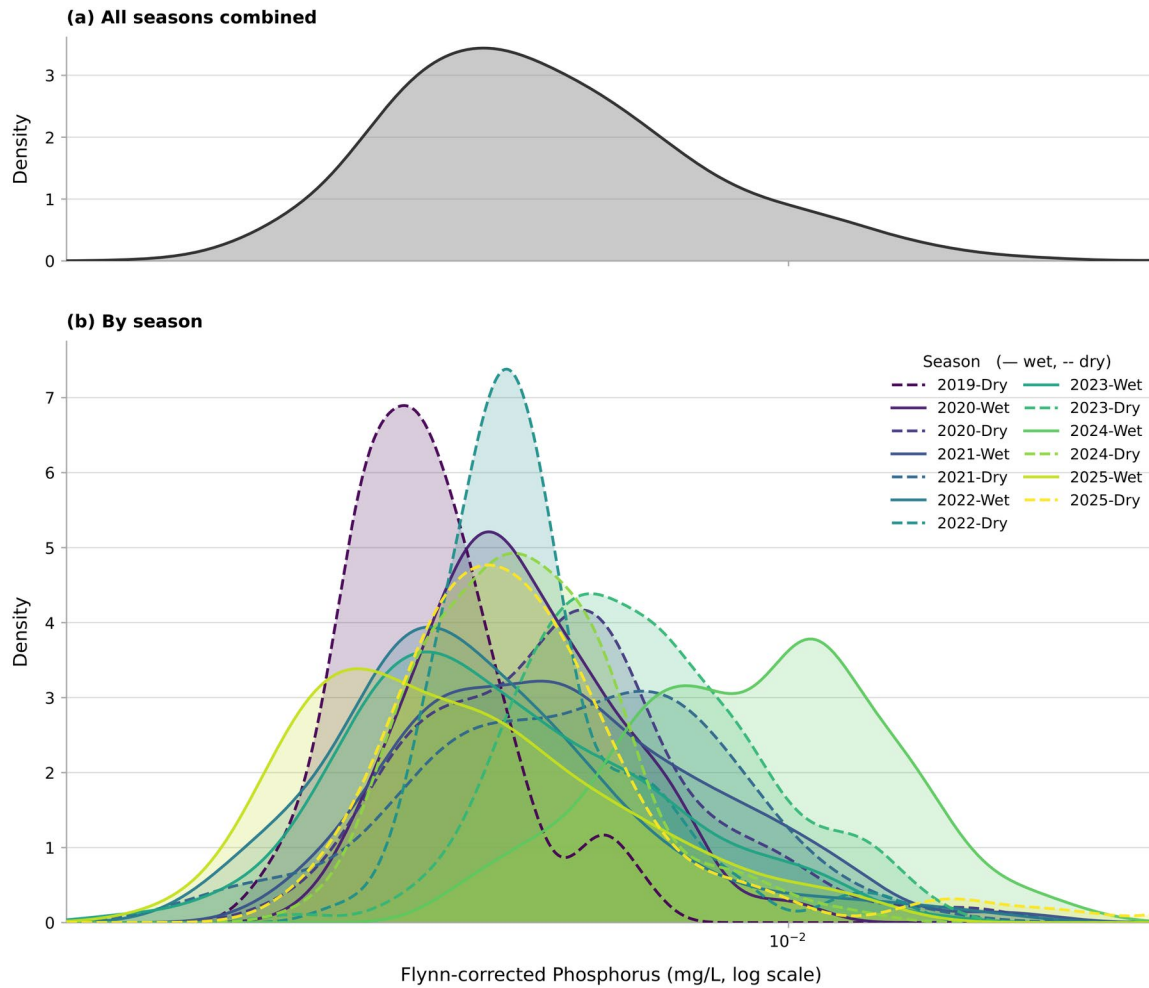


Figure A50. Total phosphorus, SERC. Distribution of values at the SERC monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

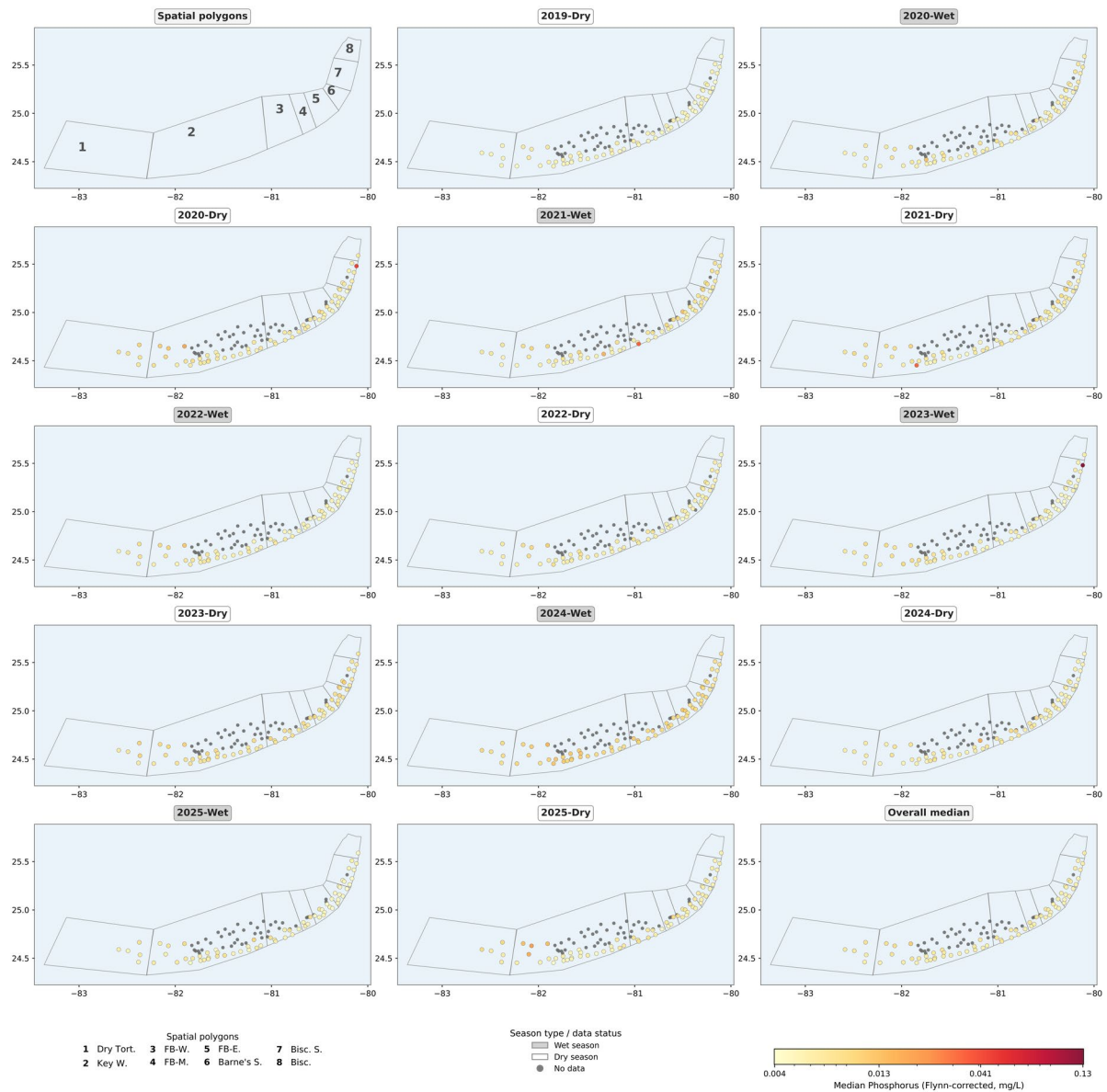


Figure A51. Total phosphorus, SERC. Per-season spatial distribution of the median across the SERC monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

SERC: Salinity

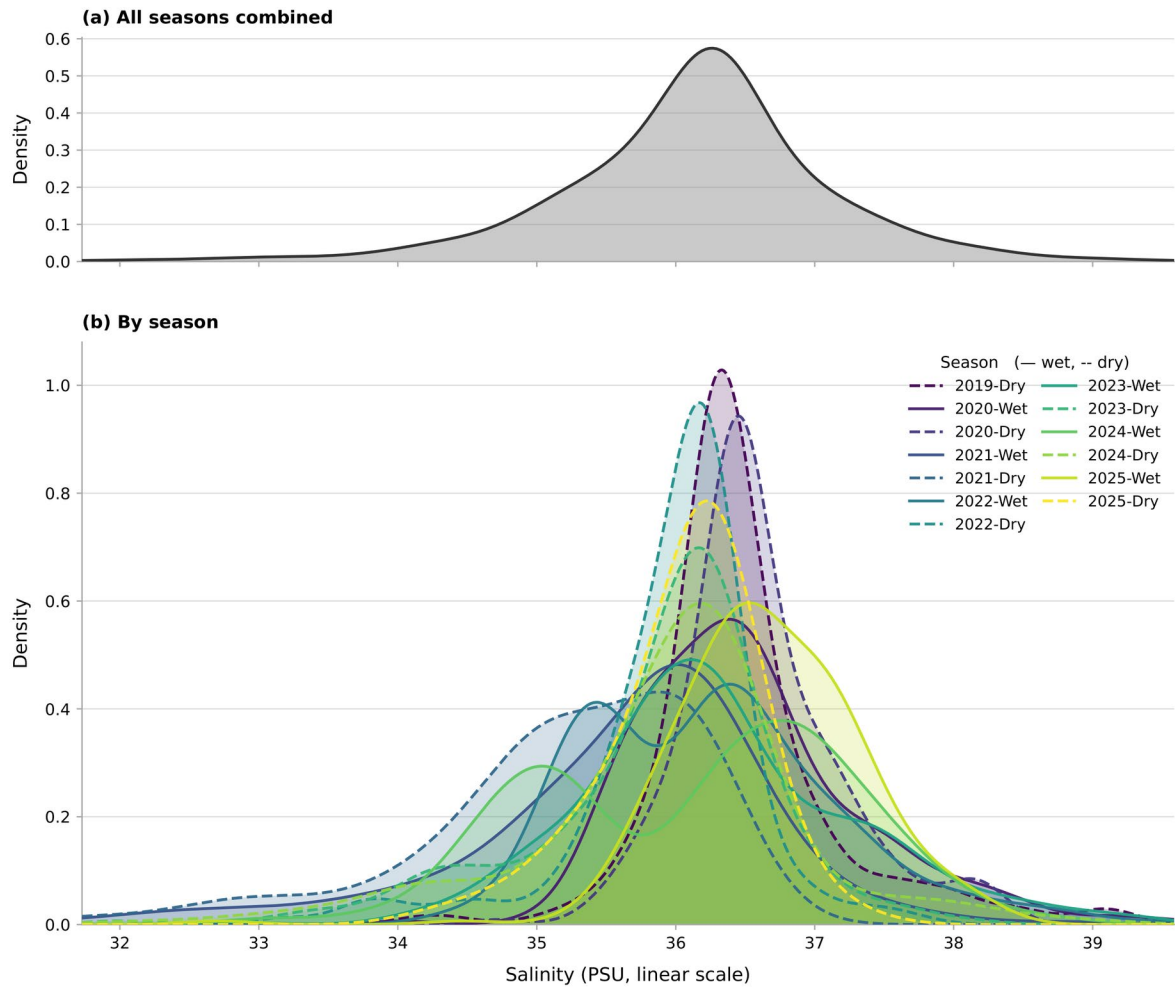


Figure A52. Salinity, SERC. Distribution of values at the SERC monitoring network. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

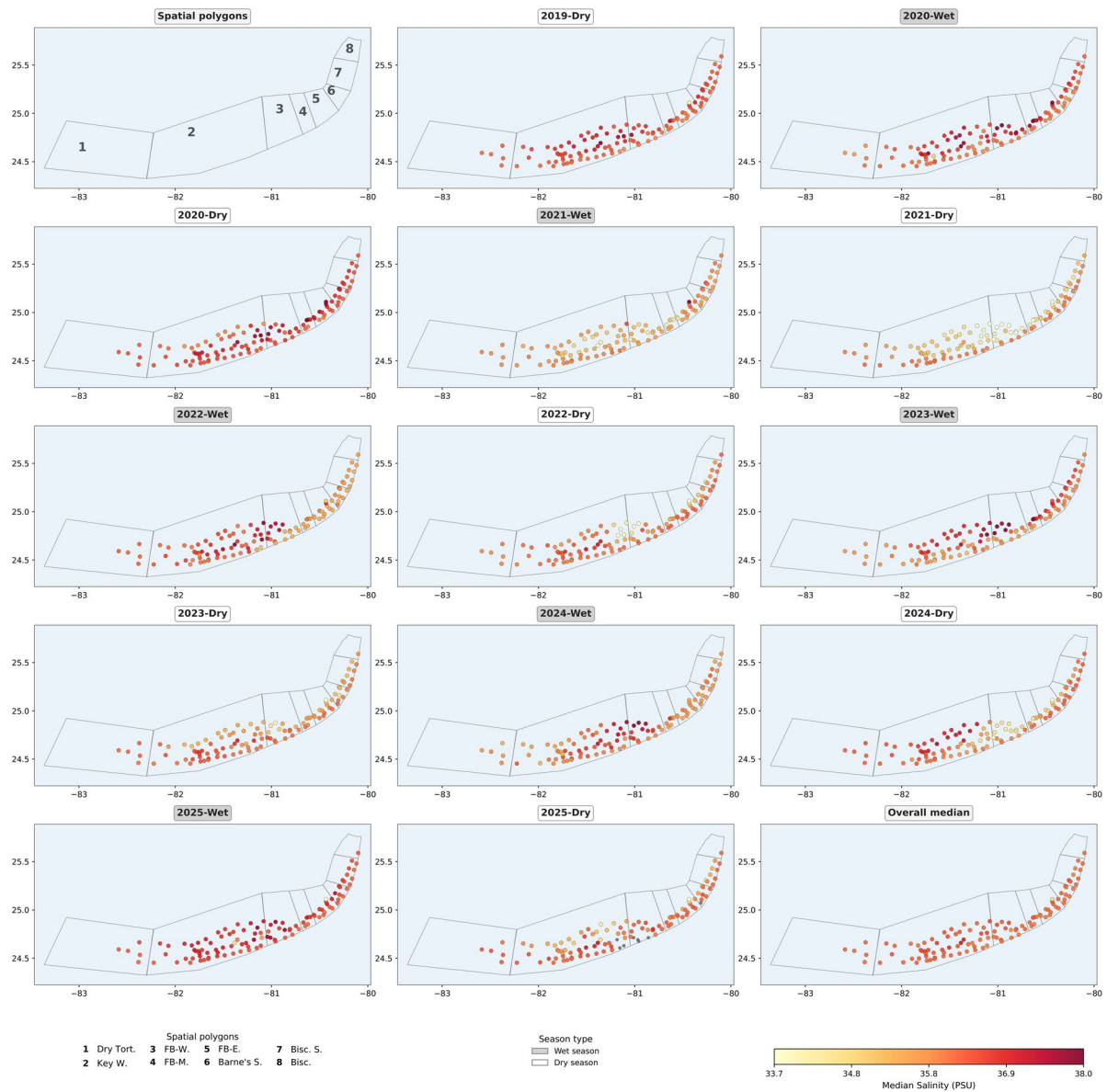


Figure A53. Salinity, SERC. Per-season spatial distribution of the median across the SERC monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

SERC: Silica

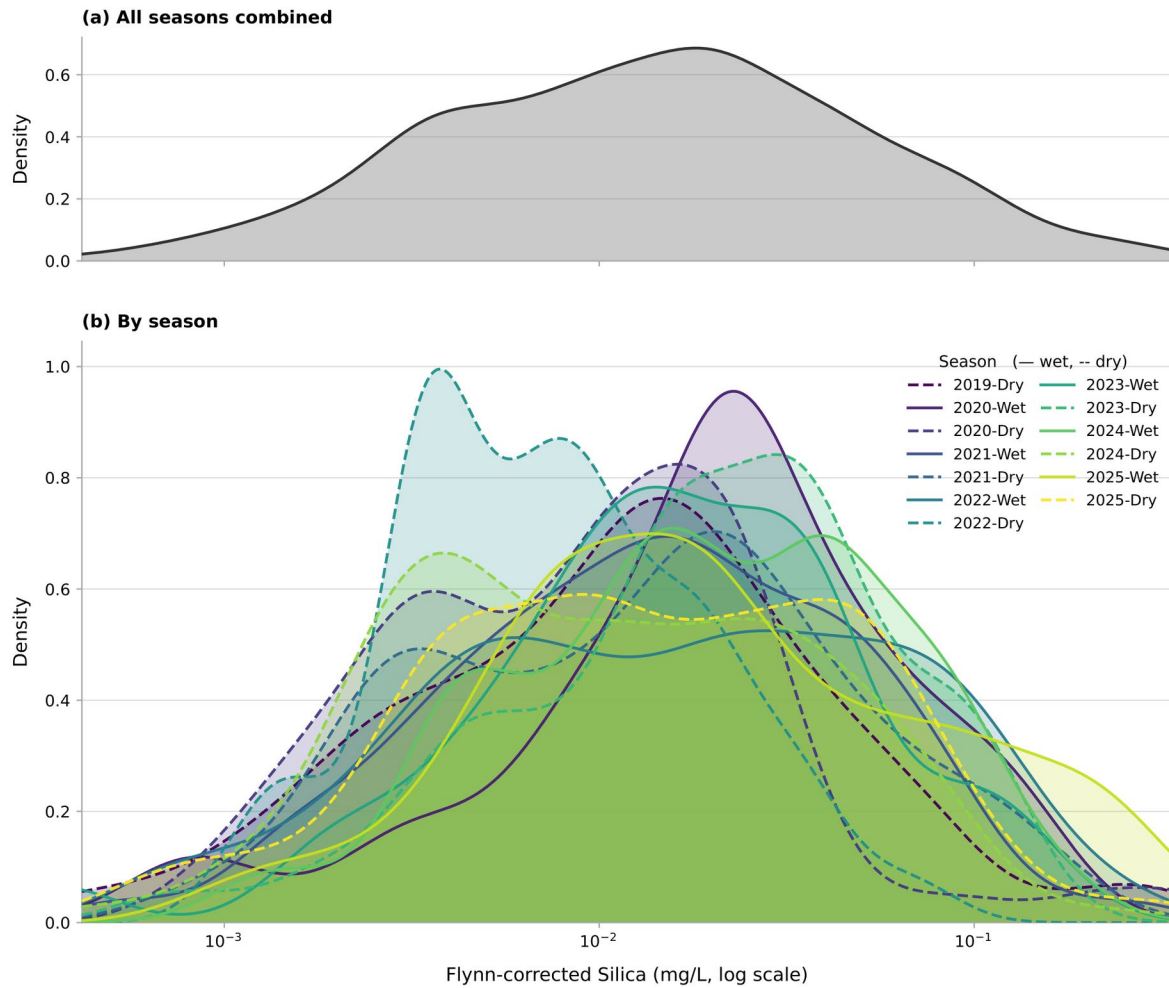


Figure A54. Silica, SERC. Distribution of values at the SERC monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

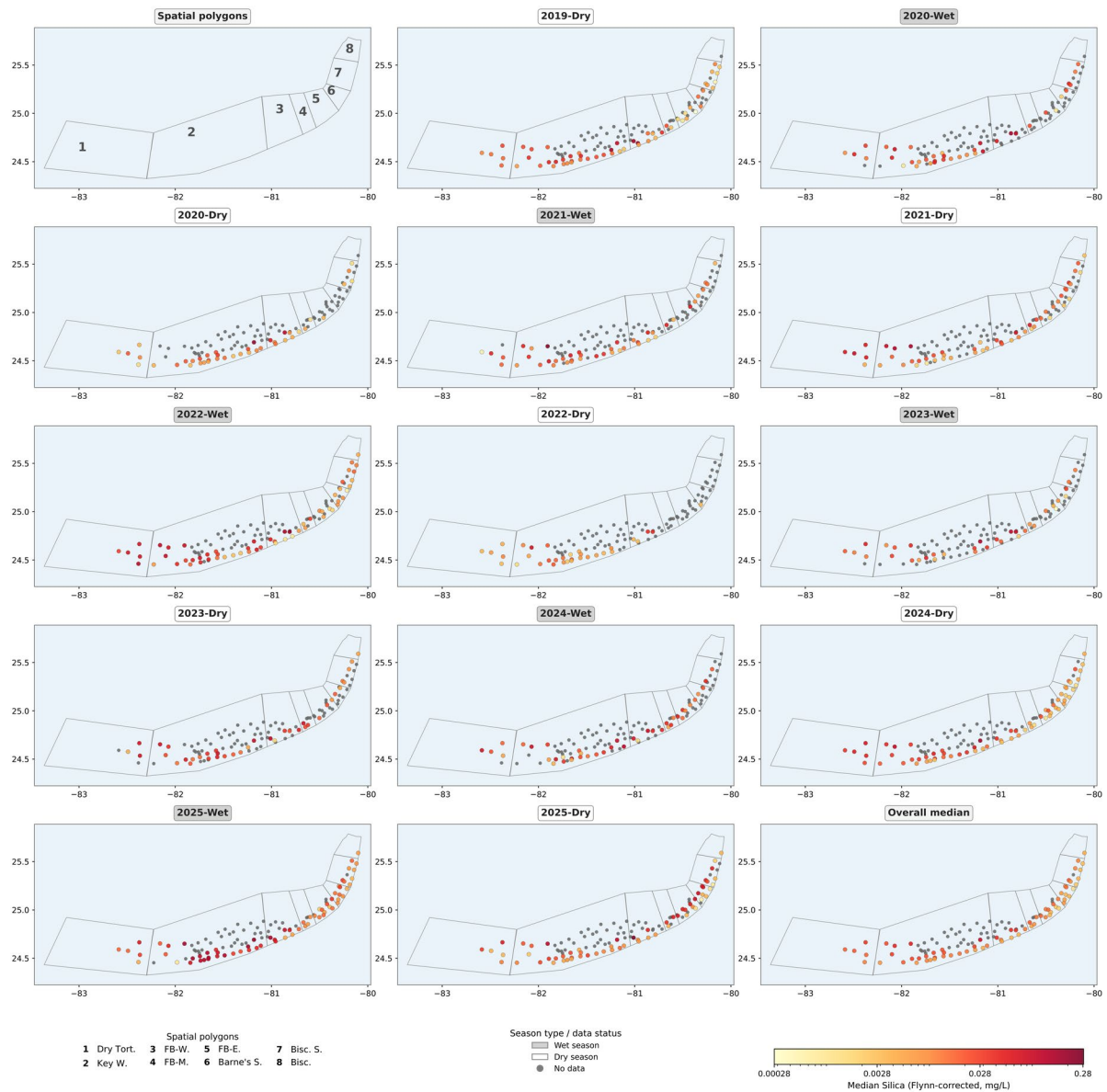


Figure A55. Silica, SERC. Per-season spatial distribution of the median across the SERC monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

SERC: Turbidity

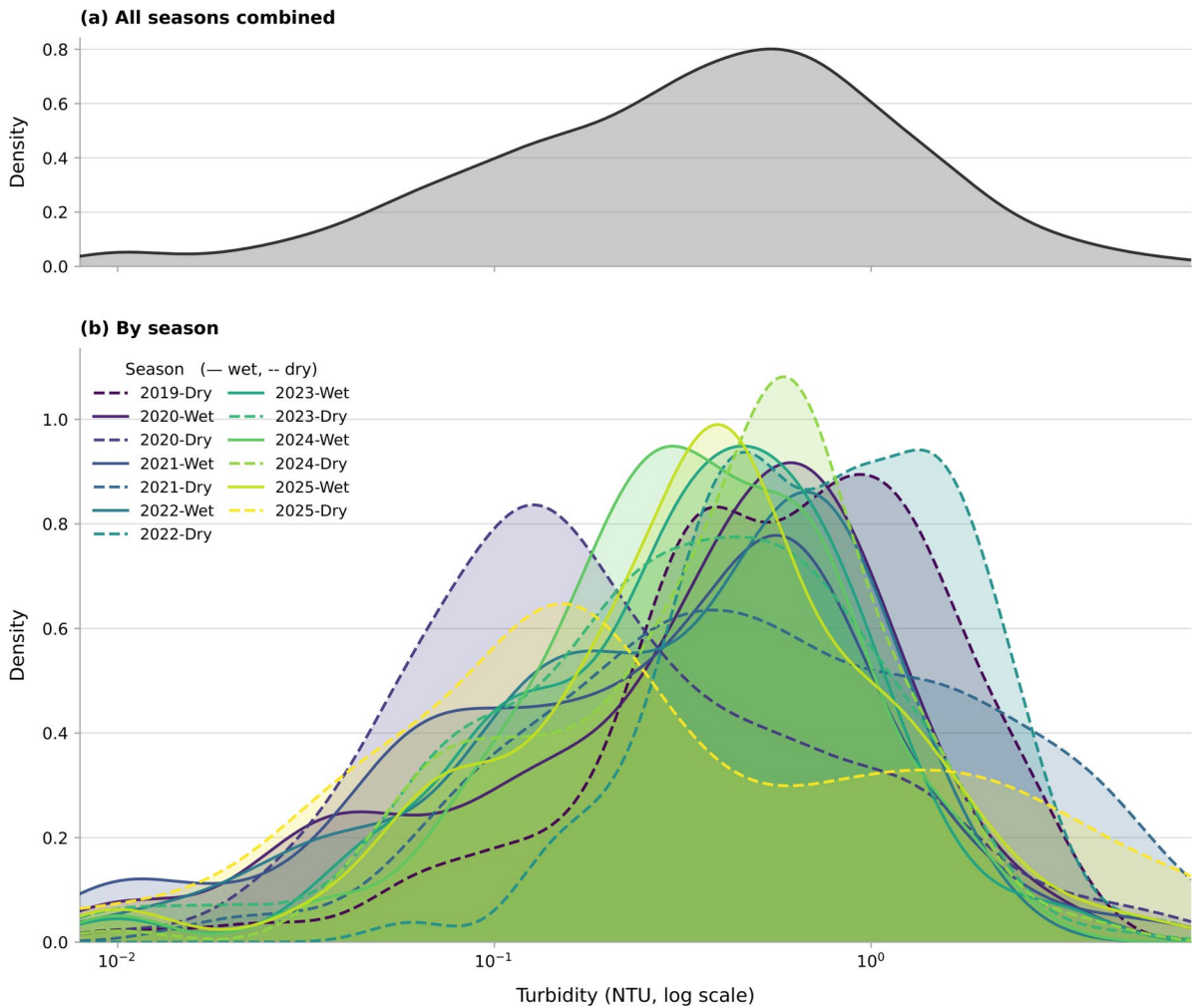


Figure A56. Turbidity, SERC. Distribution of values at the SERC monitoring network on a log scale. Panel (a) is the kernel density of all observations pooled across seasons; panel (b) shows per-season kernel density estimates, one curve per water-year season, with wet seasons drawn as solid lines and dry seasons as dashed lines.

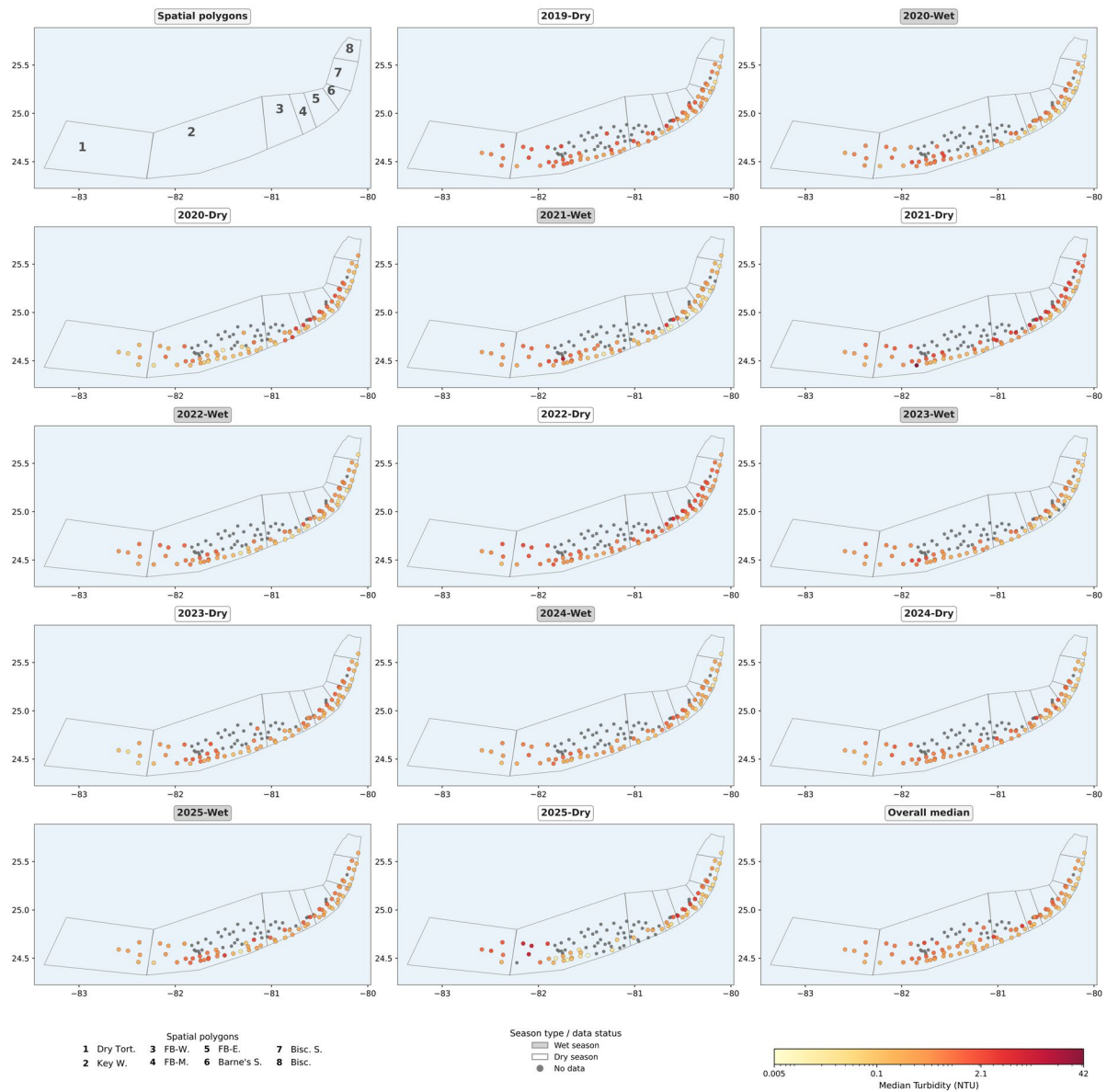


Figure A57. Turbidity, SERC. Per-season spatial distribution of the median across the SERC monitoring network, with one panel per water-year season together with an overall-median panel; site medians are shown on a logarithmic color scale. Smaller grey circles mark monitoring sites with no recorded data in that season.

APPENDIX 4. IN SITU TEMPERATURE LOGGER LOCATIONS

This appendix maps the in situ temperature logger locations described in the Methods. The HOBO temperature loggers were deployed by the CREMP, DTCREMP, and SECREMP monitoring programs across southeast Florida and the Florida Keys. These temperature data were compiled and reviewed, but were not used as predictors in the boosted regression tree models.

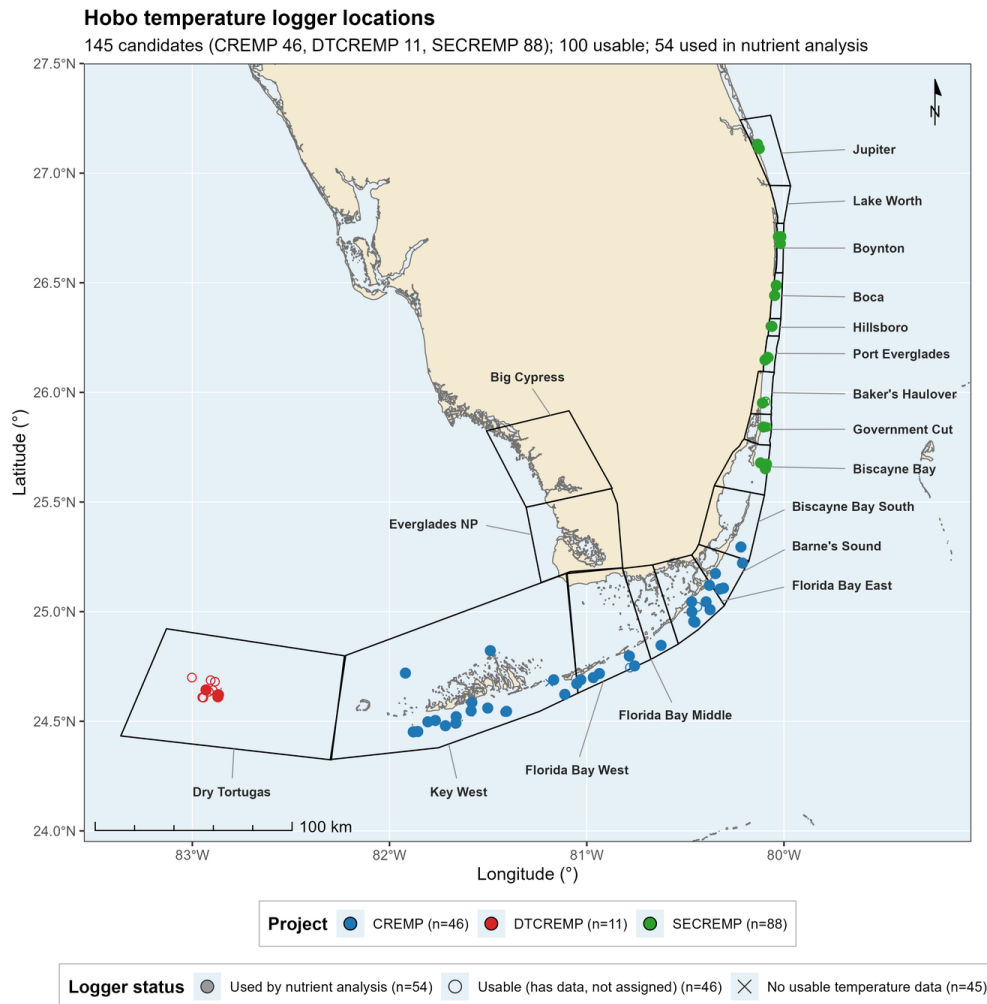


Figure A58. Locations of the in situ HOBO temperature loggers synthesized for this project, deployed across southeast Florida and the Florida Keys by the CREMP, DTCREMP, and SECREMP monitoring programs. The logger data were compiled and reviewed but were not used in the statistical models.

APPENDIX 5. PREDICTOR RELATIVE INFLUENCE

This appendix gives the full relative-influence ranking of every candidate predictor in each program's boosted regression tree models. For each program, one heatmap shows every analyte (columns) against every predictor (rows). Cell shading and the printed value give each predictor's relative influence, in percent. Predictors are ordered by their mean relative influence across the program's analytes. Each analyte's values sum to 100%.

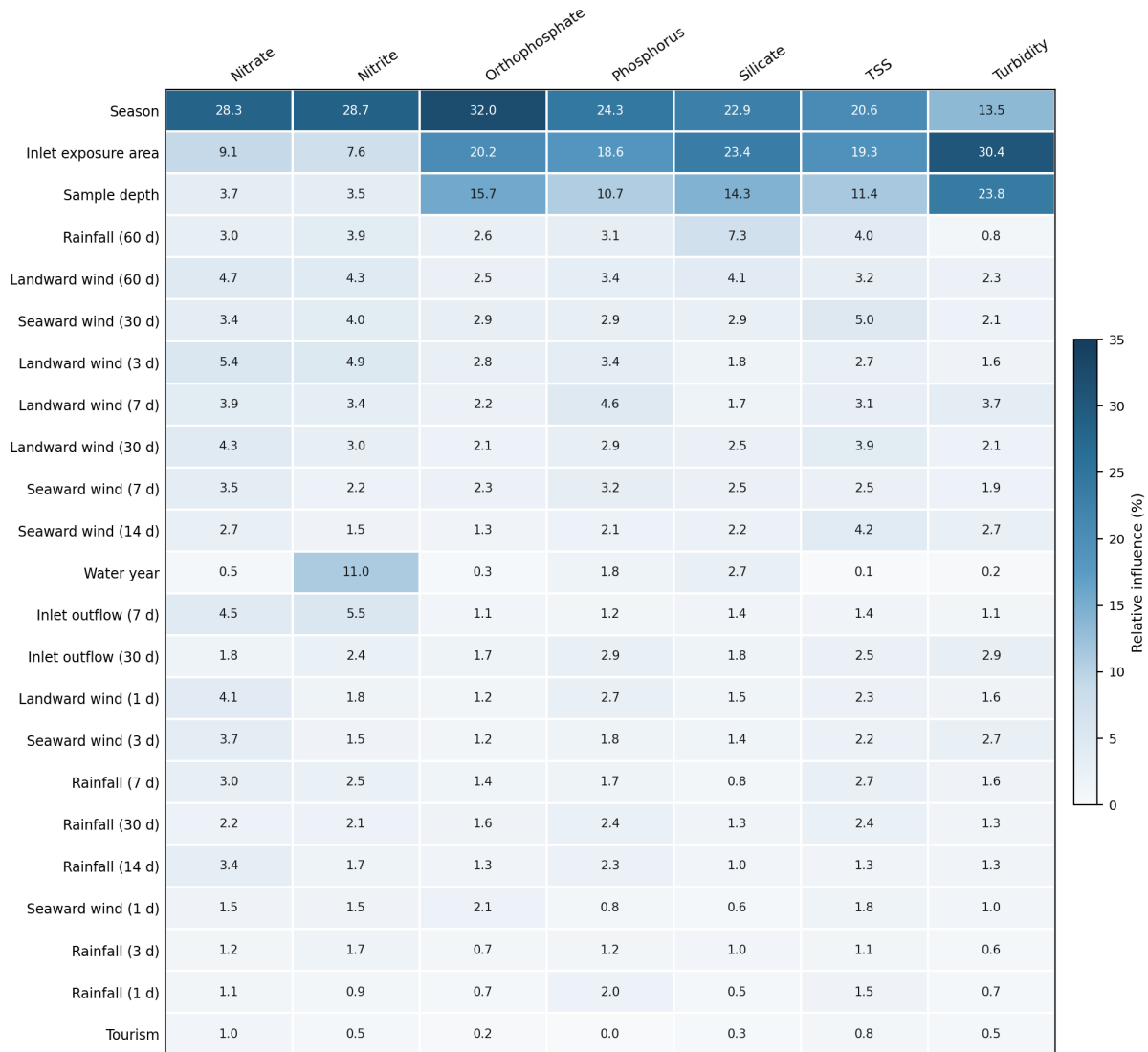


Figure A59. Relative influence of all candidate predictors in the KJCAP boosted regression tree models. Columns are the seven KJCAP analytes; rows are the predictors, ordered by mean relative influence. Each cell gives that predictor's relative influence (%) in the analyte's model; values in each column sum to 100%.

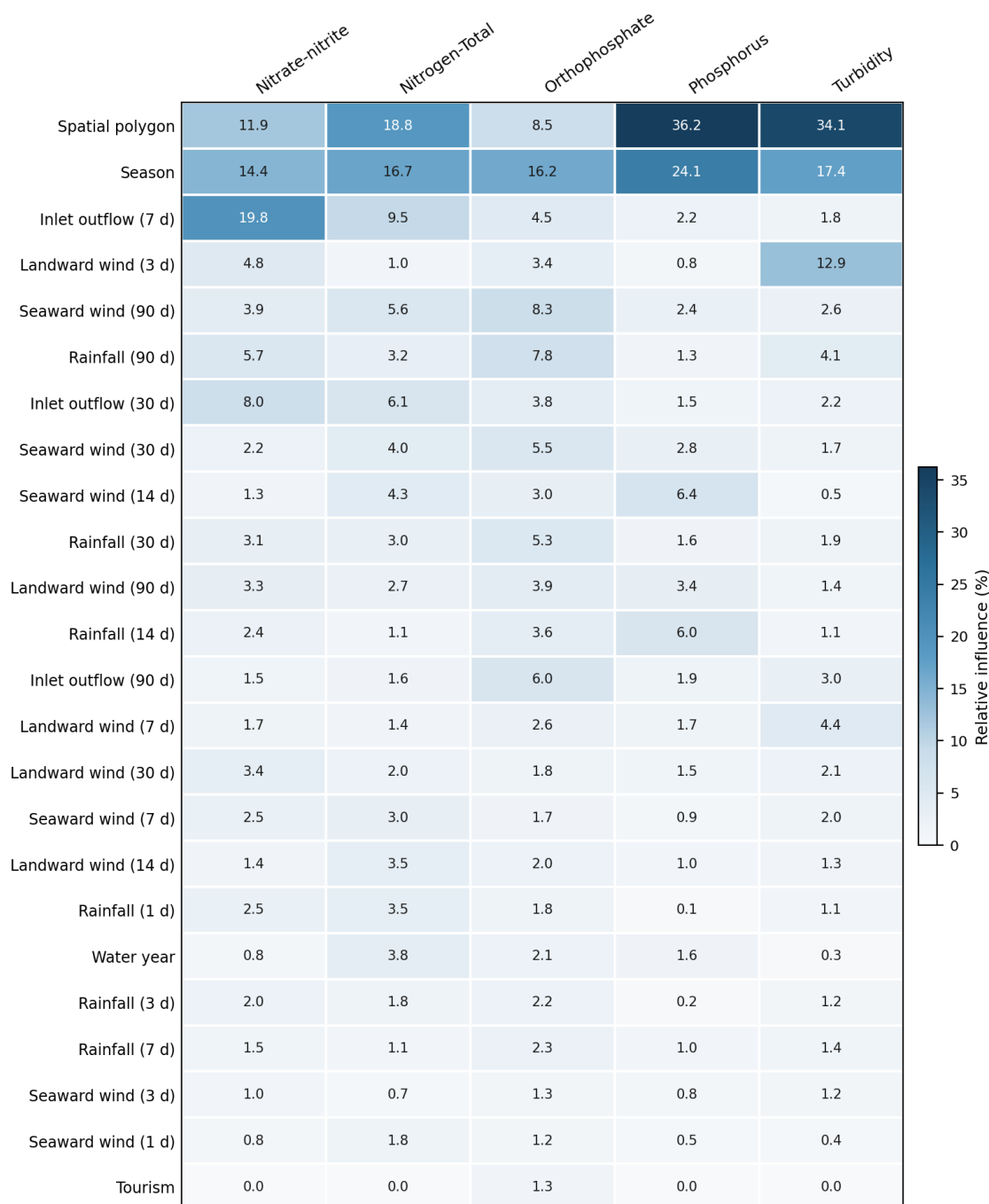


Figure A60. Relative influence of all candidate predictors in the DERM boosted regression tree models. Columns are the five DERM analytes; rows are the predictors, ordered by mean relative influence. Each cell gives that predictor's relative influence (%) in the analyte's model; values in each column sum to 100%.

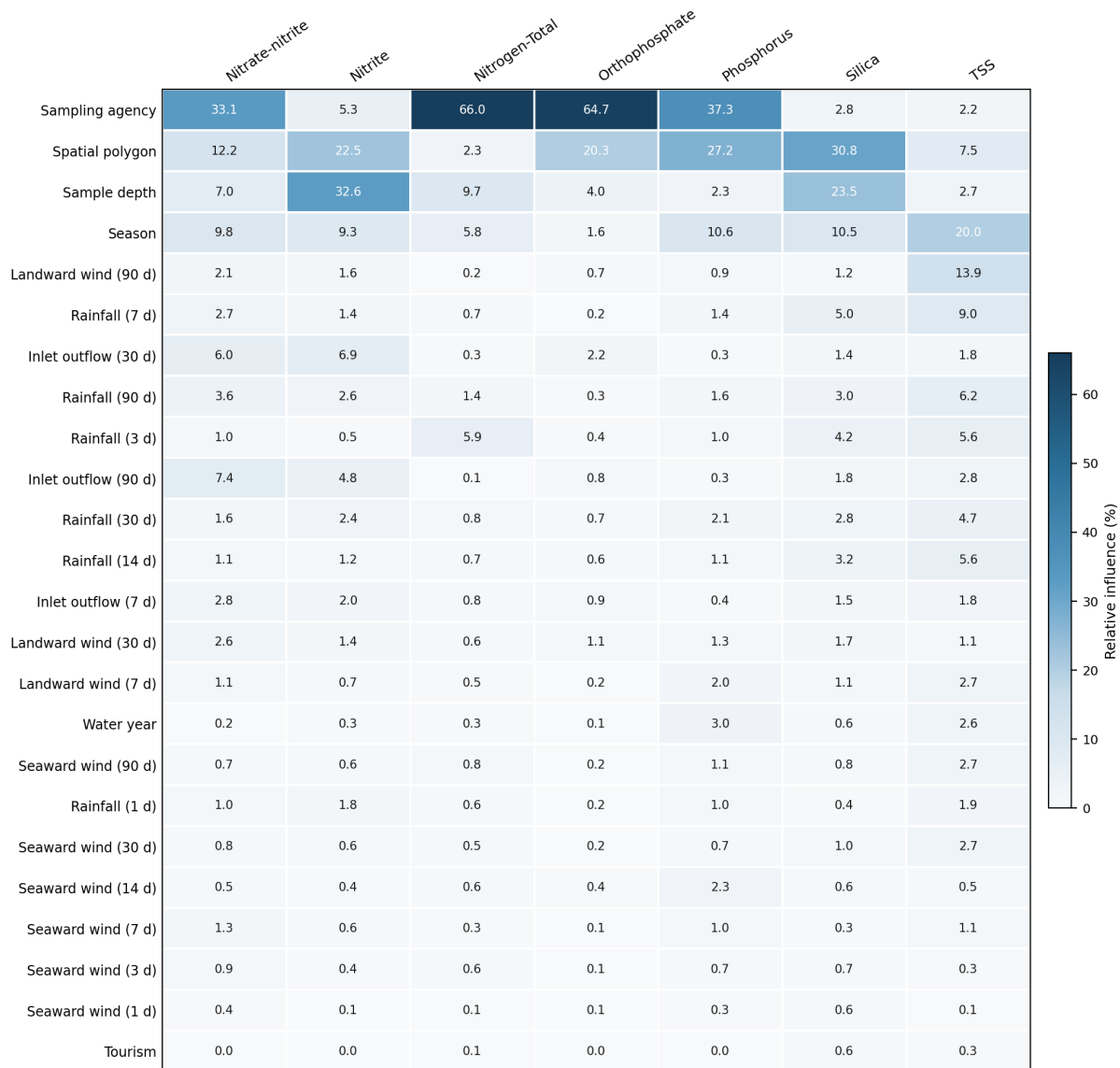


Figure A61. Relative influence of all candidate predictors in the WIN boosted regression tree models. Columns are the seven WIN analytes; rows are the predictors, ordered by mean relative influence. Each cell gives that predictor's relative influence (%) in the analyte's model; values in each column sum to 100%.

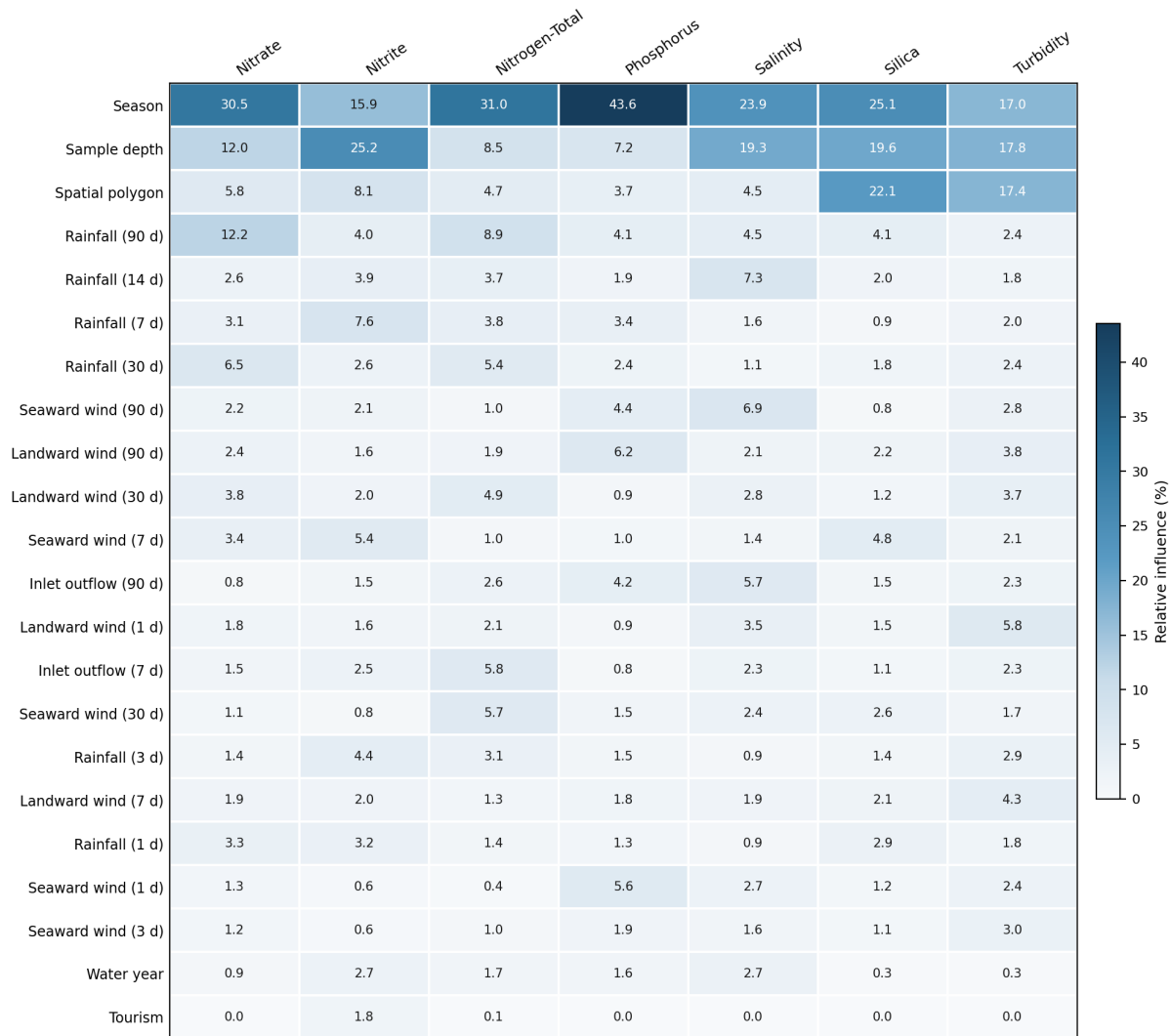


Figure A62. Relative influence of all candidate predictors in the SERC boosted regression tree models. Columns are the seven SERC analytes; rows are the predictors, ordered by mean relative influence. Each cell gives that predictor’s relative influence (%) in the analyte’s model; values in each column sum to 100%.