San Francisco Bay Nutrient Management Strategy

Pilot Study: Characterizing Relative Contributions of Nitrogen from Distinct Sources

Rachel Allen[1]
Pradeep Mugunthan[2]
Rusty Holleman[3]
Jordyn Moscoso[1]
David Senn[1]

[1] San Francisco Estuary Institute
[2] Four Peaks Environmental
[3] RMA-GEI Consultants



November, 2026

SFEI Contribution #1333

SFEI San Francisco Estuary Institute

Acknowledgements

This project was supported by funding from the San Francisco Bay Nutrient Management Strategy and the United States Environmental Protection Agency (Agreement# W9-98T54801-0, Destination Clean Bay).

This project has been funded wholly or in part by the United States Environmental Protection Agency under assistance agreement W9-98T54801-0 to the San Francisco Estuary Institute. The contents of this document do not necessarily reflect the views and policies of the Environmental Protection Agency, nor does the Environmental Protection Agency endorse trade names or recommend the use of commercial products mentioned in this document, as well as any images, video, text, or other content created by generative artificial intelligence tools, nor does any such content necessarily reflect the views and policies of the Environmental Protection Agency.

Plain Language Summary

This report describes a pilot study using a numerical modeling technique to evaluate the fate of dissolved inorganic nitrogen (DIN) entering San Francisco Bay from distinct sources, including wastewater treatment plants and major rivers. The technique will provide a more detailed understanding of nutrient losses in the Bay along with valuable information for decisions regarding nutrient management.

- Comparing model output with field observations provides insights into the spatially and temporally varying rates of DIN loss through the system.
- Modeling the spread of DIN from each source helps define their zone of influence, which is the portion of the Bay that their nutrients reach.
- Looking at the collective zones of influence creates an estimate of the relative DIN contribution from each source for any location in San Francisco Bay.
- Using a clustering technique, the model outputs can define regions of the Bay where DIN concentrations result from different groups of DIN sources. This clustering provides qualitative information about how potential load reductions by wastewater treatment plants or nutrient trading between wastewater treatment plans could impact specific regions of the Bay.
- Varying the DIN inputs to the model can also be used to assess the impacts of various future scenarios, including load reductions, nutrient trading, or even load increases.

Two additional steps are planned for this pilot effort. The next step will be a deeper dive into how DIN losses vary within target subembayments and ecosystems in the Bay to generate spatially-varying loss rates. The final step will build those spatially-varying loss rates as well as temporarily-varying loss rates into the model to improve the accuracy of this technique and its usefulness for informing management decisions.

1. INTRODUCTION

San Francisco Bay (SFB) ranks among the most nitrogen-enriched estuaries worldwide (Cloern et al., 2020), and receives the majority of its dissolved inorganic nitrogen (DIN) loads from via effluent from publicly-owned treatment works (POTWs) (SFEI, 2014a; SFEI, 2014b). Despite its elevated DIN loads, between the late-1960s and early-2000s SFB generally did not experience severe or persistent nutrient-related water quality impacts common to other nutrient-enriched estuaries, such as excessive phytoplankton blooms and low dissolved oxygen. However, observations over the past 20 years have raised concerns that SFB's resistance to elevated nutrients could be waning (SFEI, 2014a): increased phytoplankton biomass and gross primary production in deep subtidal regions of South Bay (Cloern et al., 2007, 2010); frequent occurrences of harmful algae and their associated toxins (Peacock et al., 2018; Sutula et al., 2017); and low dissolved oxygen in some tidal slough habitats (Novick et al., 2015). To address these concerns, regulators and stakeholders launched the SFB Nutrient Management Strategy Science Program in 2014 (San Francisco Bay Nutrient Management Strategy, 2012) with the aim of developing the scientific foundation necessary to inform nutrient management decisions in SFB.

One of the NMS' major program areas focuses on developing and applying numerical models to simulate SFB physics and biogeochemistry to investigate applied-science and management questions related to nutrient transport, nutrient transformations and cycling, and nutrient-related ecosystem responses. Quantifying the contributions of individual DIN sources to ambient DIN concentrations and related water quality responses is essential information for identifying effective and cost-efficient management options. However, when an estuary's DIN loads come from multiple distinct and substantial sources, tracking and quantifying their individual influence(s) water quality over space and time poses major technical challenges due to physical mixing and biogeochemical processes that transform the original DIN into other compounds.

This report presents initial results (round one) from a multiple-stage project aimed at developing numerical modeling techniques for tracking and quantifying the contributions of individual nutrient sources on ambient dissolved inorganic nitrogen (DIN) concentrations throughout SFB. The numerical modeling approach uses a well-calibrated hydrodynamic model for SFB along with a suite of customized numerical tracers that enable tracking the transport and estimating the transformations experienced by DIN from individual sources. While the method and results presented here focus on the tracer-based approach, the plan is for the tracer-based approach to be used in conjunction with full biogeochemical simulations

2. METHODS

2.1 Background

Developing and applying DIN source apportionment approaches is an on-going NMS priority, originally identified in the NMS Science Plan and Modeling Workplans for 2020-2024 (SFEI 2019a, SFEI 2019b), and in the NMS 2025-2030 Science Plan (SFEI 2025 "developing, testing, and applying efficient approaches for characterizing point-source zones of influence") . Its goals include determining the zones of influence of individual nutrient sources, quantifying the relative contributions of individual sources to the total DIN concentration, and combining reactive numerical tracers with space- and time-varying net loss rates, estimated from calibrated biogeochemical model runs or semi-empirical fits to observational data, to allow for computationally-efficient estimates of the DIN contributions from individual sources.

Initial exploratory source apportionment work, conducted in 2020-2021, utilized the full BGC model (SFEI 2021). That project's study design involved running a one-year (WY2013) baseline simulation that used each POTW's actual loads during that time, and running 37 perturbation simulations of WY2013 -- one for each POTW outfall -- in which the DIN loads from that outfall were reduced by a known percentage. The analysis then included quantifying each POTW's spatially-varying influence by comparing DIN concentrations between the perturbation results and the baseline wy2013 prediction. Although the approach allowed for using the full-BGC model and for intuitively characterizing POTWs' zones of influence (ZOI), it also had several important limitations. First, the perturbation-based approach required running independent BGC simulations for each of the 37 POTW outfalls, which if run using the high-resolution model grid would each require ~1 week of wall-clock time to simulate one year. For that reason, we used the aggregated-grid version of the model which runs much faster (1-2 hours to simulate). The aggregated-grid model results were informative and allowed for exploring a range of factors (e.g., variability of source signatures depending on how subembayment boundaries are drawn). However, the source apportionment and ZOI results also suggested that the aggregated-grid model predictions were overly dispersive (i.e., excess mixing or dilution of individual sources; SFEI 2021). The report concluded with several recommendations for subsequent rounds of source apportionment method development work, including using full resolution model runs, testing during other water years and other seasons, and using updated reactive-transport estimates (e.g., from improved versions of the BGC model).

2.2 Modeling approach

The modeling approach employed here makes use of computationally efficient techniques for estimating individual source contributions and zones of influence by simulating DIN assuming that all processes of the nitrogen cycle can be simplified to a single net first-order temperature-dependent decay rate. This approach assigns individual tracers to each point source to allow for source tracking. We made use of the Constituent-oriented Age and Residence Time (CART) approach (Deleersnijder et al., 2001), which simulates a conservative

tracer directly in the model runs, along with age-concentration, age-depth-concentration, and age-temperature-concentration tracers. From these lagrangian tracers, we can compute the age of a parcel of water released from an individual source along with the depth at which this parcel of water has spent its time and the temperature it has experienced since its release. This allows us to include a few important characteristics of denitrification in the model, specifically that denitrification happens just below the sediment-water interface in the anoxic regions of the sediment, i.e. that it happens per unit surface area of the sediment bed, not per unit water volume, and that denitrification happens faster in warmer waters. Therefore, a tracer released in shallower or warmer waters will experience greater losses than a tracer released in deeper or colder waters. We can then test different first-order decay rates incorporating the role of water depth and water temperature and determine the concentration of a decaying tracer after the run has completed.

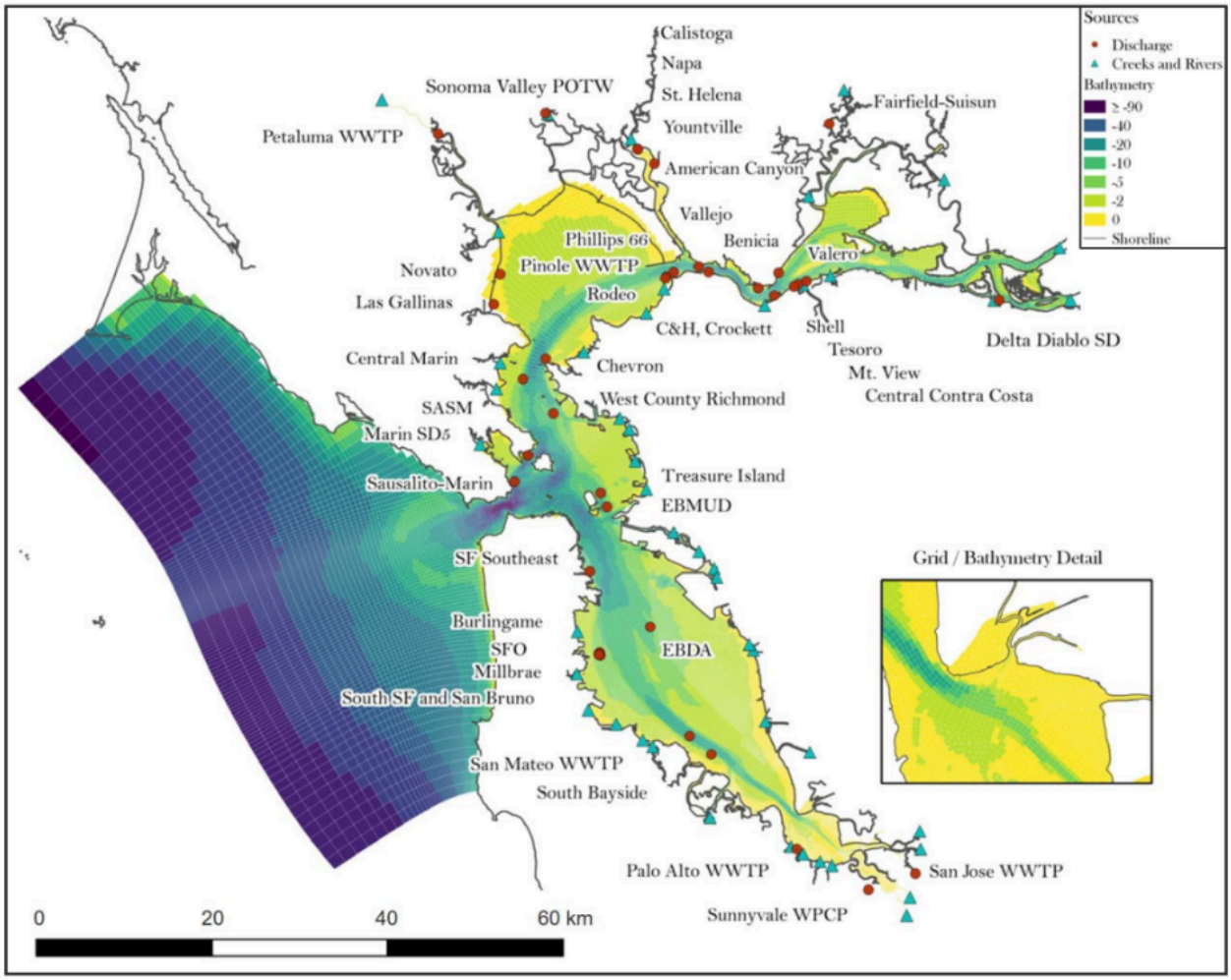


Figure 1 Model domain, grid, bathymetry for the SFB hydrodynamic and biogeochemical models, as described in SFEI 2017,2020,2023

The modeling described in this work was performed using Delwaq, coupled offline to SFEI's full-bay hydrodynamic model (grid and bathymetry shown in Figure 1, SFEI 2017, 2020, 2023). The hydrodynamic model, run using 10 vertical sigma layers in DFM, was initially calibrated for water years 2013 and 2017, and has since been improved to include temperature, calibrated to additional salinity observations, and extended to water years 2013 through 2023. The hydrodynamic model performed comparably well in WY2021 as other years. Delwaq was used purely to track the tracers, not making use of its capacity for biogeochemical transformations.

2.3 Simulations and Postprocessing

Model simulations focused on the dry season of water year 2021 (Oct 1, 2020 to Sep 30, 2021); runs were initiated on Feb 1, 2021, allowed a 3 month spin-up period, and compared with observations during May 1 through Sep 1, 2021. All point source discharges were modeled separately as tracers, with each discharge point releasing the CART tracers described above and a decay tracer. The decay tracer was used for comparison only and assumed a constant decay rate of 0.01 d^{-1}. Tracer concentrations were released at a time-varying rate based on monthly flow and concentration data reported by POTW estimated DIN releases (BACWA/HDR report, 2025). Optional boundary conditions were also included as tracer sources following the DIN inputs used in the 2021 biogeochemical model; specifically as concentrations estimated from timeseries observations within the Sacramento and San Joaquin Rivers, and constant concentration in space and time at the ocean boundary.

The tracer approach applied herein allows for estimating the zone of influence (ZOI) of each individual POTW contributing nitrogen to the Bay, for any period of time between May 1 and Sep 1, 2021. In this report, we focus on model outputs on Aug 1, 2021, showing both the incremental contribution and the relative contribution to DIN from any point source. We also use it as an indicator of system-scale nitrogen loss rates and demonstrate the utility of this tracer-based approach for exploring the potential influence of scenarios for reducing nitrogen loads. Finally, we show the partitioning of the bay into clusters based on tracers from the individual sources using k-means clustering (Pedregosa et al., 2011).

3. RESULTS & DISCUSSION

3.1 System-scale loss rates

To estimate loss rates from this simplified model, we compare the modeled tracer concentration, summed from all sources, to the amount of DIN observed in different measurements collected in 2021. This enables a comparison of the tracer model's simplified first-order decay process with the suite of processes that occur to DIN in the real world. Observations included high-frequency surveys of nitrate collected by trawling a sensor across the South Bay (Killam et al, 2023), profiles of DIN collected approximately monthly at a series of points along the Bay's deep central channel, and moorings that collect nitrate concentration every 15 min with a SUNA nitrate sensor near the Dumbarton Bridge and on the eastern shoals north of San Mateo Bridge. With each set, comparisons between observations and model

outputs indicated that temperature- and depth-dependent decay rates of approximately 0.27 m day-1 at 20 deg C appears like the best fit in South Bay. In the Central Bay, transect observations suggest that a loss rate of 0.05 m day-1 at 20 deg C is most appropriate, and in North Bay and the Delta, a loss rate of 0.15 m day-1 at 20 deg C is likely a reasonable choice. This system-wide variation implies that regions of the Bay may respond differently to the available N on a process level; for example denitrification on the bed may be more effective in the South Bay, and less effective in Central Bay.

3.2 Zones of Influence and Relative Contributions

Maps of reactive-tracer plumes from individual sources show the magnitude and extent of the nitrogen released to the Bay (Figure 2). On Aug 1, 2021, the five largest contributors, CCCSD, EBMUD, EBDA, SF Southeast, and San Jose are each contributing at least 10 µM in the immediate vicinity of their outfalls, and at least 1 µM in the adjacent embayment; these five largest sources of DIN lead to, as expected, the five largest DIN plumes within San Francisco Bay. Distinct spatial patterns to the dispersion of releases are evident: POTWs that release near the western shoal of South Bay, including Millbrae, South SF, and SFO, see their plumes largely retained along that western shore. Meanwhile, POTWs that discharge to other regions of South Bay and Lower South Bay, including further south along the western shoal like San Mateo and SVCW, show plumes with higher concentrations in the channel and along the eastern shoals of South Bay. This behavior reflects the counter clockwise residual circulation observed in the hydrodynamic model (SFEI, 2023; King et al 2026), and the limits on mixing between the western shoals and the broader South Bay.

For each individual source, we also computed the amount of reactive tracer from that source relative to the total amount in San Francisco Bay from all POTWs, refineries, and upstream sources (Figure 3). This yields the relative contribution of each source (as a percent), and enables visualizing and understanding the local importance of each. This analysis reveals that Palo Alto and San Jose are the dominant sources in Lower South Bay; far larger than the other POTW in Lower South Bay, Sunnyvale, and all of the POTWs in South Bay. It shows that SFPUC Southeast, EBMUD, and EBDA are most important in Central Bay, and that contributions from CCCSD matter far more in San Pablo Bay and Suisun Bay than other local or non-local sources.

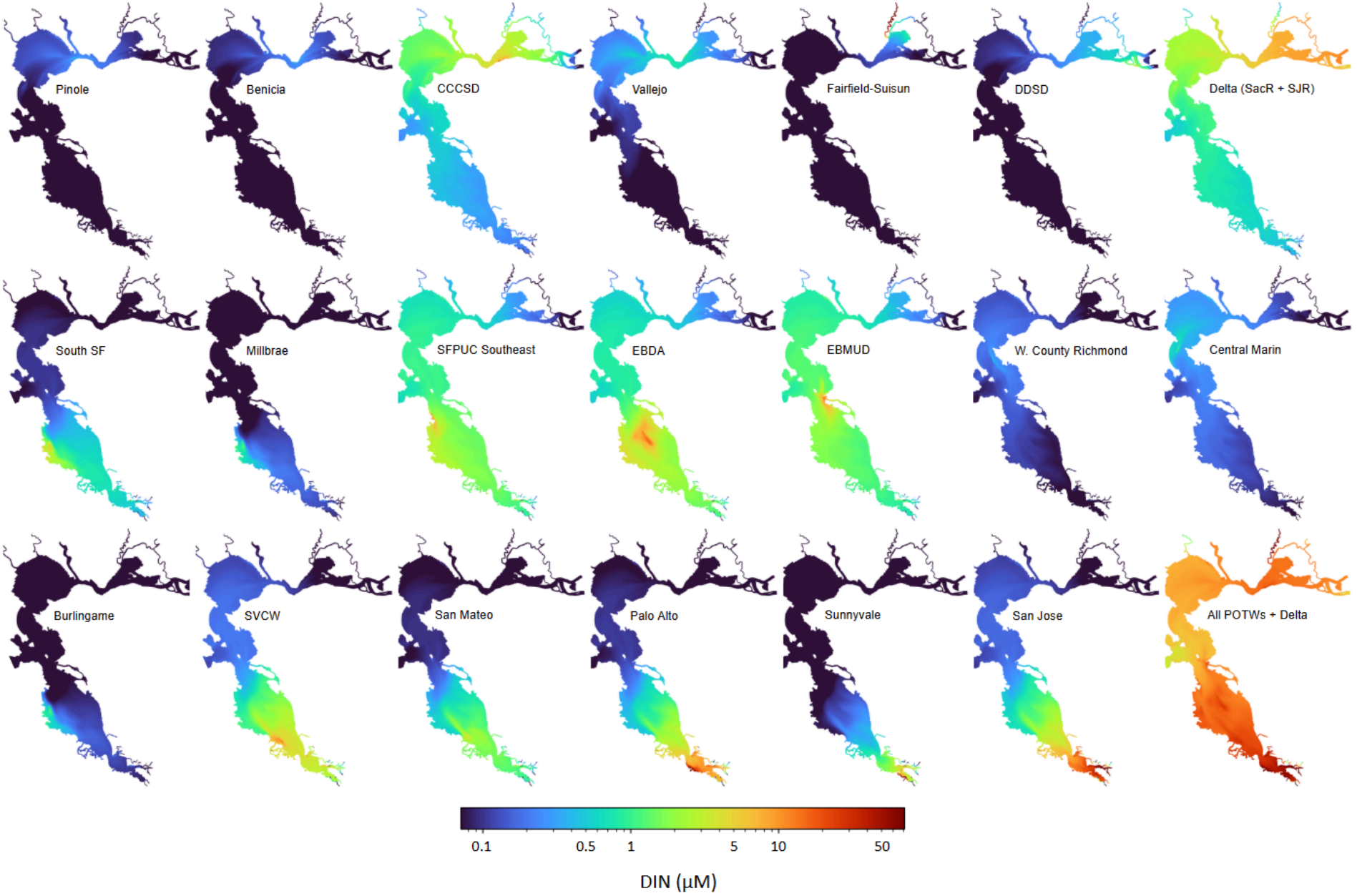


Figure 2 Zones of influence (ZOIs) of 20 sources (POTWs + Delta), presented based on their incremental contributions to DIN concentration (uM). Color represents DIN concentration on a log10-scale ranging from 0.07 to 70 µM. Bottom-right panel: Summed concentrations across all sources, which varied over a factor of ~20 range, from ~5 µM to >100 µM.

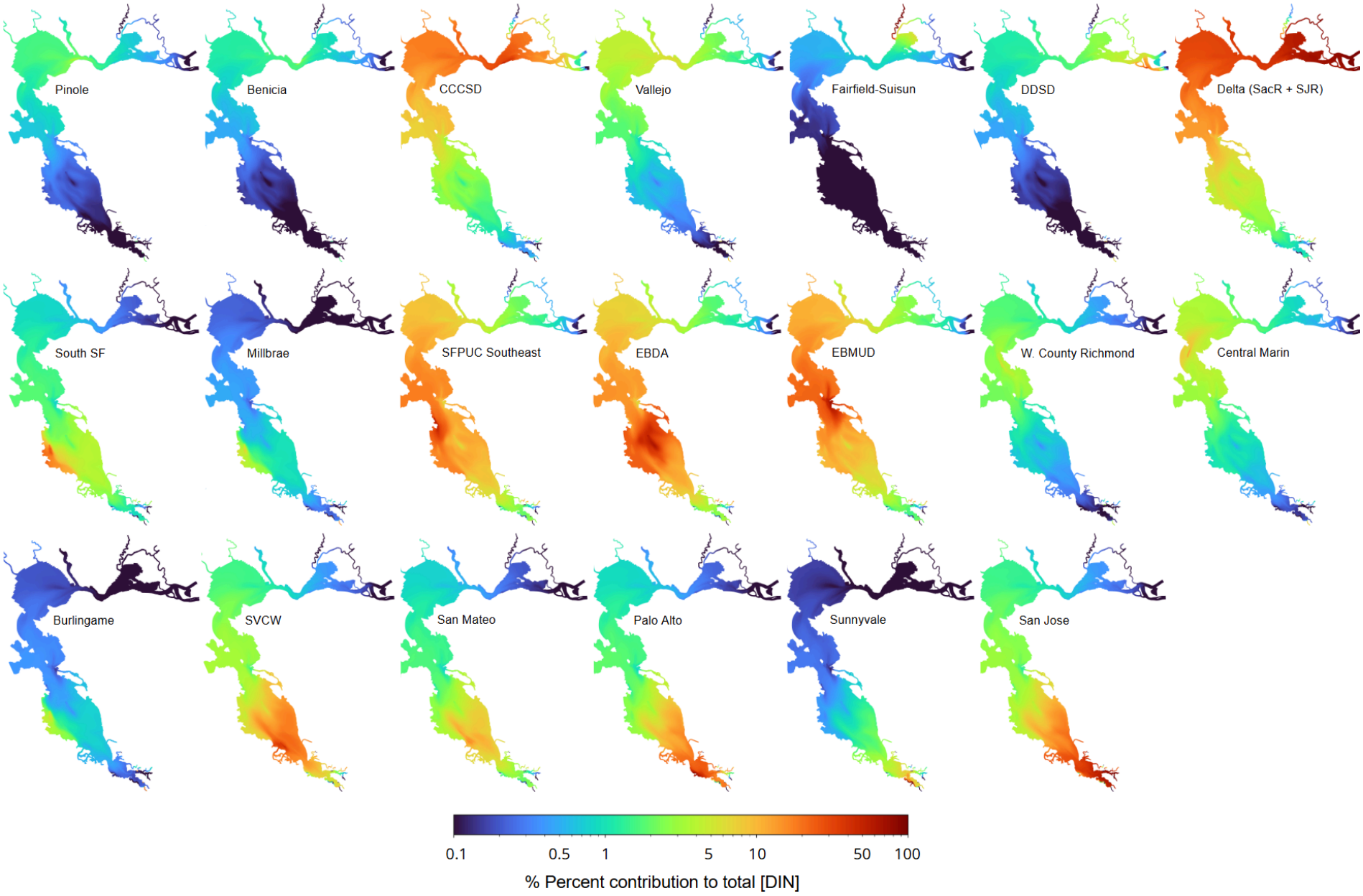


Figure 3 Zones of influence (ZOIs) of 20 sources (POTWs + Delta), presented based on their relative contributions (%) to combined DIN from all point sources + Delta. Color represents %-contribution to combined DIN, log10-scale ranging from 0.1 to 100%.

3.3 DIN Source Signatures

This set of tools also enables the determination of clusters of the bay that respond to tracer input in similar fashions. In k-means clustering, the regions of the bay that are clustered together depend on the number of clusters selected along with specifics of the data analysis including the time period, the decay process, the decay rate, and the averaging method. As an example, Figure 4 presents results for 6 clusters.

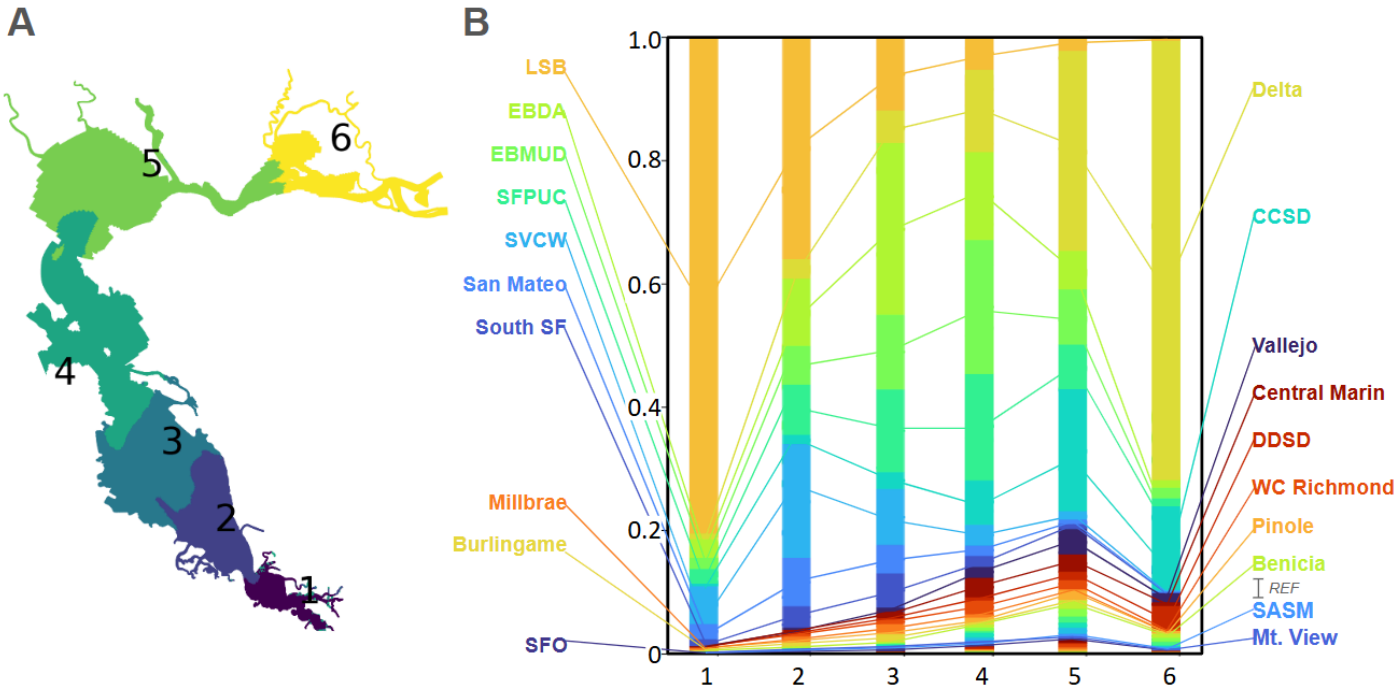


Figure 4 Subdividing SFB based on similarity of DIN source signatures. **A.** Mapview, dividing into 6 subregions based on the degree of similarity of DIN sources contributing to total DIN concentration, following the approach described in the text. **B.** The color distributions within the vertical bars 1 through 6 represent the average DIN source signatures within that numbered region in panel A. Colors indicate individual DIN sources. Within a bar, the height of each stacked color represents the fractional contribution of that source to total DIN concentration within the subregion (each subregion bar sums to 1). *Colored labels corresponding to DIN sources in B*: (*left*) sources contributing primarily to Lower South, South, and Central Bays (or signature regions #1, #2, #3, #4) and (*right*) sources contributing primarily to Suisun, San Pablo, and Central (or signature regions #6, #5, #4). *Vertically*: based on size of maximum fraction-contribution across all regions, largest to smallest. LSB and Delta were the two largest (LSB > Delta); the three smallest depicted contributions were SASM > Mt View > SFO. Labels are shown for 20 of the POTWs; the remaining 17 POTWs were also included in the analysis, and their stacked color bars all fall below lines for SFO-SASM-Mt.View; see text for further discussion. *REF* refers to refinery sources. The four largest refineries group together both by size and region: their stacked color bars fell between Benicia and SASM, contributing ~0.05-0.10 to #5 (San Pablo Bay, western Suisun), and <0.05 to #4 and #6.

There, cluster 1 represents Lower South Bay, with 80% of its contributions coming from the Lower South Bay POTWs of San Jose, Palo Alto, and Sunnyvale. The size of the bar in Figure 4 only depicts the median relative contribution from individual sources: the spatial variation on that relative contribution is shown by the box and whiskers in Figure 5. The same sources are the most important contributors to cluster 2 in the southern half of South Bay, there accounting for median 30% of the DIN, but in 50% of grid cells (25th-75th percentiles), LSB sources account for 27 to 45% of the contributions, and in 80% of grid cells (10th-90th percentiles), LSB sources account for 25 to 50% of the contributions. This shows that the contribution of LSB sources can vary by about a factor of 2 depending on the specific region within cluster 2 that we investigate. Similarly, in cluster 3, in 80% of the cells EBDA contributes between 20 and 40% of the DIN, again varying by a factor of 2 through the region. The spread between the 25th and 75th or 10th and 90th percentiles indicates the spatial variation within a cluster, demonstrating that although these clusters fraction the Bay into distinct units, there is still significant variation within a cluster that should be considered.

Figure 5 also shows the most important contributors to each cluster; the list is nearly identical for cluster 1 and cluster 2, yet LSB POTWs account for less than half of the loads in cluster 2 relative to cluster 1, and SVCW, EBDA, SFPUC, and San Mateo all account for about two or three times their contributions in cluster 2 relative to cluster 1. This shift in the balance of contributing sources due to both hydrodynamic transport and tracer decay is what leads to the distinction between cluster 1 and cluster 2.

In this way, clustering and source signatures can be used to provide qualitative information about which load reductions might be most effective at reducing DIN concentrations within specific regions of the Bay. They can also qualitatively inform the viability of trading between contributors, but they are not intended to dictate trading zones, trading ratios, or which trades are advised.

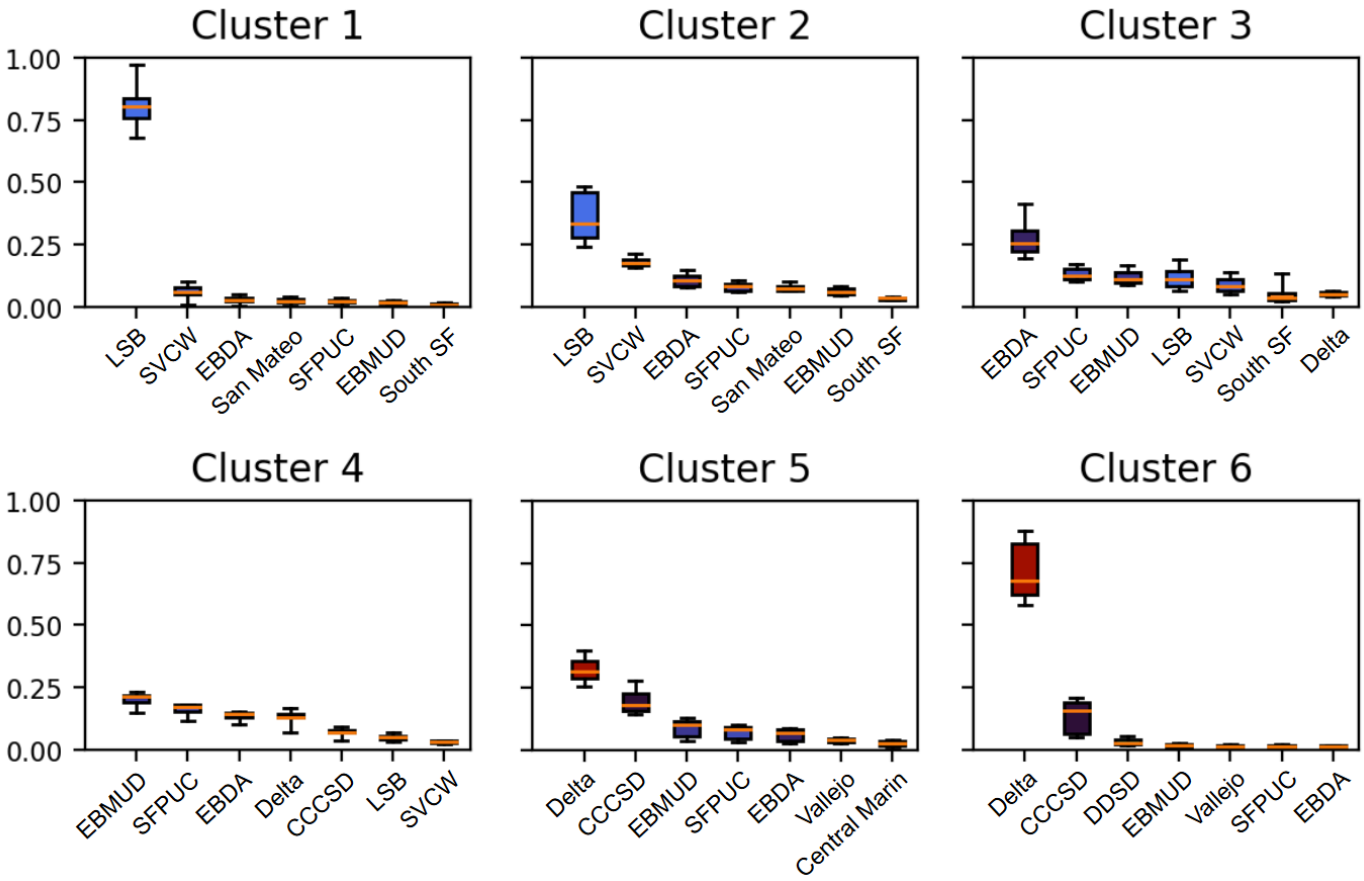


Figure 5 Variability of individual sources' relative contributions within each cluster, represented as follows: *horizontal red line*, median; *upper and lower box edges*: 25% and 75%ile; *error bars*: 10% and 90%ile. For each cluster, the seven largest contributing sources are shown.

3.4 Exploring DIN reduction scenarios

Source apportionment performed in this way enables scenario exploration in a straightforward, simple, and speedy manner; it does not require re-running a model. For example, if loads from the Sacramento and San Joaquin rivers reduced by 50%, while POTW and refinery loads remained at 100%, concentrations within Suisun Bay would reduce by about 5 µM or almost 50% (Figure 6). The impact is reduced in San Pablo Bay, and by Central Bay there is nearly no impact from reducing loads from the Delta.

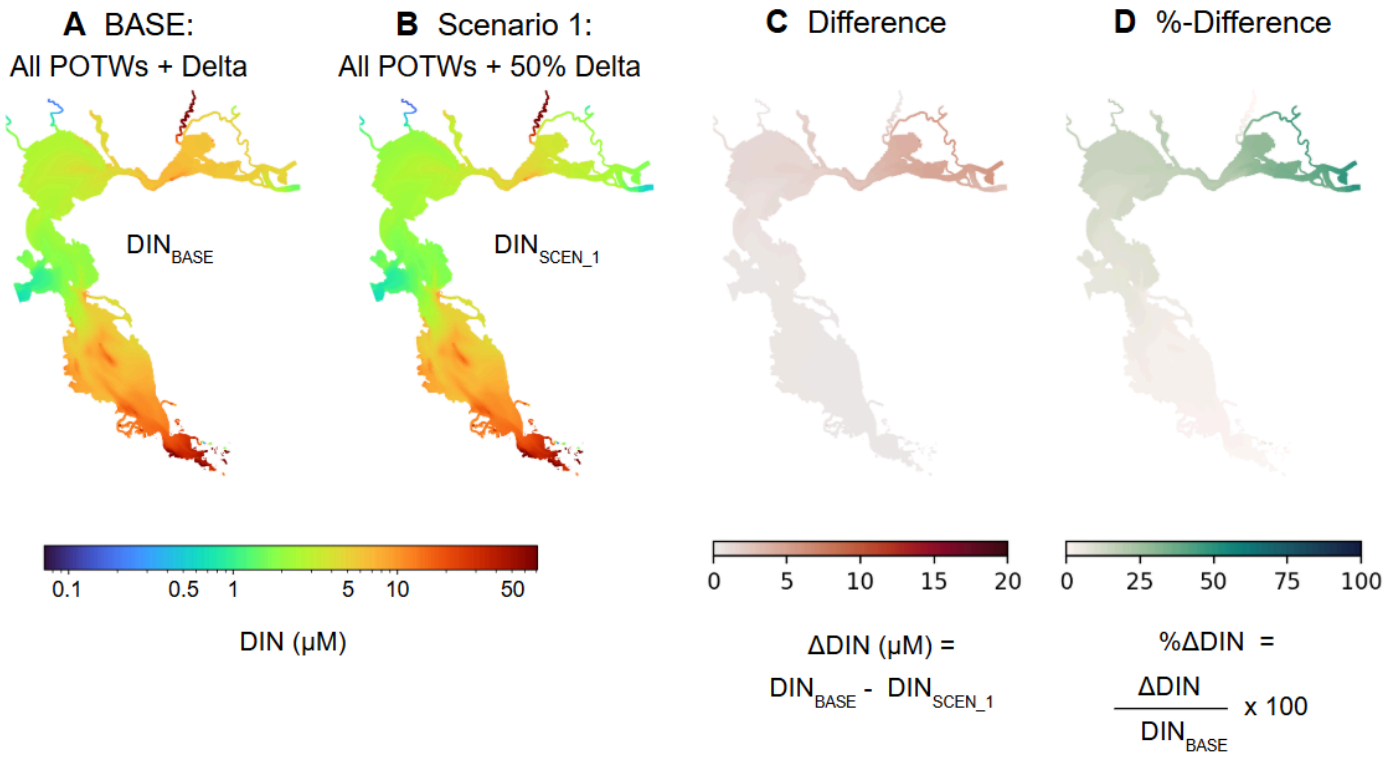


Figure 6 **A** Summed concentration of the reactive-DIN tracer (µM) from all point sources and Delta, on 1 Aug 2021. **B** Same as (A), except with loads from the Delta entering Suisun Bay reduced by 50%. **C** Difference (µM) between (A) and (B). **D** Percent difference between (A) and (B), relative to (A).

With this set of tools, additional scenarios can be explored, including, for example:

a) Temporal differences, either early in the run to reveal when the model approaches the status of "fully spun up", or later in the run to show the impacts of differences in tracer releases, tidal processes, temperature-dependent decay, or freshwater inflow including from different water years;

b) Site-specific differences, on a source-by-source basis;

c) Process differences, including different Q10 or reference temperature values;

d) Management scenarios, including applying uniform load reductions, POTW-specific load reductions, trading between POTWs, or even load increases.

SUMMARY

4.1 Conclusions

By performing source tracking with lagrangian tracers that allow a range of decay rates to be applied after model run completion, we have developed a tool that is powerful, fast, and flexible that can be used for BGC model ground-truthing, system-scale N loss rate estimation, attribution of within-Bay nitrogen to specific sources, quantification of the possible impacts of future N reduction scenarios, and determination of clusters within the bay.

4.2 Next Steps

The work detailed in this document is the first step of three planned. The second piece will include area tracers, such as a lower south bay tracer, separate south bay shoals and channel tracers, and an ocean tracer, to allow for spatially-varying loss rates, and will focus on a period with extensive water quality data available to estimate these loss rates at many points in time. The third piece will incorporate temporally- and spatially-varying loss rates directly from the calibrated BGC model and will use these rates to drive loss within this tracer model. Both step two and step three will be valuable for upcoming work, including on empirically derived N loss and potential trading efforts between dischargers within SF Bay.

REFERENCES

California Regional Water Quality Control Board San Francisco Bay Region. Order R2-2024-0013. NPDES Permit CA0038873. https://www.waterboards.ca.gov/sanfranciscobay/board_decisions/adopted_orders/2024/R2-2024-0013.pdf

Cloern, J. E., Hieb, K. A., Jacobson, T., Sansó, B., Di Lorenzo, E., Stacey, M. T., Largier, J. L., Meiring, W., Peterson, W. T., Powell, T. M., Winder, M., & Jassby, A. D. (2010). Biological communities in San Francisco Bay track large-scale c. forcing over the North Pacific. *Geophysical Research Letters*, *37*(21). https://doi.org/10.1029/2010GL044774

Cloern, J. E., Jassby, A. D., Thompson, J. K., & Hieb, K. A. (2007). A cold phase of the East Pacific triggers new phytoplankton blooms in San Francisco Bay. *Proceedings of the National Academy of Sciences of the United States of America*, *104*(47), 18561–18565. https://doi.org/10.1073/pnas.0706151104

Cloern, J. E., Schraga, T. S., Nejad, E., & Martin, C. (2020). Nutrient Status of San Francisco Bay and Its Management Implications. *Estuaries and Coasts*, *43*(6), 1299–1317. https://doi.org/10.1007/s12237-020-00737-w

Deleersnijder, E., Campin, J.-M., & Delhez, E. J. M. (2001). The concept of age in marine modelling I. Theory and preliminary model results. *Journal of Marine Systems*, *28*, 229–267.

Killam D, Chelsky A, Art K, Roberts D, Senn DB, Bergamaschi B, et al. Characterizing Lateral Variability in South Bay Water Quality to Inform Monitoring Program Design. Richmond, CA: San Francisco Estuary Institute; 2023 Apr. Report no.: 1119

King, A. T., Holleman, R., Nuss, E., Moscoso J. E., Karimpour, F., Mugunthan, P., Allen, R., and Senn, D. B. (2026). *The SFEI San Francisco Bay Hydrodynamic Model: Performance for Water Level, Velocity, Salinity, and Temperature Over Eleven Years*. SFEI Contribution No. 1283. San Francisco Estuary Institute, Richmond, CA.

Nardelli, S. C., Bouma-Gregson, K., Senn, D. B., Killam, D., Chelsky, A., Nejad, E., Richardson, E. T., Otten, T. G., Kraus, T. E. C., & Bergamaschi, B. A. (2026). Assessing Environmental Drivers and Protist Community Dynamics that Shaped the Historic August 2022 Heterosigma akashiwo Bloom in San Francisco Bay, California. *Estuaries and Coasts*, *49*(2), 39. https://doi.org/10.1007/s12237-025-01629-7

Novick, E., Holleman, R., Jabusch, T., Sun, J., Trowbridge, P., Senn, D., Guerin, M., Kendall, C., Young, M., & Peek, S. (2015). *Characterizing and quantifying nutrient sources, sinks and transformations in the Delta: Synthesis, modeling, and recommendations* (No. 785). San Francisco Estuary Institute.

Peacock, M. B., Gibble, C. M., Senn, D. B., Cloern, J. E., & Kudela, R. M. (2018). Blurred lines: Multiple freshwater and marine algal toxins at the land-sea interface of San Francisco Bay, California. *Harmful Algae*, *73*, 138–147. https://doi.org/10.1016/j.hal.2018.02.005

Pedregosa, F., Pedregosa, F., Varoquaux, G., Varoquaux, G., Org, N., Gramfort, A., Gramfort, A., Michel, V., Michel, V., Fr, L., Thirion, B., Thirion, B., Grisel, O., Grisel, O., Blondel, M., Prettenhofer, P., Prettenhofer, P., Weiss, R., Dubourg, V., … Cournapeau, D. (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research*, *12*, 2825–2830.

San Francisco Bay Nutrient Management Strategy. (2012). San Francisco Bay Regional Water Quality Control Board.

Science Plan: 2025-2030 San Francisco Bay Nutrient Management Strategy (No. 1284). (2025). San Francisco Estuary Institute. https://www.sfei.org/sites/default/files/biblio/2026-01/NMS_SciencePlan_2025-2030_v2_FINAL.pdf

SFEI (2014a). *Scientific Foundation for the San Francisco Bay Nutrient Management Strategy* (No. 979). San Francisco Estuary Institute.

SFEI (2014b). *External Nutrient Loads to San Francisco Bay* (No. 704). San Francisco Estuary Institute.

SFEI (2019a). Science Plan Update: 2020-2024. March 2019.

SFEI (2019b). San Francisco Bay Nutrient Management Strategy modeling work plan (2019-2024).

SFEI (2025). Science Plan: 2025-2030.

Sutula, M., Kudela, R., Hagy, J. D., Harding, L. W., Senn, D., Cloern, J. E., Bricker, S., Berg, G. M., & Beck, M. (2017). Novel analyses of long-term data provide a scientific basis for chlorophyll-a thresholds in San Francisco Bay. *Estuarine, Coastal and Shelf Science*, *197*, 107–118. https://doi.org/10.1016/j.ecss.2017.07.009