SAN FRANCISCO BAY NUTRIENT MANAGEMENT STRATEGY

Development of Semi-Empirical Light Extinction Estimates for Biogeochemical Modeling Applications in San Francisco Bay

Project Team: R Holleman¹, A King², F Karimpour², P Mugunthan^{3,2}, D Roberts², D Senn²

¹RMA, ²SFEI, ³Four Peaks

February 2024



SFEI Contribution #1177

Acknowledgements

This work was supported with funding from the San Francisco Bay Nutrient Management Strategy, and the San Francisco Bay Regional Monitoring Program. Thanks to Craig Jones (Integral) and Oliver Fringer (Stanford) for insightful and practical input at key junctures, and Taylor Winchell and Emma Nuss for their contributions to prior versions.

1. INTRODUCTION

In aquatic ecosystems, the light extinction coefficient (K_D , m⁻¹) determines the rate with which light, or photosynthetically-active radiation, decreases as a function of depth in the water column. In systems with high suspended sediment concentrations (SSC) like San Francisco Bay, SSC can be the primary factor determining light attenuation, with K_D positively correlated with SSC, and greater SSC and larger K_D values translating to shallower light penetration. Since phytoplankton growth rates are strongly influenced by light levels, K_D can play a dominant role regulating phytoplankton growth rates, overall system productivity, nutrient cycling, dissolved oxygen concentrations, and other water quality responses. Space-time varying estimates of K_D are therefore an important input or forcing for biogeochemical models.

Early SFB Nutrient Management Strategy (NMS) modeling results indicated that K_D is among the most important variables influencing nutrient cycling and phytoplankton growth, and identified space-time varying K_D estimates as a priority data gap (e.g., SFEI 2020). Sensitivity analyses found that temporal variations in K_D over time-scales of days were relevant for predicting phytoplankton production. While over the longer-term the plan for generating $K_D(x,y,t)$ includes the development and application of a mechanistic sediment transport model to predict SSC(x,y,t), reliable K_D estimates are needed for current biogeochemical modeling work. In the meantime, we have therefore been developing and iteratively-refining a semi-empirical, statistically-based approach for estimating $K_D(x,y,t)$. that brings together high-frequency turbidity data measured at stations along the Bay's deep channel; physical forcing data (wind speed, wind direction); output from hydrodynamic models (tidal velocity); and measured K_D data from biweekly to monthly cruises. In the most recent iteration, and in upcoming next steps, remote-sensed estimates of turbidity will be increasingly used, in particular to inform K_D estimates in data-poor shallow regions of South, Central, San Pablo, and Suisun Bays.

This technical memo provides an overview of the initial approaches for estimating K_D (Section 2), and then documents the most recent set of refinements carried out over the last year (Section 3).

2. INITIAL APPROACHES USED FOR ESTIMATING KD

V0 (<u>link</u>), V1 (<u>link</u>), V2:

- High-frequency SSC measurements at 15 USGS mooring sites across the Bay served as the initial basis for K_D estimates. Most existing data were from stations along the Bay's deep channel, measured at 15 min intervals. To address data gaps at sites (some spanning multiple years), statistical approaches (between-station correlations) were used to fill gaps using nearby site data.
- $\bullet\,$ SSC time series at the 15 mooring sites were converted to $K_{\scriptscriptstyle D}\,$ time series using

site-specific log-linear SSC-K_D relationships derived from the Polaris/Peterson cruise dataset, which includes both K_D and SSC at 1 m depth. The bay was divided into a set of polygons, one for each of the 15 USGS stations, and Kd was assumed uniform across each polygon, prior to a final smoothing step

- Building on V0, V1 took an additional step of converting SSC to K_D , multiplying by a time/space-varying coefficient that forces the predicted value through the K_D measurements made during USGS cruises.
- Building on V1, V2 replaced the linear regression model with a generalized additive model (GAM) with splines/curves for multiple independent variables, e.g., wind, freshwater inflows, tidal velocity, elevation, and seasonal average SSC. While the GAM was trained using site-specific SSC data, a major limitation of the V2 approach was that it did not use site specific independent variables (i.e., they varied in time but not space).

V3 workflow overview, with details of approach and progression presented on p 3-85

- Building on V2, V3 revised inputs to the GAM to reduce error in the infilled K_D time series. Where the GAM in V2 used inputs with no spatial variability, V3 introduces:
 - $\circ~\mbox{local}$ information for tidal velocity and winds
 - a spring-neap term, and
 - $\circ\,$ a background model for long term spatiotemporal trends in Bay-wide SSC.
- The V3 GAM was also tested more broadly for predictive skill in order to objectively identify which terms should be included or omitted. GAM terms were also constrained in some cases to reflect physically realistic relationships and prevent overfitting.
- Data from recently-installed SFEI shoal mooring sites (deployed ca. 2020) were used to improve shoal estimates, and new polygons were created based on spatial SSC correlations observed in satellite data
- (early-stage V3 work captured <u>here</u>)

2. WORKFLOW and RESULTS for V3 $\ensuremath{\text{K}_{\text{D}}}$ ESTIMATES

This section is based on project workflow and progress documentation, including working notes, interim results, refinements, and final V3 estimates..

Same GAM, different forcing

Of many combinations, best was to use updated tide velocity, add a tide hour and day of year variable, averaged wind over 4h. Best to ignore stormwater. $R^2=0.37$

Still not a great model. Following <u>this chart</u>, tried Support Vector Regression with RBF and linear kernels, with strictly worse performance than LinearGAM.

Antecedent wind speed is optimal at 30h, gets RMSE test down to 29.15. A spring-neap indicator further down to 29.01.

San_Mateo_Bridge RMSE train: 26.90 RMSE test: 29.42 std.dev: 34.54 params: {'n_splines': 8}



Summary of Present Method



polygons, smoothed

Quantifying Skill, Uncertainty

Do changes lead to better or worse results?

When are the errors "small enough"?

Approaches:

- a. Compare empirical model to observations
- b. Use a distinct data source for validation (CDFW Secchi)
- c. Leave one out validation
- d. Separate calibration/validation years
- e. Tidally-averaged maybe most relevant

Two examples of (a)...



Error Estimates for Gap-filling SSC

RMSE for GAM predicted SSC vs. observed SSC. Bias is 0 by construction



Turbid, landward sites are bad Central Bay and Delta-dominated sites are good



Error distribution for gap-filling of SSC

Red lines give the inter-quartile range in a moving window.

Overshoot lows Undershoot highs

Variance typically a bit low, missing the high outliers.





Alcatraz_Island

Error after bending

Again, bias is negligible since both observed and gap-filled SSC are bent to the same USGS cruise data.

Some stations not plotted because station period ends before 2010.

Same error trend as SSC







Error after bending



Error after bending

Lots of scatter in Lower South Bay

Overall turbid, so $4/K_D$ errors sometimes not so large.



Benicia Bridge

Error after bending

Delta-influenced stations are well-behaved.



Mallard_Island



Error Estimates



Per expert panel, estimate uncertainty in the channel-based $\rm K_{\rm d}$ values in the existing approach.

- Tidally averaged
- Relative to what sources of error?
 - esp. with bending. Could do some leave-one-out estimates against the cruise data.
 - with the bending, we force the station to follow the 30-day LP of the cruise data.
- Option A: Point comparison between final Kd field and USGS cruise Kd.
- Option B: Propagate error from each step Too hard to characterize all of these errors.
 - Subject to bandpass (36h–30d): care about tidally averaged errors, and monthly error removed by assimilation
 - Time-dependent: reference station or adjusted, gap-filled or observed
 - $ssc_{canon} \sim ssc_{true} + \epsilon_{canon}$: error when using adjusted station
 - $ssc_{qab} \sim ssc_{true} + \epsilon_{qab}$: error in SSC model.
 - \circ $\epsilon_{s_{2K}}$ error associated with conversion of SSC to K_d
- Option C: Repeat existing error estimates for gap-filling, but apply tidal lowpass.

Tidally averaged error in SSC gap-filling

Similar to non-averaged results.

Bias≈0

60 hour Hanning window low-pass

Less noisy, tighter IQ range but similar slope as tidal error.





Tidally averaged error in 4/K_D, post-assimilation

Delta-influenced stations perform well.



4/K_d obs

Tidally averaged error in $4/K_{D}$, post-assimilation

Corte Madera is a wildcard.

Richmond Bridge reasonably good.







Tidally averaged error in $4/K_{D}$, post-assimilation

Alcatraz, given the large photic depth on average, has good RMSE at 0.76m

San Mateo Bridge still pretty good, but substantial scatter at larger photic depths.



San_Mateo_Bridge



Tidally averaged error in $4/K_D$, post-assimilation

Scatters are broader, though in part because more points are concentrated on the low end of the axis.

Dumbarton is perhaps the poorest performer (ignoring Corte Madera).

Alviso is not great, though the RMSE is pretty small.





Error Post-Extrapolation

For this set of comparisons the full empirical method is applied, extrapolated and smoothed on the DFM grid, and then compared to USGS cruise data.

No tidal averaging, averaging between station, etc. is performed. That said, it's a comparison of "bent" data to the source of the bending, so we'd expect the agreement to be pretty good.





14 **USGS Station 16** Observed mean: 4.28m 12 Predicted mean: 3.60m RMSE: 1.08m Obs. std: 2.10m 10 Pred. std: 1.61m R²: 0.865 4/K_D (m) 8 6 4 2 . 0

2010 2011 2012 2013 2014 2015 2016 2017 2018

USGS Station 15

Observed mean: 3.47m Predicted mean: 3.27m RMSE: 0.85m Obs. std: 1.75m Pred. std: 1.50m R²: 0.780

12



USGS Station 23

Observed mean: 4.13m Predicted mean: 4.82m RMSE: 1.58m Obs. std: 1.94m Pred. std: 1.53m R²: 0.470

Observed mean: 3.32m Predicted mean: 2.96m RMSE: 1.00m Obs. std: 1.69m Pred. std: 1.37m R²: 0.691





USGS Station 30

Observed mean: 2.70m Predicted mean: 1.95m RMSE: 1.04m Obs. std: 1.15m Pred. std: 0.81m R^2 : 0.616



USGS Station 34

Observed mean: 1.77m Predicted mean: 1.78m RMSE: 0.34m Obs. std: 0.80m Pred. std: 0.69m R²: 0.822

USGS Station 32 Observed mean: 2.26m Predicted mean: 1.91m RMSE: 0.52m Obs. std: 0.92m Pred. std: 0.80m R²: 0.822



USGS Station 36

 $\begin{array}{l} Observed mean: 1.67m\\ Predicted mean: 1.59m\\ RMSE: 0.40m\\ Obs. std: 0.76m\\ Pred. std: 0.62m\\ R^2: 0.731 \end{array}$

Post-Extrapolation Error Analysis

Additional station plots:

https://drive.google.com/drive/folders/1_2SKAybVVVdTKIFSwMaevvbq2kfyWjLT? usp=sharing

Uncertainty in SSC⇒K_D Fits

Summary: Scale std-err of about 20%

Coefficient range 0.18 (Benicia) 0.33 (Dumbarton)

Exponent range 0.74 (Benicia) 0.48 (Alcatraz)

Fitting only when 4.5/Kd>0.5m had little effect



Uncertainty in SSC \Rightarrow K_D Fits



Uncertainty in SSC \Rightarrow K_D Fits



Uncertainty in SSC \Rightarrow K_D Fits

Conclusions:

Uncertainty surprisingly consistent at ±20%

Coefficient varies by factor of 2

Exponent centered around ²/₃

Limiting to samples with $4.5/K_{D} > 0.5$ makes minimal difference, up to ~10%



Including Depth in SSC \Rightarrow K_D

- A. Station-specific SSC_{surf}~SSC_{z-sensor} or K_D~ssc_{z-sensor}
 - a. okay if the sensor is near the station
 - b. does not account for time-varying mixing
 - c. could test by calculating magnitude of the assimilation/bending
- B. Look at USGS profiles, estimate Rouse parameter (steady or function of u²)
 - a. Rouse parameter can then be used to adjust sensor data

Rouse numbers

Fit a Rouse profile to each cast. Colors are reference concentration, 1 mab.

Profiles generally indicate wash load. In South Bay, SPB, Carquinez, nearing suspended load for high concentration. Suggests these areas directly experience strong resuspension.

Delta/Suisun and Central Bay maybe affected more by advection of wash load.

Implies that without further correction, high predicted concentrations will have an overly large effect on K_D . I.e. near-surface SSC increases slower than near-bed SSC in SFB, SPB, and CS.

Do we know sensor elevations?



Refining Empirical Model

Local tides – harmonics extracted.

Local wind

Local stormwater influence (opt. with turb)

Current bed stress

Wave bed stress

Lagged variables

Local Tidal Inputs

Potential sources:

- harmonics from DFM output best aligned with future usage.
- harmonics from SUNTANS 2D model
- timeseries from SUNTANS 2D model

Use these runs:

/hpcvol2/open_bay/Hydro_model/Full_res/WY2013/wy2013c/DFM_OUTPUT_wy2013c /hpcvol2/open_bay/Hydro_model/Full_res/WY2014-WY2016/wy2014-wy2016/runs/wy2014-wy2016/DFM_OUTPUT_w y2014-wy2016/

Generate netcdf with full NOAA harmonics for each cell.

Tidal Harmonics

37 components plus DC offset

<u>Notebook</u>

Fit stage, east velocity and north velocity.

Intertidal areas have nan stage harmonics.

Currently fit to WY2013c run. Model is 20 minutes ahead of NOAA Redwood City gauge (confirmed from harmonics and in hydro report).



Verifying Harmonics

Model harmonics are 20 minutes early, with some low frequency offset.





Local Wind

Will need to have a separate preprocessing step to extract wind from Allie's dataset at the station locations for the full time of the wind field.

For the immediate updates, not including shoal stations, need decent coverage 2009-10-01 to 2018-10-01. Existing, interpolated winds on google drive are 2013-2019. What about on HPC? Same. CSV/NC for stations are all set 2000-2019.

Use those directly, and mimic similar NN interpolation.

How does this compare with Hayward wind originally used? Not that close. Original uses an input file <u>D:\My Drive\General</u> Data\SFEI Wind 2000-2019.p

Ostensibly that pulls from the same data that I'm pulling from, Allie's CSV and netcdf files. But the data are not the same.



Local Stormwater

Hold off, see how things progress.
Bed stress

Check on Joe's paper, use tidal currents and stage to come up with a bed stress.

Lagged variables

Add some code in the fitting to generate arbitrary lag/exponential decay input data.

Testing with San Mateo Bridge

Large gap, and data changed character (sensor elevation?) between the two chunks.

Original fit: RMSE does not change much with n_splines.



RMSE does not change very much with drastically simpler fit. RMSE is not much better than stddev. of the data.

SMB Fits



Interactions

Visual inspection suggests spring-neap interacts with tidal hour (springs are more turbid, but we only see that water at certain phase of the tide which may not have high instantaneous velocity). R^2 =0.41.

As convincing as it is, the interaction term never actually improves test dataset RMSE.





"Explained deviance" reported by pygam, just from training data.

How well does this extend to other sites?

Compare the original formula and several contenders across all sites. RMSE and R² are for held-out test data (last 20% of valid samples).

New terms generally help a little, with substantial improvements at Alviso and Dumbarton.

However performance at Dumbarton is still bad and particularly important.

RMSE for test data, normalized by stddev of test data. Predicting the mean scores 1.0

RMSE for test data, unnormalized.

30-hour antecedent wind

Local tides, spring-neap, tide-hour, doy

Add stormwater back in

Original

Drop trend from Polaris/Peterson



Dumbarton



Starting point is that it trains at $R^2=0.36$, but tests at $R^2=0.07$.

In the test data there are some USGS cruises that put very high SSC near Dumbarton, yet the time series does not show any similar signal. To some extent this is just bad luck with the test period.

Dropping USGS low-frequency helps.

Antecedent Delta flow looks promising from time series, but backwards looking boxcar does little to improve results, likewise envelope follower.

Step back

The local inputs will probably be more of an improvement for other sites. For SMB, the tide data is already local, and local winds made little difference. A lot of effort to drive down the RMSE from 30.52 to 28.98.

Much more bang for the buck to some approximation to photic depth

Use approximate transform: $K_D = 0.25 * ssc^{2/3}$, and fit to $z_{photic} = 4.5/K_D$

No depth limiting: since K_D is used across large polygons, there's no single "correct" depth to use. Also easier...

Fitting to SSC but evaluating errors with z_{photic} is expectedly bad.

Small SSC error can be large 4.5/Kd error

Not really a fair comparison, but an indication of the BGC-relevant error.

Dumbarton and Richmond actually get worse.

RMSE in z_{photic} (m)

Fit SSC



site	rmse_test	rmse_test
Alcatraz_Island	1.372620	1.344909
Alviso_Slough	0.443100	0.511234
Benicia_Bridge	1.795077	0.582242
Carquinez_Bridge	0.665187	0.479295
Channel_Marker_01	7.628146	0.769297
Channel_Marker_09	1.320250	0.947352
Channel_Marker_17	0.554990	0.390104
Corte_Madera_Creek	0.883868	0.843297
Dumbarton_Bridge	0.542572	0.649772
Mallard_Island	0.386126	0.342378
Mare_Island_Causeway	13.865844	0.451553
Point_San_Pablo	1.058503	0.782002
Richmond_Bridge	0.606274	0.670627
San_Mateo_Bridge	0.701240	0.563625

Fit to z_{photic}

The good news: errors are generally less than a meter.

The bad news: half of the sites are no better than predicting the mean.



Fetch, Waves

Test at Channel Marker 9: expect wave influence.

Does the GAM figure out fetch on its own? ish

Highest wind contribution is wind to the N, NW.

Computing fetch will help if/when predicting new locations.







Fetch Calculation

Extract bed elevation and fetch as a function of angle.



Fetch-limited waves

Qualitatively seems about right, but no comparison to observations.

Could pursue comparison to observations, but not currently a priority.



GAM with wave bed stress

params:

Wave stress comes out with a reasonable smooth, but is consistently worse than a te(u wind, v wind) term (N.B. u×v has more DoF)

Some SFE field work suggests need wave stress followed by current stress, but a te(wave ante, current) term does not improve error.



What's missing at Channel Marker 9?

Underpredict very high peaks early on (2003/01)

Overpredict by a lot later on (2004/08)

Change in sensor? Adding s(year) and related te() terms helps, but extrapolation becomes questionable.











Just year, all sites. It's something...



Year and along separately are convincing.

te() doesn't help.



Allowing seasonality





Sites ordered by along-estuary distance, but fit as a factor term. Very similar to fitting as spline, though the factor cannot be used to extrapolate to additional stations.

Smoothing penalties are minimal for the site factor – pattern is effectively unsmoothed.

Slight improvement with a s(along,by=wind_spd_ante) term.

Integrating Global Fit and Station Fit

std.dev: 0.35

params: {}

Use global fit to provide a baseline, help extrapolate from one period to another.

Station fits handle variability at tidal time scales, wind events, etc.

Training omitted Point San Pablo, Richmond Bridge, San Mateo Bridge

RMSE test is good when training period brackets test data.



Taming GAM Extrapolation

Fitting to time is great, but extrapolating time outside training interval is bad.

Training omits last 20% of each site.



Next: Use this model to add another predictor for station models. Test constraint on USGS trend term



GAM Shootout

original model

tuned to maximize skill on last 20%

- s(year) for each station in addition to global trend
- s(year,128) instead of global trend

mean of the training set

Each model is tested against 20% holdout, results aggregate over which 20% is held out. Most tuning held out only the last 20%, but the **model** that emerged from that is still the best model in this test.



GAM Shootout

intercept



te(tide_hour,wl_rms) + te(glbl_log10_ssc_mgL, tide_hour) + s(year, constraints=flatends) + te(wind_u_ante,wind_v_ante) + s(delta,constraints='monotonic_inc') + te(storm,wl) + s(tdvel)

te(tide_hour,wl_rms) + s(year, n_splines=128, constraints=flatends) + te(wind_u_ante,wind_v_ante) + s(delta,constraints='monotonic_inc') + te(storm,wl) + s(tdvel)



= te(tide_hour,wl_rms) + te(glbl_log10_ssc_mgL, tide_hour) + te(wind_u_ante,wind_v_ante) + s(delta,constraints='monotonic_inc') + te(storm,wl) + s(tdvel)

San_Mateo_Bridge RMSE train: 0.22 RMSE test: 0.27 std.dev: 0.28 pseudo R²: 0.329 AIC: 7.057e+05 params: {}



Peak near low water and high water (!), stronger in spring tides. Follow global trend, Sensitive to wind slightly more so out of the SE around high/low tide. Delta not meaningful here, aside from very high flows Inverse relationship at low tide. Likely overfitting.

Resuspension (with a bit of phase lag?)

Tidally Averaged

60h Hanning window.

0.4

0.1

0.0

Alcatraz Island

s(wind) + s(tdvel) + s(wl) + s(storm) + s(delta) + s(usgs_lf)

Alviso_Slough

Benicia_Bridge

Carquinez_Bridge

5.0 tavg_rmse

Same model prevails. Typ. error 0.15 – 0.20.



te(tide_hour,wl_rms) + te(glbl_log10_ssc_mgL, tide_hour) + te(wind_u_ante,wind_v_ante) + s(delta,constraints='monotonic_inc') + te(storm,wi) + s(tdvel)

Channel Marker 01

60

Channel Marker

te(tide_hour,wl_rms) + te(glbl_log10_ssc_mgL, tide_hour) + s(year, constraints=flatends) + te(wind_u_ante,wind_v_ante) + s(delta,constraints='monotonic_inc') + te(storm,wl) + s(tdvel) te(tide hour,wl rms) + s(year, n splines=128, constraints=flatends) + te(wind_u_ante,wind_v_ante) + s(delta,constraints='monotonic_inc') + te(storm,wl) + s(tdvel)

Channel_Marker_17

intercept

Comparison of old/new GAM



Next steps

- 1. Move on:
 - a. SSC- K_D relationships
 - b. Shoal stations
 - c. Spatial extrapolation

Shoal Stations

Very spiky, but sometimes the spikes are real. Probably have to assume that anything lasting more than a few samples is real?





12-03 09 12-03 12 12-03 15 12-03 18 12-03 21 12-04 00 12-04 03 12-04 06 12-04 09 12-04 12

Correlation among stations

Confirms the need for shoal stations.

Supports having the data cleaning just among the shoal stations.



Outline of Approach - Step 1, gather inputs

Start with similar GAM-based approach. Will need to assemble these inputs for 2020-08 to 2022-05:

- **tide_hour** = fn(u_tide_local)=fn(harmonics). no problem.
- **wl_rms** = fn(wl) = observed stage at Redwood City. **Done**.
- global model does not extend to 2020. for starters drop this term.
- **local wind** from Allie's data. csvs on google drive through end of 2021. Given the location, might be enough just to use OAK or HWD airport winds.
- delta DayFlow. Easily downloadable through 9/2021. Done
- storm Alameda flow available from NWIS Done
- tdvel harmonics from SMB. Can use harmonics. Done

These inputs may help guide the data cleaning, so get them in place first.

[Step 1b: Extend SSC time series for other stations]

With enough stations, the global trend model could also be extended.

Eventually more recent periods will be useful; unsure of plans for modeling 2020, 2021, etc.

Currently not planning to do this. If/when needed, tackled by SFEI staff?

Outline of Approach - Step 2 data cleaning

- Spiky signals are sometimes real (wind event?), sometimes noise (air bubble or a leaf?), and sometimes likely to be very local (bridge pier scour at SMB, boat wake at SLM, ... ?)
- Better to use a smaller training set of more trustworthy data
- The shoal stations independently have 45k, 48k and 52k samples (this does not include pilot data from SHL).
- There are 34k times with data from all three, and 29k with data from San Mateo Bridge, too.
- Using some form of voting seems among them does not lose *too* much data and will go a long way toward robust inputs.
- Consider scaling stations if there are substantial biases between them
- Kristin mentioned QA blips, Dan mentioned revisiting QA of this data.
- *But,* come back during spatial extrapolation phase and see if we're missing something important spatially.

Outline of Approach - step 3 test GAM

Start with "best" model from existing approach

Test for possibility of greater role of wind and stormwater.

link to overall plan

2023-05-11 Regroup

- 1. Bring in the shoal moorings
 - a. includes updating the general inputs for the GAM fitting (i.e. updating wind inputs, stormwater, USGS cruises to cover the shoal mooring periods).
 - b. Probably have to modify the existing approach, at least in terms of bending the channel stations but probably not bending the shoal moorings.
 - c. During or after this process we could also look at how to bring RS data.
- 2. Potential additional data sources:
 - a. Andreas Brand's data (south of SMB, span channel to mid-shoal)
 - b. Joe Adelson's data
 - c. Consider SSA ala Schoellhamer, GAM in freq space
 - d. Consider station specific regional components (hierarchical-ish GAM?)
 - e. New turbidity near Eden Landing (+pressure sensor for waves)

Relevant code

At RMA: \\Chi-town\J

Main codebase:

https://github.com/rustychris/sfei_light

Example of bringing RS data in

https://github.com/rustychris/Kd2022_RS

2023-05-12 data for RH to find:

- shoal CSVs

Updating Time Period of Inputs

USGS Peterson updated through end of 2022

Newer SSC/turbidity downloaded (and automated for future updates) for Alcatraz, Benicia, Carquinez, Dumbarton, Mallard Island, Richmond Br.

Wind: Pulled down Allie's 2021/2022 data, goes through roughly Oct 2022.



Long-term Alcatraz Output

Data goes back to 2004.

SF Pier 24 has earlier data, but unfortunately no overlap with Alcatraz. There is also Pier 17 since 2013 that does overlap Alcatraz.


Shoal Approach

Check relevance/validity of existing GAM terms (local & global). Obvious missing terms?

Are shoals stations similar (treat as one site with 3 replicates) or distinct (treat as distinct sites)

SSC→Kd: Shoal stations are far from USGS cruise locations with actual Kd data. Use nearest cruise data anyway? Use a constant / literature relationship? Does fitting turbidity help at all?

```
# Station GAM
# Models now work in log-space
dep_var='log10_ssc_mgL'
df[dep_var]=np.log10(df['ssc_mgL'].clip(1.0))
```

```
predictor=( "te(tide_hour,wl_rms) "
    " + te(glbl_log10_ssc_mgL, tide_hour) "
    " + te(wind_u_ante,wind_v_ante) "
    " + s(delta,constraints='monotonic_inc') "
    " + te(storm,wl)"
    " + s(tdvel)"
```

```
# Global GAM
predictor="s(year, n_splines=128, constraints=flatends) +
s(along) + s(wl_rms, constraints='monotonic_inc')"
```

```
# Default turb to ssc conversion (applied if no overlapping
turbidity and SSC data are available to
# back out a site-specific conversion from USGS)
# SSC = a * turb^b
turb2ssc_a = 4.35
turb2ssc_b = 0.834
```

Comparison to HF Stations

From Farid 8/19/2023.

Omitting the 3 shoal stations and stations with no overlapping observations.

Sources of discrepancies:

- NWIS vs SFEI data
- stations not part of existing (TWDR) method
- "Bending", $\rm K_{\rm _D}$ vs turb
- Bugs



Model Kd vs HF Kd at NW



Model Kd vs HF Kd at ALV





Model Kd vs HF Kd at SMB



USGS vs SFEI data (2023-08)

SMB: Was not including most recent field data.

DMB: Different data sources. USGS vs SFEI?

ALV: Not using recent data at all.



USGS vs SFEI data

Reasonably close to default SSC ~ turb relationship, but substantial scatter.

Sources of scatter:

?

_

- Sonde elevation, sensor
- Variable calibration

10² 10¹ 10¹ San Mateo Bridge ssc. mgL

SFEI data vs USGS data Log-scaled Full time period.

Magenta line is the default power law:

 $SSC = 4.35 \ turb^{0.834}$



Updating SM Data from SFEI Mooring

Details in sfei_data_merge.ipynb

Manually censor new L3 data, combine with previously edited L3 data.

Use <u>recent turb–SSC calibrations</u> for the whole time series, using separate calibrations for EXO vs SBE.





SMB Results

Combined with previous edited L3 data, updated in DataInfo_Raw_LightField, with both turbidity and SSC.

Use separate calibration for EXO vs SBE data



Dumbarton USGS + SFEI data

USGS sensors still active, both deeper than SFEI sensor.

Substantial offsets between the various depths.

Relatively few periods during WY2021,WY2022 when USGS data is missing and SFEI L3 is present.

Existing SFEI inputs for Kd match L3 from google drive, just end sooner.

Updated Kd inputs to use L3 from google drive, and use fixed effects calibration to get SSC.

Made SFEI the primary site here, since it is at the surface.



Alviso Slough

L3 has additional data, but everything that is applicable to immediate needs is too spiky to use without considerable effort.

Usable data picks back up Sep 2022 to Feb 2023.

Leave as is.



After updating inputs

Still differ, but substantially closer.







Shoal Cleaning

Manually censor periods based on

- sharp increase followed by sharp decrease over <1d
- gradual increase followed by sharp decrease
- Period with baseline turb<0
- Elevated period at only one station.

Followed by 5 point median filter.



Further Updates

Global GAM does not include the shoal stations, but has been updated with the newer data from other SFEI moorings.

Shoal stations get slightly different predictor:

Shoal		Channel
<pre>te(tide_hour, wl_rms) + te(glbl_log10_ssc_mgL, tide_hour) + te(wind_u_ante_pd, wind_v_ante_pd) + s(delta_pd, constraints='monotonic_inc') + te(storm_pd, wl) + te(wl,speed_tide_local)</pre>	VS	<pre>te(tide_hour,wl_rms) + te(glbl_log10_ssc_mgL, tide_hour) + te(wind_u_ante,wind_v_ante) + s(delta,constraints='monotonic_inc') + te(storm,wl) + s(tdvel)</pre>

Main change is pd terms. Denotes filter with instantaneous attack and gradual decay, mimics increased erodibility following storm/wind events.

Without global GAM, pseudo-R² of 0.35 (SHL), 0.36 (HAY), 0.36 (SLM)

With global GAM, pseudo-R² 0.50 (SHL), 0.42 (HAY), 0.40 (SLM), comparable to other stations.

Using satellite imagery to guide extrapolation

222 scenes. For each pixel, fit a linear regression against station pixels. Non-negative least squares to avoid overfitting nonphysical relationships.



Station Regions

Same approach, but showing where each station dominates the coefficients.

- Mostly well behaved
- Shoal stations are very useful, but data quality
 <2020 could degrade results
- For full implementation need larger satellite coverage



Update Polygons

Minor changes to Alcatraz, Richmond Br, Dumbarton Br.

Major changes to San Mateo Br



Kd (m⁻¹)

Richmond_Bridge Alcatraz_Island SLM SHL HAY Mateo Bridge Dumbarton Bridge

Remaining Questions

Overhaul extrapolation to be based on RS imagery, or draw polygons for shoal stations by hand?

Shoal stations in earlier periods are all GAM-filled. Should they still participate in extrapolation?

Others?