Water Clarity in the Lower York & James Estuaries: Dataflow Insights and Satellite Integration

David B. Parrish (CBNERR-VA/VIMS)
Carl Friedrichs (CBNERR-VA/VIMS)
William Reay (CBNERR-VA/VIMS)
Michael Echevarria (HRSD)

Criteria Assessment Protocol Workgroup
12/8/2025

HRSD
CHESAPEAKE BAY NATIONAL ESTUARINE RESEARCH RESERVE VIRGINIA
VIMS | William & Mary
Virginia Institute of Marine Science

Seagrass Habitat & Water Clarity

- Chesapeake Bay water clarity standards established to support healthy seagrass
- CBNERR-VA has monitored shallow waters to assess water clarity for > 20 years
- In-situ observations are excellent, but spatial & temporal gaps remain
- Satellites can help fill the gaps

CHESAPEAKE BAY NATIONAL ESTUARINE RESEARCH RESERVE VIRGINIA

VIMS | WILLIAM & MARY

VIRGINIA INSTITUTE OF MARINE SCIENCE

CBNERR-VA Monitoring Platforms

Fixed Stations

Near Bottom

Shallow water areas

15-min measurements

Dataflow

Surface

2-3 sec measurements

25 knots -> sample ever 25m

CBIBS Buoy

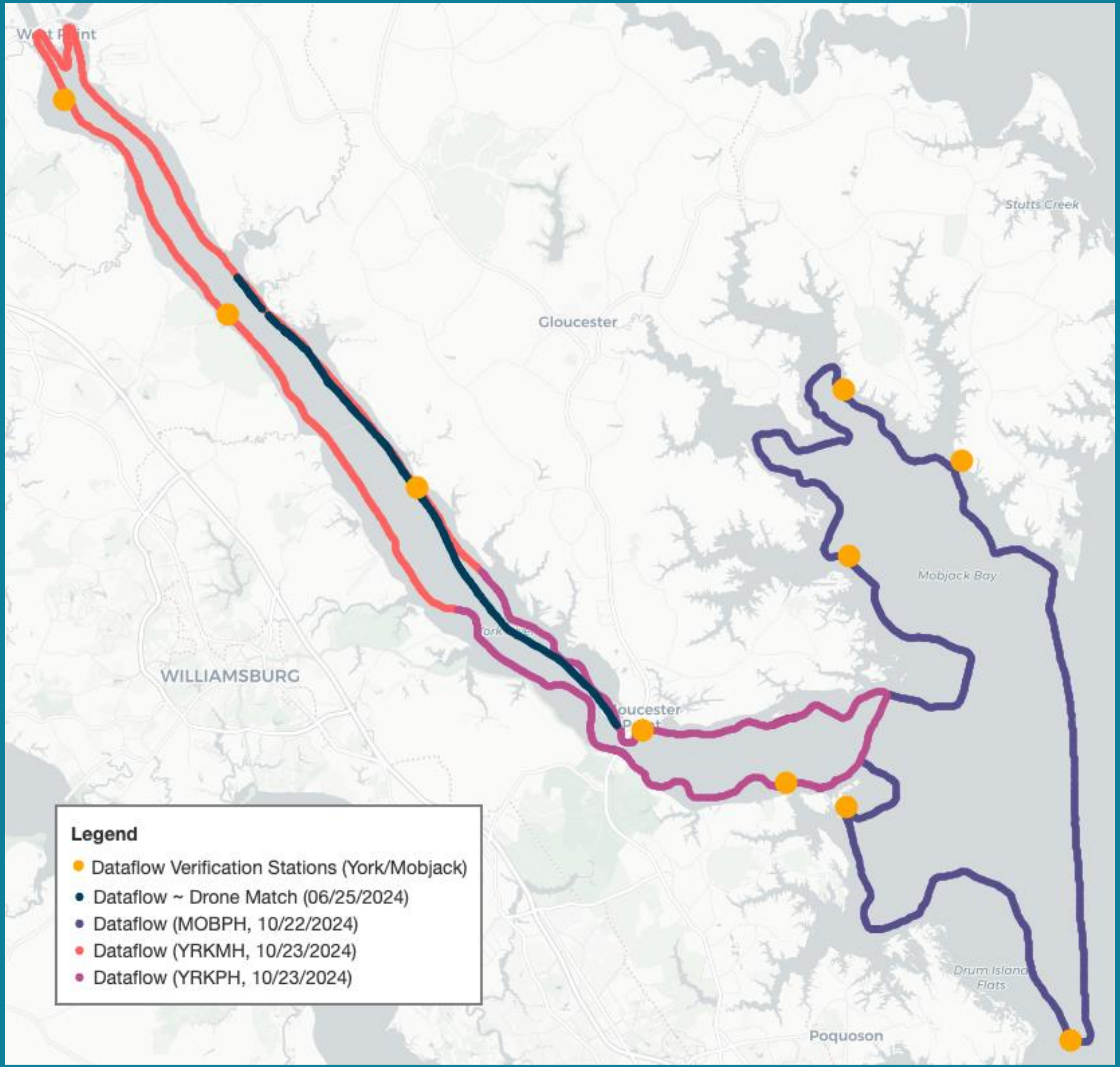
Surface

Floating buoy

6-min measurements

Verification Measurements

- Light Attenuation (K_d)
- Secchi
- Chlorophyll-a
- TSS
- Nutrients
- Profile



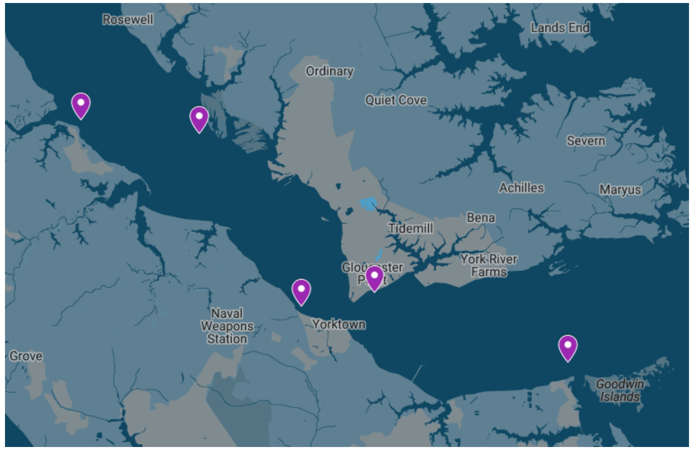
CHESAPEAKE BAY NATIONAL ESTUARINE RESEARCH RESERVE VIRGINIA

VIMS | WILLIAM & MARY

VIRGINIA INSTITUTE OF MARINE SCIENCE

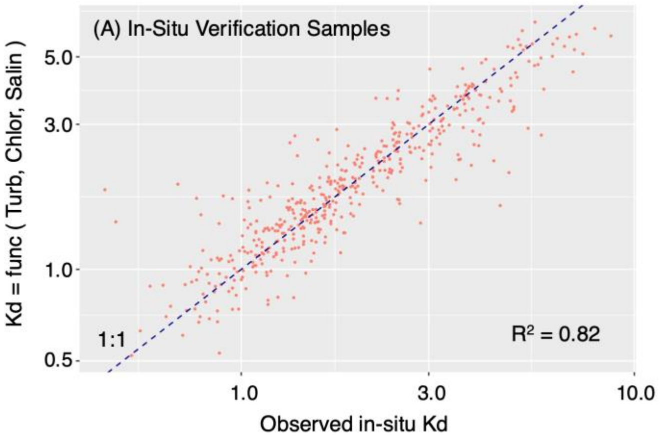
Water Clarity Assessments

Verification and Light Attenuation (Kd) Estimates



York River Polyhaline verification stations

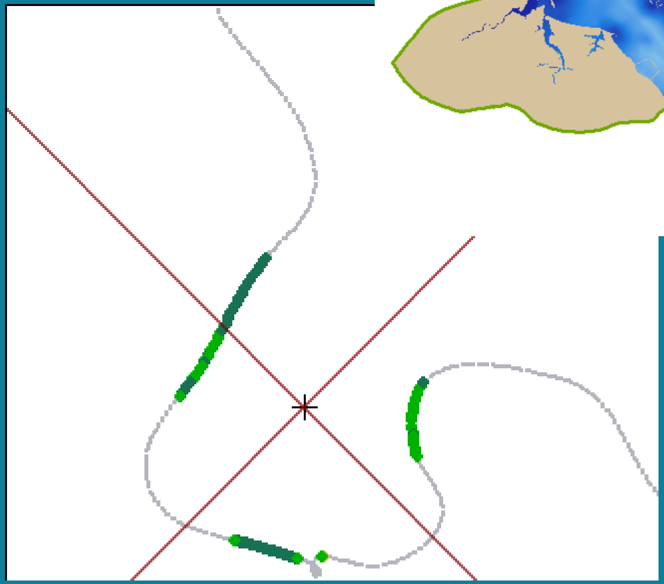
Early 2000's, York River

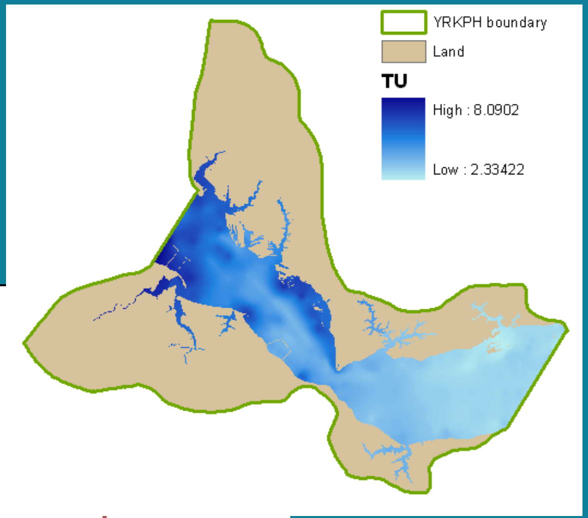


$$K_d \sim \mathcal{N}(\mu, \sigma^2)$$

$$\mu = \beta_0 + \beta_1 \cdot \sqrt[1.5]{\text{Turbidity}} + \beta_2 \cdot \text{Chlorophyll} + \beta_3 \cdot \text{Salinity}$$

Interpolation: Kriging





CHESAPEAKE BAY NATIONAL ESTUARINE RESEARCH RESERVE VIRGINIA

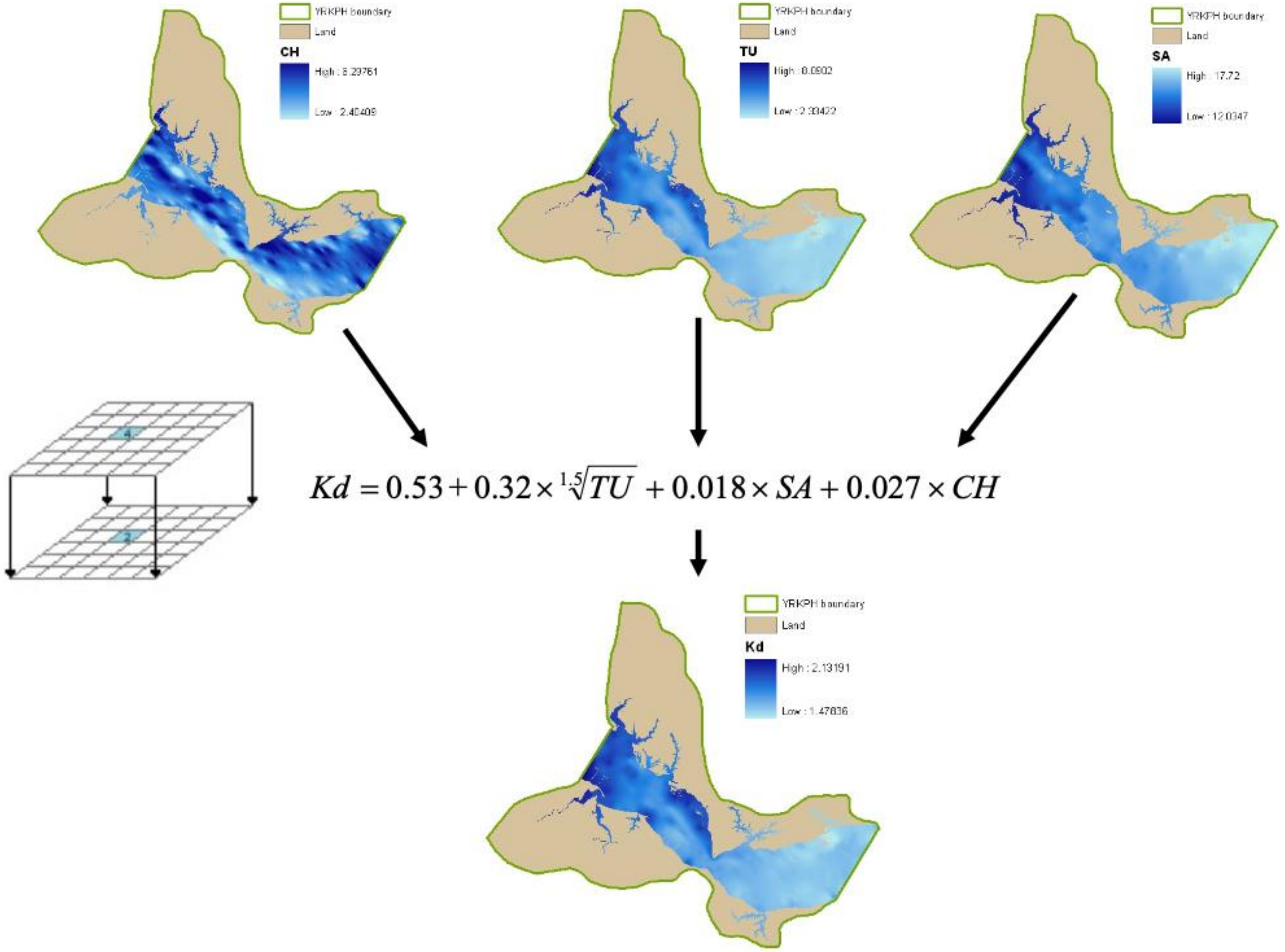
VIMS | WILLIAM & MARY

VIRGINIA INSTITUTE OF MARINE SCIENCE

Chlorophyll Fluorescence

Turbidity

Salinity

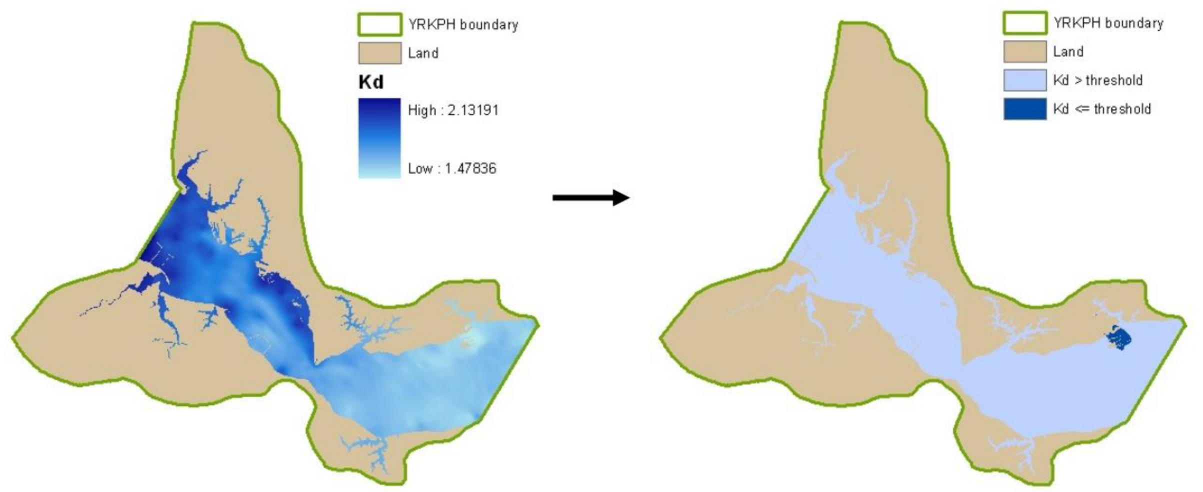


$$Kd = 0.53 + 0.32 \times \sqrt[1.5]{TU} + 0.018 \times SA + 0.027 \times CH$$

Kd Threshold

PLL	Zones	
	0-1m	1-2m
0.22	1.51	0.76
0.13	2.04	1.02

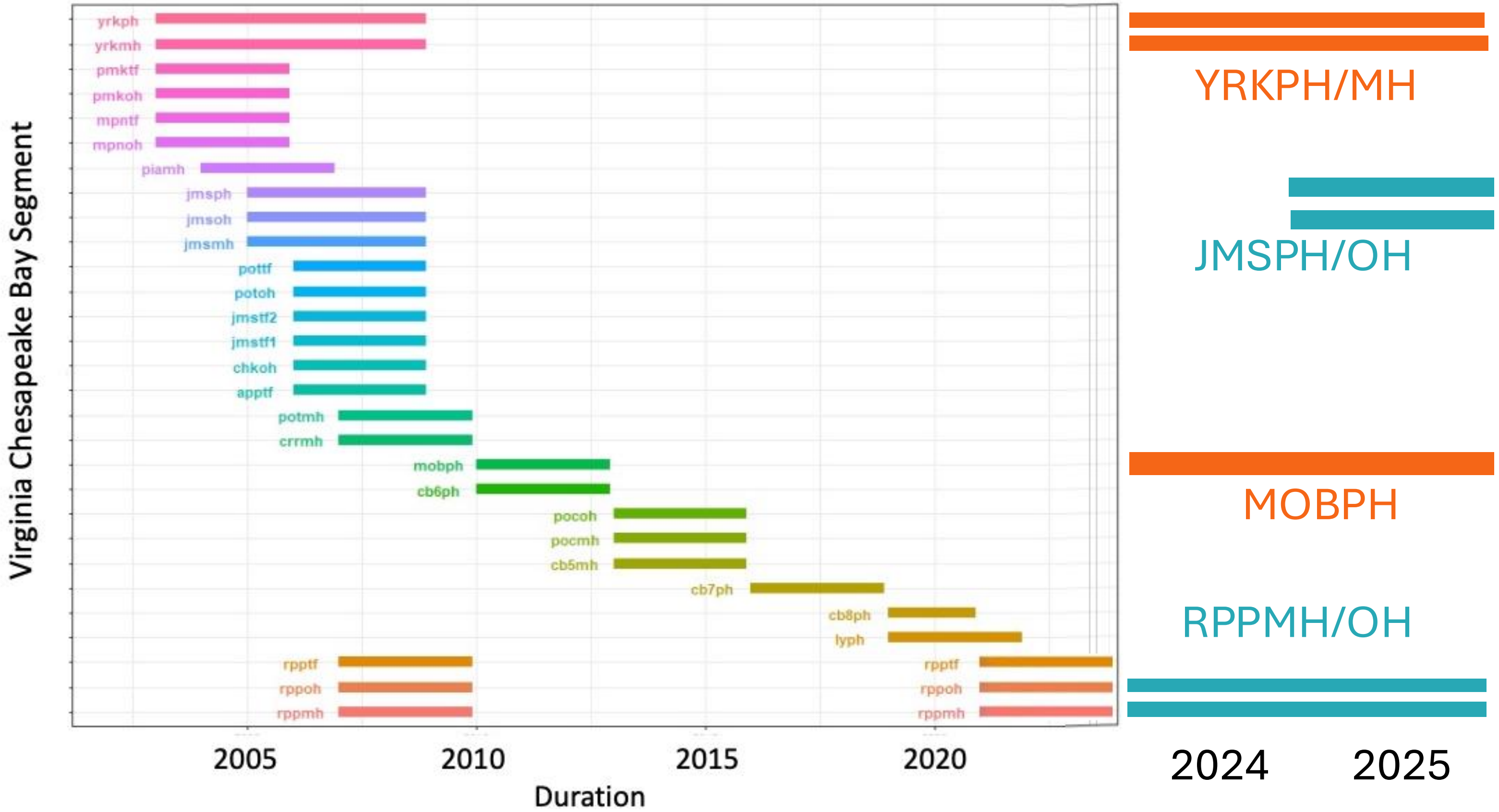
Polyhaline – Mesohaline: 22% PLL
Oligohaline - Tidal Fresh: 13% PLL



NERRS
CBIBS
Telemetered
VA-DEQ /EPA/CBP
VIMS Water Quality Initiatives
Past CMONs
Longterm "sentinel" locations

Fixed (Sentinel)
Dataflow

Over 20 years of Monitoring

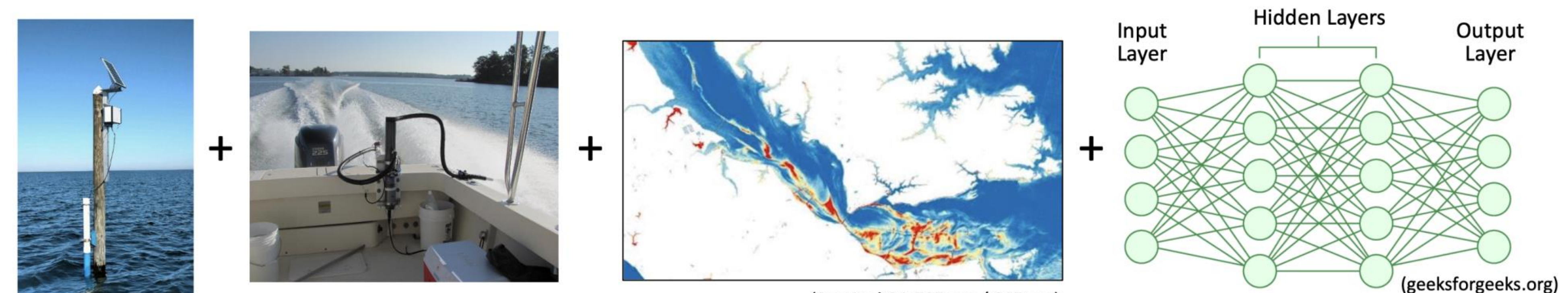


CHESAPEAKE BAY NATIONAL ESTUARINE RESEARCH RESERVE VIRGINIA

VIMS | WILLIAM & MARY
VIRGINIA INSTITUTE OF MARINE SCIENCE

Remote sensing data can help fill gaps and assess water clarity

- Anchor satellite imagery with Fixed Station and Dataflow monitoring programs
  - Dataflow - 1000’s of verification measurements in a single day
  - Fixed Stations - 100’s of verification measurements in a year

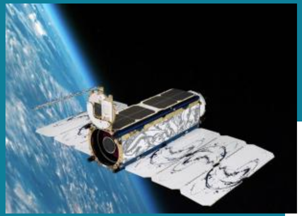


(Sentinel-2A 705 nm / 665 nm)

CHESAPEAKE BAY NATIONAL ESTUARINE RESEARCH RESERVE VIRGINIA

VIMS | WILLIAM & MARY
VIRGINIA INSTITUTE OF MARINE SCIENCE

Methods



8 bands -> Surface

Source: Vanhellemont, 2023

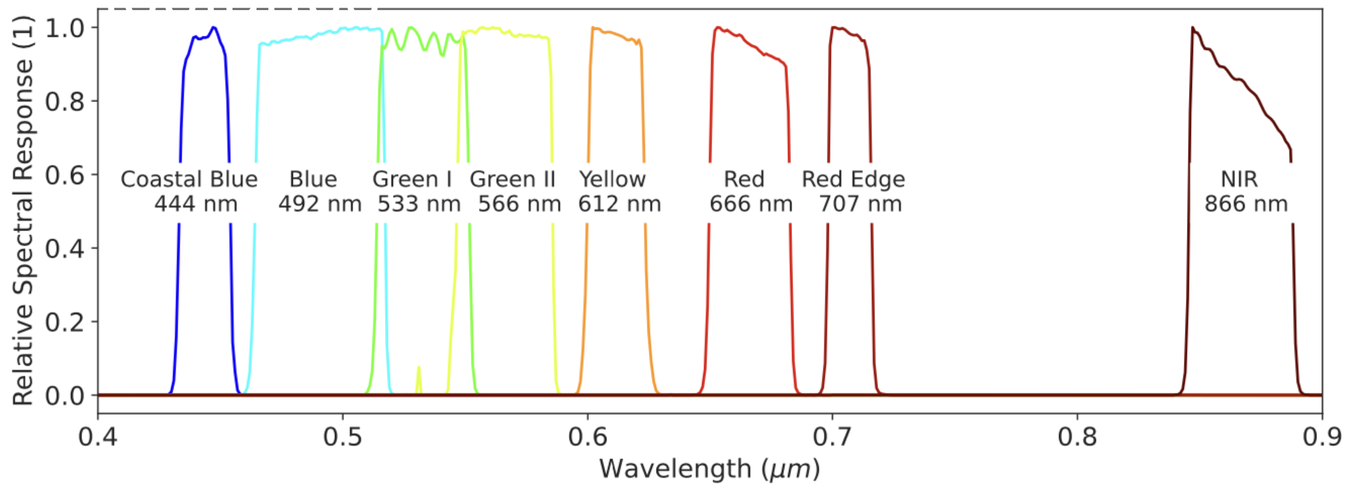
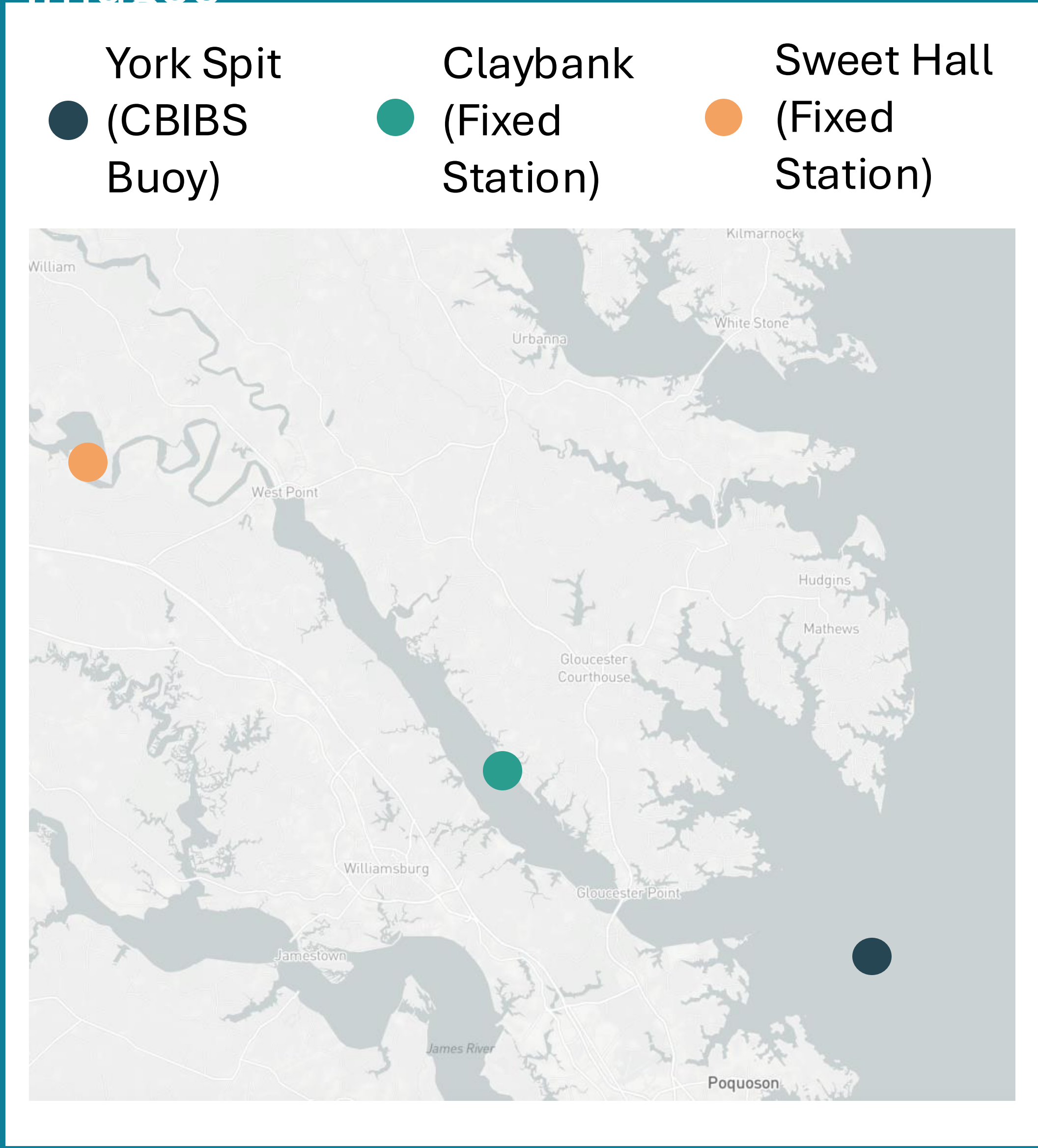


Fig. 3. SuperDove eight band relative spectral response function as provided by Planet.

- Acquire imagery from Planet
  - ~ 3 m resolution, 8 band
  - Near daily coverage in Chesapeake Bay since 2022
- Atmospheric correction (ACOLITE) -> 8 surface reflectance bands
- Match surface reflectance to dataflow and fixed stations in-situ datasets in space and time
- Fit models to matched datasets to estimate light conditions

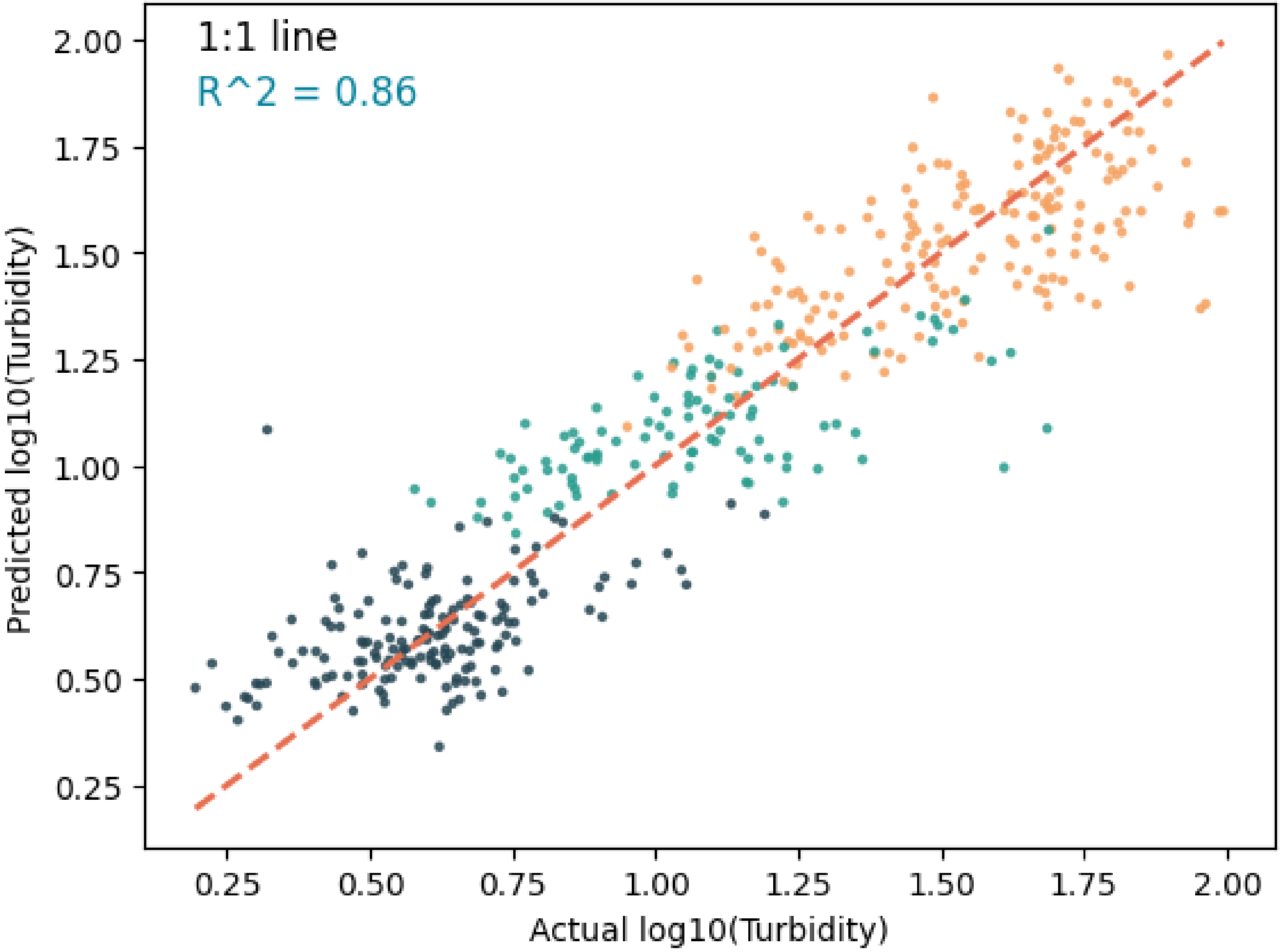
Using Fixed Stations and CBIBS Buoy to Estimate Turbidity From Satellite Images



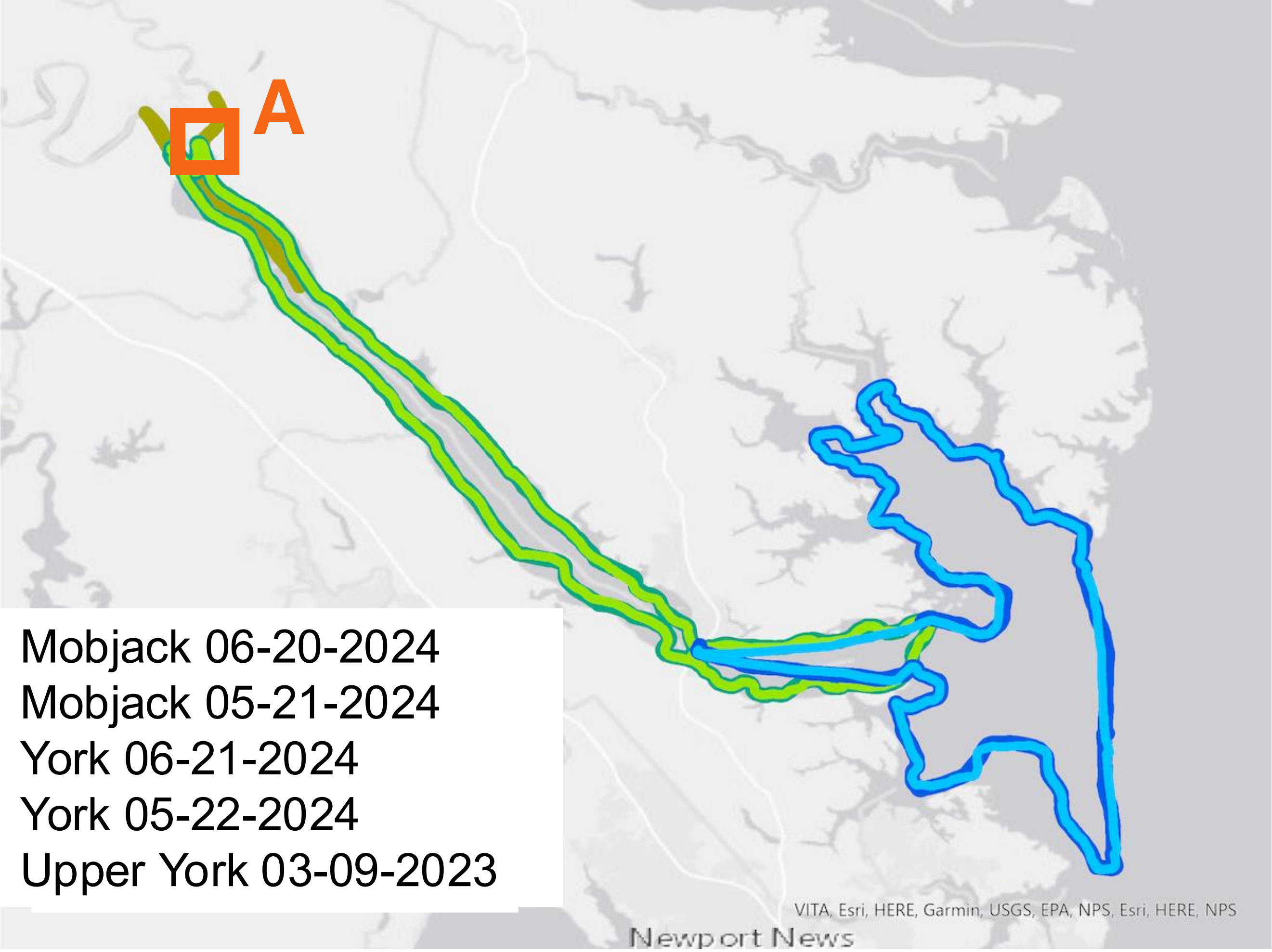
$$y_i = X_i\beta + \epsilon_i, \quad \epsilon_i \sim \mathcal{N}(0, \sigma^2)$$

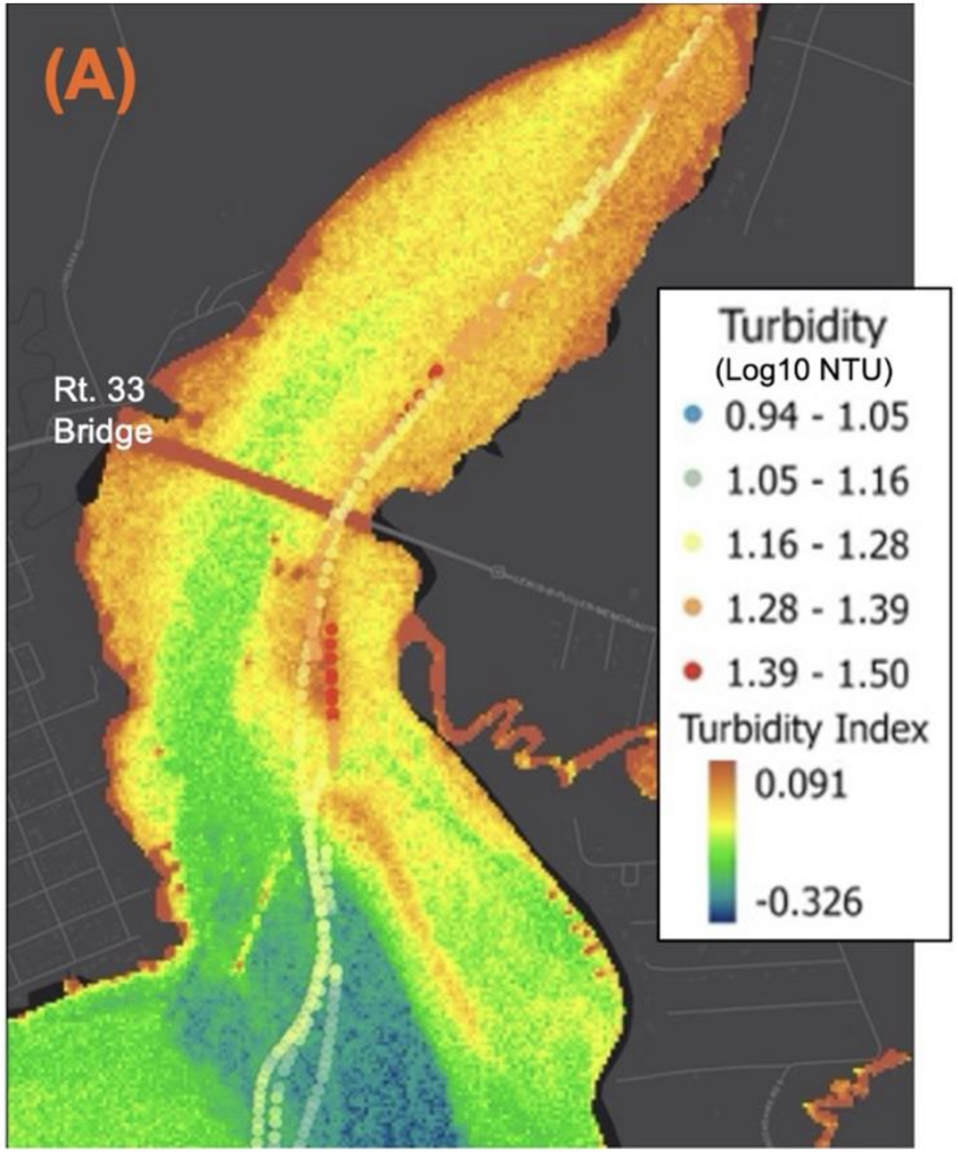
y_i = log transformed turbidity

$$X_i\beta = \beta_0 + \beta_1 \cdot \text{band}_1 + \beta_2 \cdot \text{band}_2 + \cdots + \beta_8 \cdot \text{band}_8 + \beta_9 \cdot \text{depth}$$

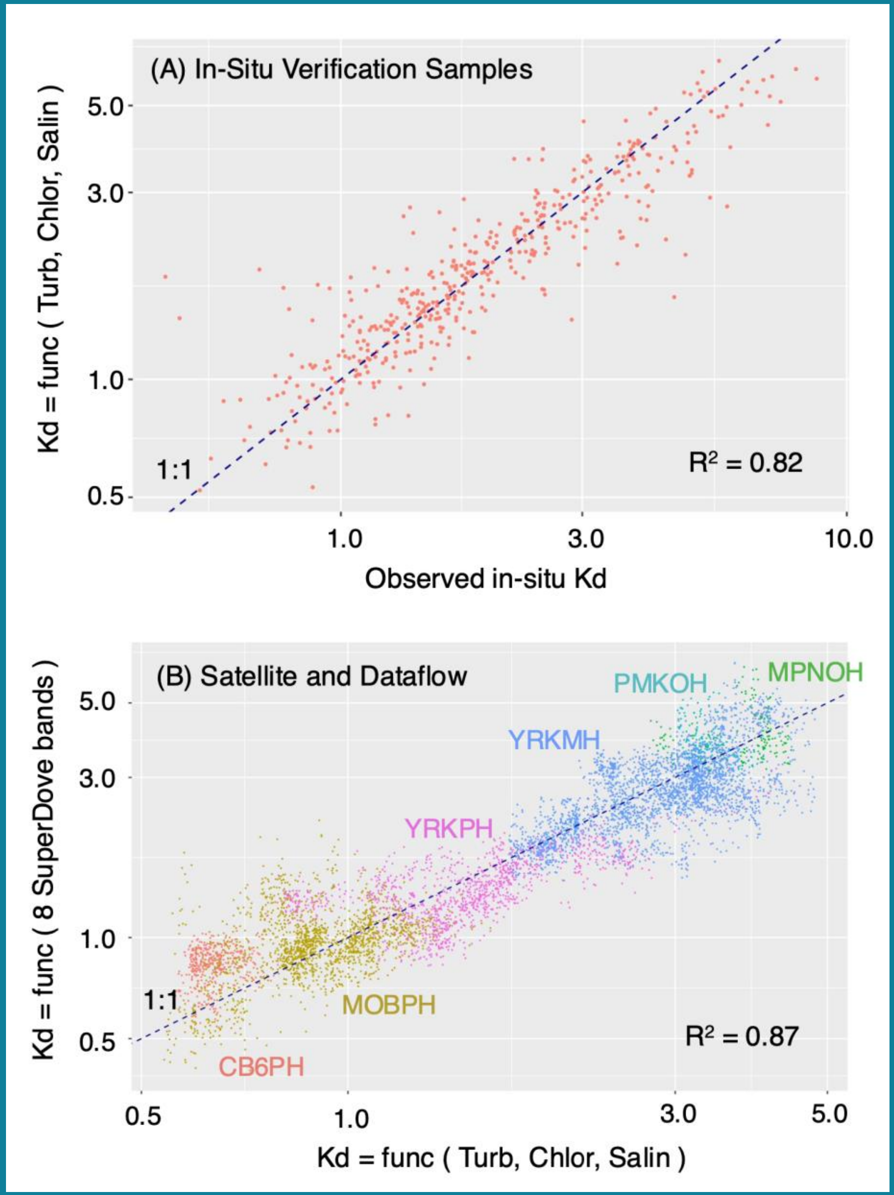


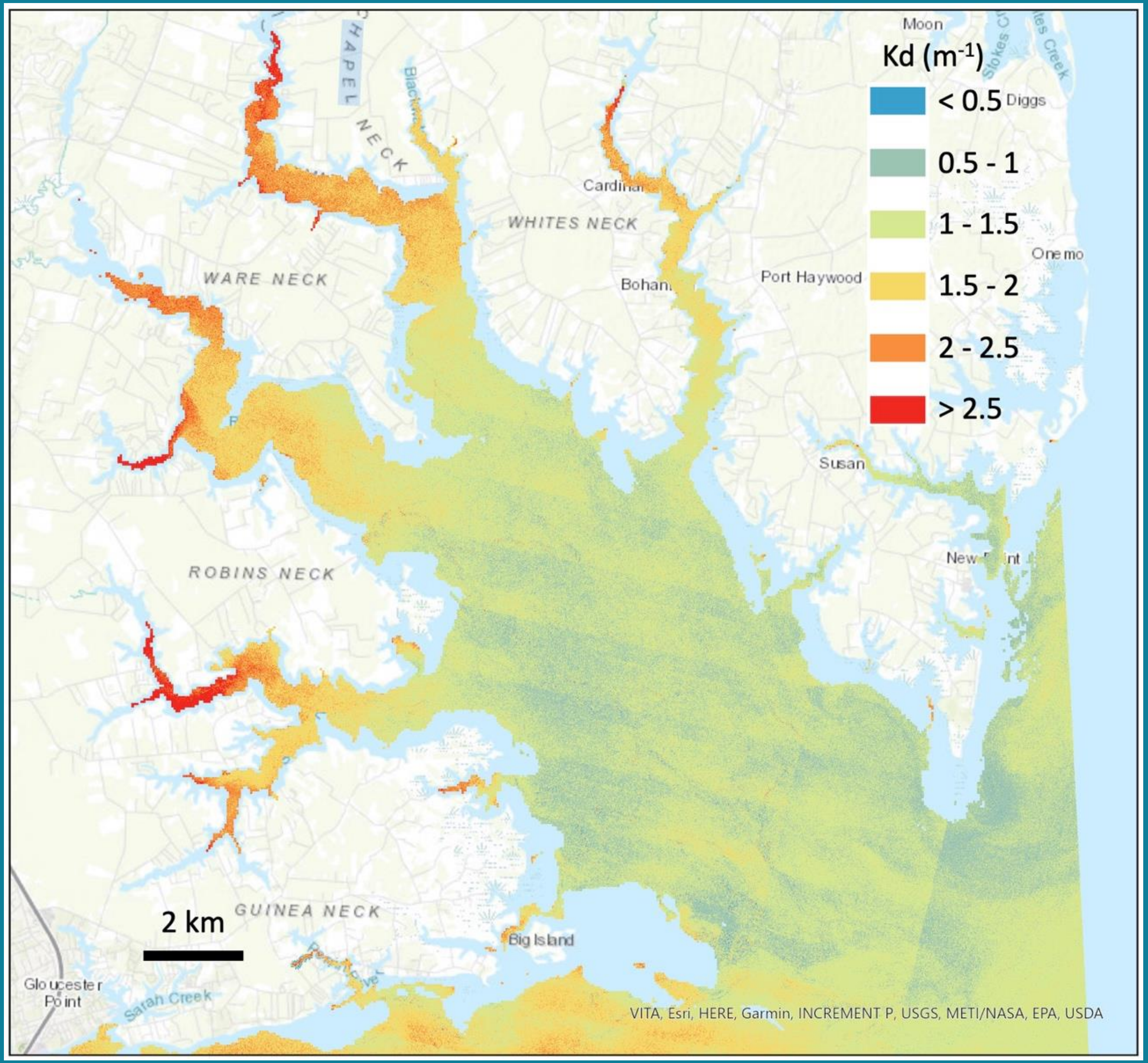
Dataflow and Satellites



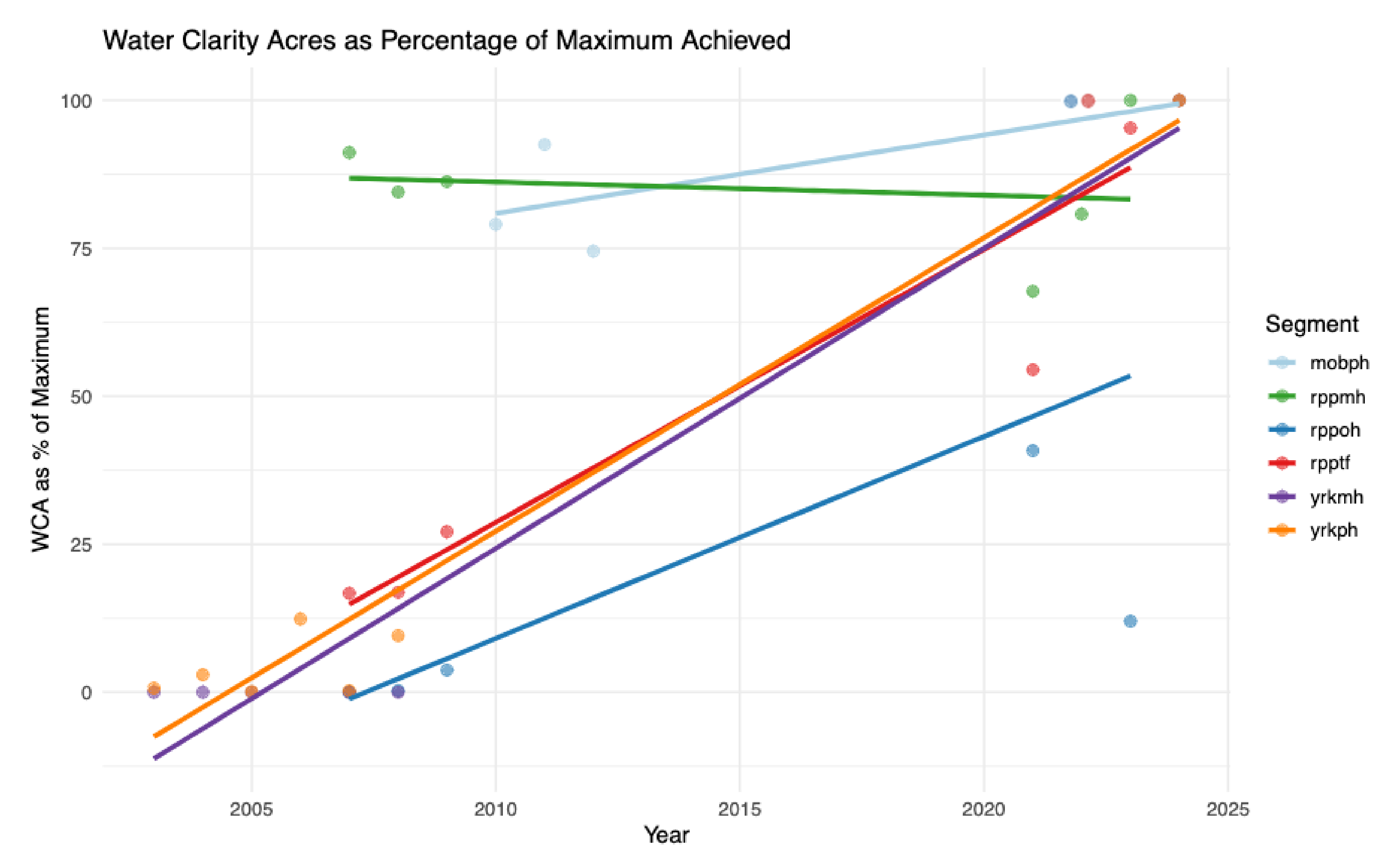


Stage 1: log(Kd) ~ log(Turb) + log(Chl-F) +Salt

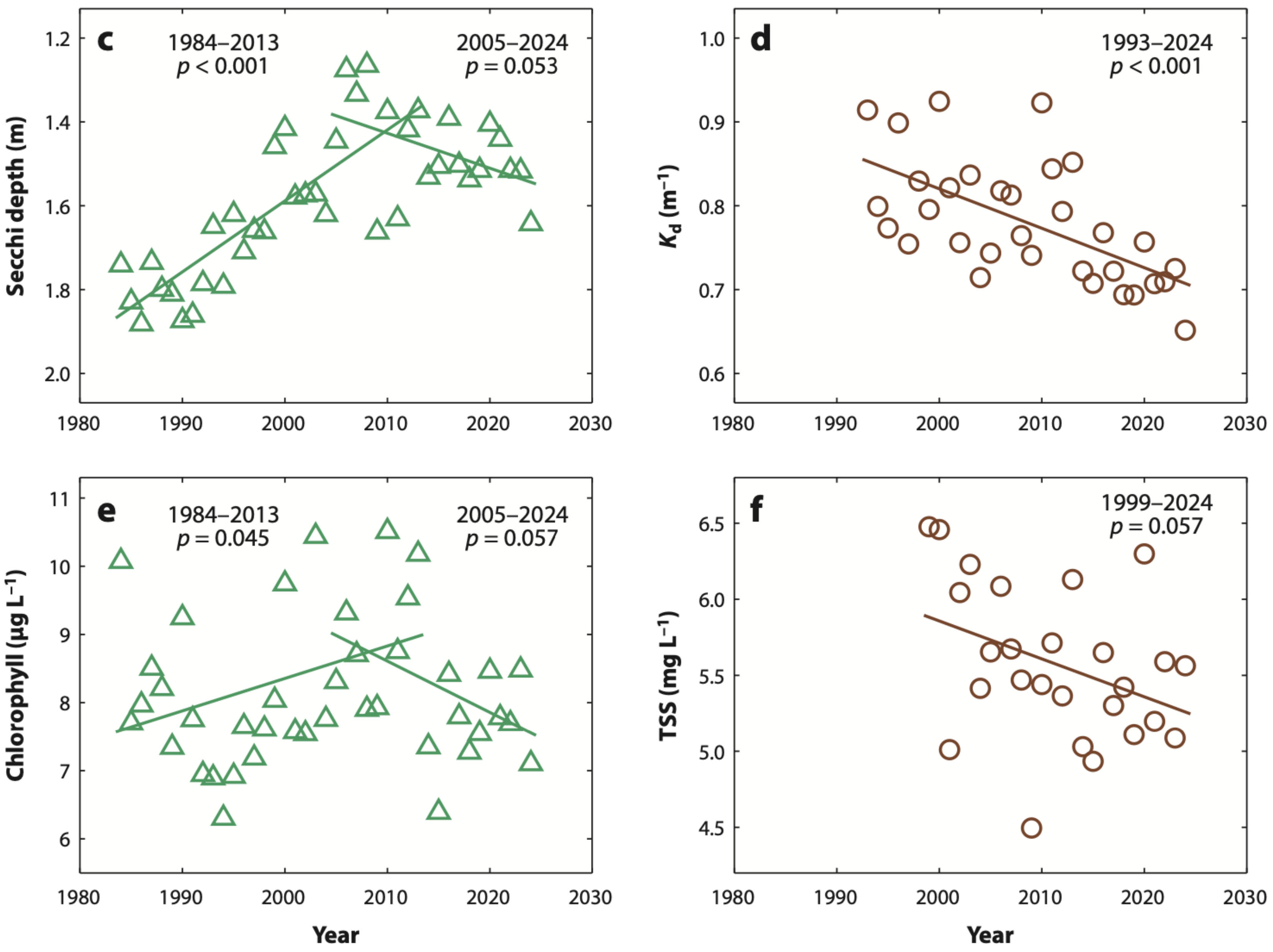




Stage 2: log(Kd) ~ band_1 + band_2 + … + band_8



CBPSEG	n_yr	first_yr	last_yr	first_wca	last_wca	change_wca	pct_change	mean_wca
rppmh	6	2007	2023	10029	11002	973	9.7	9359.5
rppoh	6	2007	2023	0	45	45	Inf	98.0
rpptf	6	2007	2023	196	1118	922	470.4	607.0
mobph	4	2010	2024	20919	26463	5544	26.5	22896.5
yrkph	7	2003	2024	20	2926	2906	14530.0	526.1
yrkmh	6	2003	2024	0	218	218	Inf	36.3

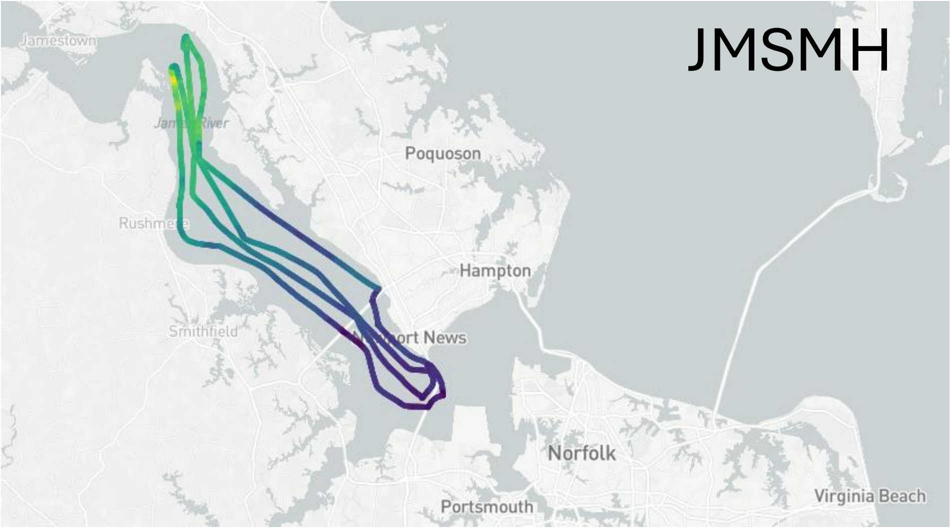


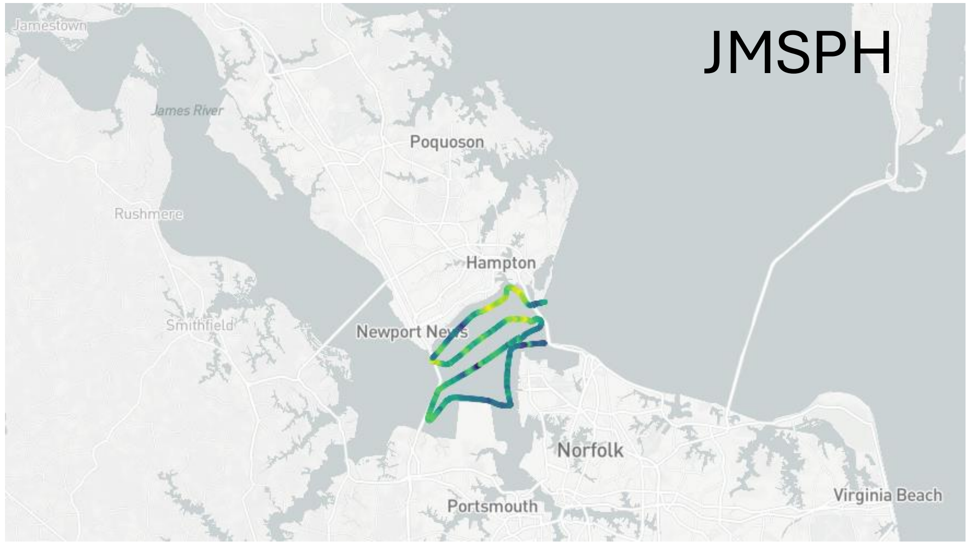
Turner, Friedrichs, Parrish & Fall (2025) Annual Review of Marine Science

Lower James Dataflow (HRSD)

HRSD

- 2 Segments: James Polyhaline (JMSPH) and Mesohaline (JMSMH) sampled since 2005
- Mar – Sep (no June) - In situ water quality
  - Kd, Turbidity, Salinity, Chlorophyll
- 2 Satellite Sources: Planet and Sentinel
- ChesROMS-ECB model (Friedrichs et al., VIMS, 2025) for surface salt
- 2017-2024 – overlap b/w in situ and satellite sources
- JMSPH: 41,211 observations across 25 unique days
- JMSMH: 16,015 matched observations across 28 unique days
- 128 Kd observations matched to in-situ/satellite
- 1179 Kd observations matched to in-situ only

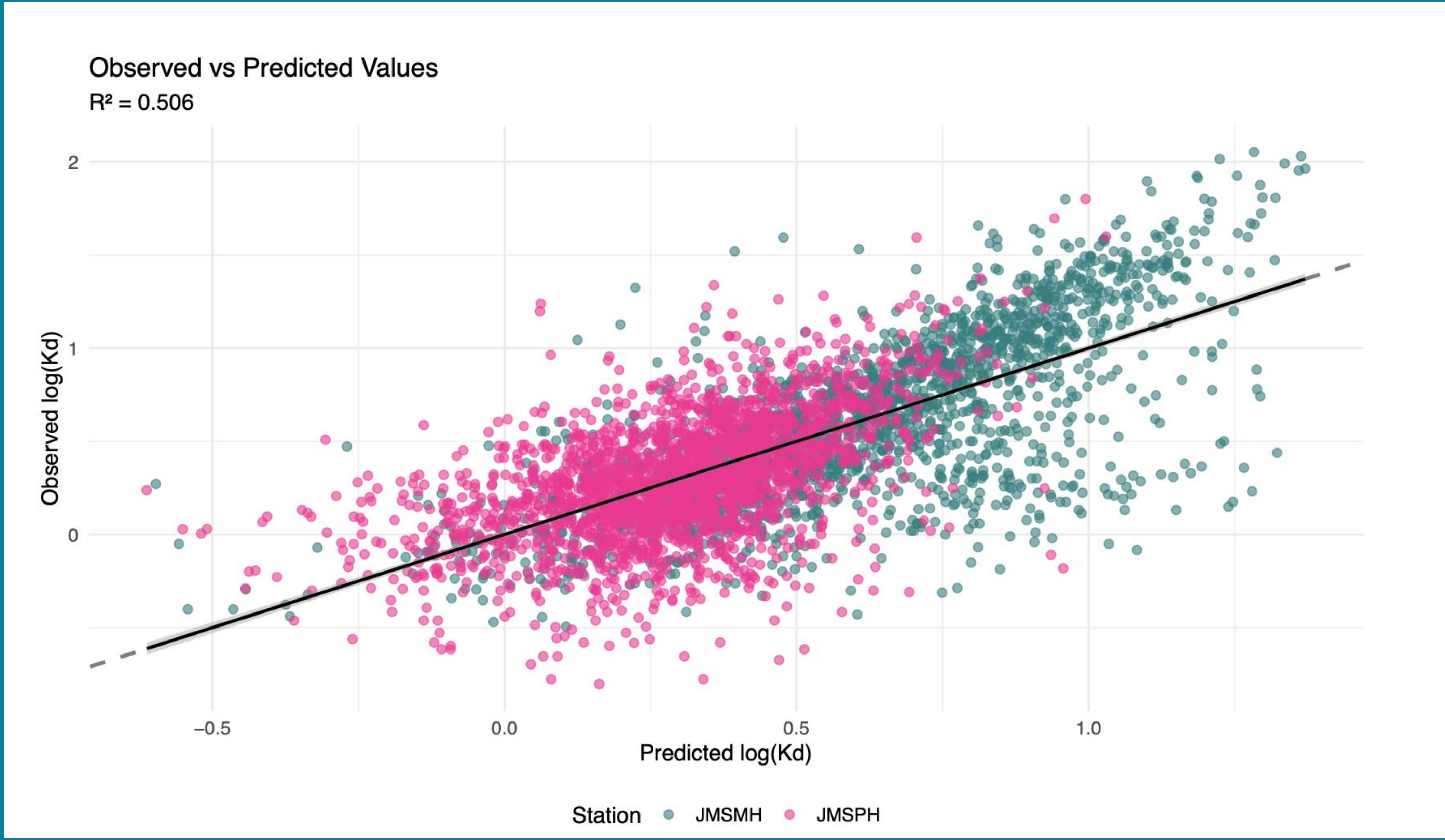




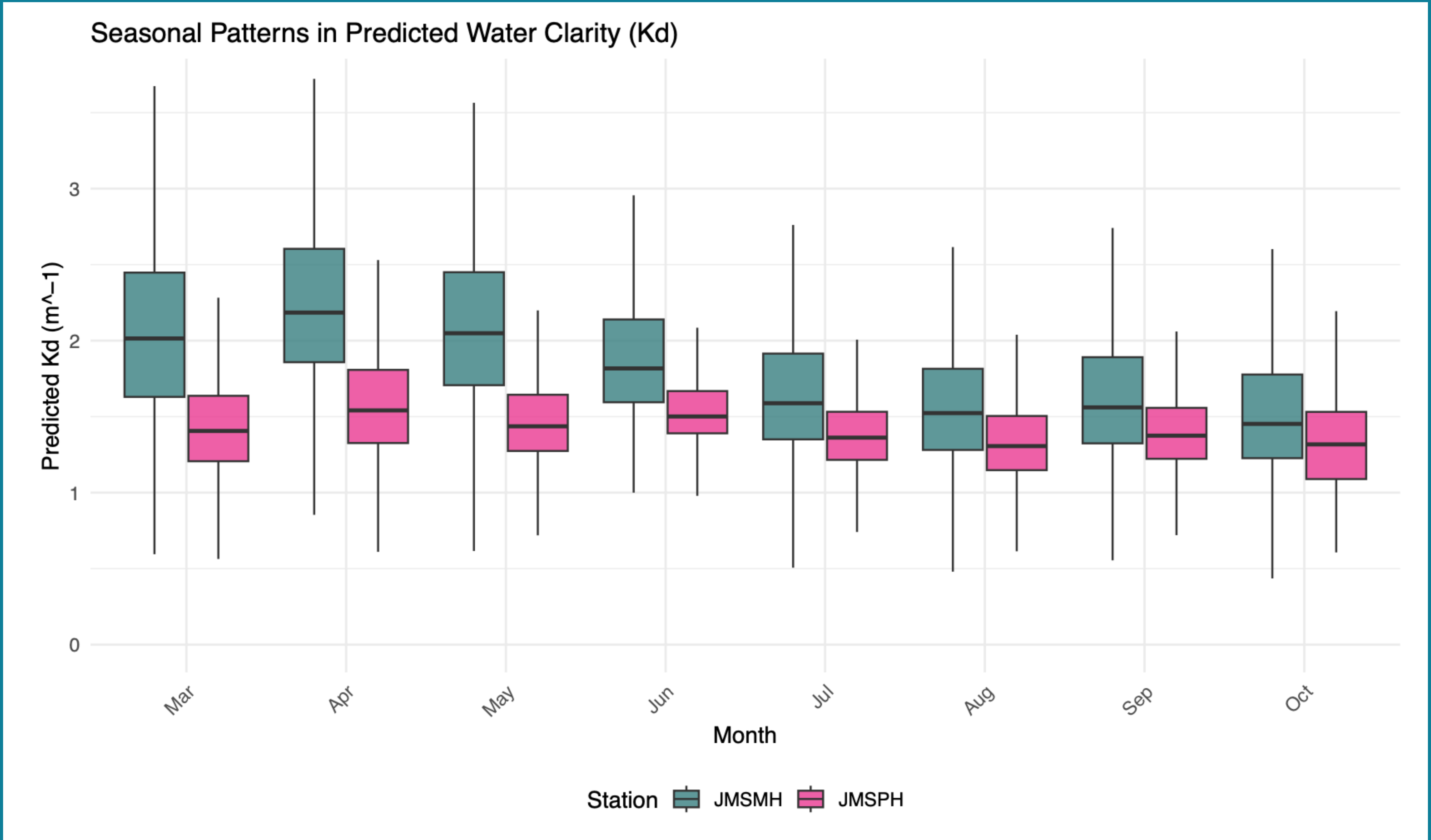
CHESAPEAKE BAY NATIONAL ESTUARINE RESEARCH RESERVE VIRGINIA

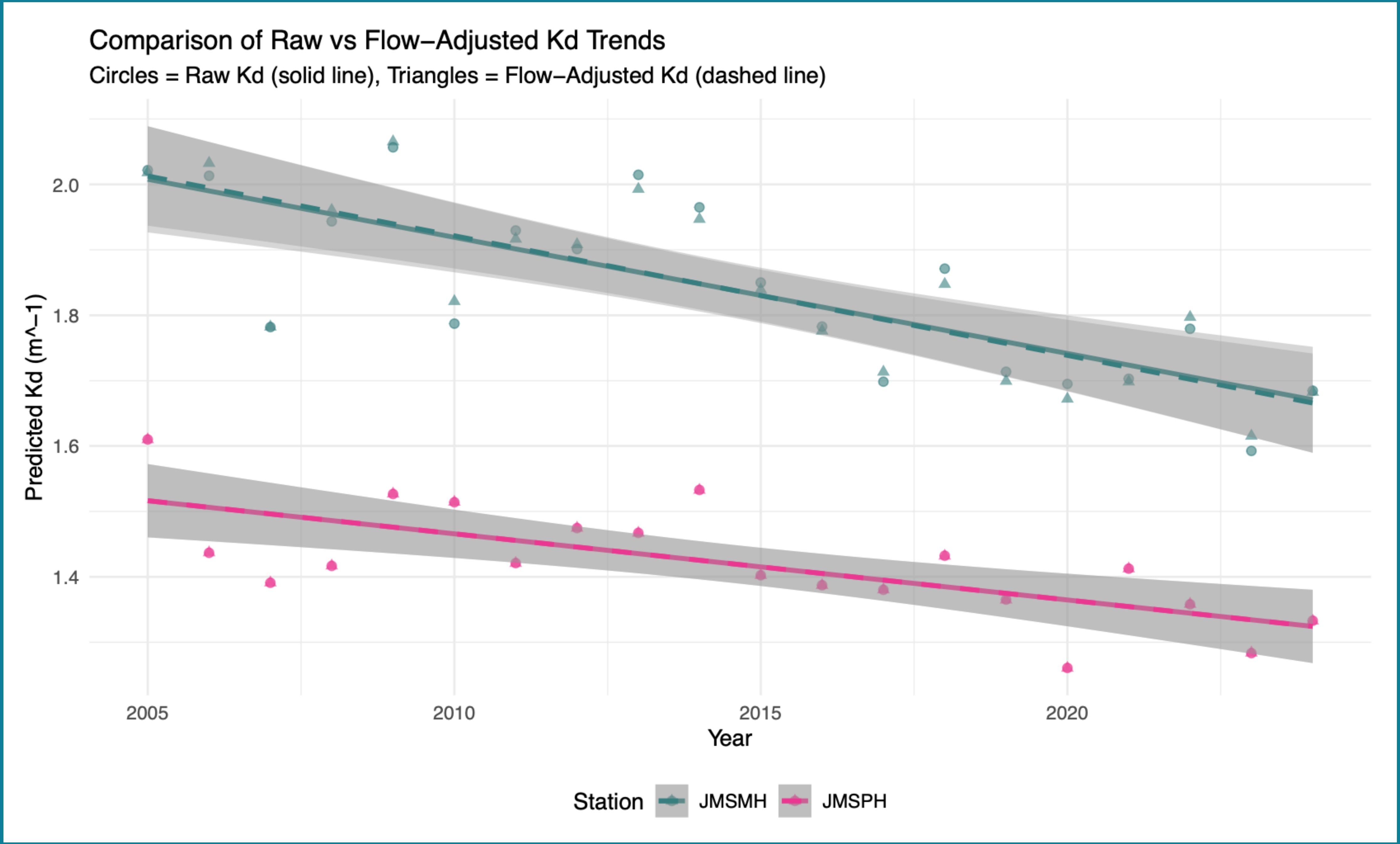
VIMS | WILLIAM & MARY

VIRGINIA INSTITUTE OF MARINE SCIENCE



Observed vs Predicted Values
R² = 0.506
Observed log(Kd)
2
1
0
−0.5
0.0
0.5
1.0
Predicted log(Kd)
Station
JMSMH
JMSPH

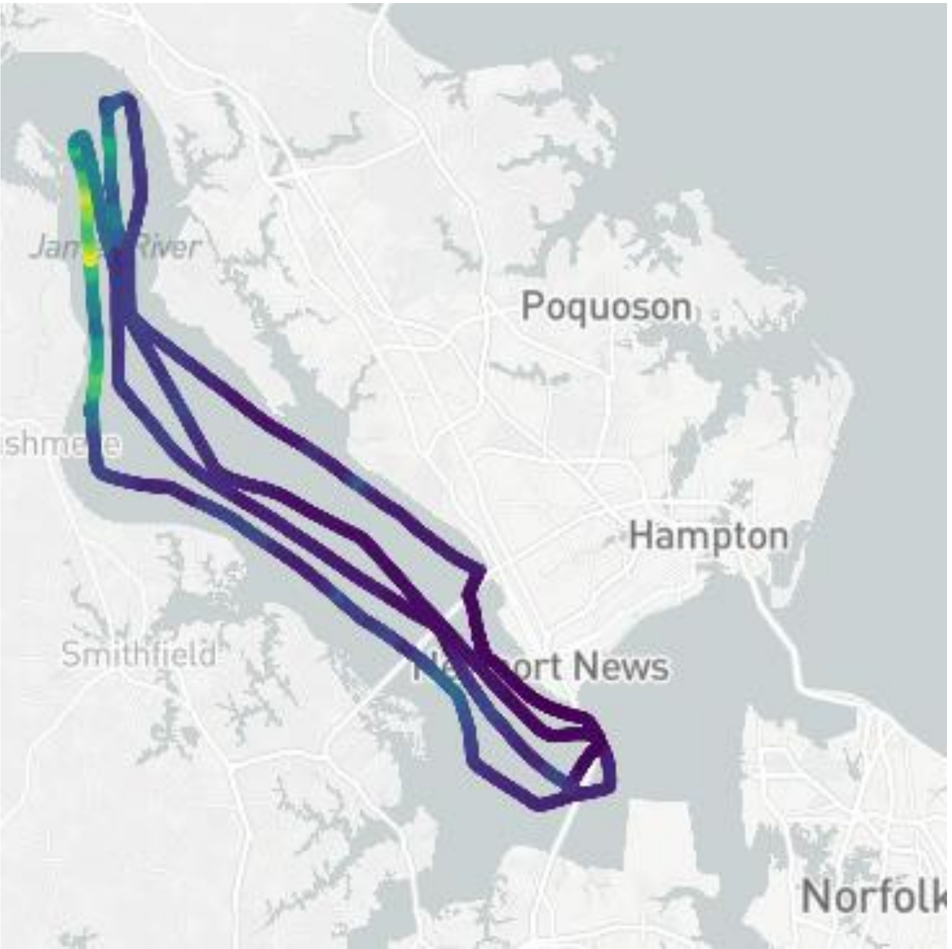

Seasonal Patterns in Predicted Water Clarity (Kd)
Predicted Kd (m^-1)
0
1
2
3
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Month
Station
JMSMH
JMSPH



Comparison of Raw vs Flow−Adjusted Kd Trends
Circles = Raw Kd (solid line), Triangles = Flow−Adjusted Kd (dashed line)
Predicted Kd (m^−1)
2.0
1.8
1.6
1.4
2005
2010
2015
2020
Year
Station
JMSMH
JMSPH

In situ observations

- Dataflow (YSI, 1000s/day): Turb, Chl, Sal
- Kd (5-10/day)



Satellite	Resolution	Revisit Frequency	Archive Length	Typical in-situ matchup rate
Planet SuperDove	3 m	near daily	2 years	~25–45%
Sentinel 2a, 2b	10–20 m	5 days	10 years	~8–12%

↓

Acolite Atmospheric Correction

↓ Band index for Turbidity

↓ Band index for Chl

ECB Model Output

↓ Salinity

Stage 1

Turbidity Model:

$$\log(\text{Turb}_j) \sim N(\mu_{T_j}, \tau_T^{-1})$$

Where:

$$\mu_{T_j} = \alpha_T + \beta_d \cdot z_{drg_j} + \beta_{sensor_T} \cdot \text{sensor}_j$$

Chlorophyll Model:

$$\log(\text{Chl}_j) \sim N(\mu_{C_j}, \tau_C^{-1})$$

Where:

$$\mu_{C_j} = \alpha_C + \beta_n \cdot z_{ndci_j} + \beta_{sensor_C} \cdot \text{sensor}_j$$

Salinity Model:

$$\text{Salt}_j \sim N(\mu_{S_j}, \tau_S^{-1})$$

Where:

$$\mu_{S_j} = \alpha_S + \beta_m \cdot z_{model\_salt_j}$$

Stage 2

For satellite-matched observations, Stage-1 posterior means are treated as noisy observations of the latent parameters:

$$\hat{\mu}_{T_i} \sim N(\tilde{T}_i, \text{Var}(\hat{\mu}_{T_i}))$$

$$\hat{\mu}_{C_i} \sim N(\tilde{C}_i, \text{Var}(\hat{\mu}_{C_i}))$$

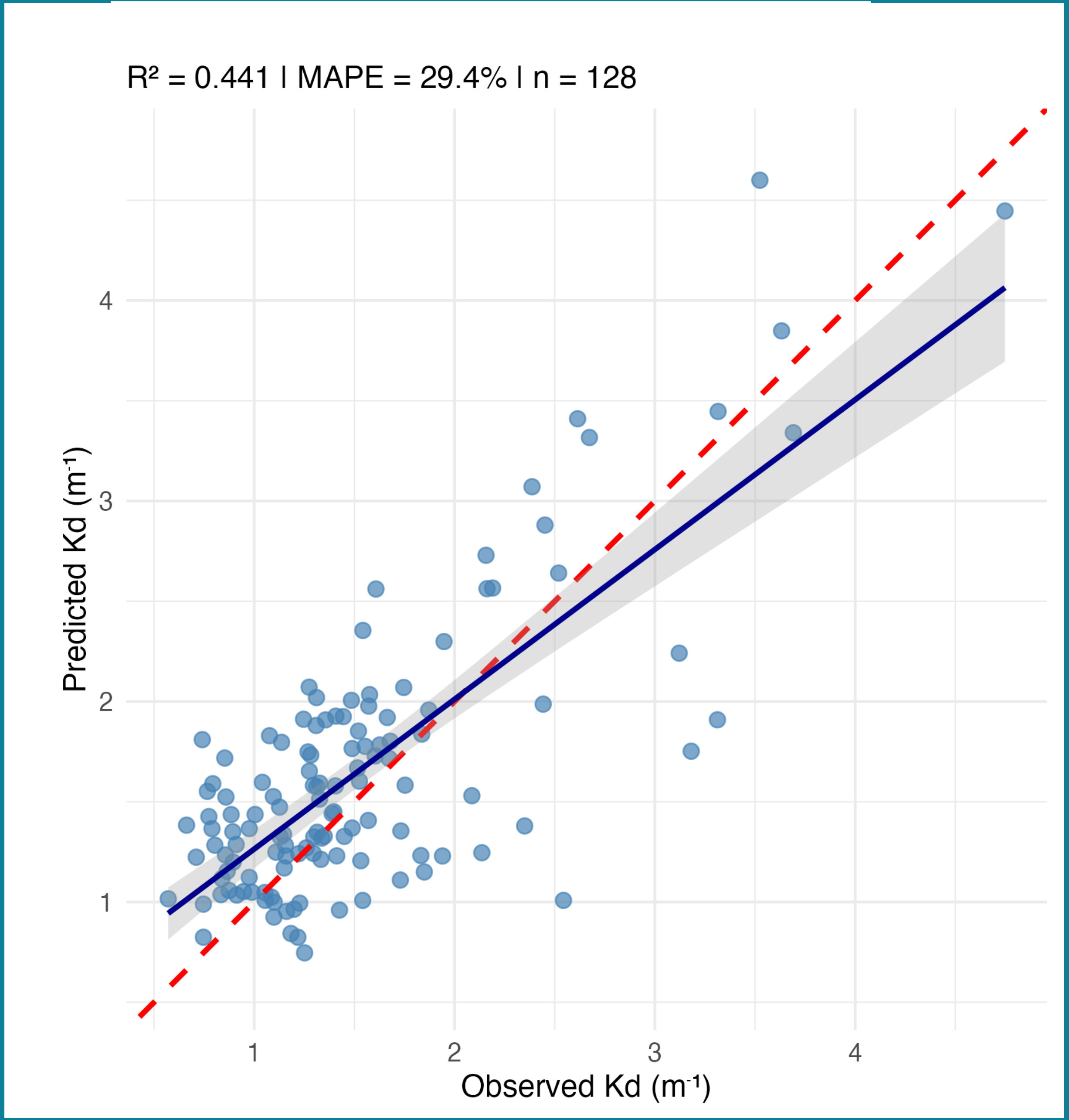
$$\hat{\mu}_{S_i} \sim N(\tilde{S}_i, \text{Var}(\hat{\mu}_{S_i}))$$

$$\log(\text{Kd}_i) \sim N(\mu_{K_i}, \sigma_{K_i}^2)$$

Where the mean is:

$$\mu_{K_i} = \alpha_K + \beta_T \tilde{T}_i + \beta_C \tilde{C}_i + \beta_S \tilde{S}_i + b_{day[i]}$$

Preliminary Bayesian Model Fit: JMSMH & JMSPH



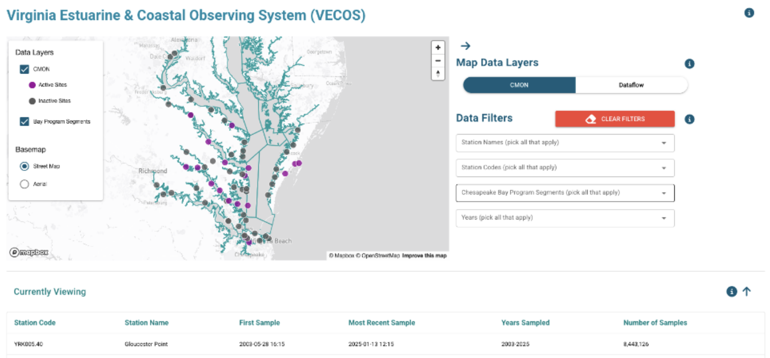
VECOS

Virginia Estuarine & Coastal Observing System (VECOS)

22 years of monitoring

213,513,000 water quality observations

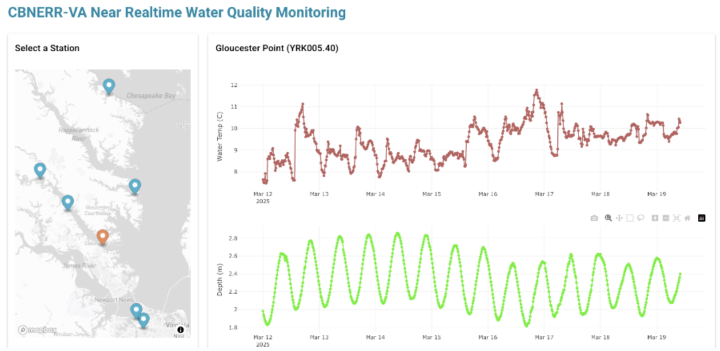
Data Dashboard



The data dashboard provides access and visualization for all quality controlled data.

GO TO DATA DASHBOARD

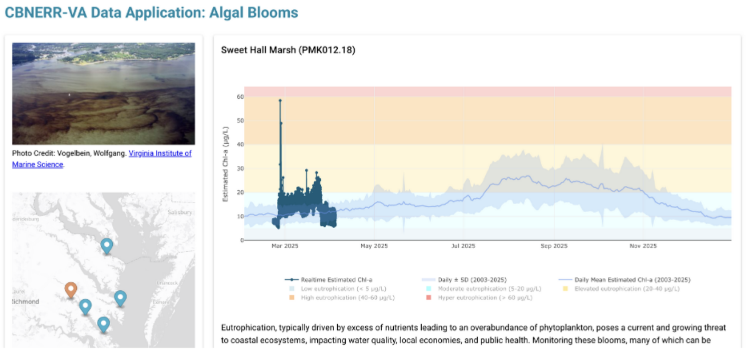
Realtime Dashboard



The realtime data dashboard provides access and visualization of recent observations collected from our fixed stations equipped with telemetry.

GO TO REALTIME DASHBOARD

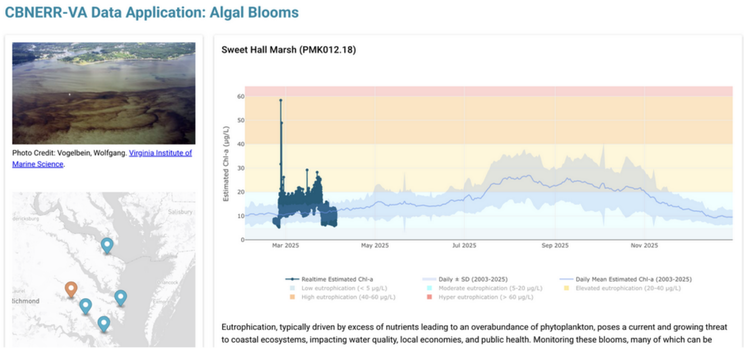
Data Applications



Our Data Applications provide environmental insights leaveraging our near-realtime monitoring data.

GO TO DATA APPLICATIONS

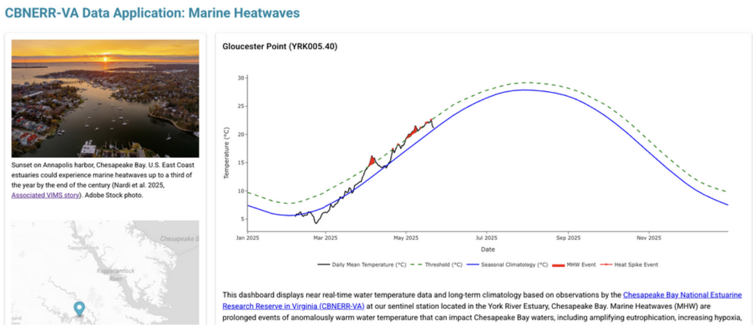
Algal Blooms



The Algal Blooms Data Application provides access to the latest data on Algal Bloom events.

GO TO ALGAL BLOOM DATA APPLICATION

Marine Heat Waves



The Marine Heat Waves Data Application provides access to the latest data on Marine Heat Wave events.

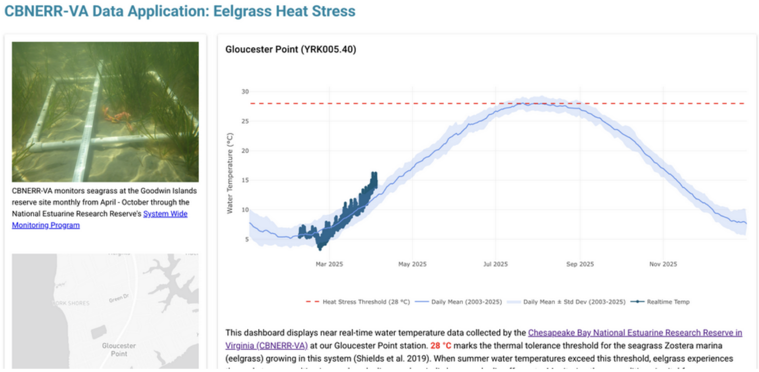
GO TO MARINE HEAT WAVES DATA APPLICATION

Acuff Center for Aquaculture Operations

This application provides recent information on aquaculture operations at the Acuff Center.

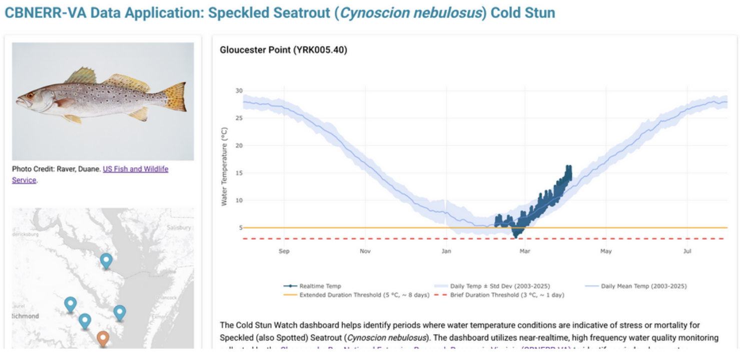
GO TO ACUFF CENTER FOR AQUACULTURE OPERATIONS DATA APPLICATION

Eelgrass Heat Stress



The Eelgrass Heat Stress Data Application provides access to the latest data on Eelgrass heat stress events.

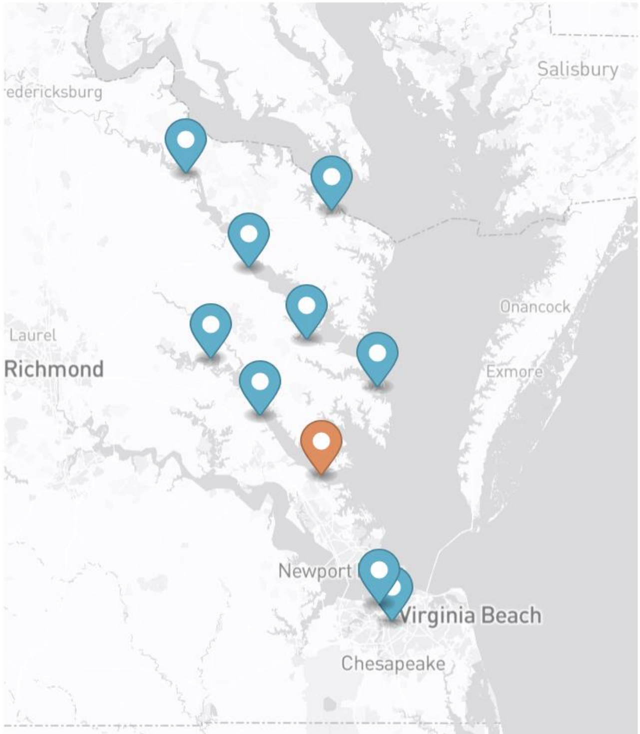
Speckled Trout Cold Stun



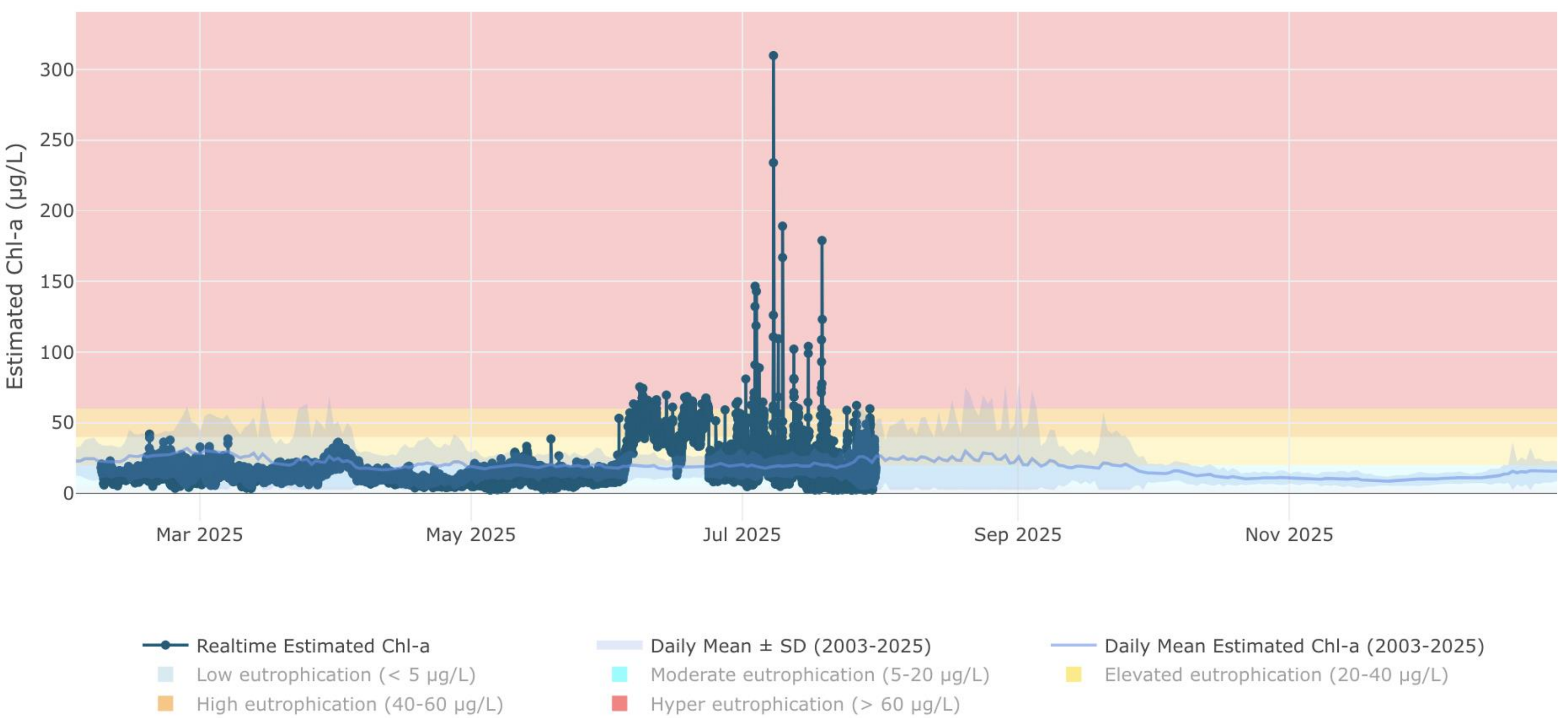
The Cold Stun Watch application provides access to the latest data on Speckled Trout cold stun events.

VECOS Data Application: Algal Blooms

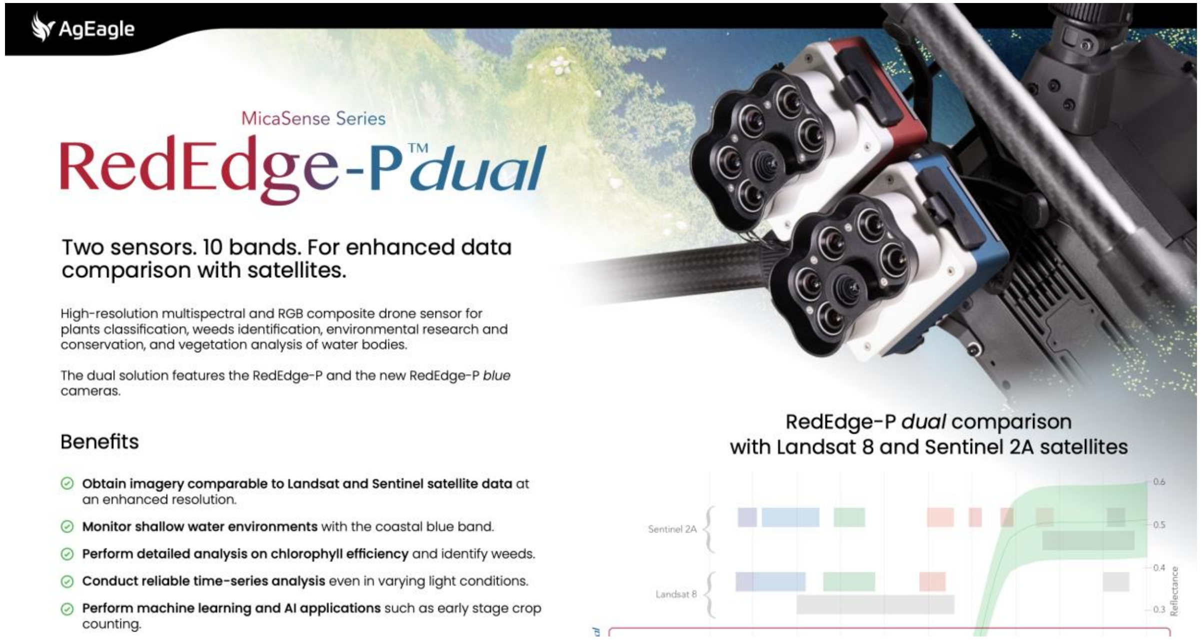
Photo Credit: Vogelbein, Wolfgang. [Virginia Institute of Marine Science](#).



Gloucester Point (YRK005.40)



Eutrophication, typically driven by excess of nutrients leading to an overabundance of phytoplankton, poses a current and growing threat to coastal ecosystems, impacting water quality, local economies, and public health. Monitoring these blooms, many of which can be harmful due to impacts on water oxygen levels or toxin production, is essential for managing coastal resources, but the complexity of environmental conditions along with the diversity of algal species, lead to detection and monitoring challenges due to highly temporal and spatial variability of algal blooms. A key indicator of algal growth is the plant pigment chlorophyll, which serves as a measure of algal biomass. To track and respond to bloom events effectively, we rely on advanced monitoring platforms that use in situ (on-site) water quality sensors capable of measuring chlorophyll fluorescence in near-real-time.


AgEagle
MicaSense Series
RedEdge-P™ dual
Two sensors. 10 bands. For enhanced data comparison with satellites.
High-resolution multispectral and RGB composite drone sensor for plants classification, weeds identification, environmental research and conservation, and vegetation analysis of water bodies.
The dual solution features the RedEdge-P and the new RedEdge-P blue cameras.
Benefits
Obtain imagery comparable to Landsat and Sentinel satellite data at an enhanced resolution.
Monitor shallow water environments with the coastal blue band.
Perform detailed analysis on chlorophyll efficiency and identify weeds.
Conduct reliable time-series analysis even in varying light conditions.
Perform machine learning and AI applications such as early stage crop counting.
RedEdge-P dual comparison with Landsat 8 and Sentinel 2A satellites
Sentinel 2A
Landsat 8
0.6
0.5
0.4
0.3
Reflectance


Playmate

- Anchoring Planet imagery with dataflow platforms shows promise
  - Fills in-situ spatial and temporal monitoring gaps
  - Opportunity to incorporate satellite data into water clarity assessment

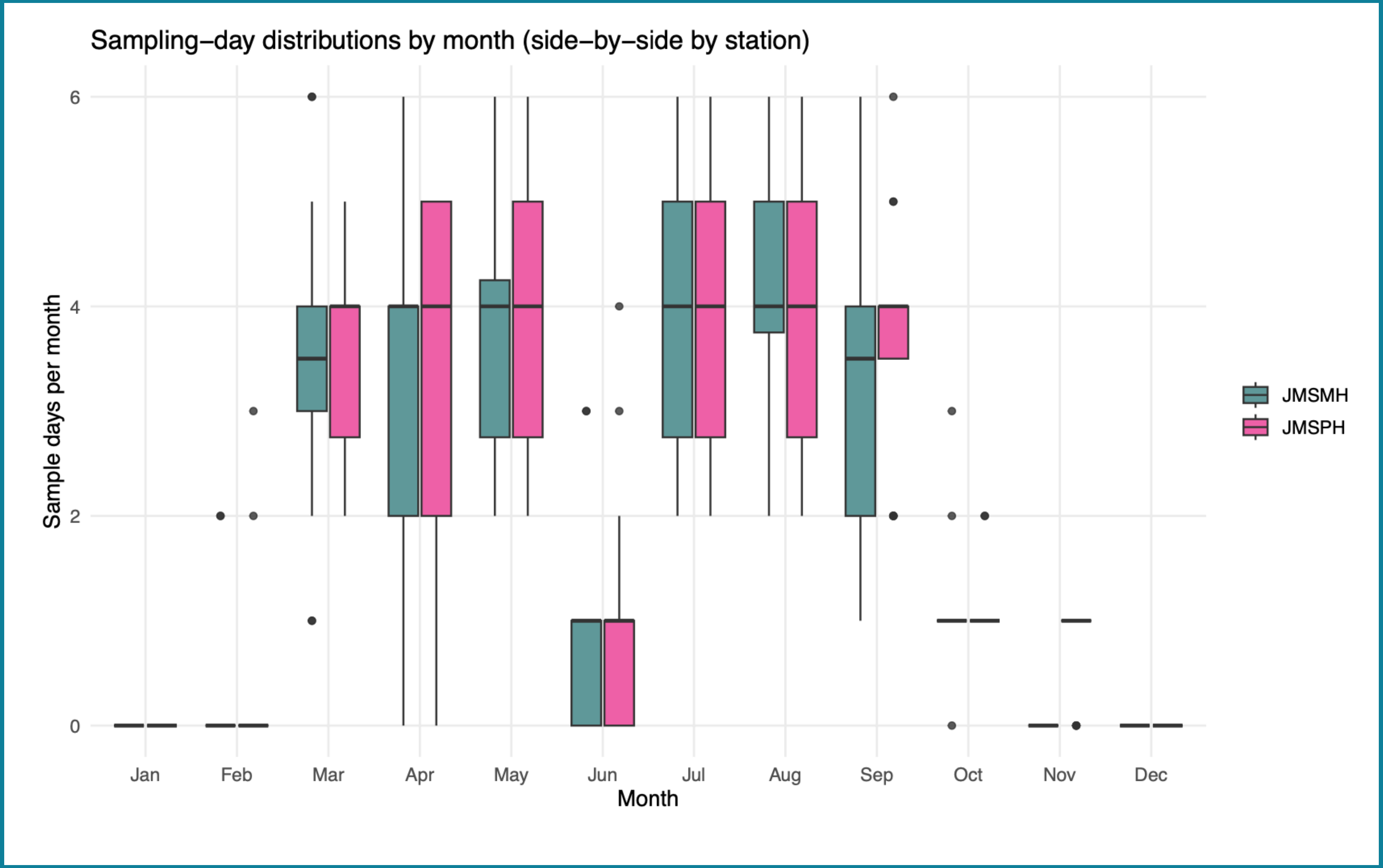
Next Steps

- Model development to operationalize
  - Bayesian and/or machine learning hierarchical models
  - Uncertainty estimates for K_d
- Scale to additional tributaries and satellite platforms
  - James River (HRSD partnership)
  - Add Sentinel imagery
- Light conditions trends analysis of fixed station and dataflow data in lower tributaries (Polyhaline and Mesohaline)

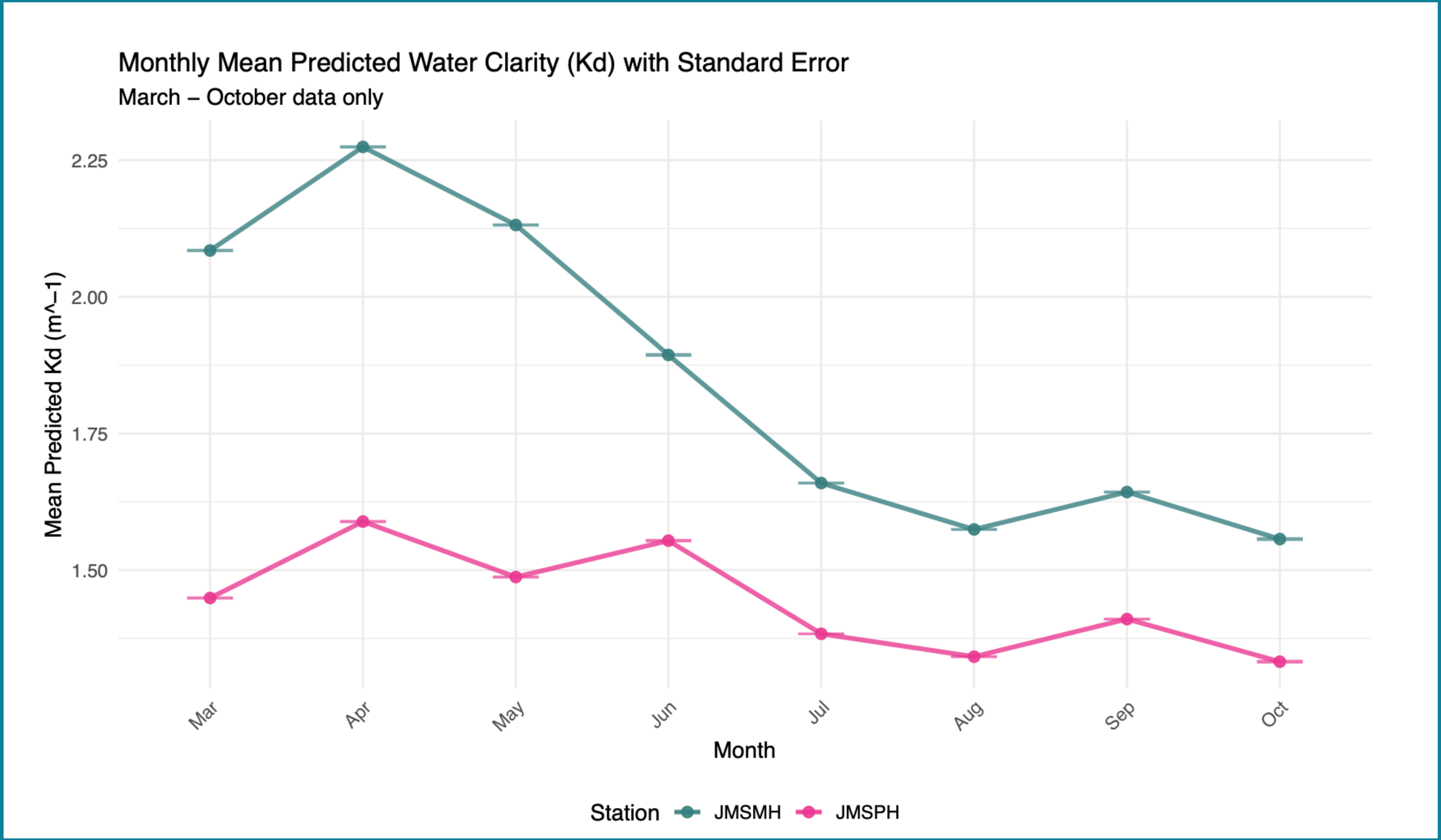
Virginia Estuarine & Coastal Observing System

vecos.vims.edu

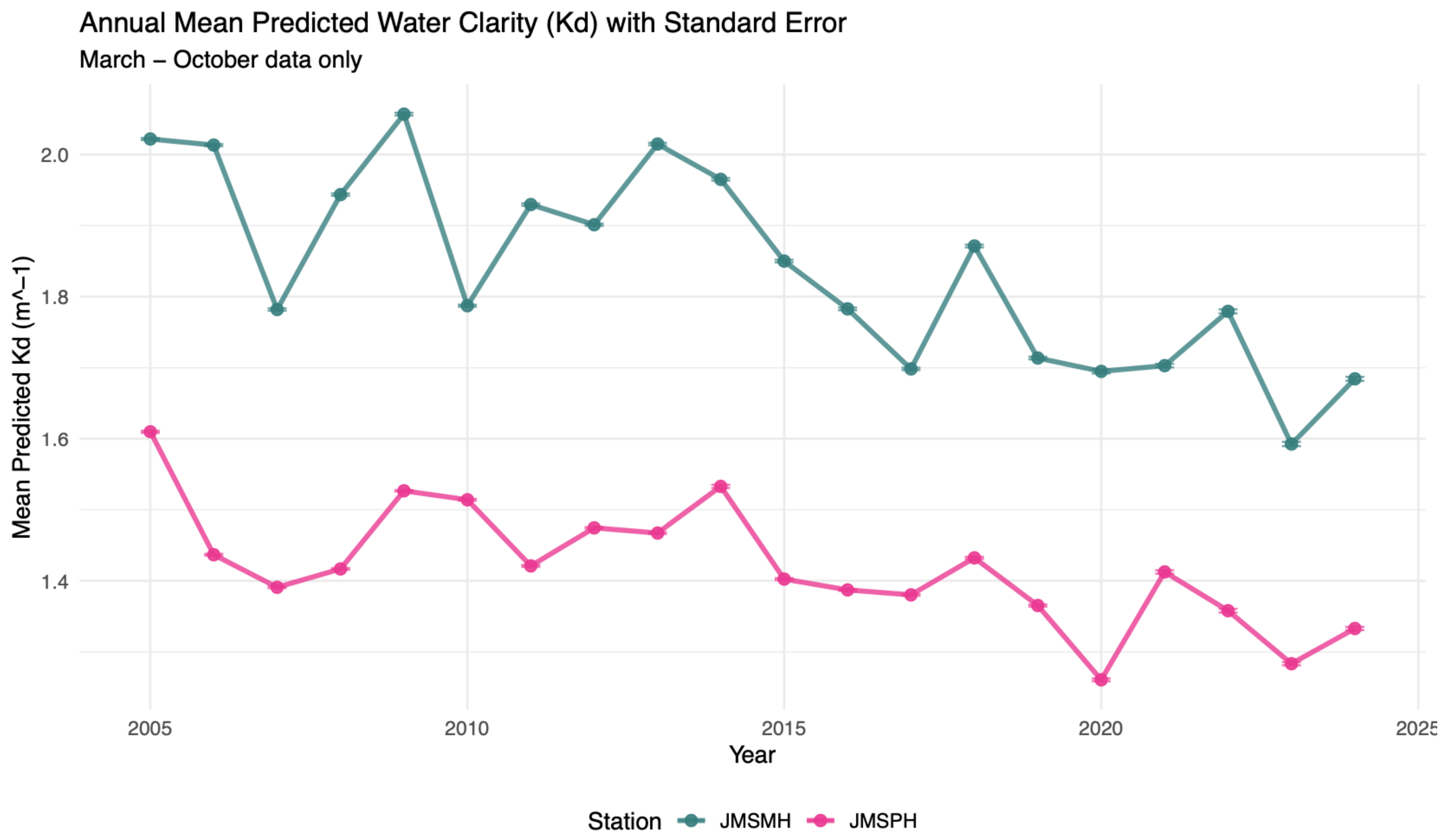
David Parrish
parrishd@vims.edu



Sampling–day distributions by month (side–by–side by station)
Sample days per month
0
2
4
6
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Month
JMSMH
JMSPH



Monthly Mean Predicted Water Clarity (Kd) with Standard Error
March – October data only
Mean Predicted Kd (m^-1)
2.25
2.00
1.75
1.50
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Month
Station
JMSMH
JMSPH


Annual Mean Predicted Water Clarity (Kd) with Standard Error
March – October data only
Mean Predicted Kd (m^–1)
2.0
1.8
1.6
1.4
2005
2010
2015
2020
2025
Year
Station
JMSMH
JMSPH

Methodology Challenges

- Segments with low goals can easily pass the water clarity acres goal by having one cruise with good clarity.
- Segments with high SAV goals and moderate/high SAV, may not pass water clarity acres due to insufficient remaining shallow water habitat due to the 2.5 multiplication factor.
- Spatial interpolation and modelling error is not accounted for in methodology
- Spatial and temporal monitoring constraints limit data coverage (1 cruise per month)
- Opportunity for development of Kd models by analyzing at a larger verification dataset (space and time) instead of focusing on current segment could improve models
- Sampling can be biased to good weather
- Opportunity to integrate other existing datasets (ex. fixed stations, satellite)

Adapted From Trice & Parrish, 2022, STAC Advanced Monitoring Workshop