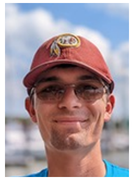
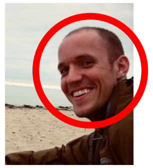
Combined In-Situ and Remote Sensing of Water Quality in Virginia Tidal Waters

Presentation to CBP Criteria Assessment Protocol Workgroup by Carl Friedrichs 3/7/24
Additional project leads: Willy Reay and Dave Parrish

Main funding sources (alphabetical order): NOAA (CBIBS, NERRS), State of Virginia (VA DEQ, VIMS), US EPA

CBNERR-VA Year-Round Staff focused largely = ○ or partly = ◌ on Water Quality





CHESAPEAKE BAY
NATIONAL ESTUARINE
RESEARCH RESERVE
VIRGINIA

VIMS WILLIAM & MARY
VIRGINIA INSTITUTE OF MARINE SCIENCE

Our team at CBNERR-VA / VIMS has been working to balance two approaches for intense, in-situ WQ sampling:

- Long-term, spatially distributed, continual monitoring, fixed stations (CMON) (w/ high-resolution in time).
- Monthly, CB segment-focused, boat-mounted, underway sampling (DataFlow) (w/ high resolution in space).

Both are based on YSI water quality sondes calibrated by field water samples and lab standards, and they are both posted on our Virginia Coastal & Estuarine Observing System (VECOS) web data portal.

YSI EXO2 Sensor Package

Salinity, temp, pressure, turbidity, pH, dissolved oxygen, chlorophyll, (and we are now starting to add fDOM)

CMON measurement every 15 minutes

DataFlow measurement every 2 sec @ 25 knots ≈ every 25 meters

K_d is then calculated from EXO2 by non-linear multiple regression of WQ parameters against in-situ LI-COR profiles.

VECOS CMON stations:

NERRS

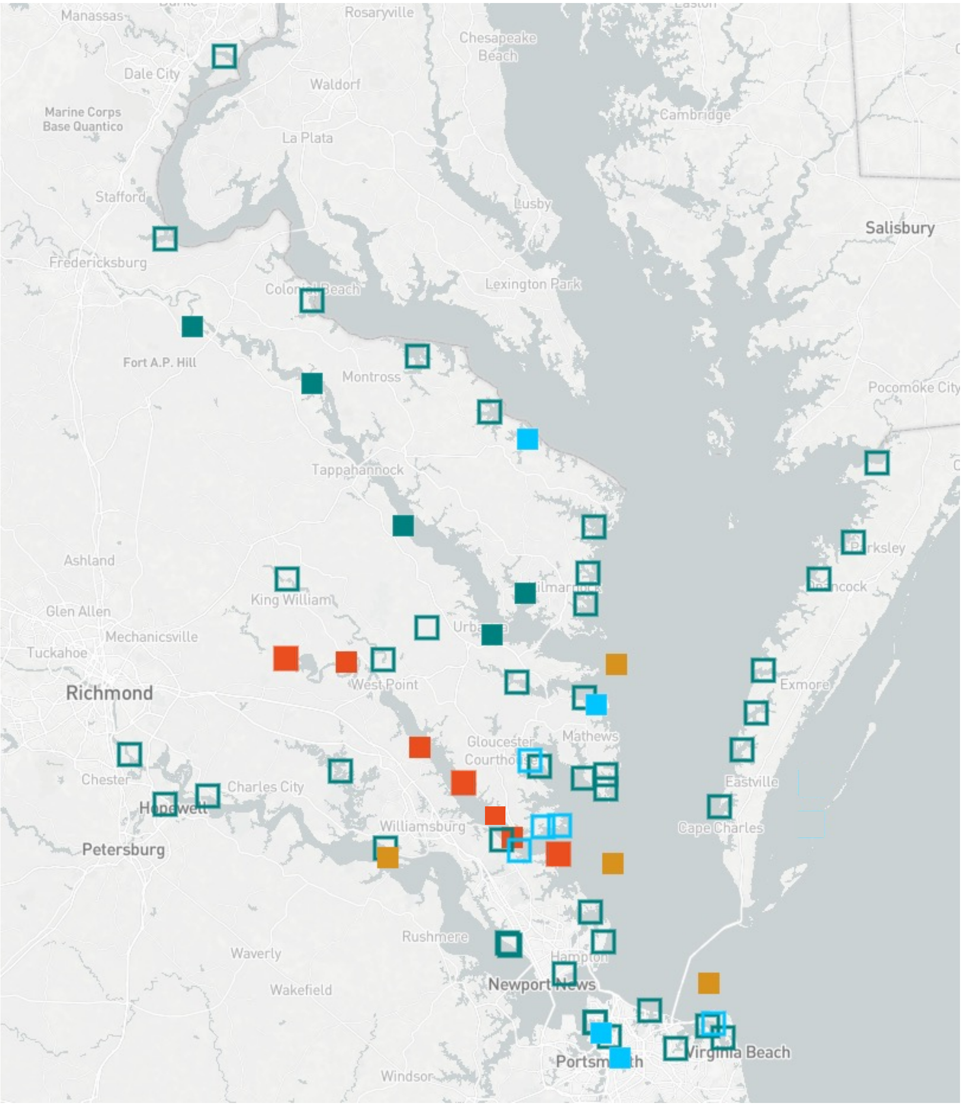
CBIBS

Active in 2023

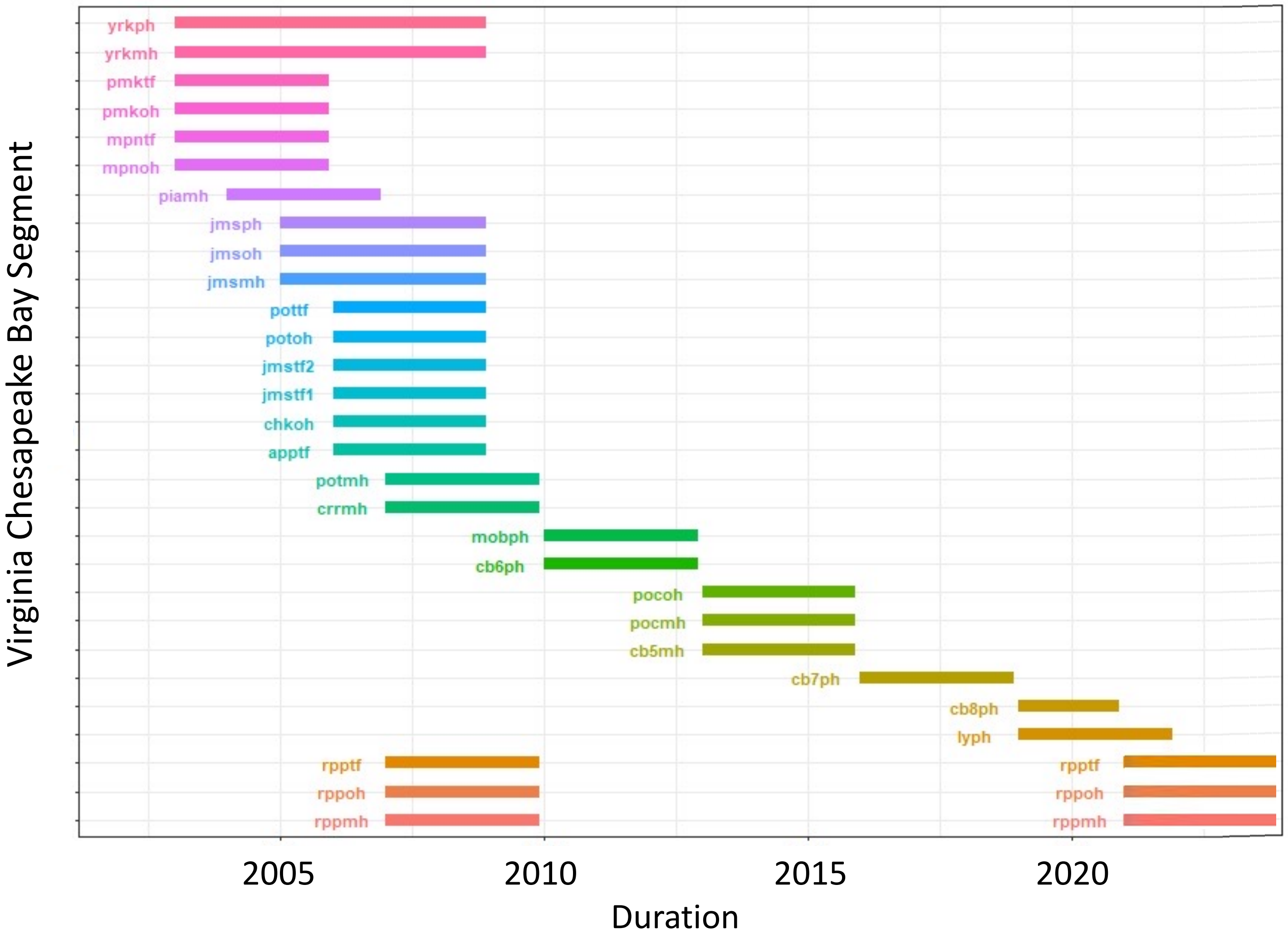
VA-DEQ /EPA/CBP

VIMS Water Quality Initiatives

Past CMONs



VECOS DataFlow History:



As pointed out by Peter Tango (at CBP Hypoxia Collaborative Team Meeting 3/4/2024):

- “Modeling community has expressed interest in the value of fixed monitoring sites for long-term reference in calibration and verification.” (e.g., CMON)
- “Habitat suitability may be interested in seasonal data, duration of data collection has not typically been specified in our discussions.” (e.g., DataFlow)

For shallow water and near-surface water water quality parameters, how can we have the best of both worlds?

- Combine CMON, DataFlow, and water sampling with drone and satellite-based remote sensing.
- Utilize machine learning to optimize remote sensing calibration and temporal interpolation.

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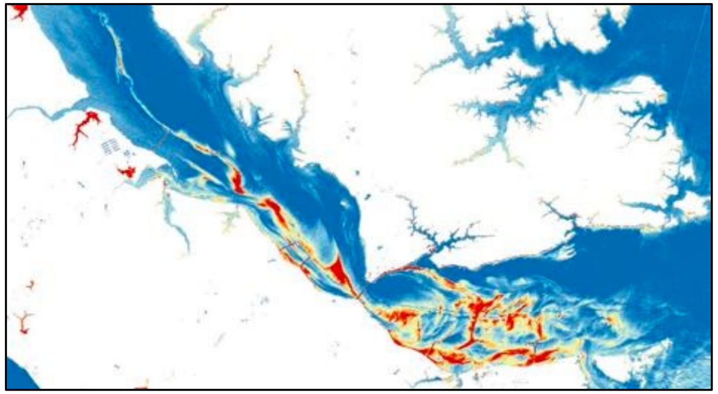

(Sentinel-2A 705 nm / 665 nm)

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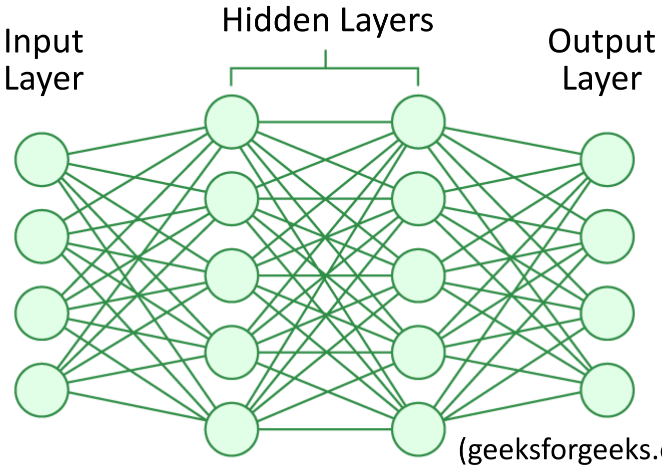


(geeksforgeeks.org)

Shown in figure: Plans for 2024 (and long-term going forward), VIMS-maintained CMON observation network for Virginia's main Chesapeake Bay tidal tributaries.

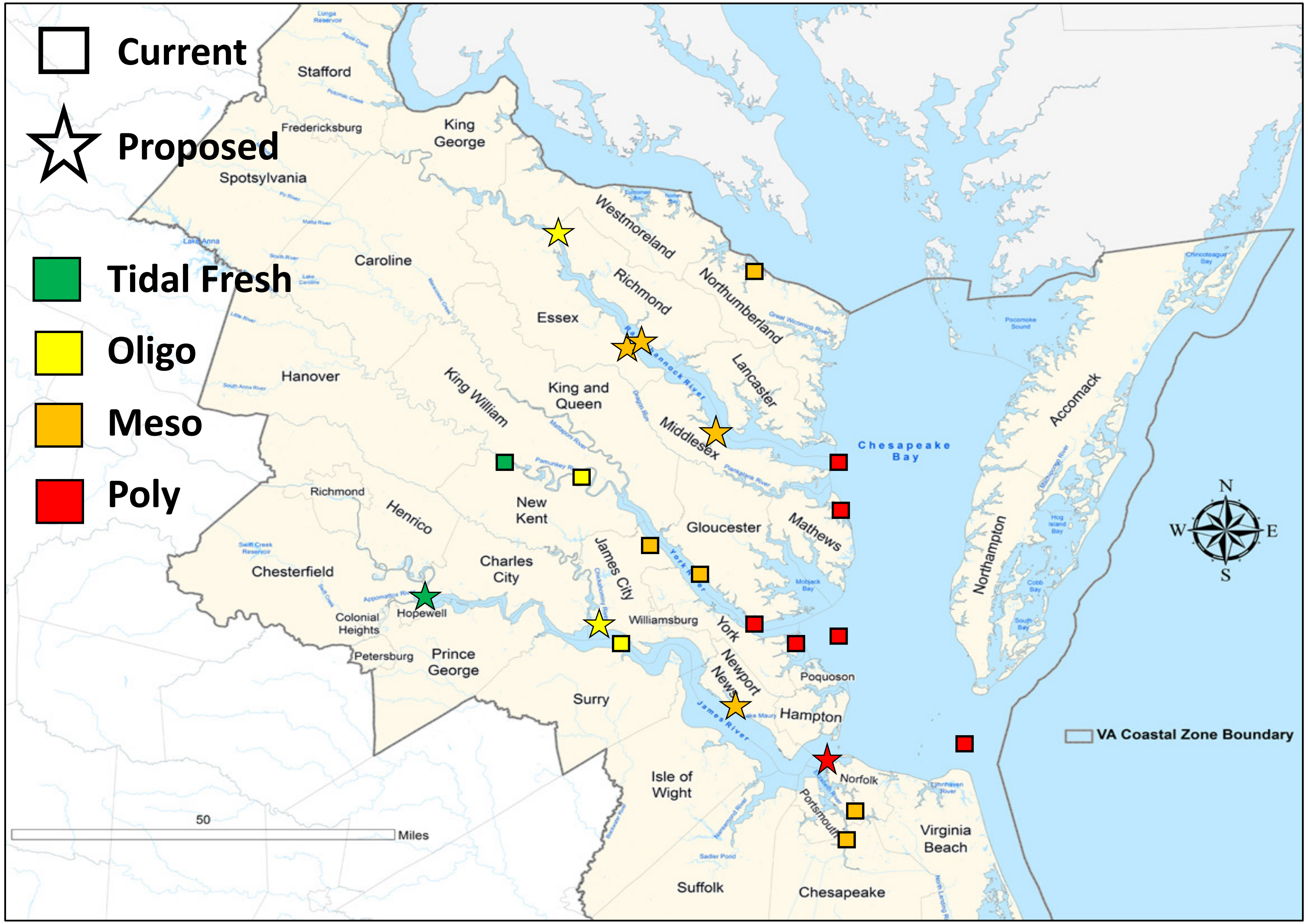
NERRS-funded network in York has been essentially continuous and year-round since 2003 (> 20 years).

VIMS/CBNERR-VA began maintaining long-term CBIBS buoys in Virginia waters in 2013 (> 10 years).

Long-term, VIMS-supported stations were added at two VA oyster hatcheries in 2020 and two Elizabeth River Project sites in 2021.

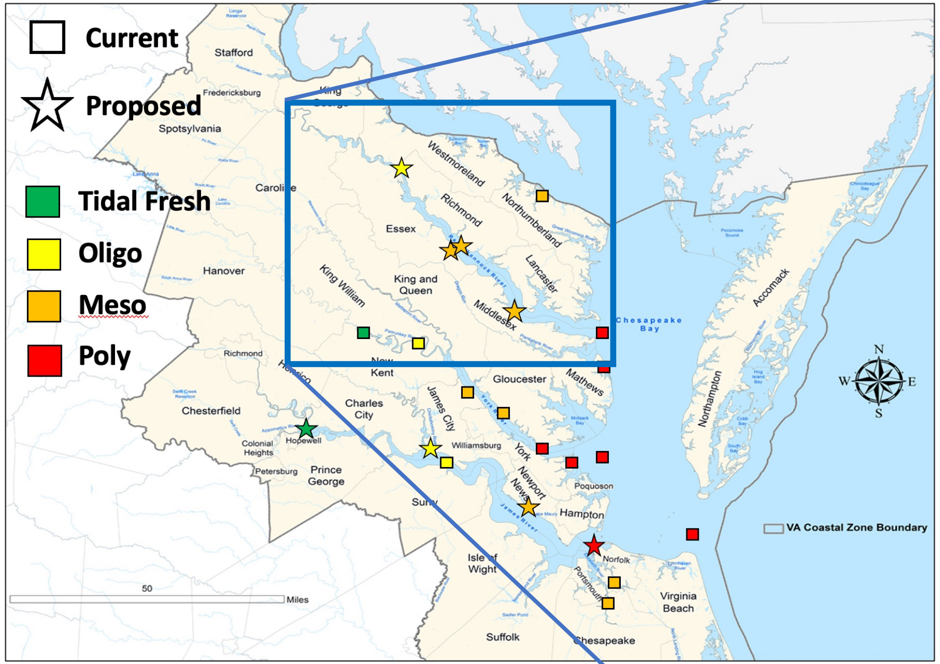
In 2024, four additional, long-term CMONs are planned to be deployed along the Rappahannock. Future expansion then likely to focus on the James.

Start of long-Term (hopefully permanent) CMON Network:



(Background map from deq.virginia.gov)

Long-Term CMON Network: Plans for VIMS/CBNERR-VA coverage of the Rappahannock in 2024



Kendale Farm, Bowlers Wharf, & Christchurch would continue sites occupied in the Rappahannock during 2021-2023.

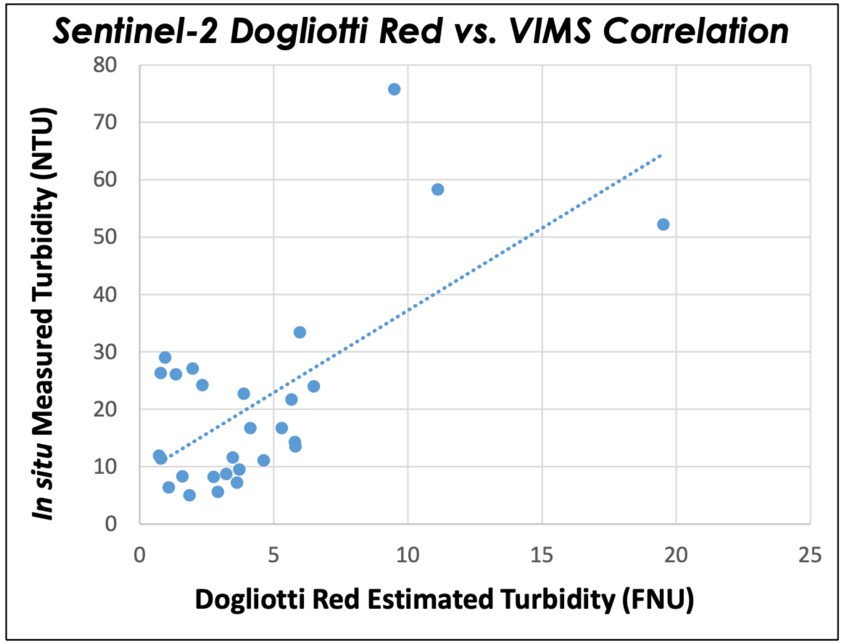
Bowlers Rock is the location of a platform in the middle of the Rappahannock at the site of the former Bowlers Rock lighthouse.

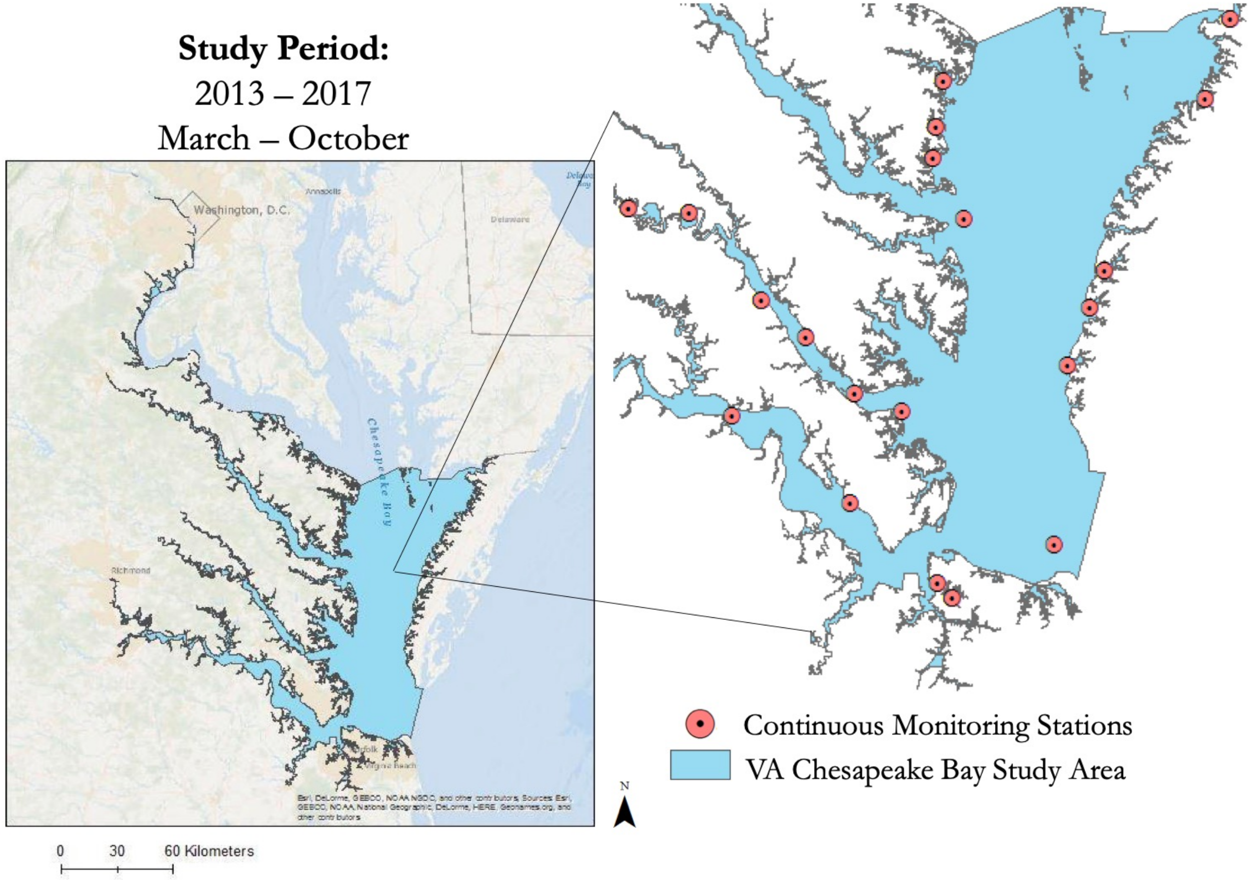
△ = VA-DEQ/CBP/EPA Rappahannock “deep water” cruise-based stations.

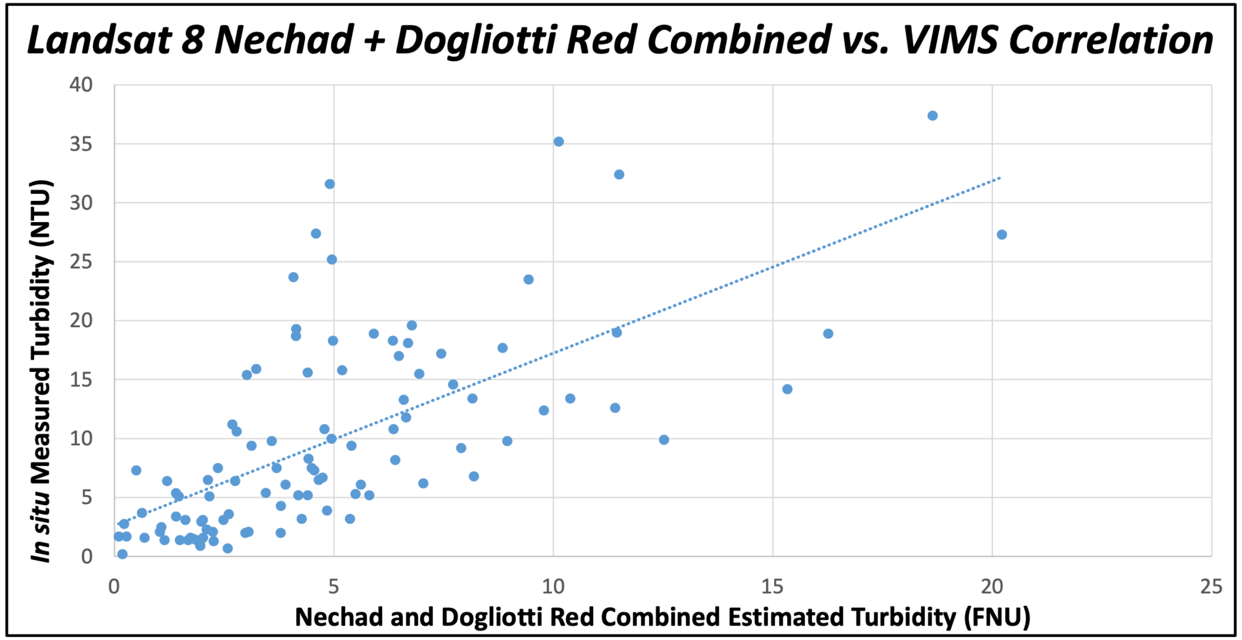
Present limitation in using CMON data to calibrate satellite images:

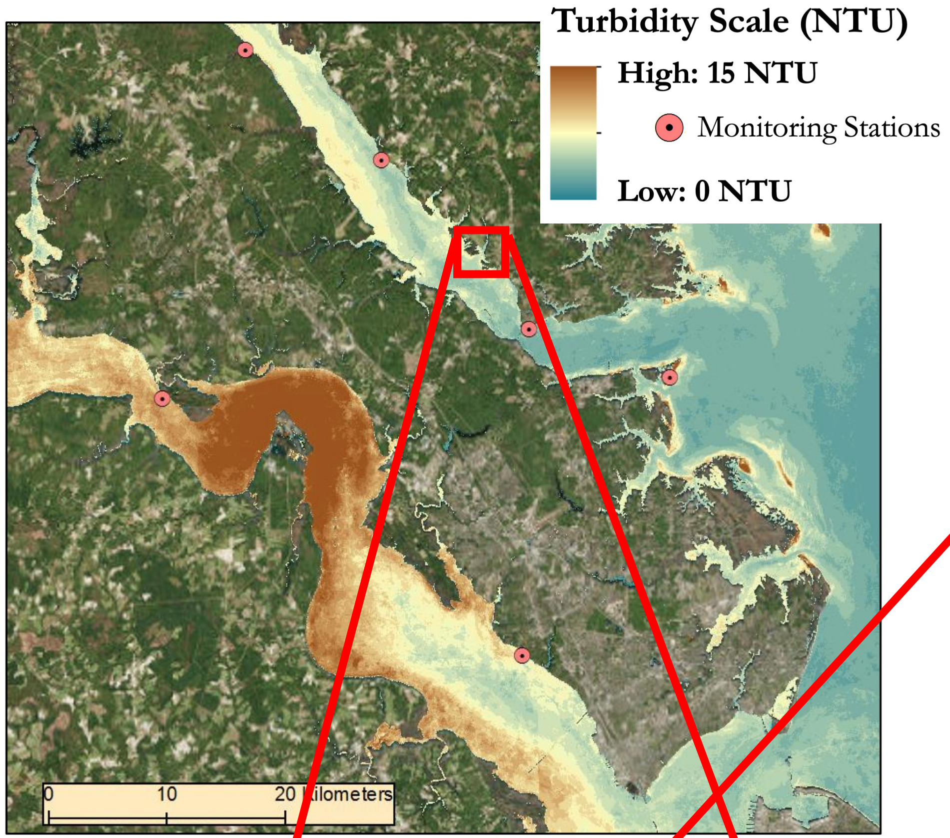
> 4 years of Landsat-8 + > 2 years of Sentinel-2 satellite coverage yielded < 150 usable co-located, near-simultaneous satellite pixels to correlate with VIMS CMON observations. DataFlow + drones linked to satellites could provide many 1000s.

Images from NASA 2017 DEVELOP Project presentations,
Advisor: Kenton Ross (NASA Langley)
Summer Team: Eli Simonson, Antonio Alvarado, Will Crowley
Partners: Tish Robertson (VA-DEQ), Peter Tango (USGS CBP)









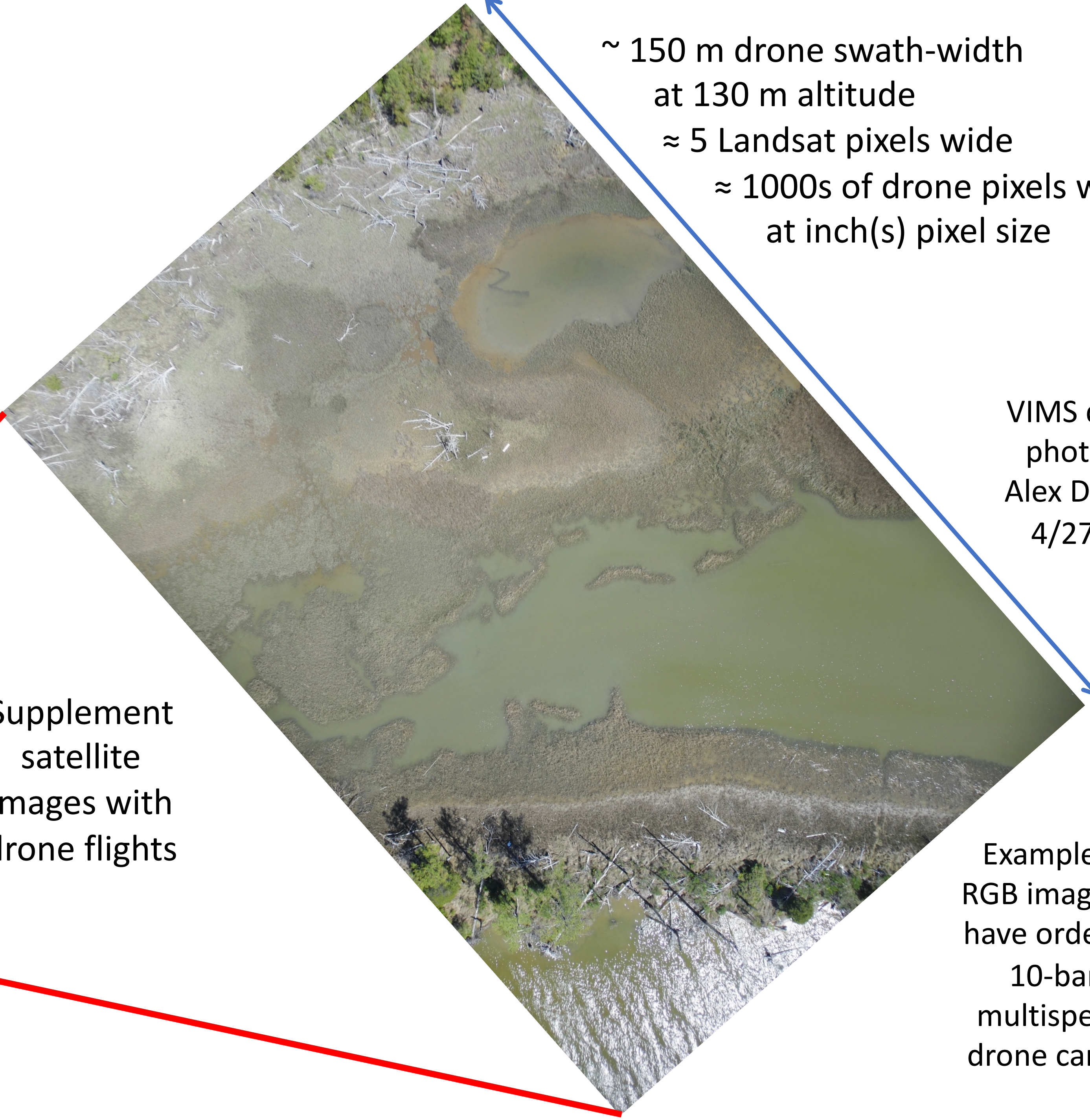
~ 3 km ≈ 100 pixels

Landsat-8
2013 mosaic

~ 30-meter
pixel size

NASA
DEVELOP
(2017)

Supplement
satellite
images with
drone flights



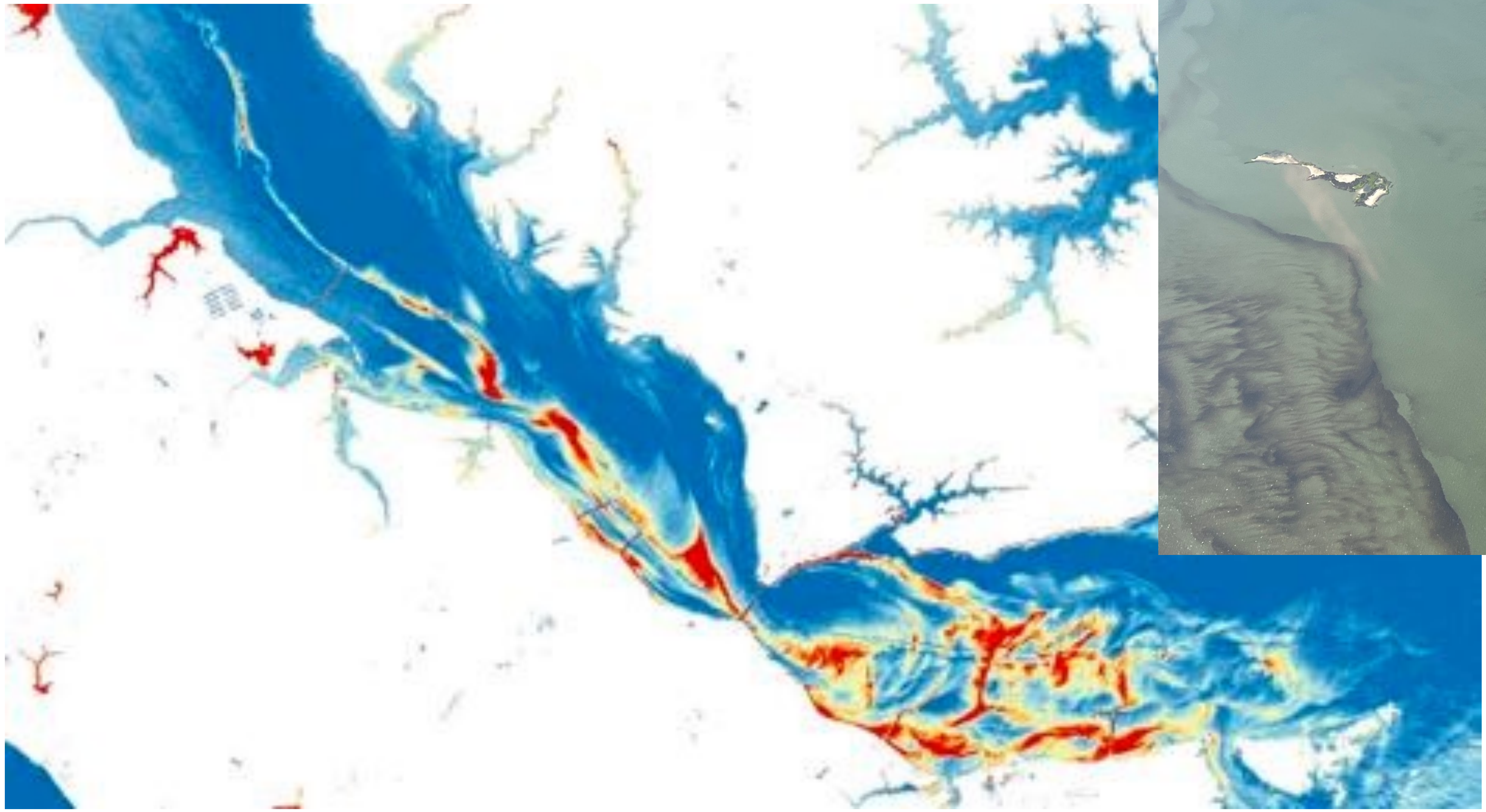
~ 150 m drone swath-width
at 130 m altitude
≈ 5 Landsat pixels wide
≈ 1000s of drone pixels wide
at inch(s) pixel size

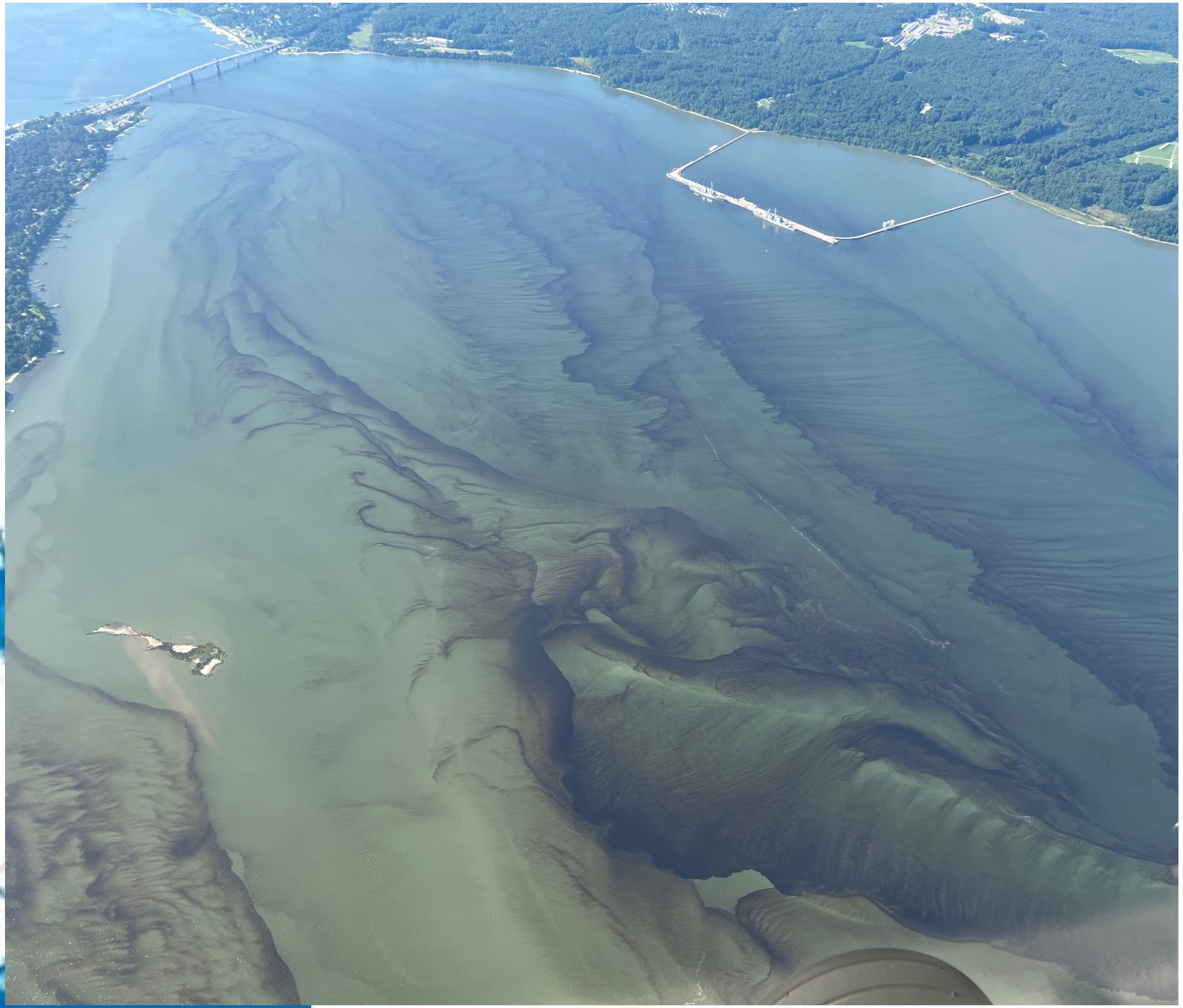
VIMS drone
photo by
Alex Demeo
4/27/21

Example is a
RGB image. We
have ordered a
10-band
multispectral
drone camera.

Also application to phytoplankton blooms

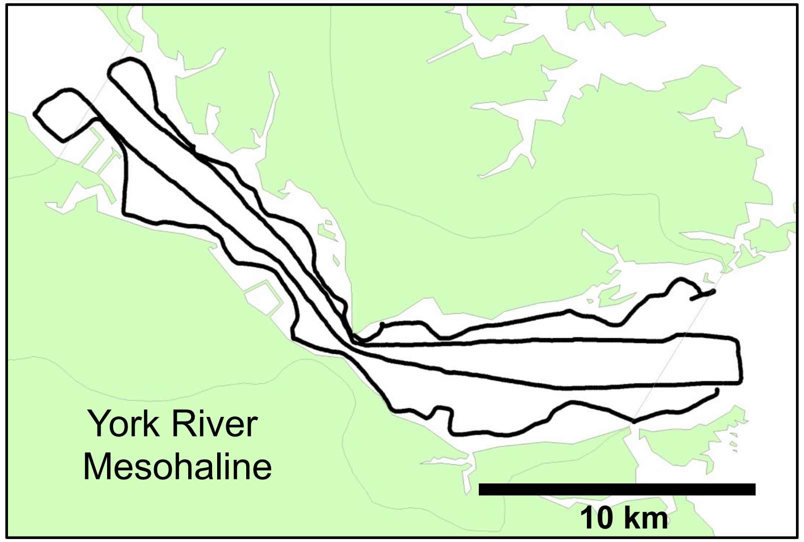
Sentinel-2A band ratio of 705 nm to 665 nm reflectance on 8/29/2016 (20-m pixel size)



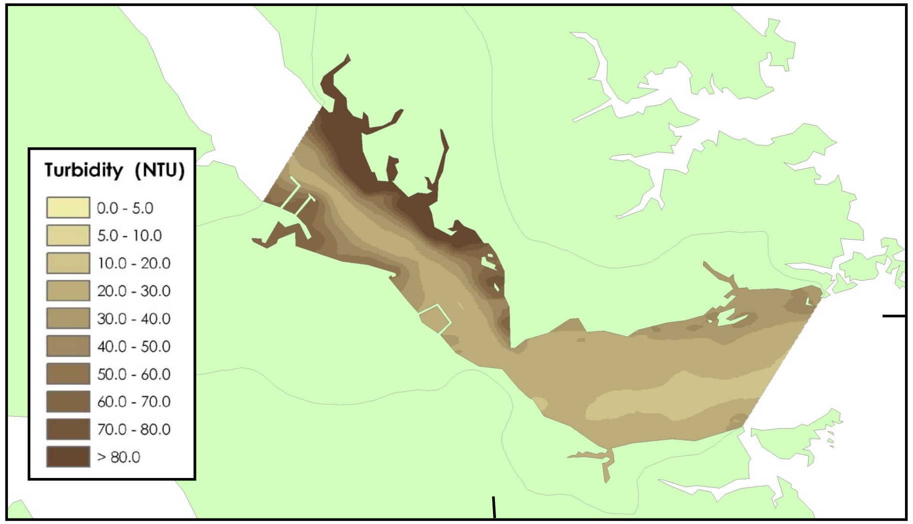


Marg bloom in the York River. 8/10/2022. Photo Credit Savannah Mapes

Combine DataFlow EXO2 cruises in the York River estuary with simultaneous drone flights and satellite images



Example of past VIMS DEQ-funded DataFlow Survey



Images from Dave Parrish (VIMS)

Example: with data collection ± 2 hours around satellite passage.

DataFlow could calibrate drone images that then calibrate satellite.

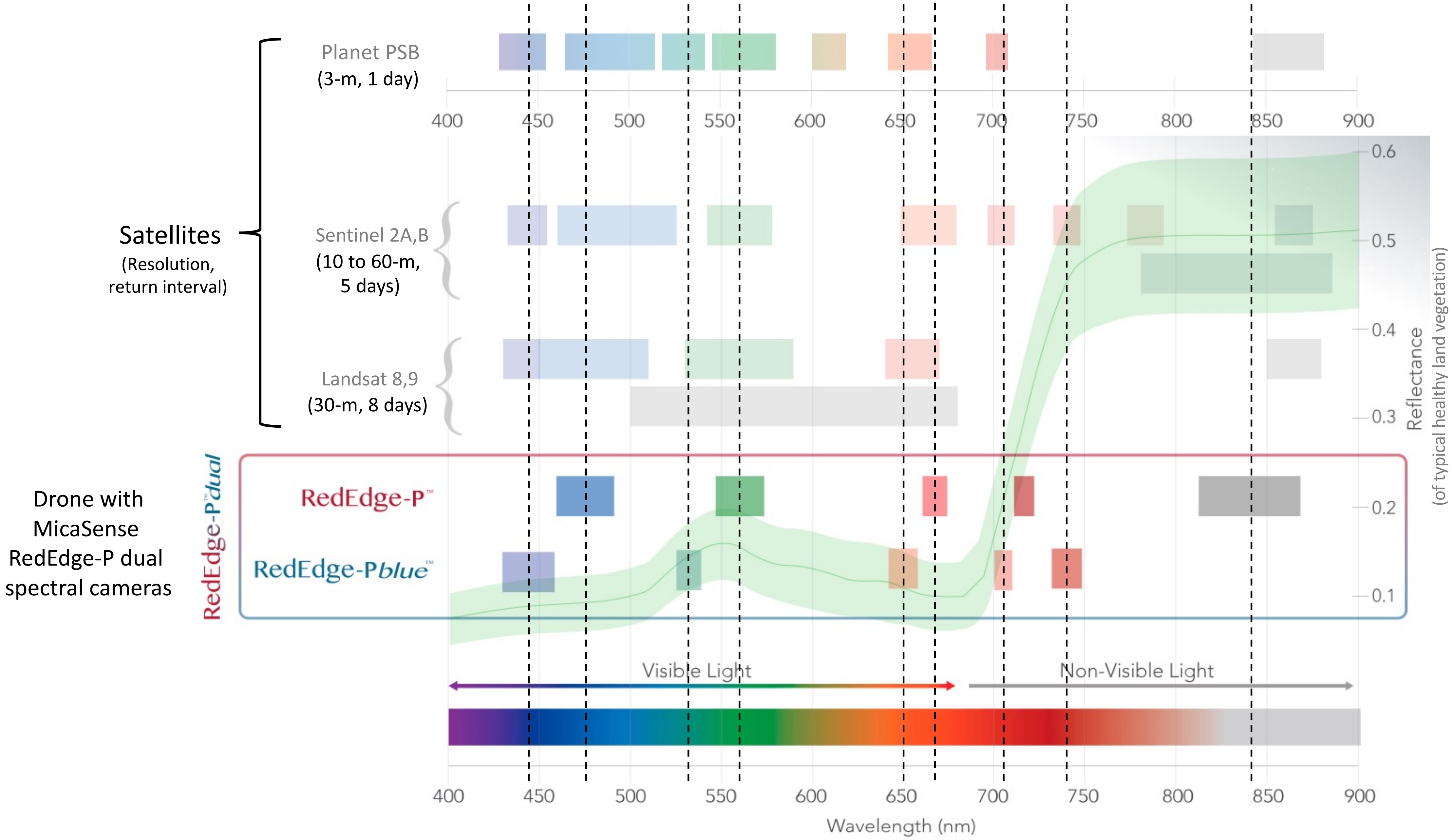
25 knots x 4 hours = up to 185 km of DataFlow lines.

Divide by 30 m → drone swath up to 6170 Landsat-8 pixels long.

x 5 satellite pixels wide → (best case scenario)

> 30,000 satellite pixels calibrated by a single DataFlow / drone survey.

Dashed lines highlight overlap of MicaSence drone camera's 10 spectral bands with satellite bands



Modified from AgEagle.com (AgEagle owns MicaSense)

Basis for most relevant empirical algorithms for satellite-derived water clarity products applied to date in the Chesapeake Bay/Mid-Atlantic Bight [*and elsewhere*] (expanded from Turner et al. 2021)

Product	Most relevant band or band ratio	Publications
Chl-a concentration	Green-to-blue	Werdell et al. (2009) Wynne et al. (2022)
	Red-to-green	Tzortziou et al. (2007) Le et al. (2013) Ioannou et al. (2014) Abbas et al. (2019)
Chl-a fluorescence	Red-edge ratio	Wynne et al. (2022)
	NIR-to-red	Gitelson et al. (2007) Ioannou et al. (2014) Gilerson et al. (2015) Xiong et al. (2023)
	Red band difference	Xiong et al. (2022) Xiong et al. (2023)
TSS	Red	Ondrusek et al. (2012) Hasan & Benninger (2017) DeLuca et al. (2018) Yunus et al. (2021)
	Red-to-green	*[e.g., Reisinger et al. (2017)]*
	Red-to-blue	Son & Wang (2012) Liu & Wang (2014)
	NIR (highly turbid waters)	*[e.g., Doxaran et al. (2003)]*

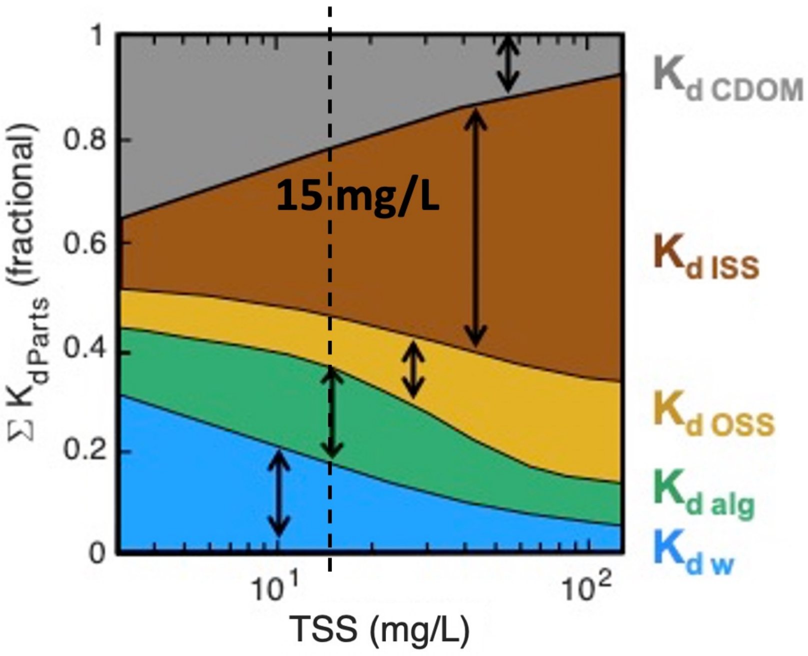
Product	Most relevant band or band ratio	Publications
Turbidity	Red	Ross & Gotschalk (2017) Simonson et al. (2017)
	Red-to-green	*[e.g., Wang et al. (2021)]*
	NIR (highly turbid waters)	*[e.g., Tao & Hill (2019)]*
K_d(490)	Green-to-blue (open ocean)	*[e.g., Morel et al. (2007)]*
	Red-to-blue (coastal waters)	Wang et al. (2009) Shi et al. (2013) Son & Wang (2015) Tomlinson et al. (2019) Xiang et al. (2023)
Secchi depth	Red	Crooke et al. (2017)
	Red-to-blue	Xiang et al. (2023)
CDOM, DOC	Green-to-blue ratio	Mannino et al. (2008) Mannino et al. (2014) Cao et al. (2018) Signorini et al. (2019)

Controls on Multiple Measures of Water Clarity in the York River Estuary

Dissertation work of Kelsey Fall (VIMS PhD, 2020)

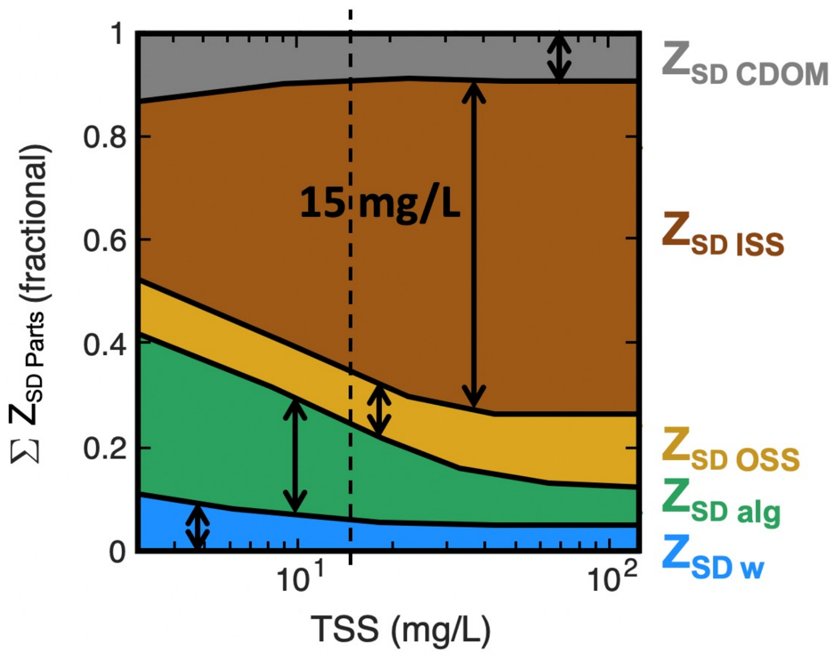
Optical equations for K_d, Z_{SD}, and Turbidity allow the relative contributions of water column to be evaluated:
CDOM = Colored Dissolved Organic Matter, ISS = Inorganic Suspended Solids,
OSS = Organic Suspended Solids (non-algal), alg = algae (associated with chl a), w = water .
Chesapeake Bay Program has identified **Total Suspended Solids (TSS) = 15 mg/L** as a critical level inhibiting Eel grass.

(1) Attenuation (Diffuse Attenuation Coefficient, K_d)



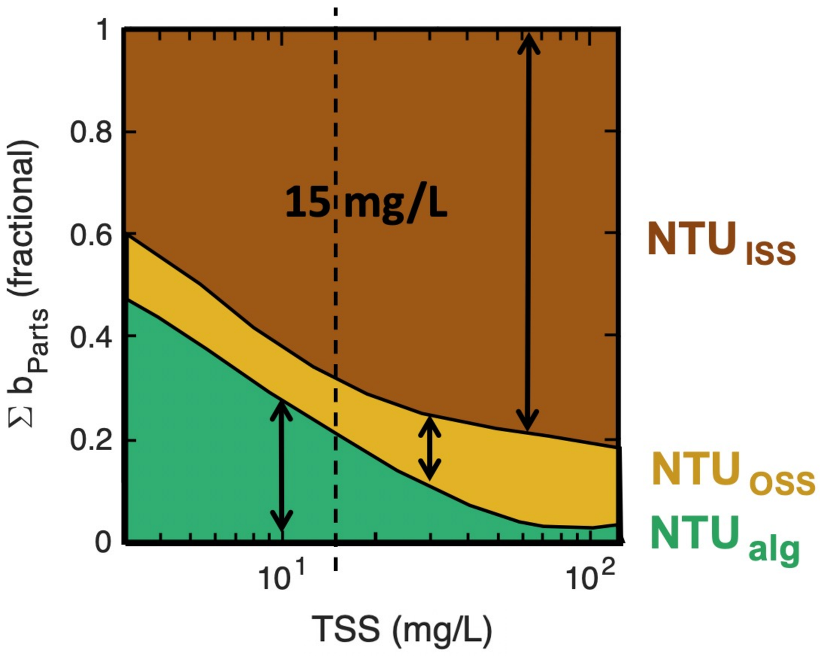
- At TSS ≈ 15 mg/L (Eel grass target), <u>ISS causes only 1/3</u> of K_d.

(2) Transparency (Secchi Depth, Z_{SD})



- At TSS ≈ 15 mg/L (Eel grass target), ISS causes ~ 58% of Z_{SD}.

(3) Turbidity (NTUs, b)



- At TSS ≈ 15 mg/L (Eel grass target), <u>ISS causes more than 2/3</u> of Turbidity.

Planned approach to transforming remote sensing reflectance into water clarity parameters:

- Utilize machine learning applied to all spectral bands shown to be relevant for water clarity.
- Apply same methodology to bands from multiple satellites (expect > 15 clear sky images per month).
- Also apply machine learning to spectral bands from drone (albeit more “proof of concept” stage…).
- Use DataFlow, CMON, and CBP “deep water” monitoring data to train machine learning.

Leverage Dave Parrish’s dissertation work, working title:

“The integration of high-frequency water quality monitoring and remote sensing data and its applications for resource management in the Chesapeake Bay, VA”

Leverage Dave’s PhD advisory committee:

- Carl Friedrichs and Willy Reay (VIMS Co-PIs on VA-DEQ/EPA funded shallow water monitoring.)
- Grace Chiu (Expert in environmental and Bayesian statistics, focus on estimation of uncertainty.)
- Tish Robertson (Expert in analysis of water quality monitoring data for standards assessment.)
- Jian Shen (Expert in water quality modeling and applications of machine learning using satellite data.)