Building the capacity of monitoring water quality in coastal waters: Pilot studies in the Chesapeake Bay

Guangming Zheng[1,2], Paul M. DiGiacomo[1], Marilyn Y. Murphy[1]

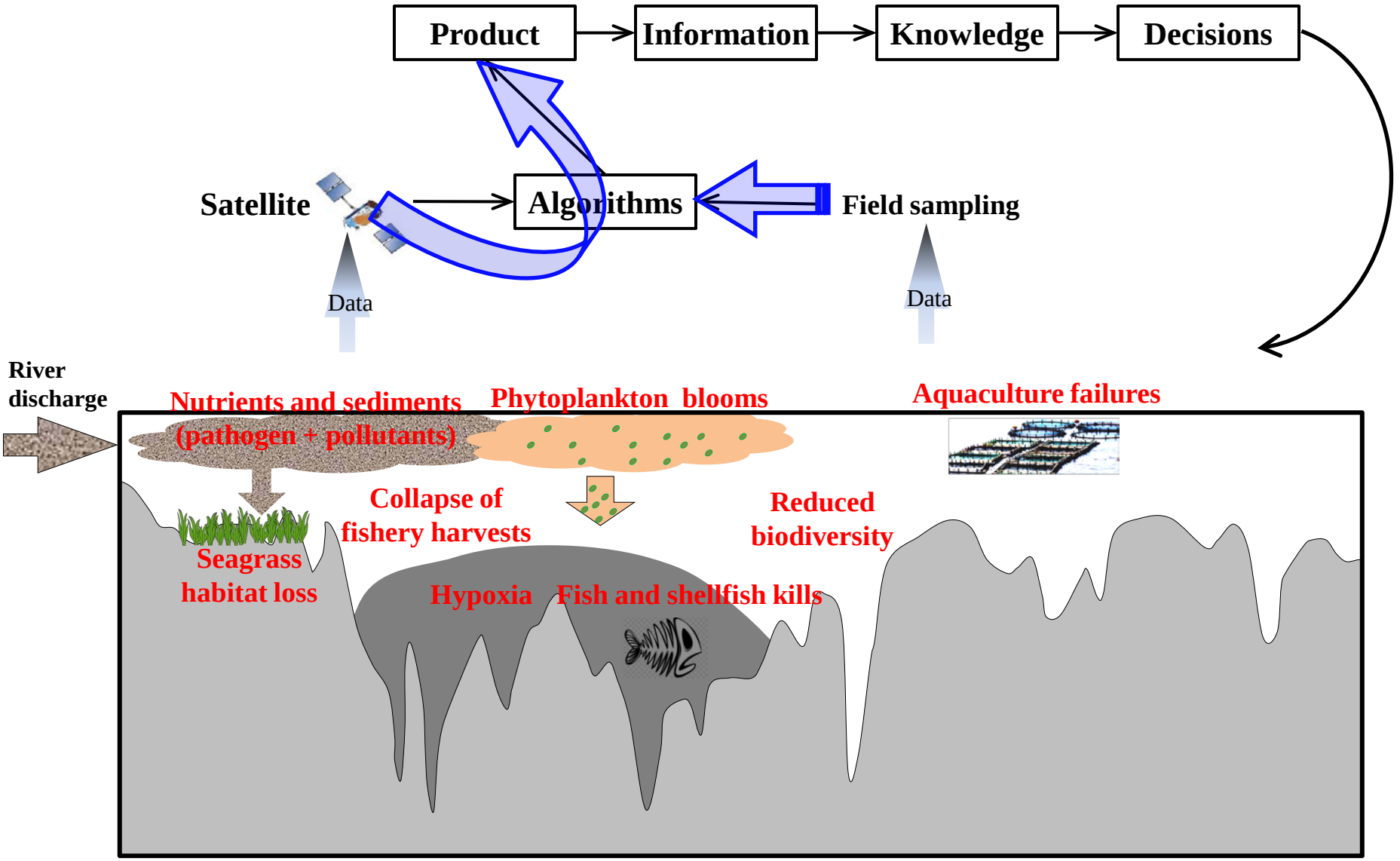
[1]*NOAA/NESDIS/STAR*

[2]*Global Science & Technology, Inc.*



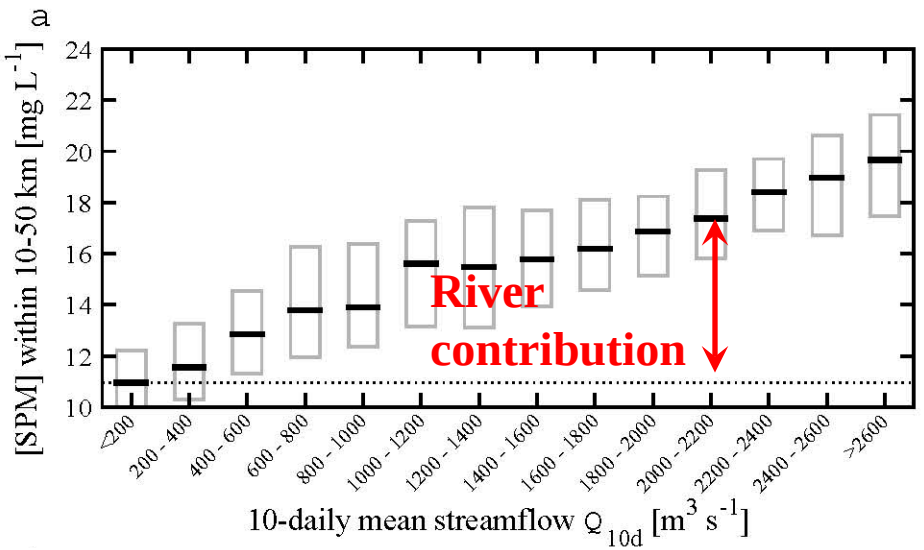


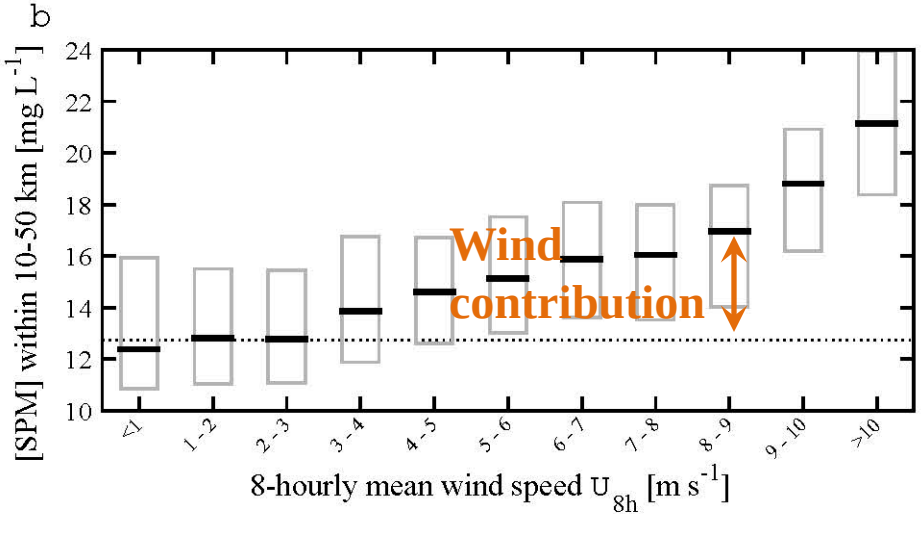
Water quality remote sensing in the Chesapeake Bay

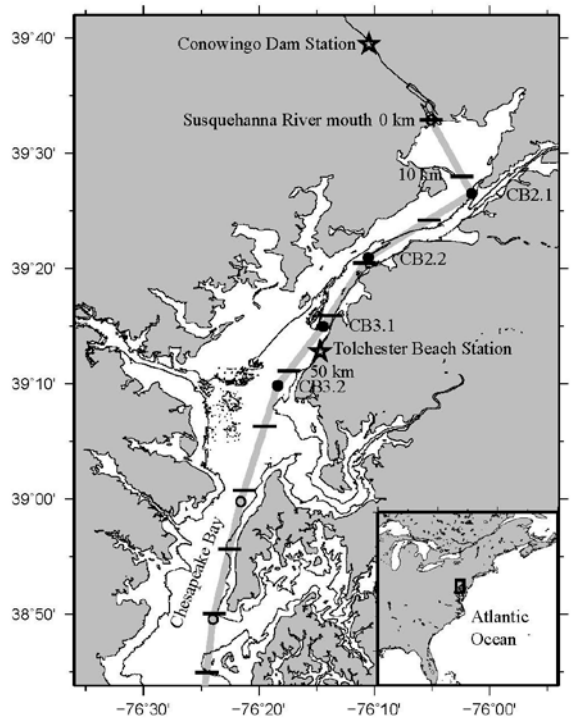


Evolution of sediment plumes in the Chesapeake Bay

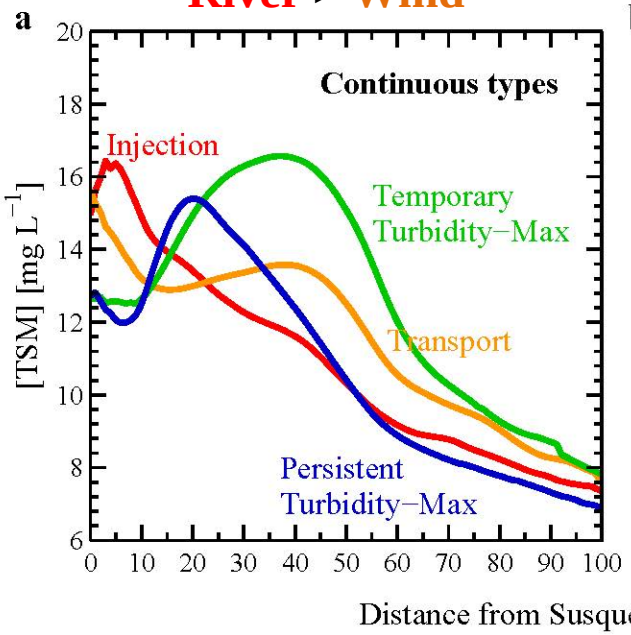
[*Zheng et al.*, 2015a]



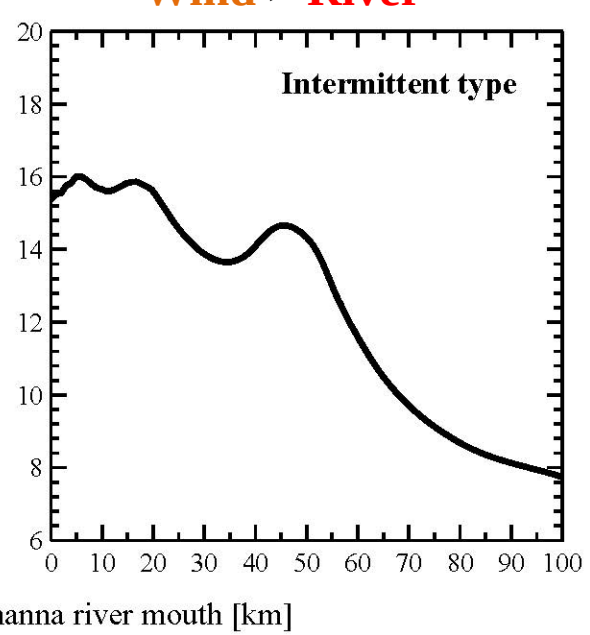




River > Wind

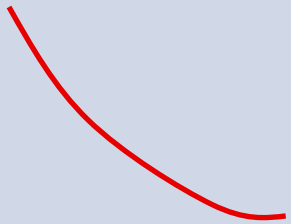
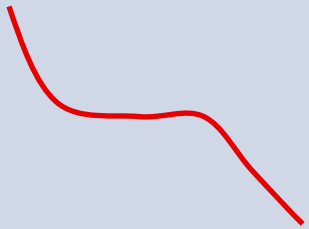
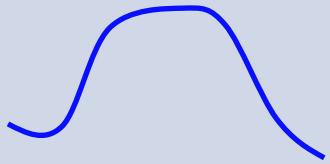
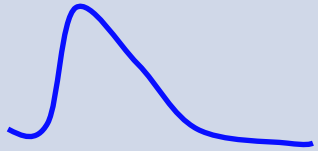


Wind > River

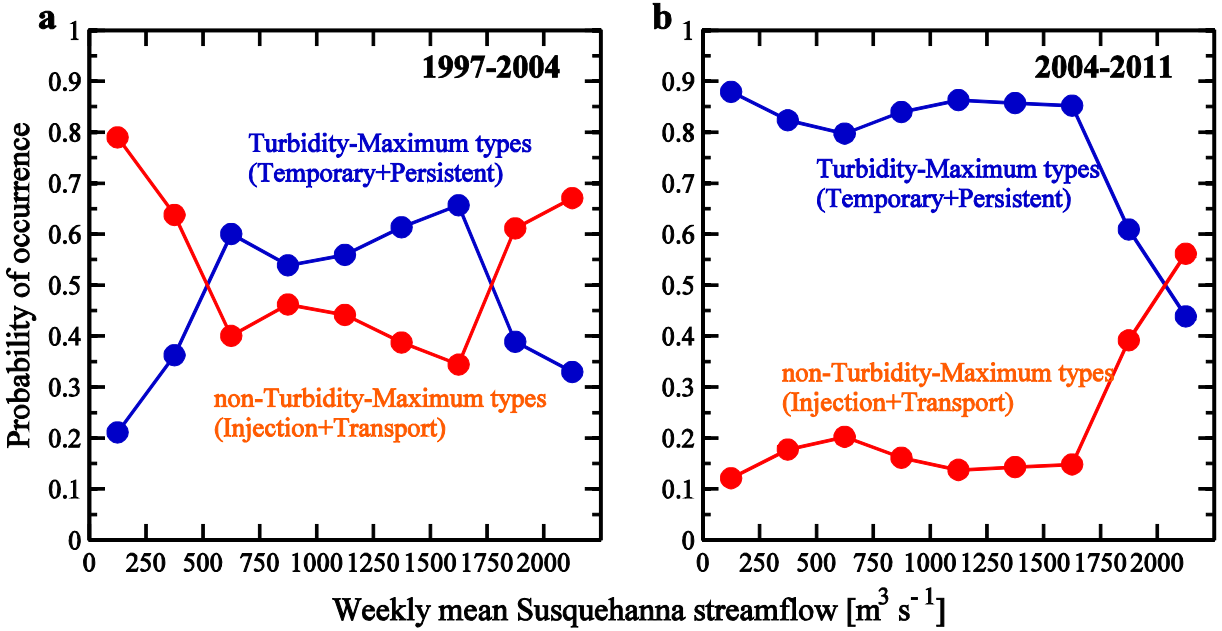


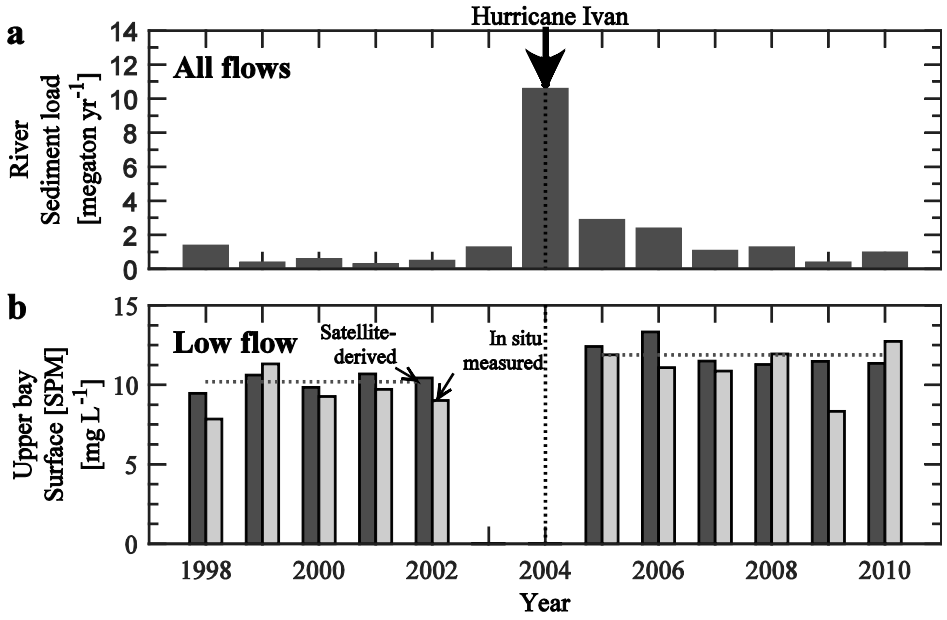
Distance from Susquehanna river mouth [km]

Short-term evolution of sediment plumes after discharge events

Types	Injection	Transport	Temporary Turbidity Max	Persistent Turbidity Max
Spatial shape of [SPM]				
Timing (days)	0–5	3–10	5–30	>13

Long-term regime shift of typology

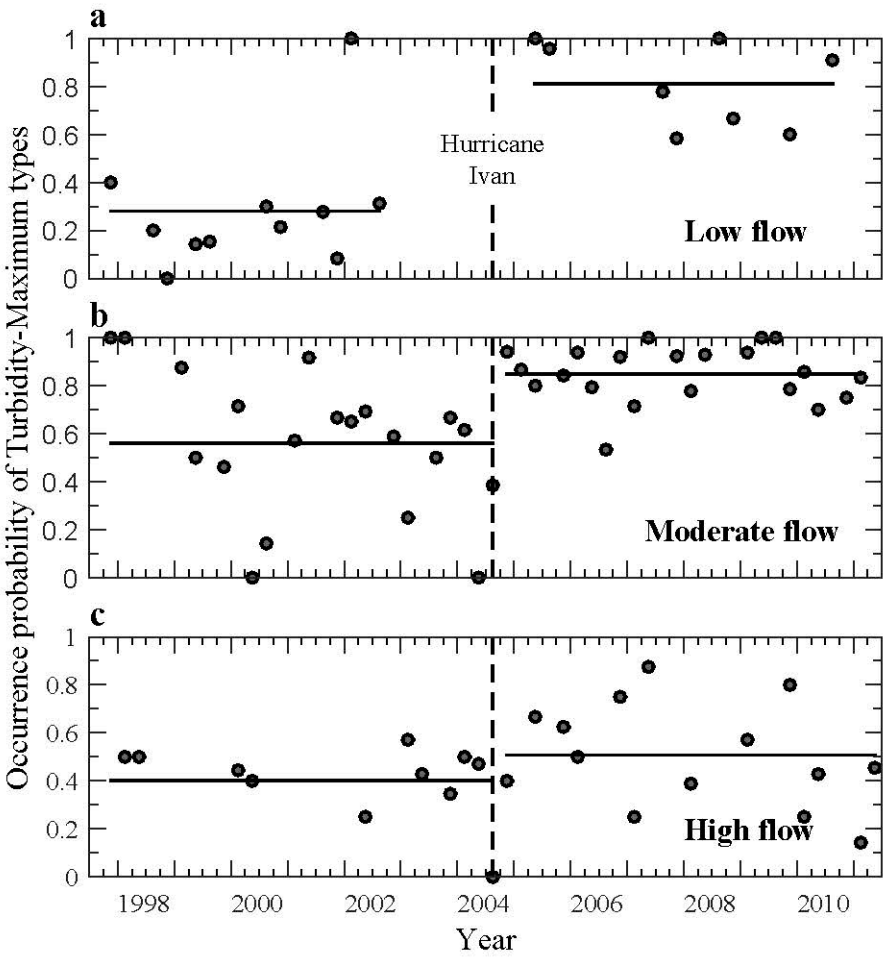




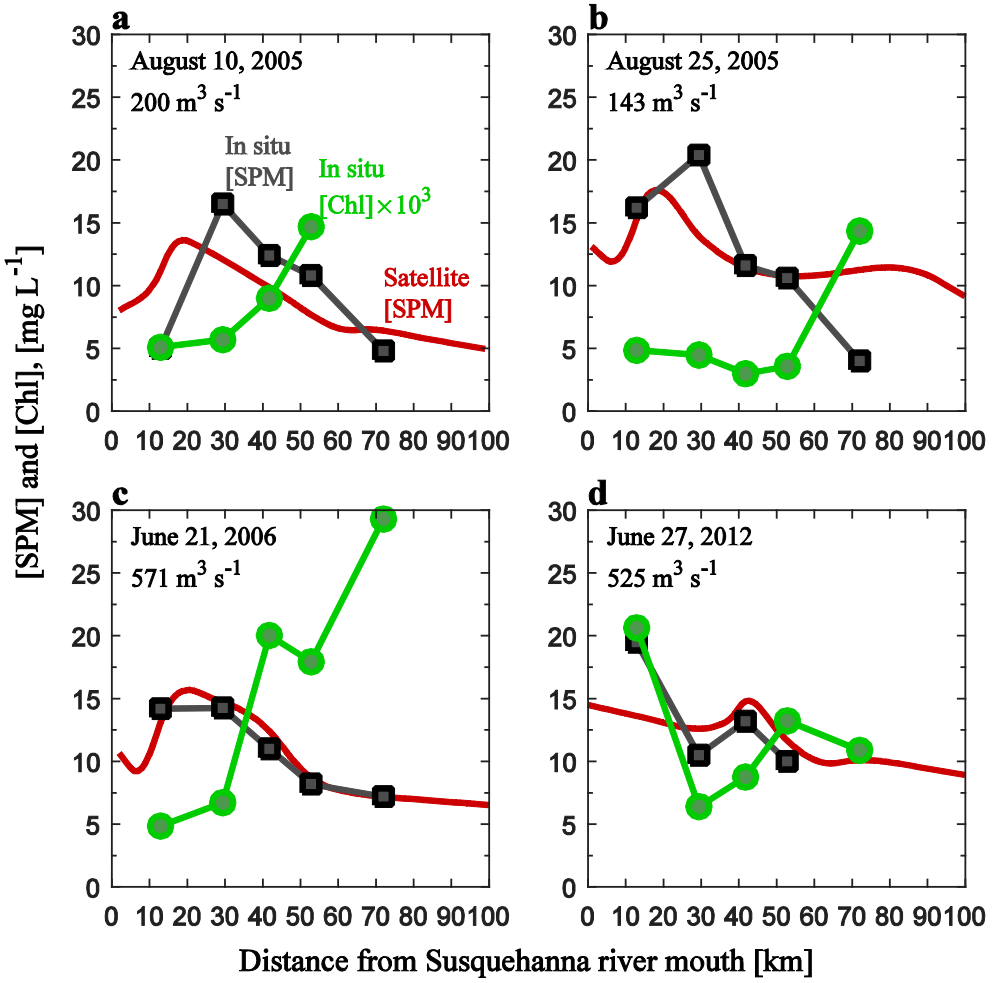
- Hurricane Ivan (2004) triggered a discharge of sediments equivalent to the total amount discharged over the preceding 10 years

- The shift in typology occurred in an abrupt manner after Hurricane Ivan

- The regime shift is likely associated with Hurricane Ivan (2004)



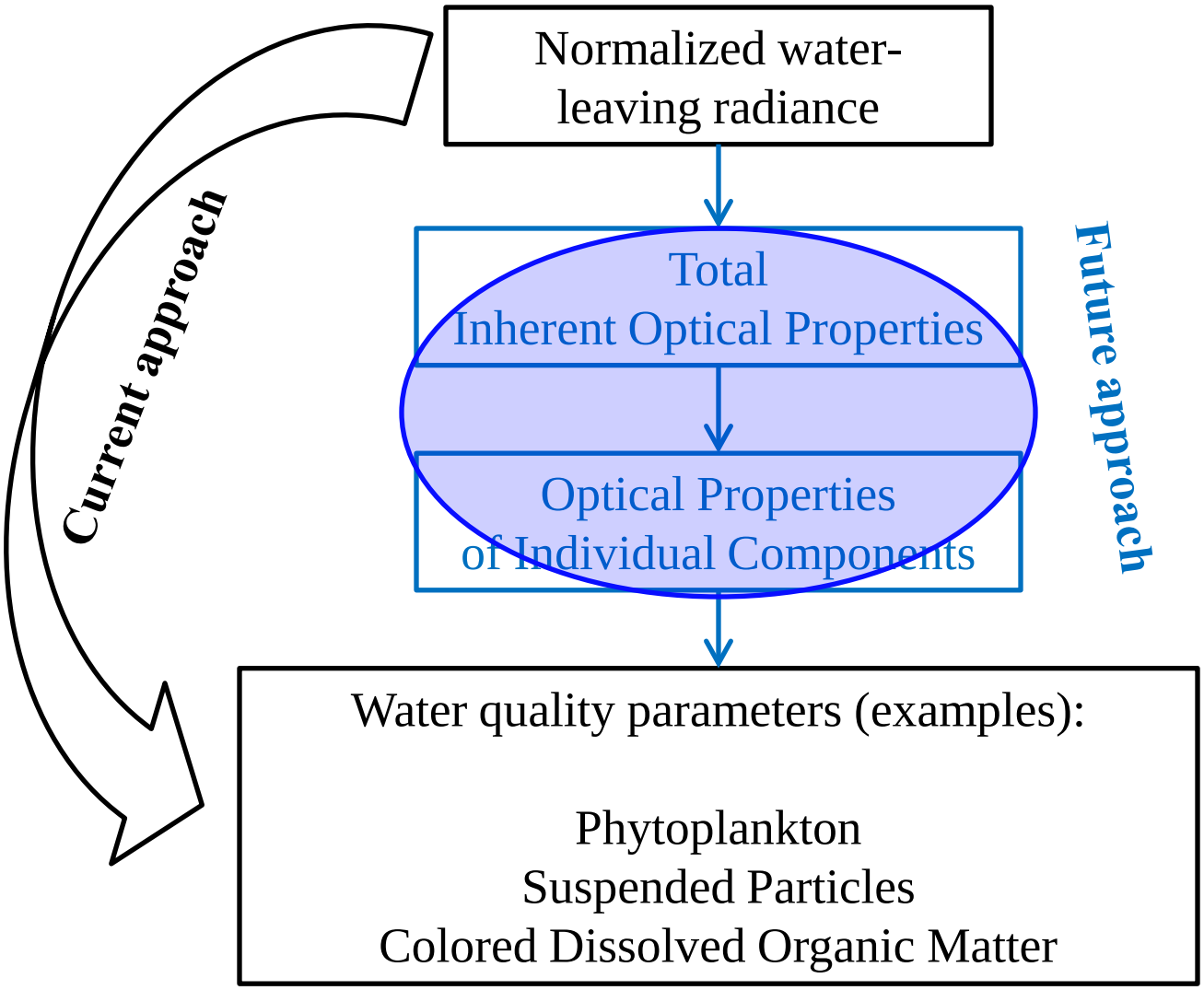
Another important detail:



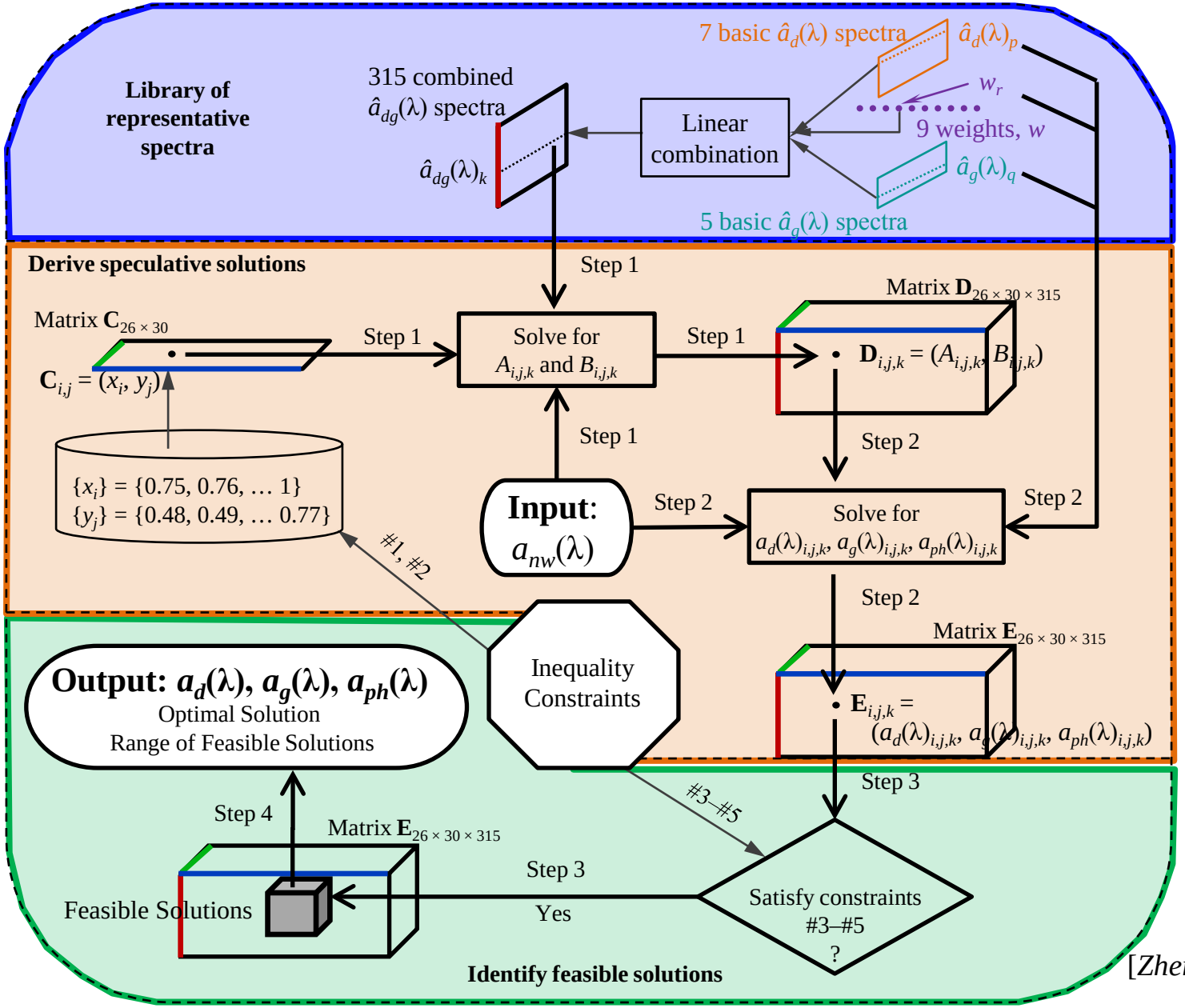
- Chlorophyll transect is decoupled from suspended sediment transect

- Higher algal biomass is located downstream of the Turbidity Max

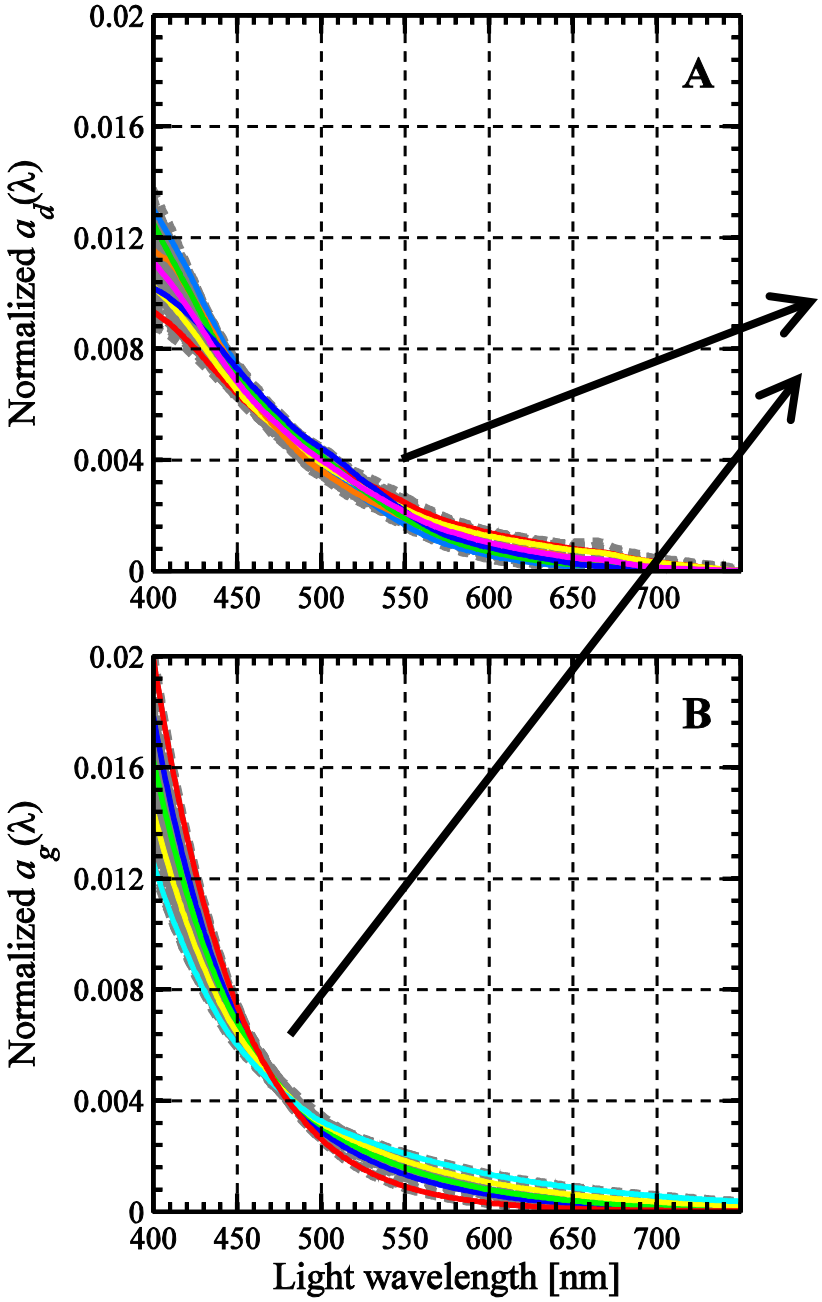
Satellite Remote-sensing of water quality parameters: Current and future approaches



Generalized Stacked-Constraints Model (GSCM)



[*Zheng et al.*, 2015b]

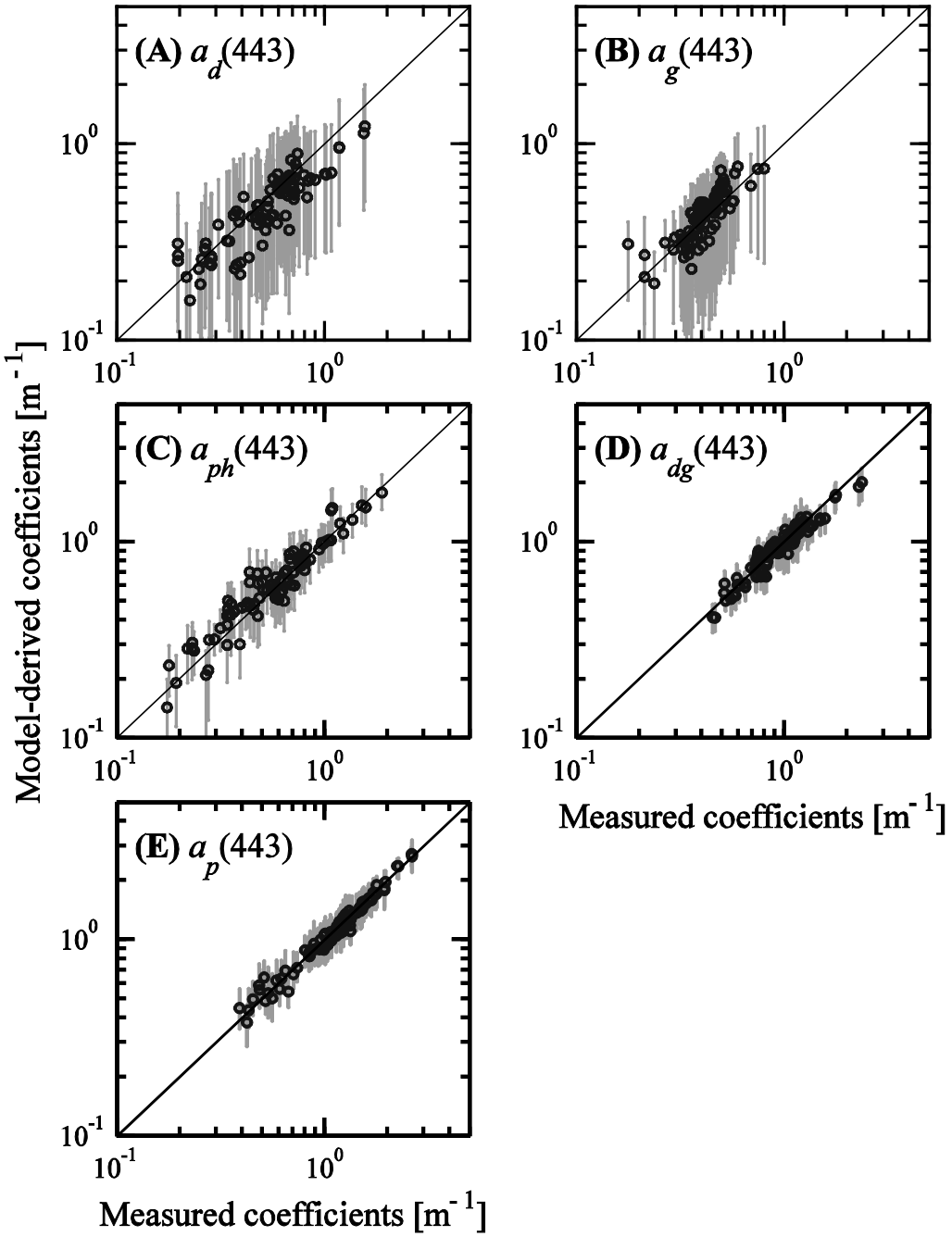


Advantages of GSCM

- Representative spectra determined from hierarchical cluster analysis using field data.

- The inequality constraints allows spectral shape of $a_{ph}(\lambda)$ to vary widely

Inequality Constraints	
#1	$0.75 < a_{ph}(412)/a_{ph}(443) < 1$
#2	$0.48 < a_{ph}(490)/a_{ph}(443) < 0.77$
#3	$0.76 < a_{ph}(469)/a_{ph}(412) < 1.13$
#4	$0.19 < a_{ph}(555)/a_{ph}(490) < 0.50$
#5	$0 < a_d(750)/a_d(443) < 0.3$



- The model-derived a_d, a_g, and a_{ph} agree reasonably well with measurements

- Small systematic error (e.g., *MR* differs within ±10% from 1 @443 nm)

- Small random error (e.g., *MPD* ranges between 11 and 17%, and *RMSD* between 0.07 and 0.14 m^{-1} @443 nm)

Application of GSCM to MODIS data

[*Zheng et al.*, in prep]

Input:

MODIS-Aqua $R_{rs}(\lambda)$
(SWIR atmospheric correction)

[*Wang*, 2007; *Wang & Shi*, 2007]

Raman-corrected $R_{rs}(\lambda)$

[*Lee et al.*, 2010]

Quasi-Analytical Algorithm (QAA), v5

[*Lee et al.*, 2009]

QAA Output:

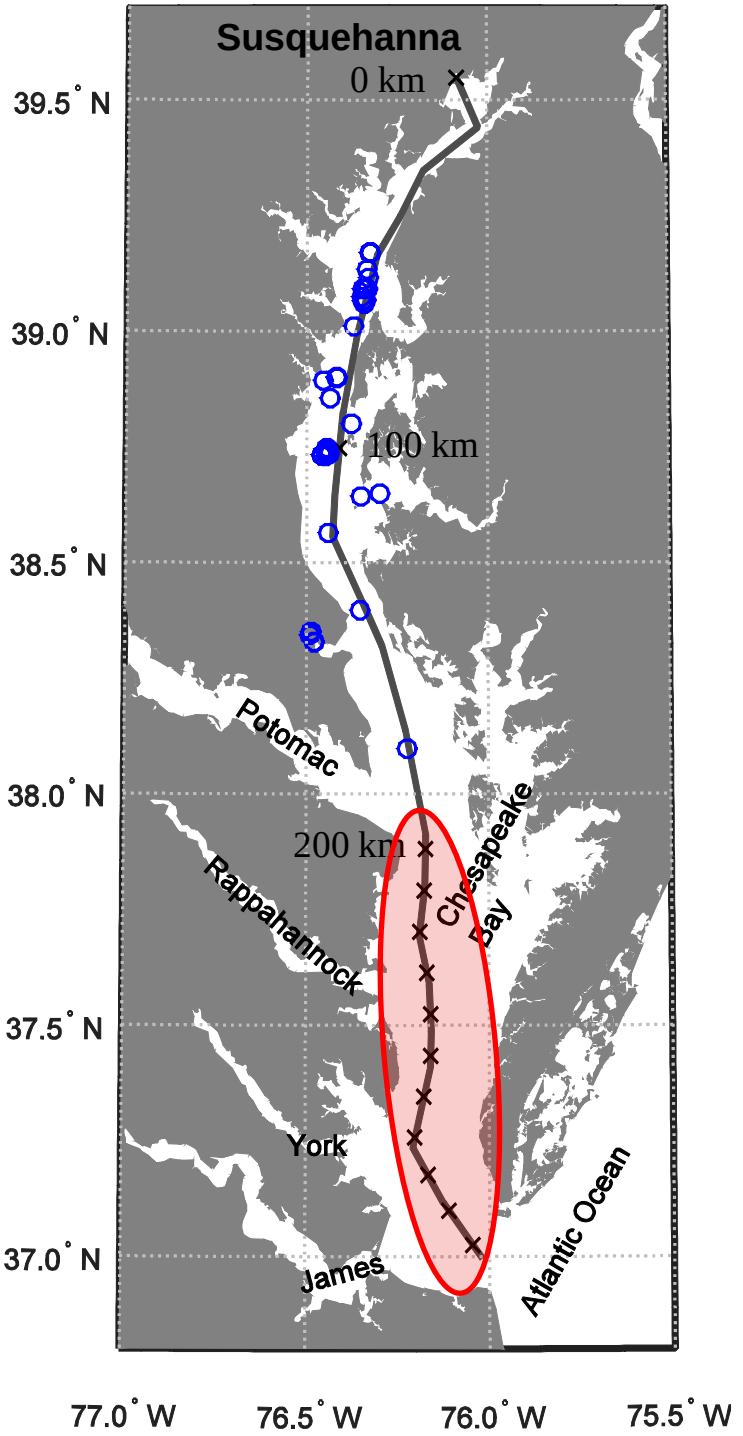
$a_{ph}(\lambda)$	$a_{dg}(\lambda)$	$a_{nw}(\lambda)$	$b_{bp}(\lambda)$
Phytoplankton	NAP + CDOM		Total particulate matter

Generalized Stacked-Constraints Model (GSCM)

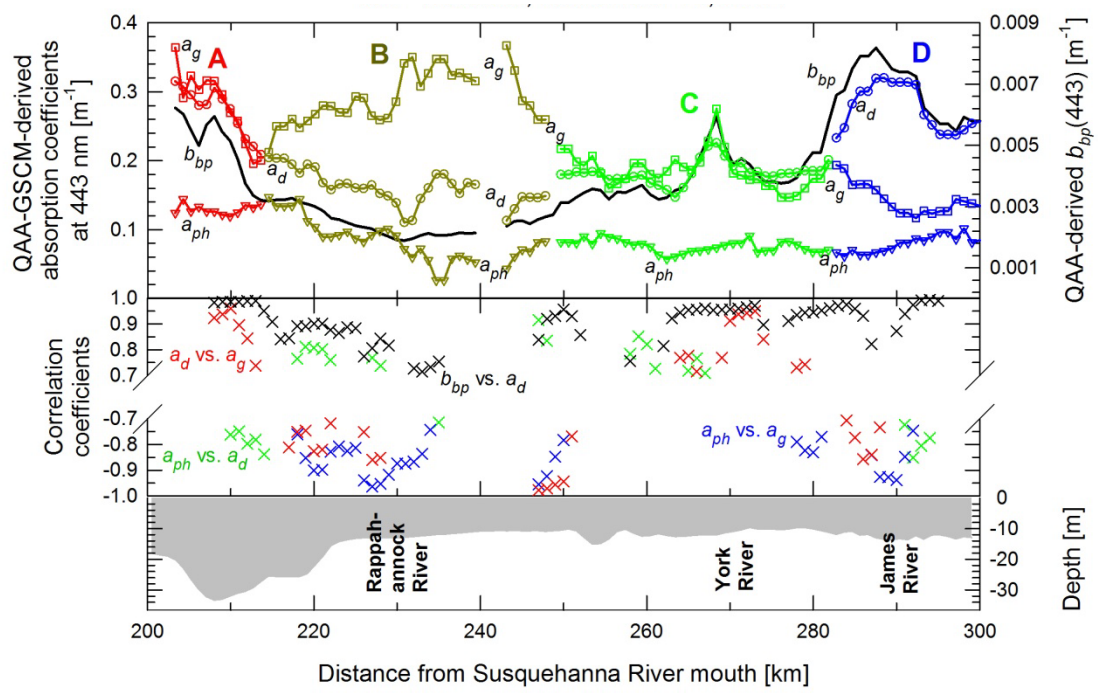
[*Zheng et al.*, 2015b]

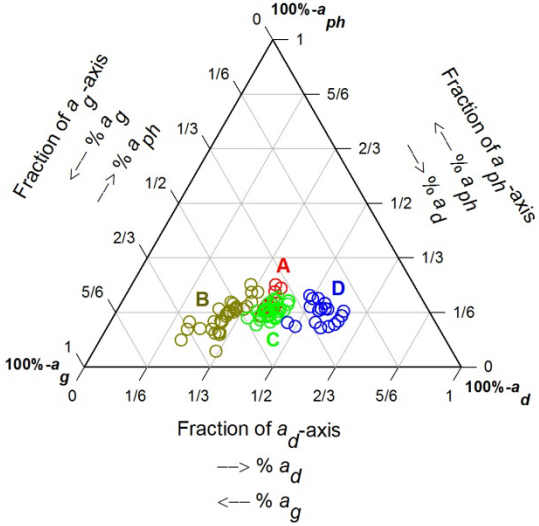
QAA-GSCM Output:

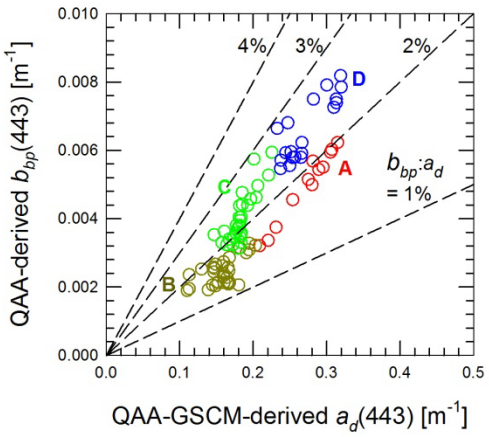
$a_d(\lambda)$	$a_{ph}(\lambda)$	$a_g(\lambda)$
NAP	Phytoplankton	CDOM



Optical identification of water mass







Fall 2002

- Water mass **A**:
  - Potomac River plume
  - CDOM and NAP dominated
  - $b_{bp}(443):a_d(443) = 1.8 \pm 0.2$ %
  - CDOM-NAP mixed plume
- Water mass **B**:
  - Rappahannock River plume
  - CDOM dominated
  - $b_{bp}(443):a_d(443) = 1.5 \pm 0.2$ %
  - "Tea-colored" plume
- Water mass **C**:
  - York River plume
  - CDOM and NAP dominated
  - $b_{bp}(443):a_d(443) = 2.2 \pm 0.3$ %
  - CDOM-NAP mixed plume
- Water mass **D**:
  - James River plume
  - NAP dominated
  - $b_{bp}(443):a_d(443) = 2.5 \pm 0.2$ %
  - "Turbid" plume

Conclusions

- Combining satellite-derived suspended sediments data and field-measured streamflow data allows us to elucidate short- and long-term trends of sediment distribution.

- The GSCM-type approach which allows the extraction of mathematically dissociated absorption coefficients of phytoplankton, nonalgal particles, and CDOM is a promising new tool for water quality research and applications.

Future research

- Improve the spectral shape of satellite-derived $R_{rs}(\lambda)$ in the blue spectral region
- Identify potential links between optical properties and water quality parameters such as toxins, harmful algal cell counts, dissolved oxygen, oxygen demands, priority pollutants, and etc.

Publications

- Zheng, G., P. M. DiGiacomo, S. S. Kaushal, M. A. Yuen-Murphy, and S. Duan (2015a), Evolution of sediment plumes in the Chesapeake Bay and implications of climate variability, *Environmental Science & Technology*, 49(11), 6494–6503, doi: 10.1021/es506361p.

- Zheng, G., D. Stramski, and P. M. DiGiacomo (2015b), A model for partitioning the light absorption coefficient of natural waters into phytoplankton, non-algal particulate, and colored dissolved organic components: A case study for the Chesapeake Bay, *Journal of Geophysical Research Oceans*, 120, 2601–2621, doi:10.1002/2014JC010604.

- Zheng, G., D. and P. M. DiGiacomo, and M. A. Yuen-Murphy, Dissociated absorption coefficients of phytoplankton, non-algal particles, and colored dissolved organic matter in the Chesapeake Bay from MODIS, *in prep*.

Acknowledgements

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We appreciate NOAA/NOS/CO-OPS, USGS, and NASA/GSFC/OBPG, for providing the wind, streamflow, and ocean color radiometric data. We thank Lide Jiang for providing the simulated tidal current data.

We thank all scientists and personnel who contributed to the collection and processing of field data of absorption coefficients used in this study. In particular, we thank L. W. Jr. Harding, C. Hu, and A. Mannino who made the data available through the NASA's SeaWiFS Bio-Optical Archive and Storage System (SeaBASS).

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