Modeling the Impacts of Water Quality on SAV in the Tidal Chesapeake Bay

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Motivation for this work:

Basic:

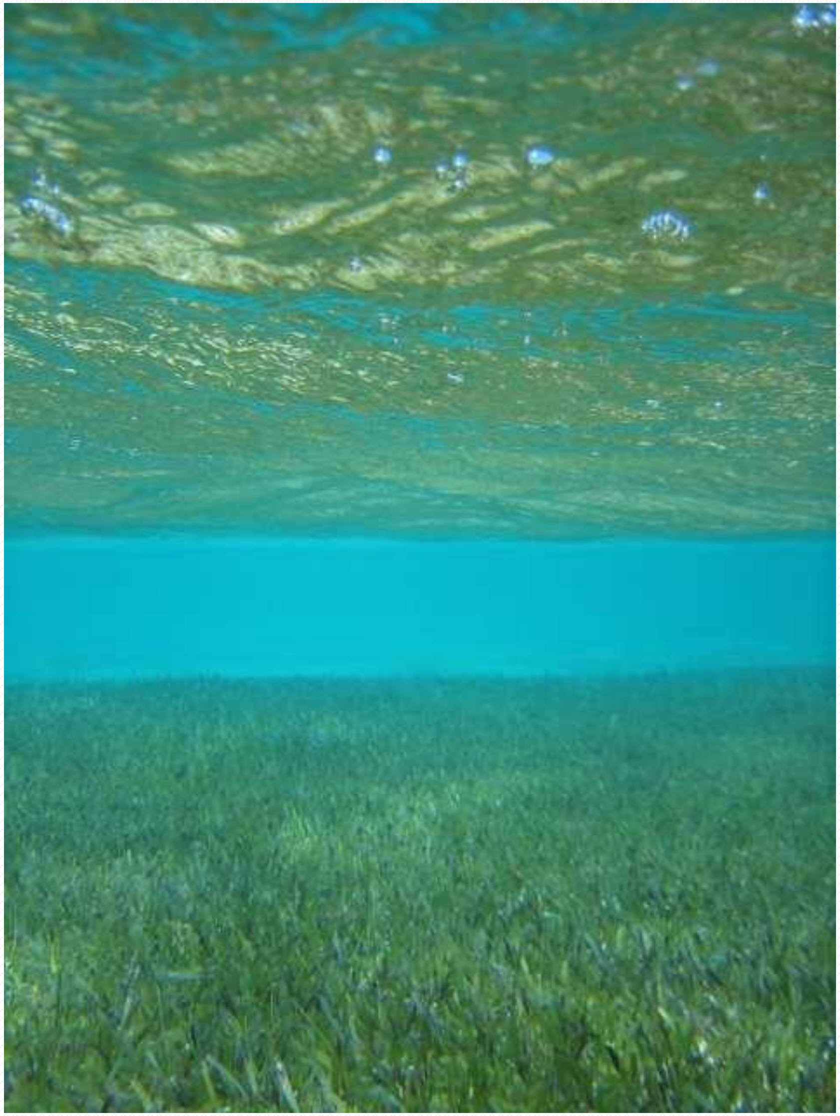
- Link hydrologic optics with physiology to develop fundamental understanding of climate impacts on aquatic photosynthesis

Applied:

- Improve our ability to model & manage the impacts of water quality on shallow water resources in the Chesapeake Bay
  - Existing Bay Model works well in the main stem of the Bay but fails to predict WQ and SAV distributions in shallow water, esp tributaries

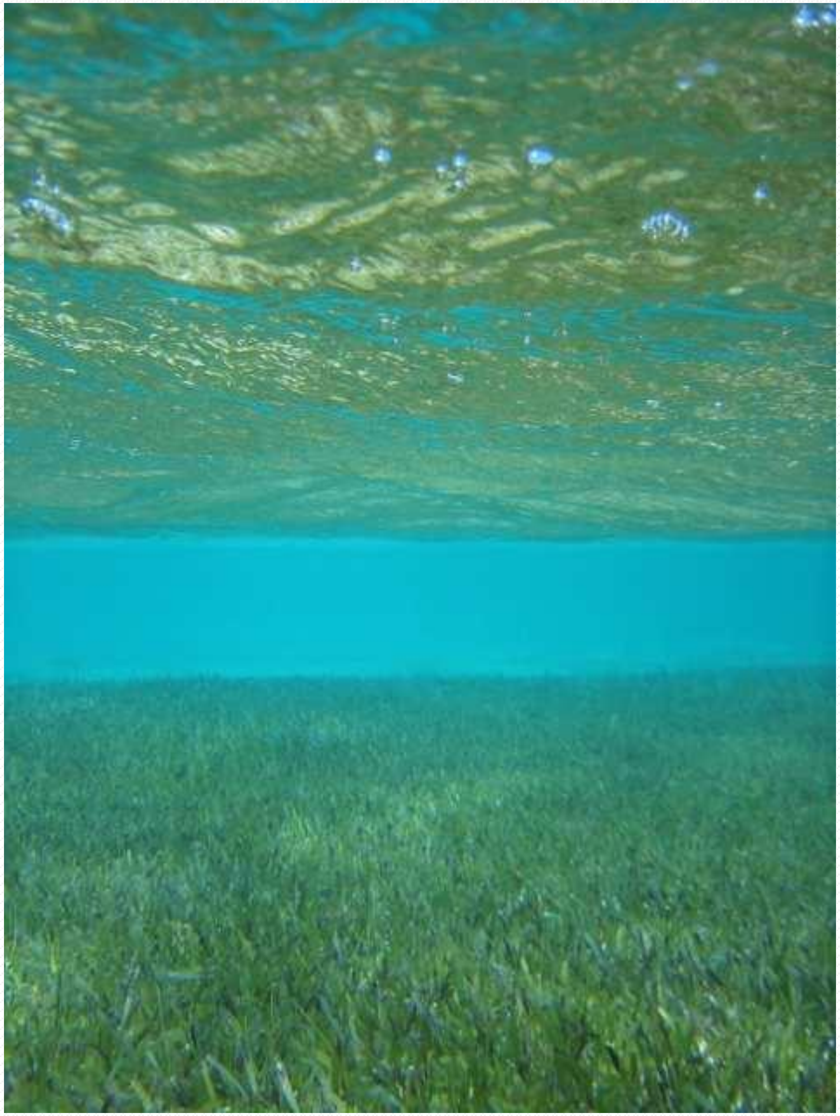
SAV and Climate Change:

- High light requirements (10 – 20% surface E)
- Vulnerable to poor water quality
- Sensitive to summer heat stress



SAV loss threatens major ecosystem services

- Habitat structure and sediment stability
  - Loss of "blue carbon" deposits
- Productivity shift from benthos to plankton
- Shifts in sediment biogeochemistry
  - Reduced flux of C_{org} and O_2 to sediments



So, what does climate change have in store for SAV?

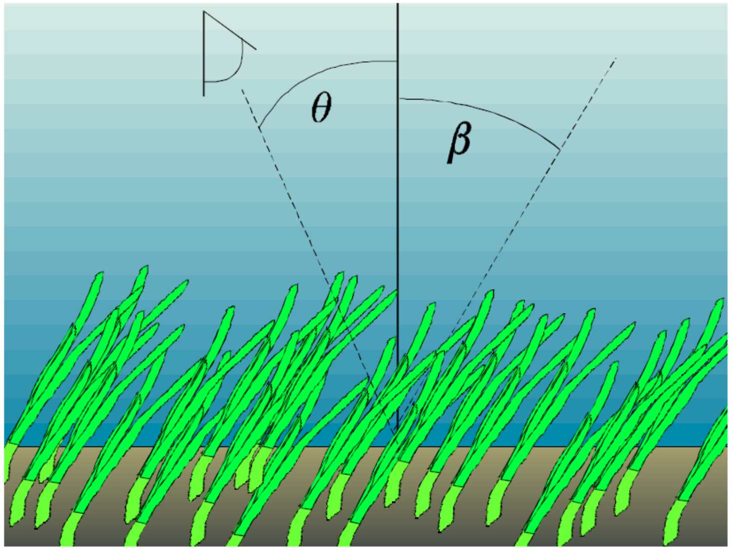
- Climate warming will increase summer heat stress
  - Chesapeake Bay eelgrass
    - Moore & Jarvis. 2008. *J. Coast. Res* **55**:135-247
  - Mediterranean *Posidonia*
    - Marbà, N. and C. Duarte. 2010. *Global Change Biology **16***:2366-2375.
- Heat stress events will become more frequent
  - European eelgrass
    - Franssen, S. and others 2012. Transcriptomic resilience to global warming in the seagrass *Zostera marina, a marine foundation species. Proc. Nat. Acad. Sci. **108: 19276-19281.***
    - Winters, G., P. Nelle, B. Fricke, G. Rauch, and T. Reusch. 2011. Effects of a simulated heat wave on photophysiology and gene expression of high- and low-latitude populations of *Zostera marina. Mar. Ecol. Prog. Ser. **435: 83-95.***
- Water quality….improving in Chesapeake Bay?

And what about Ocean Acidification?

- CO_2 availability modifies eelgrass response to temperature:
  - Increased photosynthesis and positive C balance
  - Survival & reproduction
  - Shoot Size
  - Growth
  - Below-ground biomass
- Long term experiments on whole plants support short-term responses of individual leaves

GrassLight 2.13 User's Guide

A Simulation Model of Radiative Transfer and Photosynthesis in Submerged Plant Canopies



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Predicting effects of ocean warming, acidification, and water quality on Chesapeake region eelgrass

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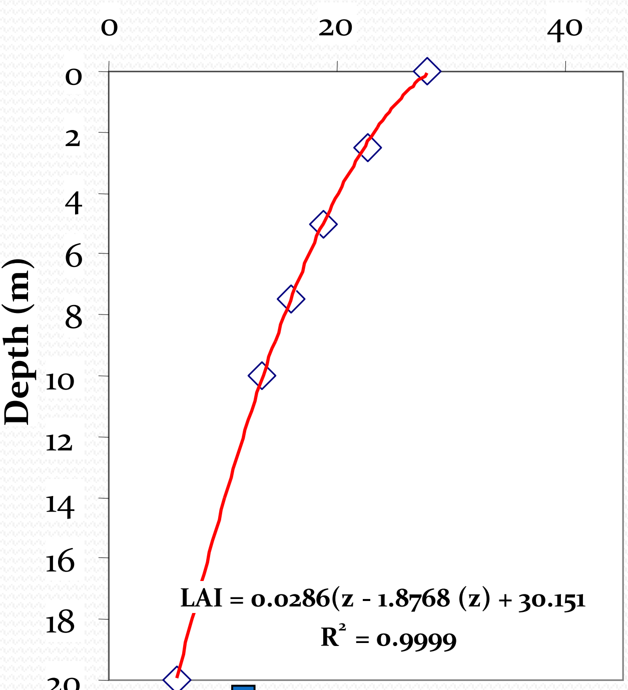
We can combine physiology with bio-optical modeling to predict SAV response to environmental forcing

The *GrassLight* Model:

Leaf Area Index as Function of Depth



Photosynthesis: Light & CO_2 Model

CO_2 dependence of P_m

$$P_m = 82 \cdot e^{(-0.53 \cdot pH)}$$

Absorptance:

$$A(\lambda) = 1 - R - \exp[a(\lambda) - a(750)]$$

Quantum Efficiency:

$$\alpha(\lambda) = \phi_{max} A(\lambda)$$

Instantaneous Photosynthesis

$$P(h,\lambda) = \int_h B(h) \cdot P_m \cdot \left[1 - \exp\left(\frac{\alpha(\lambda)E(h,\lambda)}{P_m}\right)\right]$$

Daily Production Integral:

$$\iint_{t,h} P(\lambda) = \int_h B(h) \cdot D \cdot P_m \cdot \left[1 - \exp\left(-\frac{0.67\alpha(\lambda)E(h,\lambda)}{P_m}\right)\right]$$

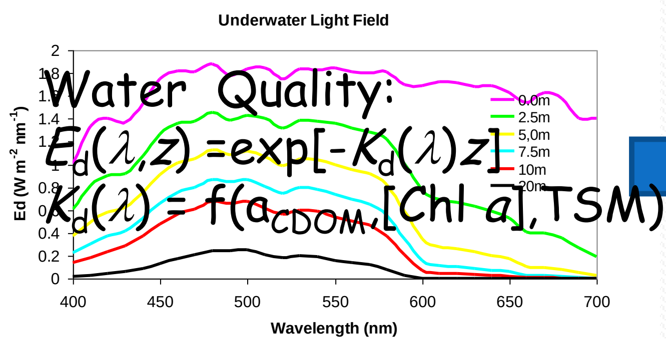
Determine maximum sustainable density at P:R=1

Result: Density and Leaf Area Index Estimate

$[CO_2]$

Temperature

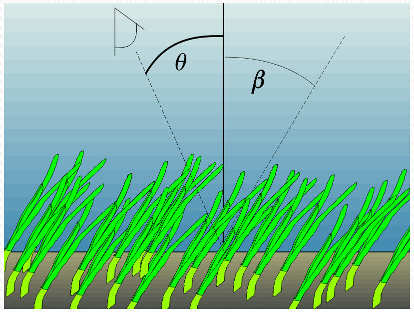
$E(\lambda,z)$

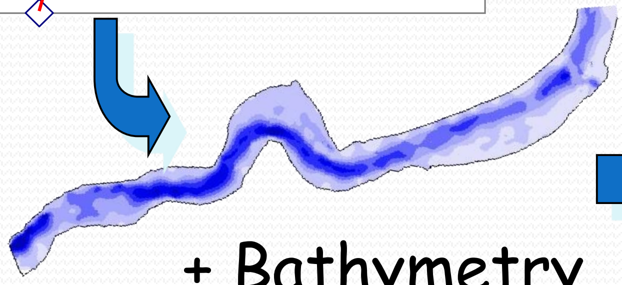


Water Quality:

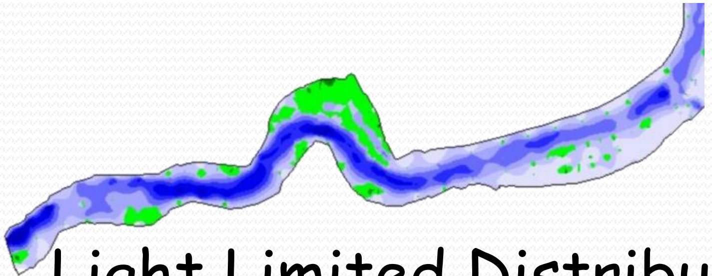
$E_d(\lambda,z) = \exp[-K_d(\lambda)z]$

$K_d(\lambda) = f(a_{CDOM}, [Chl\ a], TSM)$





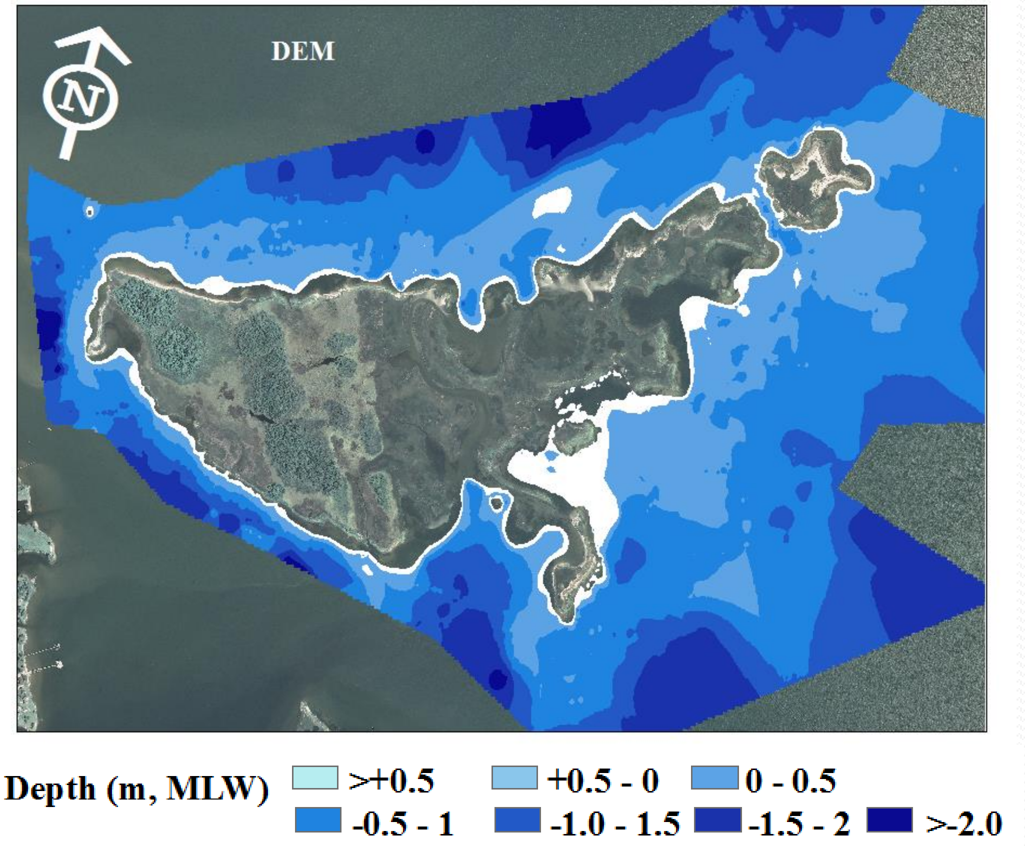
+ Bathymetry



Light Limited Distribution

Goodwin Islands NERR

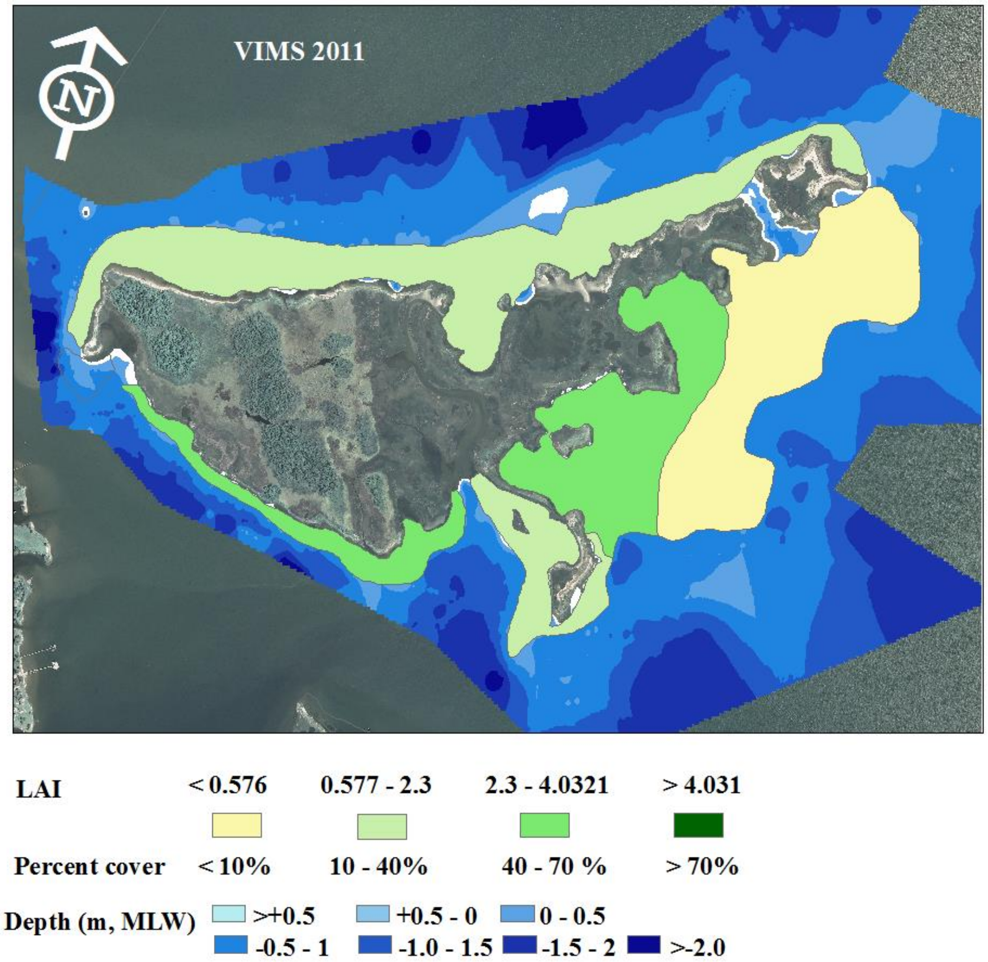
- SAV Vulnerable to thermal stress
- Time series of
  - Water quality measures to drive light availability
  - SAV abundances to compare model predictions
- Detailed bathymetry



Zimmerman, R., V. Hill, and C. Gallegos. 2015. Predicting effects of ocean warming, acidification and water quality on Chesapeake region eelgrass. Limnol. Oceanogr. **60:1781-1804.**

Predicting climate effects on eelgrass distribution

- Density decreases with depth
- Distribution limited to depths <1.5 m
- Consistent with VIMS 2011 SAV map



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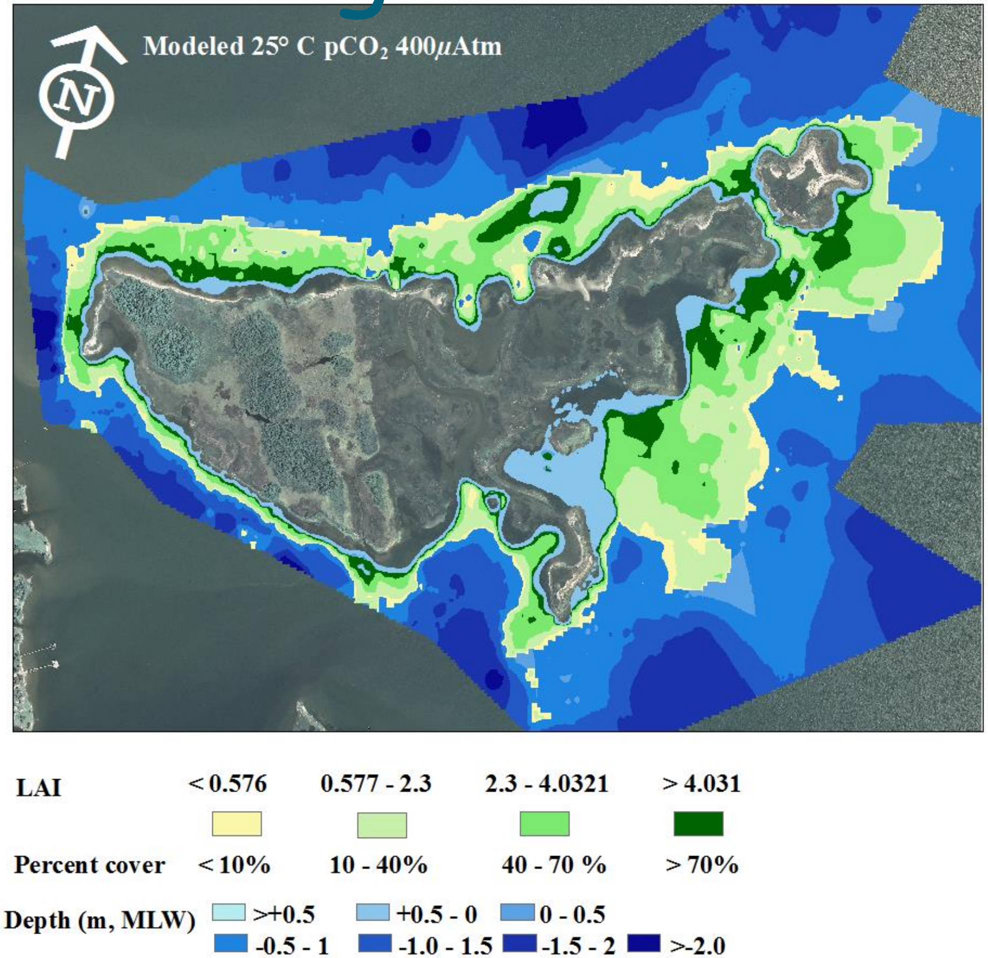
How will temperature and CO_2 interact to affect eelgrass distribution?

- Cool summer temperature
- Present-day CO_2 (pH 8)



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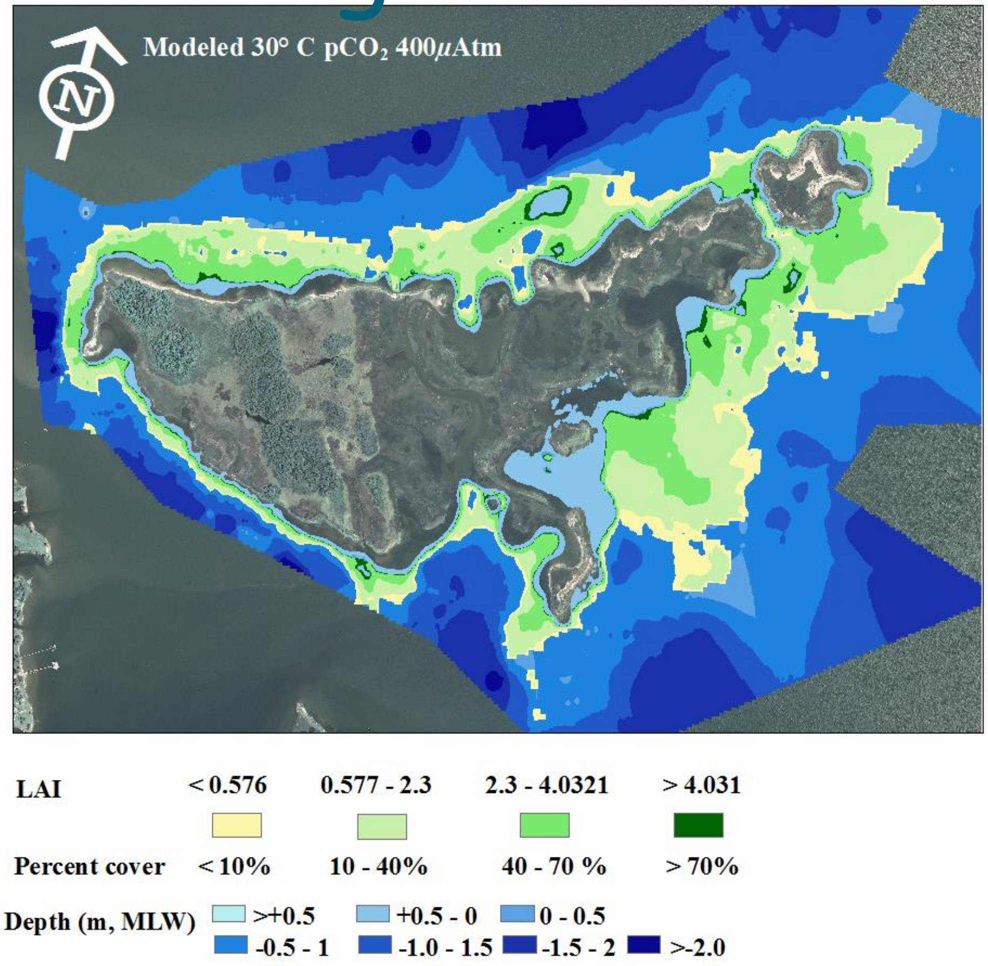
How will temperature and CO_2 interact to affect eelgrass distribution?

- Cool summer temperature
- Present-day CO_2 (pH 8)
- Warming alone causes eelgrass die-back



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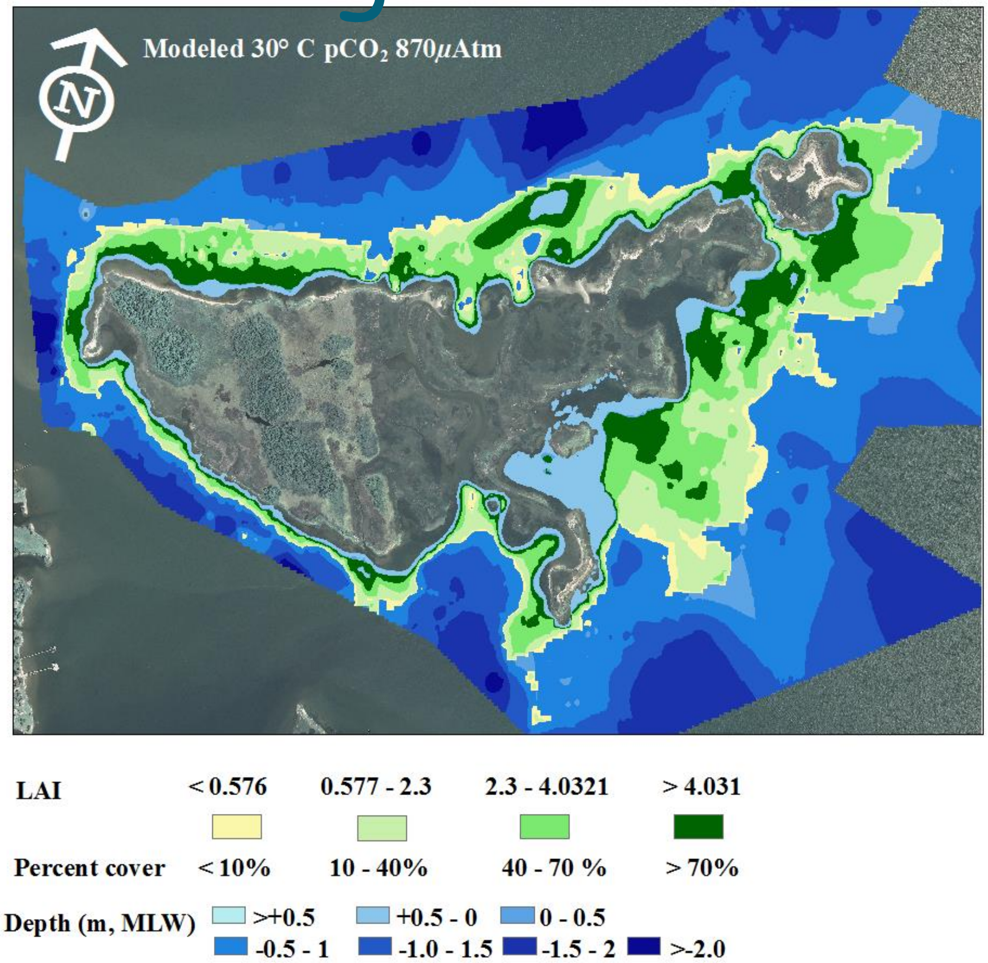
How will temperature and CO_2 interact to affect eelgrass distribution?

- Warming combined with CO_2 doubling (pH 7.8) causes re-growth of eelgrass



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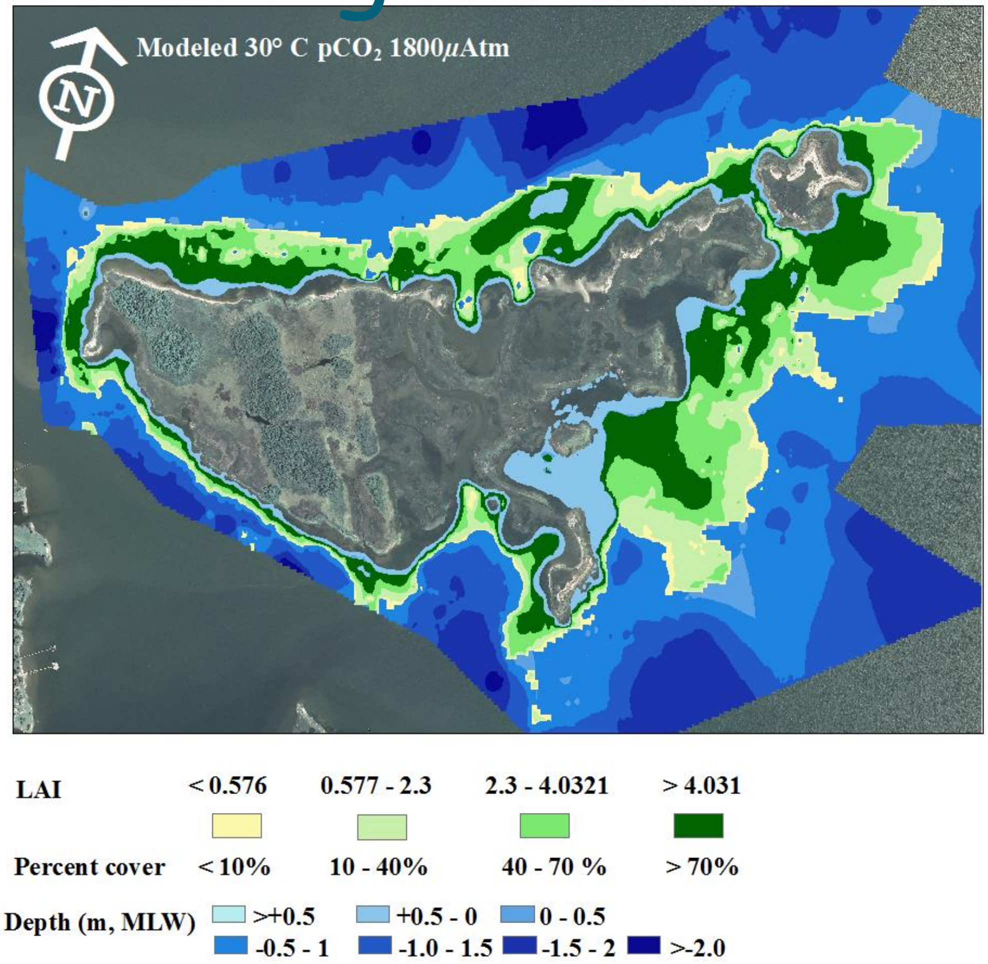
How will temperature and CO_2 interact to affect eelgrass distribution?

- Warm summer temperature
- CO_2 quadrupling (pH 7.5) further increases shallow water density
- Minimal effects on depth distribution



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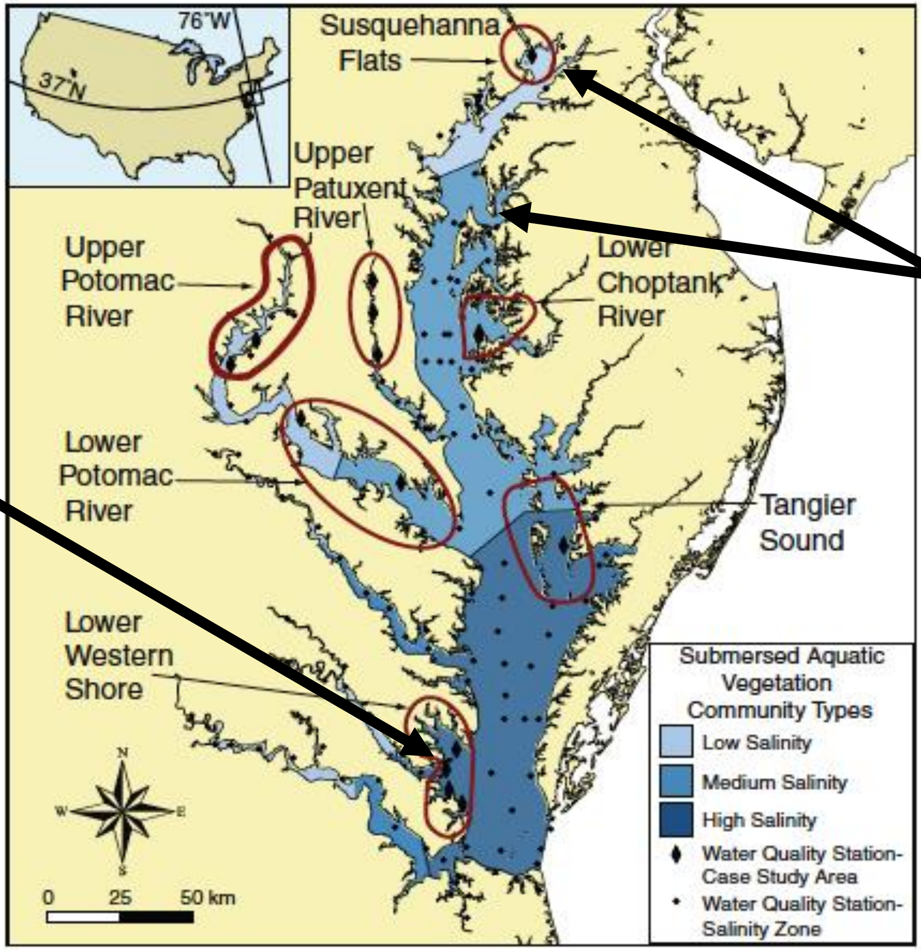
Experimental Results Support Model Predictions re: Temperature and CO_2

77 days T>25° C
No CO_2 addition

77 days T>25° C
With CO_2

So,

- The model predicts eelgrass in the polyhaline region of the Bay…



Map by R. J. Orth, VIMS

- Will it work for SAV in fresher parts of the Bay?

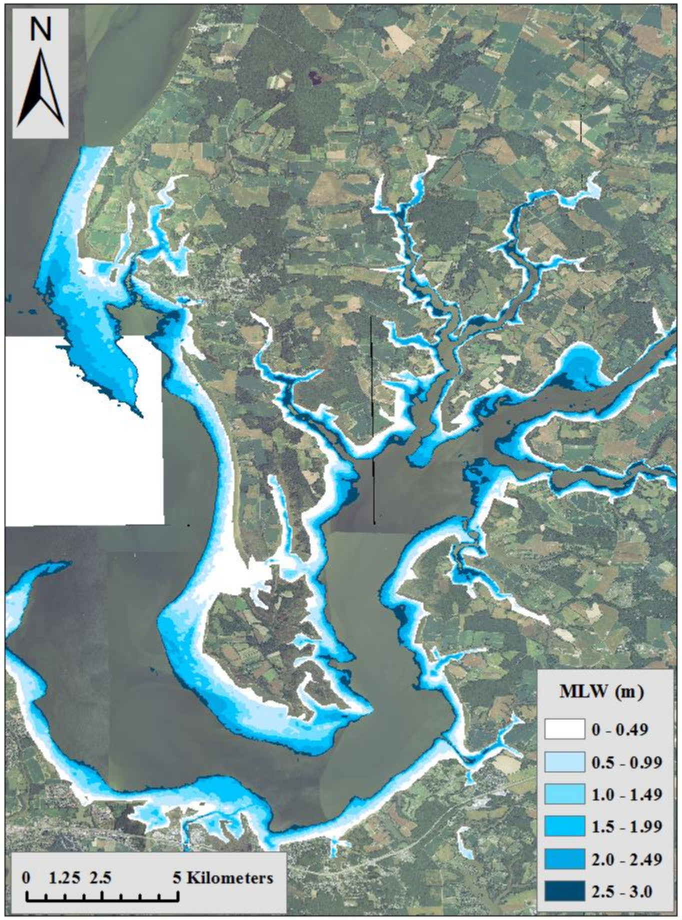
Applying *GrassLight* to the Lower Chester River

- Mesohaline tributary
- Highly turbid
  - TSM » 30 mg L^{-1}
- Eutrophic
  - Chl *a* » 20 mg m^{-3}

Applying *GrassLight* to the Lower Chester River

- Mesohaline tributary
- Highly turbid
  - TSM » 30 mg L^{-1}
- Eutrophic
  - Chl *a* » 20 mg m^{-3}
- Gridded 30 m bathymetry
- Potential SAV habitat (< 3 m depth) fringing the shore

Chester River DEM

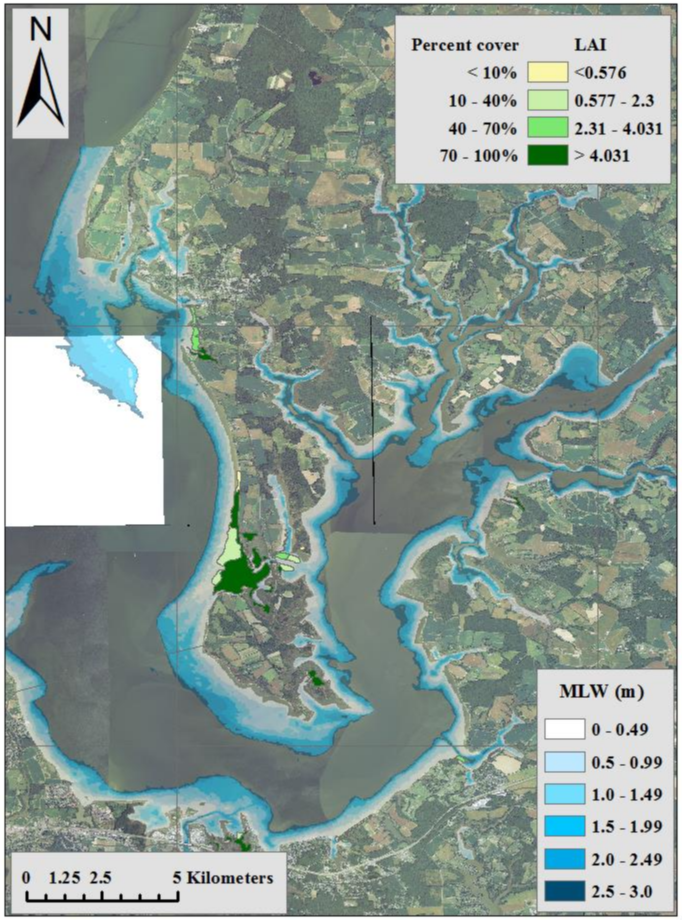


Imagery from Geospatial Data Gateway; 2013 National Ag. Imagery Program Mosaic

Applying *GrassLight* to the Lower Chester River

- SAV distribution
  - Most persistent in shallows around Eastern Neck Island and Chester shoreline
  - Species composition depends on salinity
  - Abundance depends on water quality
  - Temporally variable

Chester River VIMS SAV distribution 2011



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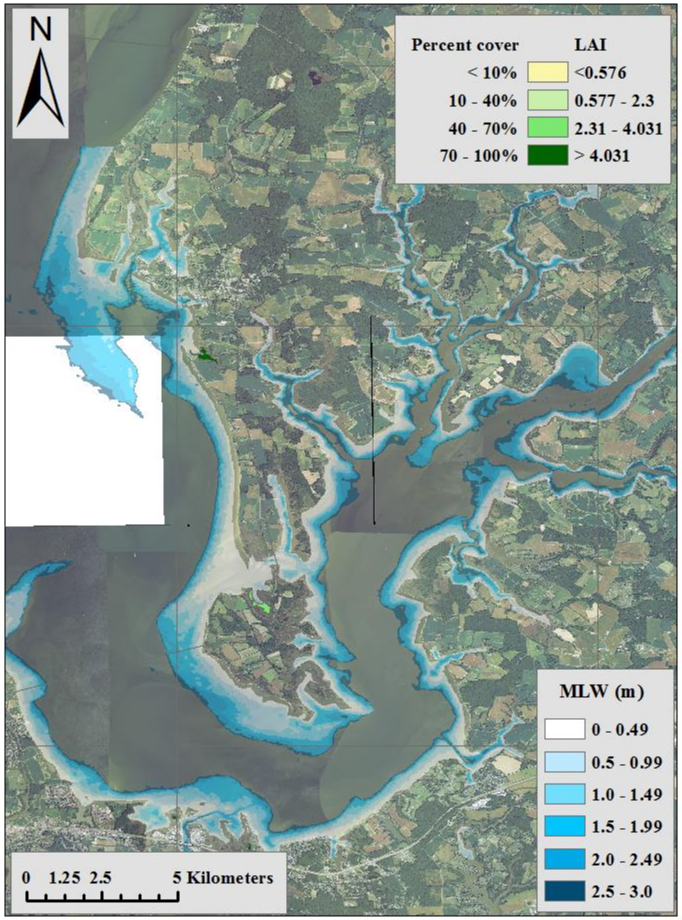
Chester River VIMS SAV distribution 2013

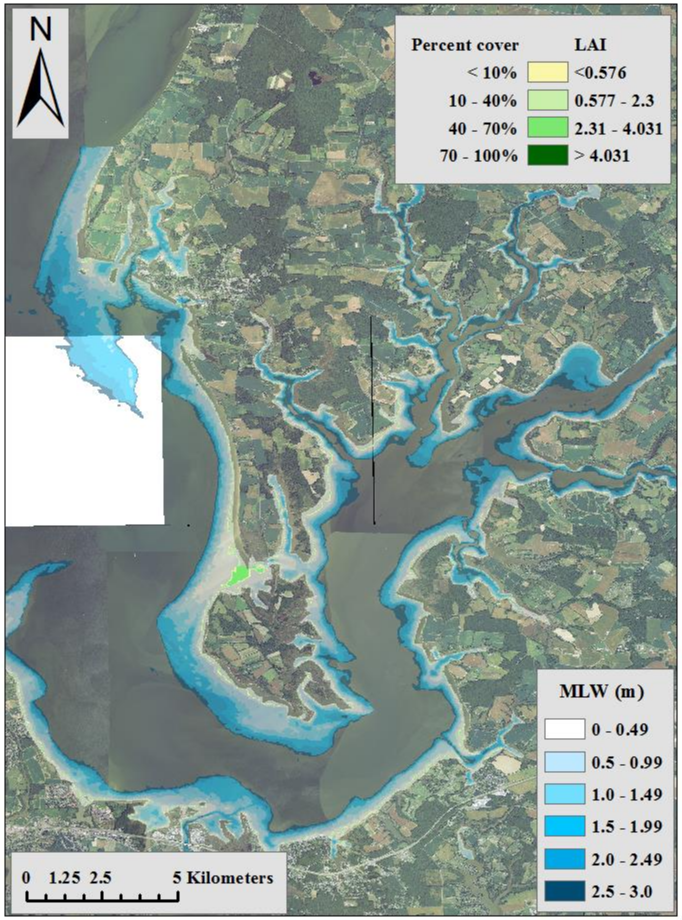


Imagery from Geospatial Data Gateway; 2013 National Ag. Imagery Program Mosaic

Applying *GrassLight* to the Lower Chester River

- GrassLight prediction of SAV density based on average WQ data is consistent with VIMS field observations
- TSM = 30 mg L^{-1}
- Chl *a* = 20 mg m^{-3}
- $z_{E(22\%)}$ = 0.2 m
- $z_{E(13\%)}$ = 0.3 m
- $z_{E(1\%)}$ = 0.8 m

Chester River potential SAV distribution Corsica WQ

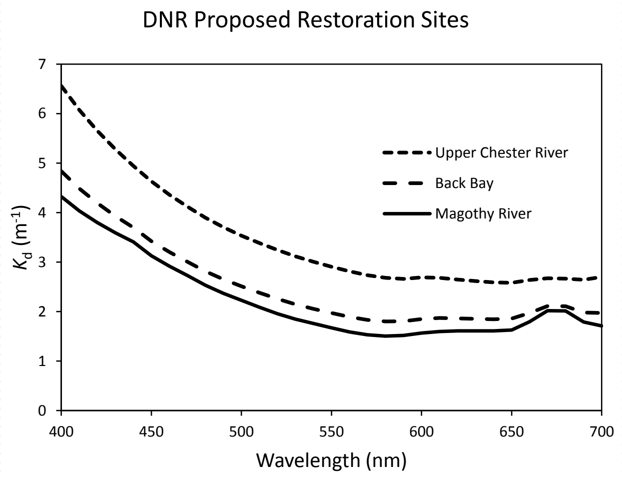


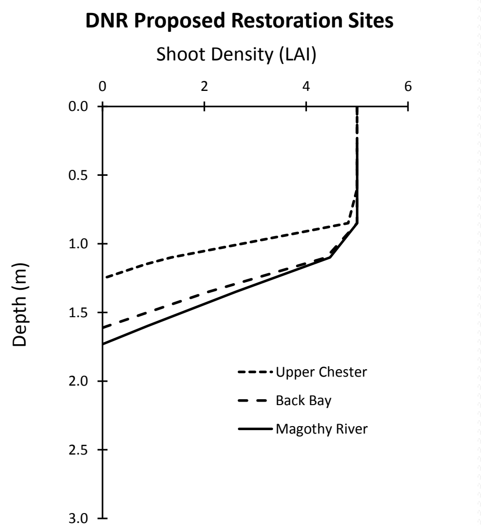
Imagery from Geospatial Data Gateway; 2013 National Ag. Imagery Program Mosaic

Applying *GrassLight* to DNR Restoration Sites: Input Conditions

	DNR Restoration Sites			Susquehanna Flats:			
Location	Back Bay	Magothy	Upper Chester	Harve de grace	Inside Bed	Edge of Bed	CONMON Site
Lon	-76.391578	-76.4521632	-76.03612	-76.0848	-76.0512	-76.056314	-76.0414
Lat	39.23445	39.0757688	39.224687	39.5478	39.515178	39.497627	39.5053
Simulation Day (Solstice)	172	172	172	172	172	172	172
Salinity	4.7	5.8	1.4	0.1	0.3	0.1	0.1
Chl a	13.9	22.8	4.0	3.7	3.7	5.2	1.4
Turbidity	10.5	8.0	17.0	9.2	3.1	9.3	5.2
CDOM	0.5	0.5	0.5	0.5	0.5	0.5	0.5
Temperature (° C)	22.20	22.90	24.45	26.52	23.87	26.20	24.48
pH	7.80	8.20	7.00	7.34	8.85	8.49	8.53
Leaf Bending Angle	10	10	10	10	10	10	10
Canopy Ht (cm)	22	22	22	22	22	22	22
Shoot Leaf area (m^2 $shoot^{-1}$)	0.005	0.005	0.005	0.005	0.005	0.005	0.005

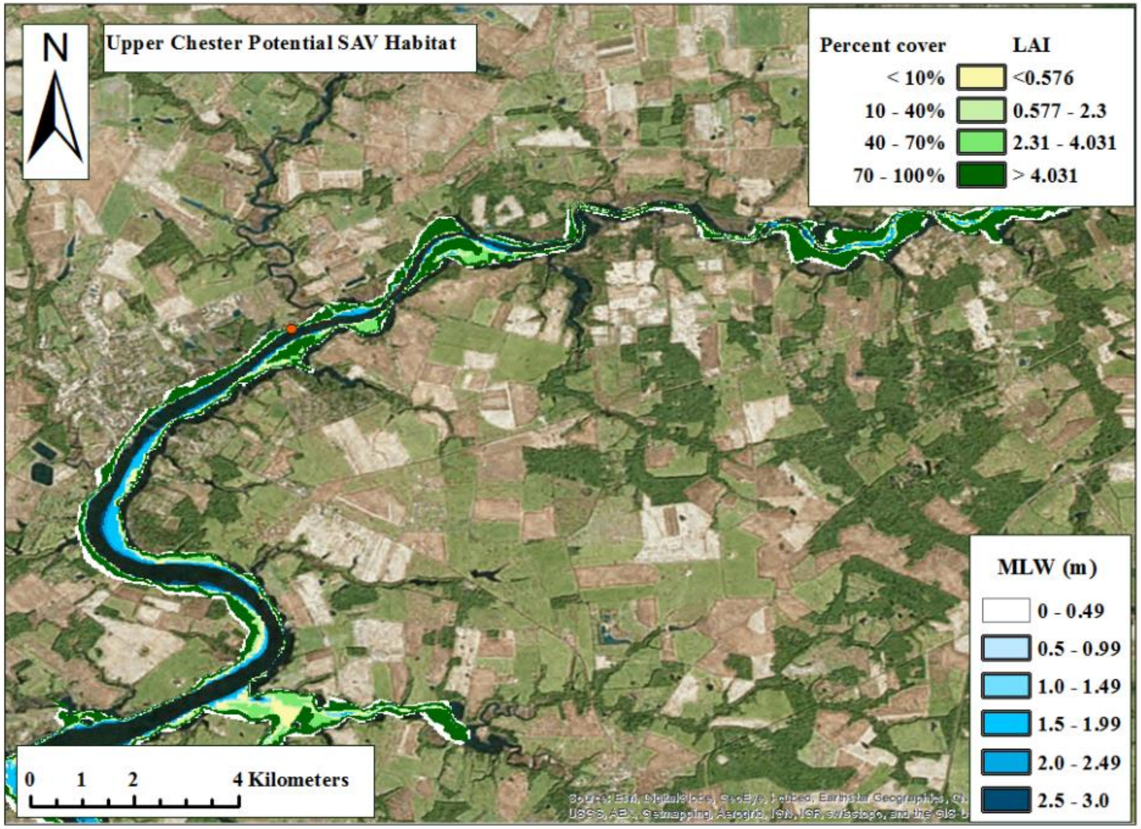
Applying *GrassLight* to DNR Restoration Sites





Applying *GrassLight* to Upper Chester River

- Highest TSM: 17 mg L^{-1}
- Lowest pH: 7.0
- Lowest Chl *a*: 4 $\mu g\ L^{-1}$
- SAV Depth Limit: 1.3 m



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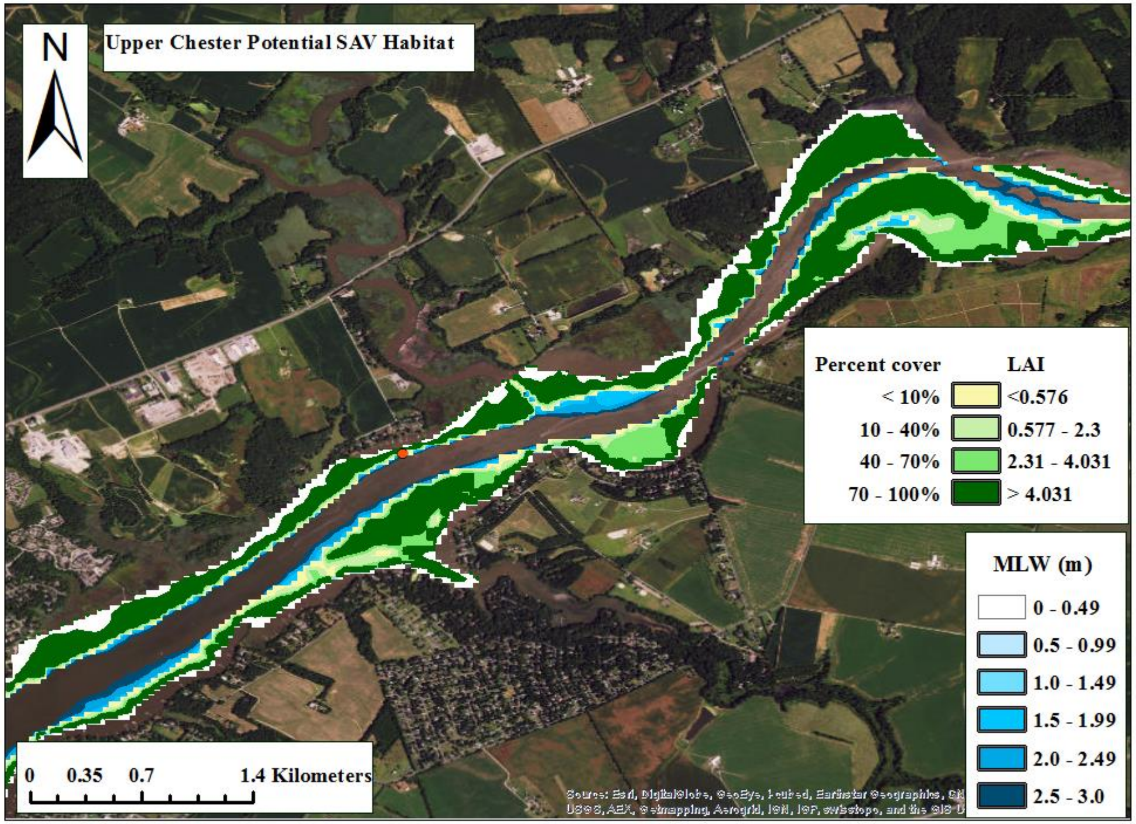
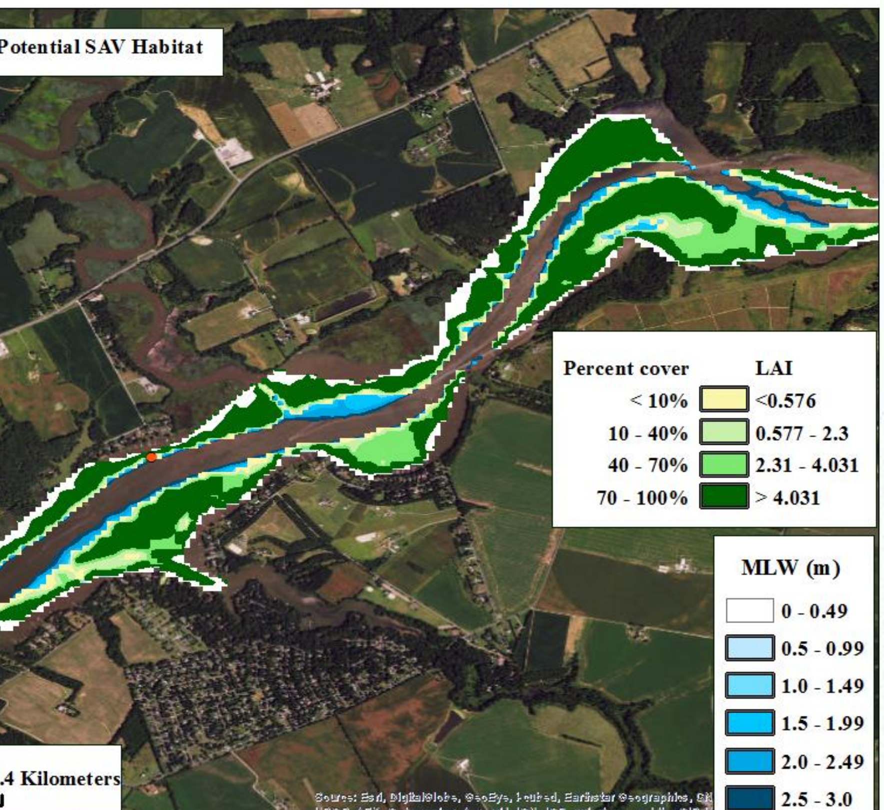
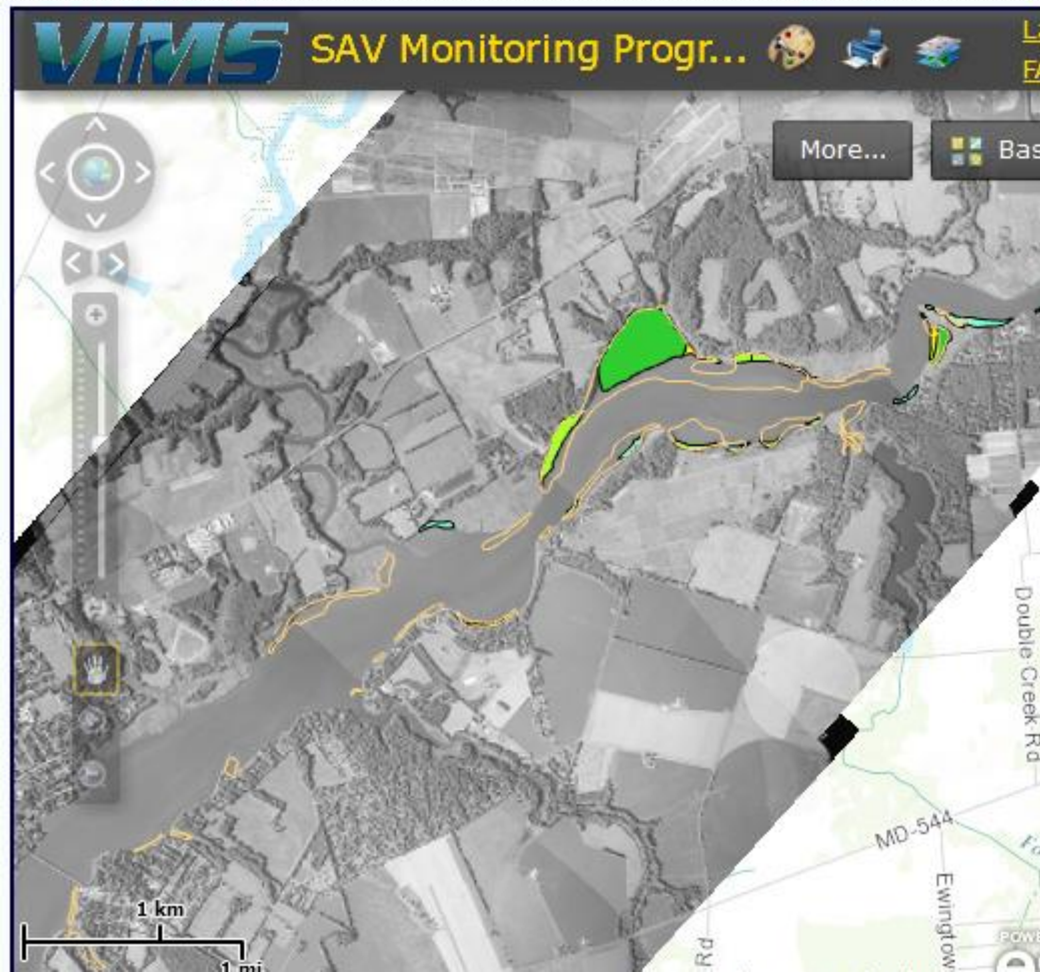


Applying *GrassLight* to Upper Chester River

- Model Prediction

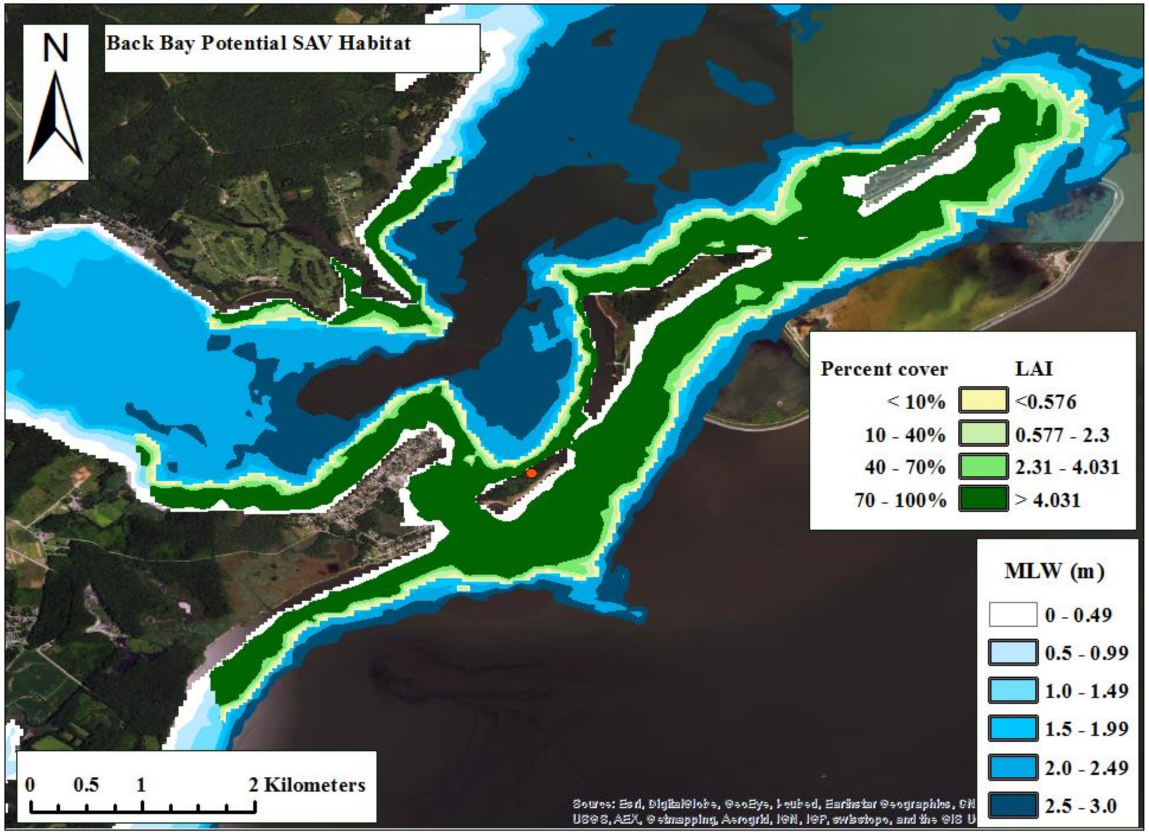


- VIMS 2015 Survey



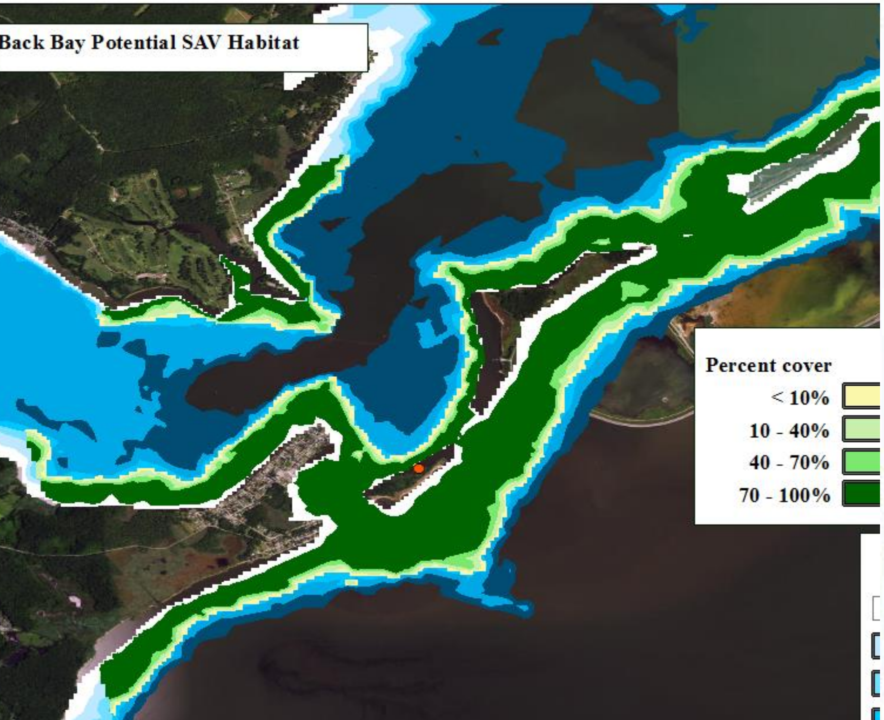
Applying *GrassLight* to Back Bay

- Lower TSM: 10.5 mg L^{-1}
- pH: 7.8
- More Chl *a*: 13.9 μg L^{-1}
- SAV Depth Limit: 1.6 m



Applying *GrassLight* to Back Bay

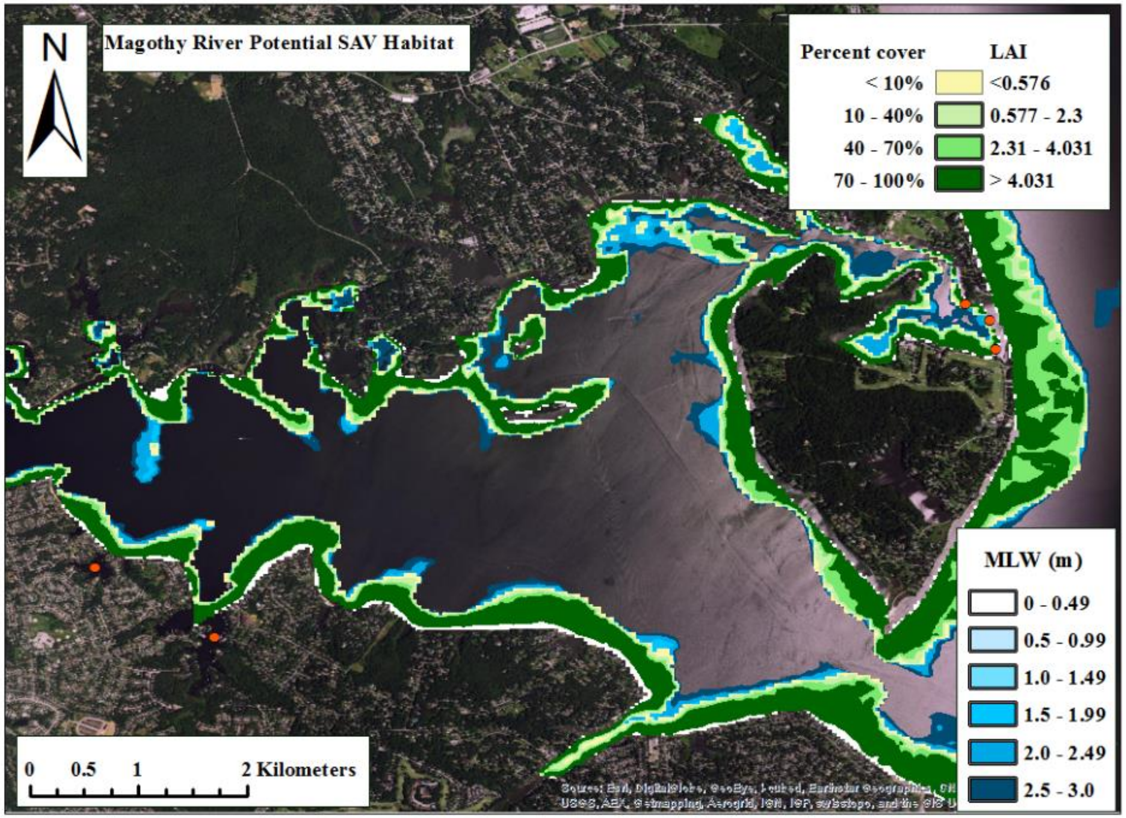
- Model Prediction



- VIMS 2015 Survey

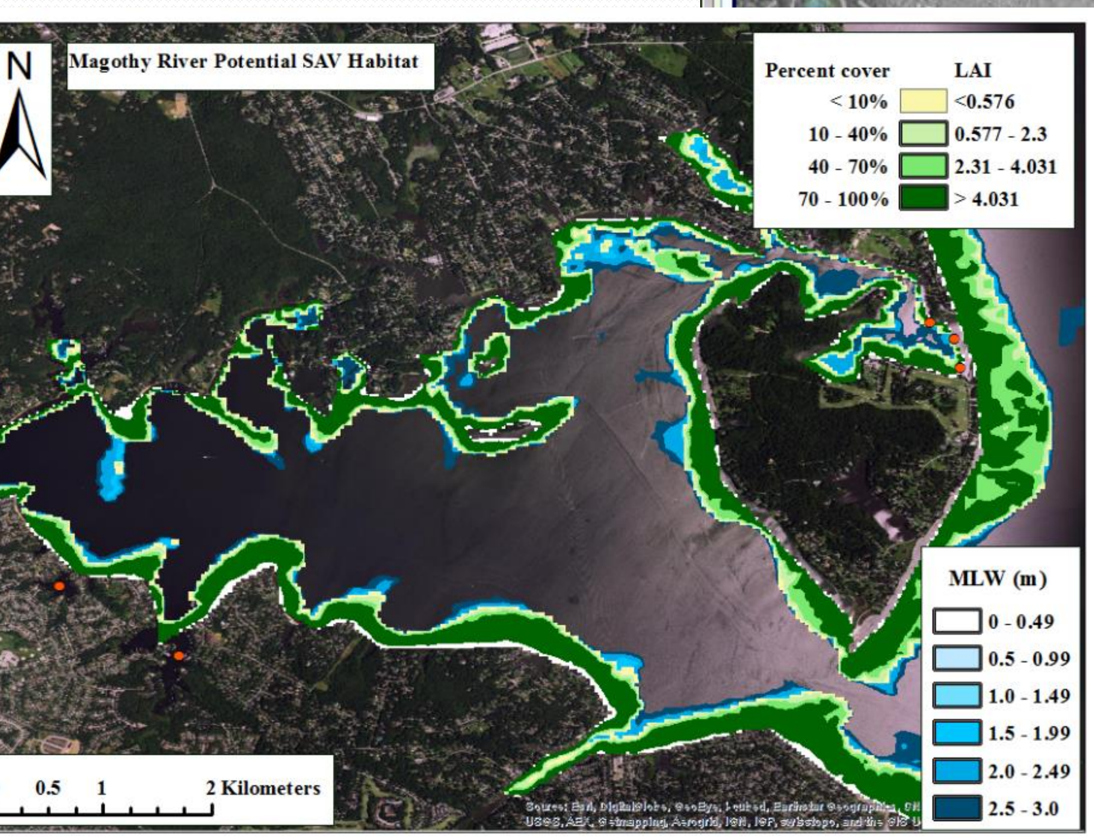
Applying *GrassLight* to Magothy River

- Low TSM: 8 mg L^{-1}
- pH: 8
- Most Chl *a*: 22.8 $\mu g\ L^{-1}$
- SAV Depth Limit: 1.7 m

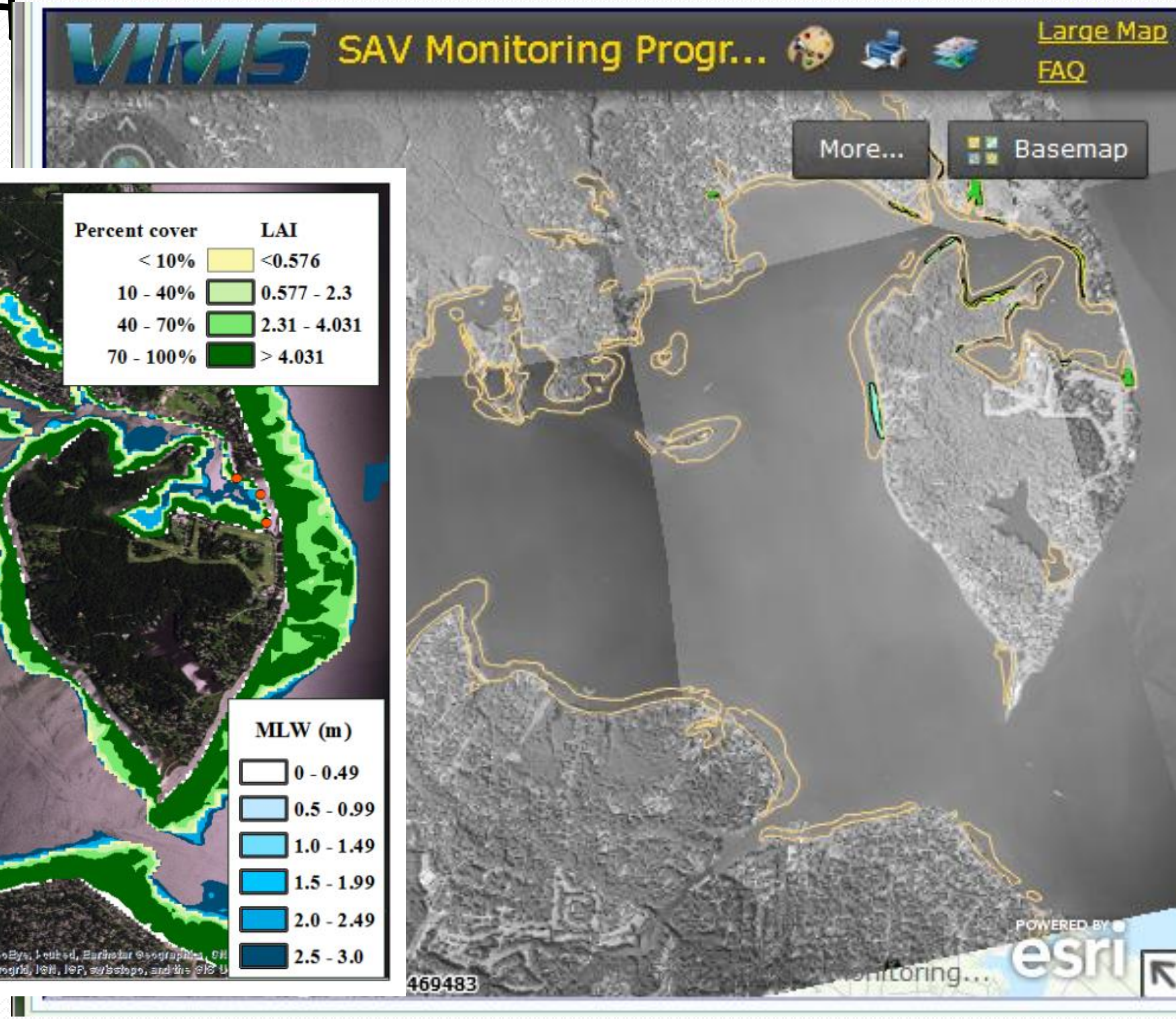


Applying *GrassLight* to Magothy River

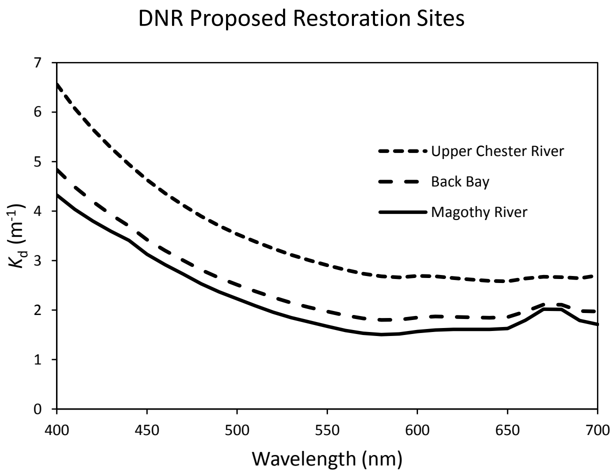
- *GrassLight* Predicti

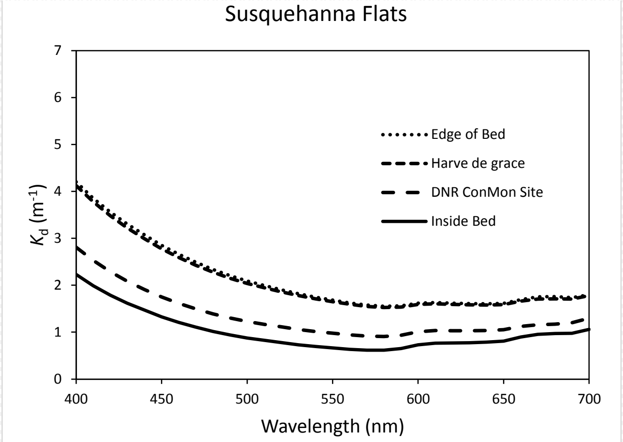


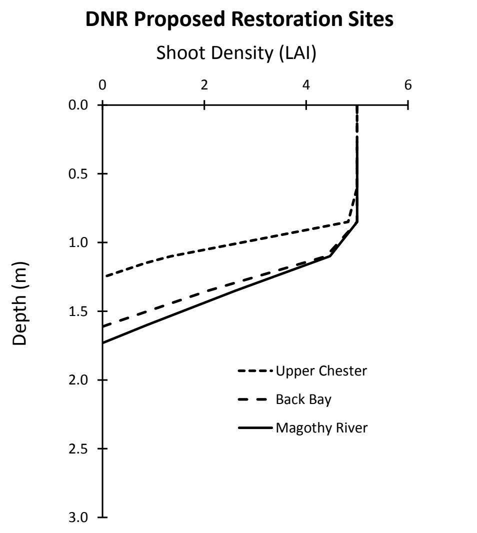
- VIMS Survey Data

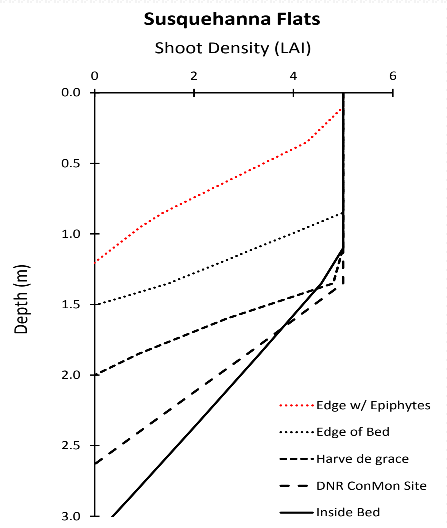


Applying *GrassLight* to Susquehanna Flats



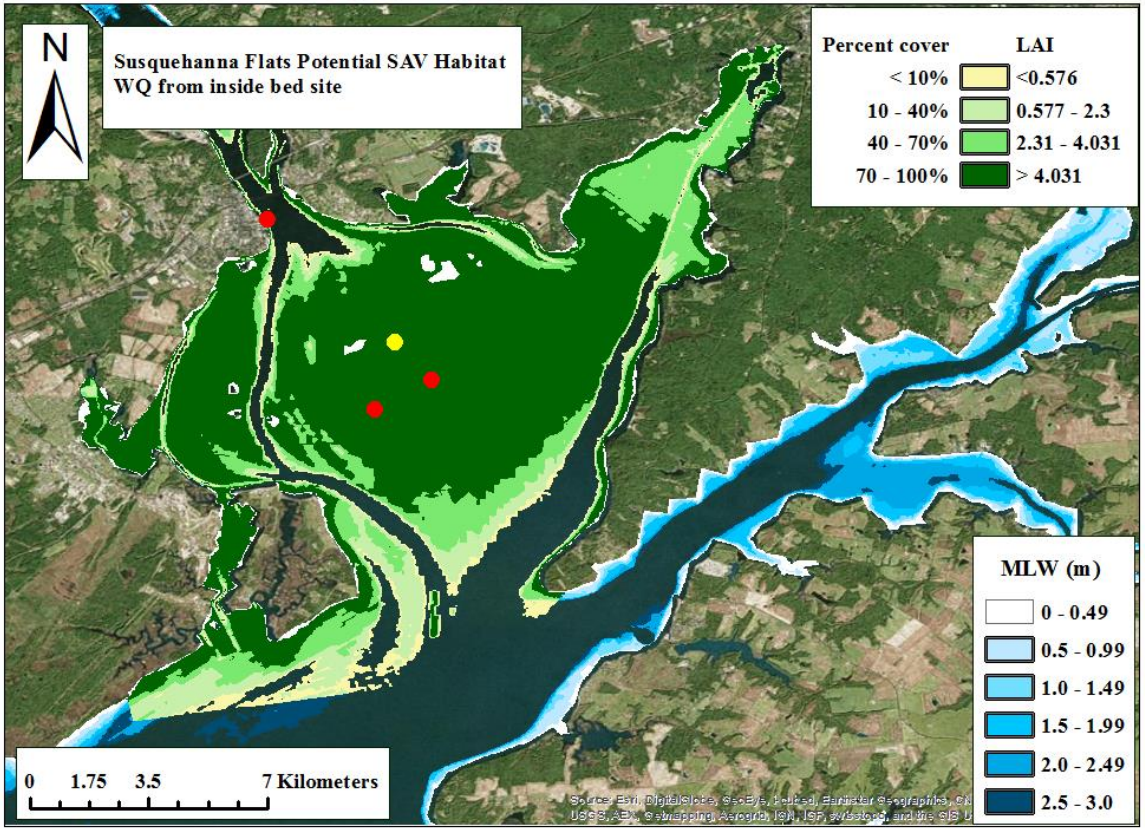






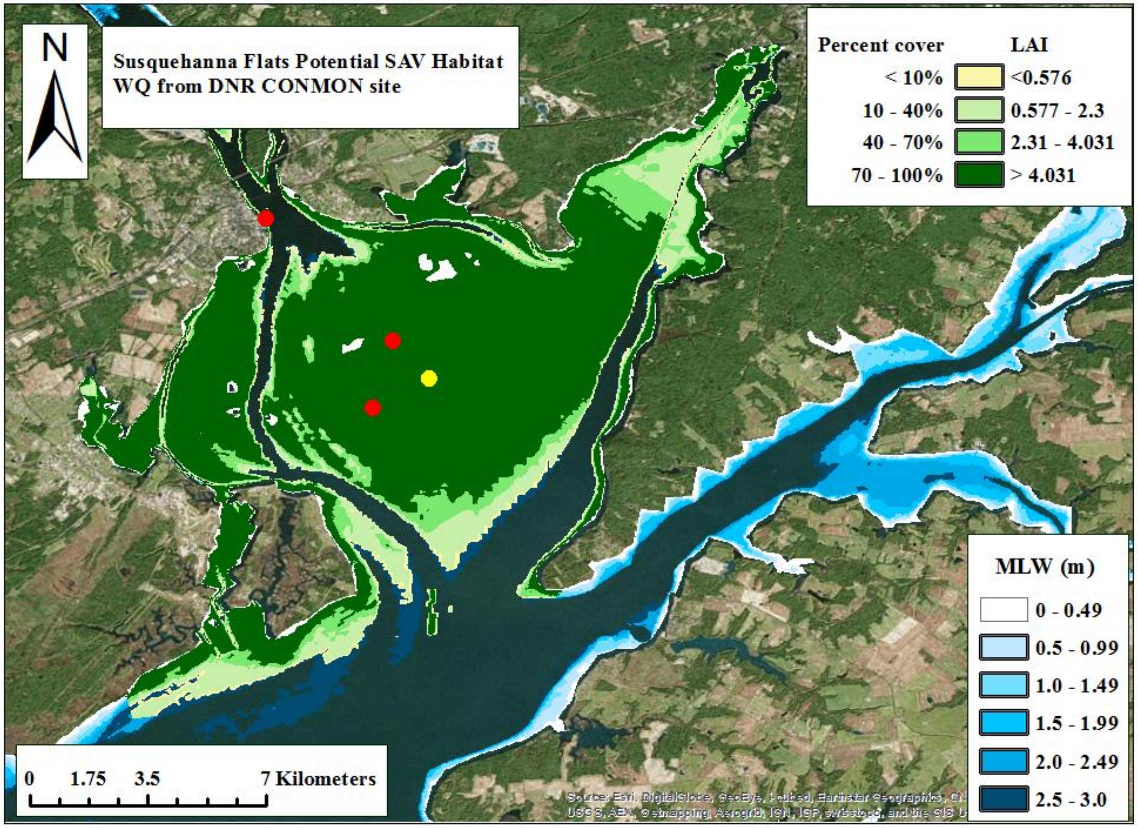
Applying *GrassLight* to Susquehanna Flats: Inside WQ

- Lowest TSM: 3.1 mg L^{-1}
- Highest pH: 8.9
- Chl *a*: 3.7 $\mu g\ L^{-1}$
- SAV Depth Limit: 3.1 m



Applying *GrassLight* to Susquehanna Flats: ConMon WQ

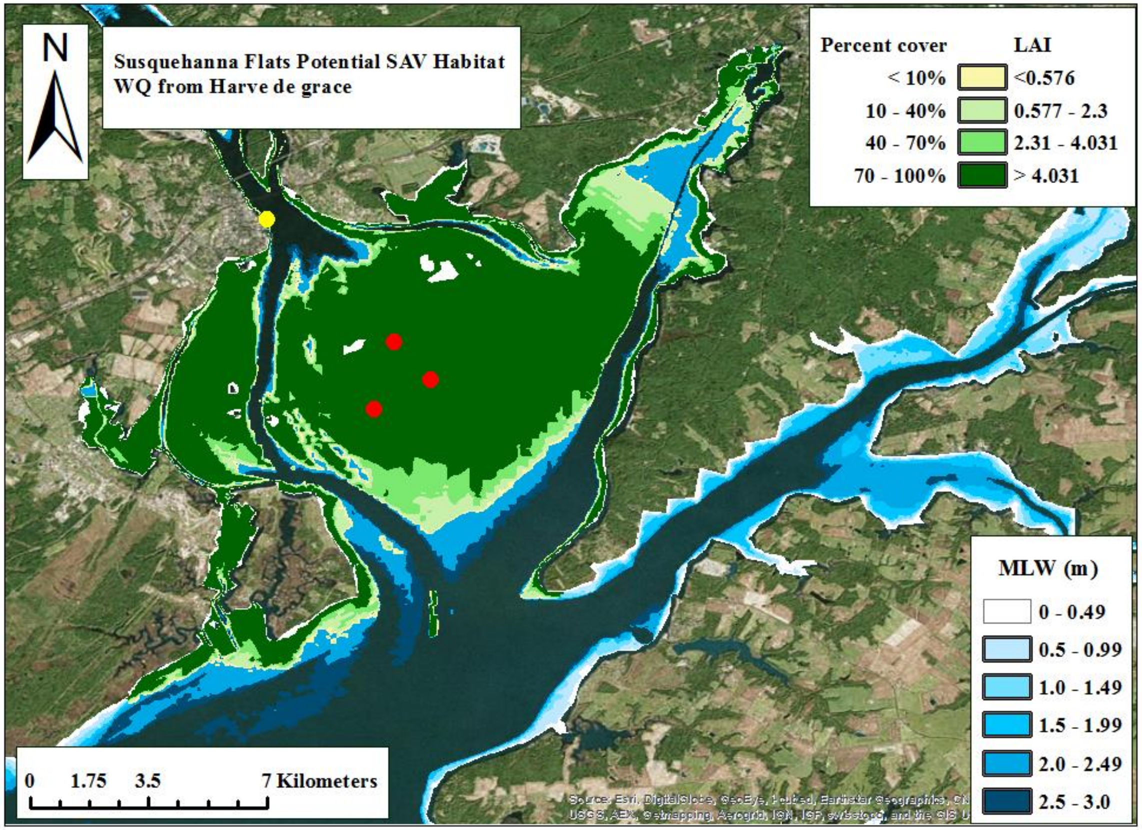
- TSM: 5.2 mg L^{-1}
- High pH: 8.5
- Lowest Chl *a*: 1.4 µg L^{-1}
- SAV Depth Limit: 2.6 m



Applying *GrassLight* to Susquehanna Flats:

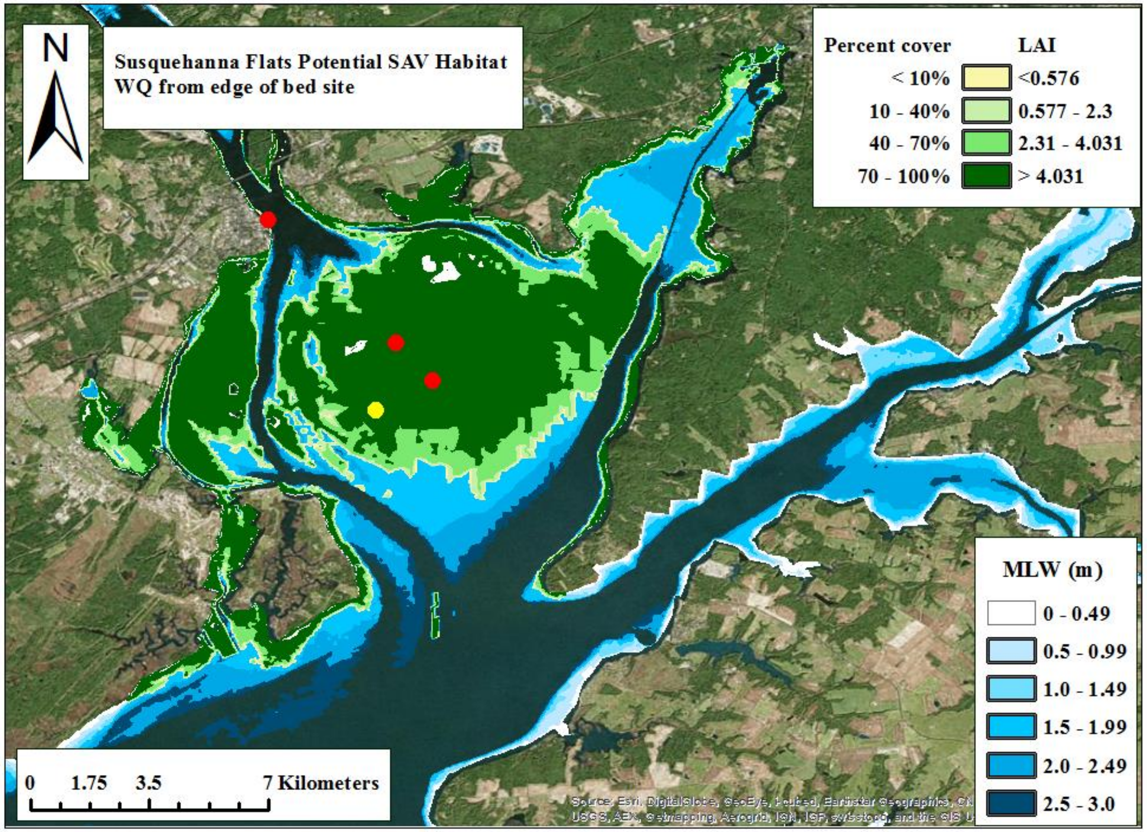
Harve de grace WQ

- TSM: 9.2 mg L^{-1}
- High pH: 8.5
- Chl *a*: 3.7 µg L^{-1}
- SAV Depth Limit: 2.0 m



Applying *GrassLight* to Susquehanna Flats: Edge WQ

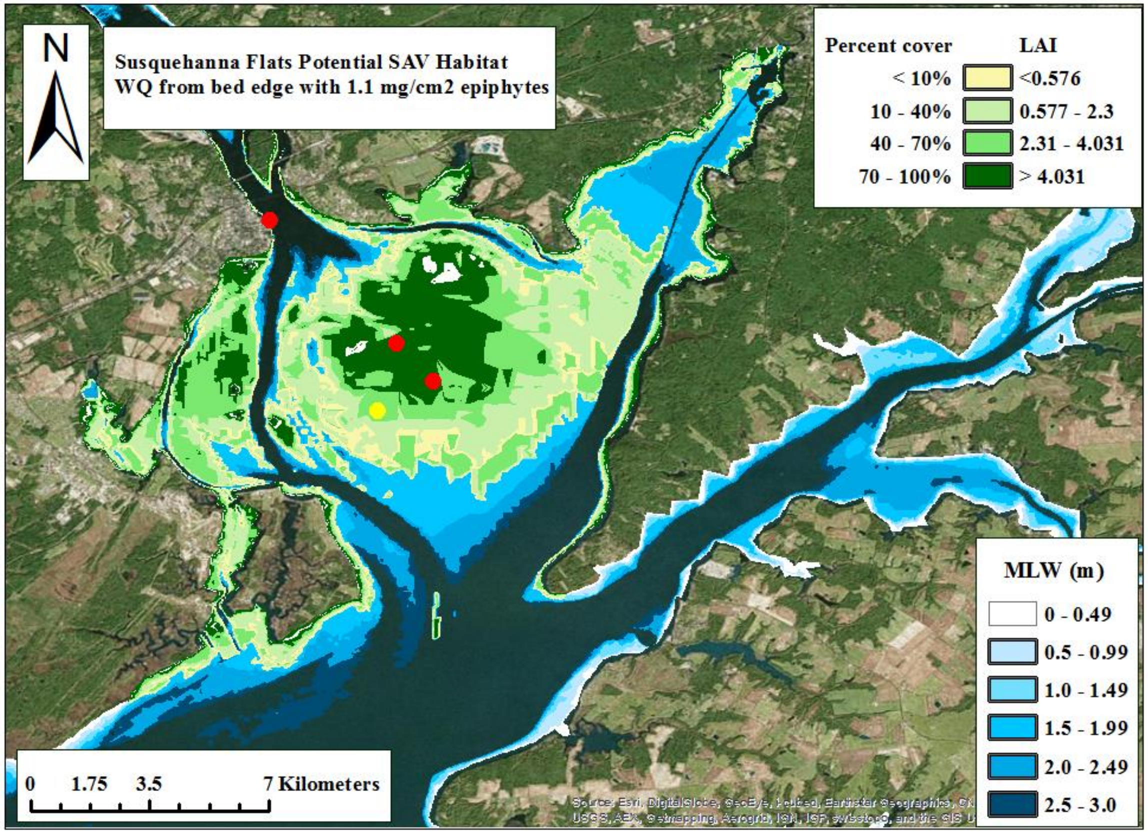
- TSM: 9.3 mg L^{-1}
- High pH: 8.5
- Chl *a*: 5.2 µg L^{-1}
- SAV Depth Limit: 1.2 m



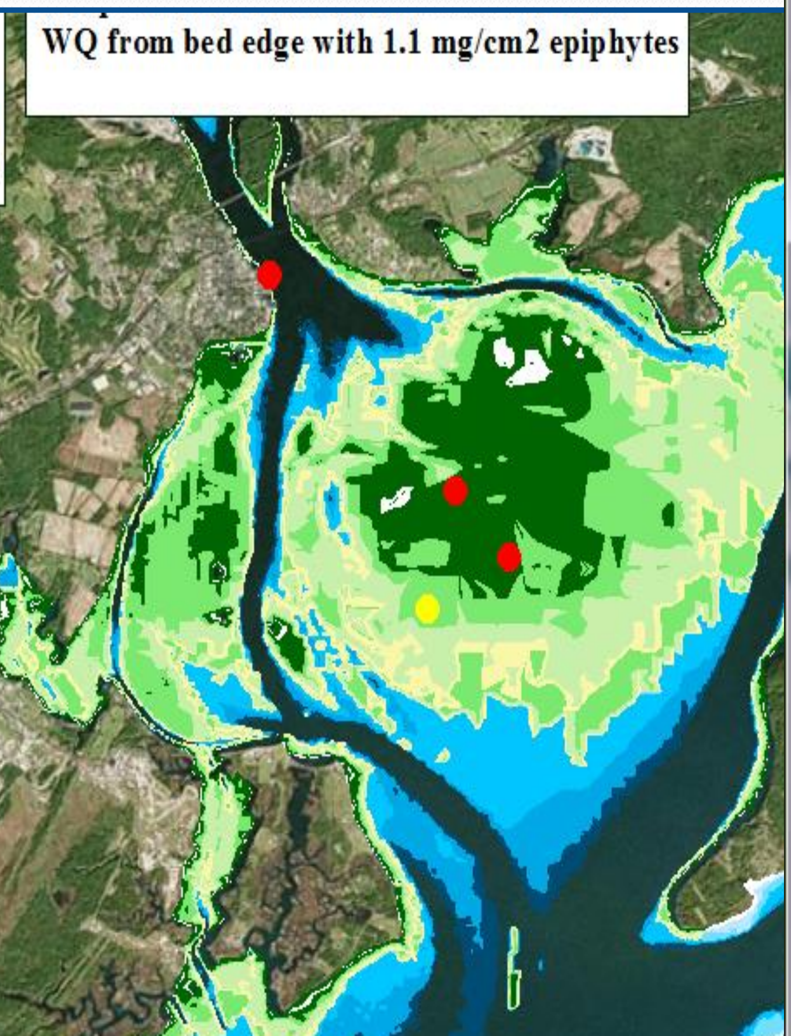
Applying *GrassLight* to Susquehanna Flats:

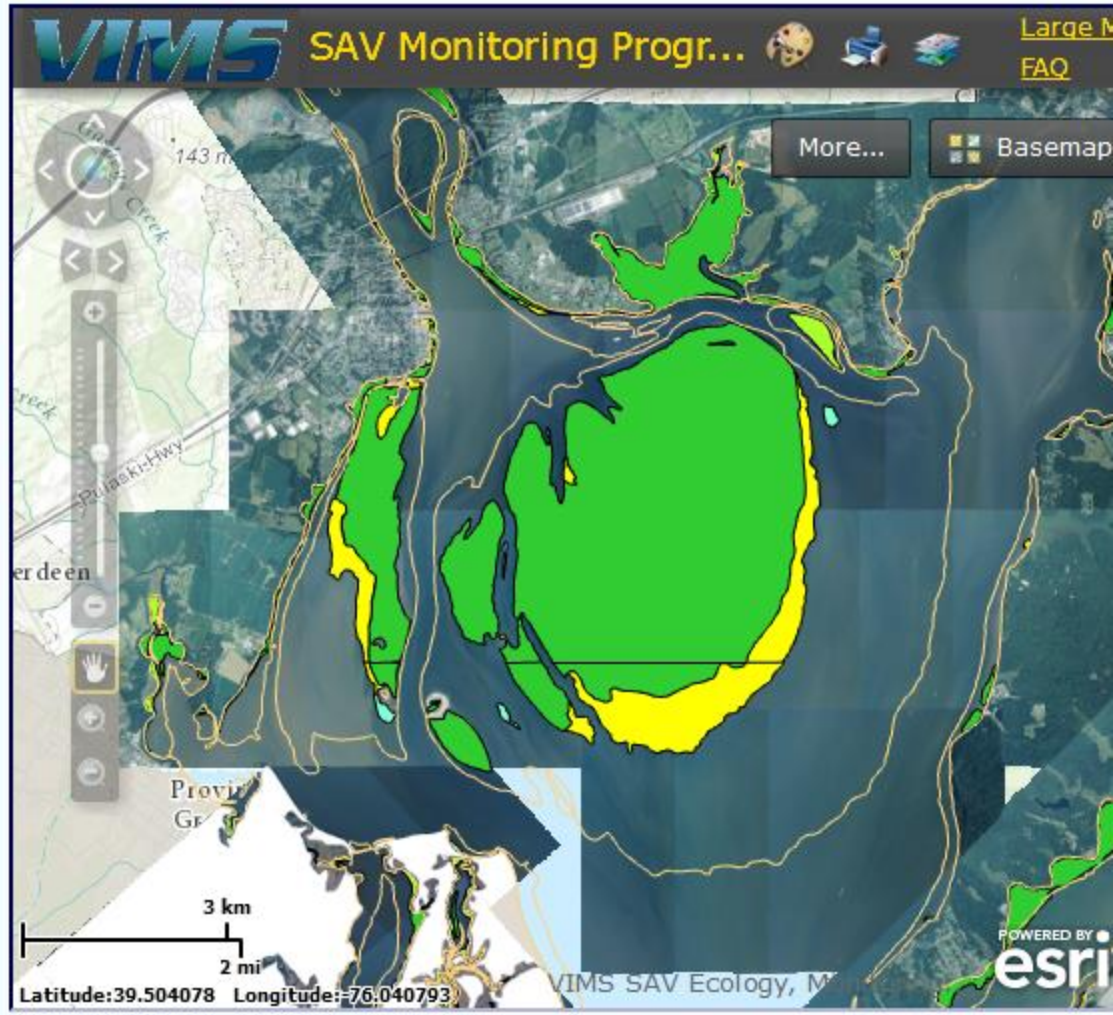
Edge w/ Epiphytes = 1.1 mg cm^{-2}

- TSM: 9.3 mg L^{-1}
- High pH: 8.5
- Chl *a*: 5.2 µg L^{-1}
- SAV Depth Limit: 1.2 m



Applying *GrassLight* to Susquehanna Flats:
Edge w/ Epiphytes = 1.1 mg cm^{-2}

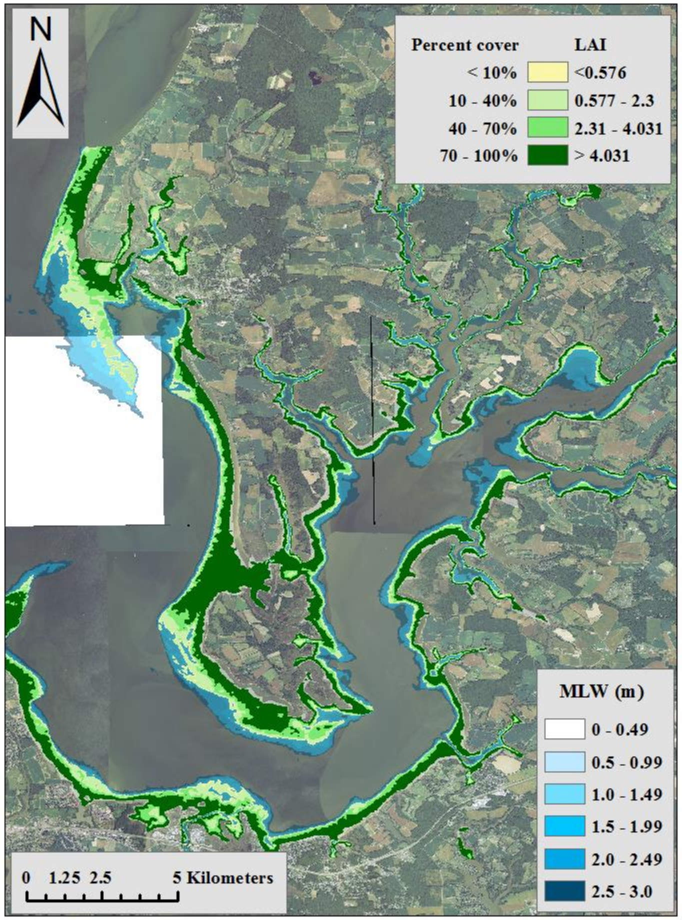




So, back to the Lower Chester River….

- Turbid water limits SAV distribution
  - TSM » 30 mg L^{-1}
  - Chl *a* » 20 mg m^{-3}
  - $z_{E(22\%)} = 0.2$ m
  - $z_{E(13\%)} = 0.3$ m
- SAV distribution expands by improving water quality to average for Sandy Point
  - TSM = 10 mg L^{-1}
  - Chl *a* = 10 mg m^{-3}
  - $z_{E(22\%)} = 0.7$ m
  - $z_{E(13\%)} = 0.9$ m

Chester River potential SAV distribution Sandy Pt WQ



Imagery from Geospatial Data Gateway; 2013 National Ag. Imagery Program Mosaic

GrassLight as a tool for predicting SAV distributions in Chesapeake Bay:

- Good predictions of light-limited distribution using:
  - Median values of Chl *a*, TSM, Temperature, pH from WQ data
  - Eelgrass morphology & optical properties
  - Light environment assumed long day length (14.8 h)
  - USGS 30 m DEM
- pH may limit density in large beds (e.g. Susquehanna Flats)
- Epiphytes are probably important
- Predictions are only as good as the underlying bathymetry

GrassLight does not consider:

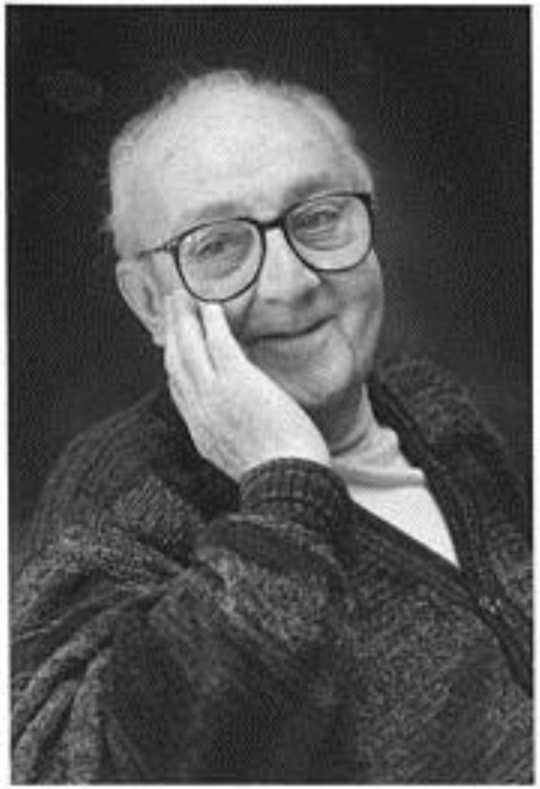
- Optical properties & canopy architecture of freshwater SAV
- Wave exposure/fetch
- Sediment characteristics
  - Sand vs. mud
  - Organic content
  - Sulfide content
- Water column anoxia

But we're working on them……….

All models are wrong but some are useful

Now it would be very remarkable if any system existing in the real world could be *exactly* represented by any simple model. However, cunningly chosen parsimonious models often do provide remarkably useful approximations. For example, the law PV = RT relating pressure P, volume V and temperature T of an "ideal" gas via a constant R is not exactly true for any real gas, but it frequently provides a useful approximation and furthermore its structure is informative since it springs from a physical view of the behavior of gas molecules.
For such a model there is no need to ask the question "Is the model true?". If "truth" is to be the "whole truth" the answer must be "No". The only question of interest is "Is the model illuminating and useful?".

Box, G. E. P. (1979), "Robustness in the strategy of scientific model building", in Launer, R. L.; Wilkinson, G. N., Robustness in Statistics, Academic Press, pp. 201–236.



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