

Monitoring Changes in the Carbon Budget of the Chesapeake Bay Watershed Caused by Agricultural Conservation through Integrating Remote Sensing Data and Modeling (22-CMS22-0027)

Chesapeake Bay Program Modeling Workgroup Meeting Quarterly Review, October 2023

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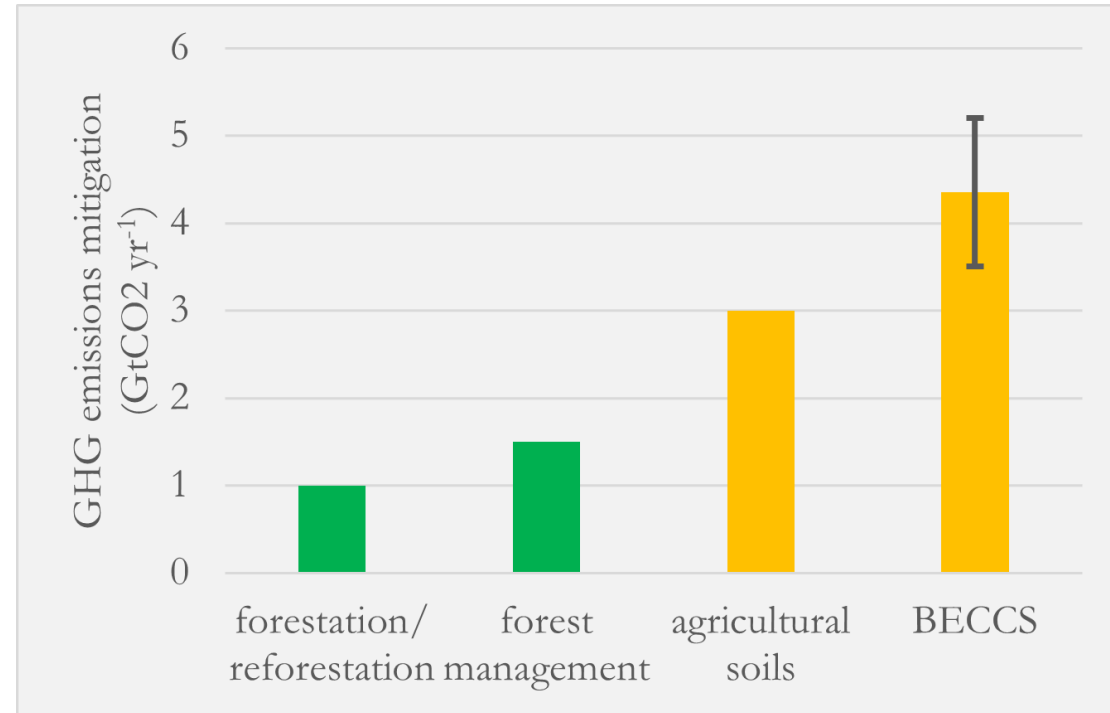
Stakeholders: Gary Shenk (Chesapeake Bay Program), Rajith Mukundan (NYC-DEP), Diana Oviedo Vargas (Stroud Water Research Center), Jason Keppler (Maryland Department of Agriculture).



Significance of agriculture-based GHG emissions mitigation

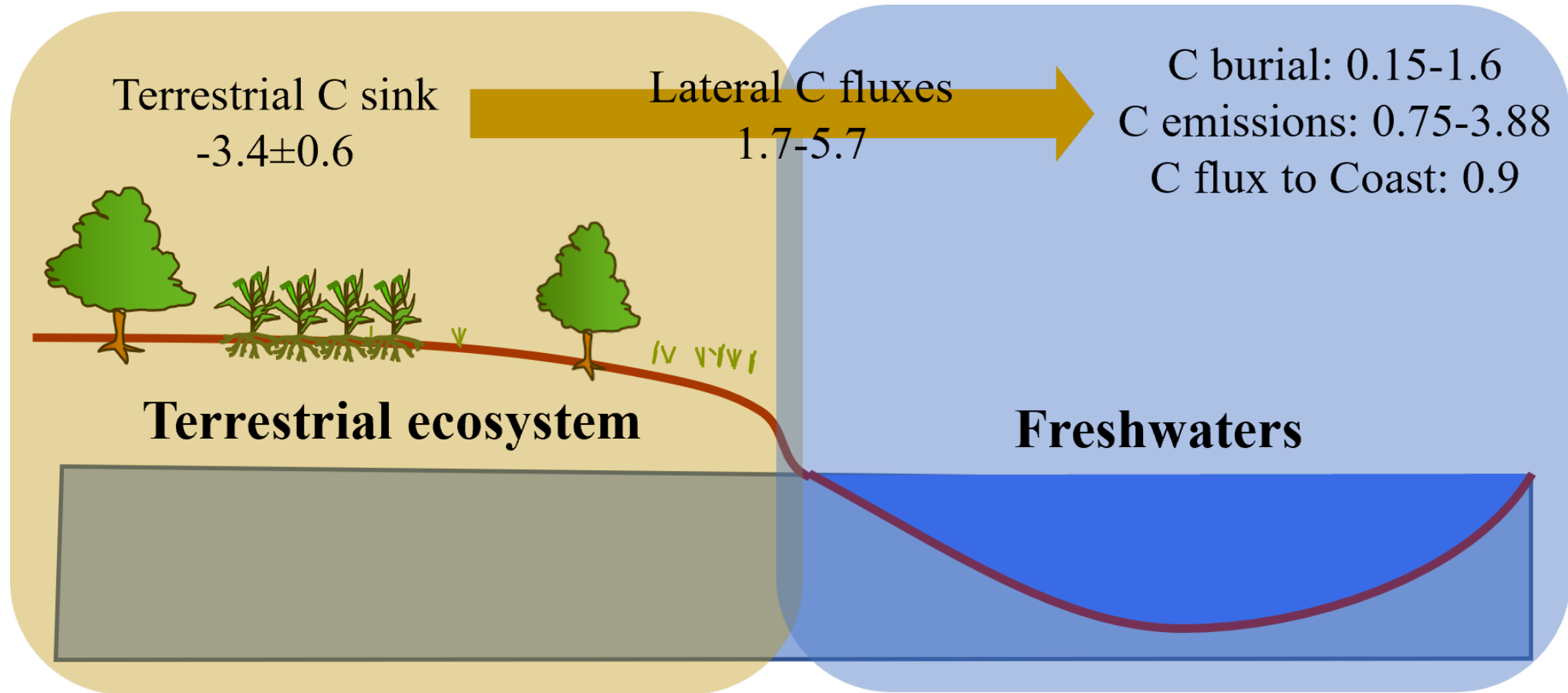
► Negative Emissions Technologies (NETs)

- Four NETs with potential to be scaled up to capture and store a significant amount of C
- Both uptake and storage by agricultural soils and biomass energy with C capture and storage are closely related to the agriculture sector.



GHG emissions mitigation potential of four major NETs identified by NASEM (2019). BECCS: Biomass energy with C capture and storage.

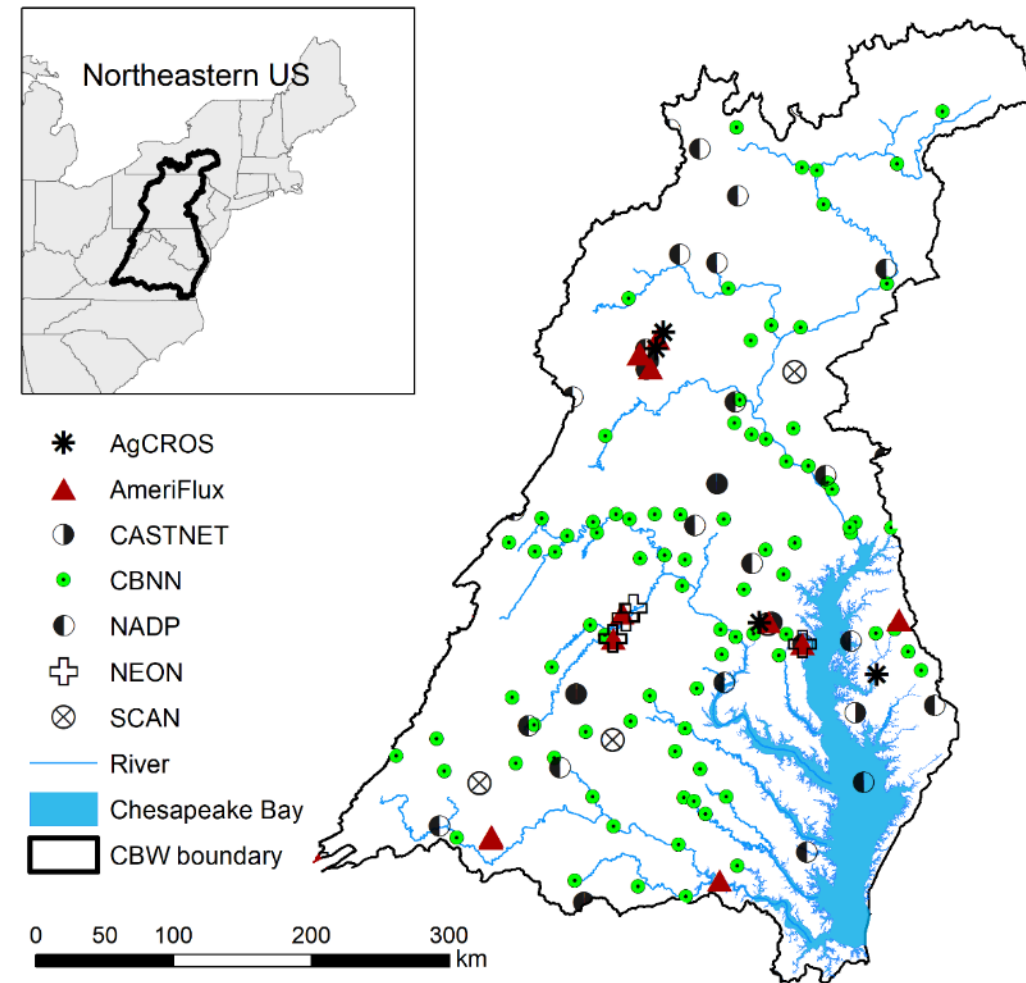
Incomplete accounting of terrestrial-aquatic carbon fluxes



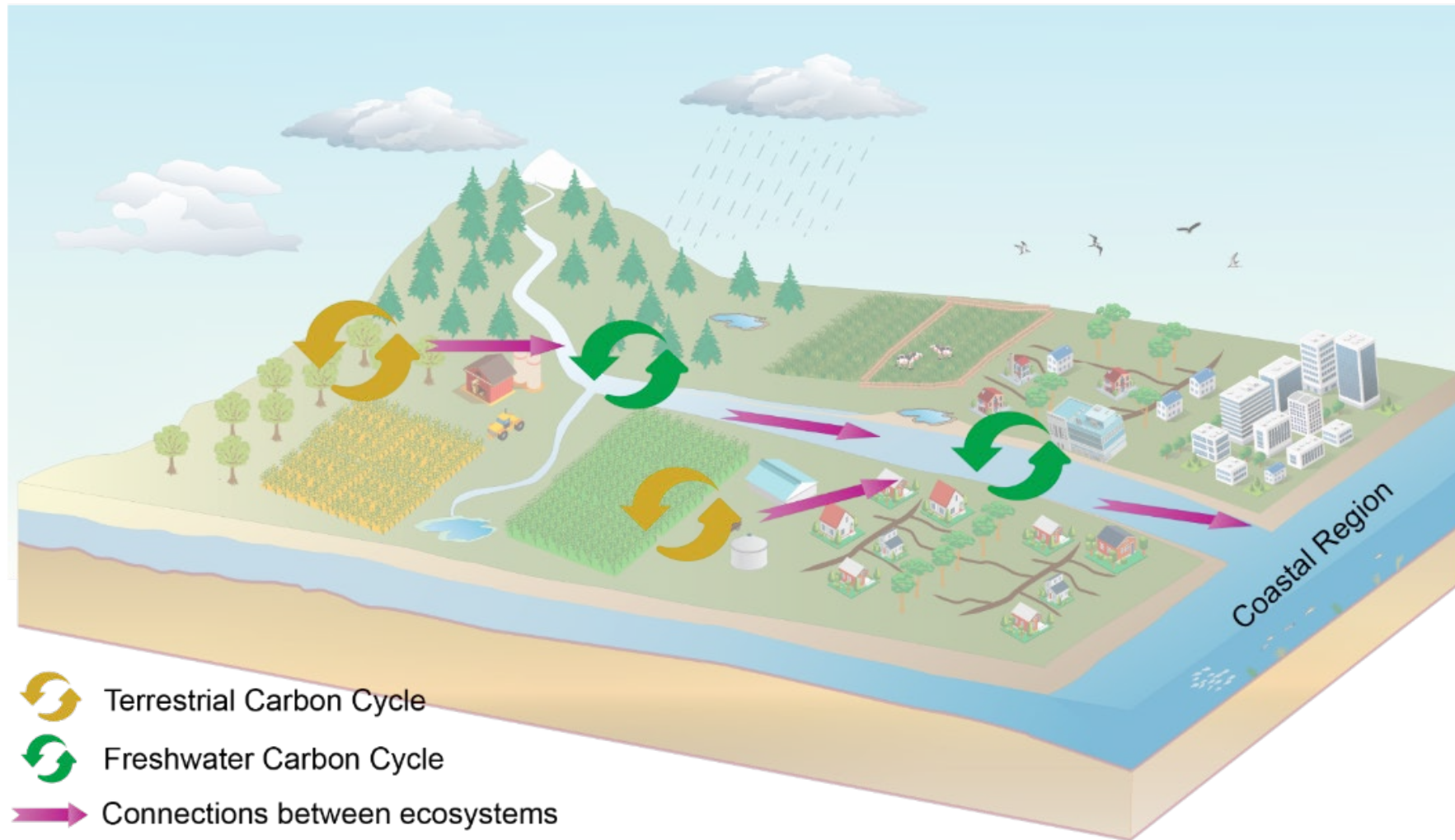
Created based on values reported by IPCC (2021) and multiple publications.

The Chesapeake Bay Watershed

- ▶ The Chesapeake Bay (CB) is the largest estuary in North America
 - nearly 167,000 km²
 - home to over 18 million people
- ▶ The Chesapeake Bay Program (CBP) has been for decades leading and coordinating federal, state, and local level conservation efforts in DC, DE, MD, NY, PA, VA and WV.
- ▶ The Chesapeake Clean Water Blueprint would increase the land and water ecosystem services by \$22.5 billion annually, from \$107.2 to 129.7 billion (in 2013 \$).

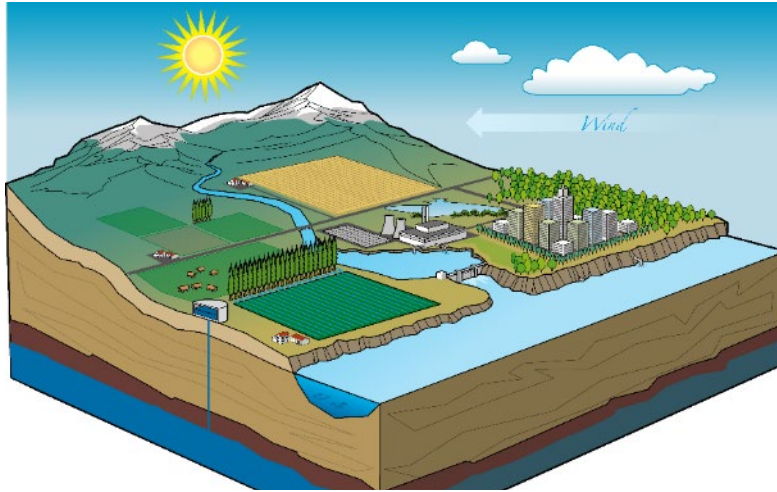


Proposed Chesapeake Bay Watershed-CMS

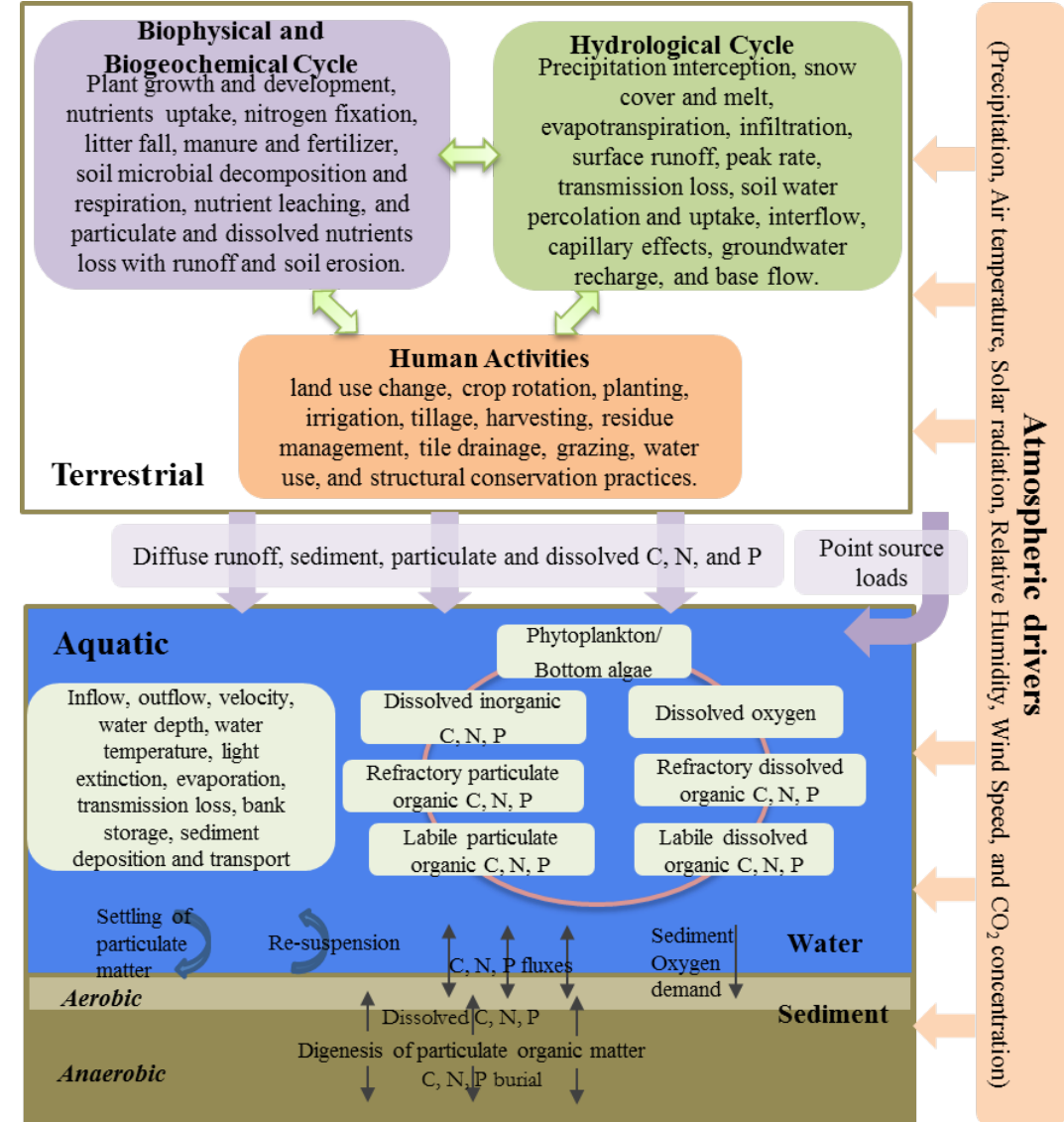


Put together pieces of the watershed scale carbon cycling puzzle

Watershed model: The Soil and Water Assessment Tool – Carbon (SWAT-Carbon)



- ▶ Over 5,000 peer reviewed journal articles
- ▶ Numerous projects across the globe
- ▶ Key improvements:
 - Terrestrial: CENTURY, EPIC, DSSAT, DNDC, and recent literature (Zhang et al. 2013, 2018; Liang et al. 2022).
 - Aquatic: QUAL2K and CE-QUAL-W2 (Du et al. 2019; Qi et al. 2019)

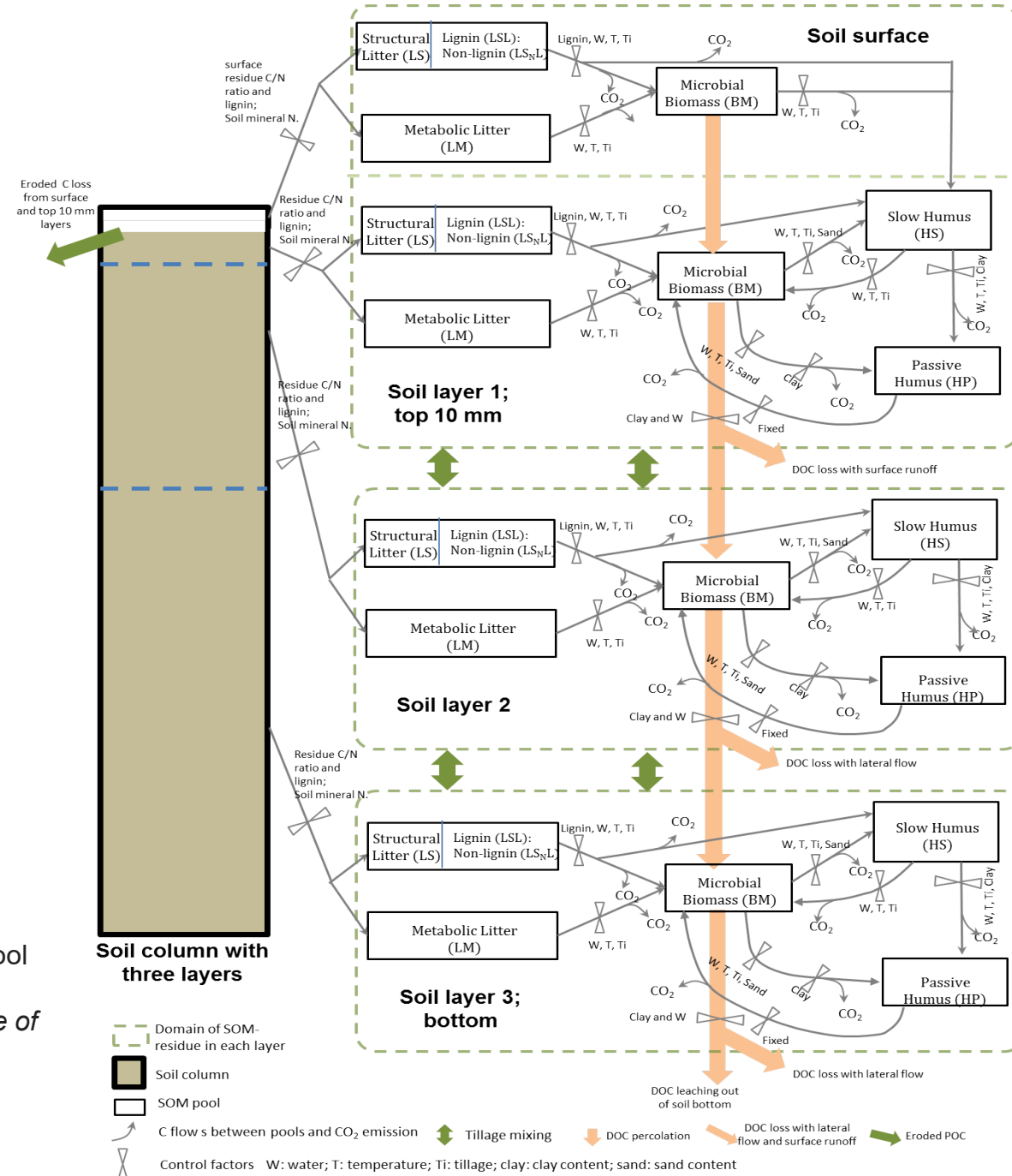


<https://sites.google.com/view/swat-carbon>

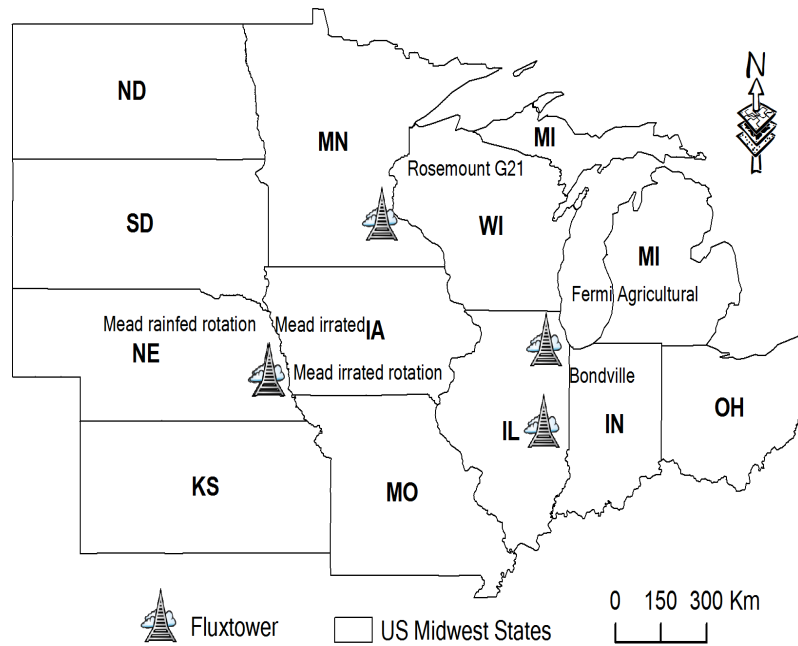
Terrestrial carbon module

- Schematic representation of new SOM-residue dynamics in SWAT.
- Algorithms are derived from CENTURY, EPIC, DSSAT, and ORCHIDEE.

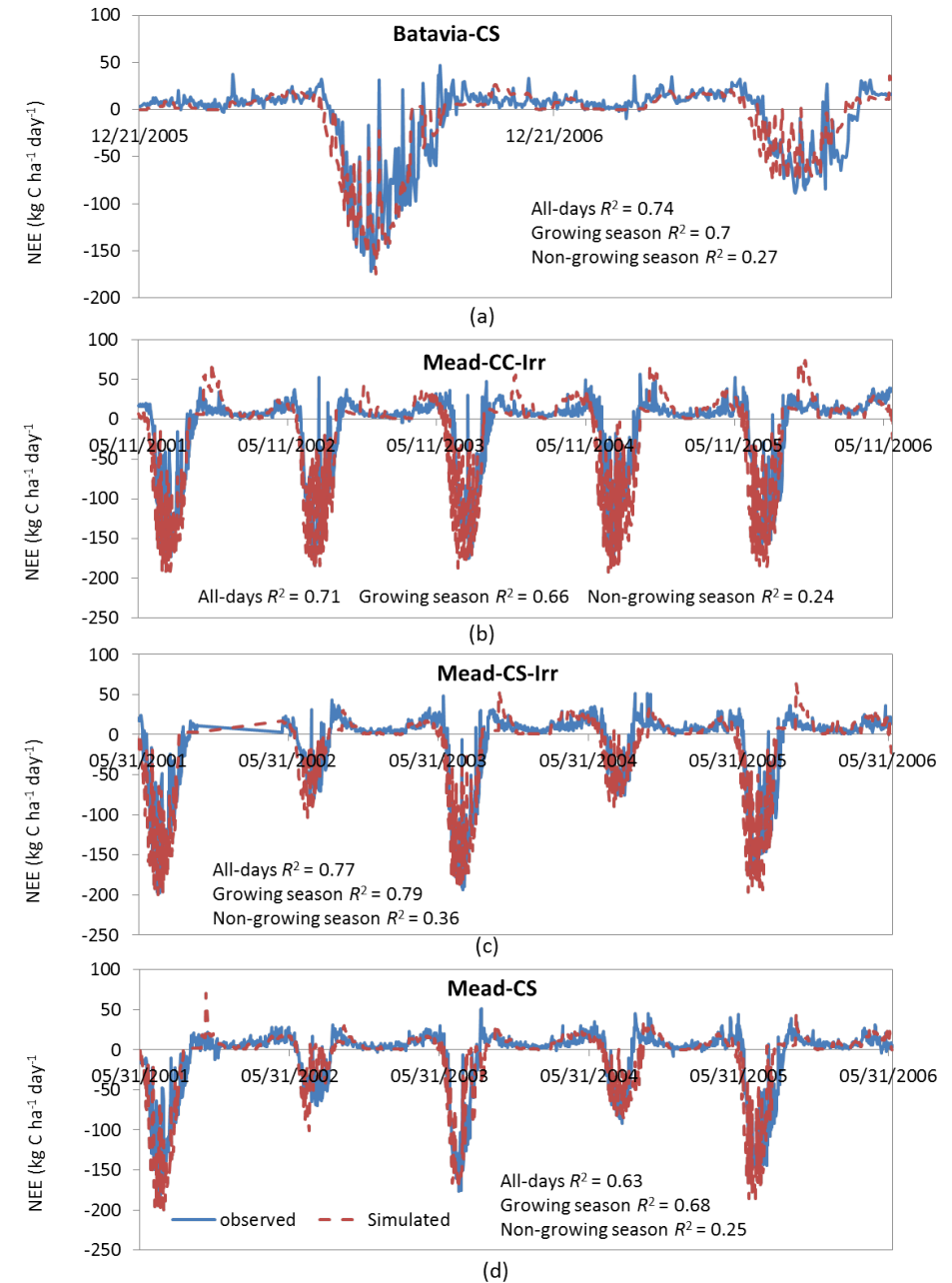
Zhang, X., Izaurralde, R.C., Arnold, J.G., Williams, J.R. and Srinivasan, R., 2013. Modifying the soil and water assessment tool to simulate cropland carbon flux: model development and initial evaluation. *Science of the Total Environment*, 463, pp.810-822.



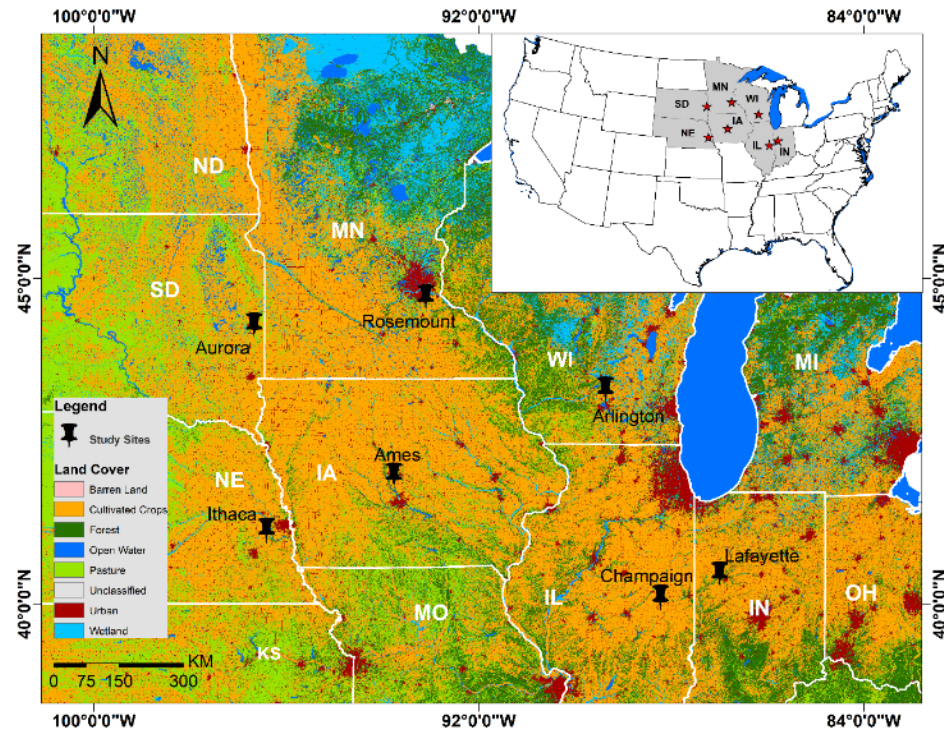
Cropland carbon fluxes at four AmeriFlux towers



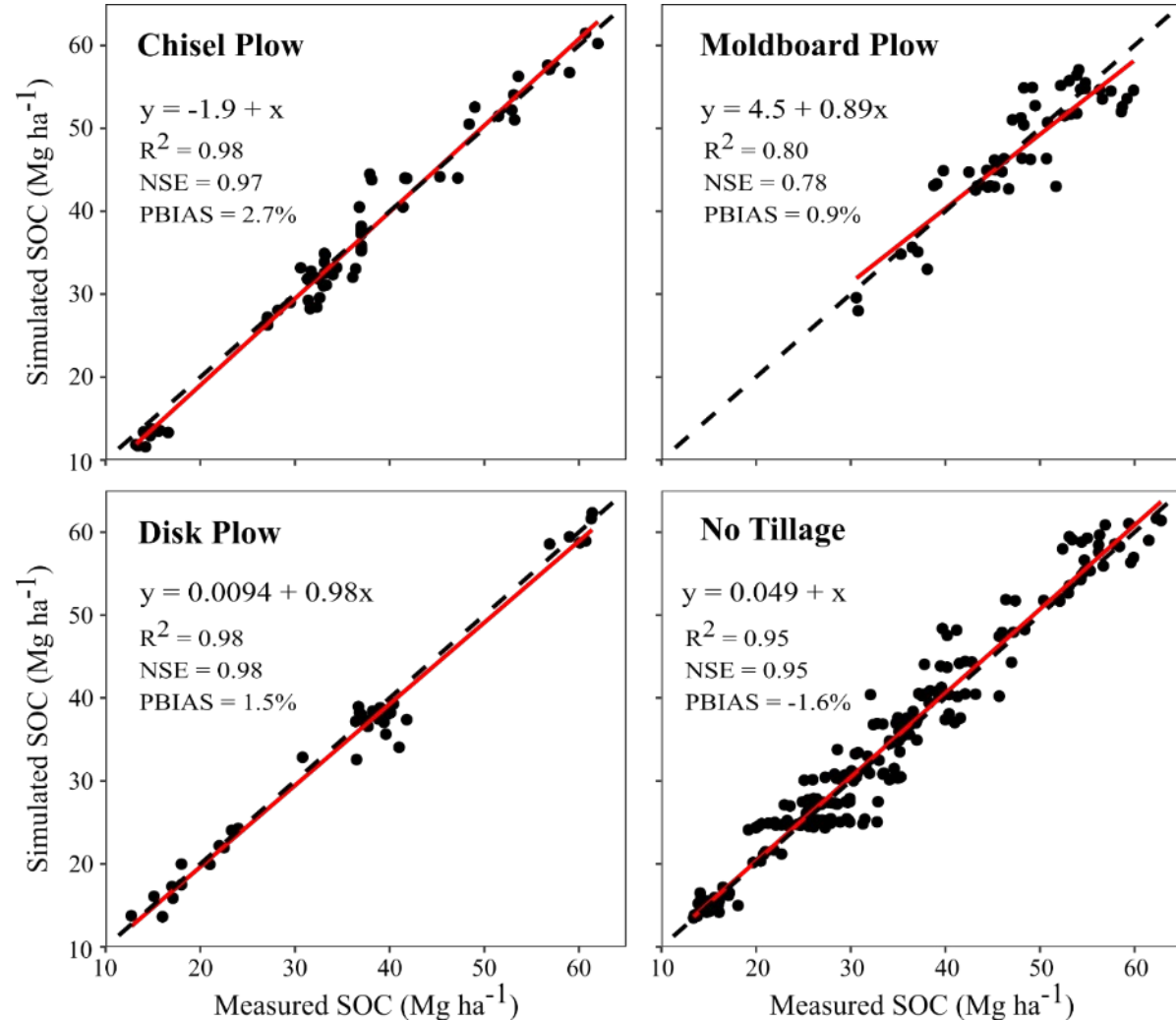
Comparison of SWAT-C simulated and flux tower observed Net Ecosystem Exchange



Evaluation of SWAT-C for soil organic carbon simulation

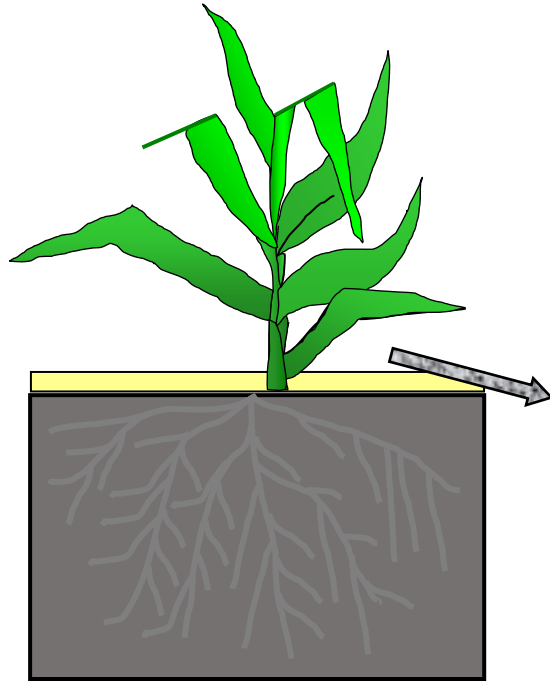


Liang, K., Qi, J., Zhang, X. and Deng, J., 2022. Replicating measured site-scale soil organic carbon dynamics in the US Corn Belt using the SWAT-C model. *Environmental Modelling & Software*, 158, p.105553.



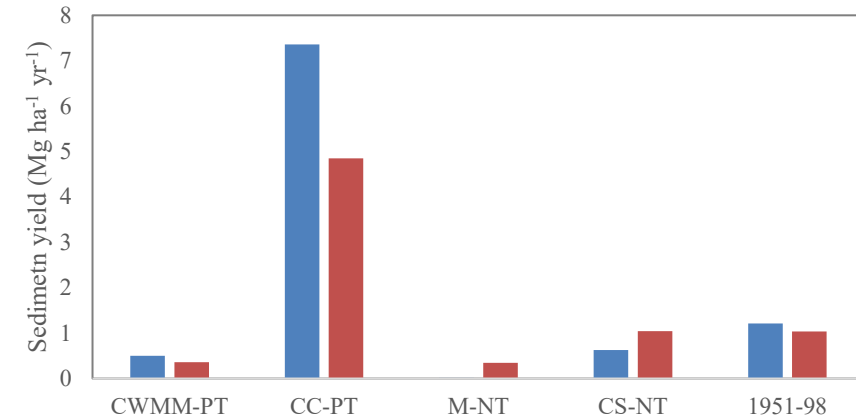
Eroded soil organic carbon

$$\text{Eroded}_{\text{SOC}} = \text{Soil_Erosion} \times \text{SOC}_{\text{content}} \times \text{Enrichment_ratio}$$

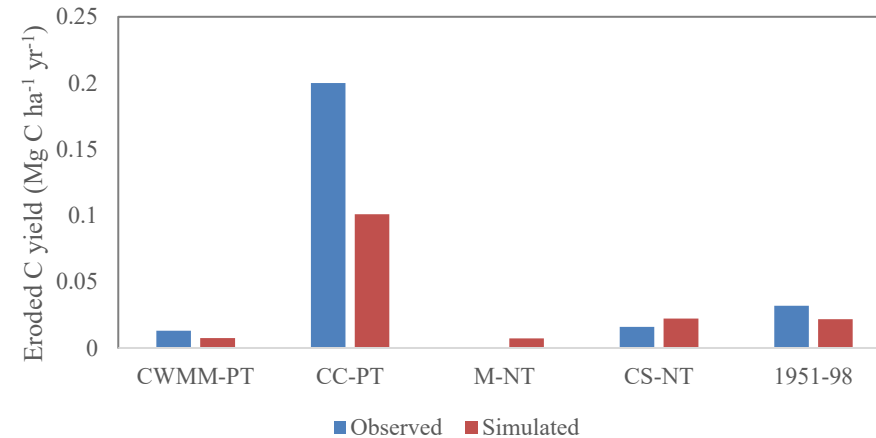


Zhang, X., 2018. Simulating eroded soil organic carbon with the SWAT-C model. *Environmental Modelling & Software*, 102, pp.39-48.

(a) Sediment yield by rotation type



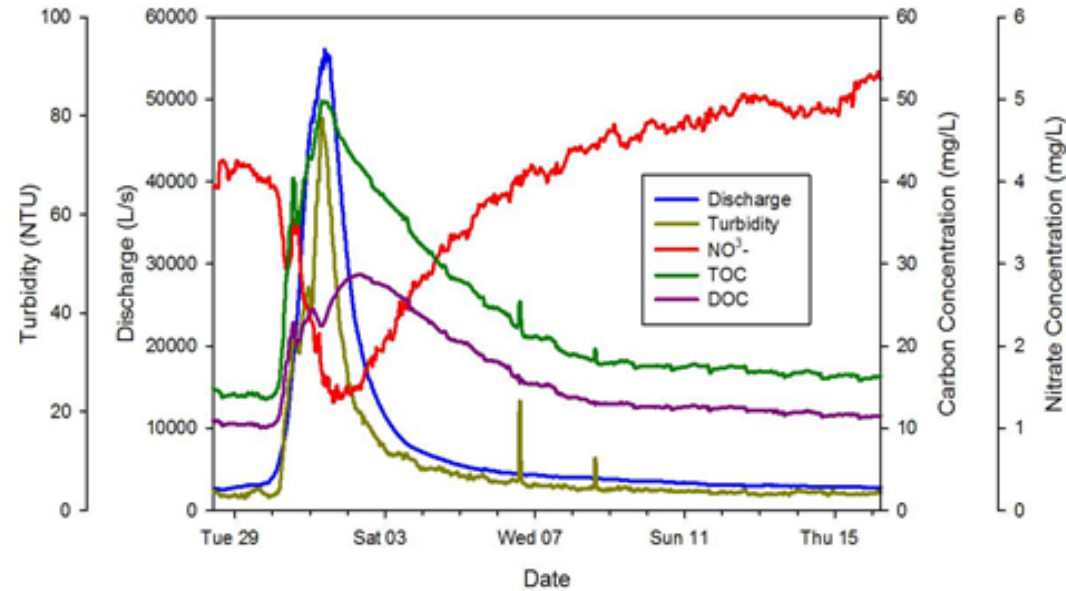
(b) Eroded C yield by rotation type



Sediment and eroded C yields for different crop rotations. 1951-1970: CWMM-PT; 1971-75: CC-PT; 1976-1983: M-NT; 1984-1998: CS-NT.

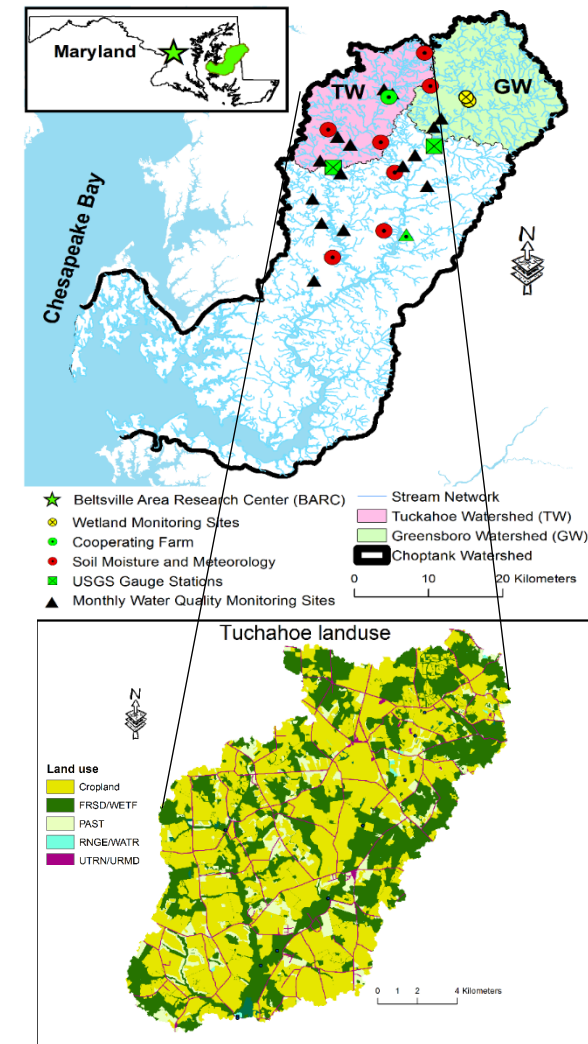
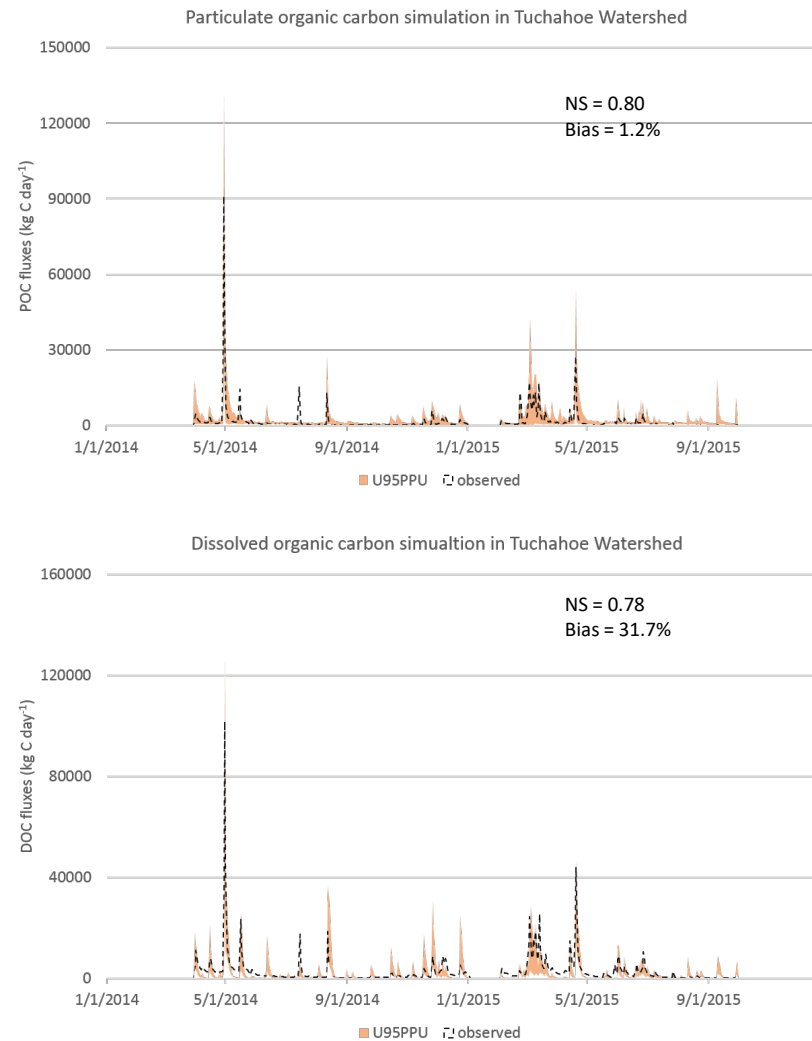
The experimental site is a small watershed (W118) located within the USDA's NAEW research station (40° 22' N, 81° 48' W) near Coshocton, Ohio.

Continuous measurements of POC and DOC at the outlet of Tuckahoe



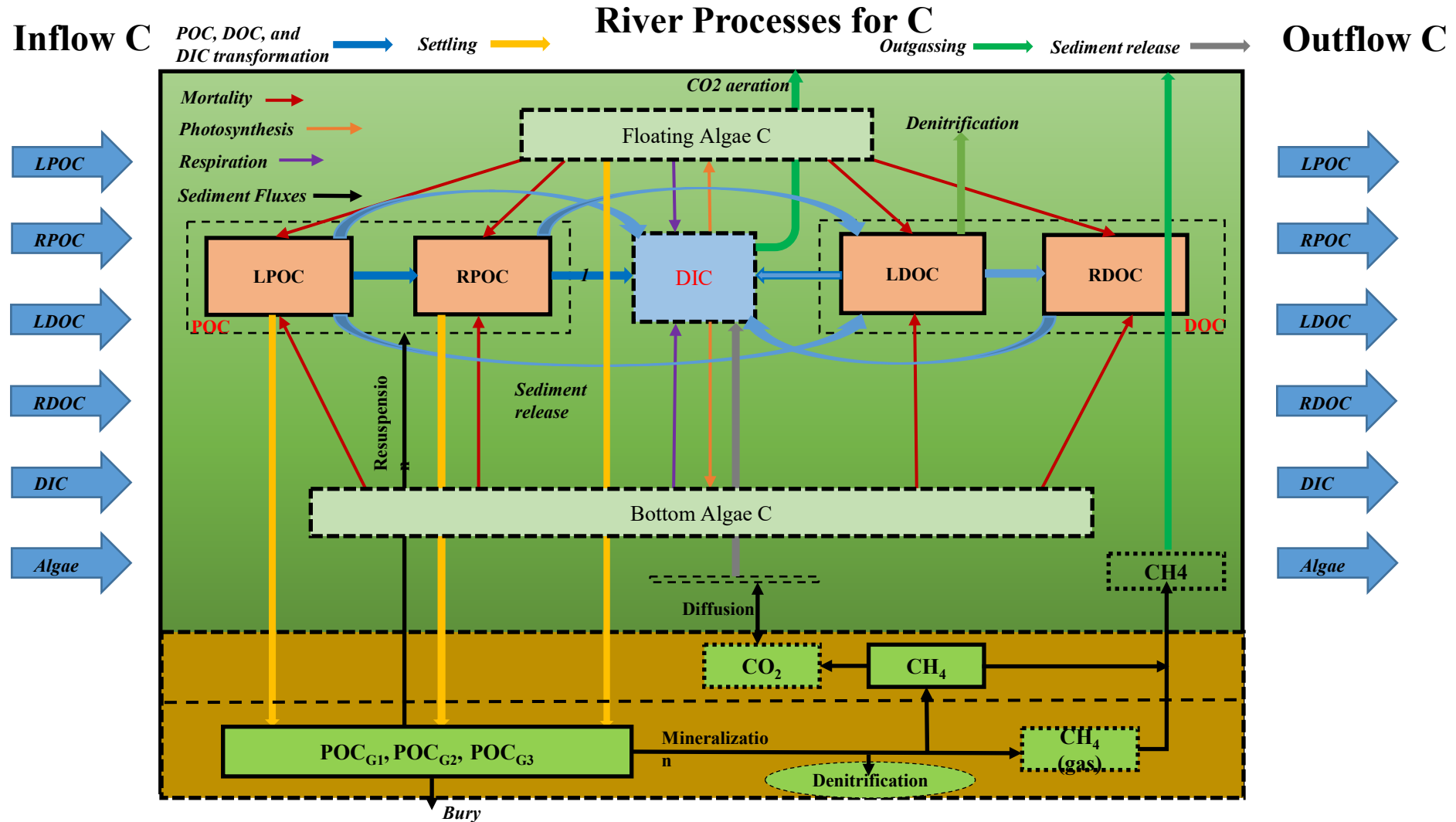
Water quality monitoring include *in-situ* instrument packages containing full spectrum (200 to 700 nm) spectrophotometer probes (S-CAN Instruments, Vienna Austria) for in-situ monitoring of turbidity, nitrate, TOC, and DOC at 30-min intervals. Exemplary measurements of riverine hydrology & biogeochemistry parameters for a continuous period of 18 days are shown Above.

Model Evaluation for POC and DOC fluxes (Tuckahoe)



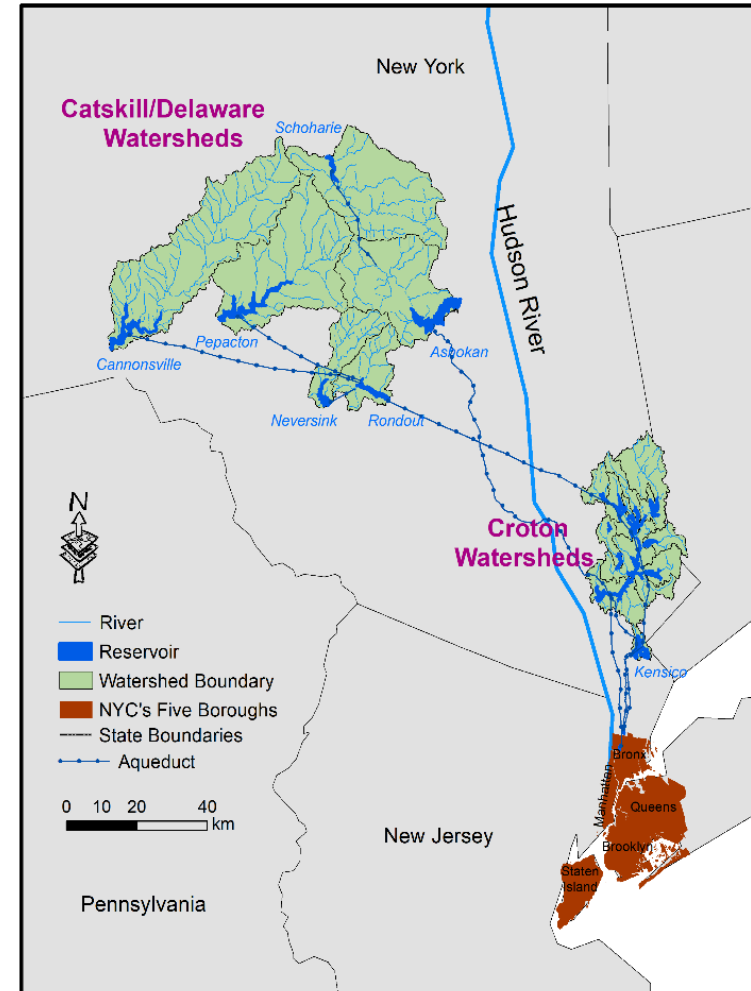
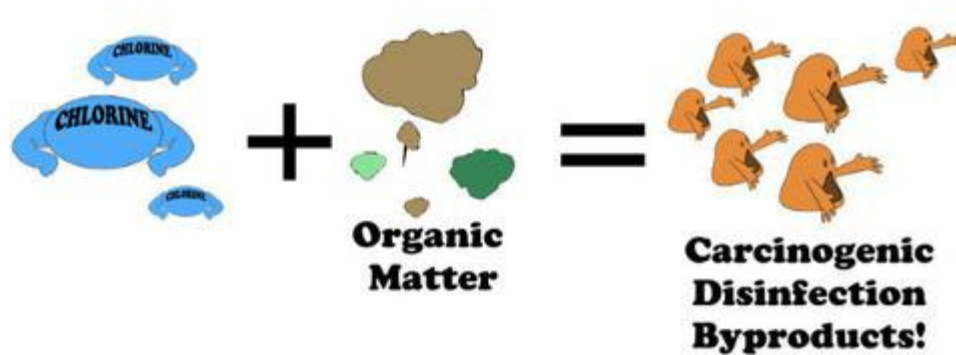
Qi, J., Du, X., Zhang, X., Lee, S., Wu, Y., Deng, J., Moglen, G.E., Sadeghi, A.M. and McCarty, G.W., 2020. Modeling riverine dissolved and particulate organic carbon fluxes from two small watersheds in the northeastern United States. *Environmental Modelling & Software*, 124, p.104601.

Continued development and evaluation of aquatic carbon processes

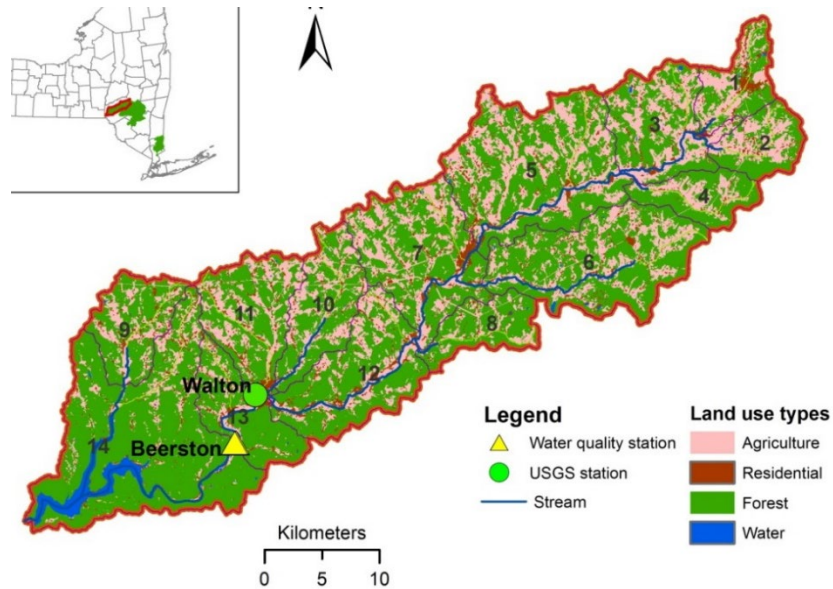


Qi, J., Zhang, X., Lee, S., Wu, Y., Moglen, G.E. and McCarty, G.W., 2020. Modeling sediment diagenesis processes on riverbed to better quantify aquatic carbon fluxes and stocks in a small watershed of the Mid-Atlantic region. *Carbon Balance and Management*, 15(1), pp.1-14.

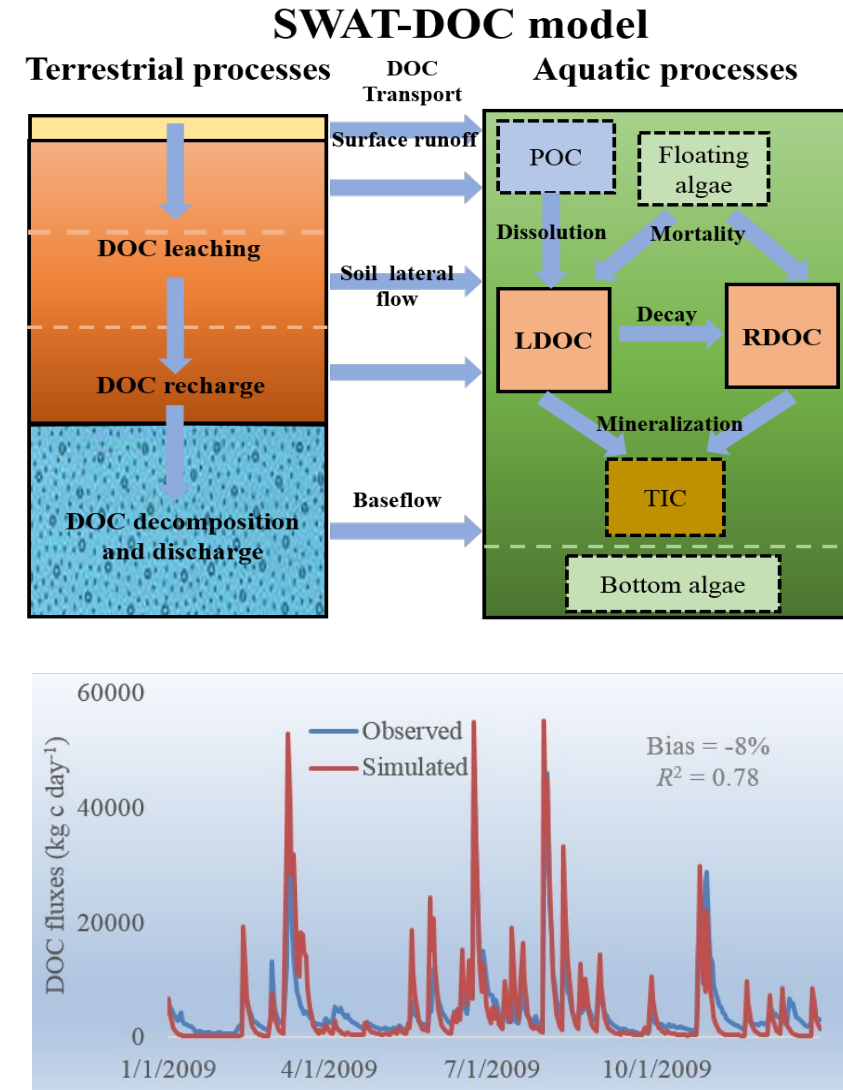
Terrestrial-aquatic carbon cycling relevant to human health



DOC modeling in NYC source watersheds

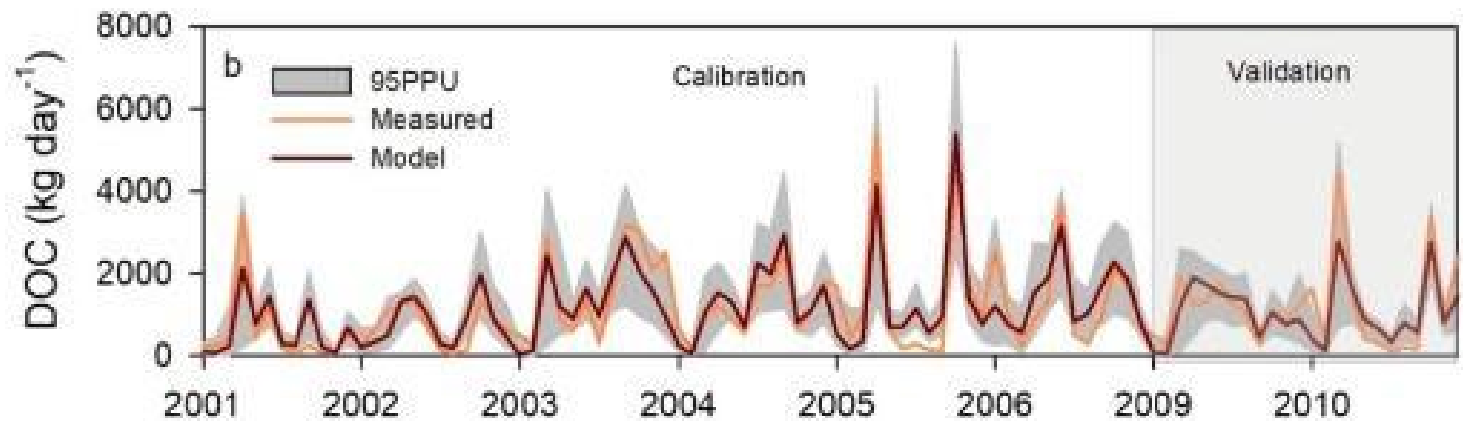
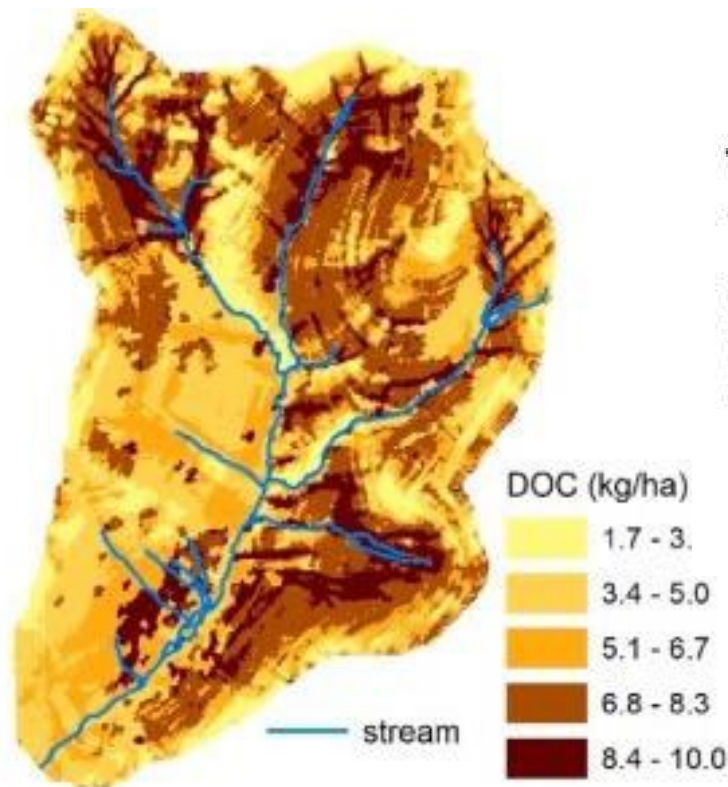


Du, X., Zhang, X., Mukundan, R., Hoang, L. and Owens, E.M., 2019. Integrating terrestrial and aquatic processes toward watershed scale modeling of dissolved organic carbon fluxes. *Environmental Pollution*, 249, pp.125-135.



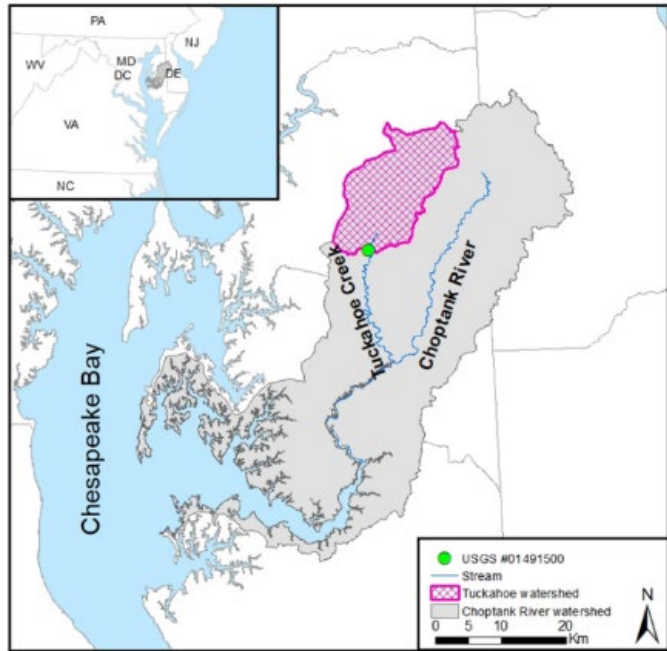
Evaluation of SWAT-C for aquatic carbon simulation

- ▶ New York City's Water Supply Watersheds (e.g., Neversink Reservoir watershed)

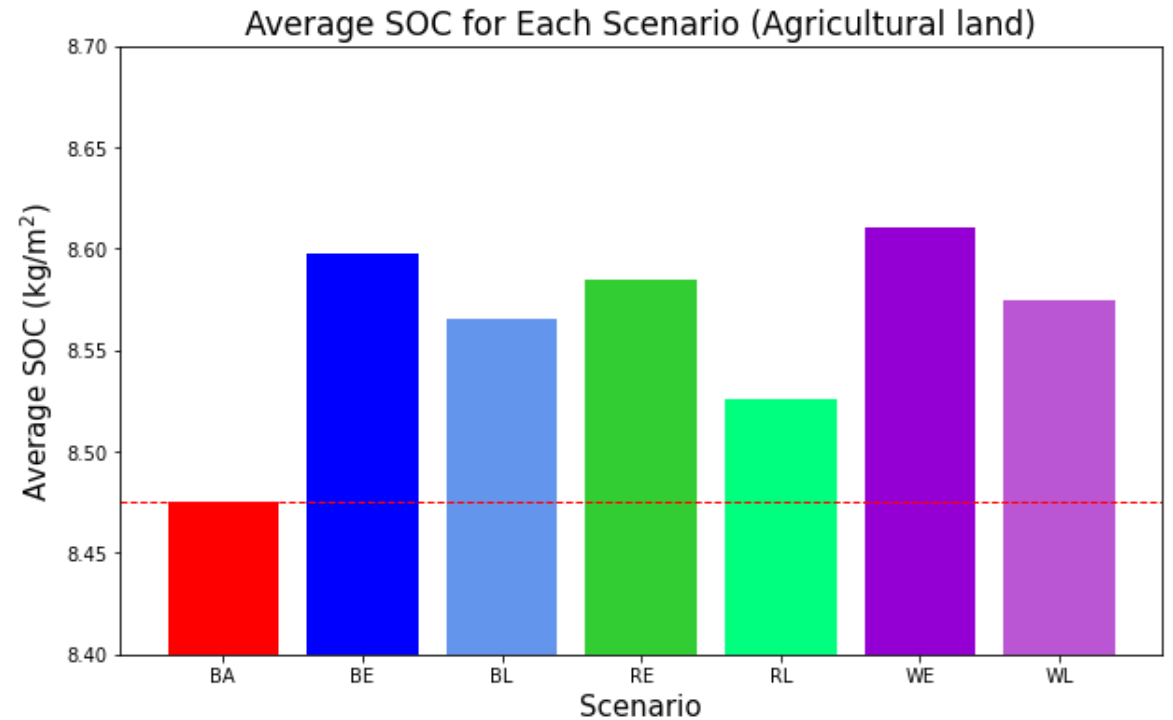


Mukundan, R., Gelda, R., Moknatian, M., Zhang, X. and Steenhuis, T., 2023. Watershed Scale Modeling of Dissolved Organic Carbon Export from Variable Source Areas. *Journal of Hydrology*, p.130052.

Preliminary modeling results: SOC impacts of cover crops (subject to changes)



- BA: Baseline condition (No cover crop)
- BE: Early Barley; BL: Late Barley;
- RE: Early Rye; RL: Late Rye;
- WE: Early Winter wheat; WL: Late Winter wheat



Courtesy of Dr. Sangchul Lee, University of Seoul

SOC on agricultural land would increase 0.5 – 1.4 MgC ha⁻¹ over 2004-2019 or a 6-year period

Previous modeling efforts: Water quality benefits drive the adoption of cover crops

Figure 1

Map of the Choptank River watershed, Maryland/Delaware, showing the boundaries for Upper Tuckahoe and Greensboro subwatersheds, along with a 2017 Cropland Data Layer (CDL) map of summer crop type showing the extent of the Tuckahoe Creek HUC8 watershed (#02130405).

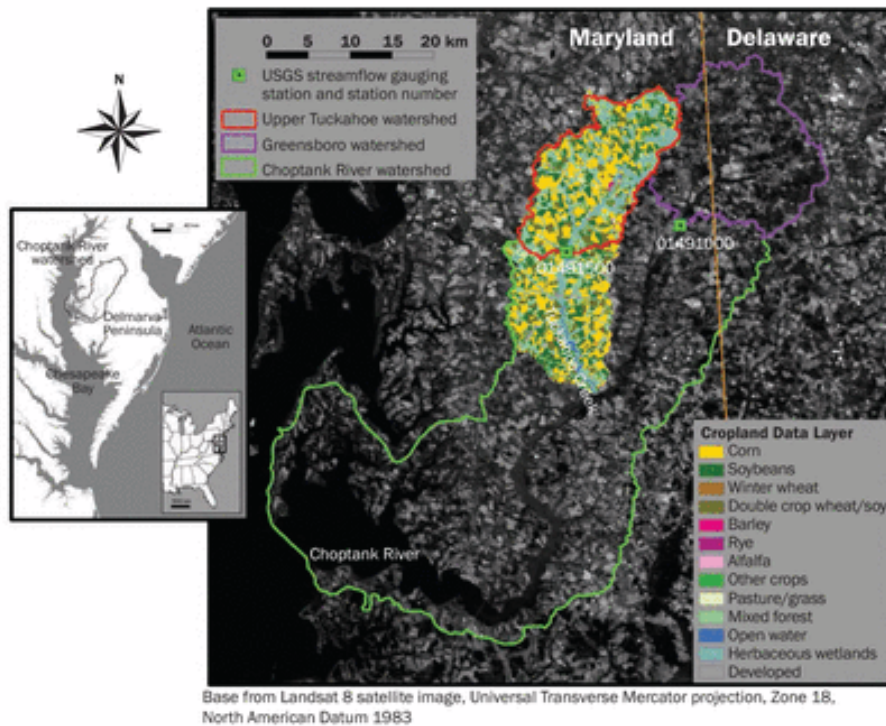
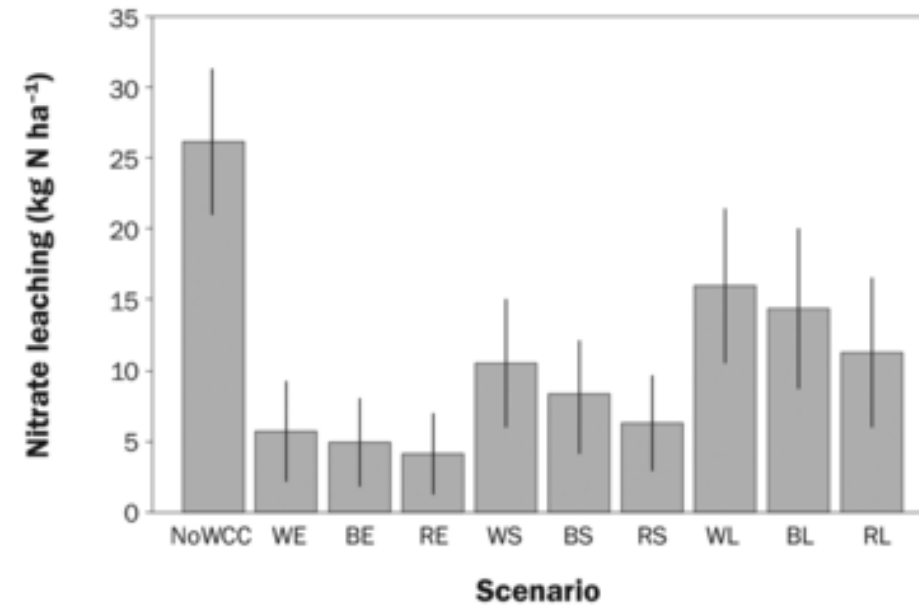


Figure 7

Ten-year average (2008 to 2017) of nitrate leaching under the baseline (NoWCC) and nine winter cover crop (WCC) scenarios during the winter period (Sept. 1 to Mar. 31): early wheat (WE), early barley (BE), early rye (RE), standard wheat (WS), standard barley (BS), standard rye (RS), late wheat (WL), late barley (BL), and late rye (RL). Error bars indicate one standard deviation from 10-year mean.



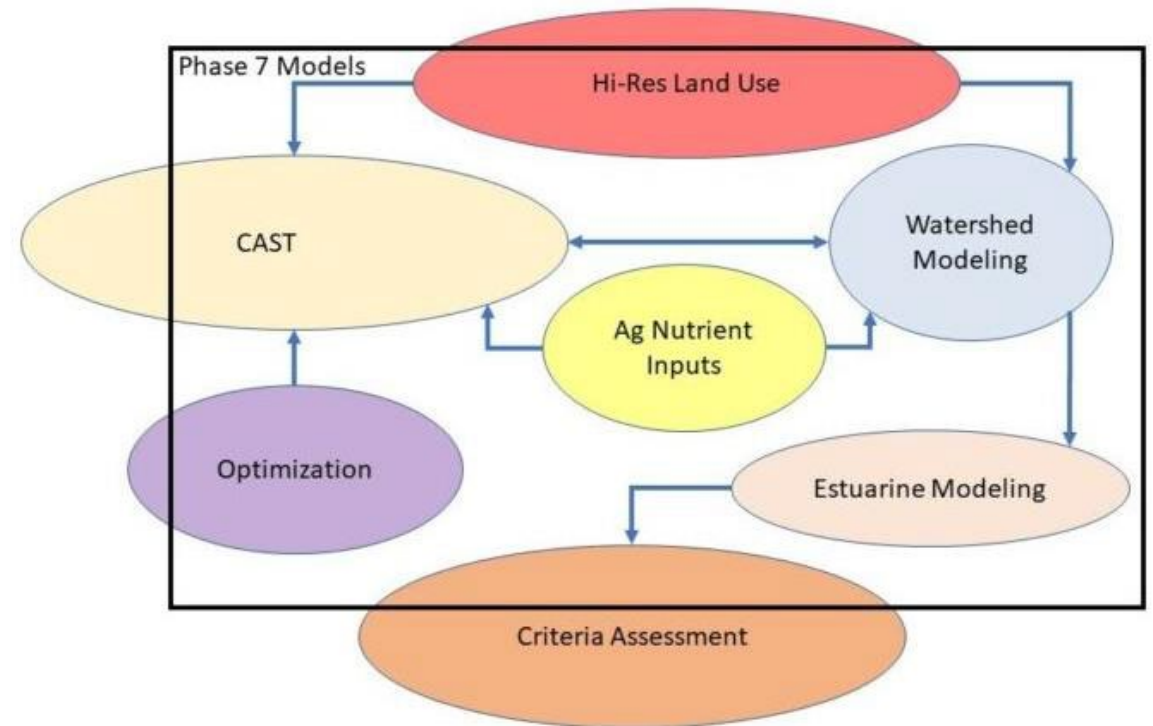
Hively, W.D., Lee, S., Sadeghi, A.M., McCarty, G.W., Lamb, B.T., Soroka, A., Keppler, J., Yeo, I.Y. and Moglen, G.E., 2020. Estimating the effect of winter cover crops on nitrogen leaching using cost-share enrollment data, satellite remote sensing, and Soil and Water Assessment Tool (SWAT) modeling. *Journal of Soil and Water Conservation*, 75(3), pp.362-375.

Engagement with stakeholders

- Chesapeake Bay Program



- Lewis Linker (Modeling team coordinator)
- Gary Shenk (Watershed modeling leader)
- Quarterly modeling review meeting
 - Oct 17, 2023
 - AI within Watershed Management
 - Phase 7 Watershed Model
 - AirShed Atmospheric Quality Modeling
 - Agricultural Nutrient Inputs
 - **Main Bay Model**
 - Temperature Dependence of Algal Growth Rates
 - Nutrient Exchanges Among Coastal Estuaries
 - Inclusion of Benthos
 - Shoreline Erosion
 - Hypoxia
 - Chesapeake Assessment Scenario Tool (CAST)
 - Scientific and Technical Advisory Committee (STAC)



Planned activities: Model and data sharing

Watershed model

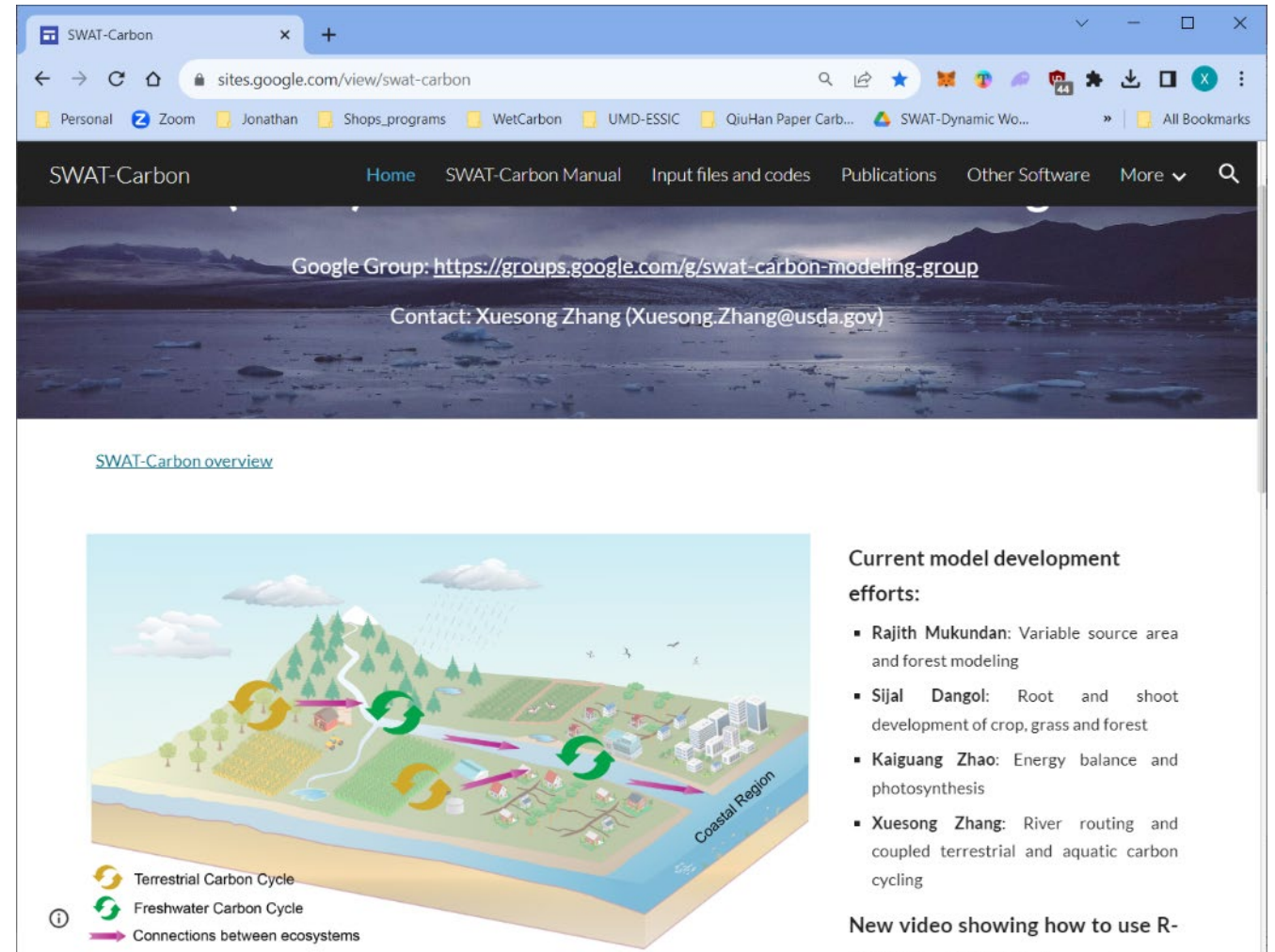
<https://sites.google.com/view/swat-carbon>

Artificial intelligence model

<https://github.com/dirt/Rbeast>

Other software:

R-SWAT



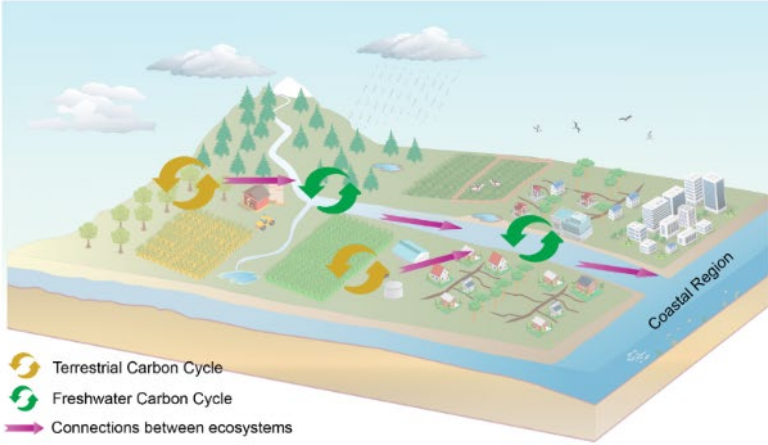
SWAT-Carbon

Home SWAT-Carbon Manual Input files and codes Publications Other Software More

Google Group: <https://groups.google.com/g/swat-carbon-modeling-group>

Contact: Xuesong Zhang (Xuesong.Zhang@usda.gov)

[SWAT-Carbon overview](#)



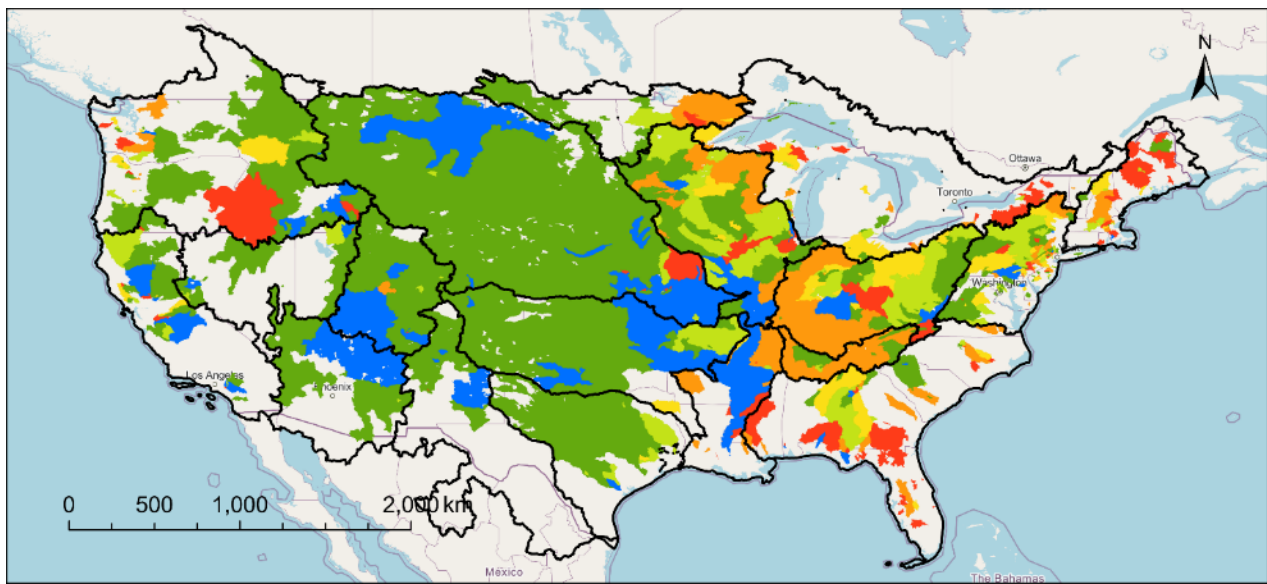
Current model development efforts:

- Rajith Mukundan: Variable source area and forest modeling
- Sijal Dangol: Root and shoot development of crop, grass and forest
- Kaiguang Zhao: Energy balance and photosynthesis
- Xuesong Zhang: River routing and coupled terrestrial and aquatic carbon cycling

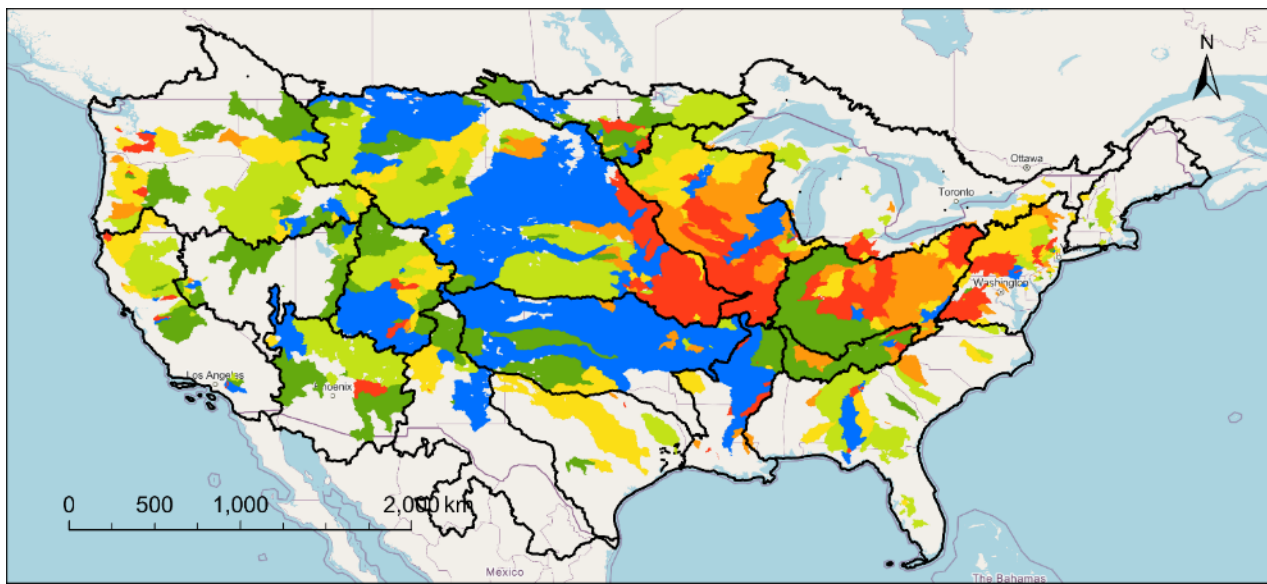
New video showing how to use R-SWAT

Planned data products: Spatially distributed carbon and nutrient yield data for model verification

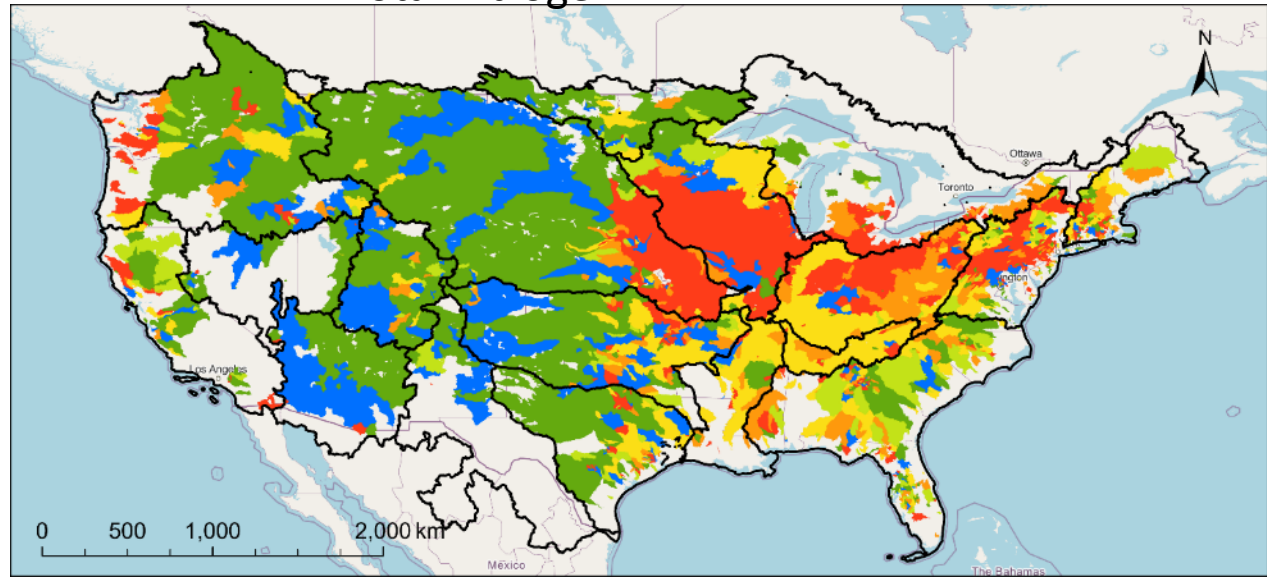
Dissolved organic carbon



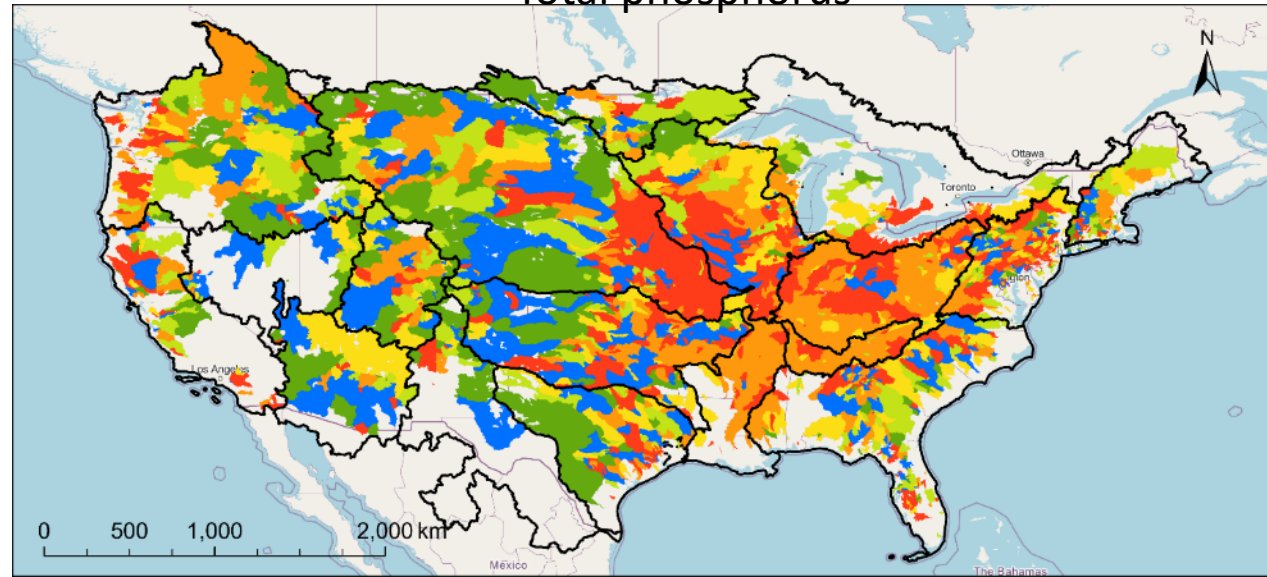
Particulate organic carbon



Total nitrogen



Total phosphorus



Mapping the outcomes of agricultural conservation practices

- Remote sensing of winter cover crop performance (biomass, fractional cover, N content)



Minimal



Low



Medium



High

Cover crops

- Remote sensing of crop residue and tillage intensity (fractional cover of non-photosynthetic vegetation)



Plow tillage
0-30% cover



Conservation tillage
30-60% cover



High residue / no-till
60-100% cover

Crop residue

On-farm conservation performance is variable

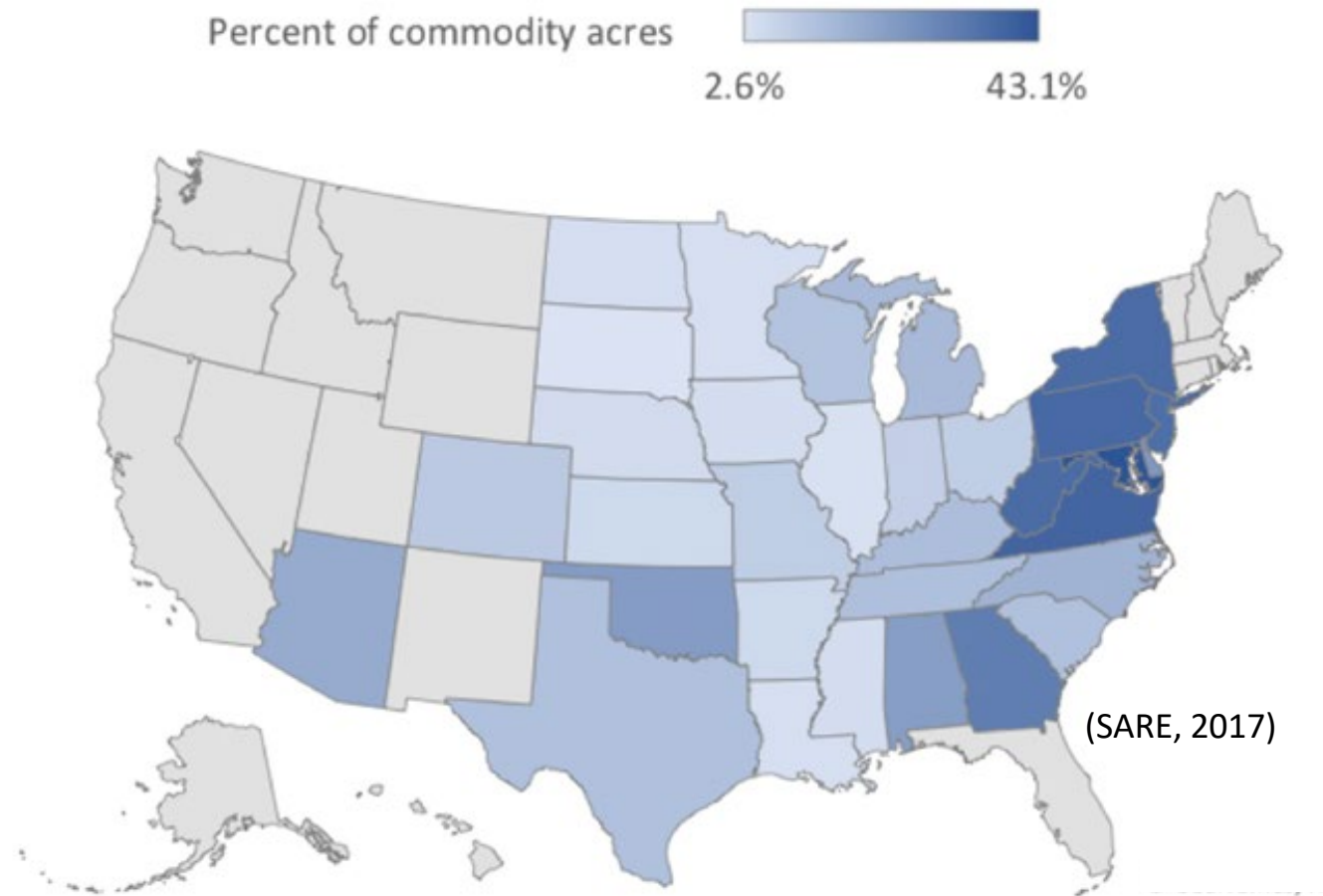
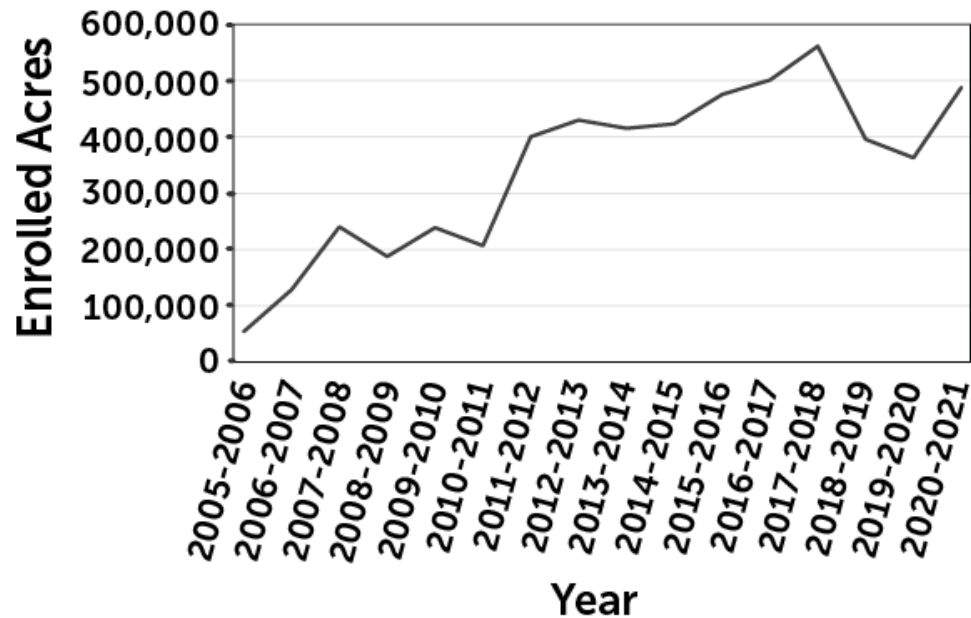
Green vegetation
crop residue
and bare soil
reflect light differently

We can measure and map performance using satellite imagery

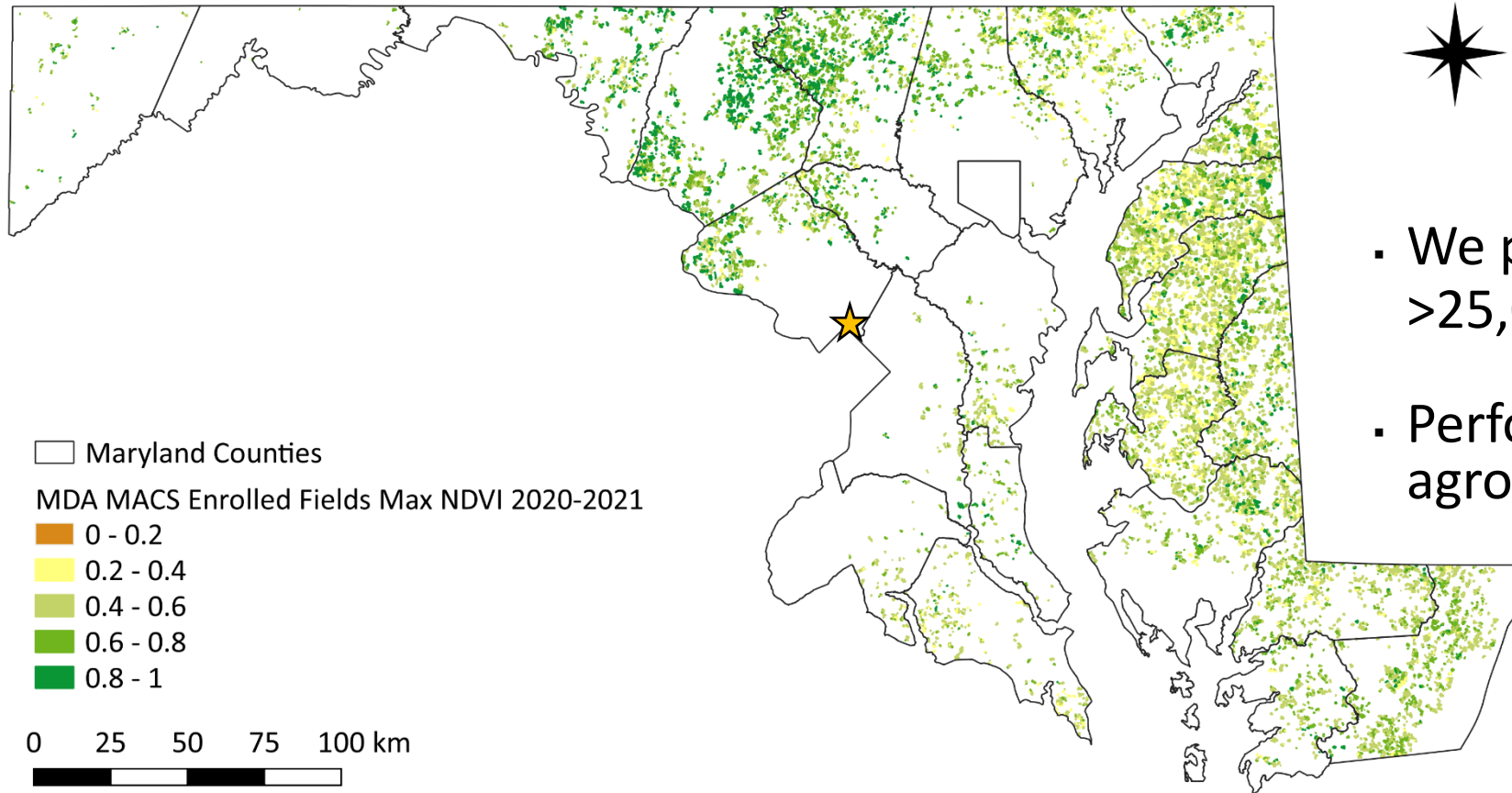


Mid-Atlantic cover crop use is highest in the nation

Maryland has the highest percent cover crop use on row crop agriculture of any state (43%)



Stakeholder: Maryland Department of Agriculture



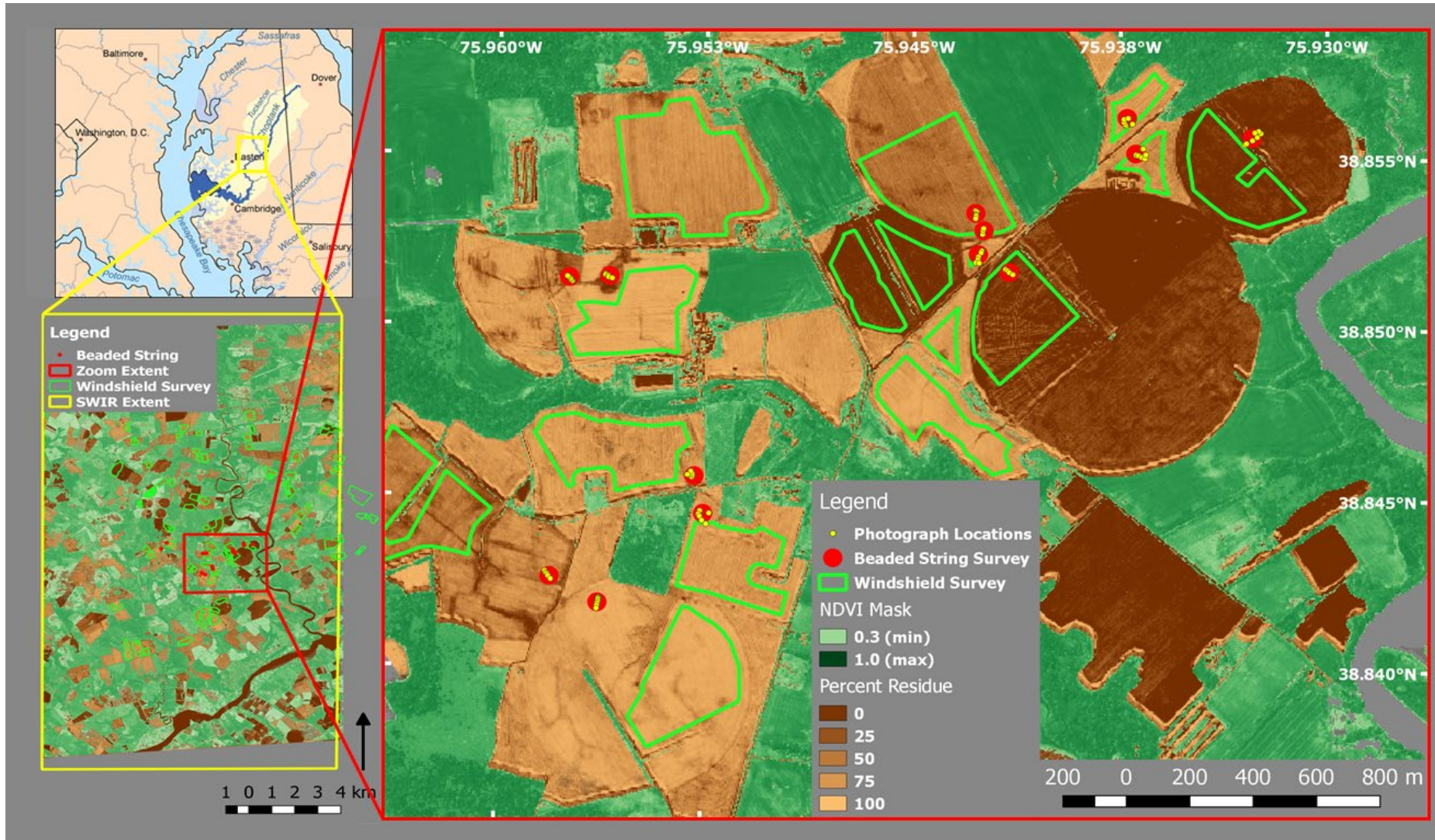
Maryland cover crop enrollment

| Year | # Fields | Acres |
|---------|----------|---------|
| 2019-20 | 26,393 | 156,900 |
| 2020-21 | 21,538 | 129,300 |

- We provide annual RS analysis of >25,000 cover crop fields
- Performance outcomes linked to agronomic management
- Influencing incentive structure
- RS replacing field visits for district staff

Research collaboration with Maryland Dept. of Agriculture allows access to site-specific cover crop management data for MD farms

Mapping crop residue using Worldview 3 SWIR imagery



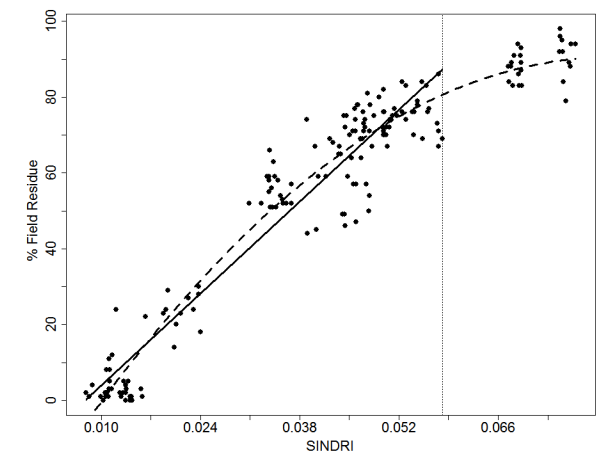
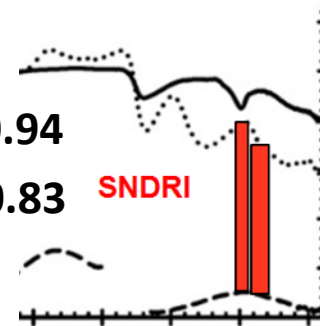
Worldview 3 SWIR imagery acquired May 14, 2015

Achieved high accuracy
in mapping crop residue
on fields with minimal
vegetation (NDVI < 0.3)

SINDRI $R^2 = 0.94$

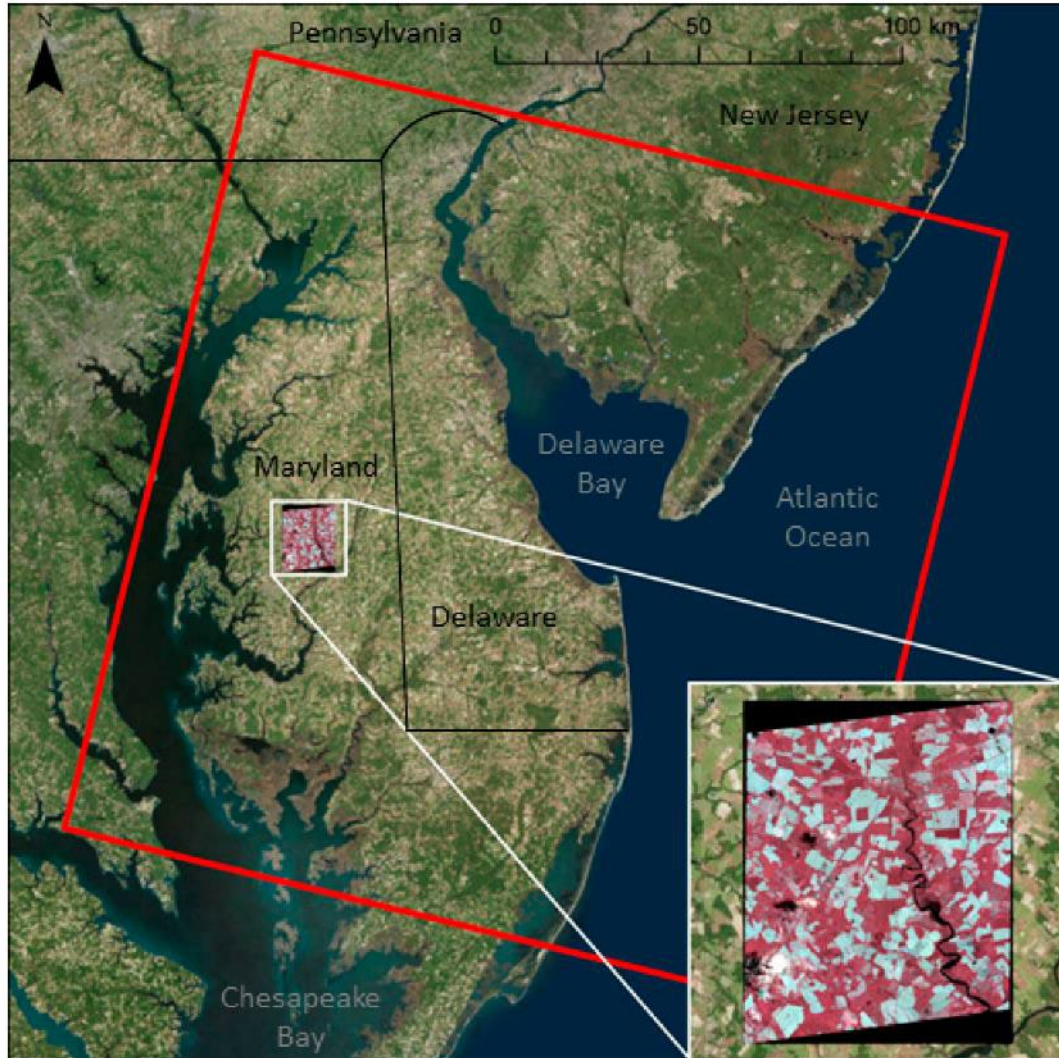
NDTI $R^2 = 0.83$

SINDRI



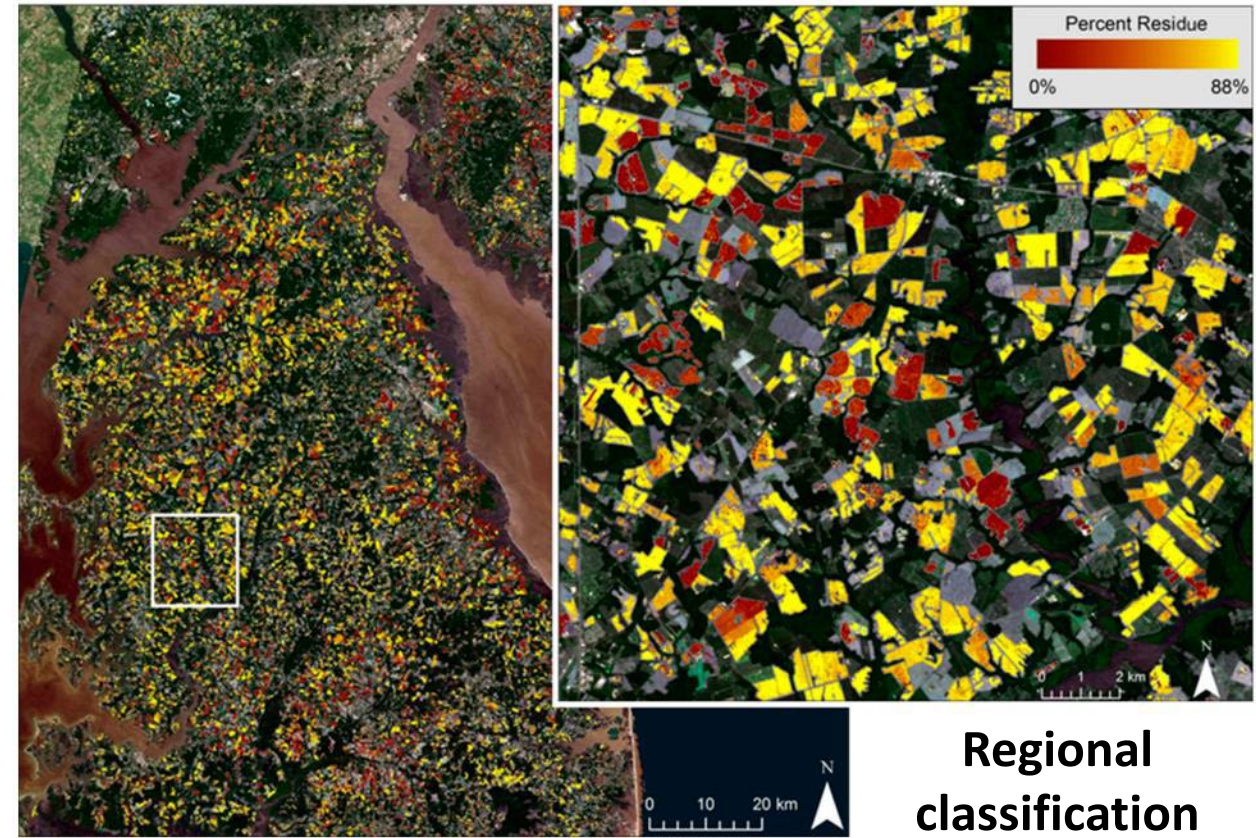
Hively et al., Remote Sensing, 2018.

Scaling up from SWIR to Landsat

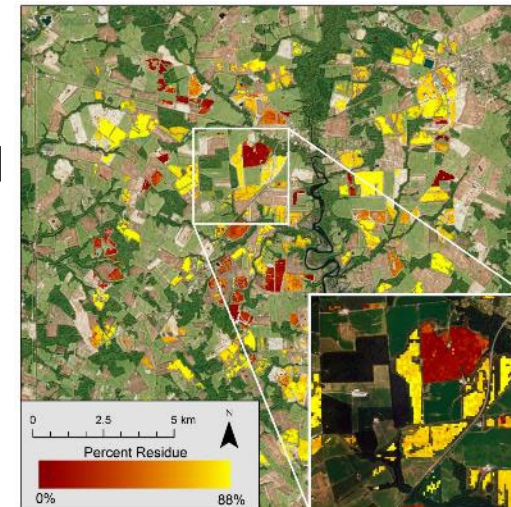


Hively et al. (2018, 2019)

SWIR-classified
residue cover
as calibration
& validation



Regional
classification

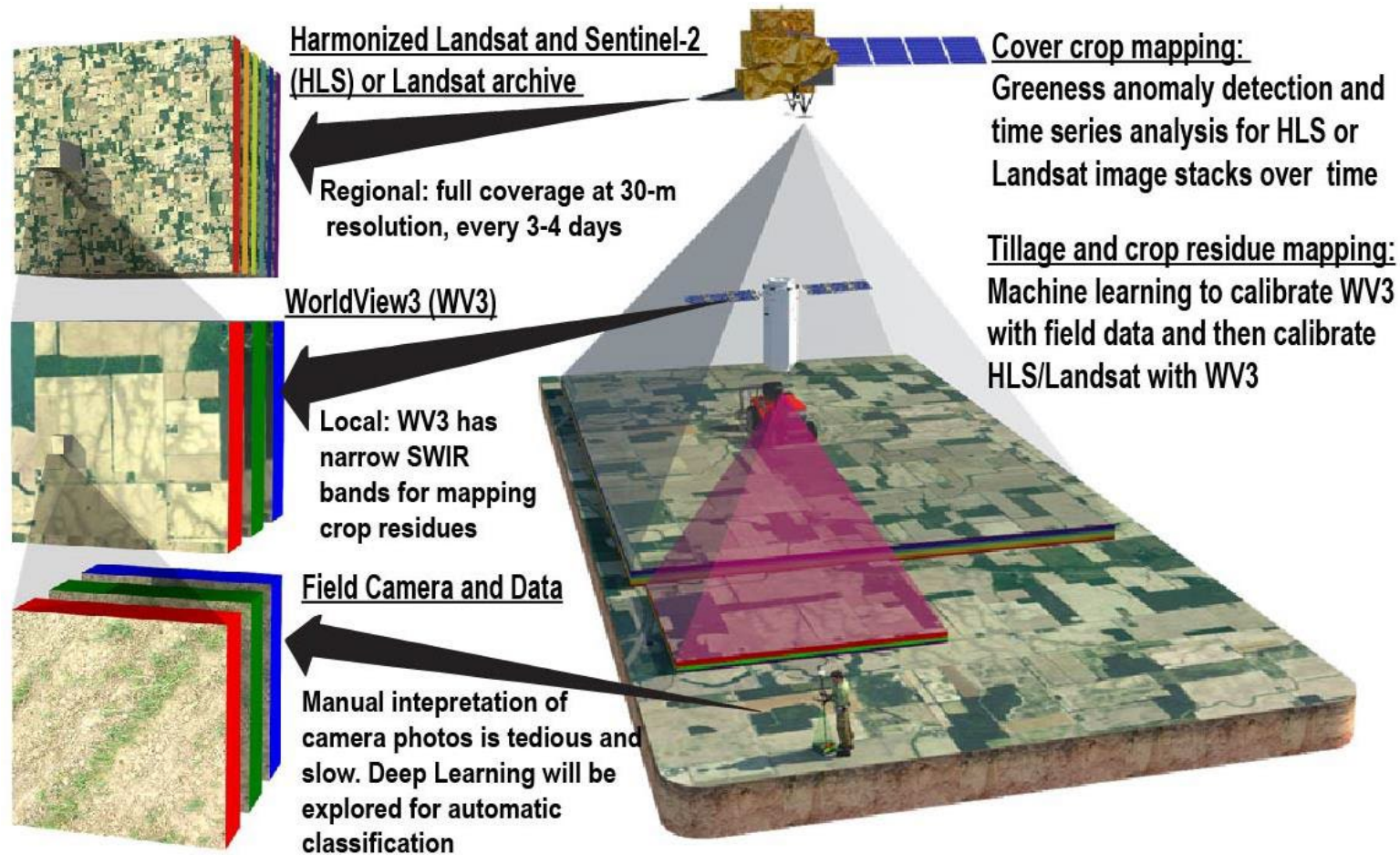


Machine learning
prediction of crop
residue cover from
Landsat 8 imagery

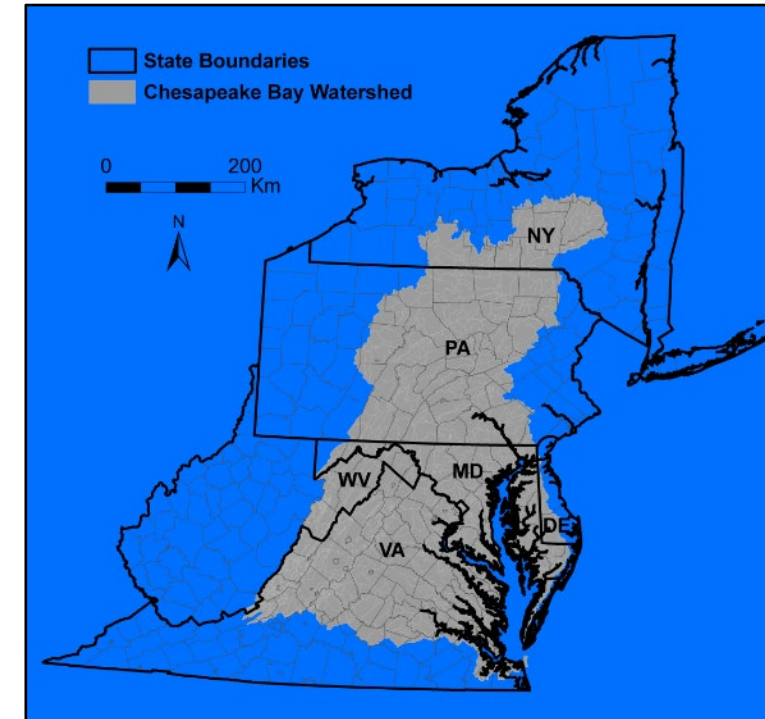
$R^2 = 0.92$ wet , 0.93 dry
vs. NDTI

$R^2 = 0.59$ wet , 0.83 dry

Chesapeake Bay input maps for SWAT-C CMS



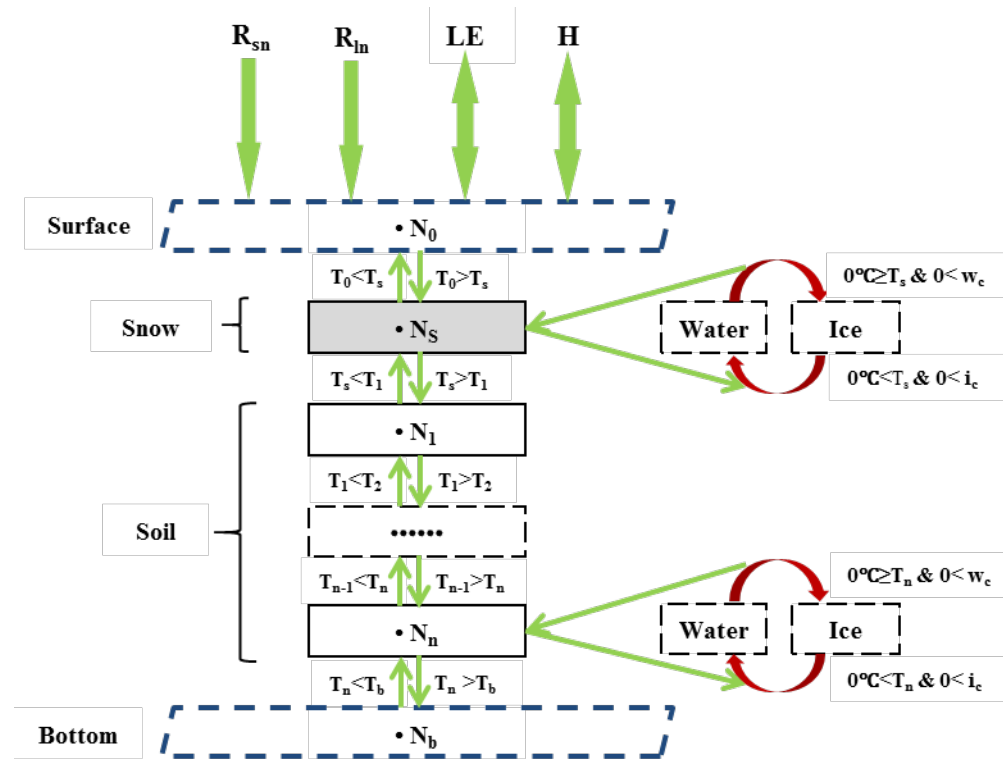
- Impact of **cover crops** (biomass, ground cover)
- Impact of **crop residue** (conservation tillage)



Goal: To produce annual maps of wintertime green biomass and spring residue cover for input to SWAT-C and Chesapeake CMS

Thank you

Physically based soil temperature and energy balance module



A physically-based soil temperature module was developed based on heat transfer theory in snow and soil layers described as in [Yin and Arp \(1993\)](#):

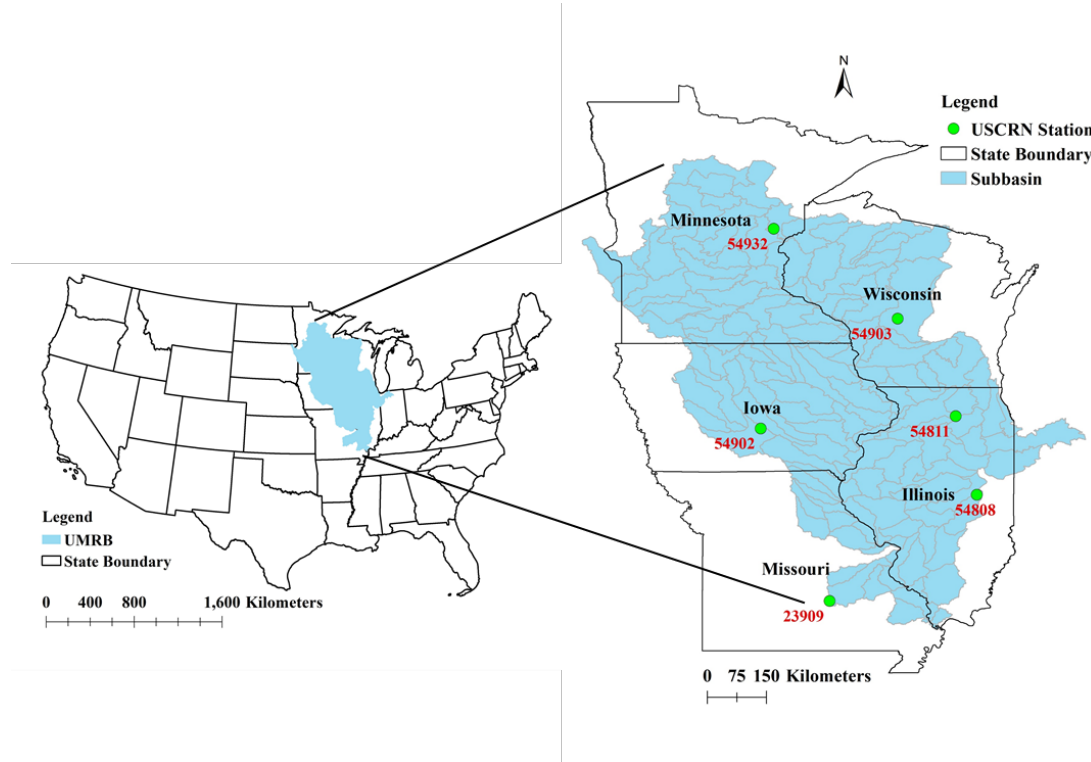
$$\frac{\partial T}{\partial t} = \frac{\partial}{\partial x} \left(\frac{k}{C} \cdot \frac{\partial T}{\partial x} \right) \frac{s}{C}$$

where T is the temperature, t represents the time step (in days), k is the thermal conductivity, C is the volumetric heat capacity, x is the vertical distance from the air-soil or air-snow interface, and s is the latent heat source/sink term.

Zhang, X., Srinivasan, R., Debele, B. and Hao, F., 2008. Runoff simulation of the headwaters of the yellow river using The SWAT model with three snowmelt algorithms 1. *JAWRA Journal of the American Water Resources Association*, 44(1), pp.48-61.

Qi, J., Zhang, X. and Wang, Q., 2019. Improving hydrological simulation in the Upper Mississippi River Basin through enhanced freeze-thaw cycle representation. *Journal of Hydrology*, 571, pp.605-618.

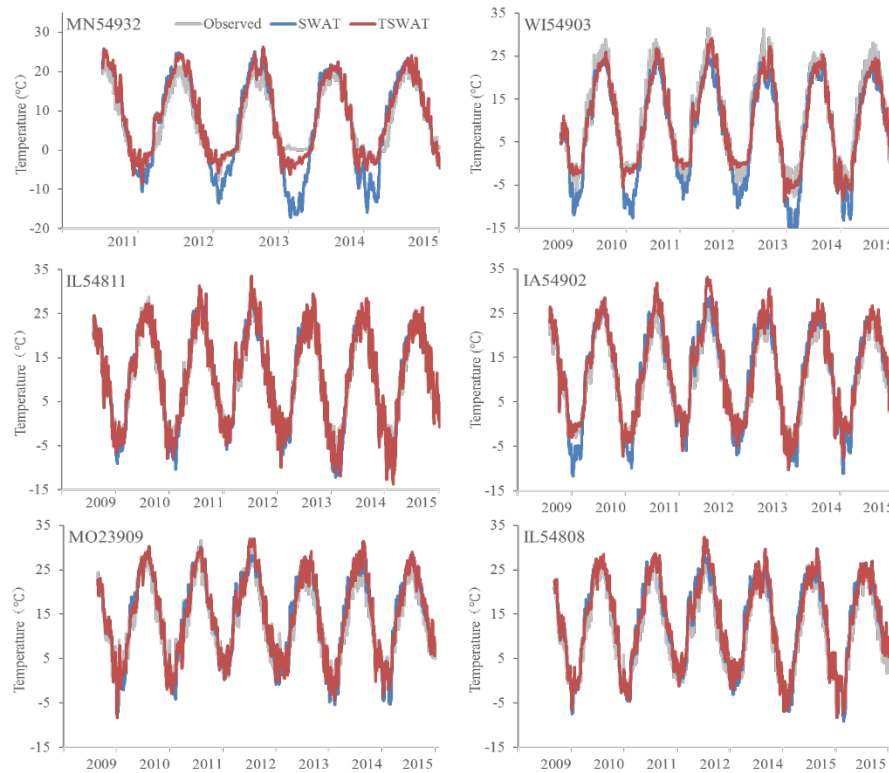
TSWAT evaluation in the Upper Mississippi River Basin



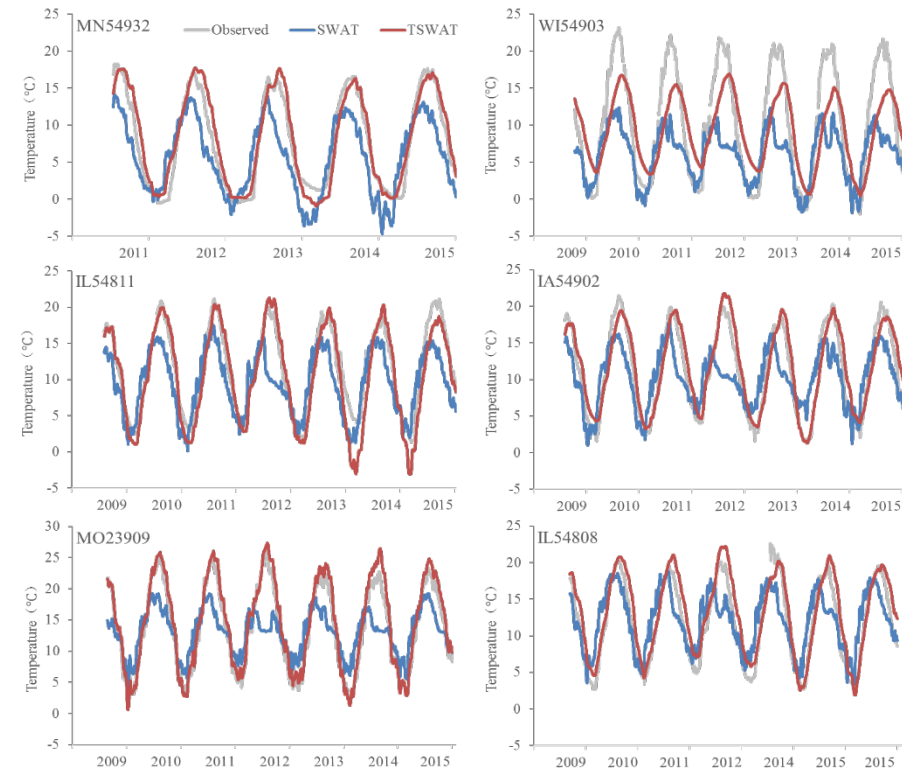
Daily surface and soil temperature records at 5, 10, 20, 50, and 100 cm depths derived from six stations of the NOAA's U.S. Climate Reference Network (USCRN) within the Upper Mississippi River Basin.

| Site Name | Station No. | Lon. | Lat. | Soil Texture | Data Used |
|--|-------------|--------|-------|--------------|-----------|
| Audubon Center of the North Woods | 54932 (MN) | -93.29 | 41.56 | Silt loam | 2011-2015 |
| Necedah National Wildlife Refuge | 54903 (WI) | -88.37 | 40.05 | Silt loam | 2009-2015 |
| Northern Illinois Agronomy Research Center | 54811 (IL) | -88.85 | 41.84 | Silt loam | 2009-2015 |
| Neal Smith National Wildlife Refuge | 54902 (IA) | -92.99 | 46.11 | Clay loam | 2009-2015 |
| White River Trace Conservation Area | 23909 (MO) | -91.72 | 37.63 | Silt loam | 2009-2015 |
| Bondville Environmental & Atmospheric Research Station | 54808 (IL) | -90.17 | 44.06 | Loamy sand | 2009-2015 |

Simulated vs. observed soil temperature

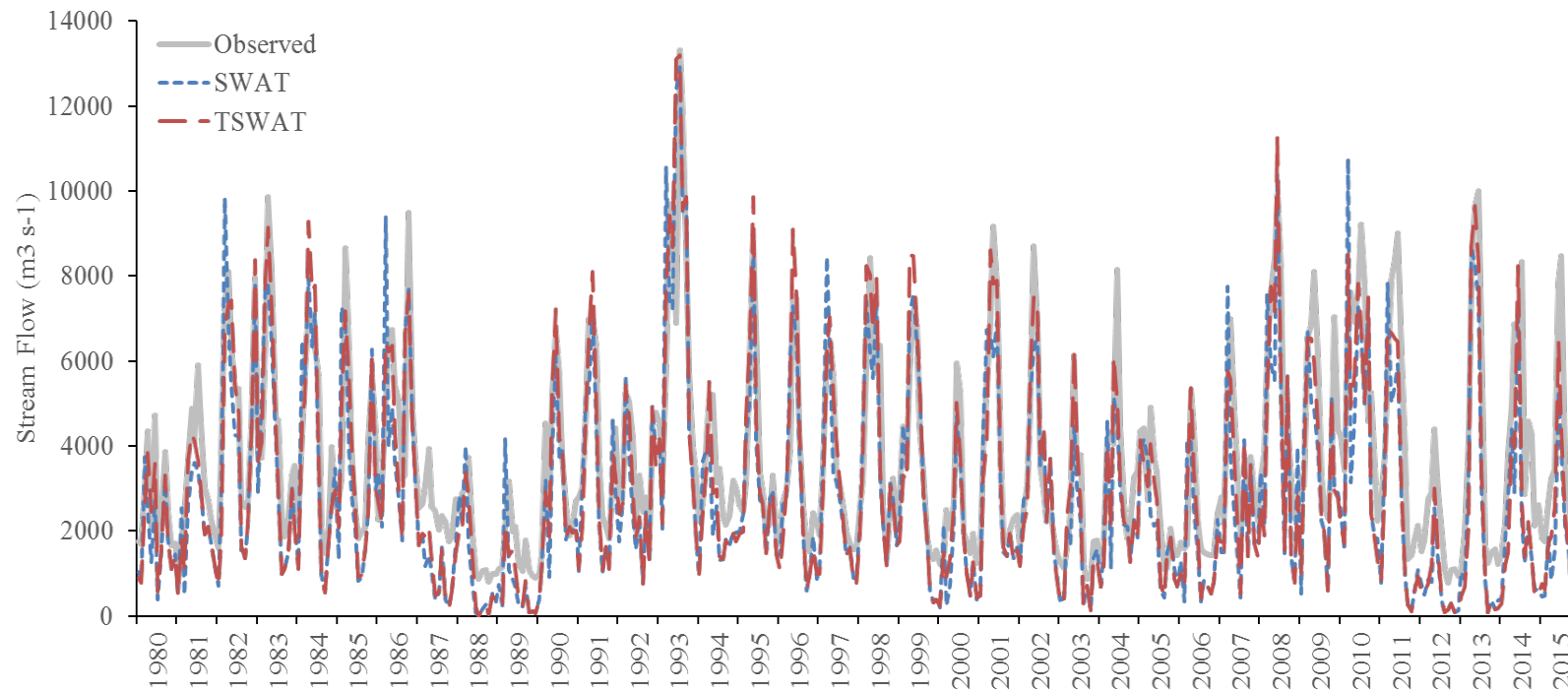


Simulated vs. observed soil temperature at 5 cm depth at six USCRN stations.



Simulated vs. observed soil temperature at 100 cm depth for the six USCRN stations.

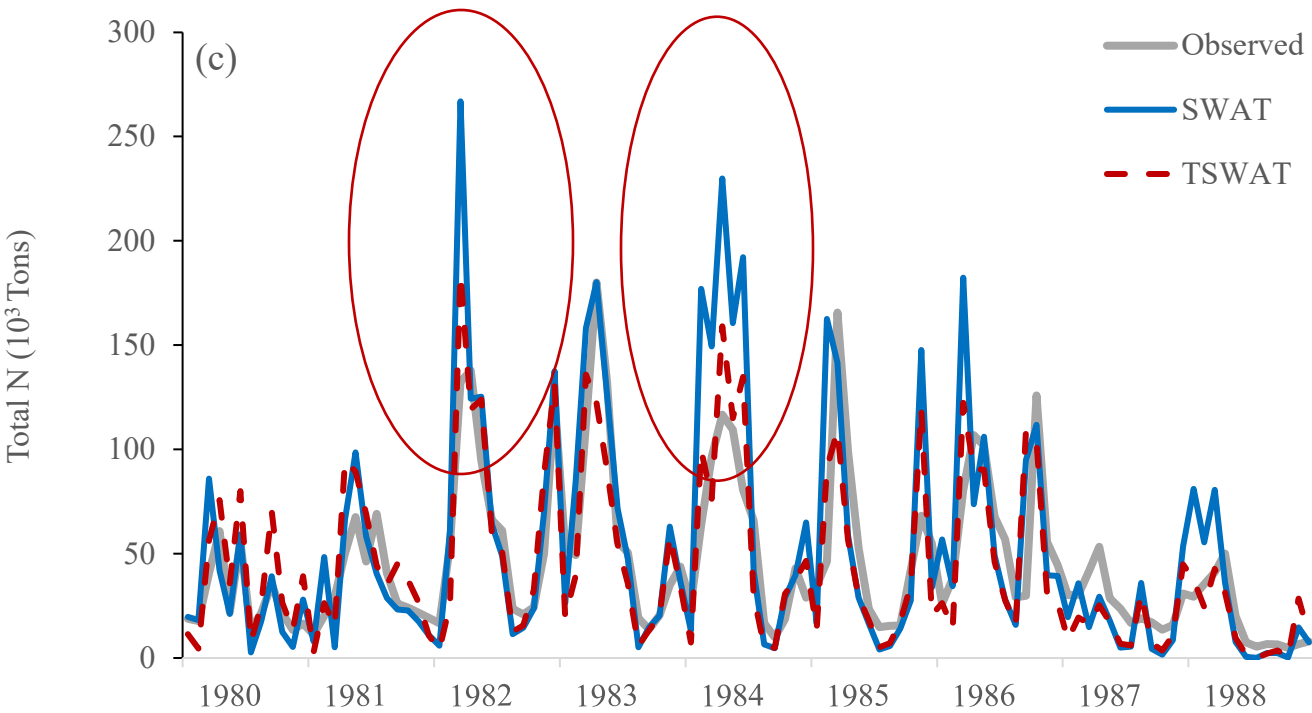
Improvements in streamflow modeling



Observed and simulated monthly stream flow at USGS gauge station #05587450 for two versions of SWAT model from 1980 to 2015.

| Period | SWAT | | TSWAT | |
|------------|------|-----------------------|-------|-----------------------|
| | NS | P _{bias} (%) | NS | P _{bias} (%) |
| Annual | 0.54 | -21 | 0.68 | -18 |
| Winter | 0.45 | -14 | 0.70 | -16 |
| Non-Winter | 0.67 | -22 | 0.74 | -14 |

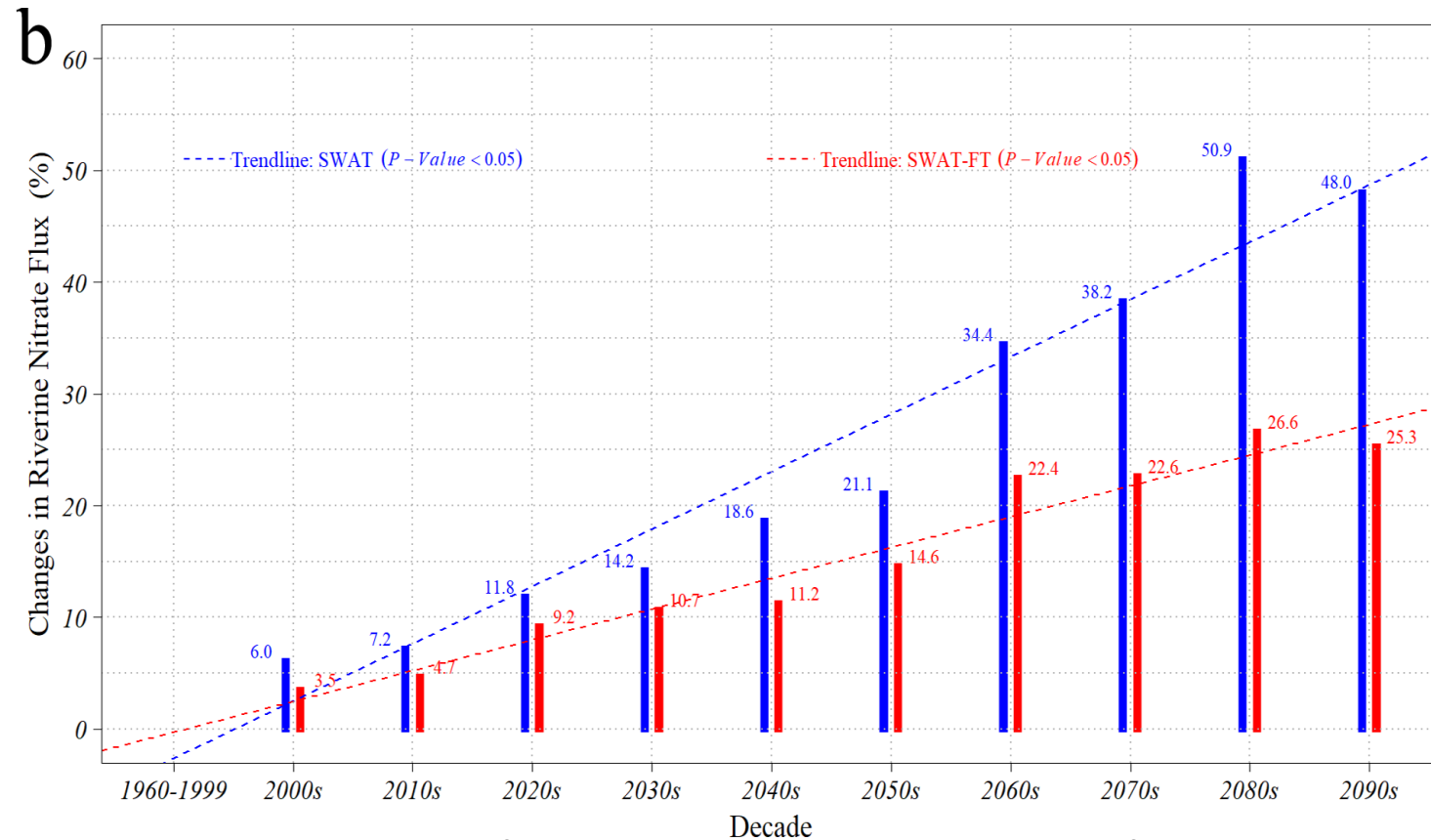
Improvements in water quality modeling



| Variable | SWAT2012 | | TSWAT | |
|----------------|----------|----------------|----------|----------------|
| | E_{NS} | P_{bias} (%) | E_{NS} | P_{bias} (%) |
| Sediment | 0.48 | -32 | 0.62 | -32 |
| NO_3^- | 0.57 | 0 | 0.61 | -2 |
| Total Nitrogen | 0.08 | 18 | 0.59 | -3 |

Qi, J., Zhang, X., Yang, Q., Srinivasan, R., Arnold, J.G., Li, J., Waldhoff, S.T. and Cole, J., 2020. SWAT ungauged: Water quality modeling in the Upper Mississippi River Basin. *Journal of Hydrology*, 584, p.124601.

Substantial difference between projected future changes in nitrate fluxes



Changes in riverine nitrate flux predicted by SWAT and SWAT-FT for each decade of the 21st century.

Wang, Q., Qi, J., Li, J., Cole, J., Waldhoff, S., Zhang, X. Projection of Future Nitrate Loading in The Upper Mississippi River Basin is Sensitive to Freeze-Thaw Cycle Representation. Water Research (In revision).