

AI-Driven Insights into Shifting Water, Sediment, Nutrient, and Salt Dynamics in the Chesapeake Bay and Beyond

Integrated Trends Analysis Team
Chesapeake Bay Program
05/20/2026

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Machine learning in hydrology and water quality

From Hydrometeorology to River Water Quality: Can a Deep Learning Model Predict Dissolved Oxygen at the Continental Scale?

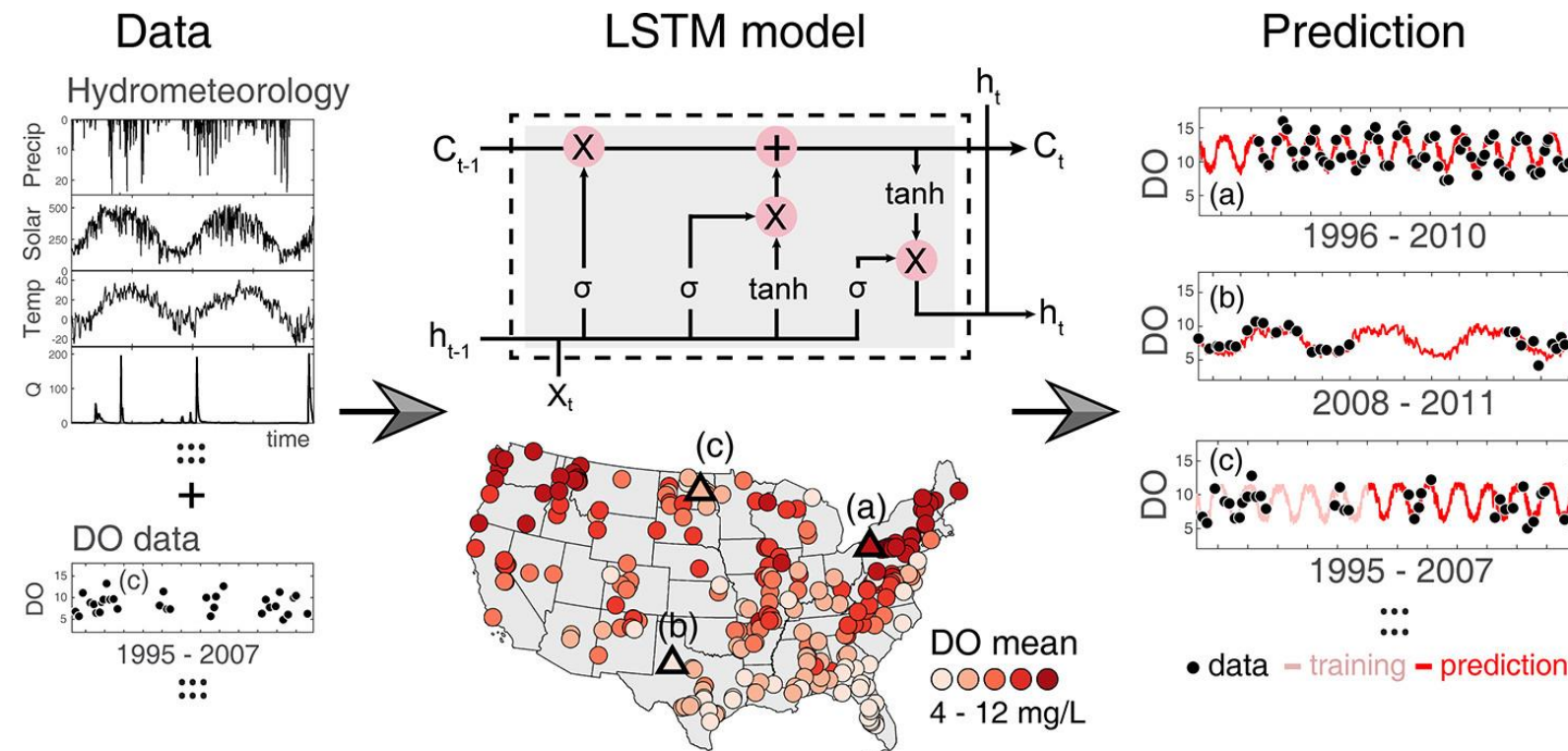
Wei Zhi, Dapeng Feng, Wen-Ping Tsai, Gary Sterle, Adrian Harpold, Chaopeng Shen, and Li Li*



Cite This: *Environ. Sci. Technol.* 2021, 55, 2357–2368



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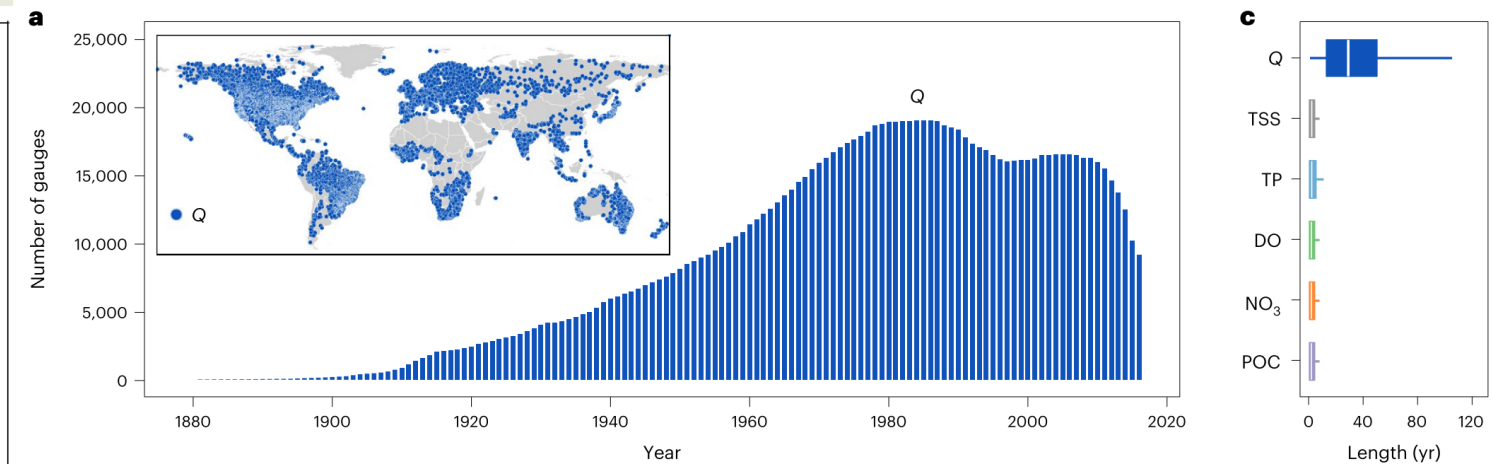
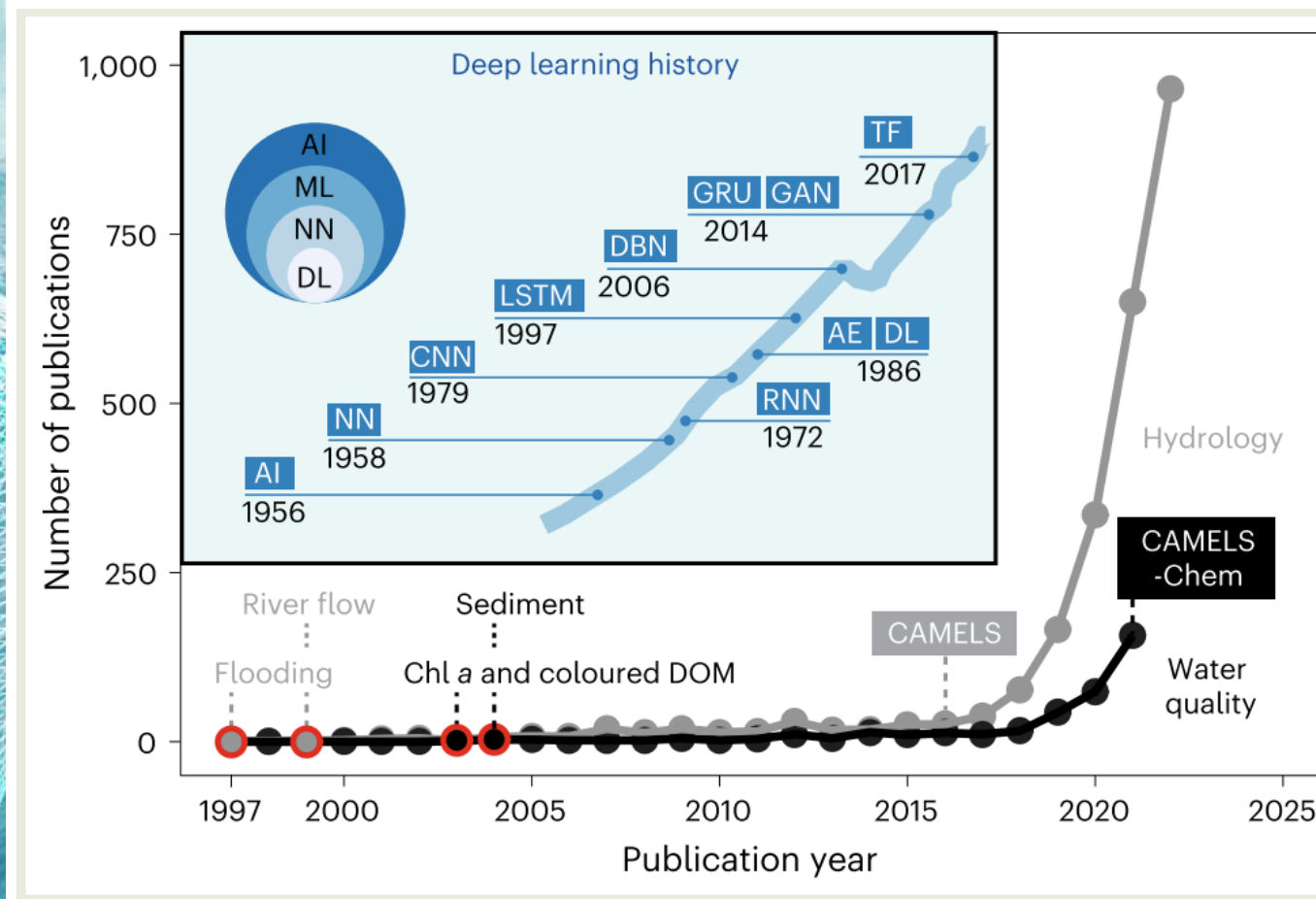
Machine learning in hydrology and water quality

nature water

Review article

<https://doi.org/10.1038/s44221-024-00202-z>

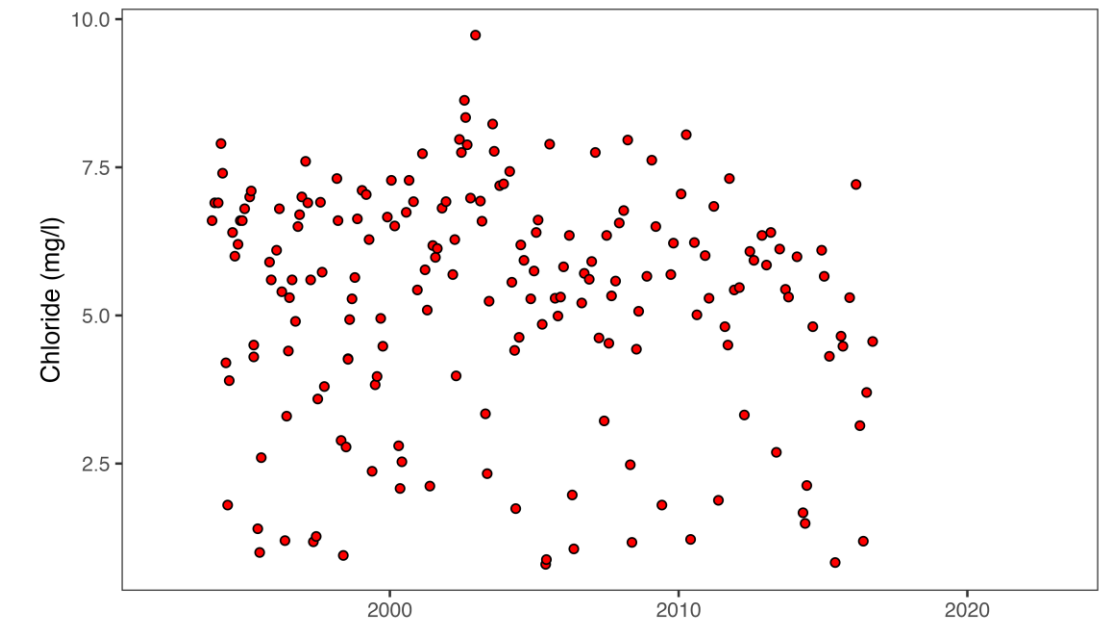
Deep learning for water quality



Machine learning in hydrology and water quality

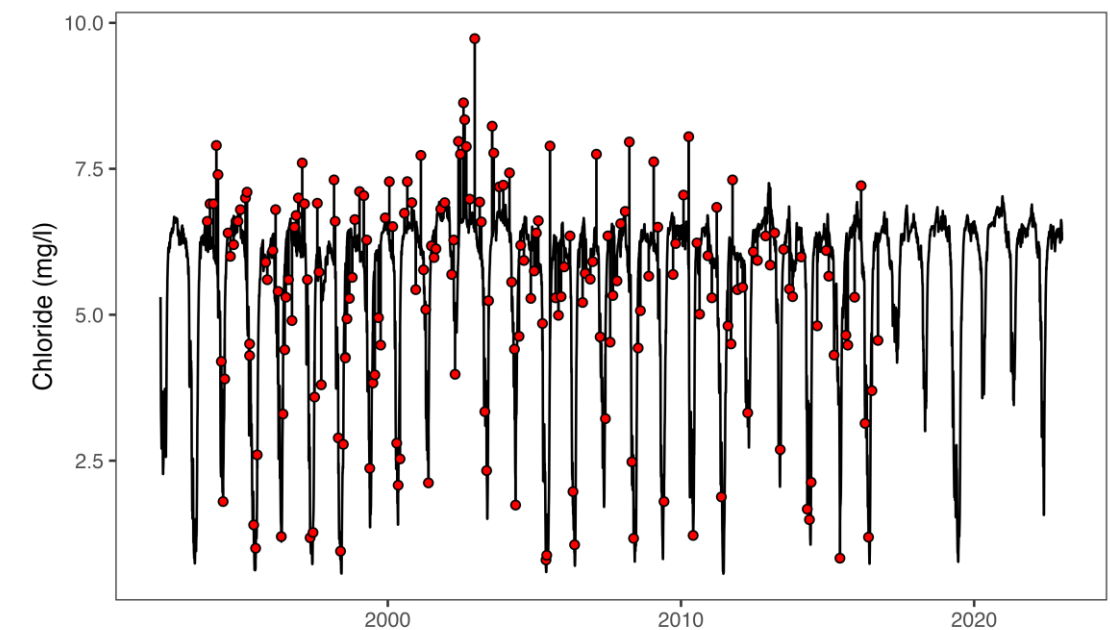
THE PROBLEM


- Suspended sediment, nutrients, and salt are transported in bursts.
- Grab samples are sparse. They sit between events.
- Concentration–discharge relationships are nonlinear and non-stationary.
- Sources, pathways, and timing are shifting under climate and land-use change.



THE OPPORTUNITY

- Continuous sensors (turbidity, SC, nitrate) deliver sub-hourly data for years.
- Neural networks learn temporal dependencies directly from the data.
- Trained globally, they generalize across climates and land covers.

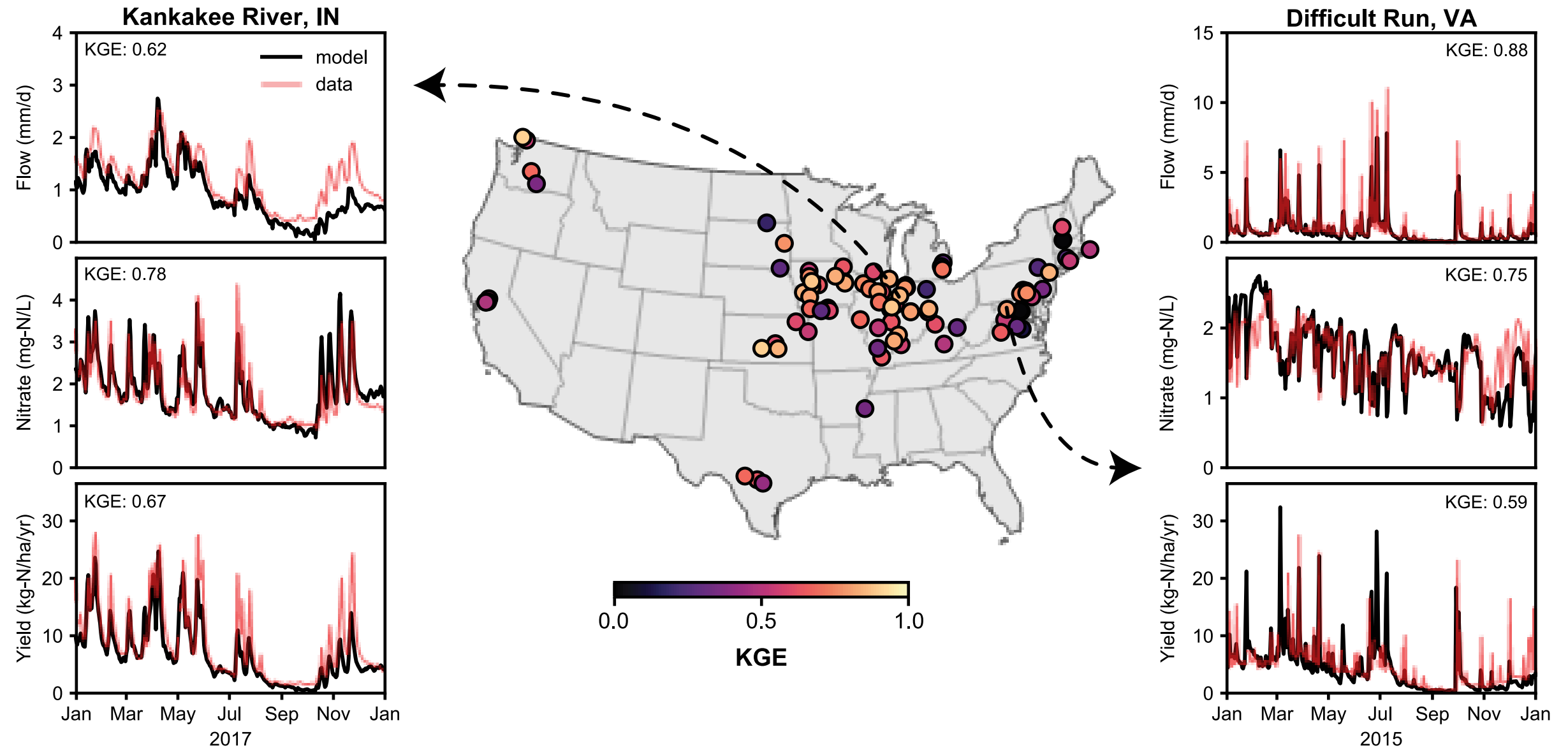




Let's have a look at how my team has used water quality sensors and deep learning ...

Example demonstrations from my group

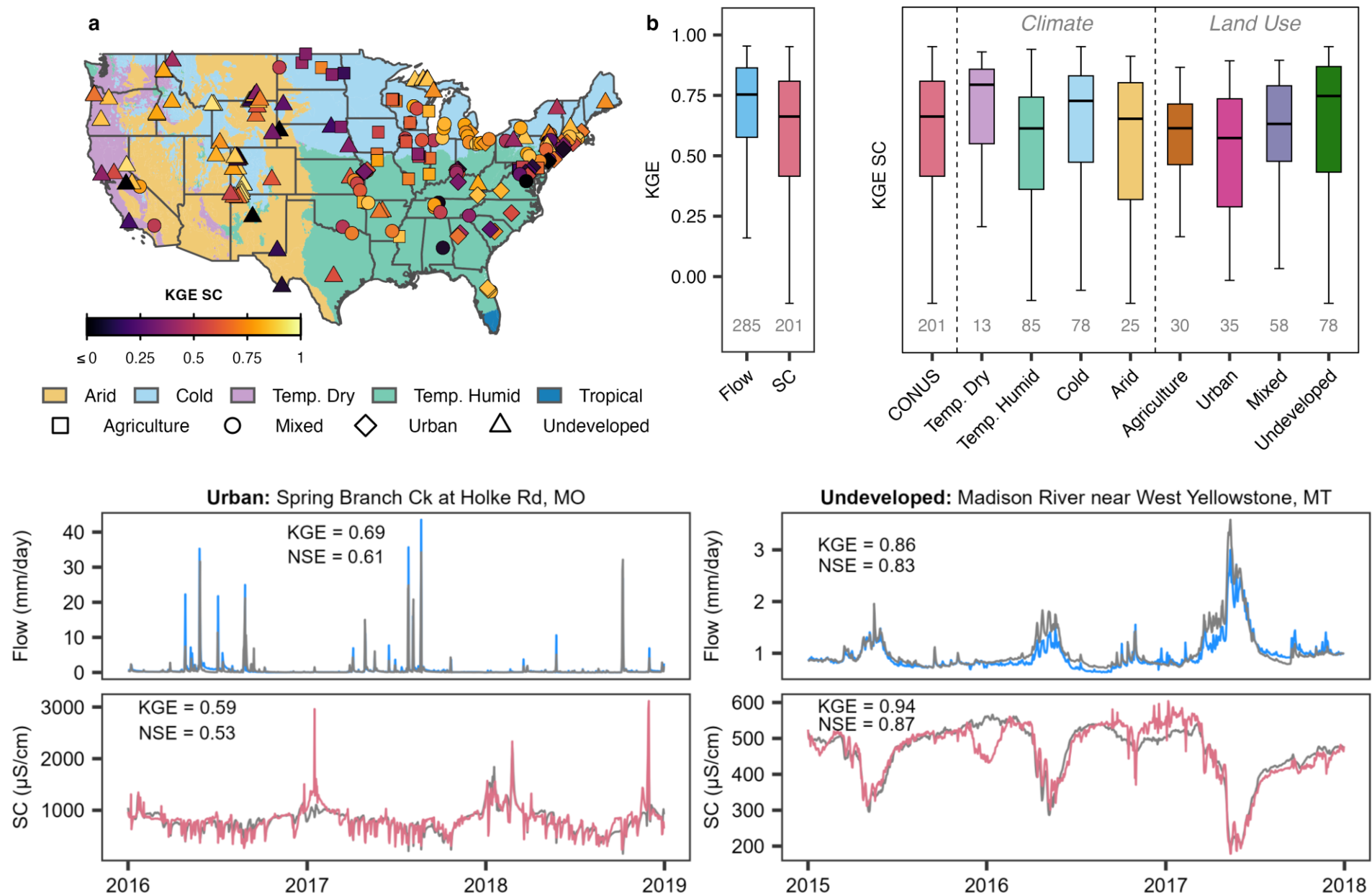
Nitrate dynamics



Pandit et al., 2025 (WRR)

Example demonstrations from my group

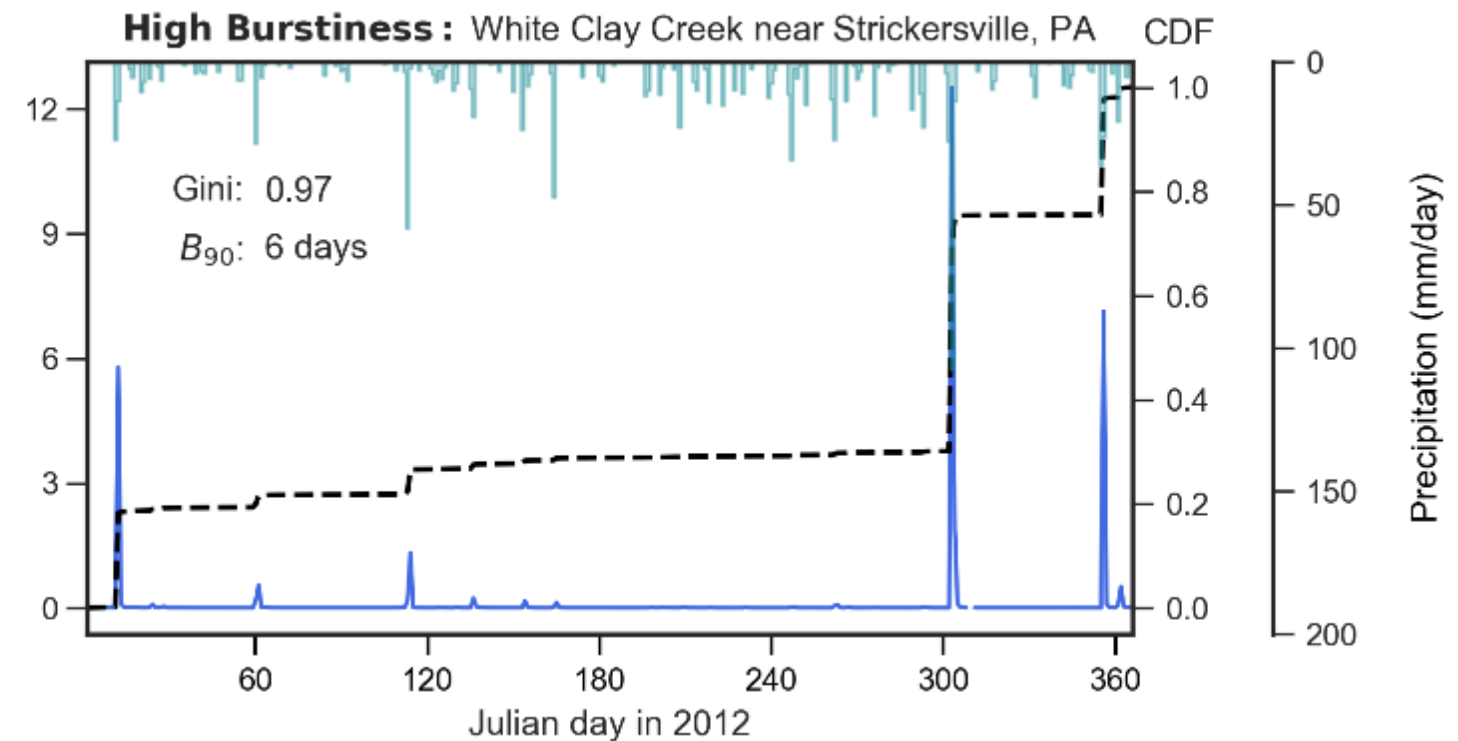
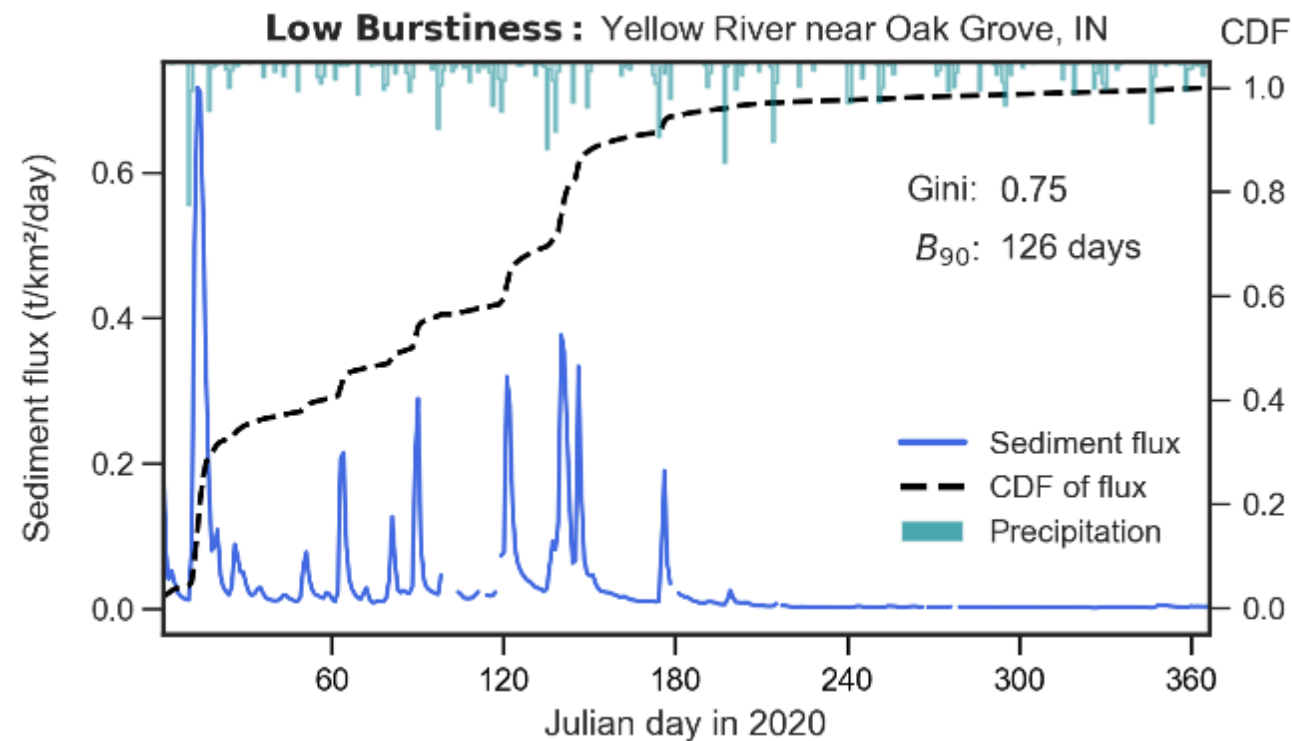
Salinity dynamics



Example demonstrations from my group

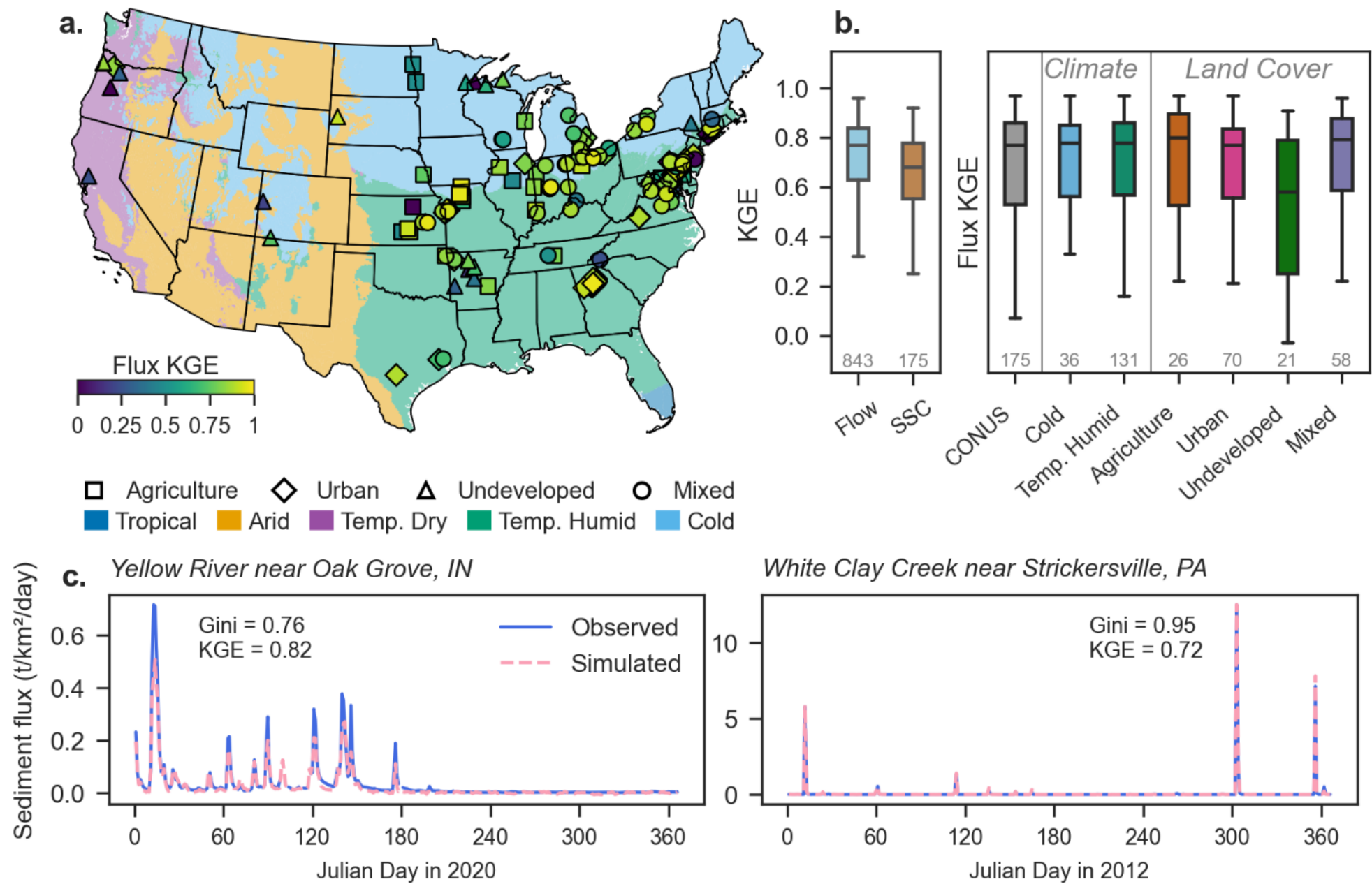
Sediment dynamics

- The temporal inequality in sediment transport has given rise to a “rule of thumb” or adage:
 - *90% of sediment is transported in 10% of the time*



Example demonstrations from my group

Sediment dynamics

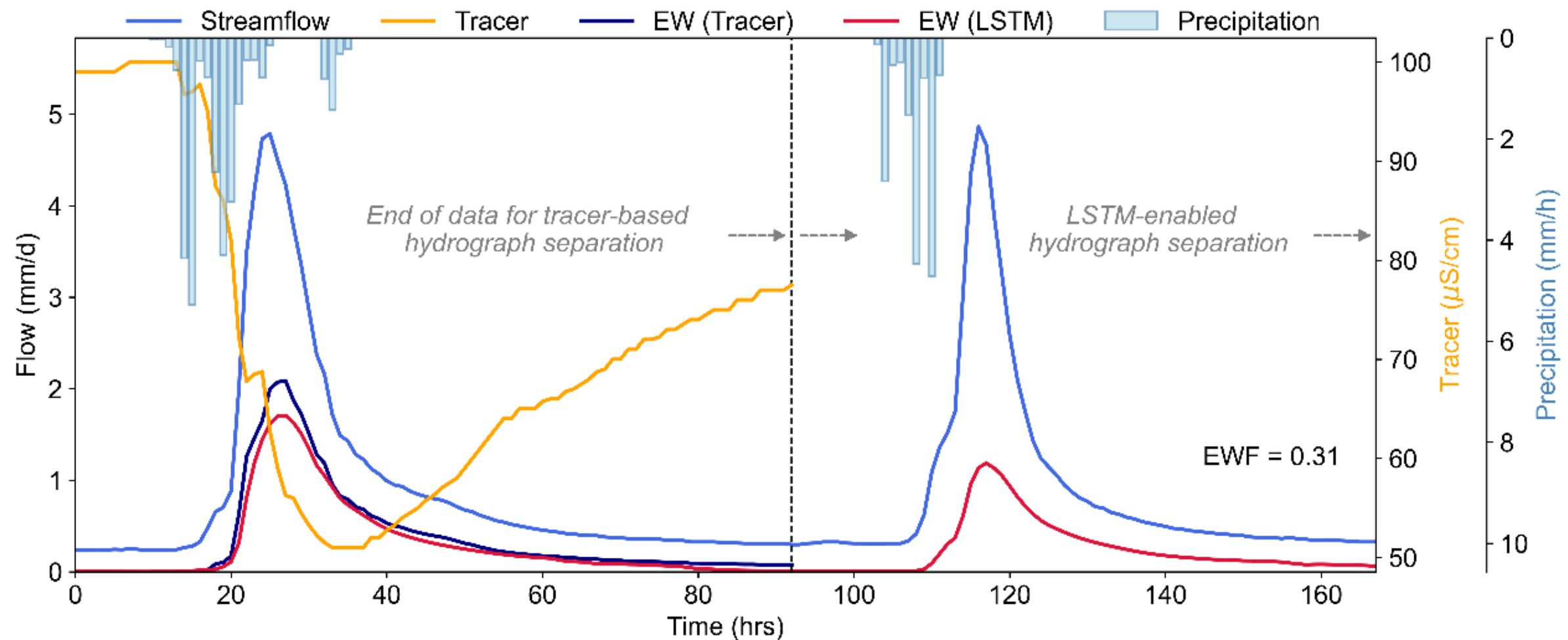


Sigdel and Husic 2026 (*in revision*)

Example demonstrations from my group

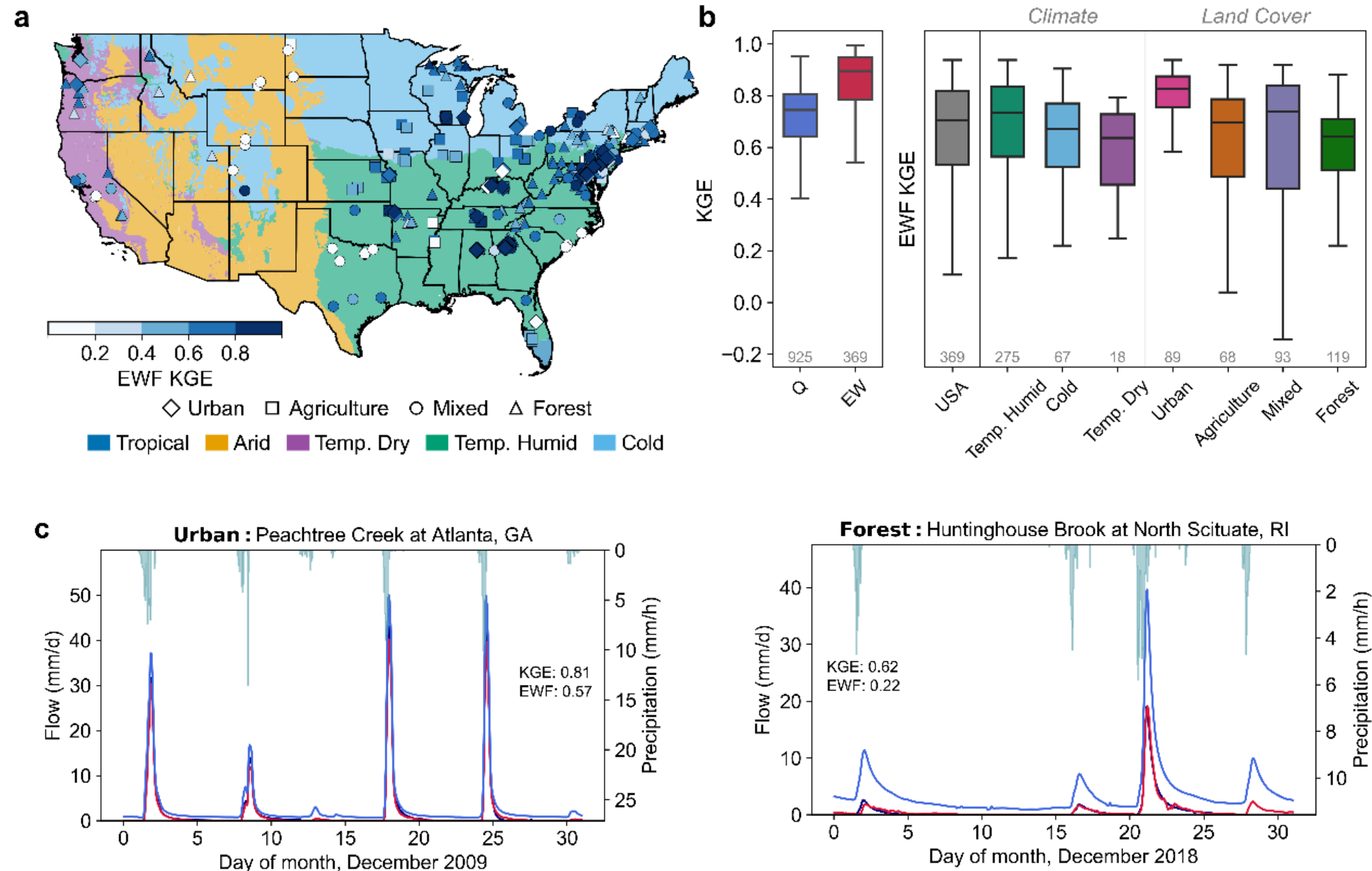
Hydrologic pathway dynamics

- When precipitation falls, it becomes either a part of catchment storage or streamflow, with the latter known as event water.



Example demonstrations from my group

Hydrologic pathway dynamics

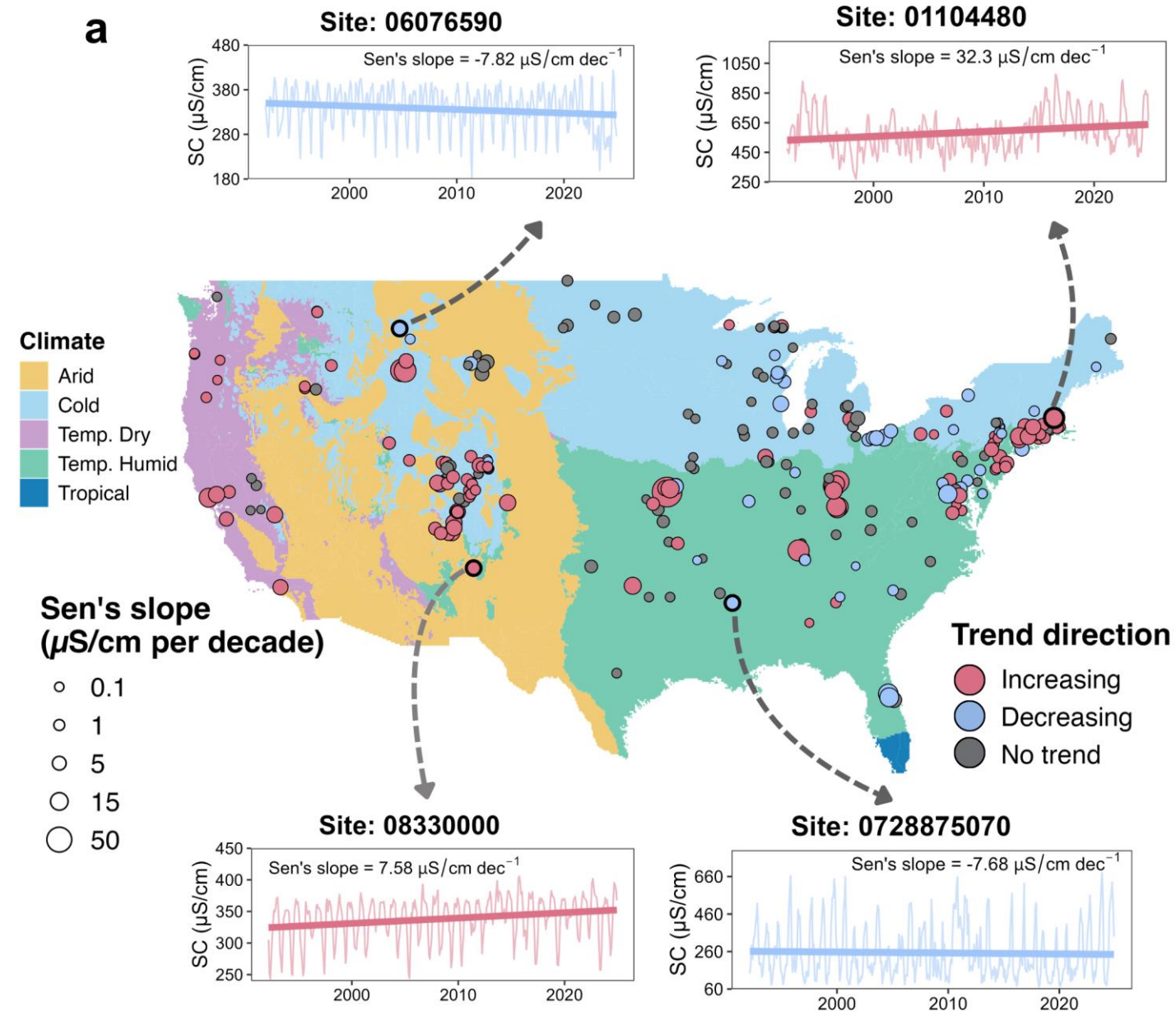




Now that we have high-fidelity models, what else?

Reconstructing historical records

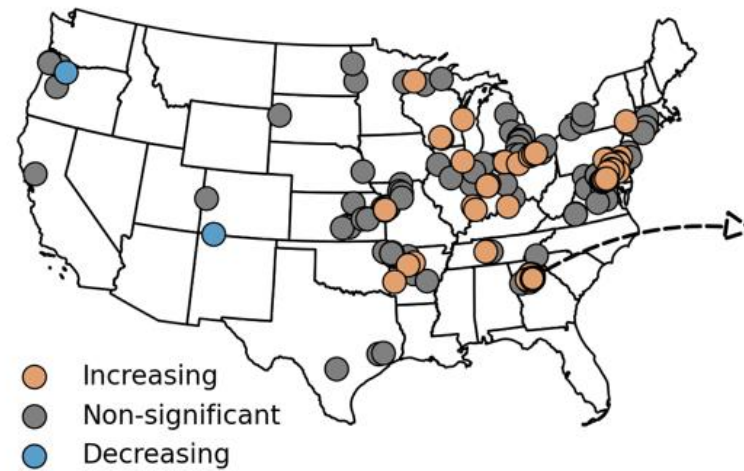
Salinity dynamics



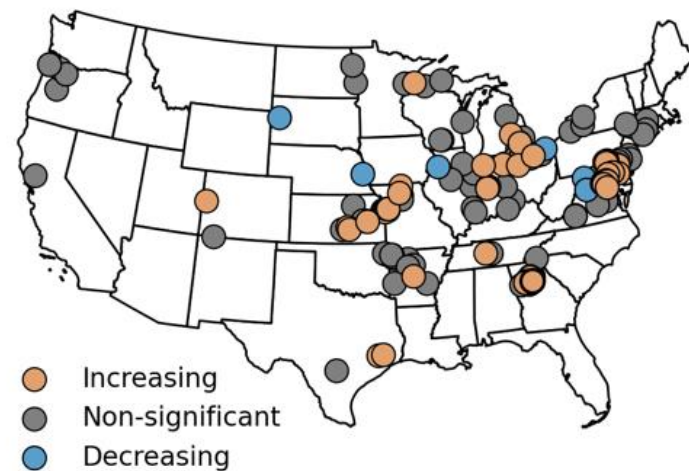
Reconstructing historical records

Sediment dynamics

a. Sediment flux

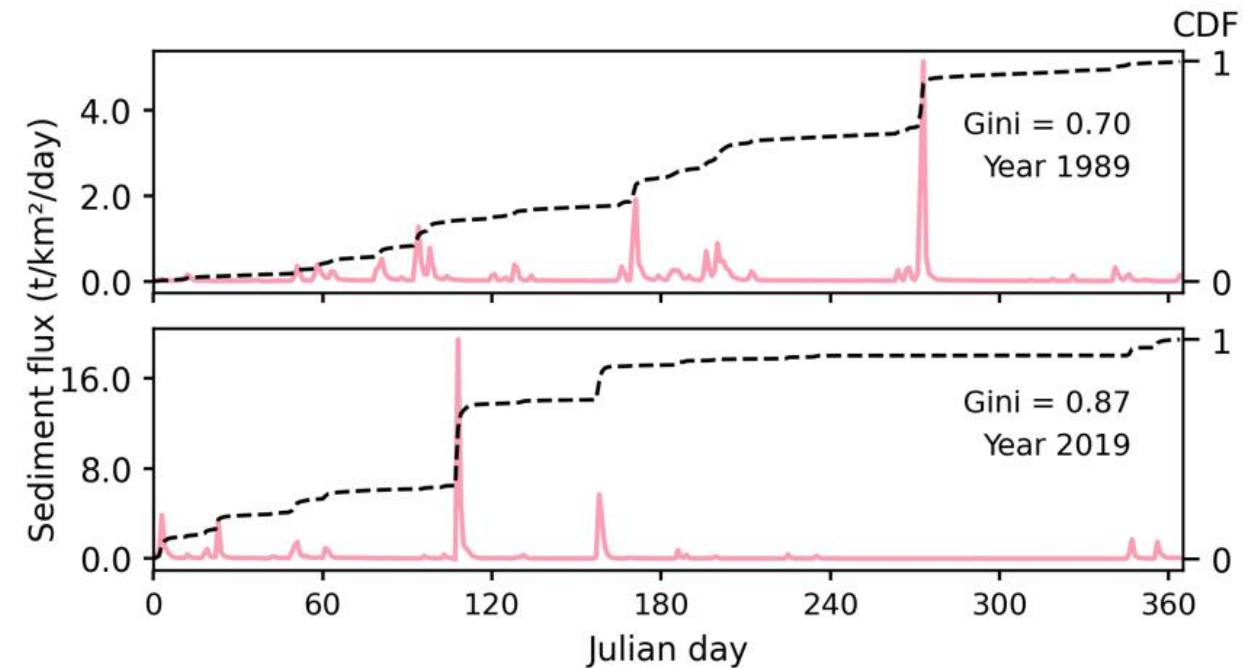
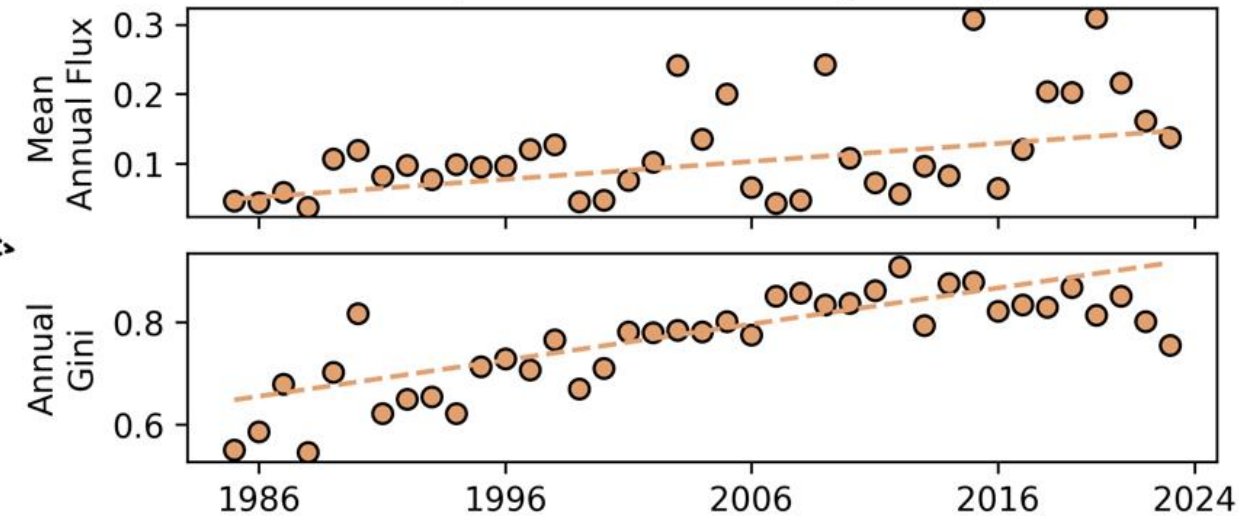


b. Gini index



c.

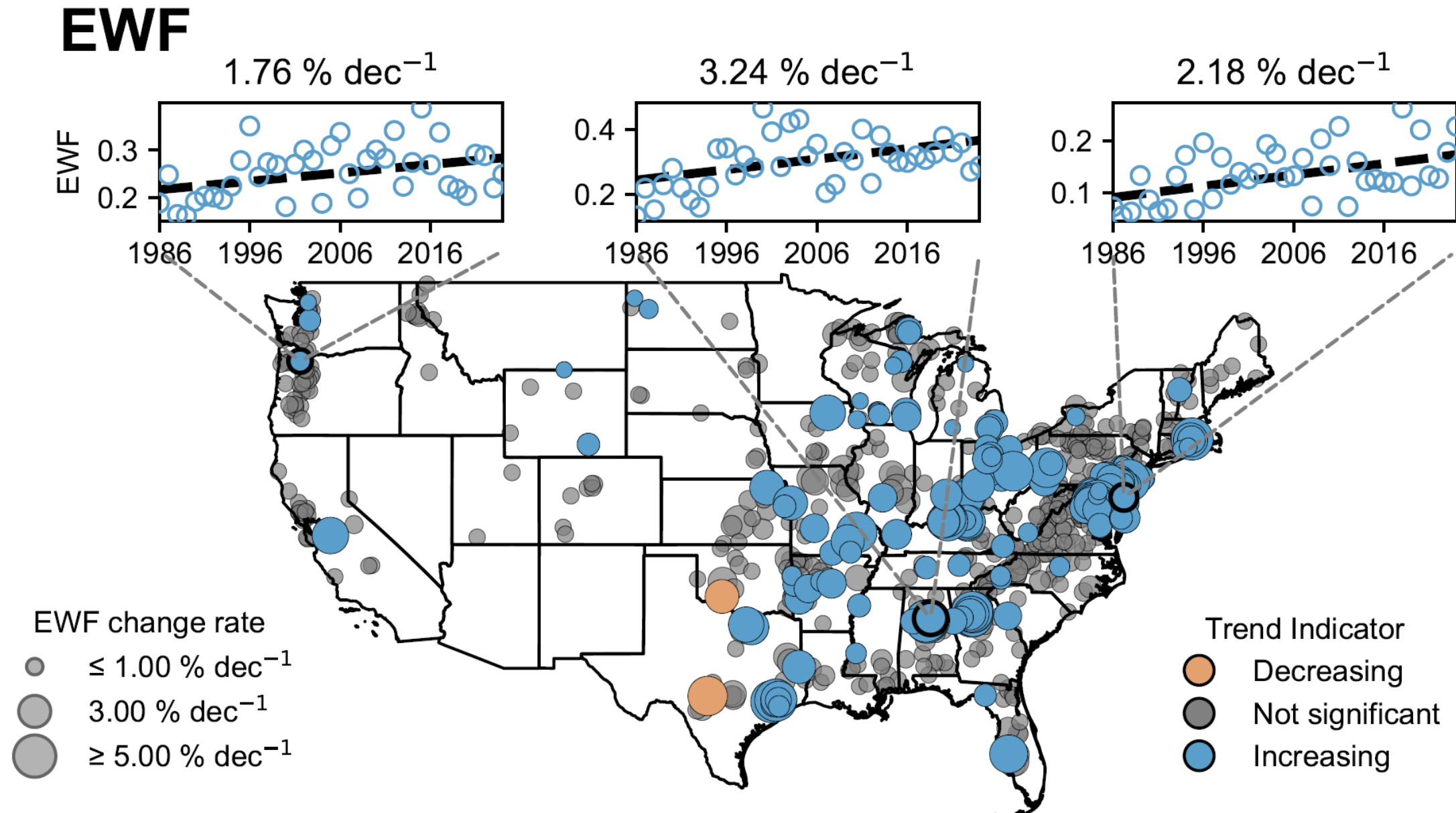
Brushy Fork Creek near Loganville, GA



Sigdel and Husic 2026 (*in revision*)

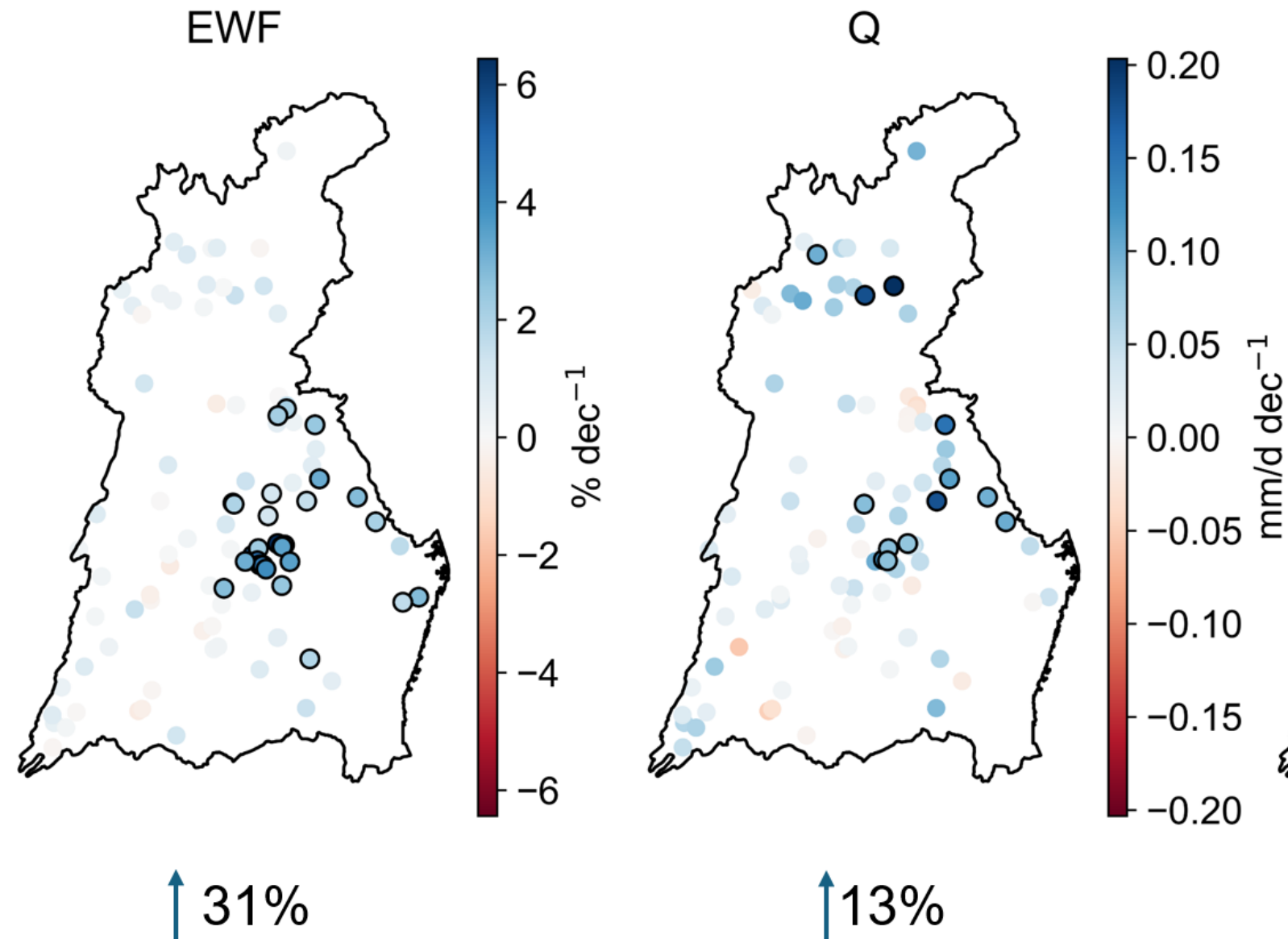
Reconstructing historical records

Hydrologic pathway dynamics



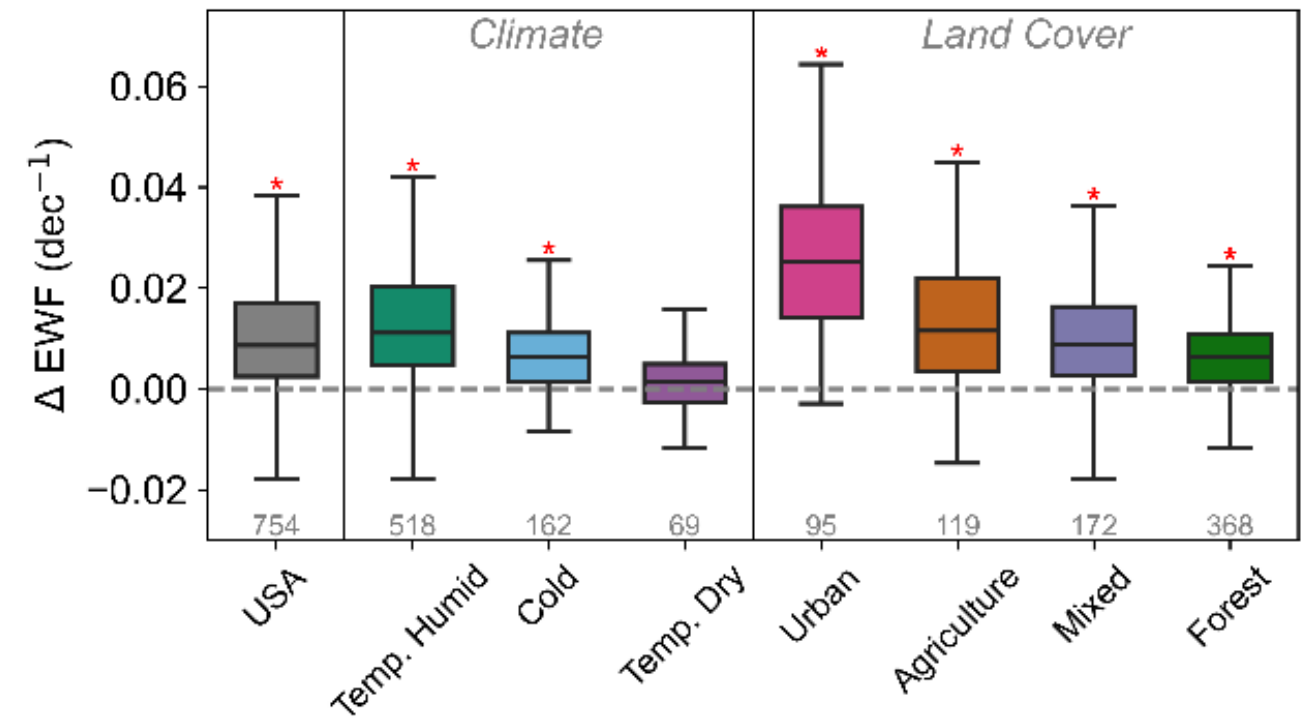
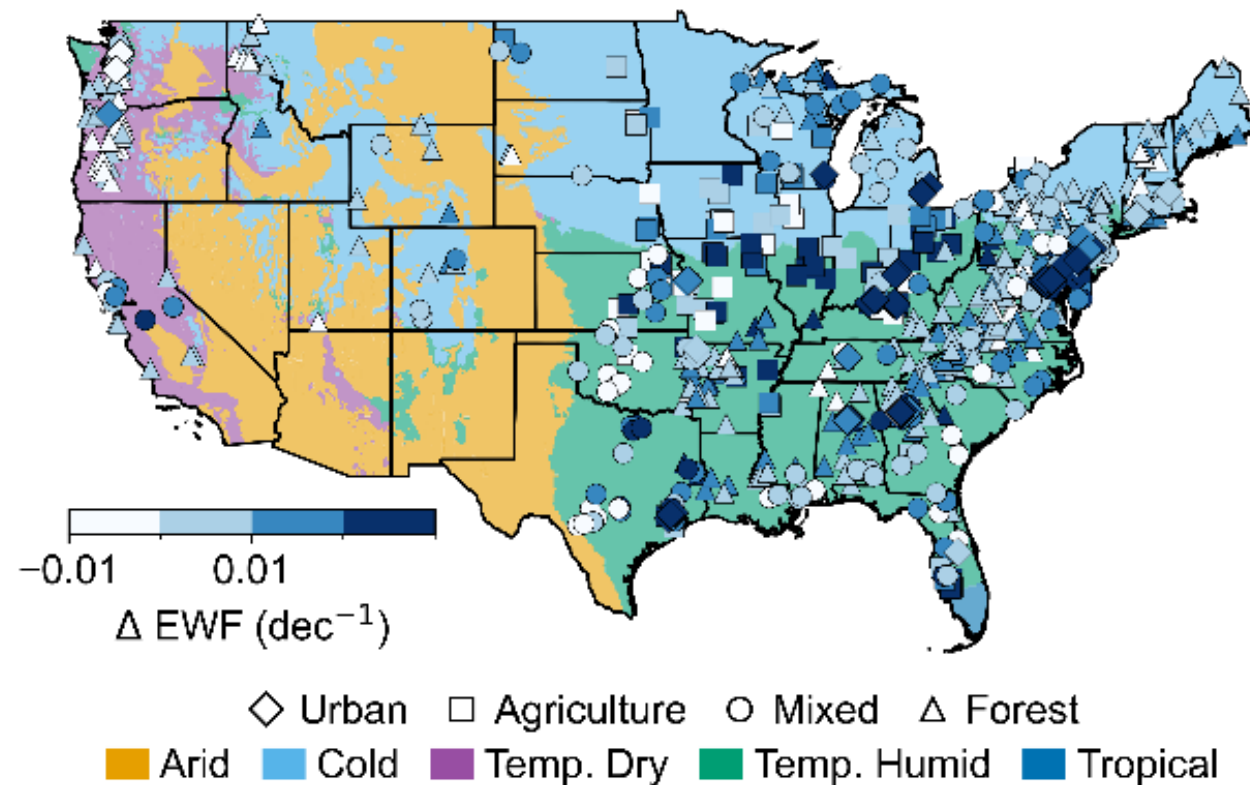
Reconstructing historical records

Hydrologic pathway dynamics



Reconstructing historical records

Hydrologic pathway dynamics

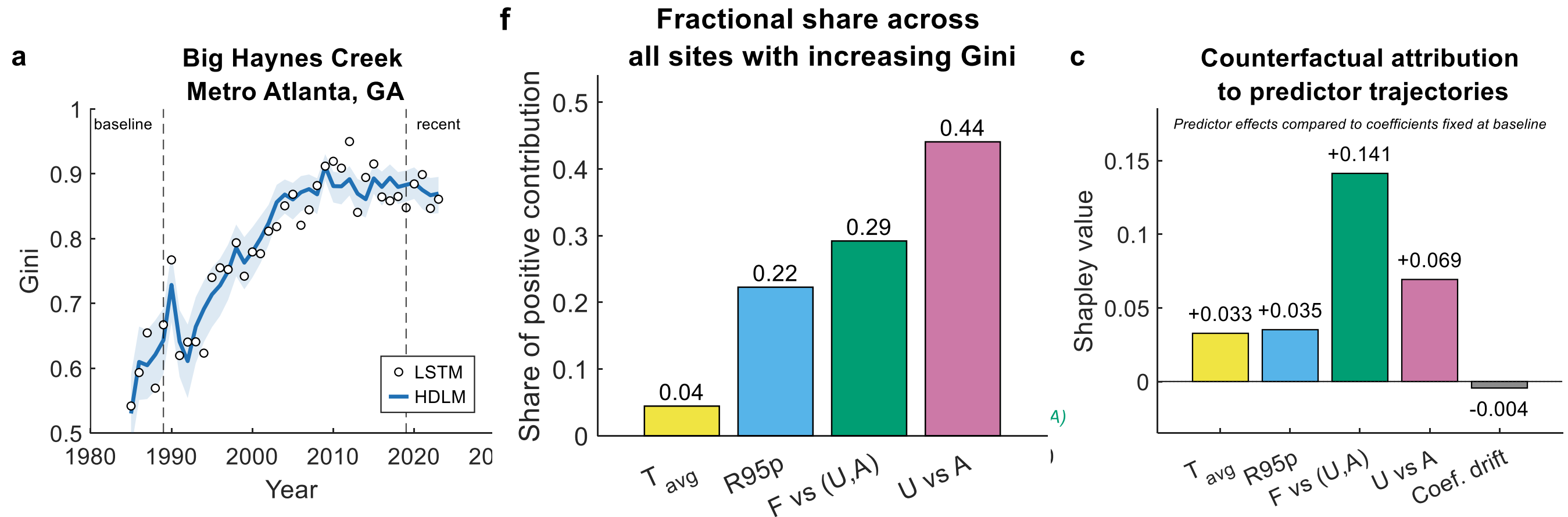




What factors are driving these systems to change over time?

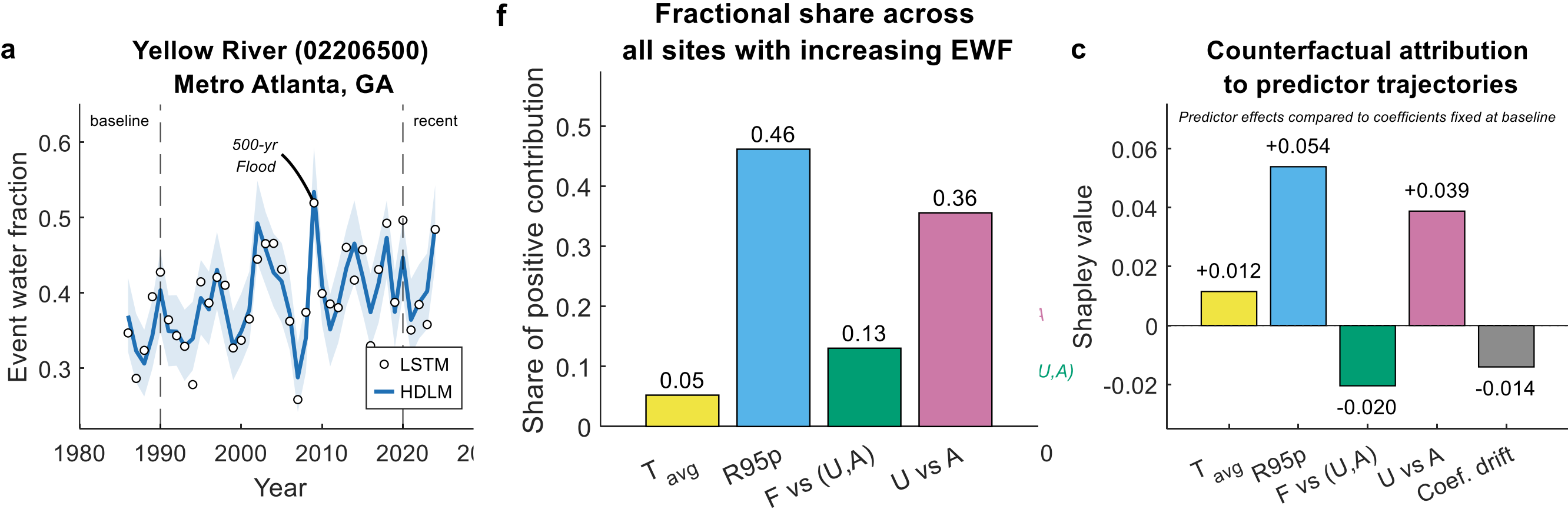
Attributing change to drivers

Sediment dynamics



Attributing change to drivers

Hydrologic pathway dynamics

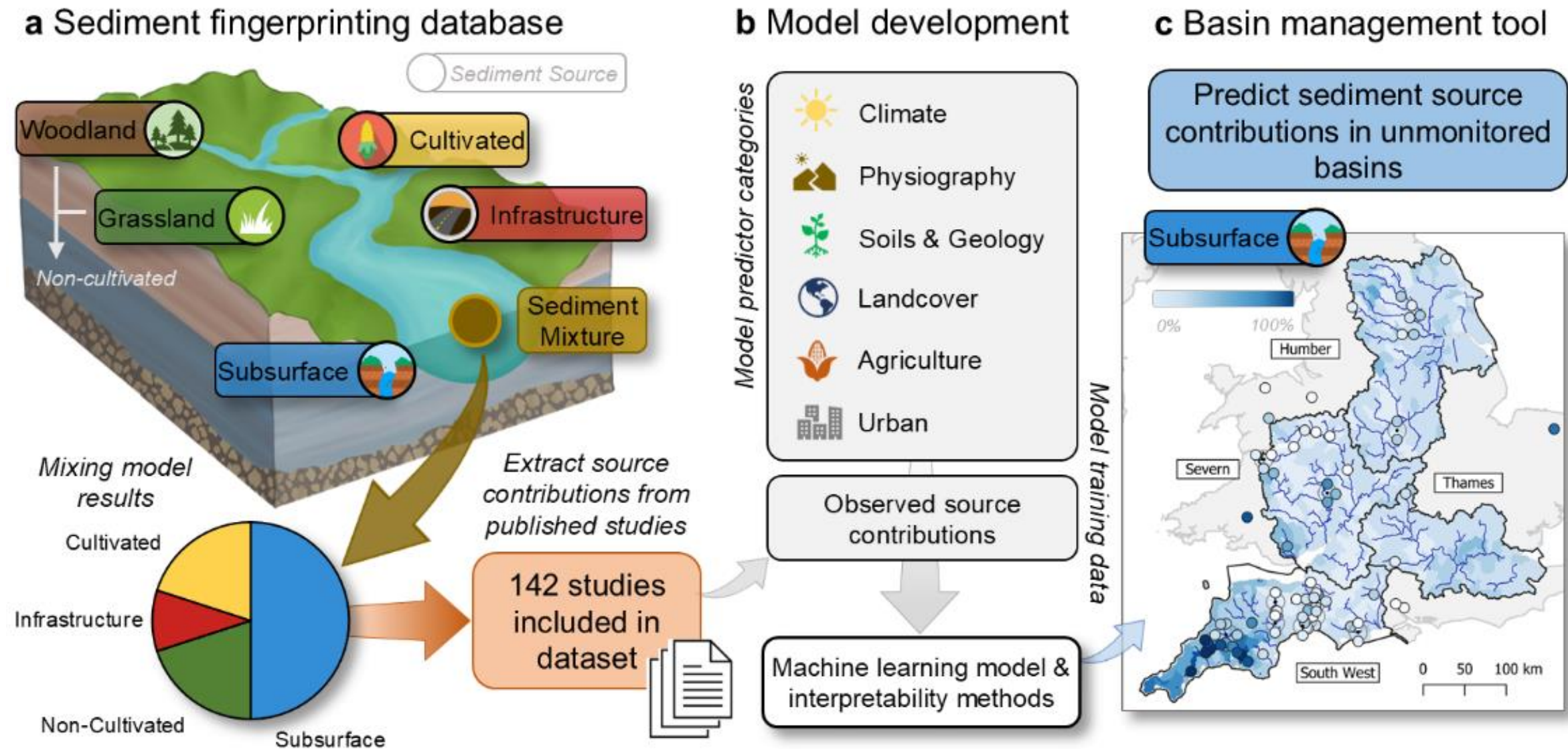




Additional work within the Chesapeake Bay ...

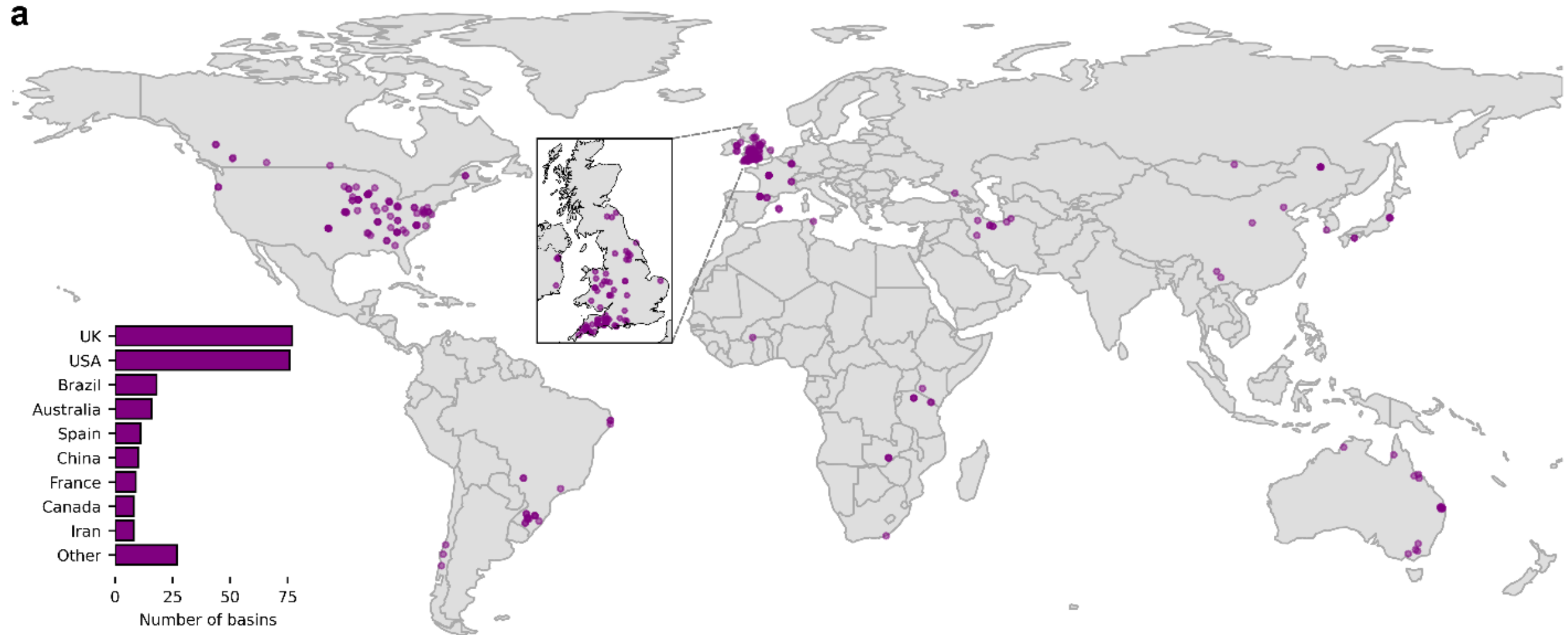
Mapping dominant sediment sources

Sediment provenance



Mapping dominant sediment sources

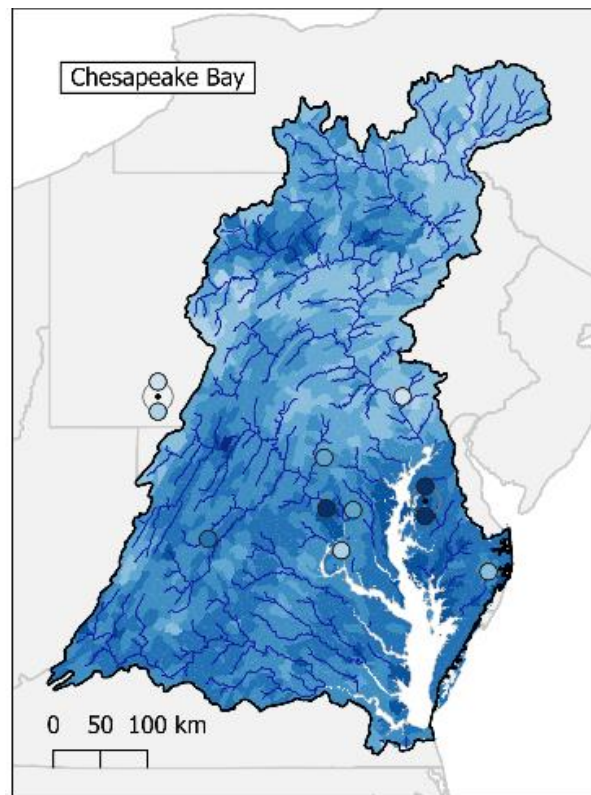
Sediment provenance



Mapping dominant sediment sources

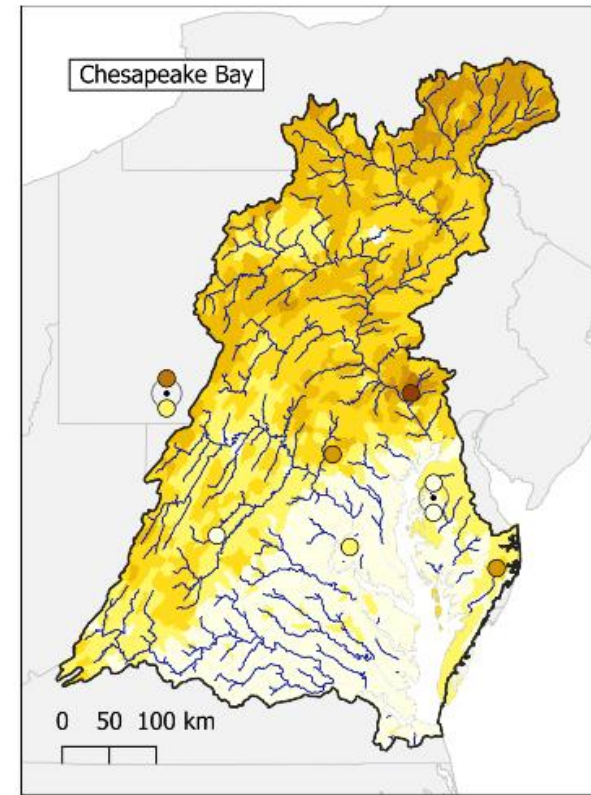
Sediment provenance

Subsurface/bank



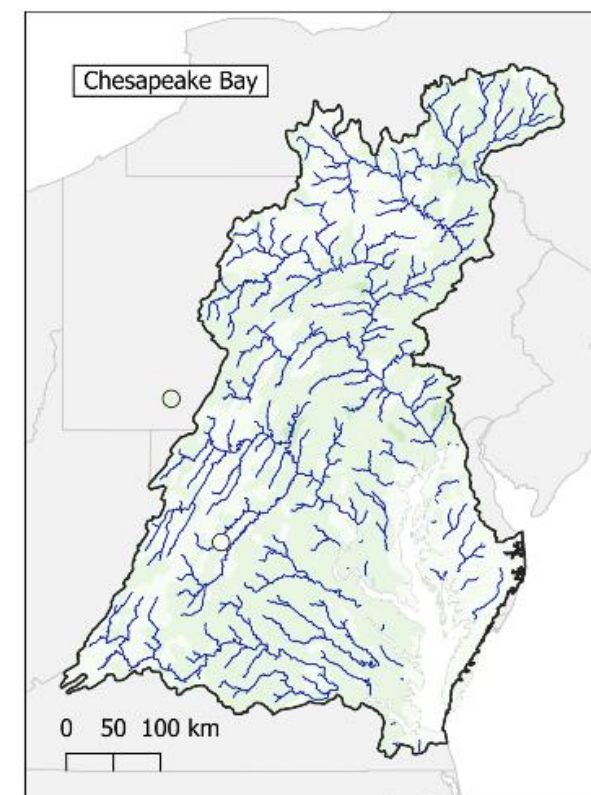
~63%

Cultivated



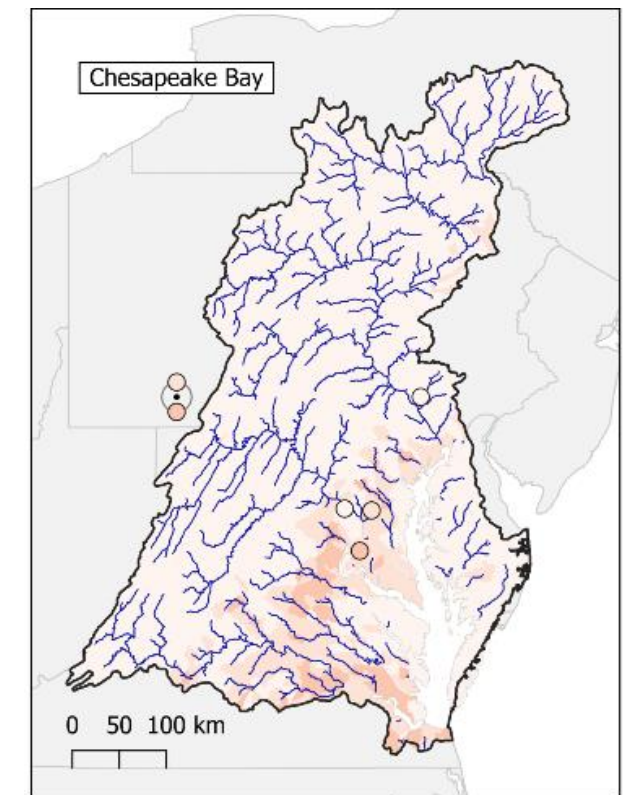
~20%

Non-cultivated



~10%

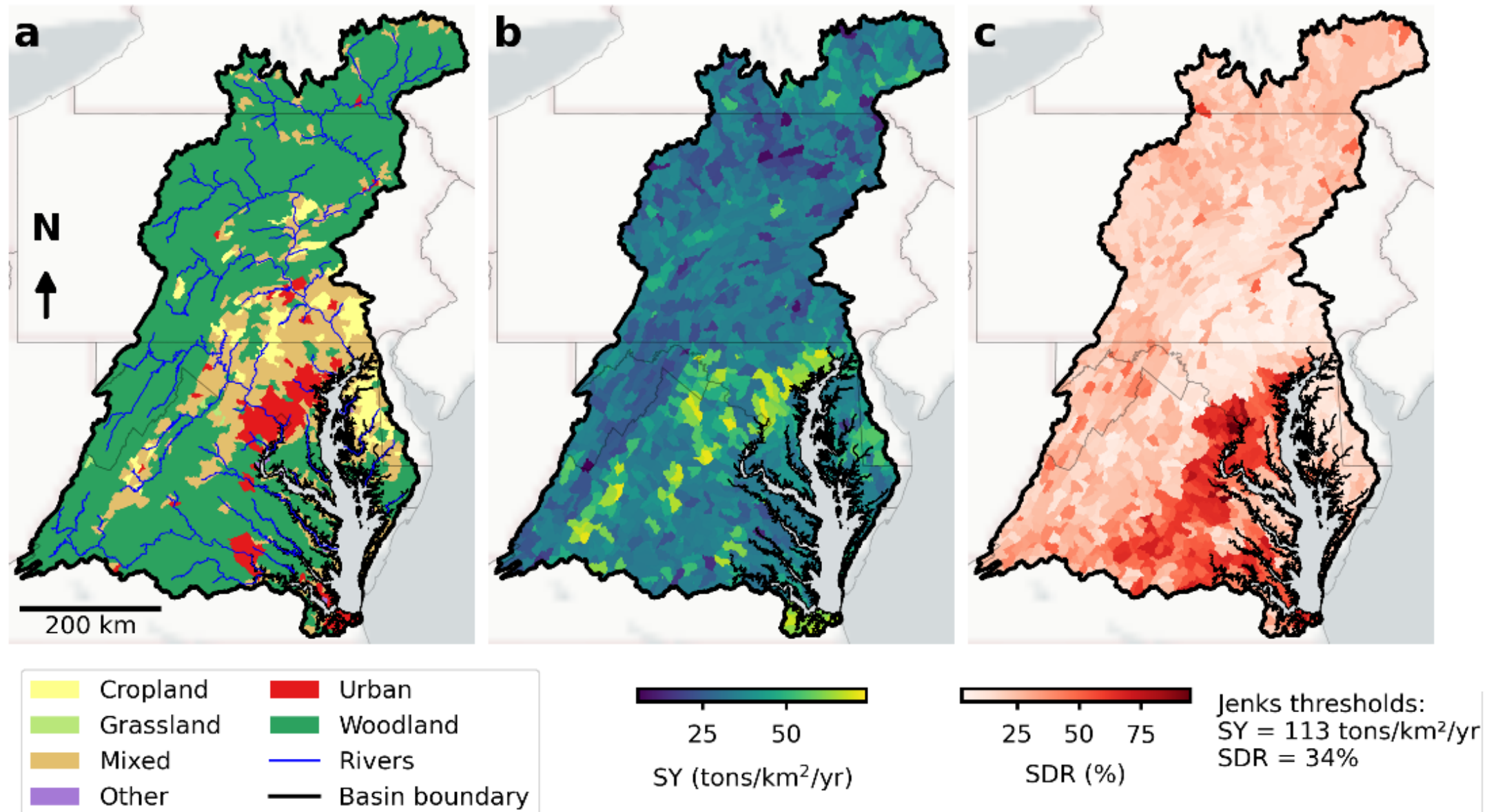
Infrastructure/road



~7%

Mapping sediment erosion

Sediment magnitude and delivery ratio



Concluding thoughts and considerations

- The nature of water, sediment, nutrient, and salt transport is changing due to climate and land use stressors.
- Increasing 'burstiness' of sediment transport reduces the management window to control erosion.
- Watersheds are converting precipitation to runoff more effectively, limiting buffering capacity.
- As we develop and apply new machine learning models to interpret the world, how much can we trust these methods to...
 - be causal rather than correlative?
 - provide novel insights as opposed to confirming existing knowledge?

Thank you!

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