Upper Mississippi River Basin Association
Water Quality Task Force Meeting

September 20-21, 2023

Agenda
with
Background
and
Supporting Materials

The Merrill
Muscatine, Iowa

Upper Mississippi River Basin Association
Water Quality Task Force Hybrid Meeting
September 20-21, 2023
Agenda

Connection Information

- Web, video conferencing, click on the following link:
    - https://umrba.my.webex.com/umrba.my/j.php?MTID=m5fbcc316669ceb8e0d9733bf5a2ea5c1
- Dial-in number: (312) 535-8110
    - Access code: 2550 462 7394
    - Passcode: 1234

Wednesday, September 20

Time	Attachment	Topic	Presenter
1:00 p.m.		**Welcome and Introductions**	***Kim Laing,*** *MNPCA*
1:05	A1-A18	**Approval of the June 13-14, 2023 WQEC-WQTF Draft Meeting Summary**	***All***
1:10	B1-B7	**UMRBA Updates** • UMR Interstate Water Quality Monitoring in 2025-2026 • UMR Interstate Water Quality Monitoring Plan Updates • UMRBA Multi-Benefit Conservation Practice October 3-4, 2023 Workshop • *How Clean is the River?* Report • Water Quality Task Force Roles and Responsibilities	***Lauren Salvato,*** *UMRBA*
2:10	C1-C15	**Upper Mississippi River Restoration Long Term Resource Monitoring** • Reconstructing Missing Data by Comparing Interpolation Techniques: Applications for Long-Term Water Quality Data	***Dr. Danelle Larson,*** *USGS*
2:40		**Break**	
3:00		**Cyanotoxins/Harmful Algal Blooms** • State and Federal Updates	***All***
3:45	D1-D11	**Nutrients** • Conclusions from 10 Years of Phosphorus Rules in Wisconsin • Gulf Hypoxia Program Sub-Basin Committee Work Plan • Nutrient Reduction Strategy Updates	***Matt Claucherty,*** *WIDNR* ***Lauren Salvato,*** *UMRBA*
4:30 p.m.		**Adjourn**	***All***

Thursday, September 21

Time	Attachment	Topic	Presenter
8:00 a.m.		Welcome and Introductions	***Kim Laing,*** *MNPCA*
8:05		Recap of September 20 Discussions	***All***
8:10	E1-E8	Chloride • Upper Limits for Road Salt Pollution in Lakes	***Dr. Chris Solomon,*** *Cary Institute*
8:35	F1	Cyanotoxins/Harmful Algal Blooms • Priorities for FY 2024	***Dr. Michael Paul*** *and* ***Dr. Anne Rea****, USEPA*
9:00		Clean Water Act • 303(d) and 305(b) Lists • TMDLs in the Upper Mississippi River Basin	***All***
9:20		Break	
9:50		UMRBA CWA Research Questions Brainstorm	***All***
10:20	G1	Statistical Survey Tools for Monitoring	***Garret Stillings,*** *USEPA*
10:50		UMRBA Updates • Potential UMR Recreation Survey	***Lauren Salvato,*** *UMRBA*
11:20		Administrative Items • WQTF Winter 2024 Virtual Meeting	***All***
11:30 a.m.		Adjourn	

ATTACHMENT A

June 13-14, 2023 WQEC and WQTF
Draft Meeting Summary *(A-1 to A-18)*

Upper Mississippi River Basin Association
Water Quality Executive Committee and
Water Quality Task Force Hybrid Meeting

June 13-14, 2023
Draft Highlights and Action Items Summary

Approval of the WQTF January 25, 2023 Meeting Summary

The UMRBA Water Quality Executive Committee (WQEC) and Water Quality Task Force (WQTF) approved the January 25, 2023 draft highlights and action items summary.

UMRBA Updates

UMR Interstate Water Quality Monitoring in 2025-2026

Lauren Salvato said the WQTF is planning to implement the fixed site network, a portion of the Upper Mississippi River (UMR) Interstate Water Quality Monitoring Plan during October 2025 to September 2026. This would include all five states as well as Metropolitan Council (regional government in Minnesota) to sample a suite of parameters at 11 fixed sites from L&D 2 to Thebes, Illinois. The five states are coordinating multiple funding sources to be able to implement the fixed site network monitoring. The WQTF met earlier on June 13 for a working session and used that time to refine its list of parameters and discuss analytical laboratory options.

USEPA Exchange Network Grant

In preparation for the next phase of implementing the UMR Interstate Water Quality Monitoring Plan, the WQTF agreed that UMRBA should centrally house a database and develop functionality to upload the data to USEPA's Water Quality Exchange (WQX). In researching potential funding sources, UMRBA staff found that the USEPA Exchange Network (EN) would support UMRBA's development of a database in alignment with the WQTF's objectives for the database.

During spring 2023, UMRBA staff confirmed with the EN Program Coordinator that UMRBA can partner with a state agency from one of its member states as long as that organization applies as the lead organization. Illinois EPA agreed to partner with UMRBA and an application was submitted for $150,000 to support UMRBA staff time and the costs of a database development contractor. This amount would include space to house UMRBA's water quantity data to support the out of basin diversion charter and conducting a cumulative impacts assessment.

Following submission, USEPA staff notified Illinois EPA that two applications were submitted from the agency. Since the agency cannot be awarded more than one application per cycle, UMRBA's application was withdrawn.

Salvato asked the WQEC and WQTF for input on additional options to fund a database for UMRBA. Glenn Skuta suggested a follow-up discussion with USEPA staff. From Minnesota PCA's standpoint the structure of the grant program is problematic as PCA was also planning to pursue a grant in fiscal year (FY) 2023. He assumes USEPA's rule is related to spreading the funding around, but UMRBA's proposal and one put forth by PCA are very distinct proposals with greatly different scopes. Kirsten Wallace asked for a more specific action item. Is a letter appropriate in this case, a meeting with USEPA HQs staff? What would be the most effective way to communicate this. Skuta suggested and other WQEC representatives agreed to start with a call to USEPA staff and determine if a letter is helpful. The message can be about the implementation challenge and suggest that UMRBA should be eligible as its own entity to apply for EN grants.

USEPA Regions 5 and 7 Science Liaison Meetings

UMRBA staff met with USEPA Regions 5 and 7 science liaisons to understand how the Upper Mississippi River can be incorporated into USEPA's research initiatives. There are several options. Regional ORD Applied Research Program (ROAR; formerly called RARE grants): the annual proposal process is internal through the regions - i.e., a partner cannot write the proposal in collaboration with USEPA regions. The science liaisons are program neutral and the true advocacy for a particular proposal comes from the water division level. There is not a large sum of funding for research projects and the funding is competed for across multiple divisions. Research ideas can be discussed with Amy Shields in Region 7 or her equivalent in Region 5, Dave Pfeifer. ROAR proposals must align with the Strategic Research Action Plans (STRAPs) priorities.

STRAPs are national level research priorities that guide four years of USEPA research. The next survey cycle will occur in 2025. Some of the ways that USEPA incorporates priorities are: 1) USEPA HQ Lisa Matthews consults with the Environmental Council of the States, 2) the regions are consulted, and 3) the Region 7 science liaison convenes a committee of the states and tribes, so the WQEC and WQTF could also submit priorities through Angela Falls (Missouri DNR) and Kathy Lee (Iowa DNR).

UMRBA staff would like direction on how to engage USEPA in future STRAP and ROAR cycles and are suggesting a brainstorm of research ideas during calendar year 2023. If the WQEC and WQTF agree to the idea, staff can utilize the following schedule:

- Summer 2023: UMRBA staff initial brainstorm
- Fall 2023: WQTF develop detailed list (in conjunction with WQTF meeting):
- Winter 2023-2024: Coordinate research questions with partner organizations – e.g., UMRCC WQ Tech Section.

The WQEC and WQTF expressed interest in this exercise. Nicole Vidales said a lot of good can come from having research questions ready. Robert Voss suggested topics such as the impact to mussels from aluminum and selenium exposure. Daniel Kendall suggested emerging contaminants research topics. Voss wondered how to prioritize the ideas and cost. Salvato replied she is open to different formats. The Upper Mississippi River Restoration (UMRR) Long Term Resource Monitoring (LTRM) recently created a set of information needs to be able to quickly respond to increased authorization. That was done using structured decision making and the expected value of information.

Micah Bennett added that a constraint of the ROAR process is that USEPA cannot directly collaborate with outside partners in developing the proposal. Laying out research priorities for the UMR and trying to get those related to regional and ORD priorities will allow USEPA staff to create projects that can meet those needs. Steve Schaff said he would check with Region 7's science liaison but there may be opportunities to do research using existing water quality data as well – i.e., if the states have data but no time to analyze it, Region 7 could potentially contribute resources or expertise to analyze it and draw conclusions.

UMRBA Multi-Benefit Conservation Practice Workshops

UMRBA received a USEPA Office of Wetlands, Oceans, and Watersheds grant to convene partners across the basin to discuss how to further accelerate the adoption of conservation practices with multiple benefits. The first workshop occurred in St. Louis, Missouri in November 2022 and the second is planned for October 3-4, 2023 in St. Paul, Minnesota. The theme of this workshop is leverage points of change. Identifying leverage points for the Upper Mississippi River Basin requires a whole system evaluation of the roots causes that, when addressed, can increase the implementation of conservation practices with multiple benefits. UMRBA and the workshop participants will work together to plan strategic efforts to address root causes: policy, financial, technical, leadership, and partnership. Examples of leverage points include improved and coordination technical assistance, innovative and streamlined funding mechanisms, peer to peer networks, and new partnerships/collaborations.

UMRBA staff have scheduled two pre workshop webinars on June 29, 2023 and September 13, 2023 to provide baseline information for workshop participants, while the October workshop is by invitation only. The pre-workshop webinars are open to everyone. Salvato added that the planning committee has been integral in shaping the workshop and is grateful for their participation.

How Clean is the River? Report

Salvato said that the report is 99 percent complete. Staff are reworking the conclusions section to ensure it is impactful and have a set of actions to address water quality issues. Staff will be presenting the report at the upcoming August 9, 2023 Missouri Water Protection Forum meeting. Wallace added that UMRBA wants to have a strategic message for UMRBA's water quality program.

Midwest CASC Proposal for Floodplain Reconnection

Wallace said UMRBA is receiving funding from USGS's Midwest Climate Adaptation and Science Center to create learning questions to inform a broader adaptive management framework and develop a suite of criteria to identify and prioritize the location of floodplain reconnection opportunities. The project will additionally illuminate the willingness of some landowners to implement floodplain reconnectivity on their respective lands.

Shawn Giblin shared his interest in this project, and asked if the proposal is meant to reconnect isolated backwaters or do levee setbacks. In response, Wallace said the proposal does not prescribe either. The proposal will be used to articulate the need for learning criteria and investment in reconnecting the floodplain. The funding is small and partners like Joint Ventures have offered to help develop social metrics. As this proposal was submitted, USFWS received $10 million to identify projects focused on climate resilience and economic and social justice. Separately, UMRR and the Navigation Ecosystem Sustainability Program (NESP) will be undergoing a project selection process. Feel free to reach out to Wallace with questions and insights.

Nutrients

Gulf Hypoxia Program Sub-Basin Committee Work Plan

Salvato reviewed that the Gulf Hypoxia Program authorized in the Bipartisan Infrastructure Law allowed for sub basin committees (SBCs) to each receive $400,000 for a three-to-five-year period. The guidance was published on June 1, 2023, and SBCs are asked to submit their workplan by July 31, 2023. USEPA wants the workplan to follow the following specific strategic outcomes to advance multi-state collaboration in the Mississippi River Basin:

1) Convene regional, state, and other stakeholders not represented on the Task Force, including additional basin states, basin tribes, agencies, and interested parties and organizations to gather input, facilitate peer-to-peer learning opportunities, and encourage collaboration across boundaries.

2) Help the states engage disadvantaged communities in nutrient reduction planning and activities within their boundaries.

3) Support states in the respective sub-basins as they implement and coordinate comprehensive nutrient reduction strategies across boundaries. For example, where states are looking to adopt programs or practices of other sub-basin states, provide coordination and assistance where possible to ensure data generated across state programs will provide a regional picture of progress.

4) Coordinate, consolidate, and improve access to data and present regional progress towards the Action Plan goals.

Salvato asked for initial feedback from the WQEC and WQTF: 1) how does the sub basin committee role relate to your state workplan? Which of the four goals do you prefer the Association work on? Do you have any guidance for UMRBA while developing the workplan? Participants shared their preference is for UMRBA staff to focus is on strategic outcome three, as listed above.

Potential examples of workplan tasks include better linking nutrient data in tributaries to what is occurring in the UMR mainstem. This would help create a storyline of what the problem and solution are. This would formally include the high-quality data of LTRM. The 2022-2035 UMRBA Water Quality Program plan also discusses work around climate change research, an adaptive management framework. Albert Ettinger suggested that UMRBA could help identify sources of nutrients in various watersheds. The science has been challenging in Illinois to parse out whether nutrient contribution is from streambank erosion, CAFOs, or other nonpoint sources. An isotopic analysis would help separate out the contributions of nutrient loading.

Nutrient Reduction Strategy Updates

Missouri – John Hoke said Missouri's Nutrient Loss Reduction Strategy (NLRS) is 10 years old. Missouri is going to gather stakeholders to reflect on what has been achieved and what the next 10 years will look like for nutrient reduction. In response to Adam Schnieders about the most exciting work that has happened in Missouri, John Hoke said the 1.0 mg/L total phosphorus statewide rule. The rule goes before the commission for vote in July 2023. Missouri DNR has gained support of industrial and municipal discharges statewide. The rule will get Missouri closer to the point source reduction goal for the Hypoxia Task Force (HTF) states.

Robert Voss said that Missouri DNR is expanding its contract with USGS and plans to have continuous nitrate sensors on the Missouri River at St. Joseph, Napoleon, and Herman, as well as on the UMR near Keokuk and Alton. There is also a nitrate sensor on the UMR near Thebes. This will give the state a better idea of nitrogen flux to do better flow weighted regression for the next three to five years. Hoke added that when Missouri DNR updated its monitoring strategy, USEPA Region 7 noted the lack of continuous sensors was one of the bigger monitoring gaps.

Illinois – Nicole Vidales said that Illinois EPA's Trevor Sample is working on the biennial report with an anticipated release in December 2023.

Iowa – Adam Schnieders said May 2023 marked the 10-year anniversary of the Iowa Nutrient Reduction Strategy (NRS). At the time, Iowa released a comprehensive data dashboard with coordination from Iowa State University. The dashboard can be found linked here: https://nrstracking.cals.iastate.edu/tracking-iowa-nutrient-reduction-strategy. Iowa has been able to invest hundreds of millions of dollars towards conservation projects. In order to see a change in the water, changes need to occur in the land and in people. Agriculture-urban partnerships and the batch and build model are good examples of partnerships and leveraging multiple benefits. A lot of new facilities are coming online with the latest nutrient removal technologies that are further reducing point source pollution.

Communication with the public, however, is challenging. The size of the Gulf of Mexico Hypoxic Zone is three million acres. Salvato emphasized the point and shared that she was interviewed by the Mississippi Ag and Water Desk when the Dead Zone size prediction came out. The reporter wanted to know what was different about previous years, and Salvato communicated the challenges of legacy nutrients and lags in water quality, but also the federal investments that have come through the Gulf Hypoxia Program Funding.

Ettinger suggested a presentation from Dr. Castellano whose research created a weather forecast for the best nitrogen rate to apply on a specific field using hundreds of different factors. Ettinger added that it is well proven in Ohio that tile drains are not helping to stop nutrients. In response to a question from Ettinger about point source limits, Schnieders responded that limits have been in Iowa's strategy since 2013 as a 10:1 shorthand. For 75% reduction you achieve 1 mg/L phosphorus. This applies to major municipalities and wastewater treatment. Forty-seven facilities are meeting nitrogen goals and 23 facilities are meeting phosphorus goals. There has been good steady progress, including in the industrial sector. Ettinger asked if phosphorus is being converted from sewage and fertilizer. Schnieders said that Ostara, a proprietary name, became too expensive. Des Moines has figured out different ways to patent a few pending technologies for the phosphorus recovery process.

Wisconsin – Adrian Stocks said through the Gulf Hypoxia Program grants, Wisconsin is working to provide administrative support to producer-led watershed groups. There are currently more than 40 in the state. The real advantage of these groups is to get conservation practices implemented with peer-to-peer knowledge sharing. A challenge is for busy farmers to set up meetings. UW Extension is a partner to provide capacity to set up events, create meetings, and focus on watershed areas and counties that could use support. The grant funding is also being used for a dedicated NRS coordinator to work solely on tracking, reporting and outreach. Wisconsin DNR is supporting county land conservation districts to develop nine key element plants. Wisconsin is continuing to develop data visualization capacity with interactive web-based maps and tracking the progress of projects. Satellite imagery will help Wisconsin better assess nonpoint source projects and implementation.

In response to a question from Ettinger about where Milwaukee Mixing Zone Study stands, Stocks said he would reach out to DNR's wastewater manager.

Minnesota – Skuta said Minnesota's NRS is 10 years old and is in active revision. Since the strategy was produced, Minnesota published a five-year progress report. The revised strategy will include documentation of efforts and programs that have launched in the previous decades. But there is more work to do and hopefully conservation implementation can be accelerated. Farmers can access funding to gain water quality certification and access certain sources of funding. MN Department of Agriculture has the groundwater protection rule where there are impacts to drinking water. The University of Minnesota's Forever Green has a host of continuous living cover that it is trying to promote. The Clean Water Fund has millions of dollars for water quality. Unfortunately, nitrogen is not reducing, it is either flat or going up.

Gulf Hypoxia Program dollars will be used for a NRS coordinator. The candidate should be announced soon. Having a dedicated person to write the NRS will allow Dave Wall to support the research. The University of Minnesota has been contracted to tell us the most cost efficient BMPs. While two-thirds of the drainage in Minnesota goes to the Gulf of Mexico, the NRS will pay more attention to the nutrient loading in the Red River Basin.

Ettinger asked about Minnesota's plan for a nitrate standard. Skuta replied that Minnesota wants to take a more holistic approach. A standard has the biggest impact of point sources in terms of implementation. Minnesota wants to use the NRS to address nitrogen pollution.

A Partnership to De-Risk Regenerative Agriculture Practices

Becca Clay, Conservation Agronomist with Practical Farmers of Iowa (PFI) described the partnership with PepsiCo to put $216 million towards regenerative agriculture. By 2030, PFI and PepsiCo estimate implementing practices like cover crops on 1.5 million acres. This partnership is aligned with PRI's vision of "healthy soil, healthy food, clean air, clean water, resilient farms and vibrant communities."

Clay reminded the audience that as of 2021, 64% of Iowa was planted in corn and soybeans in 2021. Within the shoulder seasons there are additional opportunities for biomass production which can reduce nitrate leaching. In fact, a study in the Van Zante Creek showed that nitrate loads from cover cropped fields were 32% lower than nitrate loads from non cover cropped fields.

Responding to member requests, in 2015 PFI began providing cost share of more than $10 per acre for cover crops. There is a role for large corporations like ADM and Unilever, purchasers of soybeans, and Cargill and PepsiCo, purchasers of corn, to make positive impacts on the supply chain and put more conservation requirements on the producers that grow these commodity crops. In 2023, PFI continues to offer $10 per acre cover crop cost share, which can be used in concert with publicly funded cost share programs.

PFI works directly with producers interested in regenerative agriculture and also provides farmer-to-farmer education, connecting members to the press and direct story sharing. The partnership coaches farmers on conservation practice adoption and conducts on-farm research through a cooperators program. PFI also works on market development and business support through a cover crop business accelerator program, including business support and marketing tips.

In response to a question from Salvato about the geography covered by PFI and the Soil and Water Outcomes Fund, Clay said that she believes both organizations are working in similar areas. Salvato asked Clay to share how regenerative agriculture is defined by PFI. Clay said that the term is broad and includes actions like reducing nitrogen fertilizer, conversion of granules, extending rotation, and use of cover crops. PepsiCo is purchasing a lot of grain in the Midwest and is focused on working land conservation and less on taking it out of production. Skuta asked if the shorter growing season in the Upper Midwest is a barrier to implementing cover crops. Clay replied that cover crops work in states like Minnesota, though the species that can overwinter are more limited. She knows that cereal rye is consistently used in Canada. In response to Salvato's question about continuous living cover like Kerna™, Clay said PFI is still waiting for the market to respond and for improved breeding before putting a big investment in it.

Clay responded to Salvato's initial question about how UMRBA can be helpful to PFI. She suggested engaging with policy makers, making it easier for cover crop adoption and providing flexibility to farmers as much as possible. Skuta added the data make cover crop adoption seem compelling and asked if there is more that can be done with the reauthorization of the Farm Bill, policies and specific types of funding to really advance cover crops more than they have been thus far. Clay said that there is a bill on the floor that is trying to get $5 per acre cover crop premium insurance to be formally institutionalized. The program came out during the COVID-19 pandemic as relief funding and farmers really like it and have found the program easy to use.

What's Eating the Trempealeau Lakes: The Case for Controlling Nutrient Loading

Giblin described the Trempealeau Terrace as an area with economic diversity, unique culture, homes on stilts, a mix of seasonal to year-round residents, and a lot of recreational interests such as fishing. The study area is about 30 square miles on the sand wash terrace bordering the Trempealeau National Wildlife Refuge, with permeable soils and intensive cash cropping. Because of the underlying substrate, the area is susceptible to high levels of nitrate in groundwater.

The public and recreational users of the area have complained about the changing water quality conditions and reduced recreational and ecological value. That was the driver of forming the nonprofit Friends of Trempealeau Lakes.

In 2021, Giblin and collaborators conducted sampling at six sites monthly from May to September. Parameters sampled included basic field measurements as well as nutrients, chlorophyll-a (chl-a), phycocyanin (meter measured), rooted veg cover, filamentous algae cover, and duckweed cover. The results for each of the six sites when compared to the lower limit eutrophic range, only one site was below. The backwater areas were likely nitrogen-limited for many years and now are receiving nitrogen which is causing eutrophication problems. Chl-a results were well in exceedance of the threshold for >60 µg/L for severe nuisance algal bloom and >20 µg/L the levels viewed as a problem according to public perception studies.

Giblin et al., 2022 looked at backwater residence times and the big takeaway was that as nitrogen increases, backwaters tend to have increased filamentous algae mats. Giblin suggested that eutrophication issues cannot be addressed without reducing nitrogen and phosphorus loading. Therefore, nitrogen criteria can be developed to help reach nitrogen reduction goals. Nitrogen reduction pilot programs are manageable and can help reduce nutrient loading on smaller scales.

In response to a question from Schnieders, Giblin said the backwater lakes are six to eight feet deep and the residence times range from one to 150 days. Schnieders asked Giblin what nitrogen criteria numbers would be suggested. Giblin replied the numbers are in the 1-2 mg/L range based on dissolved oxygen and biomass cover. In response to a question from Salvato about desired future conditions and nitrogen criteria development being a complimentary effort, Giblin said he recommends criteria for everything, including addressing water quality issues, as humans are a goal-oriented species.

Schnieders asked Giblin what sources of nitrogen loading there are – e.g., wastewater. Giblin said areas of the Trempealeau terrace has center pivot irrigation. Center pivot irrigated areas result in a huge loss of nutrients to groundwater. Giblin added that a forthcoming paper is working on management targets for habitat restoration that can alleviate mats with certain residence times.

Upper Mississippi River Restoration

Long Term Resource Monitoring Information Needs

Andrew Stephenson discussed the Upper Mississippi River Restoration (UMRR) Long Term Resource Monitoring's (LTRM) recent implementation planning effort. This effort is to prepare for potential increased funding resulting from increased UMRR authorization under WRDA 2020 and to develop a set of portfolios of actions that best address UMRR management and restoration information needs. In addition to identifying information needs not currently being addressed by the ongoing LTRM, the planning team developed criteria for expected benefits, estimated costs of each information need and through a ranking process, reduced the list of information needs down to 11.

Some of the list of includes:

- System-scale assessments of changes in floodplain vegetation
- Spatial and temporal distribution of higher trophic levels on the UMRS floodplain (reptiles, amphibians)
- Where and how the geomorphology of the river and floodplain is changing and can be expected to change over planning horizons of decades to centuries
- Learning from restoration and management actions
    - Floodplain vegetation change at restoration project scales
    - Effects of restoration on habitat conditions
- Ecological condition of the transitional portion of the UMRS between Navigation Pools 13 and 26.
- Aquatic plant distribution

- Community composition, abundance, and distribution of native and non-native macroinvertebrates in the UMRS

- Abundance, distribution, and status of zooplankton and phytoplankton

- Status and trends of mussel species within the Upper Mississippi River and Illinois Rivers

Stephenson elaborated on the information need "ecological condition between pools 13 and 26" which is likely an interest to the WQEC and WQTF. UMR Pools 14 to 25 are unmonitored by LTRM. The proposal includes hiring scientists to evaluate current data needs and design sampling plans for fish, aquatic vegetation, water quality, and macroinvertebrates.

Another information need, "status and zooplankton and phytoplankton," involves evaluating the abundance, distribution, and status of zooplankton and phytoplankton. The cost of evaluating the phytoplankton data in storage is $3 to 4 million. The proposal includes adding specialists and technicians at each of the LTRM study reaches to collect and analyze zooplankton data.

Next steps for the information needs team are to develop a detailed implementation plan for FY 24-26 and present the final plan to the UMRR Coordinating Committee at its fall 2023 quarterly meeting.

Kendall asked whether the team looked at a flowcam to process the phytoplankton samples instead of the traditional way of identifying the data. Jeff Houser said there is ongoing work to test out the flowcam system to see what can be gained from the results. Salvato commented that for river gradient monitoring needs, she has had discussions about incorporating UMRBA's monitoring plan design into LTRM's expansion into Pools 14-25. There is benefit to making the two sampling programs more complimentary.

Voss asked if the increased LTRM funding is over the long or short term. Wallace replied that the hope is the increase will remain unless Congress decides to revert to 2022 levels due to the debt ceiling. Karen Hagerty said typically appropriations are $55 million and the increase is up to $90 million. Wallace added that UMRR has been capped for the past several years but now with the authorization increase, the program may not go to its new cap, but the suggestion is that appropriations will be at a higher level. Stephenson also noted that UMRR's execution rate has been above 97% for the last seven to eight years, and is the highest execution rate of Corps programs. In response to a question from Skuta on what may be needed from the WQEC and WQTF, Stephenson said his update is informational for now.

UMRBA Water Quality Program

Salvato reminded participants of UMRBA's ambitious 2022-2035 Water Quality Program plan. The feedback she is hoping for is how to focus efforts in the next two fiscal years to ensure the tasks are reflective of the WQEC and WQTF's top priorities.

Before posing questions to the WQEC and WQTF, Salvato shared select FY 2023 accomplishments:

- UMRBA adopted a chloride resolution: https://umrba.org/chloride

- The Reaches 8-9 Pilot final reports were published: https://umrba.org/document/reaches8-9pilot

- UMRBA and the WQEC hosted USEPA Region 5 and 7 leadership to discuss shared priorities for the UMR

- UMRBA hosted the first of two Multi-Benefit Conservation Practice workshops in November 2022

- UMRBA staff applied for a USEPA EN grant in partnership with Illinois EPA

In the immediate short term, the following action items are on anticipated to be complete:

- Host the second Multi-Benefit Conservation Practice workshop in October 2023 and summer pre-workshop webinars

- Update the WQEC Charter

- Plan for fixed site monitoring of the UMR in fall 2025

- Collaborate with USEPA Office of Research and Development to update the UMR Interstate Water Quality Monitoring Plan and other documents

- Publish the *How Clean is the River?* Report

- Develop a workplan for Gulf Hypoxia Program funding

Wallace added that Salvato has presented at various meetings and conferences as part of the outreach goal (goal 4). Salvato asked the WQEC and WQTF to write down three water quality priorities for the Association to focus on in FY 24-25 and what success looks like in two years. She requested three successes for each priority.

Iowa – Schnieders said his top priorities are nutrients, PFAS, and total suspended solids (TSS). TSS are generally reduced through the Upper Mississippi River but during meetings with the Corps, he hears about sediment problems. In addition, Schneiders added water quality standards for aluminum. Iowa is waiting for USEPA to change its 304a criteria. Once a standard is approved, it is conditional, but the laboratory method still must be approved. Kendall anticipates the need for collaboration down the road as new aluminum methods come in, such as opportunistic sampling for aluminum at Illinois EPA's fixed site network. Salvato noted that the *How Clean is the River?* Report suggested aluminum trends are decreasing and wondered why there is a discrepancy. Schnieders replied that aluminum is super stringent. Skuta asked about sources of aluminum and Schnieders replied that there are aluminum manufacturers and fabricators in Iowa. Hoke added that Missouri has abundant clay soils and aluminum salts are added to remove phosphorus from water. It becomes a balance between eutrophication versus aluminum toxicity. In response to a question from Schnieders, Hoke said there is some discussion of ferrous salts, but Missouri has iron standards to consider too. Like with PFAS, Schnieders anticipates surveillance to get a grasp of where hot spots are occurring.

Schnieders has heard that the USDA Risk Management Agency is looking at the crop insurance industry to change insurability if PFAS is detected on a farm. Farmers may be more reluctant to accept biosolids, and all of this is driven by insurance agencies. Schnieders has observed that Wisconsin has been the most aggressive of the basin states regarding PFAS monitoring and developing standards for PFAS. For

Iowa, the purpose of some of its PFAS monitoring is to understand impacts to facilities. Once we know more, we can target practical actions, for example if PFAS is found in a well to switch to a different one.

Minnesota - Skuta said his top three items to focus on in the next two fiscal years are 1) the UMR Interstate Water Quality Monitoring plan: securing full funding for operationalization and having a data management system in place; 2) nitrogen: best practices for reducing nitrogen loading, sharing success stories, and promoting perennial crops; and 3) mussels: propagation of mussels and reintroduction to the Upper Mississippi River.

Laing said her priorities are 1) shared standards and assessments. She emphasized getting shared standards within the constraints of the state. Each state needs to adopt standards individually, yet through UMRBA the states function as an association of states. The second priority is full operationalization of the UMR Interstate Water Quality Monitoring plan, and finally data structure and availability to share the story of water quality on the UMR. While condition assessments and evaluation reports have been developed, the data should be digestible for non-technical audiences.

Missouri - Hoke shared that his priorities for UMRBA are data management and displaying the data to the public. He is also interested in nitrogen, but Missouri is not actively working on standards. Communication is important, including presentations at the Missouri Water Protection Forum. Not many of Missouri's stakeholders hear what is going on in the other states. There are many common threads - e.g., PFAS in biosolids. For PFAS, Missouri is working on MCLs, policies, and permit language.

Voss said he is interested in sediment in the lower portion of the UMR. Sturgeon need pulses of sediment, so what would sediment management look like? He would also prioritize understanding why people recreate in some areas and not others. Salvato said that the WQTF is interested in developing a UMR recreational survey to understand where and how people recreate and their feelings about water quality. This would inform the chl-a criteria as part of the UMR Provisional Assessment. Giblin added that the lake survey for Wisconsin was successful, which yielded qualitative and quantitative data about perceptions of water quality and recreation potential. Schnieders has observed that stakeholders have very different perceptions about water quality. The public generally believes water quality is declining, while barge operators generally feel that water quality has never been better.

Regarding Voss's comment about sediment, Hagerty said it is critical to recognize regional differences in water quality. Examining pre-lock and dam conditions may be helpful. Some portions of the Mississippi River are sediment starved. Wallace said that the UMRBA Board wants to move forward with longer-term sediment planning. The UMRR program evaluated 30 years of monitoring data and we have five flyers to communicate what is going on. There is one flyer focused on sediment. Wallace added that there is more sediment going into the system than what is coming out of the system. The challenge for the channel is that there are not enough placement sites for the materials. That is why there is an emphasis on beneficial reuse. Wallace suggested a focused conversation about what is happening with sediments in the channel. Giblin emphasized the public's concern about sedimentation in the backwaters. Once those backwaters are gone, we lose a lot of biodiversity.

Skuta, Wallace, and Giblin said communication is important. Even if the messages are not simple, the UMR is an integrator of everything happening in the watershed. Wallace suggested that in UMRBA's role as a subbasin committee to the HTF, staff can better connect LTRM with the states' monitoring programs. For example, results from Minnesota's buffer law can highlight how policy can impact water quality. Skuta said Minnesota has not made the quantification of nutrient reduction. This is again where

PCA gets paralyzed in communication, if it is too complicated to show causality, the agency will not say anything.

Wisconsin – Giblin said that the chloride resolution has been impactful in Wisconsin and was the impetus for forming a chloride workgroup. The resolution can be utilized to increase awareness about the harm of overapplying road salt on pavements and roadways. Giblin would like a nitrogen resolution to be developed, similar to the chloride resolution, that would emphasize living cover and BMPs specific to nitrogen reduction. He suggested that focusing on geographic hotspots like the Trempealeau terrace would enable further learning. Giblin would also like the development of an emerging contaminants resolution. It is important to have the emerging contaminants monitoring plan to investigate the decline of burrowing mayflies. They are an important food source in the UMR ecosystem and understanding drivers of the decline is important.

Illinois – Vidales said her priorities are conducting fixed site sampling on the UMR in 2025. In line with Minnesota and Missouri, having a data management system in place for UMRBA data is important. Vidales shared that having a common set of designated uses is important and having this outlined before sampling begins in 2025 would make this effort even more successful.

Wallace observed that advocacy was not discussed. She asked if the WQEC and WQTF would like UMRBA staff to educate Congress about the Gulf Hypoxia Program? That is a greater amount of work for staff. There is also a need to advocate for the UMR Interstate Water Quality Monitoring plan. Skuta suggested both would be important if resources allow. Schnieders asked about the expenditure of time and money to conduct advocacy relative to the success of the efforts. Wallace replied it takes about a week to fill out appropriations requests. Staff can develop a factsheet, do Capitol Hill visits, and coordinate letters. Altogether, it would be about three weeks of staff time. In its subbasin role, UMRBA can figure out what would be the right amount of funding to request. In the February and March 2023 congressional cycle, Salvato filled out appropriations requests for an additional capacity of $25 million for the HTF.

Steve Schaff asked for clarification if the Gulf Hypoxia Program is a "Geographic Program" dedicated to the Mississippi River and the Missouri River? US EPA has geographic programs focused on place-based efforts to protect or restore specific ecosystems of national significance. Salvato responded that the Gulf Hypoxia Program includes the 12 HTF states and would not include the Missouri River in this case. Wallace added that she believes the Gulf Hypoxia Program was authorized as an individual program, not a geographic program.

<u>Examining Biological Indicators of the Upper Mississippi River</u>

Review of 2009 Workshop Conclusions

Salvato provided an overview of the 2009 Biological Indicators workshop hosted by UMRBA with funding from the Corps and USEPA. The goals of the workshop were to frame the needs for and potential uses of indicators in the ecosystem restoration and Clean Water Act (CWA) programs on the UMR; identify key issues, evaluate opportunities for cross-program coordination, and identify next steps in the development and application of biological indicators on the UMR; learn from the experiences with indicator development and use in other large aquatic ecosystems; and evaluate current research efforts.

The workshop sought to answer the following questions about biological indicators:

- What are the potential benefits and obstacles of incorporating biological indicators into CWA and ecosystem restoration programs on the UMR?
- What biological indicator approaches from outside the UMRB can inform approaches in the UMRB?
- How should ongoing collaboration regarding indicators be sustained?
- What are the potential connections between CWA and ecosystem restoration programs in applying biological indicators on the UMR? Are there approaches to indicators for the UMR that can apply effectively in both CWA and ecosystem restoration contexts?
- How should each program area proceed in applying biological indicators on the UMR?

The workshop participants identified possible next steps:

- Establishing an ad hoc Ecosystem Restoration-CWA Interagency committee
- Engagement of CWA staff in ecosystem objective-setting for UMR reaches
- Hold a biological condition gradient workshop
- Engagement of CWA staff in LTRM analysis team refinement of indicators
- UMRBA WQTF development of biological assessment guidance for the UMR
- Inventory and comparison of sampling methods and data sets
- Examine the use of LTRM infrastructure to support enhanced monitoring
- Monitoring progress of the Lake Pepin TMDL and Mississippi Makeover effort
- Enhancing outreach and communication

Salvato was unaware that the next steps had been explicitly carried out, but she invited USGS Upper Midwest Environmental Science Center (UMESC) staff that carry out the science for the LTRM program to contribute to the discussion. She explained that she believes the workshop's conclusions are incredibly relevant given the following ongoing initiatives:

- UMRR Desired Future Conditions and UMR Interstate Water Quality Monitoring biological endpoints
- UMRR LTRM effort to piloting macroinvertebrate collection for three years
- UMRR LTRM information needs, including river gradients for UMR Pools 14-25 and Fast Limological Automated Measurements (FLAMe) proposal

- UMR Interstate WQ Monitoring completion for two pilot projects

Houser, who participated in the 2009 workshop, observed that Giblin had a number of suggestions regarding water quality indicators that were incorporated into the 2022 Status and Trends report, specifically the use of WRTDS analysis of fixed sites to better understand changes in nutrient and total suspended sediment fluxes into the system. Houser appreciates Salvato's interest and involvement in the FLAMe project. At this time, Houser does not have specific recommendations.

Hagerty noted that her career has been almost exclusively on the ecosystem, but she has been struck where the CWA and ecosystem areas diverge in some areas. For example, in the lower confluence of the Mississippi and Missouri River there is not enough sediment, so restoration efforts are not favoring native species. Hypoxia is a normal part of the ecosystem but within certain limits. The idea that we need to educate the public on what is natural for water quality to be in different reaches makes the messaging extensive. We cannot have an open bluegill fishery in the open river because it never existed. The lower impounded reach is a huge transitional area. The FLAMe project will generate data to improve understanding of the various complexities in the river. There is a lot we do not know about those areas that are more degraded and how to restore those from both an ecosystem and CWA perspective. Wallace said the desired future conditions question is a huge undertaking. When we talk about floodplain reconnection through the UMRR Coordinating committee, UMRBA staff can extend the invitation to join or have more report outs on projects/progress.

Houser recalled that the summary included the idea of more CWA connections to projects to restore the ecosystem. It does not mean there cannot be awareness of possible connections. If that is something of interest, river team meetings may be a good venue. Schnieders is unsure of a chemical response with ecosystem restoration. Biology is typically the first to respond. The public likes those types of success stories. It is harder to think about these connections within a complex large river system.

Schaff said that USEPA Region 7 hired three new staff with expertise in fish and macroinvertebrate sampling and identification. These staff will assist with finalizing Biological Condition Gradient work for the two predominant ecoregions within USEPA Region 7. Schaff is interested in the decline of burrowing mayflies and suggested UMRBA could reach out for assistance. Houser suggested Schaff contact Manish Pant with Illinois Natural History Survey's Illinois Biological Station. She is leading the LTRM macroinvertebrate work, which has funding for three years to pilot and potentially bring back the element to LTRM.

Danelle Larson provided links to the following literature that is relevant to this discussion:

- Windmuller-Campion et al., 2022 - What is a stand? Assessing the variability of composition and structure in floodplain forest ecosystems across spatial scales in the Upper Mississippi River
https://www.sciencedirect.com/science/article/abs/pii/S0378112722003796?via%3Dihub

- De Jager et al., 2018 - Indicators of Ecosystem Structure and Function for the Upper Mississippi River System
https://pubs.usgs.gov/publication/ofr20181143

- McCain et al., 2018 - Habitat Needs Assessment-II for the Upper Mississippi River Restoration Program: Linking Science to Management Perspectives
https://usace.contentdm.oclc.org/utils/getfile/collection/p266001coll1/id/8323

- Houser et al., 2022 – Ecological status and trends of the Upper Mississippi and Illinois Rivers https://pubs.usgs.gov/publication/ofr20221039

- Larson et al., 2023 - Aquatic vegetation types identified during early and late phases of vegetation recovery in the Upper Mississippi River https://esajournals.onlinelibrary.wiley.com/doi/full/10.1002/ecs2.4468

- Larson et al., 2023 - Data to quantify ecosystem states and state transitions of the Upper Mississippi River using topological data analysis https://www.sciencebase.gov/catalog/item/641097cad34e254fd35301c0

Legacy Pesticides
Analyzing Legacy Data from Illinois Rivers to Improve Pesticide Monitoring

Sparks shared that Illinois EPA's pesticide monitoring network includes 21 sites, 18 of which are long-term sites. The sites cover 11 major river basins, monitored nine times per year. Data on over forty pesticides are collected.

Sparks analyzed herbicide data collected from 1999 to 2021. Atrazine was detected 72% of the time and metolachlor 65% of the time. Comparing the 1999 to 2021 dataset to the one Matt Short analyzed from 1985 to 1998, Sparks noted that the percent difference increased in detections for metribuzin (41%), whereas atrazine's detection rate was about the same.

Data from Illinois EPA's ambient lakes monitoring program were also collected and hits for atrazine and simazine were detected more widely across the state. Sparks used the data overlain with land use to determine where to add seven additional pesticide monitoring sites.

There is seasonality to detections in acetochlor, atrazine, metolachlor, metribuzin in the May through July timeframe. Monthly averages increase in both finished and raw water samples. Sparks noted this trend increased in 2013 and his online research confirmed that the use of metolachlor and metribuzin increased during this time.

There are also relationships where herbicides groups are detected in watersheds. For example, simazine, 2,4-D, and dicamba are detected consistently in the Vermilion watershed, whereas atrazine, metolachlor, metribuzin, and acetochlor are more commonly detected in the Kaskaskia, Mississippi, and Sangamon watersheds.

For the insecticide data, most of the detections are for organochlorines as opposed to the organophosphates. Comparing the 1991 to 2021 data with the 1985 to 1998 dataset showed that insecticides like dieldrin and lindane are increasing in usage. Imidacloprid usage increased in urban areas of NE Illinois during a 2015-2016 study. The vast majority of the sites also indicated toxic conditions for invertebrates.

Another study that is occurring in 2023 will characterize insecticide use in the major tributaries of the Illinois and Wabash Rivers. Voss asked how results will be interpreted. Voss is aware that imidacloprid is used for leaf eating insects like Japanese beetles, and permethrin is used on pets. Sparks is unsure about the interpretation. Voss also suggested it would be useful to know what pest control companies are applying to better understand potential urban sources.

Laing noticed the DDT results and yet it has been banned since 1972. Does Sparks have any idea of what is happening? Sparks said that the area is outside Chicago, near Starved Rock, and it hasn't been detected since 2014. But prior to that the pattern was a spike of DDT once per year. Salvato asked if Sparks had ideas on why atrazine hot spots are occurring in particular watersheds. Sparks speculated that the watersheds that are both agricultural dominated and in rural settings, there could be differences in conservation perspectives - e.g., no-till versus tillage.

WQEC Charter

Salvato said UMRBA staff revisited the charter and made some suggested changes for the WQEC and WQTF's reflection. The main changes include adding more formal meetings, a new proposed structure of committees, and a change of roles and responsibilities in priority order. Given the significant workload in the 2022-2035 UMRBA Water Quality Program plan, staff are suggesting a more formal tie to the WQEC's charter and the program plan. The reshuffle of committees would enable a response to the increased workload of interstate water quality responsibilities. The WQEC could become the Water Quality Executive Council and oversee the work of five different committees on emerging contaminants, monitoring, nutrients, cyanotoxins, and chloride.

Salvato posed the following questions:

- What are your thoughts on the language changes?
- Does the overall package reflect UMRBA's Water Quality Program Plan?
- Do the roles and responsibilities support your goal for interstate water quality coordination?
- How will the HTF sub-basin committee function within this proposed structure? Can they reside under the WQEC?
- Do you have any additional ideas to strengthen the WQEC's role and ability to accomplish the work in the 2022-2035 UMRBA Water Quality Program plan?

Wallace added that UMRBA staff have a large portfolio. For UMRBA's work as a subbasin committee to the HTF, staff needed a delegated authority. A group of NRS coordinators has been formed and is functioning like an ad hoc group. Do they report to the WQEC or the UMRBA Board? How do we ensure there is an efficient line of communication to provide direction? UMRBA is not a compact or commission; staff need direction from the states.

Wallace also suggested formal memberships. Wisconsin, for example, has two representatives per committee. Should DATCAP be specified as a non-voting member? The UMRBA Board is structured to have a primary member that can delegate to an alternate.

Laing asked for clarification that CWA would be equally emphasized along with emerging contaminants and cyanotoxins. Wallace replied that the suggestion to keep nutrients and CWA separate was for the focus on nonpoint source pollution (NPS) and point source pollution, respectively. Participants all emphasized that while not regulated, NPS is part of the CWA and states are required to characterize the extent of the NPS through actions like NPS management plans and programming. Recent memos from USEPA have also emphasized the connection between CWA programs and NRSs.

Wallace reminded participants that some WQTF have expertise in some topic areas but not necessarily all of them. If you are not the chloride person, you are coordinating with the chloride person.
She added that UMRBA's HAB work is not very active and asked if having a formalized group could help advance the interstate work around HABs in a more strategic and efficient manner. The committees would not necessarily need to meet on a regular basis.

Laing posed her concern about state agency staff having the capacity to serve on the committees and potential duplication with USEPA Region 5 workgroups. The new committee structure would eliminate a WQTF representative to funnel and coordinate work. Schnieders views nutrients as unique as there is specific funding available through the Gulf Hypoxia Program. Staff are already stretched too thin and additional meetings would be challenging to join. Giblin likes the current layout of bringing in subject matter experts as needed. He is reticent to bring on new committees. Kendall agreed and shared his concern over increasing silos. Hoke emphasized that staff turnover is a frequent issue. Distribution lists would be outdated in a month. Wallace suggested starting with an additional spring meeting for the WQEC as the meeting calendar does not currently have a formal meeting just for the WQEC. Participants agreed with the suggestion.

Schnieders said that the WQTF is a proven model. Nutrients are different because there is federal funding coming down. Hoke agreed. Laing said that in her current role her responsibilities are broadly spread. If additional committees were added, Laing would be handing off responsibilities to someone she supervises and there would not be someone to connect the dots. That is the role that the WQTF is currently playing. Voss agreed that the WQTF is doing a better job of identifying the action items, resolutions, and leaving it to the states to coordinate internally.

Skuta reflected that the two questions are 1) should additional committees be created, and 2) what is the WQTF moving forward? Next steps include additional discussion on WQEC and WQTF structure.

<u>Administrative Items</u>

Chairs

Salvato thanked Glenn Skuta and Dana Vanderbosch for their time chairing the WQEC and thanked Robert Voss and Heather Peters for their time chairing the WQTF. The next chairs for the WQEC and WQTF are Nicole Vidales and Kim Laing, respectively.

Future Meetings

The next WQTF hybrid meeting will be scheduled for September 20-21, 2023 in Muscatine, Iowa.

Participants

Ryan Sparks	Illinois Environmental Protection Agency
Nicole Vidales	Illinois Environmental Protection Agency
Dan Kendall	Iowa Department of Natural Resources
Adam Schnieders	Iowa Department of Natural Resources
Kim Laing	Minnesota Pollution Control Agency
Glenn Skuta	Minnesota Pollution Control Agency
John Hoke	Missouri Department of Natural Resources
Robert Voss	Missouri Department of Natural Resources
Micah Bennett	U.S. Environmental Protection Agency, Region 5
Ed Hammer	U.S. Environmental Protection Agency, Region 5
Donna Keclik	U.S. Environmental Protection Agency, Region 5
Zachary Leibowitz	U.S. Environmental Protection Agency, Region 7
David Pratt	U.S. Environmental Protection Agency, Region 7
Steve Schaff	U.S. Environmental Protection Agency, Region 7
Amy Shields	U.S. Environmental Protection Agency, Region 7
Heather Golden	U.S. Environmental Protection Agency, ORD
Anna Hess	U.S. Environmental Protection Agency, ORD
Terri Jicha	U.S. Environmental Protection Agency, ORD
Erin Spry	Upper Mississippi River Basin Association
Lauren Salvato	Upper Mississippi River Basin Association
Brian Stenquist	Upper Mississippi River Basin Association
Kirsten Wallace	Upper Mississippi River Basin Association
Ashley Beranek	Wisconsin Department of Natural Resources
Shawn Giblin	Wisconsin Department of Natural Resources
Kevin Kirsch	Wisconsin Department of Natural Resources
Mike Shupryt	Wisconsin Department of Natural Resources
Adrian Stocks	Wisconsin Department of Natural Resources
Jeff Houser	U.S. Geological Survey, Upper Midwest Environmental Science Center
Danelle Larson	U.S. Geological Survey, Upper Midwest Environmental Science Center
Charles Brown	City of Moline Utilities
Albert Ettinger	Mississippi River Collaborative
Becca Clay	Practical Farmers of Iowa
Becca Trueman	Quantified Ventures

ATTACHMENT B

UMRBA Updates

- **UMRBA Multi-Benefit Conservation Practices October 2023 Workshop Draft Agenda** *(B-1 to B-6)*
- ***How Clean is the River?*** **Report:** **https://umrba.org/how-clean-river-2023**

Union Depot
St. Paul, Minnesota

UPPER MISSISSIPPI RIVER BASIN ASSOCIATION
MULTI-BENEFIT CONSERVATION PRACTICE [1] WORKSHOP
DRAFT AGENDA



Objectives

- Improve understanding and ability to communicate about conservation practices that provide multiple, stacked water quality and quantity, ecological, financial, and sustainability benefits on agricultural and urban landscapes

- Strengthen regional collaboration and coordination among individuals and organizations involved in conservation practice implementation and nutrient reduction strategies

- Increase awareness of successful implementation efforts for multiple benefit conservation practices; highlight leadership and other reasons for achieving success

- Determine strategies to trigger increases in conservation practice adoption on agricultural lands that provide additional multiple benefits beyond nutrient reduction

- Identify priorities and actionable items for states, federal agencies, and partners to pursue collaboratively

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[1] Multi-benefit conservation practices are a term to describe a singular conservation practice that provides more than one beneficial outcome. The beneficial outcomes may be any combination of agronomic, ecological, social, and financial. For example, a wetland has the potential to provide water quality improvement, flood mitigation, carbon sequestration, wildlife habitat, and more. Utilizing practices with multiple benefits may incentivize individuals, based on their goals for their land, to improve natural resources both locally and in the Upper Mississippi River Basin. Note the term is synonymous with ancillary and co-benefits and other terms.

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Implementing Multi-Benefit Conservation Practices: The Key Leverage Points

Leverage points are places within a complex system where a small change in one thing can produce big changes in everything.

Tuesday, October 3

Time	Topic	Presenter
9:00 am	**Welcome and Introductions**	***Katrina Kessler,*** *Commissioner Minnesota PCA*
9:10	**Workshop People, Products, Process** *Table Top Intros* *Individuals answer the following question in a Workshop Workbook* *1. What 3-5 things do you hope to accomplish, learn, or gain through this workshop?* *Individuals then briefly introduce themselves to each other at their table*	***Brian Stenquist,*** *UMRBA*
9:30	**Review of Pre-Workshop Webinars**	***Lauren Salvato****, UMRBA*
9:40	**Systems Perspective on Multi-Benefit Conservation Practices and Leverage Points to Enhance Implementation**	***Brian Stenquist****, UMRBA*
10:00	**Table Top Exercise** *Appreciative Inquiry about the Draft Systems Map* *Individuals answer the following questions in their Workshop Workbook* *1. What do you like about the current draft systems map?* *2. What's missing?* *3. How would you improve it?* *After everyone is done answering the questions in the workbook, individuals share one of their answers with others at the table*	***All***
10:20	**Break**	
10:30	**Important Leverage Points: A Deep Dive**	
	Financial Leverage Points Getting More for Your Money: IL Farm Bureau Examples of Leveraging Financial and In-kind Resources for Multiple Outcomes	***Raelynn Parmely,*** *Illinois Farm Bureau*
	Policy Leverage Points Identifying Policy Incentives and Disincentives to Water Retention Strategies in Agricultural Settings in the Upper Mississippi River Basin	***Kim Lutz,*** *America's Watershed Initiative*
	Participation and Leadership Leverage Points Primer for Increasing New Collaborations around Clean Water	***Annie Felix-Gerth,*** *Minnesota BSWR*

(Continued)

Producer Led Watershed Groups — ***Coreen Fallat,*** *Wisconsin DATCAP*

11:30 **Table Top Exercise**
Looking for Leverage Points
Individuals answer the following questions in their Workshop Workbook

1. *What are 3 important improvements we, as a community of practice, should make in the "financial support space" for multi-benefit conservation practices? Mark with an asterisk the ones you think might be leverage points.*

2. *What are 3 important improvements we, as a community of practice, should make in the "technical coordination support space" for multi-benefit conservation practices? Mark with an asterisk the ones you think might be leverage points.*

3. *What are 3 important improvements we, as a community of practice, should make in the "policy support space" for multi-benefit conservation practices? Mark with an asterisk the ones you think might be leverage points.*

4. *What are 3 important improvements we, as a community of practice, should make in the "participation and leadership support space" for multi-benefit conservation practices? Mark with an asterisk the ones you think might be leverage points.*

When individuals are done answering the questions in their workbook, they can break for lunch.

12:00 noon **Lunch**

1:00 **Table Top Exercise**
When individuals return from lunch, they should transcribe their answers to the 4 "Looking for Leverage Points" questions on to post it notes (each question and its set of answers on a separate post it).

When everyone is done transcribing their answers, they should share one answer each to each question with others at the table.

At 1:40, we will stop the table top conversation and ask one person at each table to share one very interesting or surprising idea that came up at their table.

At 1:55, we will take a 5 minute stretch break.

2:00	**Panel: Tribal and BIPOC Perspectives on Multi-Benefit Conservation Practices** Sara George, Renewing the Countryside, Conservation Connections Program Coordinator Helen Waquiu, Director of Tribal Affairs & Diverse Communities, Minnesota PCA Melissa King, Water Programs Coordinator, Minnesota BWSR Rodrigo Cala, Agricultural Tainer, Latino Economic Development Center	
3:00	**Break**	
3:20	**Table Top Exercise** *When individuals return from the break, they should answer the following questions in their Workshop Workbook* *1. What are 3-5 important ideas you heard from the panel?* *2. How might one or more of those ideas influence your organization's support for tribal and BIPOC implementation of multi-benefit conservation practices?* *3. What questions or additional perspectives did the panel presentations stimulate for you?* *After everyone is done answering the questions in the workbook, individuals share their answers with others at the table* *Panel members are encouraged to join a table top discussion or wander around listening in on multiple conversations* *At 4:10, we will stop the table top conversations and ask the panelists to reassemble as a group* *Table top participants or panelists may ask follow up questions or make observations about the conversation*	***All***
4:30	**Wrap Up – a brief "summary up" of the day** *Before they leave for the day, individuals will be asked to post their "Looking for Leverage Points" post its on flipcharts around the room*	***Lauren Salvato**, UMRBA*
6:00 p.m.	**Optional Evening Activity** Get to know your fellow workshop attendees at a networking event. Drinks and dinner will be available with individual checks, at cost to the attendee. Bar at Hyatt Place Downtown St. Paul 180 Kellogg Blvd. East St. Paul, MN 55101	

Wednesday, October 4

Time	Topic	Presenter
8:00 am	**Welcome to Day 2**	***Kirsten Wallace,*** *UMRBA* & ***Matt Lechtenberg,*** *Iowa DALS*
8:05	**Recap of Day One**	***Brian Stenquist,*** *UMRBA*
8:15	**Deepening the Leverage Point Framework – Strategies for Action** Finding a "Match Maker" for Conservation Actions	***Dr. Adam Reimer,*** *National Wildlife Federation*
8:35	**Table Top Exercise** *Making a Difference - Making a Change* *Individuals answer the following questions in their Workshop Workbook* 1. *What 3-5 key ideas that arose during the workshop will you share with your supervisor and colleagues when you return to work?* 2. *What small changes in your organization's approach to multi-benefit conservation practices might you begin to advocate for based on the ideas and perspectives shared during the workshop?* 3. *What deeper questions do you walk away with from this workshop?* 4. *What brings you optimism and hope as you walk away with from the workshop?* *After everyone is done answering the questions in the workbook, individuals share their answers with others at the table* *At 9:45, we will stop the table top conversations and ask individuals to transcribe onto post it notes their answers to questions 1 and 4* *(Participants can leave the post its on the table – we will collect them at the end of the workshop)*	***All***
10:00	**Break**	
10:20	**Summary and Closing Thoughts** **Final thoughts from Participants** *When individuals return from the break, we will pass the microphone around to everyone and ask them to share their one of their answers to each of the questions in the session "Making a Difference – Making a Change"* **Final thoughts from Workshop Hosts**	***All*** ***Kirsten Wallace,*** *UMRBA*
12:00	**Adjourn**	

Thank you to the planning committee!

Dave Wall	Minnesota PCA
Annie Felix-Gerth	Minnesota BWSR
Suzanne Rhees	Minnesota BSWR
Victoria Bushan	Missouri DNR
Adam Schnieders	Iowa DNR
Matt Lechtenberg	Iowa DALS
Trevor Sample	Illinois EPA
Michael Woods	Illinois DoA
Rachel Curry	University of Illinois, Extension
Karl Gesch	Wisconsin DNR
Coreen Fallat	Wisconsin DATCAP
Steve Schaff	USEPA Region 7
Janette Marsh	USEPA Region 5
Whitney King	USEPA OWOW
John Bullough	USDA NRCS

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ATTACHMENT C

Reconstructing Missing Water Quality Data with Interpolation Techniques

(C-1 to C-15)

LIMNOLOGY
and
OCEANOGRAPHY: METHODS

ASLO

Limnol. Oceanogr.: Methods 21, 2023, 435–449

doi: 10.1002/lom3.10556

Reconstructing missing data by comparing interpolation techniques: Applications for long-term water quality data

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[1]U.S. Geological Survey, Upper Midwest Environmental Sciences Center, La Crosse, Wisconsin, USA
[2]Department of Mathematics and Statistics, University of Wisconsin La-Crosse, La Crosse, Wisconsin, USA
[3]Research Experience for Undergraduates Program, University of Wisconsin La-Crosse, La Crosse, Wisconsin, USA

Abstract

Missing data are typical yet must be addressed for proper inferences or expanding datasets to guide our limnological understanding and management of aquatic systems. Interpolation methods (i.e., estimating missing values using known values within the dataset) can alleviate data gaps and common problems. We compared seven popular interpolation methods for predicting substantial missingness in a long-term water quality dataset from the Upper Mississippi River, U.S.A. The dataset included 80,000 sampling sites collected over 30 yr that had substantial missingness for total nitrogen (TN), total phosphorus (TP), and water velocity. For all three interpolated water quality variables, random forests had very high prediction accuracy and outperformed the methods of ordinary kriging, polynomial regressions, regression trees, and inverse distance weighting. TP had a mean absolute error (MAE) of 0.03 mg $(\text{L-TP})^{-1}$, TN had a MAE of 0.39 mg $(\text{L-TN})^{-1}$, and water velocity had a MAE of 0.10 m s^{-1}. The random forests' error rates were mapped and showed low spatiotemporal variability across the riverscape, indicating high model performance across many habitat types and large spatial scales. In the current era of "big data," interpolation becomes an imperative step prior to ecological analyses yet remains unfamiliar and underutilized. Our research briefly describes the importance of addressing missingness and provides a roadmap to conduct model intercomparisons of other big datasets. We also share adaptable data analysis scripts, which allows others to readily conduct interpolation comparisons for many limnology applications and contexts.

Large environmental datasets commonly contain missing data, especially those that cover large geographic scales, have long-term measures, or need continuous temporal observations. Missing data occur for a variety of reasons, such as faulty equipment or intended experimental designs. Missingness may cause a mismatch in sample sizes with other variables and lead to blank cells in data matrices, making statistical analyses difficult. Missingness also happens intentionally within some experimental or observational study designs to efficiently sample large geographic areas and reduce costs of sampling and laboratory processing. In cases of intentional missingness, addressing the data gaps can increase the spatial density of data that allow for creation of new continuous spatial data or can address new research questions that were not the focus of the original study design.

Missing data in large datasets are problematic and should not be ignored (Nakagawa and Freckleton 2008). Often missing data are assumed to be "missing completely at random," but typically are missing nonrandomly (Little and Rubin 2002). Easy but incomplete solutions to nonrandomly missing data that are commonly used include re-coding values (e.g., a missing value is replaced with a value of "0"), mean imputations or substitutions (e.g., the mean value replaces the missing value), or listwise deletion (i.e., deleting an entire record of information if any associated value is missing). These approaches can lead to significant loss of valuable information or loss of statistical power from reduced sample size (Little and Rubin 2002). Moreover, these crude approaches may introduce bias in the dataset that can cause faulty conclusions (Beheim

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et al. 2021). Ecologists tend to continue using these simplified approaches over more sophisticated techniques like simulation modeling and interpolations (Yanai et al. 2018) that can relieve scientists from some of these concerning consequences.

A specific class of methods for addressing missingness is interpolation, which is covered extensively elsewhere (Little and Rubin 2002; Molenberghs et al. 2014). Data interpolation estimates the missing values using known values within the dataset. At least 25 interpolation methods have been developed within environmental sciences. Each method differs by model features such as how the estimate is calculated, how much data are used to derive estimations, and whether errors are provided (Li and Heap 2014). Interpolation remains underutilized in part because of the statistical knowledge and computer programming skills. Few references compare the precision and accuracy of various interpolation methods, and many previous studies simply selected a single method without stated justification or intercomparisons of alternative methods (Li and Heap 2011, 2014; Louvet et al. 2016). However, intercomparison studies of interpolation are beginning in fields of study outside of limnology (Penone et al. 2014; Miao et al. 2021; Picornell et al. 2021) and within limnology (Lottig and Carpenter 2012; Song et al. 2016). Intercomparison studies and available analysis scripts will guide aquatic scientists on choosing the most promising tools among many methods available for their data.

A 30-yr water quality dataset from the Upper Mississippi River System (UMRS; Fig. 1) in the United States provides one example of typical and intentional missingness and an opportunity to expand this rare long-term dataset. The monitoring study design and sampling scheme optimizes the ratio of information: costs of data collection, and then produces unbiased water quality estimates for reach- and strata-level inferences (Soballe and Fischer 2004; De Jager and Houser 2012). Accurate interpolations of these data allow for new site-level analyses and the creation of new, continuous spatial data layers. The UMRS data were missing either randomly or nonrandomly due to incidental, intentional, and accidental causes. The data had ~ 10% incidental and nonrandom missingness for water velocity because the equipment produced unstable measurements at extreme velocities, as well as intentional missingness by not sampling in the river's main channel with extreme velocity. The sampling design intentionally sampled nutrients less frequently than other water variables because the reduced sampling regime appropriately addressed spatiotemporal variance for analyzing reach- and strata-level inferences (Soballe and Fischer 2004; De Jager and Houser 2012). The reduced nutrient sampling resulted in 66% of values that were "missing" completely at random for water column TP and TN compared to the other variables sampled more frequently (Table 1). The data were rarely missing from accidental data loss (< 1% of observations over 80,000 sampling sites as of 2020). Researchers are now interested in using this long-term data for site-level analyses and creating continuous data layers for geographic information systems, which require the data frame to have no missing values in any cell of the data frame. Using listwise deletion of this dataset for these new purposes caused the number of sampling sites to be reduced by ~ 85%. Also, imputing 66% of missing nutrient data was inappropriate. Therefore, interpolation (if accurately predictive) would provide an opportunity to expand the dataset to advance understanding and restoration of the UMRS.

We sought to compare seven interpolation methods for addressing missingness in long-term ecological datasets. Our specific study objectives were to accurately interpolate substantial missing data that occurred within the long-term data from the UMRS (Fig. 1). We evaluated seven commonly employed interpolation methods to determine a top performing method for expanding the long-term water quality dataset. We interpolated the three key water variables with substantial missingness: TN ($n = 50{,}293$ missing data points, intentional per the study design), TP ($n = 51{,}031$ missing data points, intentional per the study design), and water velocity ($n = 26{,}301$ missing data points from incidentals related to extreme readings). We compared "local" and "global" interpolation methods (Table 1). We hypothesized global methods (that use all the data and variables for interpolation) would outperform local methods because the local habitat conditions can be highly variable and due to the multivariate, interactive nature of the variables in the UMRS (Houser et al. 2022) and aquatic systems in general. Finally, we hypothesized the prediction errors may show spatial patterns within reaches; for example, prediction accuracy may decline in riverine side channels with high habitat heterogeneity compared to the main river channel. We provided analysis scripts for these seven interpolation techniques as opportunities for aquatic ecologists to consider and readily address missingness within their own data.

Materials and procedures

Study system and study design

Long-term water quality data were collected by the Upper Mississippi River Restoration Program (https://umesc.usgs.gov/ltrm-home.html) using standard protocols since 1993 (Soballe and Fischer 2004) to improve ecological understanding of this important river system. Water quality data were collected using a stratified-random sampling design to assess the status and trends of representative study reaches and strata along the river (Houser et al. 2022). Data are hierarchically nested by scale; specifically, reaches contain strata and strata contain sampling sites. Sampling covers six reaches and four strata that broadly correspond to the abovementioned habitat types (i.e., main channel, side channels, backwater lakes, and open impoundments).

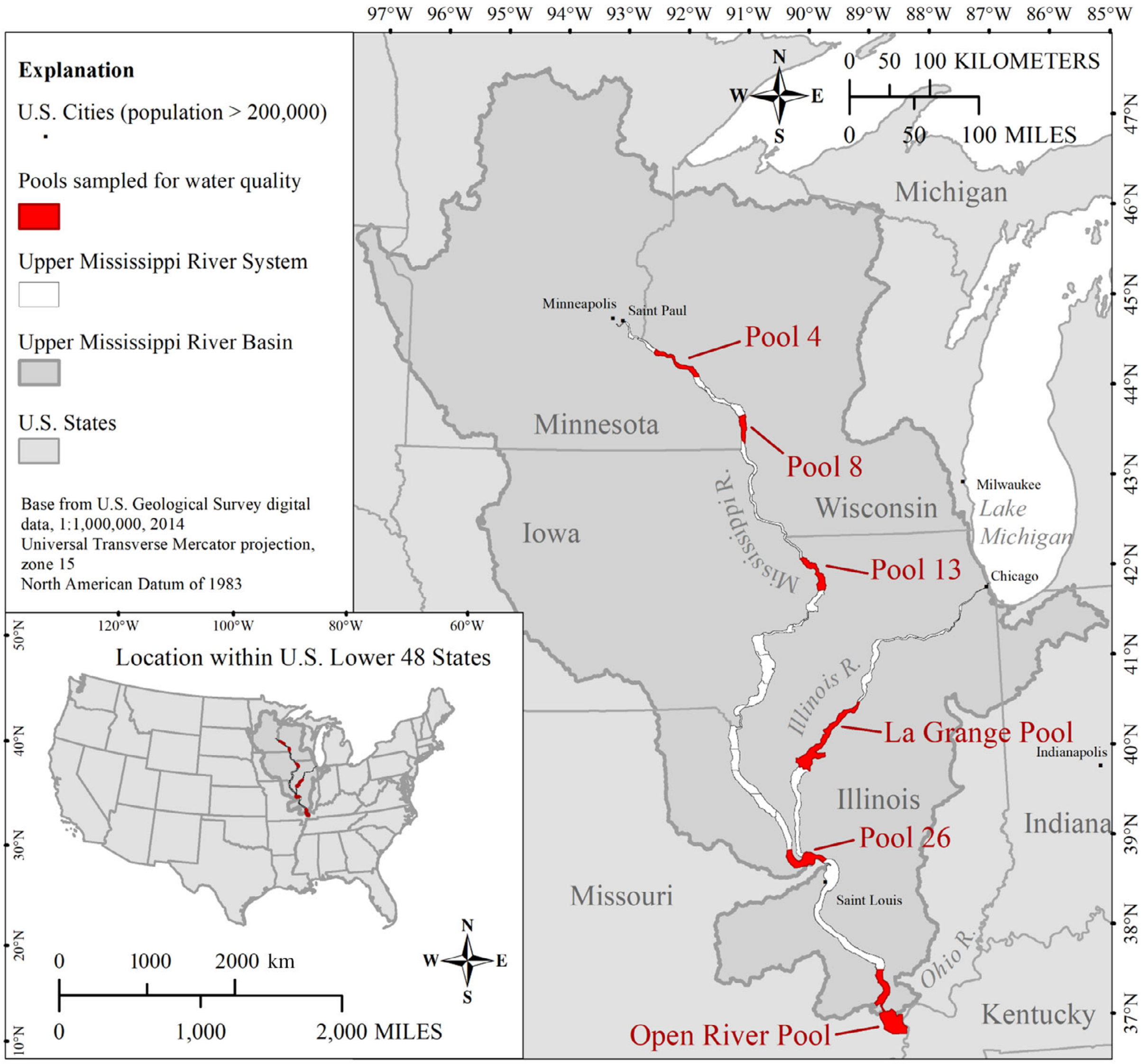

Fig. 1. A map (using Universal Transverse Mercator projection, Zone 15 North) of the Upper Mississippi River System, U.S.A. (which includes the mainstem Upper Mississippi River and the Illinois River) and the six key long-term resource monitoring study reaches highlighted in red. Water quality data were collected annually from years 1993 to 2020 at 50–150 sample sites per reach per season (winter, spring, summer, and autumn).

All water data were collected across four seasons: spring, summer, autumn, and winter. Sampling occurred on the same 2 weeks each season of each calendar year for consistency. All variables of interest were collected near the water's surface (0.2 m depth) with an average sampling time of 12:00 h. Sample readings were either collected in situ or were analyzed according to rigorous laboratory procedures (Table 2; Soballe and Fischer 2004). The primary causes of 66% missing data for TN and TP were per the study design to reduce costs associated with complex laboratory analyses, and so "missingness" is an artifact of researchers expanding the dataset for new types of analyses not originally intended with the study design (e.g., multivariate, site-level analyses). Velocity had $\sim 10\%$ missingness due to measurement errors during frequent but extreme velocity conditions (near 0 m s^{-1} and then values typically $> 1 \text{ m s}^{-1}$) and because velocity was purposely not measured in the main channel strata.

Procedures: Data preparation

We downloaded the entire water quality data and metadata on 07 June 2021 from the Upper Mississippi River Restoration Program website (www.umesc.usgs.gov/ltrm-home.html). The entire dataset included information from years 1993 to 2020, which was an initial data frame size of 204,345 rows (site data) and 133 columns (variables). For data preparation, we used software R (R Core Team 2022) and the *tidyverse version 1.3.1*

Table 1. A description of important features of interpolation methods to aid in comparison of model advantages and limitations. We describe the features used in this study, but also note alternative options are in parentheses.

	Global or local*	Deterministic or stochastic†	Convex, nonconvex, or either‡	Univariable or multivariable§	Train/test splitting‖
IDW (1 yr, 3 yr)	Local	Deterministic	Convex	Univariable	no
Kriging	Local (or global)	Stochastic	Either	Univariable (or multivariable)	no
Polynomial Reg (deg: 1, 2, 2+)	Global	Stochastic	Either	Multivariable (or univariable)	Yes
Regression tree	Global	Stochastic	Convex	Multivariable	Yes
Random forests	Global	Stochastic	Convex	Multivariable	Yes

Polynomial Reg (deg = *X*), multivariate polynomial regression with degree of *X*.
*Global methods use all available data to derive the estimation, whereas local methods operate within a small, gridded area around the point being estimated to capture local spatiotemporal variation. The approach used in this study is provided first, but an alternative is in parentheses.
†Deterministic methods only provide estimations and stochastic methods provide both estimations and associated errors.
‡Convex methods yield estimates that are bound between the minimum and maximum of the observed values, whereas nonconvex methods can estimate outside of the range of the observed values.
§Univariable methods use only one primary variable to derive the estimation, whereas multivariable methods use multiple explanatory/predictor variables to estimate the primary variable. The approach used in this study is provided first, but an alternative is in parentheses.
‖Whether or not the dataset undergoes a "train/test splitting" procedure whereby a random subset of the data are split into a training set and the remaining data are split into a testing set to evaluate model performance.

Table 2. Water quality variables selected for interpolation from the long-term water dataset for the Upper Mississippi River, U.S.A. Each variable was used either as a response variable for interpolation or a predictor variable during interpolation. Further details on the data collection and processing either in situ or the laboratory are provided in Soballe and Fischer (2004).

Variable type	Parameter	Acronym used in dataset*	Unit of measurement	Readings collected
Response or predictor	Total phosphorus	TP	mg L^{-1}	Laboratory
Response or predictor	Total nitrogen	TN	mg L^{-1}	Laboratory
Response or predictor	Water velocity	VEL	m s^{-1}	In situ (river)
Predictor only	Turbidity	Turb	Nephelometric turbidity unit (NTU)	In situ (river)
Predictor only	Total suspended solids	SS	mg L^{-1}	Laboratory
Predictor only	Secchi depth	Secchi	cm	In situ (river)
Predictor only	Chlorophyll *a*	CHLcal	μg L^{-1}	Laboratory
Predictor only	Water depth	WDP	cm	In situ (river)
Predictor only	Water temperature	Temp	°C	In situ (river)
Predictor only	Dissolved oxygen	DO	mg L^{-1}	In situ (river)
Predictor only	Conductivity	Cond	μS cm^{-1}	In situ (river)
Predictor only	Reach	Pool	Categorical: Upper Pool 4, Lower Pool 4, Pool 8, Pool 13, Open River, La Grange	Not applicable
Predictor only	Strata	Strata	Categorical: main channel, side channel, impoundment, contiguous backwater	Not applicable
Predictor only	Season	Season	Categorical: spring, summer, fall, winter	Not applicable
Predictor only	Year	Year	Categorical: years 1993–2020	Not applicable

*All water quality data are publicly available through the Upper Mississippi River Restoration Program's *Long-term Resource Monitoring* (https://umesc.usgs.gov/ltrm-home.html).

collection (Wickham et al. 2019), and recorded scripts for reproducibility (Broman et al. 2017). We extracted data only collected at the water's surface via a stratified random sampling scheme (and removed all sites that are considered "fixed sites"). We selected 11 continuous variables for the scope of our interpolations (Table 2). Although other variables are available in this dataset, they were correlated with the others (e.g., nitrate and TN) or binary (e.g., plant data) and thus omitted for modeling. Rarely (< 0.2% of samples), negative values occurred due to the measurement below the detection limit of the instrument and all negative values were set to the minimum, nonnegative value observed. The variables of interest had a corresponding column for quality flag (QF) with comments. The values with the QF codes equal to "0," "A," "8," or "64" were set to "NA" because the reported results were from inoperable equipment, nonstandard laboratory method, or marginal sample condition. All variables had many statistical outliers (defined as 1.5 times the interquartile range), which may or may not affect interpolations; however, we retained most statistical outliers for analysis because all values were deemed realistic values for the UMRS. We removed three values for TN that were not reasonable (>10 mg $[\mathrm{L\text{-}N}]^{-1}$) prior to interpolations. All cells with "NA" were considered missing data (for whatever the reason the missingness) and interpolated in next steps. The reduced dataset ($n = 82{,}481$ sites; data file titled "water_data_qfneg.csv") was subsequently used for all interpolation methods herein. The dataset was split into training (80%) and testing (20%) sets (Table 1) and described in more detail under each method's section heading below.

Procedures: Interpolation methods

We examined seven commonly employed interpolation methods for three key variables with substantial missingness: TN, TP, and velocity. Of the plethora of interpolation methods available, we chose these seven methods for intercomparisons because of their long-standing history, popularity, and general robustness for many data and applications (Li and Heap 2014). We provide a graphical description of how each interpolation method works (Fig. 2). The key model characteristics are compared in Table 1 that highlighted the main differences, advantages, and limitations of each modeling approach.

Method: Inverse-distance weighting (at two different time steps)

Inverse-distance weighting (IDW) is a spatiotemporal interpolation model that assumes data close together (in time and space) are more similar than data farther apart (Fig. 2). To interpolate for a missing variable, users could use two or more closest measured values (Lu and Wong 2008). We used two of the closest measured values to interpolate missing data. The IDW method applied a weighted sum across the actual values using the Euclidean distance to scale the interpolated value as follows:

$$c_1 \mathrm{var}_1 + c_2 \mathrm{var}_2 = \mathrm{var}_{\mathrm{interp}}$$

where $c_1 = \left[1/\left(d_{(1,\mathrm{interp})}\right)\right] / \left[\left(1/d_{(1,\mathrm{interp})}\right) + \left(1/d_{(2,\mathrm{interp})}\right)\right]$; $c_2 = \left[1/\left(d_{(2,\mathrm{interp})}\right)\right] / \left[\left(1/d_{(1,\mathrm{interp})}\right) + \left(1/d_{(2,\mathrm{interp})}\right)\right]$; var_1 and var_2 are the two known variables; and $\mathrm{var}_{\mathrm{interp}}$ is the interpolated value. The subscript with d represents the distance between the starting and ending point of samples, whereby samples closer in space or time are given more weight. The IDW distance did not account for possible terrestrial interference from river islands and side channels.

We built the IDW models using software Python 3.10.7 (Python Software Foundation 2021). For our IDW models, we accounted for both space and time for calculating "distance." We used the latitude/longitude variables for spatial distance. For temporal space, two different time steps (1 and 3 yr) were tested and reported. First, we partitioned data by season and year (either 1 yr or 3 yr) so that neighbors could only be chosen within their own subset. For IDW, errors were evaluated by first computing mean absolute error (MAE) and root mean squared error (RMSE) with all nonmissing values for each variable. Then, we interpolated the value for each known value using the two closest locations in space and time. Finally, we recorded the absolute difference and squared difference between the known and interpolated value, then averaged all the differences to obtain MAE and RMSE.

Method: Ordinary kriging

Kriging is a stochastic geostatistical interpolation method that factors in spatial autocorrelation, or the correlation of a variable with itself, over space (Burt et al. 2009). Therefore, kriging is particularly appropriate when a spatially correlated distance is known (as originally hypothesized in our water quality dataset) and therefore is a popular technique in soil and geological sciences. Kriging consists of two processing steps (Fig. 2): (1) computing the weighted average of available samples by fitting a semivariogram model to estimate the spatial autocorrelation between known values and (2) using the model to interpolate the unknown values.

Before kriging, the missing values were removed. The remaining data points were displayed in Esri's ArcGIS Desktop (Esri 2020), projected to Universal Transverse Mercator Zone 15 North, WGS 1984, and separated by river reach (Fig. 1). We used the "kriging" tool in the ArcGIS Spatial Analyst extension to generate interpolated surfaces for each missing variable and reach combination (e.g., TN for Pool 4, TP for Pool 8, velocity for Pool 13). Parameter selections for each kriging operation included the *ordinary kriging method* that assumes an unknown constant trend, a spherical semivariogram, and an output cell size of 10 m. Geoprocessing was local to limit the extent of the interpolated surface to each reach rather than interpolating among reaches. Esri's Geostatistical Wizard performs cross-validation by using all available data to compare interpolated values with observed values, which estimates the trend used during kriging and provides statistics on the prediction errors (i.e., RMSE and MAE) and report the average errors of the six reaches in Table 3.

Method: Polynomial regression

Polynomial regression uses linear or nonlinear correlations among a single or multiple variables within a dataset to build a model that predicts missing values (Sinha 2013).We used multivariable polynomial regression interpolation to predict

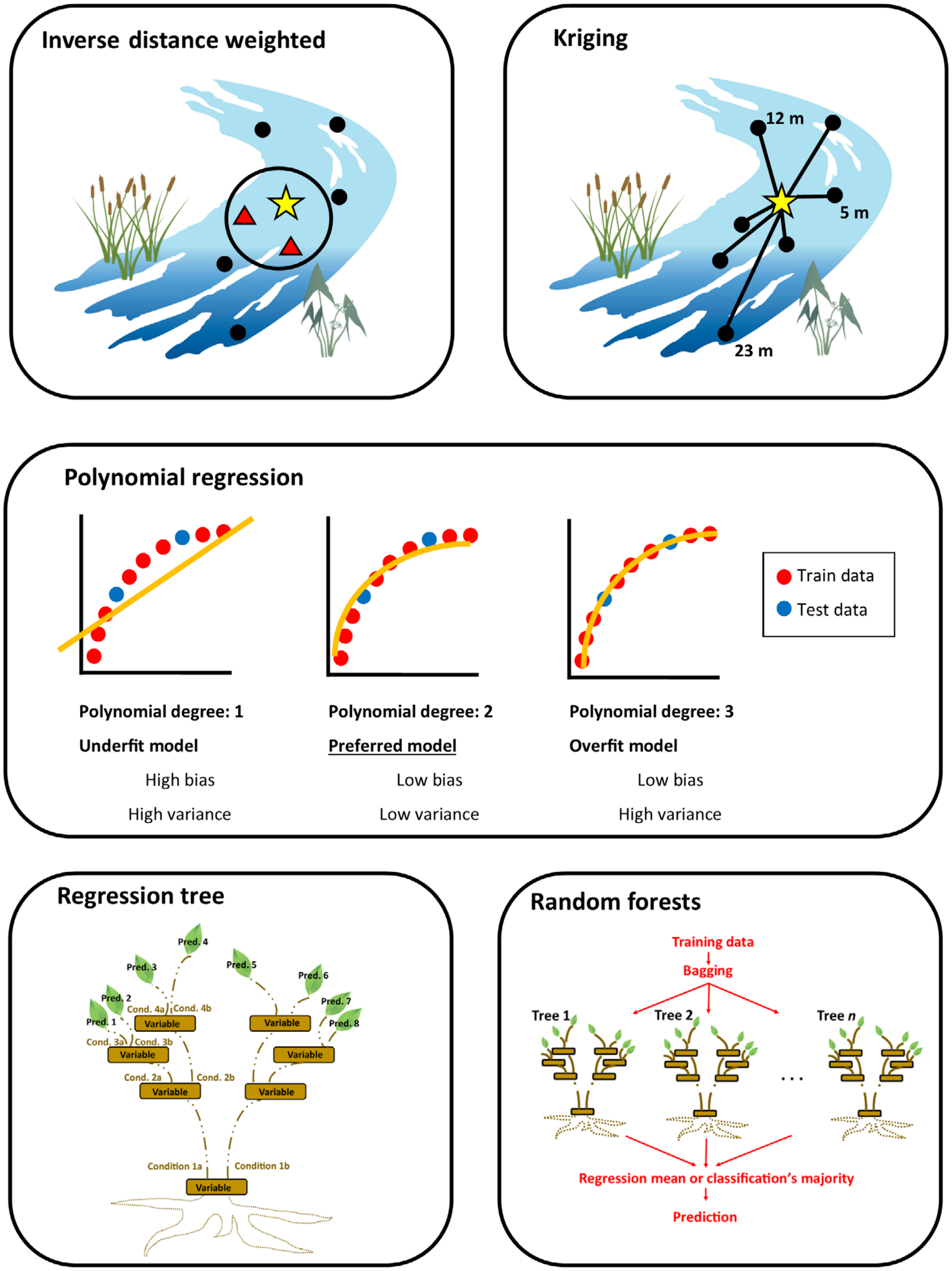

Fig. 2. A graphical representation of how common interpolation methods work. Note these are hypothetical graphics and often the parameters are changeable (e.g., the number of points used in kriging, the number of data points in a polynomial regression, or the number of splits in the regression tree). For inverse-distance weighted method, the points on the river include the interpolated value (yellow star), the nearest neighbor values considering space and time used to derive the interpolated value (red triangles), and unused sampling points (black circles). In the kriging method, all values (black circles) are used to estimate the interpolated value (yellow star) but are weighted by distance (in meters). The polynomial regression strives to model nonlinear data by optimizing the model fit with the lowest bias and lowest variance. To find the preferred polynomial regression degree, we fit several different models with various degrees and perform k-fold cross-validation to determine which model has the lowest mean absolute error on the test data. The regression tree is split at nodes (variables) based on conditions ("cond.") of binary, threshold values. After the final splitting, the tree provides predictions ("pred.") or interpolated values based on the variable splitting process. River clip art images were modified with permission by the originator, Tracey Saxby (https://ian.umces.edu/media-library/, accessed on 21 September 2022). The random forests method combines many regression trees to improve the predictive accuracy of a single regression tree. Bagging bootstraps the data to create independent replaces of the training data, and then same regression tree is applied to each bagged tree.

Table 3. A comparison of interpolation methods for a long-term water quality dataset on the Upper Mississippi River, U.S.A. The random forests model had the lowest mean absolute error (MAE) and root mean squared error (RMSE) for all variables, which indicated higher prediction accuracy than the competing models.

	TP			TN			VEL		
	n	MAE	RMSE	*n*	MAE	RMSE	*n*	MAE	RMSE
IDW (1 yr)	31,447	0.047	0.147	32,185	0.405	0.863	56,179	0.127	0.234
IDW (3 yr)	31,450	0.064	0.145	32,188	0.735	2.281	56,182	0.139	0.271
Ordinary kriging	6290	0.077	0.131	6437	0.837	1.189	11,236	0.167	0.265
Polynomial Reg (deg = 1)	6290	0.067	0.128	6437	0.854	1.176	11,236	0.175	0.295
Polynomial Reg (deg = 2)	6290	0.057	0.122	6437	0.816	1.124	11,236	0.162	0.275
Regression tree	6290	0.061	0.129	6437	0.868	1.379	11,236	0.163	0.310
Random forests	6290	0.034	0.093	6437	0.388	0.757	11,236	0.099	0.202

n, number of samples in the testing set; Polynomial Reg (deg = *X*), multivariate polynomial regression with degree of *X*; VEL, water velocity.

missing values for a desired target variable using the other 10 variables as predictors in the dataset (Tables 1, 2; Fig. 2). The sparse (< 0.1%) missing values in the predictor variables were imputed with the median. It is important to note that the missing values in the training set and testing set were imputed with their respective medians independently, because we do not want to give the model any information from the testing set to reduce bias. After median imputation, each value of the predictor variables was scaled using the *RobustScaler* in the *sklearn* module (Pedregosa et al. 2011) with the following transformation: $X_{\text{scaled}} = [(X - X.\text{median})/\text{Interquartile Range}]$. The scaler object was fitted on the training set but used to scale both the training and testing sets.

We built the models using software Python version 3.10.7 (Python Software Foundation 2021). Next, we utilize the "train_test_split method" from *sklearn* (Pedregosa et al. 2011) to randomly split the full dataset into training (80% of data) and testing (20% of data) sets for model training and evaluation. Next, we used *sklearn.preprocessing.PolynomialFeatures* (Pedregosa et al. 2011) to transform the predictor variable matrix into a higher dimensional matrix with higher order terms (depending on the degree of polynomial). Degree 1 and 2 models were trained on the entire training set for each variable and evaluated on the test set using the *LinearRegression* class in *sklearn* (Pedregosa et al. 2011) and the final polynomial model had the lowest mean squared error (MSE) on the test data. We did not optionally perform model selection to determine which predictors (Table 1) were significant to allow direct comparison to the other global models (Table 2) that contained all 10 predictors. The MAE and RMSE are reported on the test set.

Method: Regression tree

Regression tree algorithms predict a continuous target variable. They output a binary tree by implementing recursive binary partitioning, which creates branches or subsets of the data with similar target variable values (Fig. 2). The data splits according to which predictor variable value minimizes the combined sum of squares error in the two resulting partitions of data. The interpolated target variable values are the averages of the points in the tree's leaf nodes. Regression trees benefit by easily handling missing values in the predictors through surrogate splits (Therneau et al. 2019). When a predictor variable is missing for a data point, the regression tree uses a surrogate split, an alternate predictor that partitions the data similarly to the original predictor variable.

We used the "rpart" package (Therneau et al. 2019) in software R version 4.1.2 (R Core Team 2022) and interpolated the missing values for TP, TN, and velocity. The regression tree used all predictors in Table 2. For each tree, the full dataset was randomly split into training (80% of data) and testing (20% of data) sets. The complexity parameter (CP) was set to 0.011, which establishes the minimum amount that the R squared value must increase after adding a new node to the tree. This CP value was determined using the 1 standard error rule on the TP, TN, and velocity trees.

Method: Random forests

Random forests are an ensemble machine learning algorithm that combines many regression trees to improve the predictive accuracy of an individual tree (Fig. 2). The random forests are popular because they are simple to implement, perform well with little to no tuning, capture nonlinear relationships, and can handle high-dimensional data (Boulesteix et al. 2012; Biau and Scornet 2016). Researchers have applied random forests to scientific fields of ecology, land cover, soil properties, and more (Tyralis et al. 2019). The algorithm ensembles decorrelated bagged decision trees. Bagging begins with bootstrapping the data replacement to create independent resamples of the training data. On each bootstrapped resample, the same regression tree is fitted. The model adds randomness to decorrelate each bagged tree; each split in a bagged tree is limited to a random subset of all predictors.

We used the "ranger" package (Wright and Ziegler 2017) in R version 4.1.2 (R Core Team 2022) to construct the random forests model. The full dataset was randomly split into training (80% of data) and testing (20% of data) sets. The model used all predictor variables in Table 2, and the occasional missing values for predictor variables were imputed with the median. We set the number of trees to *ntree* = 500 ("ranger" default), *mtry* value of 3 (the number of randomly sampled predictors considered for each split), and *min_n* of 5 (minimum number of observations needed to further split a node).

Comparing models and evaluating model performance

We conducted error analyses on all interpolation methods using one round of cross-validation to evaluate model accuracy. For three methods, the dataset was split into training (80%) and testing (20%) sets (Table 1). We were not able to use identical train/test datasets across each method because each model's software package partitioned the data differently and at random. For the IDW and kriging methods, train/test splitting is not an option and so we used "leave one out cross-validation" (which is where we selected a known value, made a predicted value from the model, and compared the difference).

We used several lines of evidence for choosing the "best" performing model. We compared performances with two error metrics, the MAE and RMSE. The MAE and RMSE are the best overall measures of model accuracy because they summarize the mean difference in the actual units of the observed and interpolated values (Willmott 1982). Below are the formulas for these error metrics, where y_i is the actual value, $\hat{y}_i$ is the interpolated value, and n is dataset size.

$$\mathrm{MAE} = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n}$$

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}}$$

The MAE is the average difference between the measured and interpolated values and uses the same scale as the data measured and is less sensitive than RMSE to outliers. The RMSE squares the MAE, so that RMSE more heavily weights larger differences in the actual vs. interpolated values. The interpolation method with the lowest MAE and RMSE fits the data best and is the "top performing method." We also examined the summary statistics and compared the relative magnitude of the differences in MAE and RMSE for each method. Boxplots and scatterplots which paired the interpolated values and actual values compared congruence.

To report the potential biases of the "top performing model," we calculated three metrics: absolute error (AE), percent bias (PBIAS) and Kling–Gupta Model Efficiency (KGE). The AE is calculated as:

$$\mathrm{AE} = y_i - \hat{y}_i$$

where y_i is the actual value and the $\hat{y}_i$ is the interpolated value. The PBIAS and KGE bias metrics were calculated using the package "hydroGOF" (ZambranoBigiarini 2023) in R version 4.1.2 (R Core Team 2022). The PBAIS measures the averaged tendency of the predicted values to be larger or smaller than the observed values (whereby a PBIAS of 0.0 is ideal, indicating no bias). The KGE is a normalized model efficiency measure for general agreement between the predicted and observed values (whereby a KGE close to 1.0 is ideal).

The distribution of AE was plotted in histograms, where high congruence is indicated as errors being centered near zero and symmetrical. To assess spatial variability of the top model's prediction errors, we calculated the AE for each site within the dataset. The AE value was plotted for each of the three interpolated variables according to latitude and longitude, and we visually inspected the maps for any patterns of spatial variability.

Assessment

Computational costs

All interpolation methods were successfully implemented with our full data matrix of size (82,481 rows by 11 variables), with computation times ranging from 0.25 to 7 h and computers with 16 GB RAM. These computer specifications are commonly found on current laptop and desktop computers and not typically limited by memory. The random forests model was the most computationally expensive ($\sim$ 7 h) because the algorithm fitted and aggregated 500 regression trees, and then the model bootstrapped individual trees before calculating the average solution. However, the R package "ranger" (Wright and Ziegler 2017) that we used had faster run times and less memory usage compared to other random forests packages (Wright and Ziegler 2017). We provided detailed analysis scripts and example river data for all interpolation methods (Larson et al. 2023), which provide opportunity for other scientists to implement and compare interpolations using their own data.

Error metrics

We refrained from providing subjective determination of whether the MAE was "good, sufficient, or poor" for each variable and method because no industry standards exist. Therefore, those judgments should be defined by the user's purpose for the interpolated values. Using cross-validation procedures can reduce subjectivity and provide quantification of errors and reveal potential biases (e.g., spatial bias). Furthermore, calculating multiple metrics to assess bias (such as PBIAS and the KGE) can assess bias quantitatively.

The random forests method consistently had the lowest MAE and RMSE scores compared to the other methods for all three interpolated variables (Table 3; Fig. 3). The random forests had high prediction accuracy according to several error metrics (Table 3) and diagnostic tests (Fig. 4). For all three water quality variables, the random forests' scatterplots suggested that most interpolated values derived from random forests were congruent with the actual values ($r^2 = 0.74$–0.79, depending on the water quality variable). The data distributions along the 1 : 1 line in scatterplots reveal slight underprediction biases for TP and velocity; specifically, random forests predictions sometimes yielded interpolated estimates less than the actual measures that were above the upper quartile (75% percentiles) of data. Any actual value for velocity greater than a threshold of ~ 1.5 m s^{-1} (which was a statistical outlier, but there were many outliers) was always underpredicted (Fig. 4g). The boxplots comparing random forests' actual and interpolated values were well aligned within the interquartile range, and the interpolated values had fewer outliers than the actual data. Model residual error distributions were centered over zero and normally distributed, which indicated good model fits.

Although the "best" performing method was clearly identified as random forests according to several performance metrics, there was not a single "worst" performing method. The IDW (1-yr) method had the overall second-best performance (Table 3; Fig. 3). The IDW 1-yr method had comparable performance to random forests for the TN variable, as indicated by their similar MAE scores ($\sim$0.4 mg [L-TN]$^{-1}$; Fig. 3). However, random forests performed better than IDW 1 yr for the TP and velocity variables, as indicated by the differences in MAE scores of 0.01 mg (L-TP)$^{-1}$ and 0.03 m s^{-1}, respectively. For all variables, the IDW 1 yr outperformed the IDW 3 yr, which indicated spatiotemporal variation for water quality was high and that predictions were more accurate when interpolations were constrained to "nearby" water quality samples in both space and time (i.e., constrained within the same year). Both

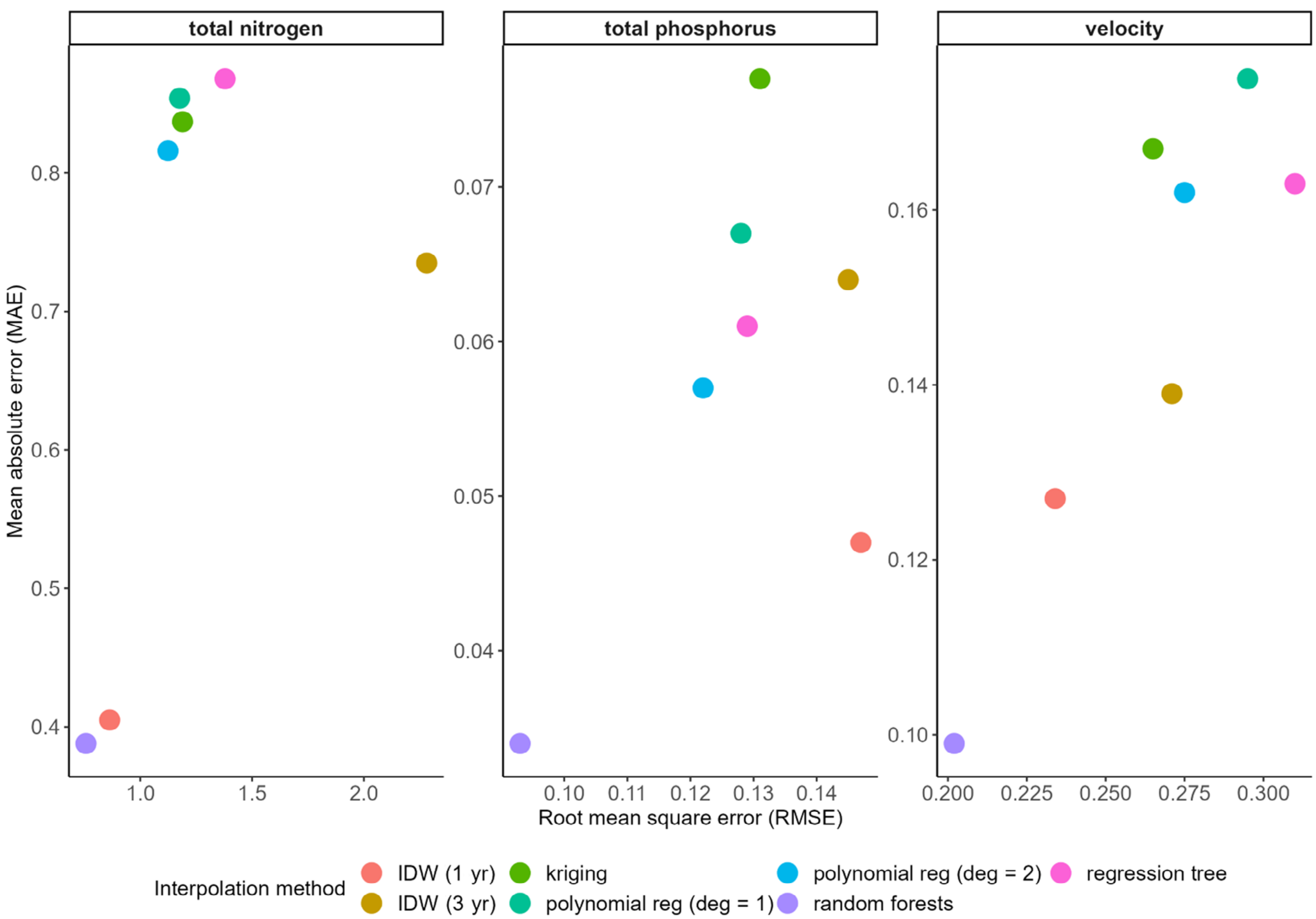

Fig. 3. The correlation between RMSE and the MAE of each interpolation method using long-term water quality data from the Upper Mississippi River System. The relative model performance for each interpolation method was compared for three key water quality variables: TN, TP, and water velocity. The method with the lowest MAE and RMSE (in these cases, "random forests" in the lower left quadrant) indicated the lowest error for the interpolated predictions. The precise values for RMSE, MAE, and sample sizes are presented in Table 2. Note the *x*- and *y*-axis limits differ based on the water quality variables. The MAE units vary by variable: TN (mg L^{-1}), TP (mg L^{-1}); and velocity (m s^{-1}).

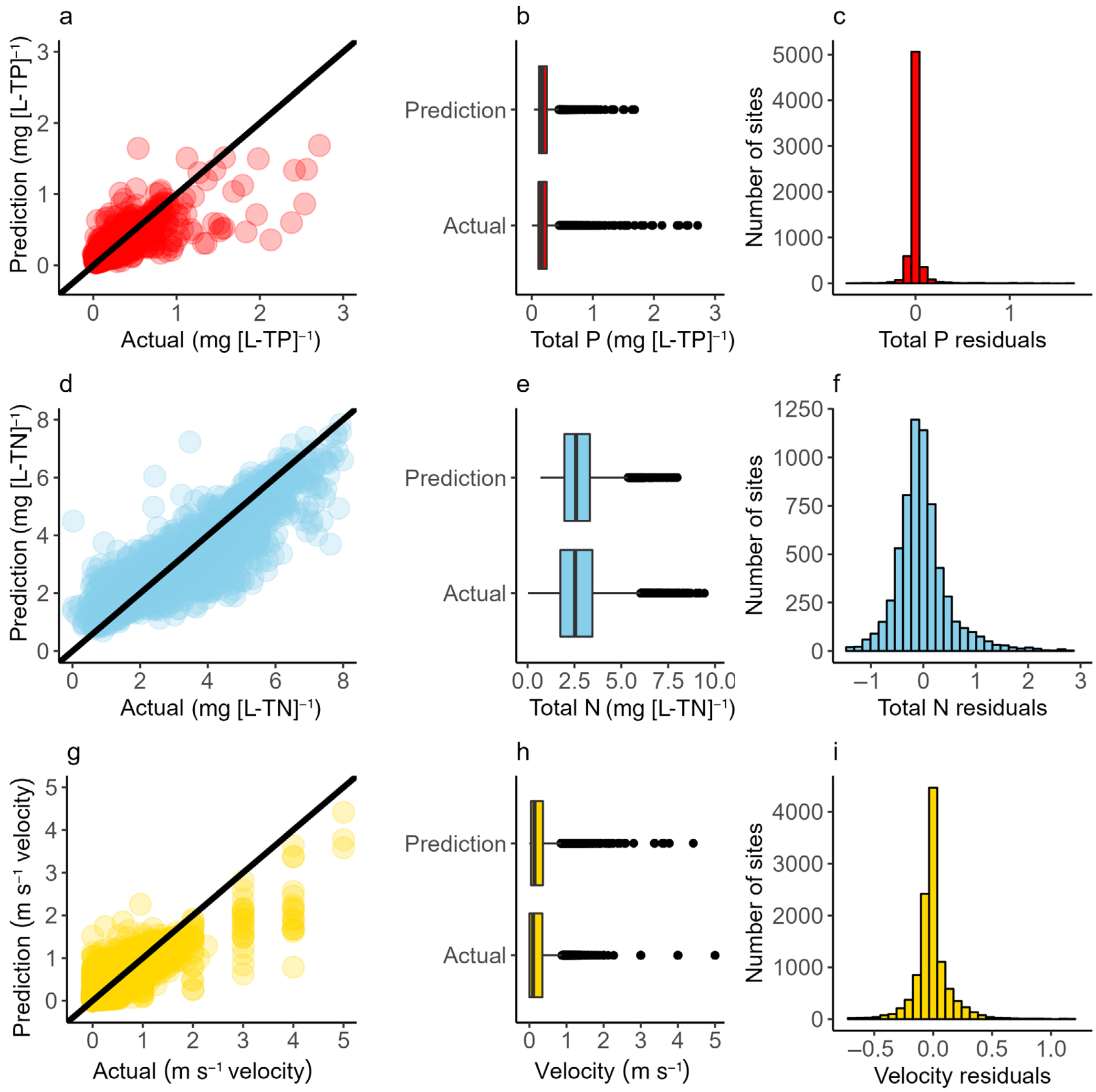

Fig. 4. Scatterplots, boxplots of distributions, and histograms of residual errors that compared congruence of the predicted and actual values for TP (red, **a–c**), TN (blue, **d–f**), and velocity (yellow, **g–i**) from Upper Mississippi River long-term data. The predicted data were obtained using interpolation from a random forests machine learning algorithm; (**a**), (**d**), and (**g**) display a 1 : 1 line for the predicted actual values. Boxplots in (**b**), (**e**), and (**h**) are standardized by boxes (containing the 25th, 50th [median], and 75th percentiles), the whiskers (containing the 0th and 100th percentiles, excluding outliers), and the dots (which are statistical outliers but retained for interpolations).

the IDW 1-yr and IDW 3-yr methods had lower MAE, but similar RMSE, compared to the regression tree, kriging, and two polynomial regressions.

The regression trees, kriging, and polynomial regressions performed similarly with relatively high correlations between MAE and RMSE (Table 3; Fig. 3). The multivariate polynomial regressions with 2nd degrees performed marginally better than the 1st degree polynomial for all variables, and polynomial regressions with higher degrees were overfit and not reported in tables. Interpolation performance may be improved using polynomial regression that explores various degrees of individual predictor variables and includes backwards model selection, which drops insignificant, higher-order terms until all terms are significant. Detailed results for each method's performance are supplied in analysis scripts found at (Larson et al. 2023).

The interpolation performance for the top method (random forests) varied depending on the water quality variables, as suggested by the RMSE and MAE metrics (Table 3; Fig. 3). TP had the greatest prediction accuracy when applying random forests, with a MAE of 0.03 mg (L-TP)$^{-1}$. TN had prediction accuracy with a MAE of 0.39 mg (L-TN)$^{-1}$, which is a reasonable MAE in this river system with very high nitrogen concentrations (up to 8 mg L^{-1}; *see* Fig. 4). The velocity variable had highest relative error (MAE of ~ 0.10 m s^{-1}). The PBIAS shows some underpredictions for TP and velocity (PBIAS = 0.2 and 0.3, respectively) but not TN (PBIAS = 0.0). The KGE metric showed generally agreement between observed and predicted values (KGE = 0.68–0.75 range for the three water variables), and Fig. 4 shows the disagreements were from underpredictions of the uncommonly high values.

Applying interpolation to address missingness and explore spatial ecology

We applied random forests to the entire water quality dataset from years 1993 to 2020 of the UMRS to interpolate blank cells in the data frame for TP, TN, and water velocity ($n = \sim$125,000 values). Merely using listwise deletion to deal with sampling sites with at least one blank cell for any water quality variable had removed 85% of the entire stratified random sampling dataset, whereas the interpolation retained the entire dataset with no missingness to allow for new types of analyses. The final data frame replaced missing values with interpolated values ($n = 76,670$ sites). The benefits of interpolation and no missingness included the ability to conduct site-level analyses and multivariable analyses with no data loss, especially in this case of retaining 85% of the dataset that would be lost using listwise deletion. The missing nutrient values are not problematic for the reach and strata (i.e., habitat type) analyses that the data were principally designed to inform (Soballe and Fischer 2004; Houser et al. 2022), but site-level analyses require properly addressing missingness prior to ecological assessments.

The drastic error differences among water quality variables (Table 3) suggested how spatiotemporal variation of riverine processes can affect modeling predictive capacity. Random forests had very high predictive ability for TP despite fairly high spatial variability (Houser and Richardson 2010) and temporal variability (Kreiling and Houser 2016) across the UMRS riverscape, which may suggest either relative stability of phosphorus or that we included appropriate covariates (Table 2) to accurately predict TP. Although nutrients are known to have spatial variability within the UMRS (Houser and Richardson 2010; Houser et al. 2022), our prediction errors did not show spatial patterns (Fig. 5), indicating the model's nutrient predictions did not have spatial biases. The variables of TN, TP, and velocity have strong seasonal patterns in this northern latitude river (Jankowski 2022), and the seasonal variability may add to the predictive capacity of interpolation. Water quality variables that do not have spatiotemporal autocorrelation due to season or other factors may have greater interpolation error. Despite hypothesizing that side channel habitats would be harder to accurately predict nutrient concentrations due to the complexity of those habitat types compared to the main river channel, this was not supported by model error predictions (Fig. 5). The random forests' error rates showed low spatiotemporal variability within multiple river channels (Fig. 5), indicating high interpolation performance across many habitat types and large spatial scales (at least 60 river km).

In contrast, water velocity had relatively lower predictive capacity for several possible reasons. Interpolation in other applications can substantially reduce concerns of nonrandom missingness (Little and Rubin 2002), but not in the case of this dataset when water velocity was commonly missing nonrandomly. The random forests interpolation is a convex method (Table 2) and thus was not able to accurately predict outside the bounds of the measured velocity values, including the (nonrandom) missing, extreme values that are commonly found and difficult to measure in the UMRS. Water velocity can quickly respond to ongoing changes in discharge and underwater features like aquatic plants or engineered structures common in the Mississippi and Illinois Rivers, and therefore interpolations may not properly capture the dynamics of discharge and fine spatiotemporal scale of velocity. Furthermore, velocity had higher field measurement error compared to TN and TP (Soballe and Fischer 2004), and therefore measurement error could propagate through interpolation and increase prediction errors.

Strengths and limitations of random forests

Until recently, random forests had limited use in the aquatic sciences despite its many strengths and applicability (Olden et al. 2008; Tyralis et al. 2019). A few of many beneficial properties of random forests for interpolation of water science data include relatively fast computations (Wright and Ziegler 2017), extensively studied in theory, and the models are nonparametric, can model nonlinear dependences among variables, can handle noisy, correlated, and several types of predictor variables (e.g., continuous and categorical), are effective with high dimensional datasets (Biau and Scornet 2016). Random forests do not necessarily require large data to be accurate (Biau and Scornet 2016), and so many ecological monitoring datasets may not be data-limited. Random forests have been applied globally to a variety of aquatic systems and topics (Tyralis et al. 2019), yet seem underutilized to-date. In this study, random forests also had advantages over the alternative methods, such as being global and multi-variable (Table 2). Interestingly, the "global, data-driven" random forests model outperformed the 'local, space–time' interpolation models with this dataset as hypothesized.

Random forests have additional applications, which are beyond the scope of these results but noteworthy. Random forests can identify and rank the variables of importance for making predictions (Tyralis et al. 2019), which can aid ecologists in recognizing which measured variables to retain in long-term monitoring, recognize if unmeasured (latent) variables exist and caused low prediction accuracy, and determine ecological relationships. Another neat application can use random forest prediction errors in space–time, such as particular aquatic habitats or periods in time, which may reveal habitat heterogeneity, spatiotemporal variability and dynamics

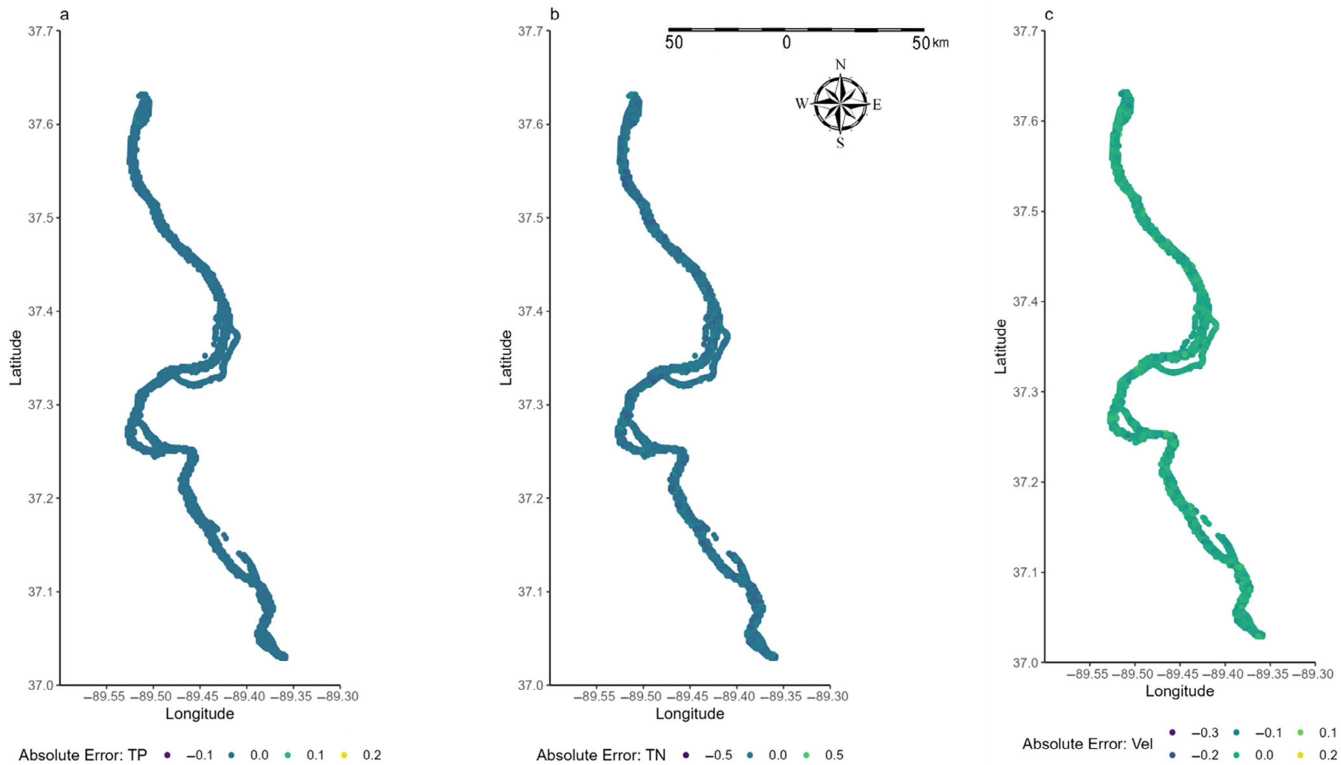

Fig. 5. Maps of the Open River reach of the Upper Mississippi River, U.S.A., showing the spatiotemporal variation of the absolute errors (actual minus predicted values) derived from a random forests interpolation model for three water quality variables: TP (**a**), TN (**b**), and water velocity (VEL, **c**). We hypothesized that absolute error rates could present patterns within a reach based on spatial and habitat heterogeneity, but the lack of patterns shows the random forests predictions were spatially unbiased.

(Chiao et al. 2012; Louvet et al. 2016; Vizcaino et al. 2016) and detect change under a range of simulated scenarios (Holloway-Brown et al. 2021). Random forest outputs can also link conceptually to places with high ecological resiliency or risk of ecological state transitions that could inform aquatic management and restoration priorities (Delaney and Larson, in review).

Like all models, there are limitations to random forests. A substantial barrier has been the difficulty for ecologists to implement and interpret machine learning (Olden et al. 2008) and not knowing how to report uncertainty and error from interpolation (Yanai et al. 2018). Random forests models are convex (Table 1) and cannot interpolate outside the bounds of the training set, which is problematic for nonrandomly missing, extreme values, and statistical outliers. From our data, the velocity predictions were always underpredicted at values > 1.5 m s^{-1}. Future velocity interpolations with random forests may be improved by including other measures like discharge and main channel connectivity in addition to the predictors in Table 2. In contrast, velocity may be better estimated using two-dimensional hydraulic models instead of interpolation models. The TP was also underpredicted at extremely high values, so caution is warranted for those estimates and inferences. Finally, scientists should not presume random forests to be the best interpolation method for all types of problems and datasets, and so intercomparisons of multiple methods is appropriate for novel datasets (Li et al. 2011).

Discussion

The method that authors choose to address missing data are important. The chosen method can either be accurately predictive and an opportunity to expand big datasets (as in this study), cause significant analytical errors and faulty conclusions (Beheim et al. 2021), or output differing parameter estimates in subsequent modeling (Song et al. 2016). Therefore, careful consideration and intercomparisons among methods for addressing missingness is imperative

Our results are not a critique of the existing UMRS water quality dataset; rather, the results show opportunities to properly address the inherent missingness expected in any long-term data and how to use interpolation to extend a dataset. Our results should not change the results or interpretations from the many previous UMRS-specific studies using this dataset for reach- and strata-level inferences as intended in the experimental design (Soballe and Fischer 2004). Our interpolated dataset expands many opportunities for new ecological analyses, particularly site-level analyses and for creating continuous spatial layers for use in geographic information systems. Our interpolated dataset now allows for rigorous site-level analyses that focus on complex, multivariate associations that was not previously possible with frequent missingness from using a dataset initially intended to answer questions at the strata- and reach-levels.

Future models could attempt to address error propagation from the interpolation to the next analytical model. Typically, scientists use a two-step procedure where first an interpolation model predicts the missing covariates with some estimates of uncertainty and error, and then those predictions and associated errors are used as input for a secondary analytical model (e.g., an ordination or regression for ecological analysis). This two-step approach is practical but not optimal because uncertainty is not transferred between the two models and error is not accounted for in the second analytical outputs.

The inherent limitation of interpolation is that the *actual, measured estimates* are still missing, and the interpolation merely created *simulated or interpolated estimates*. The concerns and consequences of having interpolated estimates compared to having actual estimates in any dataset is context- and user-dependent. Developers of aquatic sampling protocols would benefit from considering whether they require the physical collection of (often costly) limnological data to obtain actual values, or, whether the lower cost of simulated, interpolated data are sufficient. Cross-validation procedures that evaluate model performance (e.g., like the train test split procedure and comparisons of each model's RMSE and MAE in this study) are important decision tools for choosing between actual data versus interpolated data. Data analysts of large datasets should consider the sample sizes of the missingness, whether data are missing at random, and how interpolated estimates might affect the ecological analyses and interpretations. Past published analyses that used listwise deletion to datasets with substantially missing data should consider interpolating and re-analyzing the data to determine if the statistical or ecological inferences would change.

Comments

Future published works with long-term and large datasets should clearly articulate the steps and considerations they took to address missing data. Unfortunately, many ecological papers fail to mention missingness and solutions despite the many associated problems. At a minimum, scientific methods should address: How much data were missing? Were data missing at random or nonrandomly? Which methods (e.g., listwise deletion, imputation, interpolation, etc.) were compared for dealing with missingness, and how was the final interpolation method chosen? Are the analysis codes archived, available, and reproducible (Broman et al. 2017)?

It is likely that the "top performing method" may vary according to each dataset and their contexts. Data variation can impact the accuracy of all interpolation methods (e.g., *see* Table 3 for comparing the three variables), and the magnitude of impact is often method dependent (Li and Heap 2011). However, our results showed that machine learning is a powerful and underutilized tool for interpolating missing data. Scientists should attempt multiple interpolation methods for dealing with their own missing data, and the random forests algorithms and several accuracy metrics (like RMSE and MAE) should be included in their repertoire for intercomparison.

In the current era of "big data" typically not limited by computing resources, interpolation becomes an imperative step prior to ecological analyses. Interpolation literature tailored toward aquatic ecologists are available as a guide in this statistical realm (Olden et al. 2008; Tyralis et al. 2019; this paper). Interpolation code sharing like ours herein (Larson et al. 2023) allows for ecologists to test new ecological questions within the UMRS, as well as readily test and compare methods using their own datasets from any aquatic system. Interpolation can minimize information loss and maximize the accuracy of ecological inferences and forecasts, which is exceptionally important for water resource science and management.

Data Availability Statement

All water quality data are publicly available through the Upper Mississippi River Restoration Program's *Long-term Resource Monitoring* (https://umesc.usgs.gov/ltrm-home.html). The data analysis scripts and data are permanently archived on the U.S. Geological Survey's Open Source GitLab (https://code.usgs.gov/umesc/ltrm/interpolating-missing-water-quality-data) and Larson et al. 2023 (DOI: 10.5066/P9ZR7BWL). Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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ATTACHMENT D

Nutrients

- **Lesson from 10+ Years of Numeric Phosphorus Standards for Wisconsin’s Waters:** **https://pconference.files.wordpress.com/2023/05/2023-p-conference-report-4.pdf**

- **UMRBA's Proposed Upper Mississippi River Sub-Basin Committee Workplan for FY 2024 through FY 2026** *(D-1 to D-9)*

Hypoxia Task Force
Upper Mississippi River Sub-Basin Committee
Work Plan for FY 2024 through FY 2026

Grant Information

U.S. Environmental Protection Agency
Non-State Member Support for the Gulf Hypoxia Action Plan
Cooperative Grant Application
Funding Opportunity Number: EPA-I-OW-OWOW-HTF-02

Grantee Information

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Project Description

Project Description

The states of Illinois, Iowa, Minnesota, Missouri, and Wisconsin have directed the Upper Mississippi River Basin Association to convene and facilitate its Hypoxia Task Force Sub-Basin Committee for the Upper Mississippi River Basin. Through the project period, and with the available funding, the states have determined that their shared priorities for the Committee are to create an Upper Mississippi River Nutrient Reduction Strategy, an interstate system for continuous learning (also known as adaptive management), and an interstate communications strategy. UMRBA will participate in the Hypoxia Task Force and integrate the Sub-Basin Committee's actions into other interstate water planning.

Environmental Results

Through its workplan, the Upper Mississippi River Basin Association (UMRBA) aims to increase engagement and participation by traditional and non-traditional stakeholders in the Upper Mississippi River Basin (UMRB), more effectively collaborate among states and their executive agencies, and ultimately reduce nutrient pollution in the UMRB.

Organizational Information

UMRBA is the Governor-established forum for interstate water resource planning and management on the Upper Mississippi River, representing the common interests of its member states: Illinois, Iowa, Minnesota, Missouri, and Wisconsin. In part, UMRBA does this by facilitating and fostering cooperative planning and coordinated management and by creating a forum for discussion, study, and evaluation of major issues. UMRBA also serves as the Governors'-designated interstate water quality entity.

Through UMRBA, its member states work together to leverage their capacities and pull together towards common strategies or strategies that are compatible towards a common goal. Within the past few years, the states have collectively agreed to focus on building relationship and enhancing cooperative action across the Upper Mississippi River basin scale – beyond their individual state borders – to accelerate nutrient runoff reduction, including through collaborative implementation of conservation practices.

Place of Performance

Project activities will occur throughout the Upper Mississippi River Basin in the five states of Illinois, Iowa, Minnesota, Missouri, and Wisconsin.

Project Period

UMRBA is proposing that it will accomplish its work plan tasks between October 1, 2023 through September 30, 2026.

Upper Mississippi River Basin Association
Hypoxia Taks Force
Upper Mississippi River Sub-Basin Committee
Project Workplan

Project Approach

Background

The Upper Mississippi River Basin Association (UMRBA) is a Governor-established forum for interstate water resource planning and management on the Upper Mississippi River, representing its member states of Illinois, Iowa, Minnesota, Missouri, and Wisconsin. Through their steady, 40-year commitment to UMRBA, the states have worked diligently with federal partners and stakeholders to advance multi-use management of the river, facilitating and fostering cooperative planning and coordinated management of the Upper Mississippi River Basin's water and related land resources. In acknowledging the complex nature of the river system and array of human uses, UMRBA has always held that river management requires thoughtful and inclusive dialogue among the diverse suite of stakeholder representatives throughout the region.

UMRBA is the interstate, regional collaborative of state agencies implementing the Clean Water Act and nutrient reduction strategies on the Upper Mississippi River and its basin. UMRBA initiates and maintains collaborative decision-making, cooperative action, and information sharing among the five UMRBA member states regarding water quality issues on the Upper Mississippi River. UMRBA provides a policy link between collective actions and individual actions by the states. In fulfilling this role, UMRBA promotes, supports and maintains the Hypoxia Task Force's (HTF) Upper Mississippi River Sub-Basin Committee.

The proposed workplan is in support of USEPA's Goal 5: Ensure Clean and Safe Water for All Communities (Table 1).

Workplan Approach

Through this workplan, UMRBA proposes to enhance nutrient management on the Upper Mississippi River's interstate waters through the following set of tasks:

1. Compile the separate state nutrient reduction strategies into an integrated Upper Mississippi River Nutrient Reduction Strategy and identify important interstate actions that will reduce nutrient pollution in the Upper Mississippi River

2. Evaluate implementation of important interstate actions to reduce nutrient pollution in the Upper Mississippi River and incorporate insights into ongoing implementation efforts

3. Communicate with stakeholders and other actors in the Basin about important interstate actions that will reduce nutrient pollution in the Upper Mississippi River and gain their commitment to ongoing implementation efforts

4. Maintain and enhance interstate collaboration that will reduce nutrient pollution in the Upper Mississippi River by supporting the Hypoxia Sub-Basin Committee and its various work teams

5. Integrate the important interstate actions that will reduce nutrient pollution in the Upper Mississippi River with other important interstate actions, such as flood mitigation and resilience planning

Table 1: UMRBA's alignment with USEPA's Strategic Goal 5

Strategic Goal	Strategic Objective	Proposed UMR Hypoxia Sub-Basin Committee Workplan	Workplan Alignment with USEPA Strategies
Goal 5: Ensure Clean and Safe Water for All Communities	Objective 5.2: Protect and Restore Waterbodies and Watersheds	• Compile the separate state nutrient reduction strategies into an integrated Upper Mississippi River Nutrient Reduction Strategy and identify important interstate actions that will reduce nutrient pollution in the Upper Mississippi River • Evaluate implementation of important interstate actions to reduce nutrient pollution in the Upper Mississippi River and incorporate insights into ongoing implementation efforts • Communicate with stakeholders and other actors in the Basin about important interstate actions that will reduce nutrient pollution in the Upper Mississippi River and gain their commitment to ongoing implementation efforts • Maintain and enhance interstate collaboration that will reduce nutrient pollution in the Upper Mississippi River by supporting the Hypoxia Sub-Basin Committee and its various work teams • Integrate the important interstate actions that will reduce nutrient pollution in the Upper Mississippi River with other important interstate actions, such as flood mitigation and resilience planning	• Protect and restore water quality, especially in historically underserved and underrepresented communities • Share water quality data to inform decision making of policies and natural resource management • Inform progress of the Hypoxia Task Force member states to reducing nutrient pollution to the Gulf of Mexico "Dead Zone" • Understand how climate change is impacting nonpoint source pollution and water quality • Amplify and coordinate successful state programs to make further progress in reducing nonpoint source nutrient pollution

Each workplan action as stated above is in line with USEPA's strategic goals for sub-basin committees (Table 2).

Table 2: UMRBA's workplan tasks and their alignment to USEPA's strategic goals for sub-basin committees. Each workplan task is associated with strategic goals one through four.

UMR Hypoxia Sub-Basin Committee Workplan Task	Alignment with Strategic Goals 1-4 for Sub-Basin Committees
Compile the separate state nutrient reduction strategies into an integrated Upper Mississippi River Nutrient Reduction Strategy and identify important interstate actions that will reduce nutrient pollution in the Upper Mississippi River	1. Convene regional, state, and other stakeholders not represented on the Task Force, including additional basin states, basin tribes, agencies, and interested parties and organizations to gather input, facilitate peer-to-peer learning opportunities, and encourage collaboration across boundaries 2. Help the states engage disadvantaged communities in nutrient reduction planning and activities within their boundaries 3. Support states in the respective sub-basins as they implement and coordinate comprehensive nutrient reduction strategies across boundaries. For example, where states are looking to adopt 4. Coordinate, consolidate, and improve access to data and present regional progress towards the Action Plan goals
Evaluate implementation of important interstate actions to reduce nutrient pollution in the Upper Mississippi River and incorporate insights into ongoing implementation efforts	This action relates to all four strategic goals for the Sub-Basin Committee.
Communicate with stakeholders and other actors in the Basin about important interstate actions that will reduce nutrient pollution in the Upper Mississippi River and gain their commitment to ongoing implementation efforts Maintain and enhance interstate collaboration that will reduce nutrient pollution in the Upper Mississippi River by supporting the Hypoxia Sub-Basin Committee and its various work teams Integrate the important interstate actions that will reduce nutrient pollution in the Upper Mississippi River with other important interstate actions, such as flood mitigation and resilience planning	These actions relate to all four strategic goals for the Sub-Basin Committee.

Outreach Strategies

UMRBA and the UMR HTF Sub-Basin Committee will maintain existing relationships and reach out to new individuals and organizations as UMRBA implements the proposed workplan. UMRBA will focus on developing new relationship with individuals and communities that have not been engaged effectively by past pollution reduction activities, such as native nations, ethnically diverse individuals, and economically disadvantaged communities.

UMRBA will utilize social research and professional experience to identify individuals, communities and organizations with whom we want to develop new relationships.

UMRBA will employ communication activities (focused by our communications plan) and convene in-person and virtual meetings (focused by our collaborative management strategies) to enhance participation among existing and new stakeholders.

Equity Statement

As the leading organization in the Midwest dedicated to solving the complex water resource challenges facing the Upper Mississippi River Basin, UMRBA recognizes the essential importance of including all people and communities in the process of creating and implementing solutions to these challenges. UMRBA welcomes, respects, and appreciates all of the ways individuals identify by race, ethnicity, gender identity, sexual orientation, religion, disability, and socioeconomic stratum, and is consistently striving to expand the range of voices, experiences, and perspectives that are heard in the discussions we convene throughout the Basin. UMRBA is also committed to understanding and addressing the impact that its policies and programs have on different people and communities, and working to ensure equity in opportunity and outcomes.

Budget Resources

A quality management plan and quality assurance project plan are not applicable to this workplan.

UMRBA will not be utilizing subawards for this workplan.

Environmental Results

Anticipated Outcomes

- Reduced nutrient pollution in the Upper Mississippi River
- More engagement and participation by traditional and non-traditional stakeholders in the Basin
- More effective collaboration among states and their executive agencies

Anticipated Outputs

- Data, analysis, and information about status and trends in nutrient pollution in the Upper Mississippi River

- Interstate actions that contribute to nutrient pollution reduction in the Upper Mississippi River
- Annual evaluations of interstate actions to continuously improve design and implementation
- Messages, meetings, workshops, and other stakeholder participation opportunities
- Regular meetings of the UMR Hypoxia Sub-Basin Committee and its work teams

Anticipated Products

- An integrated Upper Mississippi Nutrient Reduction Strategy
- An Adaptive Management Framework
- An Upper Mississippi Nutrient Reduction Communications Plan
- Notes and records of meetings of the UMR Hypoxia Sub-Basin Committee and its work teams

Milestone Schedule

For the project period of October 1, 2023 to September 30, 2026 (federal fiscal years 2024 through 2026), the proposed milestone schedule is as follows in Table 3.

Table 3: Milestones for accomplishing workplan tasks. An "X" denotes when the subtasks are expected to be completed.

Tasks	FY 2024	FY 2025	FY 2026
Compile the separate state nutrient reduction strategies into an integrated Upper Mississippi River Nutrient Reduction Strategy and identify important interstate actions that will reduce nutrient pollution in the Upper Mississippi River	X		
Communicate with stakeholders and other actors in the Basin about important interstate actions that will reduce nutrient pollution in the Upper Mississippi River and gain their commitment to ongoing implementation efforts	This work is ongoing.		
Maintain and enhance interstate collaboration that will reduce nutrient pollution in the Upper Mississippi River by supporting the Hypoxia Sub-Basin Committee and its various work teams	This work is ongoing.		
Integrate the important interstate actions that will reduce nutrient pollution in the Upper Mississippi River with other important interstate actions, such as flood mitigation and resilience planning	This work is ongoing.		
Evaluate implementation of important interstate actions to reduce nutrient pollution in the Upper Mississippi River and incorporate insights into ongoing implementation efforts		X	X

Transferability of Results and Dissemination to Public

UMRBA will utilize its existing networks to disseminate information by email, newsletters, and listservs, UMRBA's and USEPA's HTF website, social media, webinars and presentations. UMRBA will utilize its partnerships, both those are existing and cultivated as part of developing the UMR Interstate Nutrient Reduction Strategy, Adaptive Management Framework, and an Interstate Communications Strategy to further bolster the distribution of information – e.g., UMRBA Board, HTF, the North Central Region Water Network, Upper Mississippi River Restoration program, and the Navigation and Ecosystem Sustainability Program.

Detailed Budget Narrative

The budget for the workplan is below and is intended to be evenly divided among three FYs (October 1, 2023 through September 30, 2026).

Budget Category	Amount
Personnel	195,000.00
Fringe	78,146.00
Travel	7,500.00
Supplies	2,102.00
Contractual	16,000.00
Other	5,805.00
Total Direct Cost	304,552.00
Indirect Cost	95,447.00
Total	**$400,000.00**

The budget for this workplan by project is estimated as follows:

Workplan Task	Amount
Upper Mississippi River Nutrient Reduction Strategy	131,870.00
Upper Mississippi River Interstate Communications Strategy	142,065.00
Upper Mississippi River Nutrient Reduction Continuous Learning Framework	126,066.00
Total	**400,000.00**

Personnel

The personnel costs include the covering the time of five UMRBA staff amount to **$195,000.00.**

Fringe

Fringe benefits total **$78,146.00**. Note that fringe benefits include benefits (30%), paid non-working rate (0.173 of wages and benefits), and SS/Med (0.0765 of wages and benefits).

Travel

Proposed spending for travel is **$7,500.00** to cover lodging, airfare or rental car, and food per diem for travel to HTF CC meetings, planned meetings hosted by UMRBA to fulfill workplan needs, and other relevant nutrient meetings – e.g., Illinois Nutrient Loss Reduction Strategy annual conference.

Supplies

The requested amount for supplies is **$2,102.00**. The amount includes a computer and necessary technology supplies for the Project Coordinator to be able to perform their role. A computer will be used for a number of reasons, but not limited to email communication, hosting meetings, and writing documents.

Contractual

A communications consultant will help provide strategic direction for the components of a communications strategy for the UMRB. The estimated cost is **$16,000.00**.

Other

Meeting expenses such as renting a venue and providing light refreshments are estimated at **$5,805.00**.

Indirect Costs

For an indirect rate of 31.34 percent, the estimated indirect costs are **$95,447.00**.

Quality Assurance

The project does not include funding for the collection of environmental data. If data is used as part of project activities, the approaches for data collection and analysis will be thoroughly documented.

ATTACHMENT E

<u>Chloride</u>

- **Upper Limits for Road Salt Pollution in Lakes** *(E-1 to E-8)*

LIMNOLOGY AND OCEANOGRAPHY
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LETTER

Upper limits for road salt pollution in lakes

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Scientific Significance Statement

Concentrations of road deicing salt are increasing in many inland waters. High salt concentrations can negatively impact aquatic organisms and ecosystems. Few frameworks exist for predicting how high road salt concentrations might become in lakes. We present a simple, generalizable model that predicts equilibrium road salt concentrations in lakes as a function of salt application rate, road density, and runoff.

Abstract

Widespread and increasing use of road deicing salt is a major driver of increasing lake chloride concentrations, which can negatively impact aquatic organisms and ecosystems. We used a simple model to explore the controls on road salt concentrations and predict equilibrium concentrations in lakes across the contiguous United States. The model suggests that equilibrium salt concentration depends on three quantities: salt application rate, road density, and runoff (precipitation minus evapotranspiration). High application combined with high road density leads to high equilibrium salt concentrations regardless of runoff. Yet if application can be held at current rates or reduced, concentrations in many lakes situated in lightly to moderately urbanized watersheds should equilibrate at levels below currently recommended thresholds. In particular, our model predicts that, given 2010–2015 road salt application rates, equilibrium chloride concentrations in the contiguous United States will exceed the current regulatory chronic exposure threshold of 230 mg L^{-1} in over 2000 lakes; will exceed 120 mg L^{-1} in over 9000 lakes; and will be below 120 mg L^{-1} in hundreds of thousands of lakes. Our analysis helps to contextualize current trends in road salt pollution of lakes, and suggests that stabilization of equilibrium chloride concentrations below thresholds designed to protect aquatic organisms should be an achievable goal.

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Author Contribution Statement: CTS conceived the study, built and analyzed the model along with HAD and SEJ, and wrote the manuscript along with HAD, WDH, and SEJ.
Data Availability Statement: All of the data used in this paper are available in public repositories with DOIs, which are cited throughout the manuscript, supplementary material, and code. All code to access those data and reproduce the analyses and figures is available at https://github.com/MFEh2o/salt-model (doi: 10.5281/zenodo.7858887).

Additional Supporting Information may be found in the online version of this article.

Anthropogenic increases in salt concentrations of freshwaters are a widespread phenomenon with important implications for aquatic ecosystems, aquatic biota, and ecosystem services (Evans and Frick 2001; Kaushal et al. 2005, 2021; Cañedo-Argüelles et al. 2013, 2019; Hintz and Relyea 2019; Kinsman-Costello et al. 2023). These increases—together with increases in alkalinity that share some of the same drivers—have been recognized as part of an emerging global "freshwater salinization syndrome" (Kaushal et al. 2018, 2021). High salt concentrations can negatively impact aquatic ecosystems at multiple levels of organization, ranging from individual growth, reproduction, and survival to ecosystem-level nutrient cycling and energy flow (Hintz and Relyea 2019).

A leading cause of freshwater salinization in regions with cold winters is the application of road deicing salt (Thunqvist 2004; Kelly et al. 2008; Kaushal et al. 2018, 2021). The use of salt for road deicing in the United States began in a few locations around the late 1930s, and rapidly spread and intensified as new jurisdictions took up the practice, the area of salted road surface grew, and the rate of salt application per unit of road increased (Jackson and Jobbágy 2005; Hintz et al. 2022*b*). Recent data suggest that annual usage of road salt – mostly sodium chloride (NaCl)—is approximately 24.5 million tons in the United States, 7 million tons in Canada, and 0.15 to 2 million tons across several European countries (Arnott et al. 2020).

The intensification of road salt application has driven large and widespread increases in chloride concentrations in both surface and ground waters (e.g., Thunqvist 2004; Chapra et al. 2009; Likens and Buso 2010; Cassanelli and Robbins 2013; Kelly et al. 2018). A recent synthesis of long-term data from hundreds of lakes in North America demonstrated that increasing chloride trends are common; that there is substantial variation in current chloride concentrations and the rate at which they are changing; and that current trends suggest that many lakes may be at risk of reaching chloride concentrations that exceed regulatory guidelines for chronic exposure (Dugan et al. 2017).

These trends led us to wonder how high chloride concentrations might become in lakes influenced by road salting, and how that might vary across the landscape. To build insight about those questions we formulated and analyzed a simple model of lakes and their watersheds. We then used empirical estimates of the model parameters to predict equilibrium chloride concentrations in lakes under a wide range of conditions, and considered the implications of our findings for the management of road salt and the protection of freshwater ecosystems. Our analysis abstracts away some of the complexity of the real world and considers equilibrium conditions as a simple heuristic to help understand underlying patterns.

Model of road salt chloride in a watershed and lake

Road salt applied in a watershed is transported into and out of lakes by hydrologic fluxes. We used the following simple dynamic model of road salt chloride in the watershed (S_W; kg Cl^-) and road salt chloride in the lake (S_L; kg Cl^-) to describe these processes:

$$\frac{dS_W}{dt} = \alpha\delta A - r\phi S_W, \tag{1a}$$

$$\frac{dS_L}{dt} = r\phi S_W - rA\frac{1}{V}S_L. \tag{1b}$$

Here, chloride is added to the watershed by application at rate α to roads, which are present at density δ across the area

Table 1. State variables and parameters for a simple model of the mass of road salt (as chloride, Cl^-) in lakes and watersheds. Note that SI units are used in all cases; for example, "lane-m" is "lane-meters," which is different from the convention of reporting salt data in lane-miles in the United States. A lane is the width of road necessary for one car to move in one direction (so, e.g., a road that allows a car to move in each direction at the same time is a two-lane road). Lane width varies with road type and other conditions but is often $\sim$ 3.0–3.5 m.

State variable or parameter	Description	Units
S_W	Mass of road salt in the watershed	kg Cl^-
S_L	Mass of road salt in the lake	kg Cl^-
α	Application rate of road salt	kg Cl^- (lane-m road)$^{-1}$ yr^{-1}
δ	Density of roads in the watershed	lane-m m^{-2}
A	Area of the watershed	m^2
r	Runoff (precipitation − evapotranspiration)	m yr^{-1}
ϕ	Relative salt yield of the watershed per unit of runoff	m^{-1}
V	Lake volume	m^3

of the watershed, A. Precipitation that is not evaporated nor transpired becomes surface or subsurface runoff, r, which removes chloride from the watershed and delivers it to the lake, depending on ϕ, the relative chloride yield of the watershed per unit of runoff. Chloride in the lake is removed by hydrologic outflow. Descriptions and units for all the state variables and parameters of the model are provided in Table 1.

We made several simplifying assumptions in formulating this model. We ignored the distinction between surface and groundwater flows, treating all of the precipitation input to the watershed (net of evapotranspiration) as a single hydrologic flow path that moves from the watershed, to the lake, and then downstream. This allowed us to forego tracking the temporary but potentially long-term storage of chloride in soils or groundwater (Kelly et al. 2008). Instead the model mimics storage via ϕ, the parameter describing the proportion of the chloride currently in the watershed that is exported per unit of runoff; if ϕ is low the chloride in the watershed is exported very gradually (Fig. 1). We assumed that ϕ is constant; that the lake is exorheic, well-mixed on an annual scale, and has constant volume; and that direct precipitation on and evaporation from the lake are equal or negligible. Our model shares many assumptions and structural features with diverse previous models (e.g., Sonzogni et al. 1983; Bowser 1992; Novotny and Stefan 2010; Bailey et al. 2019; Dugan and Rock 2023), but combines a focus on the watershed-level features that determine water and chloride loads with a relatively abstracted and simple structure. It omits chloride derived either from natural weathering, which accounts for 0–10 mg Cl^{-} L^{-1} in most lakes and much more in some naturally saline lakes (Last and Ginn 2005; Hintz and Relyea 2019); or from anthropogenic sources other than road salt, which can be significant (Kaushal et al. 2021).

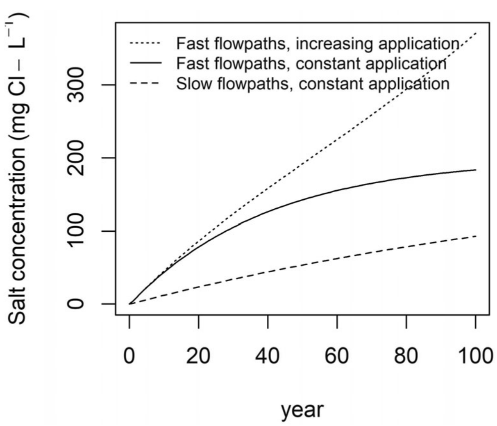

Fig. 1. Modeled trends in road salt chloride concentration in a lake through time. The relative yield of chloride from the watershed (φ) influences the rate at which the concentration of chloride in the lake approaches equilibrium. *Dotted line*: If the rate of salt application or the density of roads increases through time, chloride concentrations increase without reaching equilibrium. *Solid line*: Chloride concentration in the lake equilibrates rapidly to a constant rate of salt application in the watershed if relative yield from the watershed is high, as might occur because hydrologic flow paths to the lake are short or dominated by surface runoff. *Dashed line*: Equilibration to the same final concentration occurs slowly if relative yield from the watershed is low, as might occur if flow paths are dominated by slow groundwater flows.

Note that while the state variables in the model are masses of Cl^{-}, the concentrations of Cl^{-} in the lake (C_L) or in the lake's hydrologic inflow (C_I) can be calculated as:

$$C_L = \frac{S_L}{V}, \tag{2a}$$

$$C_I = \frac{r\phi S_W}{rA} = \frac{\phi S_W}{A}. \tag{2b}$$

To facilitate interpretation we present results as concentrations of Cl^{-}, converting units to mg L^{-1}.

The masses of road salt chloride in the watershed and the lake at equilibrium are given by:

$$S_W^* = \frac{\alpha\delta A}{r\phi}, \tag{3a}$$

$$S_L^* = \frac{\alpha\delta V}{r}. \tag{3b}$$

Substituting Eq. 3b into Eq. 2a demonstrates that the equilibrium concentration of road salt chloride in the lake depends only on the rate of application to roads, the road density, and runoff:

$$C_L^* = \frac{\alpha\delta}{r}. \tag{4}$$

Comparing model predictions to empirical observations in one well-studied watershed suggests that predicted equilibrium chloride concentrations are plausible. Likens and Buso (2010) estimated annual chloride budgets for Mirror Lake, New Hampshire from the late 1960s through 2007, documenting the impacts of two roads that were built through the watershed around 1970. We used data from their paper, along with Eq. 4, to calculate the predicted equilibrium chloride concentration in the lake under two scenarios, assuming that engineering controls intended to prevent salt runoff to the lake from one of the roads were either 100% or 0% effective (*see* Supporting Information for details). Predicted equilibrium Cl^{-} concentrations under these two scenarios were 0.6 and 31 mg L^{-1}, while the actual Cl^{-} concentration was $\sim$3–4 mg L^{-1} in 2007 and has varied between 3 and 5 mg L^{-1} between 2008 and 2021 (*see* Supporting Information).

We applied the model in three ways to build insight into equilibrium road salt chloride concentrations in lakes. First, we solved the model through time to *see* how chloride concentrations approach equilibrium. Next, we explored general patterns in equilibrium chloride concentration across wide but realistic ranges of road salt application rate and road density, for three different values of runoff representing the range of climates across the northern United States. Finally, for each lake or reservoir larger than 1 ha in the contiguous United States (Cheruvelil et al. 2021; Lehner et al. 2022), we calculated the equilibrium road salt chloride concentration expected if salt application were to be held at reported 2010–2015 levels (Falcone et al. 2018). Details on each of these three model applications are provided in the Supporting Information. All of the code to reproduce our analyses is publicly available (Dugan and Solomon 2023).

Results

The equilibration of lake road salt chloride concentration to the rate of road salt application in the watershed may occur slowly (Fig. 1; *see* also e.g., Novotny and Stefan 2010; Dugan and Rock 2023). How slowly depends on several features of the lake's hydrologic setting, as indicated by Eq. 1b. These include runoff from the watershed; the ratio of watershed area to lake volume; and the extent of temporary storage in the watershed via slow hydrologic flow paths, which is represented in the model via the relative salt yield parameter, ϕ. During the approach to equilibrium, the increase in chloride concentration is essentially linear for many years or even many decades (Fig. 1). Furthermore, increases through time in road density or salt application rate shift the equilibrium concentration higher and delay equilibration (Eq. 4; Fig. 1).

High road density combined with high salt application rates leads to high equilibrium chloride concentrations, regardless of regional runoff conditions (Fig. 2). For instance, even in a wet climate where high runoff dilutes salt inputs, equilibrium chloride concentration is > 200 mg $Cl^- L^{-1}$ if road density in the watershed exceeds 0.010 lane-m m^{-2} and application rate exceeds 10 kg Cl^- (lane-m)$^{-1}$ yr^{-1} (Fig. 2C). These are high but realistic values for both road density (Fig. 2D) and application rate (Dugan et al. 2017; note that 10 kg Cl^- (lane-m)$^{-1}$ yr^{-1} is equivalent to 29 US tons NaCl (lane-mile)$^{-1}$ yr^{-1}). In drier climates equilibrium chloride concentrations can exceed 200 mg $Cl^- L^{-1}$ even in watersheds with substantially lower road density or application rates (Fig. 2a,b).

If road salt application can be held at current rates or reduced, road salt chloride concentrations in many lakes situated in lightly to moderately urbanized watersheds should equilibrate at levels below 230 mg $Cl^- L^{-1}$, the current U.S. Environmental Protection Agency threshold for chronic exposure (Fig. 2). In wet climates in particular, even watersheds with road densities of 0.014 m m^{-2}—a value typical of major suburbs such as Westchester County, New York or Middlesex County, Massachusetts—are predicted to have equilibrium road salt chloride concentrations below 230 mg $Cl^- L^{-1}$ if salt application rates are kept below 13.5 kg Cl^- (lane-m road)$^{-1}$ yr^{-1}.

Most of the lakes and reservoirs ("lakes") larger than 1 ha in the contiguous United States for which the model predicts

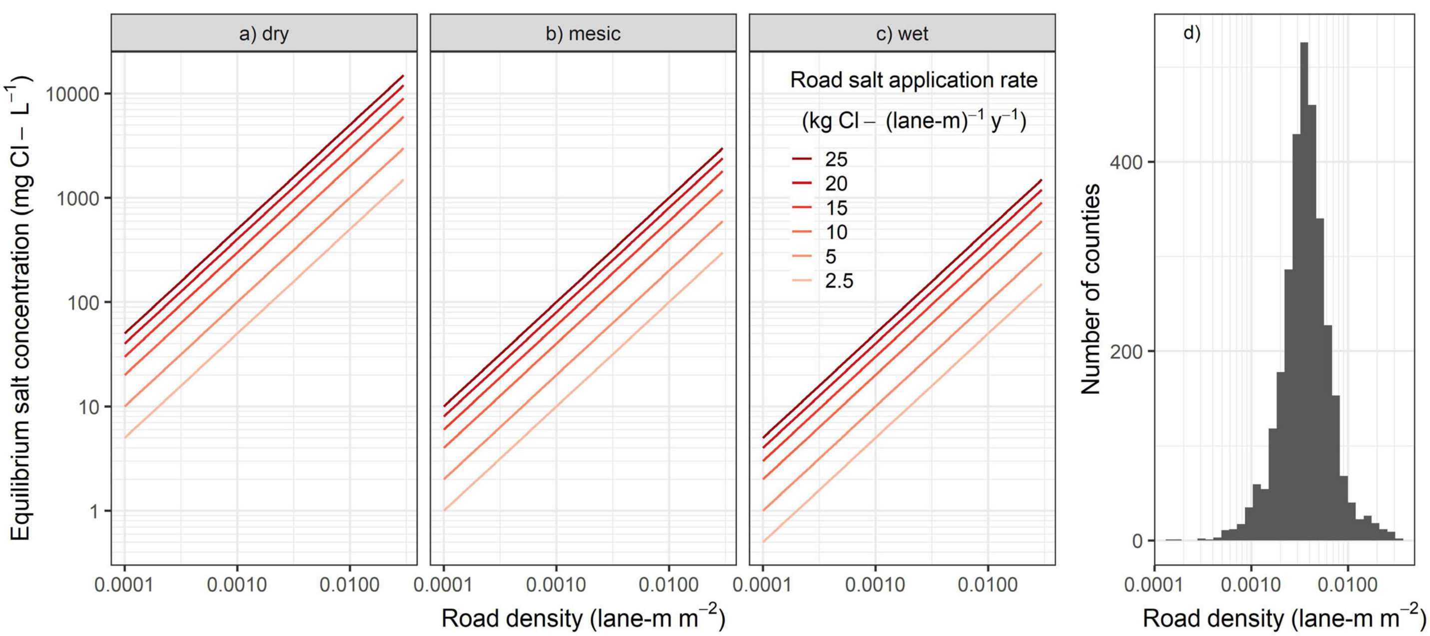

Fig. 2. (**a–c**) Equilibrium road salt chloride concentration varies with runoff (precipitation − evapotranspiration), road density, and road salt application rate. Panels give model predictions for dry, mesic, and wet climates (runoff = 0.02, 0.25, or 0.50 m yr^{-1}, corresponding roughly to the climates of Montana, Michigan, and Connecticut, USA), across ranges of road density and road salt application rate corresponding to empirically observed ranges. (**d**) Road density distribution for county-level administrative units in the contiguous United States. *See* text and Supporting Information for additional details.

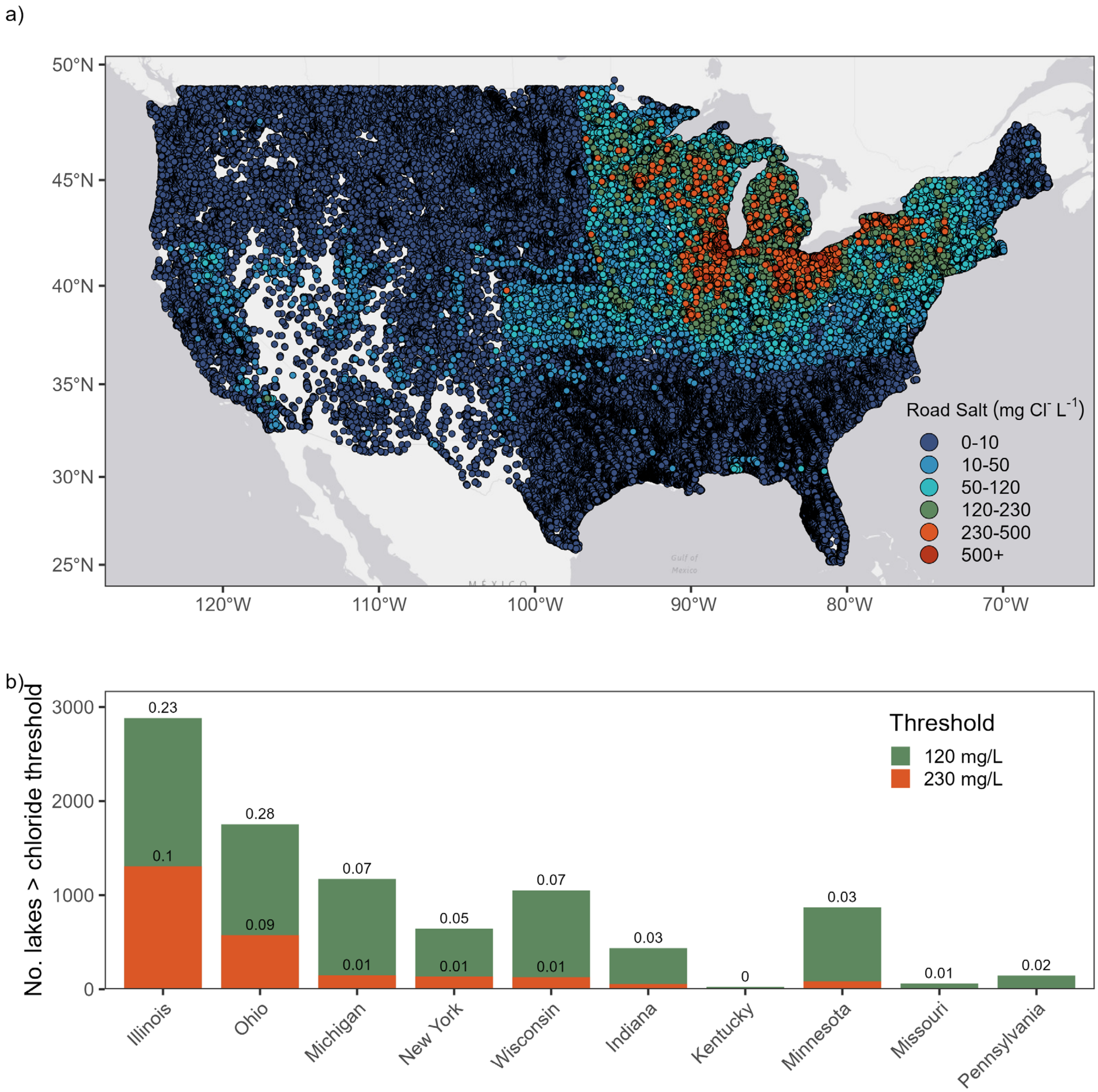

Fig. 3. (**a**) Predicted equilibrium road salt chloride concentration for 461,567 lakes and reservoirs ("lakes") larger than 1 ha in the contiguous United States. These predictions rest on a number of important assumptions, including that road density and salt application rate per lane-m of road remain constant at mean 2010–2015 levels, and that evaporation from and precipitation on the lake surface are equal or negligible; they should be interpreted with caution. (**b**) State-level summary of the abundance of lakes for which the predicted equilibrium road salt chloride concentration exceeds 120 or 230 mg Cl^{-} L^{-1}. Results are shown for all states where at least 25 lakes have predicted equilibrium concentrations > 120 mg Cl^{-} L^{-1}. Numbers printed above bars indicate relative abundance, that is, the proportion of lakes in the state that exceed each threshold; relative abundances <0 .01 are not shown. States are ordered left to right in decreasing order of the proportion of lakes in the state that exceed the 230 mg Cl^{-} L^{-1} threshold.

high equilibrium road salt chloride concentrations, given reported 2010–2015 salt application rates, are in the Northeast and Midwest (Fig. 3). The road network is densely developed in many places within this region, and salt application rates are often high. Lakes larger than 1 ha with predicted equilibrium chloride concentrations in excess of the 230 mg Cl^{-} L^{-1} threshold were most abundant in Illinois and Ohio, where they represented 9–10% of all lakes larger than 1 ha (Fig. 3b). Lakes with predicted concentrations above this threshold were also present in Indiana, Iowa, Kansas, Michigan, Minnesota, New York, Pennsylvania, and Wisconsin, where they represented < 0.1% to 1% of lakes larger than 1 ha, and in the District of Columbia, where they represented 17% of 12 lakes. Lakes with predicted equilibrium road salt chloride concentrations above the 120 mg $Cl^- L^{-1}$ threshold used as a water quality guideline in Canada were much more abundant: in Illinois and Ohio 23–28% of lakes had predicted concentrations above this threshold, and in several other states 1–7% of lakes were above this threshold (Fig. 3b). Across the contiguous United States, more than 9000 lakes (2%) were predicted to have equilibrium road salt chloride concentrations in excess of 120 mg $Cl^- L^{-1}$.

Discussion

As our model emphasizes, the concentration of road salt chloride in a lake is ultimately controlled by the amount of salt applied in its watershed and by runoff. Increases in road salt application rates and road density, and gradual equilibration to those changes, have all contributed to the increases in chloride concentrations that have been observed in many surface waters since the widespread adoption of road salting in the mid-1900s.

Our analysis suggests that it should be possible in many places to stabilize average road salt concentrations at levels below the current EPA threshold (230 mg $Cl^- L^{-1}$) for protection of aquatic life. Simply limiting salt application rates to current business-as-usual levels might achieve this goal in watersheds which have low to moderate road density and mesic to wet climates, while reducing application rates may be particularly important where road density is high or increasing (Fig. 2). Emerging evidence suggests that it is possible to reduce application rates without degrading road safety, via changes in technology and practices (Kelly et al. 2019; Hintz et al. 2022*b*). Reduced application rates generate an ongoing cost savings for transportation authorities, but the upfront costs of implementing new technologies can be substantial. Programs to help defray upfront costs could accelerate the transition to lower application rates and pay substantial economic and environmental dividends.

An important question is whether stabilizing average road salt chloride concentrations at 230 mg $Cl^- L^{-1}$ would be sufficient to protect aquatic ecosystems from undesirable changes. There are at least five reasons for caution here. First, even concentrations well below this threshold may be many times higher than the background concentrations arising from natural weathering, and thus well outside the range that aquatic organisms were historically exposed to (Hintz and Relyea 2019). Second, this EPA chronic toxicity threshold was developed based on laboratory experiments with only three aquatic organisms, and there is increasing evidence that negative impacts on some aquatic organisms occur at chloride concentrations well below 230 mg L^{-1}, particularly in waters with low background concentrations of calcium, magnesium, and other ions (Elphick et al. 2011; Arnott et al. 2020; Dugan and Arnott 2022; Hintz et al. 2022*a*; Wersebe et al. 2023). Given this evidence it seems prudent to take a precautionary approach in managing road salt application and controlling road salt pollution. Regulatory agencies in some jurisdictions such as Canada and Michigan use lower thresholds of 120–150 mg $Cl^- L^{-1}$. Third, road salt is only one of many potential contributors to salinization, along with other anthropogenic impacts such as irrigation runoff and accelerated mineral weathering (Kaushal et al. 2018). Fourth, we know very little about how salt mixtures from multiple sources will affect aquatic organisms (Kaushal et al. 2019). Fifth, even if average concentrations equilibrate below 230 mg $Cl^- L^{-1}$, much higher concentrations may occur in the lake at some times and places, due to vertical concentration gradients during winter or high winter or spring chloride loads that are subsequently flushed (Novotny et al. 2008; Corsi et al. 2010; Novotny and Stefan 2010). More elaborate models than ours, whether existing or new, could help describe these temporary excursions from equilibrium and the more rare but important cases when very high levels of salt input induce permanent stratification and meromixis (Smol et al. 1983; Ladwig et al. 2023). In addition, further work is clearly needed to better understand both the acute and chronic effects of high chloride concentrations on aquatic organisms and ecosystems.

While the general conclusions of our analysis seem fairly robust, the lake-specific predictions of equilibrium road salt concentrations that we present in Fig. 3 should be interpreted with caution. Some model assumptions are clearly violated for some lakes. For instance, lakes where evaporation dominates hydrologic losses, which are common in semi-arid regions, will concentrate road salt inputs substantially beyond the levels predicted by the model and thus will be particularly sensitive to high road density and high salt application rates. Our lake-specific predictions also make a number of assumptions in addition to those embedded in the model structure, including that actual road salt application rates are held constant indefinitely at mean 2010–2015 levels as reported by Falcone et al. (2018), and that road density and runoff also remain constant. Furthermore, because our model's treatment of hydrologic flow paths is highly abstracted, it is probably best suited for considering how equilibrium road salt chloride concentrations vary across the landscape in response to road density, salt application rate, and climate, not for understanding detailed temporal dynamics within a given system.

Our model also assumes that the relative chloride yield of the watershed per unit of runoff (ϕ) is constant, and in particular that it does not vary with the amount of chloride in the watershed. This assumption, like others that our model makes, is a simplification of reality. While chloride does generally behave conservatively (particularly at long time scales and high input rates), it nonetheless can be immobilized in ecosystems by processes including adsorption onto iron and aluminum oxides, uptake by microbes and vegetation, and conversion to organic forms (Svensson et al. 2012). A more elaborate model might allow some sort of saturating increase in ϕ as the mass of chloride in the watershed increases, to mimic saturation of these immobilizing processes. This change would likely result in somewhat lower predicted equilibrium chloride concentrations for lakes in watersheds receiving low inputs of road salt, where immobilizing processes might play an important role.

Two additional extensions of the simple approach that we took here seem potentially valuable as next steps, in addition to the use of more elaborate hydrological and limnological models. First, additional efforts to compare the model predictions to data in places where salt inputs and lake chloride concentrations have been documented over many years, as in the Mirror Lake example that we considered, would help clarify the usefulness of the model as a heuristic. Second, it would be interesting to use the model to explore how other forms of global change—such as land use or climate changes that alter the balance of precipitation and evapotranspiration or the frequency with which road salt applications are necessary—might influence road salt concentrations in lakes.

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ATTACHMENT F

Cyanobacterial Harmful Algal Blooms (CyanoHABs) in Water Bodies: U.S. Environmental Protection Agency

https://www.epa.gov/cyanohabs

ATTACHMENT G

Statistical Survey Tools for Monitoring

- **USEPA Survey Design Tool (v.1.1.0):**
  https://owshiny.epa.gov/survey-design-tool/

- **USEPA National Aquatic Resource Survey (NARS) Population Estimate Calculation Tool (v.2.2.0):**
  https://owshiny.epa.gov/nars-popest/

- **USEPA NARS results from 2018-2019 for the Upper Mississippi River:**
  https://riverstreamassessment.epa.gov/dashboard/?&view=indicator&studypop=rs&subpop=upper+mississippi&label=none&condition=good&diff=2v3