

THESIS

POST-FIRE CHLOROPHYLL-A DYNAMICS IN HEADWATER RESERVOIRS AND A
TOTAL ORGANIC CARBON DECISION SUPPORT SYSTEM FOR MUNICIPAL
OPERATORS IN THE CACHE LA POUDE WATERSHED

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ABSTRACT

POST-FIRE CHLOROPHYLL-A DYNAMICS IN HEADWATER RESERVOIRS AND A TOTAL ORGANIC CARBON DECISION SUPPORT SYSTEM FOR MUNICIPAL OPERATORS IN THE CACHE LA POUDE WATERSHED

Severe wildfires increasingly threaten western municipal water supplies by altering headwater catchments. This thesis addresses source water risks in the Cache la Poudre (CLP) River watershed following the 2020 Cameron Peak Fire through two separate studies: evaluating upstream reservoir responses post-fire and developing operational decision-support tools for municipal treatment operators to track Total Organic Carbon (TOC).

First, I evaluated wildfire impacts across seven high-elevation reservoirs and their downstream reaches using field sampling and remote sensing. Burned reservoirs exhibited elevated sediment (18%) and potassium (11%) concentrations, and elevated spring nitrate levels beginning in the second-year post-fire. Extensively burned reservoirs displayed consistently higher total dissolved nitrogen, sulfate, and dissolved organic carbon. Chlorophyll *a* (Chl-*a*) concentrations were 18% higher in burned reservoirs, though remote sensing revealed no immediate secchi disk depth decrease amidst long-term warming trends. While mainstem Chl-*a* remained low (0.5–1.5 $\mu\text{g L}^{-1}$), reservoirs exerted localized influences on downstream Chl-*a*. These results indicate that reservoirs may modulate wildfire impacts by transforming nutrient enrichment into algal biomass that propagates downstream, but in this study downstream Chl-*a* remained low.

Second, we designed two machine-learning tools to support municipal early warning of elevated in-stream TOC. To estimate upstream TOC concentrations in real-time, I trained an Extreme Gradient Boosting (XGBoost) model ensemble on multi-parameter sonde data. To support longer-term planning, I developed a generalized additive model (GAM) incorporating historical grab sample data (2010–2025), SNOTEL snowmelt rates, and NOAA streamflow forecasts to predict TOC seven days in advance at the CLP raw water intake. Both tools were integrated into a live operational dashboard. Developed through an iterative, stakeholder-driven process with municipal partners, this framework demonstrates how academic-practitioner partnerships can successfully transition environmental data science into operational water management.

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AI disclosure:

This study used generative AI tools for text editing and software development (Google, 2026). All AI-generated text and software were carefully reviewed, validated, and, where necessary, modified. I maintain full responsibility for the ideas, text and analyses represented.

Note:

Any commercial equipment, instruments, or materials are identified in this paper in order to specify the experimental procedure adequately and does not imply endorsement or recommendation by the USFS Rocky Mountain Research Station or regional water providers, nor is it intended to imply that the materials or equipment identified are necessarily the best available for the purpose.

Please refer to Appendix A for the mentioned supplemental information (SI) figures or tables mentioned throughout Chapter 1, and Appendix B for SI figures or tables mentioned throughout Chapter 2.

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INTRODUCTION

As wildfire frequency and severity increase under climate change (Alizadeh et al., 2021; Cunningham et al., 2024), the impacts to water quality and municipal water supplies sourced from forested headwater catchments are expected to intensify. Forested catchments supply approximately 60% of municipal and agricultural water across the western United States (N. Liu et al., 2021) and represent high-quality source waters (N. Liu et al., 2022). Wildfires reduce canopy cover and plant water uptake while decreasing surface albedo, resulting in earlier, faster, and larger snowmelt (Kampf et al., 2022; A. P. Williams et al., 2022) and flashier responses to precipitation events (Miller et al., 2025). Post-fire water quality impacts which can impair downstream water treatment (Wall et al., 2026; Writer et al., 2014) include elevated exports of sediment (Ryan et al., 2024), dissolved organic carbon (DOC) (A. T. Chow et al., 2019; Clow et al., 2024; Hohner et al., 2019; Rhoades et al., 2019), and nutrients (Fernandez et al., 2024; Ruckhaus et al., 2025; Silins et al., 2014), particularly nitrogen (N) (Brucker et al., 2025; Hampton et al., 2022; Rhoades et al., 2019). However, less is known about how these impacts manifest in the high-elevation reservoirs that municipal water systems rely on to store water through the late summer (Barnard et al., 2023), and whether these water bodies modulate or amplify post-fire loads of DOC, N, and phosphorus (P) (McCullough et al., 2019; Paul et al., 2022).

Elevated N and P loading, coupled with warming lake temperatures under climate change (Christianson & Johnson, 2020; Kraemer et al., 2021), may increase the risk of phytoplankton blooms (Nydick et al., 2004; Oleksy et al., 2020a, 2020b). Because reservoirs supply the majority of late-summer streamflow, algal growth in reservoir bodies and outflows could

propagate downstream and impair treatment at municipal raw water intakes (Rounds et al., 2015; Ruhl et al., 2023; Schmadel et al., 2024).

This study collected water samples across seven water supply reservoirs and the rivers that drain them in the Cache la Poudre (CLP) watershed from 2021–2024, following the 2020 Cameron Peak Fire. We investigated whether reservoir water quality responded similarly to nearby burned streams (Rhoades et al., 2025), whether reservoirs with burned catchments exhibited elevated chlorophyll-a (Chl-*a*), a proxy for phytoplankton abundance, and whether reservoirs influenced downstream Chl-*a* in the river mainstem. We supplemented contemporary field observations with historical (1990–2024) remotely sensed estimates of Secchi disk depth and lake surface temperature (Steele et al., 2026b, 2026a) to assess whether a sustained shift in reservoir clarity or temperature occurred following the fire.

While these results characterize post-fire reservoir dynamics, they were not sufficiently actionable for day-to-day drinking water plant operations. Operators identified total organic carbon (TOC) as a key operational metric that influences pre-treatment water quality for municipal supply, because TOC reacts with chlorine during disinfection to form disinfection byproducts (DBPs) in finished water (Cadee et al., 2025). DBPs are harmful to human health (Cadee et al., 2025; S. D. Richardson et al., 2007; S. D. Richardson & Postigo, 2015), and because of this TOC removal is regulated at both the national (U.S. Environmental Protection Agency, 2015) and Colorado state level (5 CCR 1002-11.24 - Disinfection Byproduct Precursors Rule, 2024). In snow-dominated hydrologic systems (Hensley et al., 2022; Raymond et al., 2016; Zarnetske et al., 2018) TOC peaks during snowmelt and can also be mobilized in intense post-fire storm events (Hohner et al., 2019). To meet TOC removal requirements, utilities can blend raw water from multiple sources to increase alkalinity and improve coagulation

efficiency prior to chlorination (Cadee et al., 2025; S. D. Richardson & Postigo, 2015). Despite daily TOC measurements at treatment plants and operators' institutional knowledge of seasonal TOC dynamics, management has remained largely reactive, responding to elevated TOC rather than anticipating it.

To address this challenge, in the second chapter of this thesis I co-designed with CLP operators an early warning TOC decision support system. Development followed an iterative co-design process built around four practices: structured elicitation of operator needs and decision windows (Houser et al., 2025; J. A. Olsson & Andersson, 2007); transparent communication of model risks and limitations before asking operators to act on outputs (B. Roy, 2005; Wątróbski et al., 2019); systematic incorporation of operators' institutional knowledge of seasonal TOC dynamics and treatment thresholds into model design (Baroni et al., 2014; Gregory et al., 2001); and operator-led performance evaluation, where end users defined acceptable error targets and provided feedback on operational utility (Fogli & Guida, 2013). We deployed 19 sensors across the CLP basin and trained an XGBoost model ensemble (Chen et al., 2014) on multiparameter sensor data to estimate real-time upstream TOC along the river mainstem and larger tributaries, alongside a GAM-based seven-day probabilistic intake forecast driven by NOAA HEFS streamflow projections (Demargne et al., 2014), both integrated into an operational dashboard.

CHAPTER 1: POST-FIRE EFFECTS ON HIGH-ELEVATION RESERVOIRS AND RESERVOIR IMPACTS ON RIVERINE DYNAMICS

Chapter Overview

The 2020 Cameron Peak Fire, the largest in Colorado history, burned 579 km² of the upper Cache la Poudre River watershed, and broadly increased nutrient and sediment delivery to streams within the watershed. These changes coupled with earlier snowmelt and flashier responses to rain events impacted water supplies and water treatability for regional municipal water providers. In this study, we collected water samples and used remote sensing observations across seven high elevation reservoirs and their downstream reaches to answer two broad questions: A) how does fire impact water quality in high elevation reservoirs? and B) how do differences in reservoir chlorophyll *a* concentrations alter downstream Chl-*a* concentrations, if at all?

Consistent with previous post-fire stream chemistry studies, burned reservoirs exhibited greater sediment (18%) and potassium (11%) concentrations indicative of ash transport. We also observed elevated Spring nitrate peaks began in the second-year post-fire. Additionally, we found that two extensively burned reservoirs had consistently higher total dissolved nitrogen, sulfate, and dissolved organic carbon (DOC) than unburned reservoirs. Chl-*a* concentrations were 18% higher in burned catchments compared to unburned catchments, with increased NO₃⁻ appearing to drive this response. Remote sensing did not identify an immediate decrease in post-fire water clarity and no shift in the trend of warming reservoir surface temperatures. The majority of mainstem Chl-*a* concentrations were low (0.5-1.5 µg L⁻¹) but reservoirs increased Chl-*a* concentrations up to 15 km downstream. Although the lack of pre-fire Chl-*a* and chemistry data in these reservoirs limits direct attribution, comparisons between burned and unburned

systems indicate that reservoirs modulate wildfire impacts by transforming nitrogen enrichment into Chl-*a* increases that propagates downstream.

LITERATURE REVIEW

Wildfire and Climate Change 2.1

In the Western United States, more than 60% of water supplies come from headwater streams originating from high elevation forests (N. Liu et al., 2021, 2022). In many locations, this water is stored in upstream reservoirs (Simeone et al., 2024) then transported along the river main stem to municipal water intakes. Water suppliers rely on these high quality sources to provide clean drinking water, which minimizes treatment costs for communities throughout the West (Abildtrup et al., 2013; N. Liu et al., 2022; Writer et al., 2014). However, forests of the Western United States are changing rapidly as a result of climate change (Petrie et al., 2017), land use changes (Kueppers et al., 2008; Theobald et al., 2011), and wildfires (Cunningham et al., 2024; Stevens-Rumann et al., 2018; Weber & Yadav, 2020; Zhuang et al., 2021). The increasing prevalence of wildfire at higher elevations increasingly threatens high-elevation headwaters and forests, ecosystems that have not historically experienced frequent burning (Alizadeh et al., 2021).

Wildfire Impacts to Stream Water Quality 2.2

Wildfires increasingly concern regional water providers due to their impacts on plant infrastructure (K. W. Jones et al., 2023), snowmelt timing (Kampf et al., 2022), streamflow dynamics (Barnard et al., 2023; Miller et al., 2025), and water quality (Ruckhaus et al., 2025). Wildfires generate higher flood risk and debris flows (Moody & Martin, 2001; White et al., 2006) which elevate stream sediment - particularly during intense summer rainstorms (Hohner et al., 2016; Ryan et al., 2024). In burned watersheds, ash mobilization and reduced uptake of nutrients by vegetation drive elevated stream concentrations of dissolved organic carbon (DOC)

(Clow et al., 2024; Hohner et al., 2016; Writer et al., 2014), nitrogen (N), particularly nitrate (NO_3^-) (Raoelison et al., 2023; Rhoades et al., 2025; Ruckhaus et al., 2025), phosphorus (P) (Fernandez et al., 2024; Ruckhaus et al., 2025; Silins et al., 2014), potassium (K^+) (J. S. Evans et al., 2021; Fernandez et al., 2024), and heavy metals (Abraham et al., 2017; Raoelison et al., 2023; Wall et al., 2026). These impacts can last for decades as fires can cause large decreases in forest cover and increasing prevalence of grasslands (Rodman et al., 2024; Stevens-Rumann et al., 2018), altering nutrient dynamics and elevating nitrate concentration as much as ten years post-fire (Rhoades et al., 2019). However, the magnitude and duration of these effects vary by solute and are modulated by burn severity and extent of burned area within the catchment, vegetation recovery since fire, and the mechanism of delivery of solutes from the catchment to surface waters. Subsurface flow mobilizes solutes gradually, often elevating concentrations on the rising limb of hydrographs, while storm-driven surface runoff produces intense but short-lived peaks in solute concentration often accompanied by elevated sediment loads (Brucker et al., 2025; Rhoades et al., 2025)

Much of the motivation driving studies on post-fire impacts on stream water quality is to better understand how fires directly impact drinking water treatment plant operations (Emelko et al., 2011; Hohner et al., 2019; Writer et al., 2014). Most of these studies are concentrated in 1st to 3rd order streams where paired watershed studies (Raoelison et al., 2023; Rhoades, et al., 2025; Rust et al., 2019) allow for a more precise accounting of fire impacts on stream and watershed dynamics. Yet, drinking water plants are not directly diverting their water from small streams, or even high elevation water supply reservoirs, but rather from the higher order rivers that integrate all of these upstream inputs. In contrast to the current understanding of fire impacts to streams,

less is known about how wildfire impacts lakes and reservoirs, particularly high elevation ones, and even less is known about how networks of reservoirs and rivers cumulatively respond to fire.

Here, we propose a conceptual framework (Figure 1a) linking fire disturbance to watershed and lake processes that elevate the risk of phytoplankton algal growth (hereafter ‘algae’) and downstream impacts to water providers (Figure 1b).

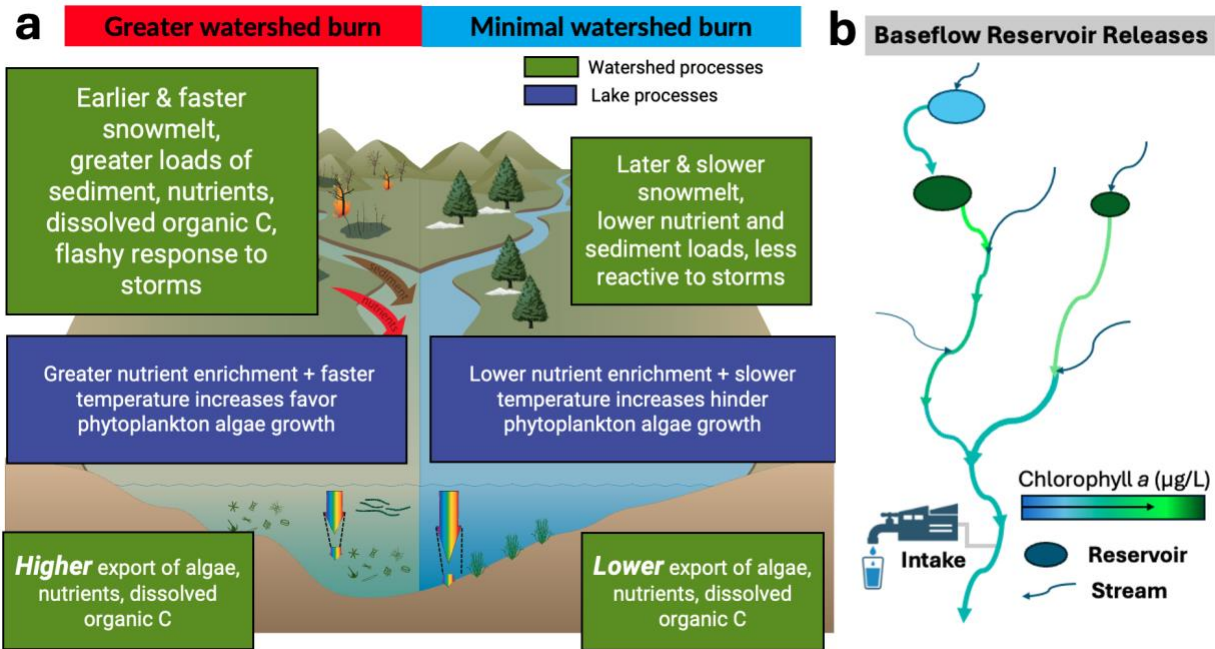


Figure 1: Conceptual framework of post-fire reservoir and riverine dynamics. (a) Watershed (green) and lake (blue) responses to wildfire disturbance. Burned watersheds (left) have flashier hydrology and release more sediment and nutrients. These drivers facilitate reservoir algal proliferation and convert them into hotspot for algae export to downstream reaches (right). (b) Influence of reservoir connectivity and discharge on downstream water quality. During baseflow, reservoir releases and localized Chl-*a* concentrations dominate the network, increasing risk to municipal intakes.

Reservoir Impacts on Downstream Water Quality 2.3

Even in the absence of fire, reservoirs modify the physical, chemical, and biological characteristics of water before it is released downstream by increasing temperatures (C. A. Murphy et al., 2021; Y. Xu et al., 2021; Zaidel et al., 2021), exporting planktonic algae (N. E.

Jones, 2010; J. S. Richardson & Mackay, 1991; Ruhl et al., 2023), and enhancing nutrient retention due to uptake and sedimentation within a reservoir (Akbarzadeh et al., 2019; Schmadel et al., 2018; X. Wang et al., 2022). Reservoirs regulate downstream trophic status through two mechanisms. Reservoirs can act as a source of planktonic algae, exporting biomass during high-productivity periods (Rounds et al., 2015; Ruhl et al., 2023; Schmadel et al., 2024). Second, reservoirs create outflow conditions that are favorable for benthic algae proliferation (Flinders & Hart, 2009; C. A. Murphy et al., 2021; J. S. Richardson & Mackay, 1991), and transport (Carpenter et al., 2013, 2025; Peipoch et al., 2025). The magnitude of these controls will be strongest during baseflow, when reservoir releases dominate river flows usually occurring in the late summer (Barnard et al., 2023; Henson et al., 2007) (Figure 1b). Increases in algae concentrations may be transient and contingent on the magnitude of reservoir releases and stream processes (Bruns et al., 2022; Graham et al., 2012).

Wildfire Impacts on Watershed Processes and Lake Impacts 2.4

Elevated sediment and nutrients delivery from burned headwater streams to reservoirs, may create hotspots of productivity and nutrient processing, potentially increasing algal growth beyond what unburned reservoirs would experience under equivalent climatic conditions. Their position on lower-order streams with small watersheds and little upstream buffering makes headwater reservoirs or lakes particularly sensitive to localized disturbances like wildfire (Gardner et al., 2019). Lakes and reservoirs exhibit a wide variety of physical, chemical and biological responses of lakes to fires (McCullough et al., 2019). Some studies have observed similar post-fire trends to streams; for example, increases in sediment (Carignan et al., 2000; East et al., 2025), and N and P loading (McCullough et al., 2019; Paul et al., 2022). However, other studies have observed the opposite effects (C. D. Evans et al., 2017; McColl & Grigal,

1977; McEachern et al., 2000), and hypothesize that watershed (soil, topography, vegetation) and lake (shape, size, trophic status) characteristics exert a strong control on lake responses to wildfire.

Wildfire-driven canopy loss reduces shading and vegetation water uptake, while ash deposition decreases albedo and soil hydrophobicity, together resulting in earlier and faster snowmelt (Kampf et al., 2022; A. P. Williams et al., 2022). Faster and earlier snowmelt has been linked to warming lake temperatures (Christianson & Johnson, 2020), though the pathway from wildfire to lake warming remains less directly studied and may be masked by global increases in lake temperatures (Kraemer et al., 2021). Warmer lake temperatures, and increased N and P delivery, common in post-fire stream literature, are known to increase the primary productivity of lakes and increase the risk of algal growth in oligotrophic lakes (Beaulieu et al., 2013; Nydick et al., 2004; Oleksy, et al., 2020a, 2020b). Post-fire algal responses in streams are mixed; some studies document increased algal biomass (Bixby et al., 2015; Kelly et al., 2006; Klose et al., 2015) and reduced nutrient limitation (Graziano et al., 2026; Rhea et al., 2021), while a broader meta-analysis found no consistent directional effect across studies (Paul et al., 2022). Whether or not post-fire nutrient loading produces a more predictable algal response is unclear (Barnard et al., 2023; McCullough et al., 2019; Olson et al., 2023). Cumulatively, many conditions must also align for an algal bloom to propagate to a municipal water supply. However, as climate change (Beaulieu et al., 2013; Oleksy, et al., 2020a, 2020b) and wildfire (Emelko et al., 2011) increases the risk of problematic algal blooms, a predictive understanding of the conditions that promote algal blooms after wildfire are essential for water providers.

In this study, we investigated the water chemistry, suspended sediment, and chlorophyll a (Chl-*a*) concentrations of the high elevation reservoirs in the Upper Cache la Poudre River

watershed for four years (2021-2024) following the 2020 Cameron Peak Fire, and the downstream impacts reservoirs to algae concentrations and nutrient dynamics in the river mainstem. Additionally, run-of-river conditions in the South Fork watershed for the first two years, followed by resumed reservoir filling and releasing operations, provided a natural experiment linking reservoir operation to downstream chlorophyll-*a* concentrations. Through this study, we hoped to answer two broad questions:

1. How does fire impact water quality in high elevation reservoirs?
2. What influence do reservoir chlorophyll *a* concentrations have on downstream chlorophyll *a*, if at all?

METHODS

Study Area 3.1

The Upper Cache la Poudre (CLP), located west of Fort Collins, Colorado, has a total watershed area of 2,900 km², and average cumulative annual flows of 3 million m³ yr⁻¹ with peak flow occurring in early June following snowmelt (Colorado Department of Water Resources, 2026a). The CLP watershed covers a wide elevational gradient from 1,600 m to 4,109 m, with a mean elevation of 2,600 m (Hollister, 2017). Annual precipitation averages at 550 mm, though it ranges from 400 mm to 1,200 mm across the watershed, increasing with elevation and the majority falling in the winter as snow (PRISM Climate Group, 2026). The dominant landcover pre-fire was evergreen forests, primarily made up of Ponderosa pine (*Pinus ponderosa*) and Douglas fir (*Pseudotsuga menziesii*) in lower elevations, mixed forests at sub-alpine areas with subalpine fir (*Abies lasiocarpa*), lodgepole pine (*Pinus contorta*), and Engelmann spruce (*Picea engelmannii*), and alpine tundra at the highest elevations (LANDFIRE, 2025). The CLP represents a significant portion of the drinking water supplies that support over 330,000 residents served by the cities of Fort Collins, Greeley and the Soldier Canyon Water Treatment Authority. The CLP also provides considerable agricultural water for the region of Northern Colorado. The CLP's key sources of water are from four large tributaries: Big South (CLP mainstem), Joe Wright Creek, South Fork of the CLP, and the North Fork of the CLP (Heath & Thorp, 2023). The CLP is also supplemented by transbasin water diversions from the Michigan River via Michigan Ditch, Colorado River via the Grand Ditch, and Laramie River via the Laramie-Poudre Tunnel (APPENDIX A SI 1, APPENDIX A SI Table 1, Figure 2).

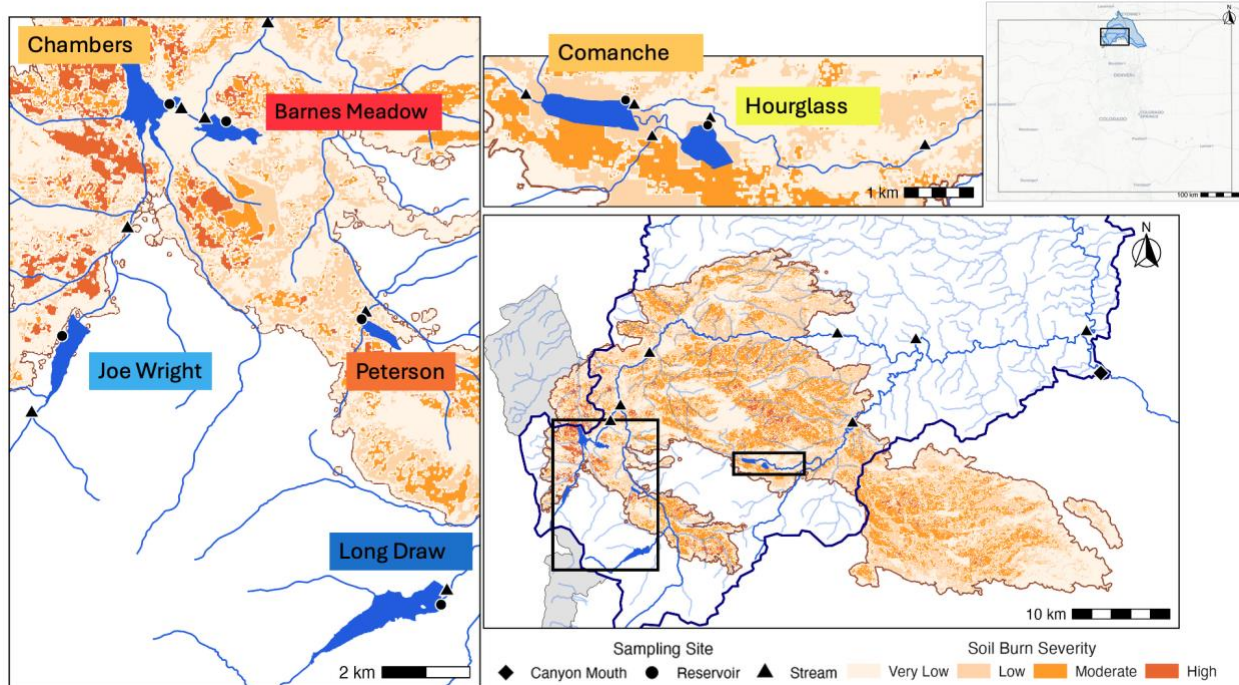


Figure 2: Study area and sampling sites within the Cache la Poudre (CLP) watershed, Colorado. (Top right) Regional context showing the CLP HUC8 boundary (blue outline) and study area extent (black box) within Colorado. (Bottom right) Watershed-scale view of the CLP study area with trans-basin diversion watersheds (grey), stream sampling sites (triangles), and approximate location of municipal intakes (Canyon Mouth, diamond) overlaid on BAER soil burn severity data (USDA Forest Service, 2023). (Left and top center) Detailed views of reservoir and stream sampling locations (circles and triangles, respectively). Reservoir labels are color-coded by upstream burn extent, ranging from blue (low) to red (high); catchment-specific metrics are summarized in Table 1.

The 2020 Cameron Peak Fire burned 579 km² (19.8%) of the CLP watershed (including trans-basin diversion watersheds) across a range of soil burn severities: 7.2% low, 4.8% moderate and 7.8% high (USDA Forest Service, 2023). This disturbance drove substantial land cover change across the watershed. NLCD pre-fire (2019) and post-fire (2023) classifications show evergreen forest cover declining from 48% to 35% and herbaceous cover increasing from 25% to 36% post-fire (United States Geological Survey, 2025), consistent with early post-fire succession. Excluding the North Fork of the CLP, which contributes a low proportion of flow but has a large watershed area, 40% of the CLP mainstem watershed area burned. This catchment

underwent a greater shift in NLCD-classified land cover, with evergreen forest declining from 56% to 29% and herbaceous cover increasing from 20% to 44% in the years following the fire.

This study focuses on seven high elevation water supply reservoirs in the Upper CLP watershed: Barnes Meadow, Chambers Lake, Comanche, Hourglass, Joe Wright, Long Draw and Peterson Lake (Figure 2 Inset and Table 1). These reservoirs provide storage for agricultural and municipal water supplies and are operated by three entities: Water Supply and Storage Company, the City of Greeley, and the City of Fort Collins. Notably, Joe Wright and Chambers Lake form a cascading reservoir system along Joe Wright Creek, with Joe Wright Reservoir releasing directly into the watershed upstream of Chambers Lake, which also receives inflow from several additional smaller tributaries. Three reservoirs receive trans-basin diversions: Long Draw supplemented via the Grand Ditch, and Joe Wright Creek reservoirs supplied by the Michigan Ditch (APPENDIX A SI 1, APPENDIX A SI Table 1). Under typical operations, reservoirs fill between April and June, reaching capacity by early July before releasing water from July through October for downstream demand. Barnes Meadow is the one exception, primarily releasing water between December and April as part of a joint agreement to maintain winter baseflows of $0.3 \text{ m}^3\text{s}^{-1}$.

All reservoir watersheds are high elevation ($>2,800 \text{ m}$) (Hollister, 2017), have snow-persistence lasting past mid-May (Hammond, 2020), and receive mean annual precipitation exceeding 900 mm (PRISM Climate Group, 2026). Pre-fire vegetation in the reservoir catchments was dominated by subalpine fir (*Abies lasiocarpa*), lodgepole pine (*Pinus contorta*), and Engelmann spruce (*Picea engelmannii*), transitioning to alpine tundra and bare rock at higher elevations (LANDFIRE, 2025). Among the five burned reservoir watersheds, 38.2% of the total area burned, with notably high proportions of moderate (8.2%) and high (17.5%) burn

severity. Fire effects were most severe in the Chambers, Comanche, Peterson, and Barnes Meadow watersheds, where NLCD classifications show dominant land cover shifting from evergreen forest to herbaceous cover between 2019 and 2023, with Hourglass experiencing a 20% reduction in forest cover over the same period (United States Geological Survey, 2025).

Table 1: Reservoir watershed attributes. Watershed Burn Class categorizes the overall catchment status based on total watershed burn extent and severity; 200m Buffer High Burn (%) quantifies the percentage of high soil burn severity occurring within a 200-meter buffer surrounding the reservoir shoreline and 200m Buffer Burn Class categorizes this near-shore impact zone. All burn parameters were derived from Soil Burn Severity (SBS) data maps (USDA Forest Service, 2023). Additional attributes (dominant landcover, watershed slope, and watershed snow cover dates) available in APPENDIX A SI Table 2

Site (site code)	Watershed Extent Burned (%)	Watershed Area (km ²)	Reservoir Elevation (m)	Normal Storage Capacity (Mm ³)	High Burn (%)	Watershed Burn Class	200m Buffer High Burn (%)	200m Buffer Burn Class	Watershed
Barnes Meadow Reservoir (BRNR)	91.3	7.8	2764	2.9	60.9	Extensive	23	Mid	Joe Wright Creek
Peterson Reservoir (PTRR)	56.1	6.7	2893	1.5	36	High	48.3	High	Big South
Comanche Reservoir (COMR)	52.5	30.8	2859	3.2	34.3	High	48.7	High	South Fork
Chambers Reservoir (CBRR)	29.7	95	2778	10.9	19.9	Mid	39.9	High	Joe Wright Creek
Hourglass Reservoir (HORR)	22.9	11.2	2852	2.1	20	Mid	67.6	Extensive	South Fork
Joe Wright Reservoir (JOER)	7	27.5	3020	8.8	3.5	No/Low	1.4	No/Low	Joe Wright Creek
Long Draw Reservoir (LNGR)	0	72.1	3057	13.4	0	No/Low	0	No/Low	Big South

Stream Water Sampling and Processing 3.2

From 2021 to 2022, five reservoirs (Long Draw, Joe Wright, Chambers, Peterson, and Barnes Meadow) were sampled weekly from June to November as they represented a gradient of burn conditions and were in a localized area. During these years, the City of Greeley operated Comanche and Hourglass reservoirs under run-of-the-river conditions (i.e. leaving outflows open so that water was only retained due to underlying topography) to mitigate post-fire sedimentation threats. We conducted monthly baseline sampling across these systems from their inflows down to Beaver Creek and the South Fork CLP. From 2023 to 2024, all reservoir, inflow and outflow sites were sampled bi-weekly in May and June and monthly from July to October. Reservoir sampling was conducted using a 2 m swing sampler at 0.25 to 0.75 m depth, 5 to 10 m from the bank, with all flowing outflows also sampled. At Joe Wright and Chambers Lake, inflow sites were also sampled. Mainstem CLP stream sampling began in 2021 with weekly sampling from April to July and monthly sampling from July to December, excluding chlorophyll *a* (Chl-*a*). From 2022 to 2024, a full suite of analytes and Chl-*a* samples (described below) were collected bi-weekly from April to November.

Stream water samples were analyzed at the US Forest Service Rocky Mountain Research Station (RMRS) biogeochemistry lab for Chl-*a*, total suspended solids (TSS), turbidity, DOC, total dissolved nitrogen (TDN), and major cations and anions (see Data Availability). During each site visit, three samples were collected with high-density polyethylene (HDPE) bottles: one 250 mL and two 1000 mL. Bottles were triple-washed with deionized water and triple-rinsed in stream water prior to collection.

The 250 mL sample was aliquoted for water chemistry analyses. One aliquot was filtered through a 0.7 μm glass fiber filter (Whatman International, Ltd.) and analyzed for DOC and

TDN on a combustion TOC analyzer (TOC-L, Shimadzu) after inorganic carbon was purged via HCL addition. A second aliquot was filtered through 0.45 μm filters (MilliporeSigma) and analyzed by ion chromatography for dominant cation (Ca, Mg, Na, K, NH_4) and anion (SO_4 , PO_4 , Cl, NO_3) concentrations (Thermo-Fisher Corporation, Waltham, MA, USA) within 72 hours of collection. Specific conductance, pH, and acid neutralizing capacity (ANC) were measured on unfiltered samples via autosampler (InMotion T5, Mettler Toledo) following EPA methods 120.1, 150.1, and 310.1, respectively. Detection limits for ions and TDN were 0.01 mg L^{-1} , and 0.04 mg L^{-1} for DOC.

Chl-*a* samples, up to 1000 ml, were filtered using vacuum pumps through 0.7 μm glass fiber filters (Whatman) in the field or within 4 hours of collection, stored on ice, and frozen until analysis. Chl-*a* was measured following EPA method 445 (Arar and Collins, 1997) using the non-acidified fluorometric method with a Trilogy Laboratory Fluorometer (Turner Designs), corrected for volume filtered, following method in Graziano et al. (2026). Turbidity was measured on the same instrument using the nephelometric method. TSS was determined by filtering a 1000 mL sample through 0.7 μm glass fiber filters (Whatman), drying at 105°C for 24 hours, and weighing. Full QA/QC protocols are documented in detail in Fegel (2024).

Remote Sensing of Study Reservoirs 3.3

To assess pre-fire conditions in the absence of *in-situ* data, *lakeSR* and *siteSR* data products (Steele et al., 2026b, 2026a) were leveraged to estimate surface temperature and Secchi disk depth (SDD) at our study sites. To get historical estimates of SDD, remotely sensed surface reflectance and temperature observations were obtained from *lakeSR*, which compiles Landsat Collection 2 Surface Reflectance data for waterbodies across the United States, while *siteSR* provides paired water quality measurements and near-coincident Landsat observations. We

corrected surface reflectance for inter-mission sensor differences using handoffs from Roy et al., (2016). We used a regional subset (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming) of *siteSR* SDD data matched with remote sensing summaries to train an five-fold XGBoost ensemble (Chen et al., 2014), with each fold trained on 80% of data and validated on the remaining 20%. Hyperparameters (max_depth and min_child_weight) were tuned via grid search, with all other parameters held at default values. This ensemble was then applied to the *lakeSR* dataset to generate SDD estimates for all available observations at the study lakes from 1990-2024. Surface temperature was obtained directly from *lakeSR* and bias-corrected following established procedures (King et al., 2025; Steele et al., 2026a). To minimize the influence of ice and other seasonal artifacts not fully captured by quality assurance filters, all *lakeSR*-derived estimates were restricted to days of year 120-300 (approximately May-October).

Statistical Analysis 3.4

We processed data in R (R Core Team, 2025) using the *tidyverse* (Wickham et al., 2019), *stats* (R Core Team, 2025), *car* (Fox & Weisberg, 2019), *rstatix* (Kassambara, 2019), *lme4* (Bates et al., 2015), *glmmTMB* (McGillcuddy et al., 2025), and *emmeans* (Lenth & Piaskowski, 2017) packages. Due to right-skewed distributions, water chemistry data were log-transformed to improve normality. Nitrate (NO_3^-) data remained non-normal following transformation and were assessed using a generalized linear mixed model (GLMM) with a Gamma distribution and log link. All other parameters were assessed using linear mixed models (LMMs). See SI 12 specific fixed and random effects for each model. We evaluated the overall significance of fixed effects (year, site, or unburned vs burn) using likelihood-ratio tests and specific group differences with pairwise comparisons. Site-specific variance was assessed via Levene's test. Results are reported as percent change in the geometric means, with significant difference defined as $p < 0.05$.

Seasonal analyses were conducted using the follow groups: winter baseflow (December–February), rising limb (March–April), peak flow (May–June), falling limb (July–August) and fall baseflow (September–November). Comanche and Hourglass were excluded from all statistical analyses due to insufficient data across the study period but are included in visualizations and discussion. To maximize statistical power, reservoirs were aggregated into binary burn groups: burned (Chambers, Peterson, Barnes Meadow) and unburned (Long Draw, Joe Wright).

Seasonal trends in remote sensing figures were computed using the *time_decompose()* function from the *anomalize* (Dancho & Vaughan, 2018) package. Pre-fire (2016–2019) and post-fire (2021–2024) conditions of LST and SDD were evaluated across study sites using LMMs, with raw parameter values predicted by the interaction of site and time-period, and a random effect for year.

RESULTS

Reservoir Water Quality Post Fire 4.1

Water Chemistry 4.1.1

We found that potassium (K^+) and total suspended solids (TSS) were 11% and 17% higher in the burned reservoirs compared to the unburned reservoirs, Joe Wright and Long Draw. (Figure 3). TSS concentrations were 16–20% higher in the most extensively burned reservoirs, Peterson and Barnes Meadow, compared to the unburned reservoirs, Joe Wright and Long Draw. TSS concentrations across all reservoirs remained consistent between years, suggesting no basin-wide increases in suspended sediment following the wildfire. Potassium concentrations were highest in the year immediately following the wildfire (2021) and lowest in 2023, with all reservoirs showing consistent yearly patterns across all study watersheds. Most reservoirs, except Barnes Meadow and Peterson Lake, had significantly different K^+ concentrations from one another, with the largest differences (11–14%) occurring between unburned reservoirs and the most severely burned reservoirs.

Burned reservoirs did not have significantly higher nitrate (NO_3^-), total dissolved nitrogen (TDN), sulfate (SO_4^{2-}), or dissolved organic carbon (DOC) than the unburned reservoirs post-fire. However, burned reservoirs had greater variability in NO_3^- and all concentrations greater than 1 mg L^{-1} were observed in burned catchments. Across all reservoirs we observed a 55% increase in NO_3^- levels between 2021 and 2022. However, in unburned reservoirs, this increase was smaller (48%) and concentrations were not significantly different from 2021 - 2024. In contrast, NO_3^- in burned reservoirs continued to increase through 2023, with 2021 NO_3^- concentrations being 80% lower than 2023 NO_3^- concentrations in burned reservoirs. Increases in

burned reservoirs decreased by 2024 and had similar levels between 2021 and 2024 ($p = 0.43$). Similar to NO_3^- , TDN exhibited no difference between burned and unburned reservoirs and TDN concentrations were highest in the first year (2021) post-fire across all reservoirs. The extensively burned reservoirs, Barnes Meadow and Peterson Lake, had the highest observed TDN concentrations, approximately 3–6% higher than other study reservoirs. While Long Draw Reservoir had lower TDN concentrations than the burned reservoirs, it consistently had higher NO_3^- concentrations than them, indicating a greater proportion of inorganic nitrogen relative to the TDN pool.

Across all sites excluding Comanche and Hourglass, DOC concentrations were highest in 2021 and declined modestly in subsequent years (10% decrease from the start to end of the study period), with relatively little change between 2022 and 2024. Burned reservoirs were not found to have significantly higher DOC levels than any of the unburned reservoirs. However, Barnes Meadow and Peterson exhibited higher DOC concentrations than all other reservoirs, with the largest increases (19–23%) observed relative to the unburned reservoirs, Long Draw and Joe Wright.

Across all reservoirs, NH_4^+ concentrations were below the quantification limit (0.05 mg L^{-1}) in most samples ($n = 232$ of 280), with Peterson Lake having the greatest number of quantifiable samples ($n = 21$ of 50, 42%), most collected in 2021. Orthophosphate (PO_4^{3-}) detections (> 0.01 mg L^{-1}) in reservoirs were even rarer ($n = 7$ of 280, 2.5%), occurring at least once at all sites except Chambers. Detectable concentrations occurred in two samples in 2021 ($n = 91$, 2.2%), five samples in 2022 ($n = 118$, 4.2%), and with no detections in 2023 ($n = 0$ of 39) or in 2024 ($n = 0$ of 32). Orthophosphate was more frequently detected at reservoir inflows ($n = 12$ of 200, 6 %), outflows ($n = 14$ of 296, 4.7%), and mainstem ($n = 26$ of 520, 5%) sites than

reservoir sites, with the majority of detections occurring in 2021. We found no significant difference in SO_4^{2-} between burned and unburned reservoirs but found that SO_4^{2-} concentrations were highest in the first year (2021) post-fire across all reservoirs. Long Draw exhibited consistently elevated and high variability in SO_4^{2-} concentrations throughout the study period (APPENDIX A SI 9), and SO_4^{2-} consistently increased throughout each year. Whereas burned reservoirs had higher concentrations in 2021 and 2022, and declined in 2023 and 2024. Although several additional parameters (Ca^{2+} , Mg^{2+} , SC, pH, and ANC) differed significantly among burn groups (APPENDIX A SI 1), these differences showed patterns less consistent with burn status and more likely reflect variations in watershed characteristics, geology, or lake sediment properties (Heath & Thorp, 2023; McCullough et al., 2019; Ruckhaus et al., 2025).

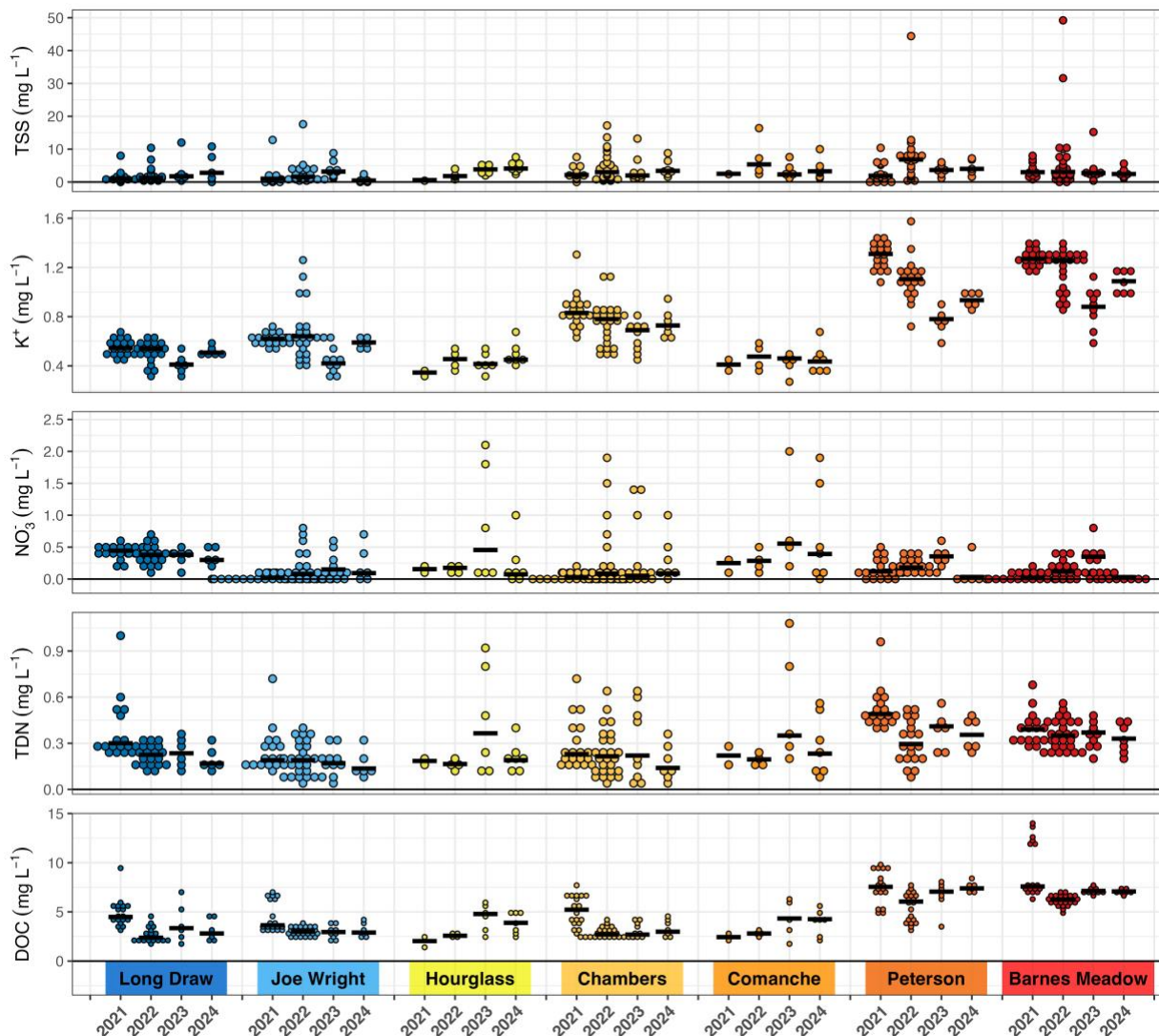


Figure 3: Values (circles) and yearly medians (black bars) of select constituent (TSS, K⁺, NO₃⁻, TDN, DOC) concentrations collected at reservoirs during the study period (2021–2024). Sites are colored from blue to red with increasing watershed burn extent from left to right. See Table 1 for exact values. Because Hourglass and Comanche sampling was limited in 2021–2022, these sites are not included in the statistical analyses.

Chlorophyll a Concentrations 4.1.2

For our primary study reservoirs (excluding Comanche and Hourglass), Chl-*a* values ranged from 0.22 to 16.6 µg L⁻¹. During the study period, seven samples exceeded the eutrophic threshold for Colorado cold water lakes (i.e., 8 µg L⁻¹ Regulation No. 31 - The Basic Standards and Methodologies for Surface Water, 2024, § 31.5). Exceedances were observed at all

reservoirs other than Long Draw, with Barnes Meadow and Chambers exhibiting the highest frequency of exceedances ($n = 3$ and $n = 2$, respectively). However, none of the reservoirs studied had Chl-*a* levels exceeding the state's criteria for impairment: "...summer (July 1–September 30) seasonal average of values from the mixed layer..." (Regulation No. 31 - The Basic Standards and Methodologies for Surface Water, 2024, § 31.5). Across the study period, burned reservoirs had 18% higher concentrations than unburned sites and exceeded the mesotrophic threshold (i.e., $2.6 \mu\text{g L}^{-1}$ US EPA, 2009) more often, with exceedances in 49.4% of observations compared with 12.4% at unburned sites. Chl-*a* across all study reservoirs was lowest in 2021, followed by successive increases of 10%, 15%, and 14% in 2022, 2023, and 2024, respectively. Long Draw had consistently lower Chl-*a* than all other reservoirs while Joe Wright was only significantly different from Barnes Meadow. Barnes Meadow had significantly greater Chl-*a* from all other reservoirs and was mesotrophic or eutrophic for 64% of samples. Chambers Lake was not statistically different from Joe Wright or Peterson Reservoirs across the study period. No significant relationship was found between reservoir Chl-*a* and TDN concentrations. In contrast, a significant positive relationship between NO_3^- and Chl-*a* ($\beta = 0.67$, $p < 0.001$) and a significant negative relationship between DOC and Chl-*a* ($\beta = -0.31$, 95% CI: -0.51 to -0.11, $p = 0.004$) were identified across study reservoirs after accounting for season and reservoir identity, though both relationships explained minimal variance in Chl-*a* (marginal $R^2 = 0.054$ and 0.047 , respectively) (APPENDIX A SI 4).

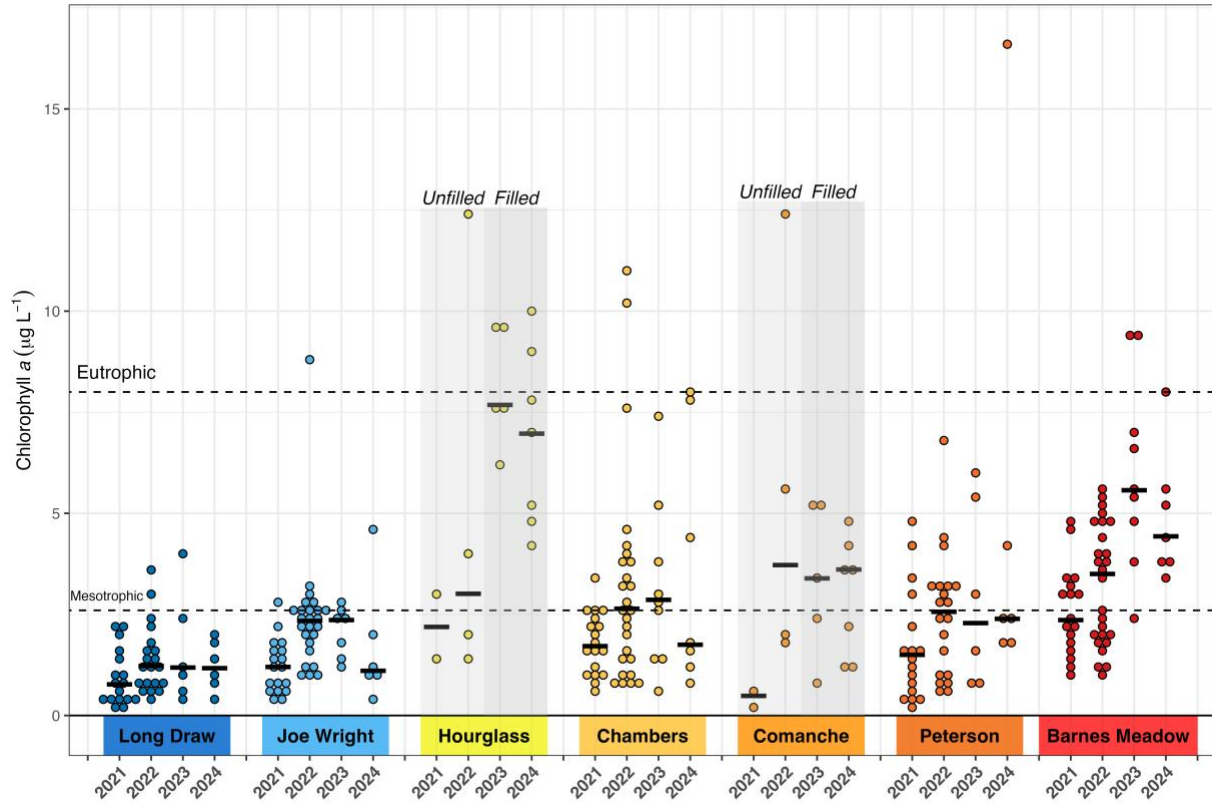


Figure 4: Chlorophyll *a* concentrations (circles) and yearly medians (black bars) collected at reservoirs during the study period (2021–2024). Sites are colored from blue to red with increasing watershed burn extent from left to right. Mesotrophic and eutrophic conditions for cold water lakes in the state of Colorado are defined at 2.6 and 8 $\mu\text{g L}^{-1}$, respectively. Grey boxes indicate Comanche and Hourglass samples, which were not included in statistical analyses as they were not in full operation for 2021–2022 and were not samples as frequently.

Remote Sensing of Reservoirs 4.1.3

Analysis of long-term (1990–2020) remote sensing records show that lake surface temperatures (LST) across the study sites covary and exhibit a steady warming trend over the last 20 years. These LST increases are consistent with air temperature increases, with the study period averaging 0.98°C above the 1991–2020 climate normals across the study area (PRISM Climate Group, 2026). Post-fire LST (2021–2024) remained consistent across all study sites with no clear trend divergence in burned reservoirs compared to unburned reservoirs ($p > 0.05$). Remote sensing estimates of Secchi disk depth (SDD) showed high inter-annual variability and

less regional consistency across all reservoirs during the pre-fire period (1990–2019), fluctuating between high (>4 m) and low (<2 m) clarity, likely reflecting operational differences in reservoir management and water right portfolios among operators. Comparing the pre-fire window (2016–2019) to the post-fire period (2021–2024), SDD remained statistically similar across all reservoirs ($p > 0.05$) except Chambers which exhibited a minor increase in clarity (0.72 m, 95% CI: 0.18–1.26 m; $p = 0.009$). Although no significant mean shift was detected at Barnes Meadow Reservoir, visual inspection of the time series suggests a declining trend in SDD from 2023–2024 (Figure 4) and warrants continued monitoring. No significant relationships were found between remote sensing metrics (SDD and LST) and discrete water chemistry variables, likely due to low data density; there were less than ten annual remote sensing measurements per reservoir and even fewer match-ups with water chemistry sampling.

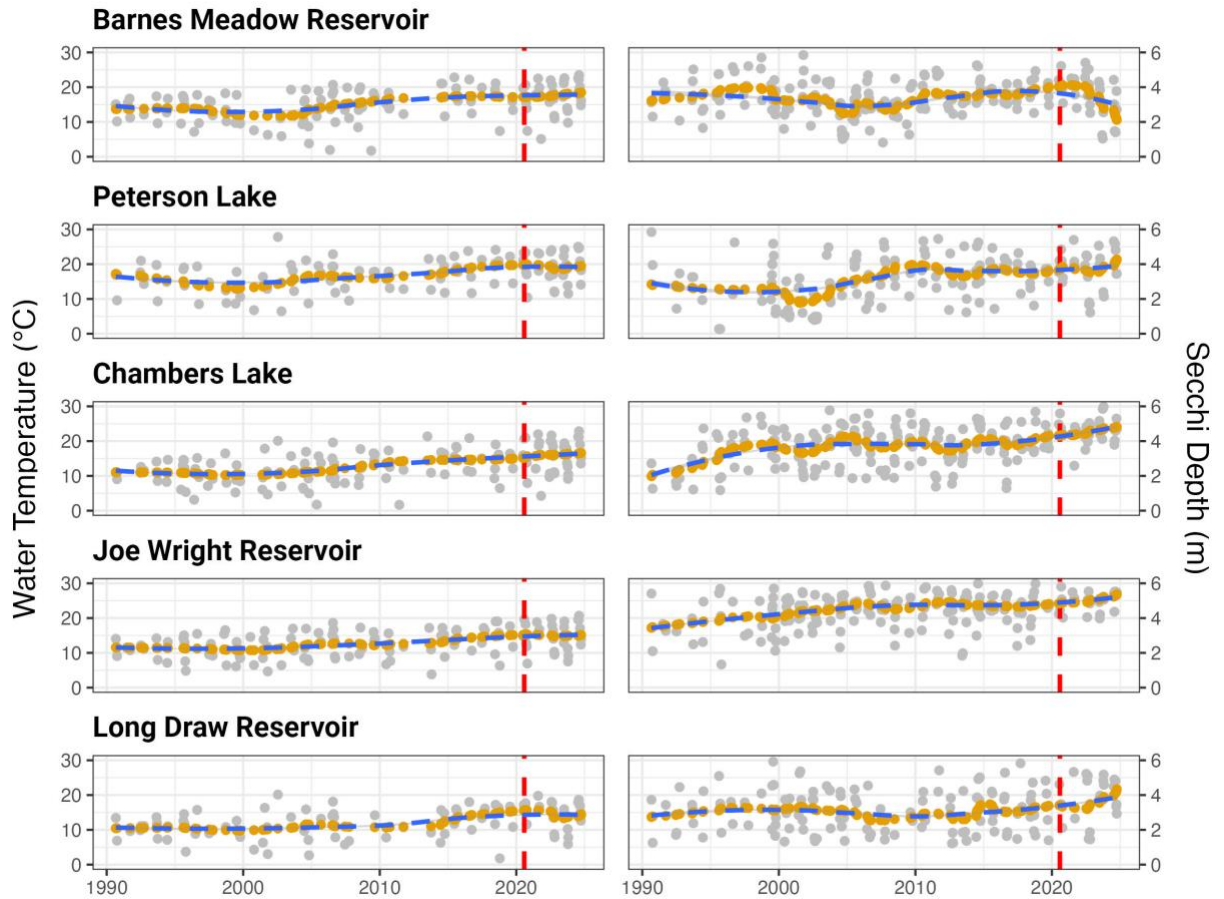


Figure 5: Lake surface temperature (left) and Secchi disk depth (right) remote sensing estimates from 1990–2024 for all study reservoirs. Grey dots indicate remote sensing observations, orange dots are seasonal adjusted trends, and blue dashed lines are year-to-year trends. The vertical red dashed line indicates the start of the Cameron Peak Fire, August 2020. Comanche and Hourglass data were removed due to reservoir operations in 2021 and 2022, see details in Methods.

Longitudinal Impacts of Reservoirs on Riverine Chlorophyll a 4.2

To better characterize how nutrient dynamics shape longitudinal patterns in algal growth across a cascading reservoir system, we investigated trends in NO_3^- , TDN, DOC, and Chl-*a* within the Joe Wright Creek watershed (Figure 4). We observed a significant shift in relative abundance of N forms along the Joe Wright Creek system. Between the Joe Wright inflow and reservoir across all paired samples, there was an 83% reduction in NO_3^- concentrations, while Chl-*a* and DOC increased by 27% and 15%, respectively and TDN levels remained stable between these sites ($p > 0.05$). We also observed a persistent downstream increase (16%) in Chl-

a concentrations between the Joe Wright Reservoir inflow and outflow sites. A similar longitudinal pattern was observed at Chambers Lake, where Chl-*a* increased 21% between the inflow and outflow sites. Between the inflow and reservoir, there was a 62% reduction in NO₃⁻ concentrations, a 23% increase in Chl-*a*, and no significant changes in DOC or TDN concentrations. During snowmelt periods between 2022–2024, peak NO₃⁻ concentrations at the Chambers Lake inflow, reservoir and outflow sites increased and coincided with higher Chl-*a*. In contrast to our expectation that warmer lake temperatures would result in higher Chl-*a*, the highest concentrations of Chl-*a* were measured during peak flows and were 8.5% and 9% higher during this period than the falling limb and fall baseflow periods, respectively. The nearest downstream site to Chambers Lake, Joe Wright Creek, and the Chambers Lake outflow were not significantly different ($p > 0.05$) in NO₃⁻, TDN, DOC or, Chl-*a* levels across the study period, indicating strong connectivity between the sites in nutrients and Chl-*a*.

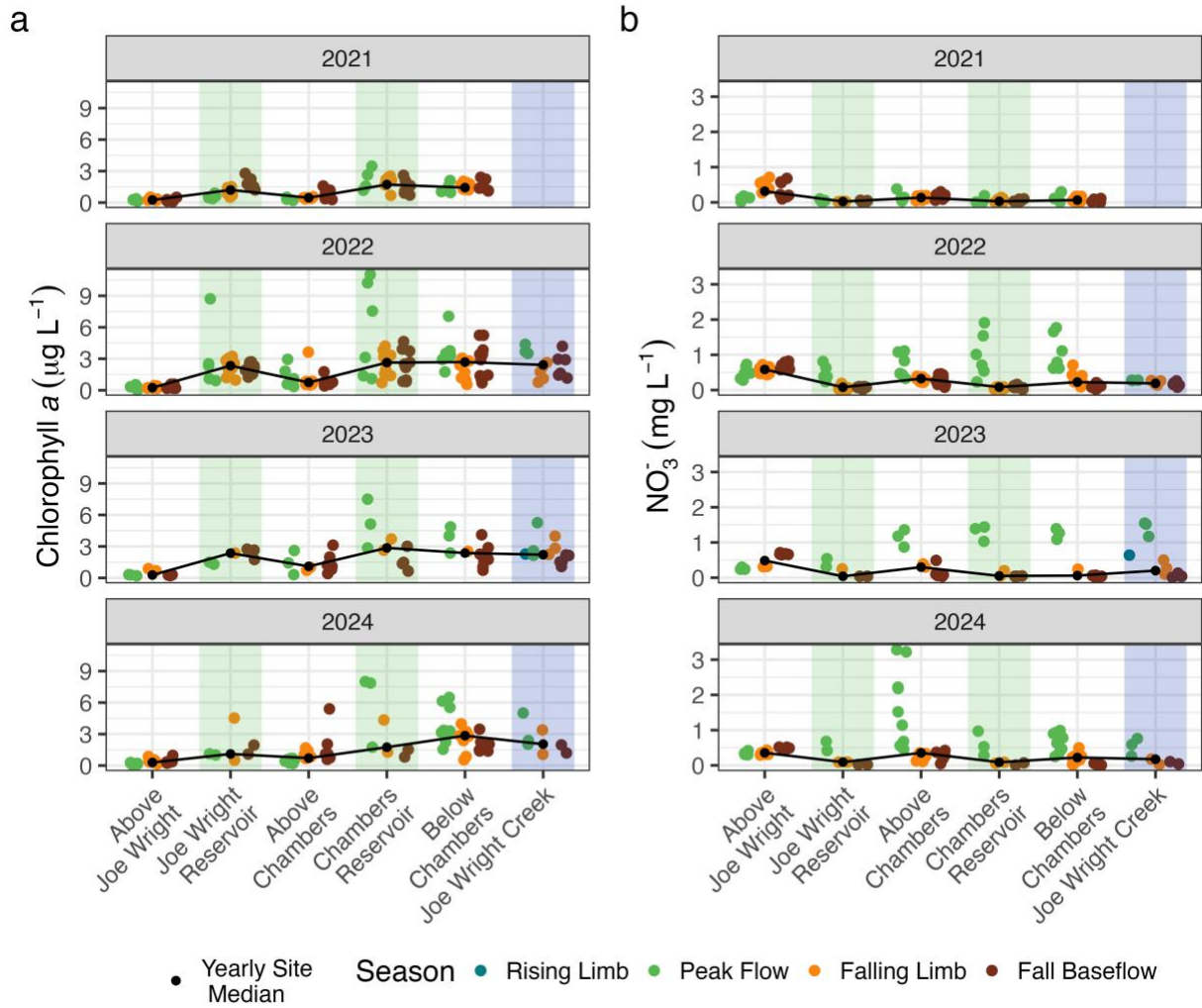


Figure 6: Spatiotemporal dynamics of chlorophyll *a* and nitrate (NO_3^-) within the Joe Wright Creek (JWC) reservoir complex (2021–2024). Longitudinal profiles of (a) Chlorophyll *a* and (b) nitrate concentrations from headwaters to the JWC confluence. Green shaded regions denote reservoir locations (Joe Wright and Chambers Lake); the blue shaded region indicates the monitoring site (JWC) downstream of the network. Black points and lines track yearly site medians, while individual samples are color-coded by hydrologic season (see Methods).

Moving downstream from Joe Wright Creek (80 km upstream) into the nearest mainstem site (Poudre Falls, 74 km upstream), mean Chl-*a* concentrations decreased by 18.6%. Mean Chl-*a* at the Joe Wright Creek site was 36% greater than in the Big South (grey points at 77 km). Similarly, concentrations at the downstream mainstem CLP sites of Poudre Falls and Poudre below Rustic (47.3 km upstream) were 14.6% and 8% higher than in the Big South, respectively. However, mean Chl-*a* concentrations remained consistent from the Poudre Falls site to the

Canyon Mouth ($p > 0.05$) and the majority (96.7% of samples) of Chl-*a* concentrations in the river mainstem were below 2.6 $\mu\text{g/L}$. However, five of the seven mainstem sites measured concentrations $\geq 2.6 \mu\text{g/L}$ at least once during the study period (Figure 6). Nitrate concentrations showed the opposite pattern: Joe Wright Creek concentrations were 41% lower than Poudre Falls and 66% lower than Big South, while Big South concentrations were 42% higher than Poudre Falls. Observed TDN and K concentrations had no clear longitudinal pattern in the river mainstem, although significant differences were detected among some sites.

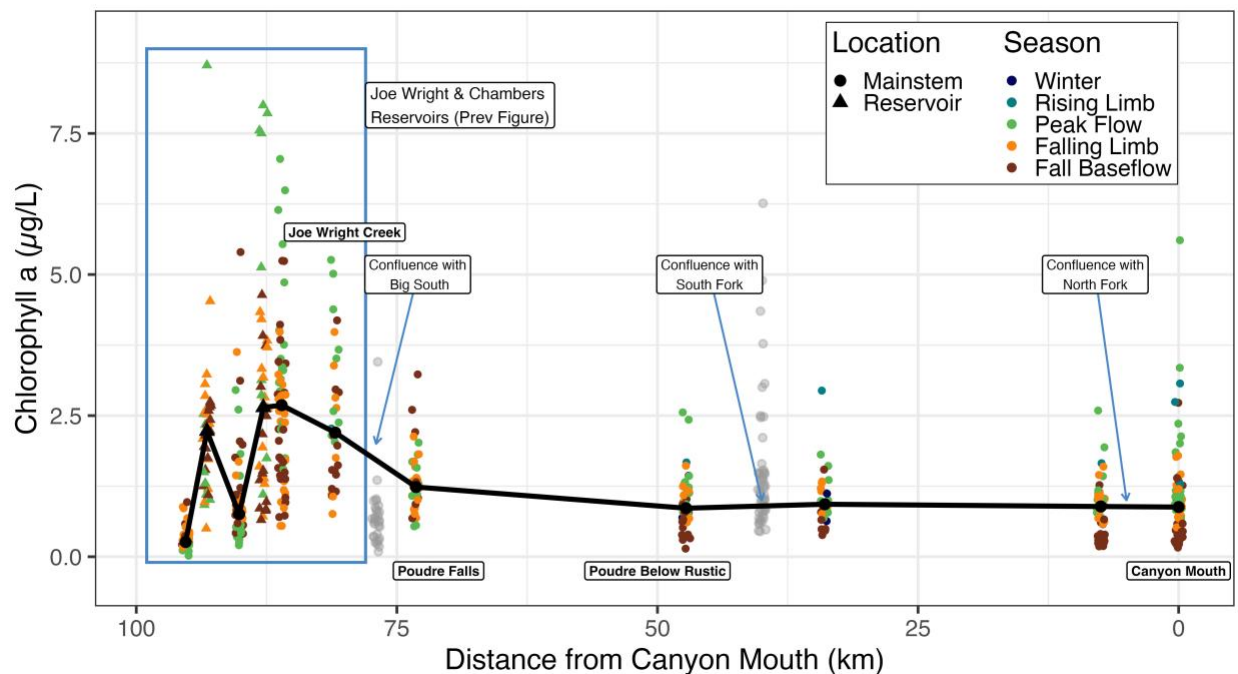


Figure 7: Longitudinal Chl-*a* profile from Joe Wright Creek (JWC) through the Cache la Poudre (CLP) mainstem. Chlorophyll *a* concentrations are plotted by distance from the canyon mouth, with the blue box highlighting the Joe Wright and Chambers reservoir network. Individual samples are color-coded by hydrologic season; black points and lines represent median concentrations across the study period. Grey points indicate tributary concentrations at their respective confluences to demonstrate the longitudinal effects of mixing and dilution. No samples were collected on the North Fork.

DISCUSSION

The goal of this study was to better understand how wildfires impact water quality at the scale of an entire watershed, with a focus on reservoirs and rivers that supply drinking water for Northern Colorado. In this context, a key uncertainty is how interconnected reservoirs and river segments regulate water quality before water reaches the treatment plant intakes (Figure 1b), and how wildfire-driven changes move through these hydroscales.

Our results suggest that more severely burned watersheds had higher nutrient and sediment concentrations, even though some differences may have predated the fire. Reservoirs with burned watersheds had elevated K^+ and TSS concentrations, while reservoirs with extensively burned watersheds (Barnes Meadow and Peterson) had significantly higher TDN, SO_4^{2+} and DOC concentrations than unburned reservoirs. Chambers Lake, Comanche Reservoir and Hourglass Reservoir also had spring NO_3^- peaks greater than 1 mg L^{-1} in 2022, 2023 and 2024. These findings are consistent with nearby stream research (Rhoades, et al., 2025), highlighting that wildfire can increase nutrient delivery from burned watersheds to downstream reservoirs.

However, reservoir processes and operations appear to mediate how these constituents are stored, transformed, and exported. Burned reservoirs had the highest Chl-*a* concentrations across the four-year study period, but no reservoirs showed a marked increase in Chl-*a* from 2021–2024 or sustained eutrophic conditions ($> 8 \text{ } \mu\text{g L}^{-1}$) for more than one week. Similarly, remote sensing estimates of Secchi disk depth showed little immediate post-fire warming patterns. Together, these results suggest that wildfire increased nitrate and sediment inputs to

some reservoirs, but in-reservoir dynamics may have dampened or delayed the broader water-quality responses within and downstream of them.

Localized reservoir controls on downstream Chl-*a* were observed but did not reach raw water intakes. Because reservoirs did not sustain eutrophic conditions for more than two weeks, they likely did not propagate significant algae into the river mainstem. This helps explain why municipal operators reported only episodic (1–24 hour) pulses at intakes rather than chronic impairments. This network-scale analysis demonstrates that smaller internal shifts in reservoir Chl-*a* do not always translate to downstream supply risks unless the duration of the bloom and size of reservoir contribution is sufficient to overcome river dilution.

How does fire impact water quality in reservoirs? 4.1

The lack of pre-fire nutrient data limits our ability to attribute reservoir differences solely to wildfire. However, we found that reservoirs with the highest burn extent and severity, Peterson and Barnes Meadow, consistently had higher nutrient (K^+ , NO_3^- , TDN, DOC) and sediment (TSS) concentrations than our unburned sites. Elevated K^+ concentrations in these reservoirs is consistent with post-fire ash transport (Bodí et al., 2014; Rhoades, Fegel, Fowler, et al., 2025), as K^+ is commonly enriched in ash and has less biological demand than many other nutrients (Mast et al., 1990). However, K^+ patterns were more variable at moderately burned sites, likely reflecting a combination of factors including variable ash redistribution by wind and storms, reservoir connectivity to the burned hillslopes, and differences in watershed geology. For example, the consistently low K^+ concentrations at Hourglass and Comanche may reflect local weathering baselines that obscure fire-derived pulses (McCullough et al., 2019). Because K^+ can reflect both ash inputs and geologic sources, future work should continue to pair high-frequency monitoring with broader regional surveys that utilize elemental ratios, such as $K^+ : Ca^{2+}$

relationships, to isolate ash delivery from background weathering products (J. S. Evans et al., 2021; Fernandez et al., 2024; Rhoades, et al., 2025).

Consistent with stream studies in Colorado (Hohner et al., 2019; Rhoades et al., 2019; Rhoades, et al., 2025), reservoir nitrate peaks began in the second year post-fire, were highest during spring snowmelt runoff, and were greater in burned reservoirs than in unburned reservoirs (Figure 2). We also observed persistently elevated NO_3^- throughout burned reservoirs, consistent with other studies showing that stream nitrate can remain elevated for more than a decade after wildfire (Rhoades et al., 2019). These sustained increases suggest that post-fire export may remain a long-term concern, likely mediated by the pace of vegetation recovery and associated nitrogen uptake (Rust et al., 2019). Additionally, elevated post-fire NO_3^- deliver to reservoirs may also coincide with spring turnover, when vertical mixing delivers nutrients to the photic zone, potentially further stimulating phytoplankton growth (Oleksy, et al., 2020a). Despite lower overall burn extent, Chambers, Comanche, and Hourglass Reservoirs exhibited consistently elevated NO_3^- peaks in 2023 and 2024. All three reservoirs had high soil burn severity in the 200 m riparian buffer around them (Table 1), suggesting that proximity of burned soils to the water's edge may facilitate more direct NO_3^- delivery and rapid transit through the reservoir during spring snowmelt.

Reservoir NO_3^- concentrations were still generally lower than those measured at inflows or in the river mainstem, consistent with the established relationship between residence time and increased nitrogen uptake (Bernhardt et al., 2005; Hall et al., 2002; Oleksy, et al., 2020a). This dynamic is further illustrated by the cascading reservoirs along Joe Wright Creek, where elevated stream NO_3^- declined within the receiving reservoirs while TDN and Chl-*a* remained stable or increased, suggesting a shift from inorganic nitrogen into organic biomass as algae in reservoirs

(figure 5). A similar pattern was observed in Barnes Meadow Reservoir, which had the highest watershed burn extent and stable summer water levels: despite lower peak NO_3^- than some other burned reservoirs, it had some of the highest TDN and Chl-*a*. Conversely, the unburned comparison, Long Draw Reservoir, displayed the opposite trend of higher NO_3^- , lower TDN, and Chl-*a*. Together, these contrasting reservoirs support the hypothesis that in-reservoir nitrogen transformation promotes algal growth in post-fire environments. In contrast, PO_4^{3-} was rarely detected in reservoir samples, indicating that any increases in PO_4^{3-} from fire impacts were quickly assimilated by biological organisms (Dodds & Prisco, 1990; McEachern et al., 2000) or that intense rainstorms that would have mobilized this constituent into the reservoirs (Rhoades, et al., 2025) did not occur in these watersheds.

While we did observe elevated Chl-*a* within burned reservoirs, they were not sustained and they did not scale uniformly with burn severity. These findings are consistent with other post-fire lake literature showing that while algal biomass often increases, localized primary producer responses remain highly variable and inconsistent (McCullough et al., 2019; Paul et al., 2022). These inconsistencies may reflect the tradeoff between light and nutrient limitation in post-fire environments. When DOC inputs increase without corresponding nutrient enrichment, light attenuation by DOC suppresses lake primary productivity (Oleksy et al. (2024). This idea is supported by the negative relationship between DOC and Chl-*a* in our reservoirs (APPENDIX A SI 8) suggesting that post-fire DOC may have been a factor in limited algal growth.

Due to the lack of pre-fire Chl-*a* data, we cannot definitively state that the trophic state of these lakes has changed. However, lake clarity can serve as helpful alternative metric to assess lake trophic state (Meyer et al., 2025; Oleksy et al., 2022; Sillen et al., 2024). Thus, our remote sensing approach allowed us to contextualize current conditions against historical baselines. At

Barnes Meadow Reservoir, we observed satellite-estimated Secchi disk depth decreases and outflow Chl-*a* increased in 2023 and 2024, indicating a potential shifting in trophic state likely driven by a combination of post-fire mobilization of nutrients and warming lake surface temperatures (Figures 3, 4). However, across all study reservoirs, we did not detect an immediate post-fire shift in either lake surface temperatures or SDD; instead, both continued their multi-decade, pre-fire trends of warming and increasing clarity, respectively (Figure 4).

Several compounding factors explain why a distinct post-fire signal was largely absent or masked across most reservoirs. First, sampling locations were determined due to logistical constraints and did not involve sampling deeper in the reservoir from a boat or collecting sub-surface samples. Second, a post-fire temperature signal is likely masked because the climate change signal is greater (Huang et al., 2024; Kraemer et al., 2021), and internal factors such as lake size and bathymetry can result in differing reservoir surface temperatures from catchment signals (Dory et al., 2025; O'Reilly et al., 2015). Second, reservoir shape and tributary positions may also result in localized sediment plumes from sub-catchments that do not distribute evenly across the entire reservoir (East et al., 2025; Reneau et al., 2007), preventing the detection of post-fire sediment responses in remote sensing or localized water sampling. Without conducting a sediment survey, it is unknown how specific inflows or hillslopes may have transported ash or sediment (East et al., 2025; Reneau et al., 2007). And crucially for nutrient cycling, the composition of the ash transported into these reservoirs is still unknown (Bodí et al., 2014; Rhoades et al., 2025; Schenk et al., 2025). Lastly, reservoir operations can cause rapid and substantial fluctuations in water levels, and interannual variability in operating schedules influences the water surface area captured in each image or sample, potentially introducing bias into our dataset.

What influence do reservoir chlorophyll *a* concentrations have on downstream chlorophyll *a*, if at all? 4.2

We observed increased chl *a* levels at reservoir outflows and further downstream (up to 15 km from Chambers Lake into the mainstem CLP) (Figure 5, 6), indicating that these reservoirs exert controls on downstream water quality, as seen in other studies (Graham et al., 2012; Rounds et al., 2015; Schmadel et al., 2024; Soares et al., 2026). However, by the time water reaches the raw water intakes 80 km downstream, dilution from free-flowing streams and in-stream grazing pressure was sufficient to reduce chlorophyll *a* to background levels between $0.5 \mu\text{g L}^{-1}$ and $1.5 \mu\text{g L}^{-1}$ for the majority of the study period. (Figures 1b, 6). We rarely detected values greater than our mesotrophic threshold ($2.6 \mu\text{g L}^{-1}$), nor any mesotrophic events lasting greater than two weeks, and mesotrophic riverine samples exhibited no clear seasonal pattern (Figure 6). These findings are consistent with network-scale dilution, whereby mixing at tributary confluences reduces localized disturbance signals before they propagate to high-order streams (Abbott et al., 2018; Gardner et al., 2019; Plont et al., 2023). For the CLP, the 80 km of free-flowing mainstem between headwater reservoirs and raw water intakes appears sufficient to buffer post-fire algal export to background concentrations under the conditions observed during this study.

The South Fork watershed (Figure 2, top center) provides a natural experiment illustrating reservoir control on downstream chlorophyll *a* (Figure 8). In 2021 and 2022, Comanche and Hourglass reservoirs were drained for repairs, allowing us to compare water-quality patterns under unfilled and filled reservoir conditions. During unfilled years, reservoir Chl-*a* and outflow Chl-*a* were 34% and 36% higher than inflows, respectively. At Beaver Creek, 4.5 km below the reservoirs, Chl-*a* concentrations were not significantly different from reservoir

outflows ($p > 0.05$), suggesting that the reservoir outflow signal persisted over this distance despite minor tributary inputs. Farther downstream, at the South Fork of the Cache la Poudre, more substantial tributary dilution reduced Chl-*a* by 38.8% relative to reservoir outflows, returning concentrations to levels comparable to reservoir inflows ($p > 0.05$) and consistently below the mesotrophic threshold of $2.6 \mu\text{g L}^{-1}$.

When reservoirs returned to service in 2023 and 2024, inflow and outflow Chl-*a* did not differ significantly from unfilled conditions ($p = 0.94$), likely because inflows Chl-*a* levels remained low and outflow algal propagule export were similar across both operational states. However, in-reservoir Chl-*a* increased by 19.3% during filled years ($p = 0.007$), consistent with longer residence times promoting planktonic algal growth. Although downstream Chl-*a* increases at Beaver Creek (16.5%; $p = 0.13$) and the South Fork site (10.7%; $p = 0.11$) were not statistically significant, both sites exceeded the mesotrophic threshold of $2.6 \mu\text{g L}^{-1}$ on multiple occasions during filled years. This suggests a biologically meaningful signal that our limited sampling may have been insufficient to detect. Regardless, reservoir influence did not propagate beyond the South Fork confluence, as mainstem Chl-*a* at the Poudre Below South Fork site remained unaffected across both reservoir conditions ($p = 0.38$; Figure 8).

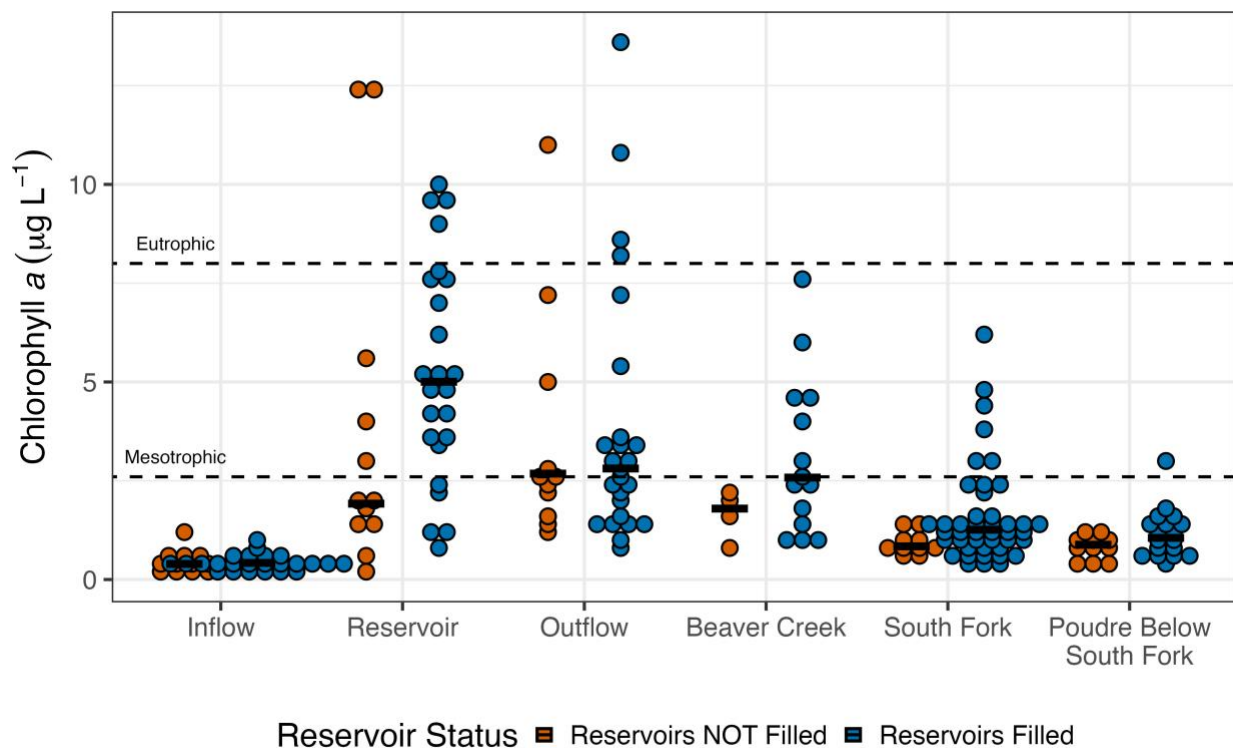


Figure 8: Longitudinal Chl-*a* concentrations through the South Fork Cache la Poudre reservoir network, from reservoir inflows (left) to the mainstem Poudre River downstream (right). Data are categorized by reservoir operational status: unfilled conditions in 2021–2022 (orange) and standard filled conditions in 2023–2024 (blue). Solid black lines indicate medians for each site and reservoir status. Dashed lines represent mesotrophic and eutrophic thresholds.

Generally, our findings confirmed observations from regional municipal treatment operators who have reported short term (1–24 hour) impacts from changes in reservoir operations (i.e., reservoirs releasing significant volumes of water during late-summer baseflow conditions) that do not lead to wide-spread eutrophic conditions in the river mainstem. However, our sampling design may have missed short-lived algal transport events associated with reservoir releases or storms. Because we did not sample immediately during or after these events, measured free-floating algae may underestimate the amount of algae reaching city intakes, particularly when algae are transported with sediment pulses or mobilized through scouring of benthic algal communities (Carpenter et al., 2025; Dolph et al., 2017; Henson et al., 2007; N. E.

Jones, 2010; C. A. Murphy et al., 2021; Peipoch et al., 2025). Overall, fire and reservoir operations may have increased the likelihood of episodic algal transport, but sustained in-stream phytoplankton growth appeared to remain limited by nutrients, water temperature, light availability, macroinvertebrate grazing pressures, and flow conditions during the study period.

Future Work 5.1

Remote sensing of lake surface reflectance has also been shown to estimate trophic status in lakes (Meyer et al., 2024; Sillen et al., 2024; Topp et al., 2021; Werther et al., 2021), but these efforts were not evaluated in this analysis. Future analyses of these lakes can leverage national data aggregation efforts of Chl-*a* (Brousil et al., 2024) or lake trophic state (Meyer et al., 2023), similar to the *lakeSR* and *siteSR* data products used in this study (Steele et al., 2026b, 2026a), to determine if the Cameron Peak Fire has caused a long-term (>5+ year) shift in reservoir color, trophic status, or frequency of algal blooms.

In-situ high frequency sensors may also allow us a greater understanding of how specific reservoir releases may impact riverine chlorophyll *a* on shorter timesteps (Bertone et al., 2018; Booth et al., 2023; Foster et al., 2022). However, in-stream algae remain difficult to monitor accurately from fluorescence sensors (Bertone et al., 2018; Zamyadi et al., 2012). This limitation is particularly relevant for the Cache la Poudre, where chlorophyll *a* concentrations were generally low during the study period, with most samples below 2.6 $\mu\text{g L}^{-1}$. At these low concentrations, sensor measurements may be especially sensitive to biofouling (Koren & McGraw, 2023), instrument noise (Foster et al., 2022), turbidity interference (Bowling et al., 2013), and nonphotochemical quenching (Foster et al., 2022). Together, these factors may reduce sensor reliability by increasing false positives associated with turbidity, biofouling, and noise, while also increasing false negatives associated with nonphotochemical quenching. Beyond

chlorophyll-*a* and sediment inputs, reservoir releases and wildfire can also impair drinking-water treatability by increasing disinfection byproduct formation potential (Carpenter et al., 2013; Chow et al., 2019; Hohner et al., 2016; Writer et al., 2014). These effects are primarily driven by changes in the quantity and composition of carbon in source waters, which are often monitored using in-situ sensors, chiefly fluorescent dissolved organic matter (fDOM) (Akie et al., 2024; Booth et al., 2023; Carpenter et al., 2013; Clow et al., 2024; Demaree et al., 2026). For example, a study of source waters in the Clackamas River basin, Oregon, successfully paired Chlorophyll-*a* and fDOM sensors to capture benthic algae sloughing events and reservoir pulses. By utilizing fDOM to quantify algal-associated organic carbon, the study directly informed water treatment operators of heightened risks from disinfection byproduct precursors.

CONCLUSION

Post-fire water quality research has historically prioritized headwater streams, where the influence of burn severity is more easily isolated from watershed-specific or human-controlled variables. However, municipal supplies in the Western United States rely on complex networks of reservoirs, canals, and mainstem reaches, where treatability is determined by the integration of all sources. This study demonstrates that headwater reservoirs can act as strong biological reactors, modulating wildfire impacts by transforming nutrient enrichment into algal growth and downstream propagation. While no marked shift in trophic status was observed in the Cache la Poudre watershed following the Cameron Peak Fire, risks to treatability are controlled by reservoir characteristics (Oleksy et al., 2022; Summers & Ryder, 2023), river network shape (Gardner et al., 2019; Graham et al., 2012; Graziano et al., 2026; Plont et al., 2023; Schmadel et al., 2024), antecedent algal composition and abundance (Klose et al., 2015; Peipoch et al., 2025; Rounds et al., 2015), hydro-climatic conditions (Bruns et al., 2022), and ultimately the position of raw water intakes in a watershed (Carpenter et al., 2013, 2025). Future assessments of post-fire trophic shifts should prioritize regional assessments through remote sensing applications (Meyer et al., 2024, 2025; Oleksy et al., 2022; Sillen et al., 2024), or reservoirs with pre-fire baselines (Paul et al., 2022). Furthermore, in-stream continuous monitoring is critical to resolve how pulsed reservoir releases and storm events impact riverine quality at shorter timesteps, providing actionable data for downstream water resource managers and treatment facilities.

CHAPTER 2: Real-Time and Forecasted Total Organic Carbon for Water Treatment Decision Support in the Cache la Poudre Watershed

Chapter Overview

The goal of this chapter was to develop two decision-support tools to inform drinking water treatment operators about Total Organic Carbon (TOC) conditions across the Cache la Poudre (CLP) River watershed.

1. Real-time estimates of TOC at upstream locations instrumented with multi-parameter sondes

Treatment operators already use field deployed real-time multi-parameter sonde data, particularly turbidity, to make proactive treatment decisions (Heath & Thorp, 2023). However, turbidity and TOC do not always co-vary. TOC can increase during snowmelt without a corresponding turbidity signal, and vice versa. To supplement existing sonde data with TOC estimates, we deployed a network of sensors across the CLP watershed and collected paired grab samples to build a harmonized training dataset. We then trained an Extreme Gradient Boosting (XGBoost) model ensemble to estimate TOC concentrations from continuous sensor data in real time. End-users can use this tool to track upstream increases in TOC and make proactive decisions in the event that the increase does not dissipate during transport.

2. Seven-day forecasts of TOC at the Poudre Raw Water Intake

A daily TOC sample is collected at this site, and the value is shared across municipalities (Fort Collins, Greeley, Soldier Canyon Water Treatment Authority), making it a familiar and operationally useful monitoring point. A seven-day forecast at this location would allow operators to anticipate short-term changes and plan changes in their blend of CLP River and

Horsetooth Reservoir water. To develop this tool, we used historical TOC data collected by the City of Fort Collins Utilities (2010–2025) to train an ensemble generalized additive model (GAM) incorporating seasonal forcing, snowmelt rates from SNOTEL stations, and basin flow forecasts from NOAA's Hydrologic Ensemble Forecast System (HEFS).

Both of these tools were then integrated into an operational dashboard displaying live-streaming sensor data, sensor-estimated TOC, forecasted TOC, and basin hydrology including snowpack and streamflow conditions. Throughout development, feedback was solicited from end-users to inform project direction, dashboard design, and build operator trust in machine learning approaches underlying model development.

LITERATURE REVIEW

Treatability Importance and Regulations 2.1

Health and Safety Concerns 2.1.1

Disinfection byproducts (DBPs) are formed during drinking water treatment when natural organic matter (NOM) in raw water reacts with chemical disinfectants, primarily chlorine (S. D. Richardson & Postigo, 2015; Sedlak & von Gunten, 2011). Many DBPs are harmful to human health, with regulated compounds including trihalomethanes (THMs) and haloacetic acids (HAAs) linked to increased cancer risk and adverse reproductive outcomes at elevated exposure levels (Cadee et al., 2025; S. D. Richardson et al., 2007; S. D. Richardson & Postigo, 2015). The quantity and character of DOM in source water is the primary determinant of DBP formation potential, making its measurement and removal a priority for drinking water treatment plants (DWTPs) (Cadee et al., 2025; Fernández-Pascual et al., 2023).

State and Federal Regulations 2.1.2

Total organic carbon (TOC) is a widely used operational metric for assessing NOM loading in source waters as it is directly tied to United States' regulatory DBP removal requirements (U.S. Environmental Protection Agency, 2015). Although other optical proxies, including ultraviolet absorbance at 254 nm (UV254), fluorescence excitation-emission matrices (EEMs), and parallel factor analysis (PARAFAC), can more precisely characterize DOM composition and in some cases better predict DBP formation potential (Fernández-Pascual et al., 2023; Pifer & Fairey, 2014), TOC remains the primary operational metric for most DWTPs in the United States (Cadee et al., 2025)

For operators in the Cache la Poudre River watershed and the State of Colorado more broadly, TOC is the primary treatment trigger and the metric around which treatment decisions, including coagulant dosing and blending with alkaline sources, are organized (Table 2 adapted from (5 CCR 1002-11.24 - Disinfection Byproduct Precursors Rule, 2024)). Raw water alkalinity is co-managed with TOC concentrations as low alkalinity may reduce the effectiveness of enhanced coagulation. The primary coagulant used in these DWTPs is alum, which is acidic by nature, and consumes alkalinity. If the raw water has insufficient alkalinity, the pH may decrease too rapidly, potentially hindering the formation of the flocculation needed for effective particle and NOM removal (Nabors et al., 2011), or resulting in a pH too low for other treatment procedures.

Table 2: Source water TOC removal thresholds for DTWPs in Colorado from CDPHE

Source Water TOC (mg L⁻¹)	Source Water Alkalinity, mg L⁻¹, as Ca CO₃		
	0-60	60-120	>120
2.0 – 4.0	35%	25%	15%
4.0 – 8.0	45%	35%	25%
>8.0	50%	40%	30%

Source Water TOC 2.2

Globally, DOM export is an enriching variable, where increases in precipitation and runoff result in increased export of DOM and its various forms, including TOC and dissolved organic carbon (DOC) (Alvarez-Cobelas et al., 2012; Meybeck, 1982; Tank et al., 2010). The quantity and character of DOM has been shown vary between catchments (Zarnetske et al.,

2018) and are a function of land use (Butman et al., 2015; Graeber et al., 2012), soil composition (Ewing et al., 2006), wetland density and prevalence (Creed et al., 2008; C. J. Williams et al., 2010), and runoff regimes (Hensley et al., 2022; Raymond et al., 2016).

In snowmelt-dominated headwater catchments of the Colorado Front Range, TOC are primarily sourced from near-surface soil horizons and riparian organic matter, which are mobilized to streams as infiltrating meltwater flushes terrestrial carbon stores during spring snowmelt (Boyer et al., 2000; Hood et al., 2003). As snowmelt continues, the most accessible soil carbon pool is depleted over the course of the snowmelt season (Hensley et al., 2022), resulting in a hysteretic relationship between flow and TOC where rising limb samples occupy higher TOC values than falling limb samples at equivalent flows. These dynamics are evident in the 15-year record of TOC at the Poudre River Intake (Figure 9), where concentrations consistently peak on the rising limb before maximum discharge and decline through the falling limb. This period presents a significant operational challenge: snowmelt-induced dilution lowers riverine alkalinity when TOC loading is at its maximum, thereby hindering the efficiency of enhanced coagulation. To mitigate this, operators blend source water with high-alkalinity water from Horsetooth Reservoir to maintain the necessary buffering capacity for effective TOC removal.

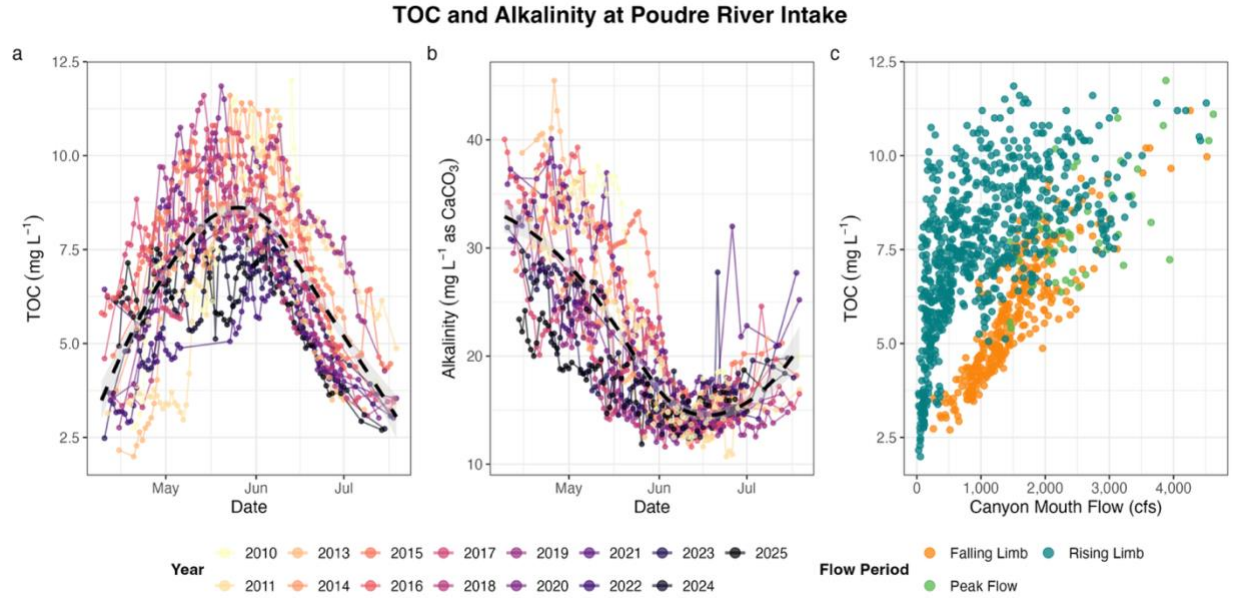


Figure 9: Daily TOC and alkalinity concentrations measured at the Poudre River Intake during the snowmelt period (day of year 100–200, approximately April through mid-July). (a) Daily TOC concentrations colored by year from 2010 to 2025. The dashed line is a loess fit to the full multi-year dataset illustrating the seasonal trend in TOC. (b) Daily alkalinity concentrations colored by year, from 2010 to 2025. The dashed line is a loess fit to the full multi-year dataset illustrating the seasonal trend in alkalinity. (c) TOC as a function of Cache la Poudre Canyon Mouth discharge, colored by flow period. Rising limb: days preceding the 90th percentile flow for each water year. Peak flow: days exceeding the 90th percentile flow. Falling limb: days following peak flow through day of year 200.

As discussed in Chapter 1, wildfire may also alter watershed carbon dynamics. Short-term post-fire water quality degradation following high-intensity rainstorms can force water treatment plants to shut down due to extreme sediment and TOC delivery in post-storm water (Brucker et al., 2025; Hohner et al., 2016, 2019). Long-term monitoring of the 2002 Hayman Fire in Colorado demonstrated that stream TOC export patterns were altered up to ten years post-fire (Rhoades et al., 2019) and a regional analysis of the Western United States found sustained TOC exports 5 to 8 years post-fire (Brucker et al., 2025). Previous work in the CLP watershed following the 2012 High Park Fire showed that wildfire altered the dissolved organic matter character of source water and ultimately required higher coagulant dosing for TOC removal (Hohner et al., 2016). Field and laboratory studies have further documented elevated risks of

toxic DBP formation in treated water during storm events in post-wildfire watersheds (Cawley et al., 2018; Tsai et al., 2017; Writer et al., 2014). The 2020 Cameron Peak Fire further raised the risk prolonged C enrichment (Rhoades, et al., 2025) and challenges treatment operations during intense rainfall events (Heath & Thorp, 2023).

Decision Support Framework 2.3

Effective translation of research into operational tools requires a structured, iterative process of co-design between researchers and end users (Baroni et al., 2014; Gregory et al., 2001; Ross et al., 2015). Fogli & Guida (2013) describe this process as cycling through four stages: elicitation, modeling, integration, and validation. These stages are connected by dialogue, interviews, naturalistic observation, and critique. This framework recognizes that operational users hold system-specific knowledge that researchers lack, and researchers hold analytical capacity that operators may not. Critically, this cycle is not linear: critique and dialogue at the integration stage may trigger a new round of modeling before a tool is integrated or return the process to elicitation.

Within this cycle, method selection is a particularly consequential decision point. Wątróbski et al. (2019), drawing on Roy's four-stage decision framework (B. Roy, 2005), argue that selecting an appropriate analytical method depends not only on the problem structure but also on the decision-maker's familiarity with available methods and the software supporting them. This has direct implications for participatory modeling: stakeholders are more likely to trust and adopt tools built on methods they can interpret, and academics should therefore present multiple approaches with accessible explanations of their tradeoffs rather than defaulting to the highest-performing method (Baroni et al., 2014). Soliciting stakeholder input on methods or

datasets they are already familiar with can also surface approaches that researchers may not have considered.

The original conception of this project began with three objectives: monitoring Chlorophyll-*a* (Chl-*a*) releases from reservoirs (Chapter 1), forecasting turbidity events, and modeling TOC concentrations. These objectives were identified by source-water managers and treatment operators as the three key operational variables. Efforts to detect and predict Chl-*a* releases were limited by non-photochemical quenching during daytime hours, a known issues with Chl-*a* fluorescence sensors (Foster et al., 2022), a narrow range of grab sample values, and weak seasonal signal in the dataset. While Chl-*a* prediction was not pursued further, operators expressed interest in retaining relative fluorescence units (RFUs) from deployed sensors as a qualitative proxy for Chl-*a* increases.

Turbidity forecasting was similarly deprioritized following stakeholder engagement and initial modeling efforts. Skillful turbidity forecasts require highly accurate precipitation forecasts, particularly during intense convective storms that remain difficult to forecast in the Colorado Front Range (Heever et al., 2021; Moreno et al., 2014). Further, any forecast would need to outperform the existing early warning network, where operators have access to 15-minute turbidity data from two upstream monitoring stations. Finally, developing and optimizing this model would require sufficient high-turbidity events, and exceedances of Fort Collins' treatment threshold (>100 NTU) occurred fewer than five times per year in the available record and were disproportionately prevalent in the years following the High Park and Cameron Peak fires.

Following these attempts, the project shifted to an upstream real-time early warning network for TOC and an intake forecast of TOC, delivered through an operational dashboard.

TOC was a more tractable forecasting target for several reasons: it follows a well-defined seasonal pattern tied to snowmelt in the CLP (Figure 1), its treatment thresholds span a wider range (Table 2), and small errors (< 50 CFS) in flow forecasts are less likely to affect operational decisions during snowmelt.

TOC Prediction 2.4

To predict TOC accurately, we developed real-time and forecasting models using machine learning (ML) methods, Extreme Gradient Boosting (XGBoost) and Generalized Additive Models (GAMs), respectively. Machine learning for water quality prediction has greatly increased in the last decade (Appling et al., 2022; Yan et al., 2024; Zhu et al., 2022) as the availability of large hydrology and water quality datasets has also increased (Cheruvilil et al., 2021; Kratzert et al., 2023; E. K. Read et al., 2017; Ross et al., 2019) and interest in ML methods has grown (Lofton et al., 2023; F. Olsson et al., 2025; Varadharajan et al., 2022). Broadly, ML differs from traditional process-based and regression models through its ability to capture non-linear relationships, autonomously identify patterns in large datasets, and algorithmically minimize predictive error (Appling et al., 2022). While these represent benefits to ML approaches, careful selection and reduction of input datasets is necessary to: carefully evaluate of model error, reduce over-training on the dataset, multicollinearity among predictors and temporal autocorrelation of features. These limitations can be overcome by selecting input features tied to hypothesized processes (J. S. Read et al., 2019; Robson, 2014), using datasets that accurately represent the system, and thoughtfully splitting data for training, validation, and testing (Costa et al., 2024; Garcia et al., 2024; Ploton et al., 2020). These types of careful design of ML models can ultimately increase end-user trust in a black box prediction.

Real-Time Estimation 2.4.1

Various studies have approximated TOC concentrations using hydroclimatic variables, particularly discharge, and statistical approaches (Erlandsson et al., 2008; Raymond & Saiers, 2010; Samson et al., 2016; Senatore et al., 2023; Zarnetske et al., 2018; Zhi et al., 2020). A comparison of statistical approaches across six New York City water supply catchments found that Generalized Additive Models (GAMs) outperformed linear and time-series alternatives, attributed to their ability to capture the nonlinear and seasonally varying relationships between TOC and hydroclimatic drivers (K. Wang et al., 2025). However, these models depend on long-term discrete grab sampling records and may fail to capture TOC dynamics during episodic high-flow events that are frequently undersampled (A. T.-S. Chow et al., 2022).

Recent advances in fluorescent dissolved organic matter (fDOM) sensors have improved the temporal resolution of TOC monitoring by providing continuous proxy measurements at minute to hour intervals (Akie et al., 2024; Booth et al., 2023; Carpenter et al., 2013; Clow et al., 2024; Crawford et al., 2015; Hensley et al., 2022; Shultz et al., 2018). In a snowmelt-driven western US watershed, fDOM sensors were used to characterize the daily hysteresis patterns of snowmelt TOC export (Hensley et al., 2022). These sensors were used to quantify TOC loads from burned watersheds where episodic concentration spikes frequently exceeded drinking water treatment thresholds (Akie et al., 2024; Clow et al., 2024). Machine learning approaches have extended this further, with recent work combining fDOM, turbidity, and other sensor inputs to build generalized TOC prediction models (Demaree et al., 2026), though the inclusion of static land use covariates in such model raises questions about transferability across basins. Despite their promise, fDOM-based approaches carry meaningful operational burdens: sensors require regular maintenance to maintain data quality (Akie et al., 2024; Lee et al., 2015), corrections for

turbidity interference of optical path (Booth et al., 2023; Downing et al., 2012), correction of temperature-dependent fluorescence (Booth et al., 2023; Watras et al., 2011), and potentially site- or sensor-specific calibration to fDOM-to-DOC relationships (Akie et al., 2024; Downing et al., 2012; Saraceno et al., 2017).

Forecasting 2.4.2

While real-time quantification of DOC is widely understood, forecasts of DOC are less well studied. More recent work has focused on the application of ML methods to create short-term (1–7 day) forecasts (He & Ma, 2024; Howard et al., 2026). At longer timescales, integrated seasonal climate forecasts coupled with hydrological and carbon models have produced seasonal to annual predictions of DOC for water providers. While these seasonal approaches are valuable for long-term planning, the complexity of the required process-based models and large historical datasets needed to produce them may not be available to all end users (Pedregal-Montes et al., 2026). Across timescales, forecast uncertainty in DOC is compounded by the dynamic and nonlinear nature of organic carbon transport, uncertainty in discharge forecasts increases with time (Li et al., 2025), and climate change is expected to further alter these relationships in ways that reduce the reliability of predictions based on historical conditions (Paíz et al., 2025).

METHODS

Study Area 3.1

The Upper Cache la Poudre (CLP), located west of Fort Collins, Colorado, has a total watershed area of 2,900 km², and average cumulative annual flows of 3 million m³ yr⁻¹ with peak flow occurring in early June (Colorado Department of Water Resources, 2026a). The CLP watershed covers a wide elevational gradient from 1,600 m to 4,109 m, with a mean elevation of 2,600 m (Hollister, 2017). Annual precipitation averages at 550 mm, though it ranges from 400 mm to 1,200 mm across the watershed, increasing with elevation (PRISM Climate Group, 2026). The CLP represents a significant portion of the drinking water supplies that support over 330,000 residents from the cities of Fort Collins, Greeley and the Solider Canyon Water Authority. Additionally, the CLP provides considerable agricultural water for the region of Northern Colorado. The CLP's key sources of water are from four large tributaries: Big South (CLP mainstem), Joe Wright Creek, South Fork CLP, and the North Fork of the CLP. The CLP also receives trans-basin water diverted from the Colorado River via the Grand Ditch, Laramie River via the Laramie River Tunnel, and Michigan River via the Michigan Ditch (APPENDIX A SI 1)

The CLP River continues through the City of Fort Collins and flows are altered by water removal for agricultural and municipal supply, and addition through tributaries (Dry Creek, Boxelder Creek, and Spring Creek) and return flows from urban and agricultural areas. In this study, monitoring efforts concluded at River Bluffs Open Space (35 km downstream from the Canyon Mouth) (*Figure 10b*). Annual precipitation averages at 400 mm (PRISM Climate Group,

2026) across this portion of the watershed and covers a smaller elevational gradient (1,550 m to 1,460 m) (Hollister, 2017).

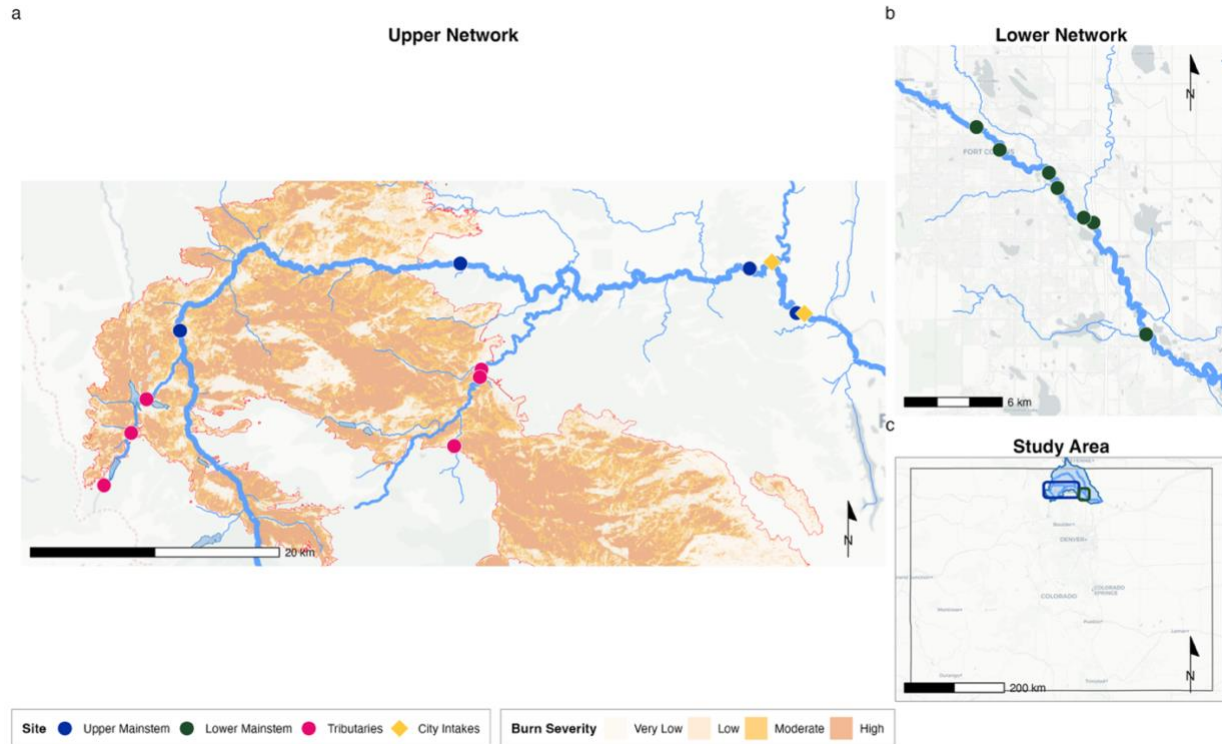


Figure 10: Map of study locations throughout the Cache la Poudre (CLP) Watershed, Colorado, USA. (a) Upper CLP monitoring sites, city water intakes, and BAER Soil Burn Severity from the 2020 Cameron Peak Fire. Burn severity classes follow USDA Forest Service BAER classification (Very Low–High). (b) Lower CLP mainstem monitoring site locations. (c) State of Colorado with the CLP watershed (HUC8: 10190007, blue shading) and study area extents highlighted (a, blue outline; b, green outline). Flowline widths are scaled by stream order.

Site Selection and Timeline 3.2

Sites above the canyon mouth (Upper Network) were selected from previously established sampling locations associated with the Upper Cache la Poudre Monitoring Program (Heath and Thorp, 2023) and USFS RMRS research sites described in Rhoades et al. (2025). These sites represent key source water areas for downstream treatment operators and provide continuity with long-term water quality monitoring efforts in the upper watershed. Sites below the canyon mouth (Lower Network) were selected to align with the previously established

Poudre Water Quality Network and the sampling locations of the Lower Poudre Monitoring Alliance, both of which target key stormwater, wastewater, and agricultural inputs to characterize long-term water quality dynamics through the City of Fort Collins.

Sensor deployment and water sampling were conducted across 19 sites in the Cache la Poudre River watershed between September 2023 and November 2025. Sensors were operated during the ice-free period, generally March through November in the Lower Network and April or May through October or November in the Upper Network, depending on site-specific conditions. Full site descriptions, deployment periods and locations are provided in Table A 1.

Sample Measurements 3.3

Sample Collection and Timeline 3.3.1

Samples ($n = 546$) were collected and handled following a similar approach outlined in Chapter 1 (Stream Water Sampling and Processing 3.2), however many of these ($n = 191$) samples were only collected to run total organic carbon (TOC), turbidity, and chlorophyll *a* as these were identified as key constituents by operators. Samples were collected within 10 m of the deployed sensor with care taken not to disturb the sensor or area around the sensor, except for the Poudre River at Manner's Bridge site where sampling access was not allowed due to private property and was sampled 300 m downstream on public land.

Monitoring locations were sampled from September 2023 – November 2025, with sampling frequency varying by site and season and no sampling occurring during winter (Dec-Feb). Intensive weekly sampling (4 samples/month) was concentrated during the 2024 and 2025 snowmelt and storm seasons (April–July). Bi-weekly sampling (2 samples/month) was conducted at most sites during shoulder seasons (March, September–November), while monthly

sampling (1 sample/month) was sporadic and largely limited to 2023. Monthly sampling was conducted primarily at Lower Network sites or tributary sites to determine baseline conditions and test model generalizability. Opportunistic samples were collected during storm events or reservoir releases.

Sample Processing and Quality Assurance 3.3.2

Samples were processed following the approach outlined in Chapter 1 (Section 1.2.1). Unfiltered samples were analyzed on a total organic carbon analyzer (TOC-V Combustion, Shimadzu) for TOC using EPA Method 415.3. Lower Network samples with specific conductance exceeding 1,000 $\mu\text{S}/\text{cm}$ required dilution with DI water to bring concentrations within instrument calibration ranges; corrected concentrations were calculated by RMRS lab managers using Equation 1. Quality assurance followed the procedures described in Section 1.2.1, including field duplicates and blanks.

$$C_{\text{sample}} = C_{\text{measured}} \times \left(V_{\text{total}} / V_{\text{sample}} \right) \quad \text{Equation 1}$$

Samples followed quality assurance protocols outlined in (Fegel, 2024) and in the previous chapter (See Section 3.2). Sample data was managed by USFS RMRS lab managers and provided on a biannual basis. This data was appended with watershed metadata and published to the *Zenodo* publication (Struthers et al., 2025) on a biannual basis.

City of Fort Collins' Sampling Methodology 3.3.3

Water quality samples collected by the City of Fort Collins were used to supplement model training and validation (See Section 3.6.3). Samples were collected by City technicians from the stream bank by hand or with a swing sampler following standard City operating procedures, with

date and time recorded in field notes. Samples were stored on ice during transport and processed in the City's Process Control laboratory following the methods described City SOPs (City of Fort Collins, 2021, 2022). Briefly, TOC samples were preserved in 40 mL amber glass vials with 1:1 phosphoric acid, analyzed on a TOC analyzer (Sievers M5310 C) using Standard Method 5310, and rerun if standards exceeded 5% error. Field duplicates and matrix spikes were collected daily at separate locations following a standard quality assurance schedule (City of Fort Collins, 2022). Data were shared as Excel workbooks for integration with study records.

Timeseries Measurements 3.4

Sensor Deployment Configuration and Maintenance 3.4.1

Each monitoring station was equipped with an In-Situ Inc. AquaTROLL multiparameter sonde (In-Situ Inc., Fort Collins, Colorado), though sensor configurations varied by site. At minimum, all sites measured five parameters: specific conductance, water temperature, turbidity, fluorescent dissolved organic matter (fDOM), and chlorophyll-a (Chl-*a*) fluorescence. fDOM sensors operate with an excitation wavelength of 375 nm and emission detection between 460 and 530 nm; Chl-*a* sensors excite at 430 nm and detect between 675 and 750 nm. Select sites were additionally equipped with dissolved oxygen and pH/ORP sensors, though these parameters were not used in this study. Sondes were equipped with an anti-fouling wiper and was set to clean at 15-minute intervals. Sensors logged data at 15-minute intervals, either stored internally and downloaded during site visits or transmitted in real-time to In-Situ Inc.'s cloud platform (HydroVu).

Sondes were deployed in 4-inch PVC pipe housings mounted securely in the channel, with telemetry units attached above the waterline. Housings were designed to keep sondes submerged across the full range of flow conditions while allowing safe instrument deployment and retrieval

without entering the water. The exception is the Udall site, which requires a low-flow housing configuration due to site-specific channel conditions. Housings were preferentially mounted vertically where site conditions permitted, though several stations required angled deployment at approximately 45 degrees due to site conditions.

Sensors were calibrated monthly following the methods outlined Table A2, with the exception of Chl-*a* sensors, which were calibrated annually per manufacturer recommendations. Recalibration or sensor replacement was performed outside the regular schedule if malfunctions or anomalous data were identified. Stations were inspected biweekly, during which sensor faces and sonde were cleaned with tap water and a microfiber cloth to remove biofilm and sediment accumulation. Additional cleaning visits were conducted when anomalous data were detected via the real-time data stream.

Timeseries Processing, Quality Assurance and Correction Methods 3.4.2

Logged sensor data were processed and summarized from log files or the HydroVu API using functions from the *ross.wq.tools* (De La Torre et al., 2026), *tidyverse* (Wickham et al., 2019), *zoo* (Zeileis & Grothendieck, 2005), *RcppRoll* (Ushey, 2013), and *arrow* (N. Richardson et al., 2019) packages in R (R Core Team, 2025) and RStudio (Posit team, 2025). Raw sensor data were summarized to 15-minute intervals and grouped by site-parameter combination. Raw sensor records were segmented into windows bounded by successive valid calibrations and where necessary, back-calibrated using slope and intercept coefficients extracted from calibration files. A linear temporal weighting factor was applied to blend the bounding calibration coefficients across each window.

Prior to manual review, an automated quality control pipeline was applied to all sensor records using functions from the *ross.wq.tools* R package. Single-parameter flags were first

applied to each site-parameter time series independently, identifying field visit periods, missing data, repeating values, depth shifts, optical sensor drift, and exceedances of manufacturer specification ranges and seasonally defined thresholds based on historical data. A second flagging pass operated across parameters within each sonde simultaneously, identifying periods of frozen water (temperature below 0°C), sonde burial, and unsubmerged conditions based on depth and specific conductance thresholds. A network-level check was then applied across all sites in longitudinal order to identify and remove flags when conditions were consistent with concurrent upstream and downstream observations.

All automated flags were subsequently reviewed manually to identify and remove additional anomalous data or reduce over-flagging from automated methods, with flagging decisions informed by concurrent flow and climate records, technician field notes, and cross-site comparisons with upstream and downstream stations. Following manual review, biofouling drift in turbidity and fDOM records was corrected within each inter-cleaning interval using a one-point drift correction anchored to pre- and post-cleaning sensor readings. Each drift instance was classified by drift shape (linear or exponential) and correction method (additive or multiplicative), with a corresponding temporal blending function applied accordingly. In practice, turbidity drift corrections were predominantly multiplicative while fDOM drift corrections were predominantly additive and linear. Data bounded by unresolvable erroneous calibrations or drift were excluded from the final dataset.

Following drift correction, short (< 1 hour) data gaps were filled by linear interpolation, and a low-pass smoothing filter was applied to turbidity and fDOM time series to reduce residual noise. fDOM data were corrected for temperature dependence (fDOM_c) following methods described in Booth et al. (2023). Inner-filter effect corrections for turbidity were not applied, as

In-Situ Inc. sensor specific correction factors were not derived, and turbidity is expected to be accounted for implicitly within the XGBoost model framework.

External Datasets 3.5

Flow Data 3.5.1

Measured flow gage data was collected from the Colorado Department of Water Resources (CDWR) API using the *cdssr* package (Watters, 2026). Data was downloaded using the *get_sw_ts()* function to retrieve daily average flow data from the Poudre River Canyon Mouth (CDWR Guage ID: CLAFTCCO) station for the water years 2000 through 2026 (Colorado Department of Water Resources, 2026b).

Daily NOAA Hydrologic Ensemble Forecast System (HEFS) (Demargne et al., 2014) streamflow forecasts were retrieved for the canyon mouth site (NWPS gauge ID: FTDC2) for the period April 1 through November 15 across the 2023 to 2026 water years using the NOAA Water API (National Oceanic and Atmospheric Administration (NOAA), 2026). Forecasts were retrieved as 30-day 30-member ensemble predictions of instantaneous discharge issued daily at 12:00 UTC. Data were accessed programmatically via the NOAA HEFS API, with each ensemble member retained as a separate record. Forecasts with missing or zero discharge values were excluded, and limited to a 7-day horizon.

SNOTEL Snow Datasets 3.5.2

Snow water equivalent (SWE) data was collected from the SNOTEL network stations in the Cache la Poudre River watershed (HUC8: 10190007) (USA Natural Resources Conservation Service, 2026) using the *snotelr* package (Koen Hufkens et al., 2024) function *snotel_download()*. To reduce the dimensionality of the multi-station SWE record into a single watershed-scale

snowpack index, a principal components analysis (PCA) was performed on the complete daily SWE records across all stations using the *stats* package (R Core Team, 2025) in R, with variables centered and scaled prior to analysis. The first principal component (PC1) was retained as a composite SWE index representing the dominant mode of variability across stations. Snowmelt rates were then derived from this index at a 7-day and 14-day lag intervals by calculating the change in PC1 per day over each preceding period, providing medium-term estimates of melt intensity as predictor variables for downstream modeling.

XGBoost Model Development 3.6

Feature Dataset Harmonization 3.6.1

Grab sample TOC concentrations from ROSS field campaigns and City of Fort Collins monitoring were combined into a single dataset and matched to the nearest hourly sensor observation within a three-hour window using the sample collection datetime. Matches were preferential to sensor data following sample collection but instances without future sensor data were joined to sensor data before sample collection. Daily average streamflow from the Canyon Mouth gage (Section 3.5.1) was appended to each matched record. In addition to the raw sensor parameters, a set of derived predictor variables were computed from the sensor time series prior to matching and included in the final modeling dataset (Table 3). The final matchup dataset comprised 629 samples across all sites and years.

Table 3: Feature variables created for testing in XGBoost and GAM Model Development. Bold variables are direct sensor values and italicized values indicate features retained in final models

Variable	Description	Real-Time	Forecast
FDOMc	Fluorescent Dissolved Organic Matter (RFU) corrected for temperature dependence	X	
<i>Specific Conductivity</i>	Specific Conductance at 25 °C	X	
<i>Temperature</i>	Water Temperature (°C)	X	
<i>Turbidity</i>	Turbidity NTU	X	
<i>daily_flow_cfs</i>	Mean Daily Canyon Mouth flow (cfs), HEFS forecasted flow for GAM	X	X
<i>fdom x turb</i>	fDOM multiplied by turbidity	X	
<i>fdom x sc</i>	fDOM multiplied by specific conductance	X	
<i>fdom_turb</i>	fDOM divided by turbidity	X	
<i>DOY</i>	Day of Year		X
<i>swe_14_day</i>	14-day SNOTEL melt rate		X
<i>swe_7_day</i>	7-day SNOTEL melt rate		X
<i>log_turb</i>	Log transformed turbidity		
<i>Sc_sd_24hr</i>	24-hour rolling standard deviation of specific conductance		
<i>Turb median 12hr</i>	12-hour rolling median turbidity		
<i>Turb median 6hr</i>	6-hour rolling median turbidity		
<i>FDOMc 6hr</i>	6-hour rolling median fDOMc		

Features were scaled from 0-1 using the scales *rescale()* function (Wickham et al., 2011) based on the ranges available in the full sensor timeseries. All lagged features were ultimately removed due to high correlation ($|r| > 0.9$) with sensor features which may run the risk of splitting feature importance in model training. The derived variables, *fdom_turb* and *log_turb*, were also removed due to low feature importance.

Cross Validation Approach 3.6.2

The matchup dataset was split into a holdout testing set and a training/validation set. The holdout set comprised 2025 samples from five sites spanning the upper watershed (CHD, SFM, PBR, PMAN, PBD) and was withheld entirely from model development. The remaining samples

formed the training and validation set, which was partitioned into three site-based cross-validation folds. Sites were assigned to folds manually to ensure each validation set contained approximately 30 to 35% of the total training/validation samples and represented a similar TOC distribution and mix of network positions (upper mainstem, upper tributaries, and lower mainstem) as the corresponding training set (Figure A1). The holdout testing set was skewed toward higher TOC values relative to the training/validation set, reflecting the emphasis on sampling April through July sampling period of the 2025 data. This distributional difference is a known limitation of the current dataset and is expected to improve as future samples are collected (Figure 11).

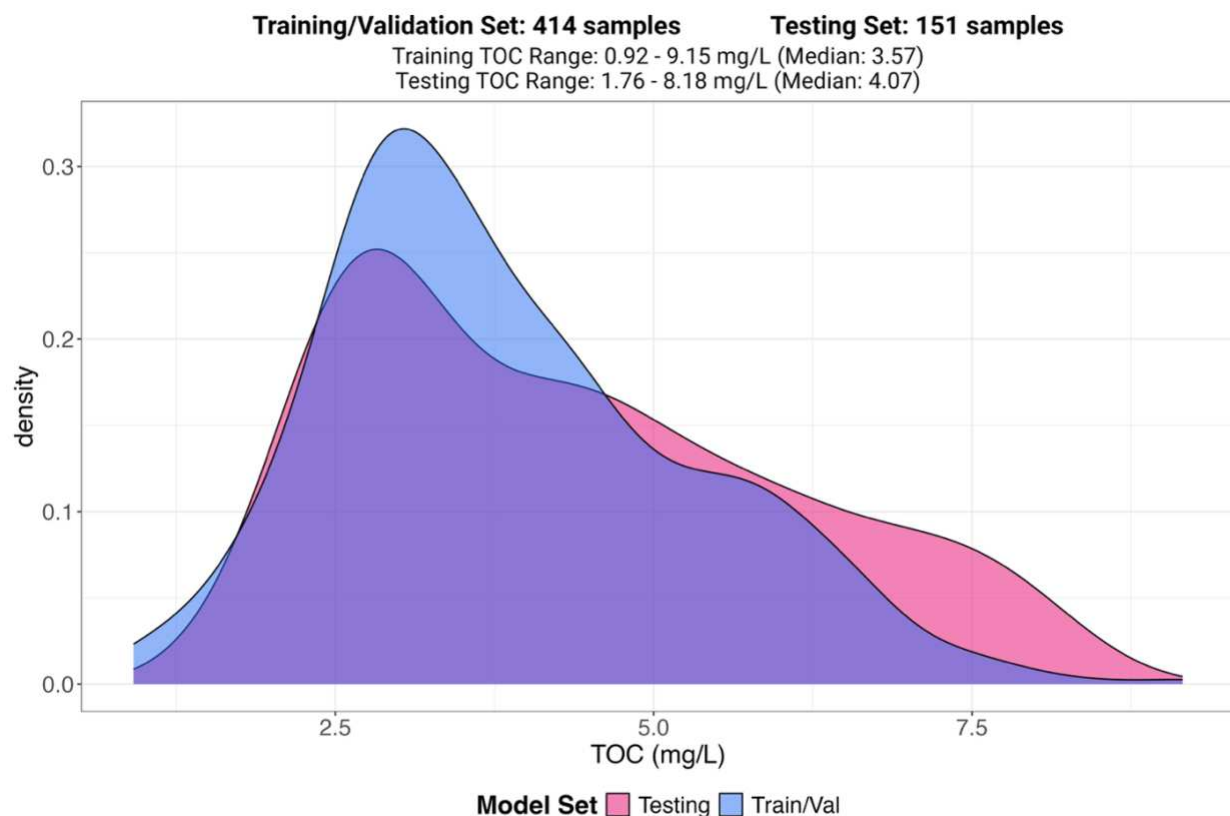


Figure 11: Density plot of TOC (mg L^{-1}) sample concentrations between training and validation data (blue) and holdout testing data (pink). Testing data is skewed to the higher range of TOC values.

Model Training and Evaluation 3.6.3

Three-fold models were trained using XGBoost (Chen et al., 2014) and tuned using site-stratified cross-validation. For each fold, hyperparameters were selected via grid search over hyperparameters (*Table A3*), with up to 1,000 boosting rounds and early stopping applied to prevent overfitting based on the learning rate. The objective function was squared error and RMSE as the evaluation metric. To reduce bias toward low TOC observations, which dominate the training dataset, a log-scaled sample weighting function was applied that assigned unit weight to samples with TOC at or below 4 mg L⁻¹ and increasing weights for higher concentrations. Maximize model performance and minimize overfitting, fold model selection was first limited to the lowest 10 hyperparameter combinations by validation RMSE, and from those, the six with the smallest absolute difference between training and validation RMSE. Performance was evaluated using Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and bias using the *Metrics* package (Hamner & Frasco, 2012) on both training and validation sets. Plots of learning curves and observation vs prediction results were inspected for each candidate model to determine if a model was overfit to the training data and performance on validation set. Ultimately a single model was selected for each fold. The three-fold model is applied to new data, and the ensemble prediction is the mean of all three predictions with the minimum and maximum predictions representing the possible model range. Feature importance was evaluated using SHAP (SHapley Additive exPlanations) values, which allows observation-level contributions from individual input features to assess of both the magnitude and direction of each feature's influence across training and test set using the *shap.prep()* and *shap.plot()* functions from the *SHAPforxgboost* package (Y. Liu & Just, 2019).

GAM Model Development 3.7

Dataset Harmonization and Model Training Approach 3.7.1

Daily TOC values (2010-2025) provided by the City of Fort Collins for the Poudre Raw Water Intake (Section 3.3.3) were joined to daily mean canyon mouth flow (Q) (Section 3.5.1) and the calculated 14-day melt rate derived from SNOTEL data (Section 3.5.2); day of year (DOY) was also calculated for each observation. Data were split into training and test sets using a temporal holdout approach, with 2017 and 2024 reserved for testing. Because the HEFS discharge forecast already incorporates a model ensemble, a single GAM was trained across all remaining years.

The model was trained using the *gam()* function from the *mgcv* package (Wood, 2000). The model was built iteratively, beginning with DOY as the sole predictor, then Q and finally testing SWE PCA values and 14-day and 7-day melt rates. At each step, interaction terms were evaluated to capture nonlinear covariation between predictors. Model complexity was increased only when doing so improved predictive accuracy without degrading GAM diagnostics or introducing signs of overfitting. GAM diagnostics were assessed using the *gam.check()* function, with well-specified models expected to show: confirmed convergence with a near-zero gradient and full model rank; a positive-definite Hessian indicating the optimizer did not settle in a local minimum; a basis dimension ratio (k'/edf) near 1; and a p-value above 0.05, which indicates the chosen basis dimension is sufficient to capture the smooth's complexity. When the estimated degrees of freedom (edf) approached the maximum allowable (k'), the basis dimension was increased; conversely, when edf was well below k' at a given complexity level, a lower k was preferred to reduce the risk of overfitting.

Three GAM models were sufficiently accurate at predicting TOC in the training dataset while not overfitting data: DOY + Q, DOY + Q + SWE 14d, DOY + Q + SWE 7d. These models were validated using the holdout dataset to understand how they generalized to an unseen dataset. Models were evaluated for Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and bias using the *Metrics* package (Hamner & Frasco, 2012) and visual inspection for fit on upper-end data.

Forecasting Model Performance Evaluation 3.7.2

Forecasting performance was evaluated on two TOC datasets: Data collected from Jan 2023 through December 2025 and Spring (March-mid-May) 2026 data. The recent (2023-2025) dataset was chosen to easily access historical forecasts from the NOAA API and the 2026 data was chosen due to extremely anomalous snow and flow dynamics experienced during this period (shown in *Figure A8*). In both model evaluations, SNOTEL melt rates were joined with HEFs flow forecasts, and predictions were made using GAM models. Similar to forecasting conditions, SNOTEL melt rates are assumed to be fixed over the forecast. As the HEFS forecast model is a probabilistic forecast (Demargne et al., 2014), forecasts were also evaluated using the Continuous Ranked Probability Score (CRPS), which is a method to assess error with probabilistic predictions and is calculated as:

$$CRPS = \int (F(y) - H(y - y_{obs}))^2 dy \quad \text{Equation 2}$$

where y_{obs} are the observed values, y are the forecasted values, $F(y)$ is the cumulative distributed function of the probabilistic forecast at y , and H is the step function. CRPS is analogous to MAE

in deterministic methods and was computed using the *crps()* function in the *verification* package (Gilleland, 2004).

To test model skill, a reference model of TOC was made using the historical dataset where forecasts are represented by the mean of samples collected on that day of year from 2010-2022 when testing the 2023-2025 dataset and 2010-2025 when testing the 2026 dataset. The forecast range is estimated from the standard deviation of samples from that day of year. For days with less than 2 samples, the standard deviation is set to the mean standard deviation across the year. A CRPS value was also computed for this baseline model so as to compute a Continuous Ranked Probability Skill Score (CRPSS), which evaluates a forecasts' skill in comparison to a baseline model. CRPSS for each observed timestep is compute as:

$$CRPSS = 1 - \frac{CRPS_{model}}{CRPS_{reference}} \quad \text{Equation 3}$$

and is summarized to an aggregate score for the model:

$$CRPSS_{agg} = 1 - \frac{\overline{CRPS_{model}}}{\overline{CRPS_{reference}}} \quad \text{Equation 4}$$

where $CRPS_{model}$ represents the CRPS values from the developed GAM models and the $CRPS_{reference}$ represents the CRPS values from the baseline model developed from historical averages. CRPSS is a range from 1 to $-\infty$, with 1 representing perfect forecast of the observed values, zero indicating no improvement over the reference model, and negative values representing poorer skill than the reference model. CRPS, CRPSS, and $CRPSS_{agg}$ were summarized by forecast day horizon to assess the stability and skill of the forecast over time.

To isolate the effect of forecast input uncertainty on model performance for 2026, GAM predictions were generated under four input conditions: (1) observed canyon mouth flow and observed SNOTEL melt rates (i.e., a perfect-input baseline representing the best achievable model performance), (2) HEFS ensemble mean flow forecasts paired with observed SNOTEL melt rates, (3) observed canyon mouth flow paired with a constant melt rate (7-day or 14-day) held fixed at the issue date value across all forecast horizons, and (4) HEFS ensemble mean flow forecasts paired with a constant melt rate (7-day or 14-day) held fixed at the issue date value across all forecast horizons. Comparing performance across these three conditions allows the contribution of flow forecast error and melt rate assumption error to be attributed separately. Model performance under each condition was evaluated at horizons 1–7 days using RMSE, MAE, and ME, with horizon 0 representing the perfect-input baseline.

Stakeholder Engagement and Feedback 3.9

Stakeholder engagement was conducted throughout the study period through quarterly meetings with water treatment and source water protection staff at the City of Fort Collins and City of Greeley, held independently given each utility's distinct treatment processes and water rights. Meetings were used to communicate project progress, present current sampling and modeling approaches, and discuss model confidence and limitations. Meeting notes were taken to document how operators perceive model accuracy and evaluate the risk tolerance associated with incorporating model outputs into operational decisions. Feedback on dashboard layout and usability was solicited at each meeting and incorporated iteratively into dashboard development. Site visits to each treatment facility were conducted to document treatment processes, identify

data sources currently used in operations, and understand how treatment decisions are made, providing context for translating model outputs into operationally relevant information.

RESULTS

Real-Time TOC Model Development 4.1

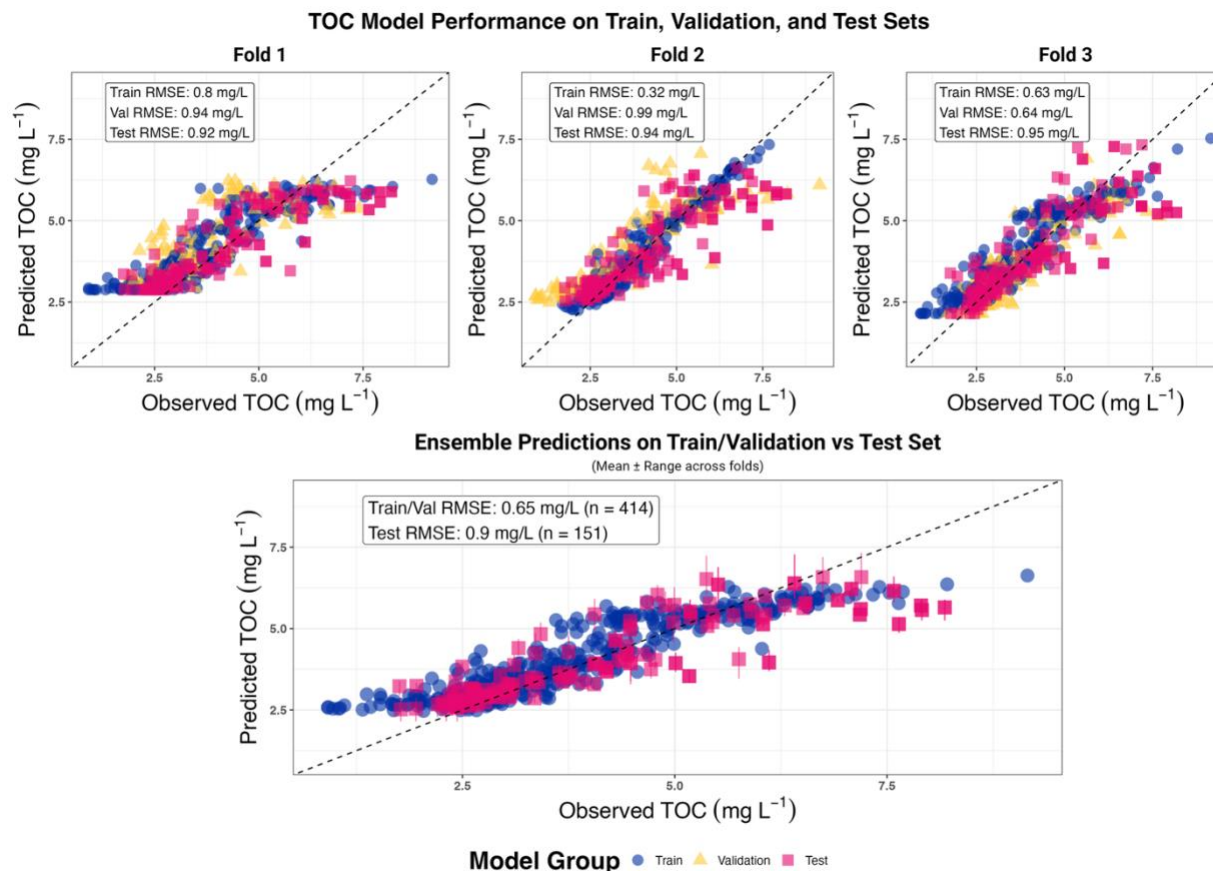


Figure 12: Total Organic Carbon (TOC) predictive model performance across individual cross-validation folds and the final ensemble. Top panels display observed versus predicted TOC pairings for individual training folds 1, 2, and 3, tracking partition-specific Root Mean Squared Error (RMSE) across the training (blue circles), validation (yellow triangles), and testing (pink squares) subsets. The bottom panel shows the ensemble mean prediction and aggregated performance metrics for combined training data versus the independent test set, with vertical error bars indicating the full prediction range across all three folds.

The real-time TOC model achieved RMSE below 1 mg L⁻¹ on both validation and test sets across all three folds, with stronger performance at concentrations below 5 mg L⁻¹, which represent the majority of observations in the dataset. Fold-level performance varied in character

despite comparable test set RMSE values. Fold 1, which contained the greatest diversity of validation sites ($n = 6$) and a validation set more concentrated at the lower end of the TOC range relative to its training data (Figure A1), exhibited a visible prediction bench near 6 mg L^{-1} across all data partitions, suggesting the model encountered a structural ceiling when extrapolating to conditions not well-represented in training. Fold 2 showed signs of overfitting to its training set but maintained similar RMSE between validation and test partitions, with a moderate positive bias on the validation set and less severe benching than Fold 1. Fold 3 produced the most consistent performance across training and validation sets and outperformed the other folds, though its test set RMSE remained comparable (Figure 12). SHAP analysis confirmed that fDOM was the most important predictor (mean test SHAP value: 0.60), followed by turbidity (0.32), canyon mouth flow (0.14), and the interaction between fDOM and specific conductance (0.14) (Figure A2), with feature importances remaining consistent between training and test sets.

When the ensemble mean was applied to the test set, overall RMSE was 0.9 mg L^{-1} with a pronounced bench near 6 mg L^{-1} , consistent with the Fold 1 behavior described above. Ensemble spread was lower below 5 mg L^{-1} , indicating strong convergence across folds in this range. However, consistent benching at 2.5 mg L^{-1} indicates a lower concentration limit of model performance, this is consistent with few samples less than 2 mg L^{-1} ($n = 31$ of 565, 5.5%) and 55% ($n = 17$) of these samples located at the Joe Wright Reservoir Inflow. The test set posed a particular challenge for the model: it was weighted toward the upper end of the TOC range and comprised three sites the model had not previously encountered (Figure 11). These sites were primarily mainstem Upper Network locations, and the only comparable training data from sites of similar size and fDOM composition came from the Canyon Mouth (2024) and Poudre Falls (2024 & 2025). Overall, the cross-validation approach yielded a moderately accurate ensemble

model; its primary strength was in characterizing prediction uncertainty at unseen locations, enabling conservative and defensible estimates when communicating new results to stakeholders.

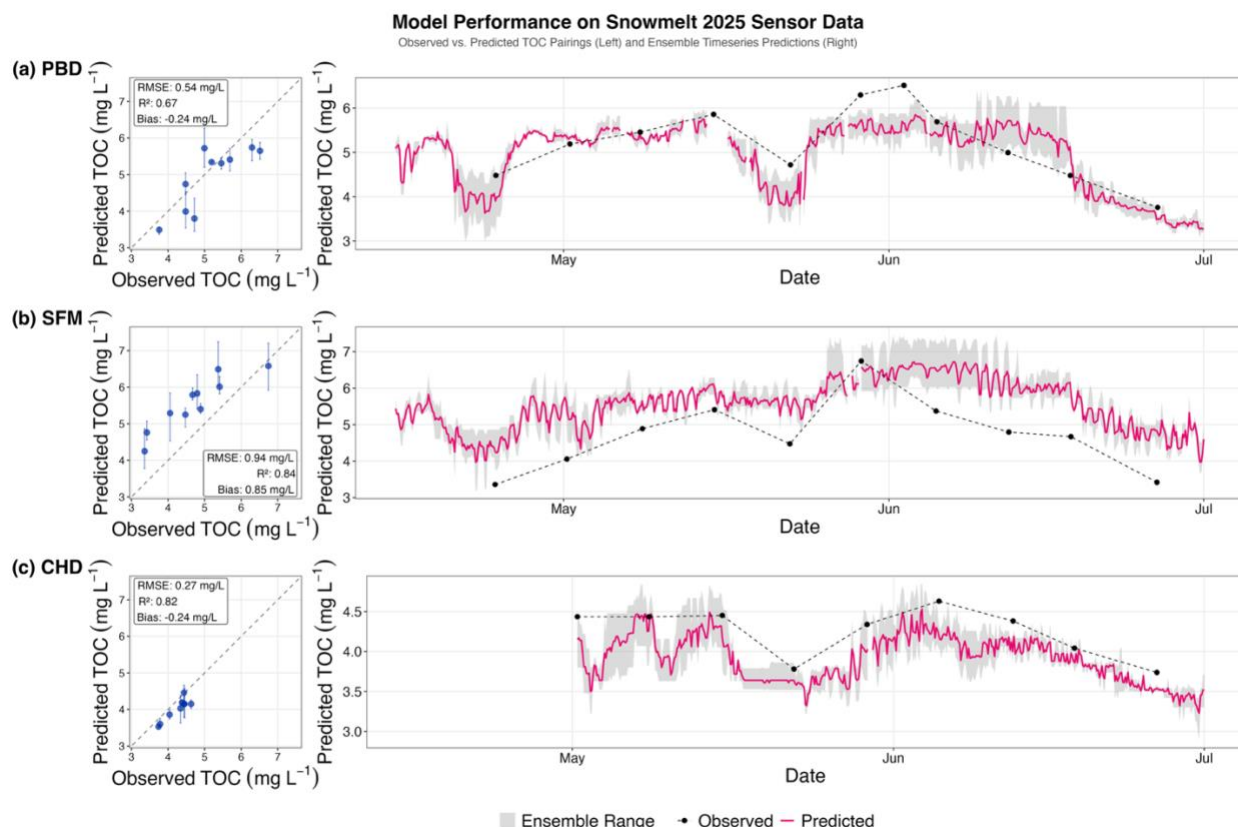


Figure 13: Real-time predicted Total Organic Carbon (TOC) concentrations across three Cache la Poudre basin sites (top to bottom), specifically Canyon Mouth (PBD), South Fork (SFM), and Chambers Lake Outflow (CHD), during the 2025 snowmelt season. Predictions were made using a three-member XGBoost ensemble model. Left panels display observed versus predicted TOC pairings, where the dashed line represents a relationship, error bars denote the full ensemble range, and diagnostic metrics indicate local model performance. Right panels display continuous time-series predictions from May through July 2025, tracking the median prediction (pink line) and total ensemble uncertainty envelope (grey shading) against discrete observed grab samples (black points).

Site-level analysis of test set predictions revealed some site-wise bias, in line with prior work documenting the need for site-specific fDOM-to-TOC relationships (Akie et al., 2024; Saraceno et al., 2017). Performance was reasonable at the Canyon Mouth site, where the model captured variability in TOC across a relatively broad concentration range (3.5 to 6.5 mg L⁻¹) during the snowmelt period with minimal bias (Figure 13a). However, RMSE at the Canyon

Mouth site was significantly higher (1.0 mg L^{-1}) in the test set dataset than in the training dataset (0.5 mg L^{-1}), indicating that the model is slightly overfit to historical conditions. In contrast, the Chambers Outflow site exhibited a persistent negative bias during snowmelt, with the model consistently underpredicting observed concentrations (Figure 13b). This site sits directly below a reservoir, where TOC composition is more heavily influenced by algal biomass and thus more dependent on chlorophyll-a than the allochthonous fDOM signal the model was trained to interpret. Inclusion of concurrent chlorophyll-a data may improve performance at reservoir-influenced sites in future model iterations, however due to non-photochemical quenching of chlorophyll a sensors, this will need to be computed as a lagged parameter.

The South Fork CLP site exhibited the opposite bias to Chambers Outflow, with the model consistently overpredicting observed TOC values. This tributary has consistently lower specific conductance and higher turbidity than other sites in the network. Both variables are positively associated with increased TOC in model SHAP values (Figure A2), as they are associated with peak runoff, and is likely leading to the over-predictions at this site. The site also exhibited larger diurnal variability in fDOM, introducing additional daily variability in TOC predictions in a longer timeseries (Figure 13c) and resulting performance metrics are more sensitive the accuracy of joining sample and sensor data.

Across all sites except Chambers Outflow and CLP at Archery Range, the ensemble model explained more than 70% of the variance in observed TOC values ($R^2 > 0.7$), with 15 of 20 sites achieving $R^2 > 0.8$. The model also demonstrated strong spatial generalizability across the Cache la Poudre basin, performing well at lower mainstem sites such as CLP at Lincoln St (Figure A3). The lower performance at CLP at Archery Range may reflect the influence of a nearby upstream wastewater treatment plant on the fDOM to TOC relationship. RMSE was less

than 0.6 mg L^{-1} at most training sites, with test sites generally exhibiting higher error, indicating some over-fitting to the training set. Samples collected by our group had lower RMSE (0.65 mg L^{-1}) than those collected by the City of Fort Collins (1.22 mg L^{-1}), a difference potentially attributable to biofouling: our samples were typically collected immediately following sensor cleaning during site visits, whereas the sensors were not cleaned prior to City sampling majority and the majority of City samples were in the test set ($n = 96$ of 122 ; 79%). City of Fort Collins samples were also negatively biased (-0.71 mg L^{-1}), while our samples showed a small positive bias (0.22 mg L^{-1}).

Short-term TOC Forecast Development 4.2

GAM model development achieved RMSE values comparable to the real-time operational model across a longer evaluation timespan and greater range of observed values at the Poudre River Intake. Models incorporating SWE melt metrics yielded lower RMSE and MAE values overall, and the model incorporating 14-day melt rates achieved the best test set performance (RMSE: 0.89 mg L^{-1}). The DOY-only model produced a significant prediction bench at 9.5 mg L^{-1} , while the DOY + Q model captured the majority of variance in the dataset but exhibited lower performance on high TOC value and had lower performance metrics. Specifically, the DOY + Q model exhibited greater prediction error distinguishing between portions of the rising and falling limbs. All models exhibited positive prediction bias on the test set (Figure 14).

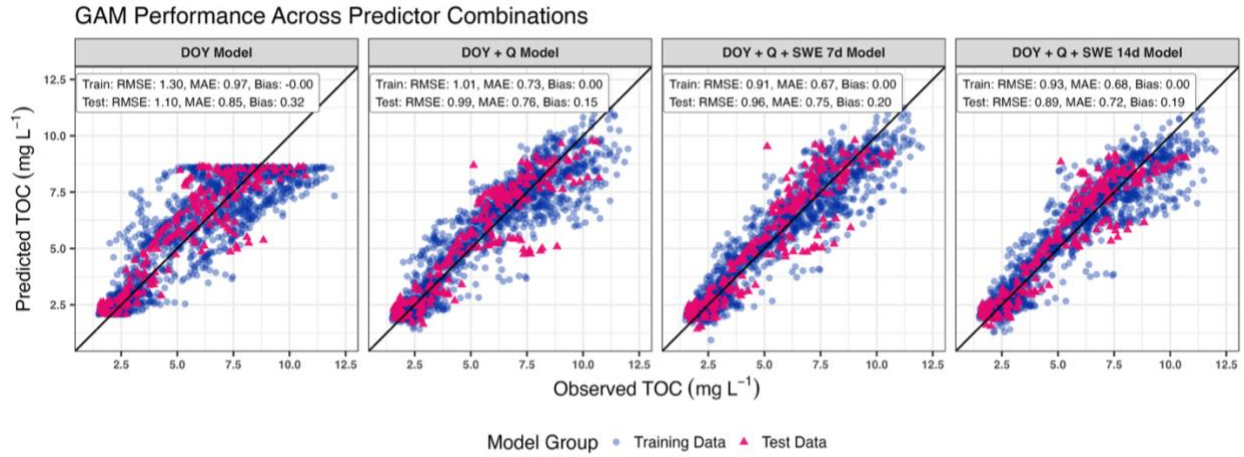


Figure 14: GAM model performance across predictor combinations for predicting TOC (mg/L) at the Poudre Raw Water Intake. Each panel shows observed vs. predicted TOC for training (blue circles, 2010–2025 excluding holdout years) and test (pink triangles, 2017 and 2024) datasets with performance metrics (RMSE, MAE, Bias) for each set and model. Models progress in complexity from left to right: day of year (DOY) only, DOY plus canyon mouth discharge (Q), and DOY plus Q plus snowmelt rates (7-day and 14-day).

Forecasts applied to 2023 through 2025 data demonstrated consistent skill across a seven-day horizon, with median CRPS scores near 0.5 mg L⁻¹ across all three models (Figure A6). Forecast versus observed plots showed little degradation over the seven-day forecast window; however, specific outlier events were consistently poorly captured by the SWE-based models across all forecast timesteps (Figure A5). Additionally, all models across all horizons exhibited a positive bias due to the positive bias in HEFS forecasts (Figure A4). Median CRPS Skill Scores for the 2023 through 2025 period confirmed that all three GAM forecasts improved upon the DOY climatological baseline (Figure A5). Aggregate CRPSS values over the same period and summarized across forecast horizons further supported this finding, with scores of 0.127, 0.07, and 0.115 for the DOY + Q and the two SWE-based (7d + 14d) models, respectively.

Despite this overall skill improvement, model biases were apparent during the transition from peak flow to the falling limb, as illustrated by forecast performance during June across 2023 to 2025 (Figure A7). At shorter horizons, forecasts exhibited positive mean error, which

shifted toward negative mean error as the horizon increased. Over this period, CRPS Skill Scores for the models including SWE declined with increasing forecast horizon, and absolute CRPS rose modestly, suggesting that the DOY + Q model may be more effective once the snowmelt signal has dissipated and the TOC falling limb is driven primarily by the trajectory of discharge. Although forecast skill during the peak-to-falling limb transition remains an area for improvement, the DOY + Q + SWE 14d model demonstrated the strongest overall performance across the test set and 2023 to 2025 forecast period, and its explicit inclusion of snowmelt dynamics reflects operator intuition about TOC behavior at the CLP intake.

Iterative Design with Stakeholders and Dashboard Development 4.3

As discussed in the introduction, a real-time upstream warning system and intake-specific TOC forecasts were the agreed-upon targets for this operational tool. Because the real-time system would be actively used by water treatment operators, accurate characterization of model uncertainty at telemetered sites was essential. All samples collected from livestreaming sites during 2025 were therefore allocated to the test set to provide an honest estimate of real-world performance in the 2026 roll out of the dashboard. Although presenting these results to stakeholders initially prompted concern about model accuracy, transparency about model construction and limitations ultimately increased operator understanding and prompted productive discussion about how the estimates should be interpreted and applied in practice.

Stakeholder engagement also drove a fundamental shift in the scope and design of the forecasting product. The original forecast framework used a bi-weekly to monthly grab sample dataset collected across the basin (Heath & Thorp, 2023) to produce a distributed, basin-wide TOC forecast. However, operators indicated that this approach would have limited practical value, as their decisions are centered on intake conditions rather than upstream basin-wide

patterns. This feedback redirected the project toward an intake-specific forecast, and stakeholders provided the long-term historical record at the Poudre River Intake on which the forecast model is based.

Initial presentation of the DOY + Q intake forecast model received mixed reviews. Stakeholders indicated the model would not be operationally useful unless performance at high TOC concentrations improved, as these are the conditions that drive treatment decisions. This feedback prompted a targeted investigation into the drivers of peak TOC, which revealed that peak TOC concentrations consistently preceded peak discharge (Figure 9). The incorporation of 14-day SWE melt rates into the model improved estimation of these peak values (Figure 14), and upon re-presentation, stakeholders opted to integrate the forecast into the data dashboard for a one-year operational trial.

Dashboard Development 4.3.1

Dashboard design prioritized accessibility and clarity, reflecting how operators actually engage with monitoring data in their daily workflow. Operators noted that they rely more heavily on trends than on absolute values when making treatment decisions, as operational adjustments involve some lead time and flexibility. Consequently, the interface was designed around continuous timeseries displays that allow operators to anticipate sustained or large-scale shifts in water quality rather than react to individual data points.

We build a real-time data dashboard and deployed it using *shiny* (Chang et al., 2012) and *rsconnect* (Atkins et al., 2016) R packages and was made accessible to project partners. All code and GitHub Actions Workflows are available at the ROSSyndicate *uclp_dashboard* repository:

[`https://github.com/rossyndicate/uclp\\_dashboard`](https://github.com/rossyndicate/uclp_dashboard)

Due to computation limitations, the sensor data was retrieved, aggregated and quality controlled on an hourly basis via a scheduled GitHub Actions workflow and passed through an automated flagging pipeline using *ross.wq.tools* functions (Section 3.4.2) to remove erroneous observations. Automated flagging tools in the *ross.wq.tools* approach errs toward overflagging rather than under flagging, which aligned well with operator preferences expressed during stakeholder engagement. Operators emphasized that they would rather miss an occasional event than receive frequent false alarms that create user fatigue and erode trust in the system over time.

To generate TOC forecasts at the Poudre River Raw Water Intake, HEFS streamflow forecasts and SNOTEL SWE data were retrieved and aggregated once daily at 3:00 AM MST via a separate GitHub Actions workflow. To simplify user experience, only the DOY + Q + SWE 14d model was display on the dashboard but other models were used for additional testing and analysis. HEFS forecasts were limited to a 7-day horizon, the 14-day lagged melt rate was computed for the basin, and ensemble quantiles (minimum, 25th percentile, median, 75th percentile, maximum) were derived for each forecast day. Both datasets were archived in the dashboard repository and accessed dynamically by the application. Sensor data are formatted for input to the real-time TOC model (Section 3.6) within the application as these steps are less computationally intensive.

We designed the dashboard user interface around two operational timescales reflected in Figure 15: near-term planning across a 1 to 7-day horizon and immediate decision support spanning 1 to 72 hours. These categories map directly onto the four pages of the dashboard and informed decisions about data loading, interactivity, and layout throughout development.

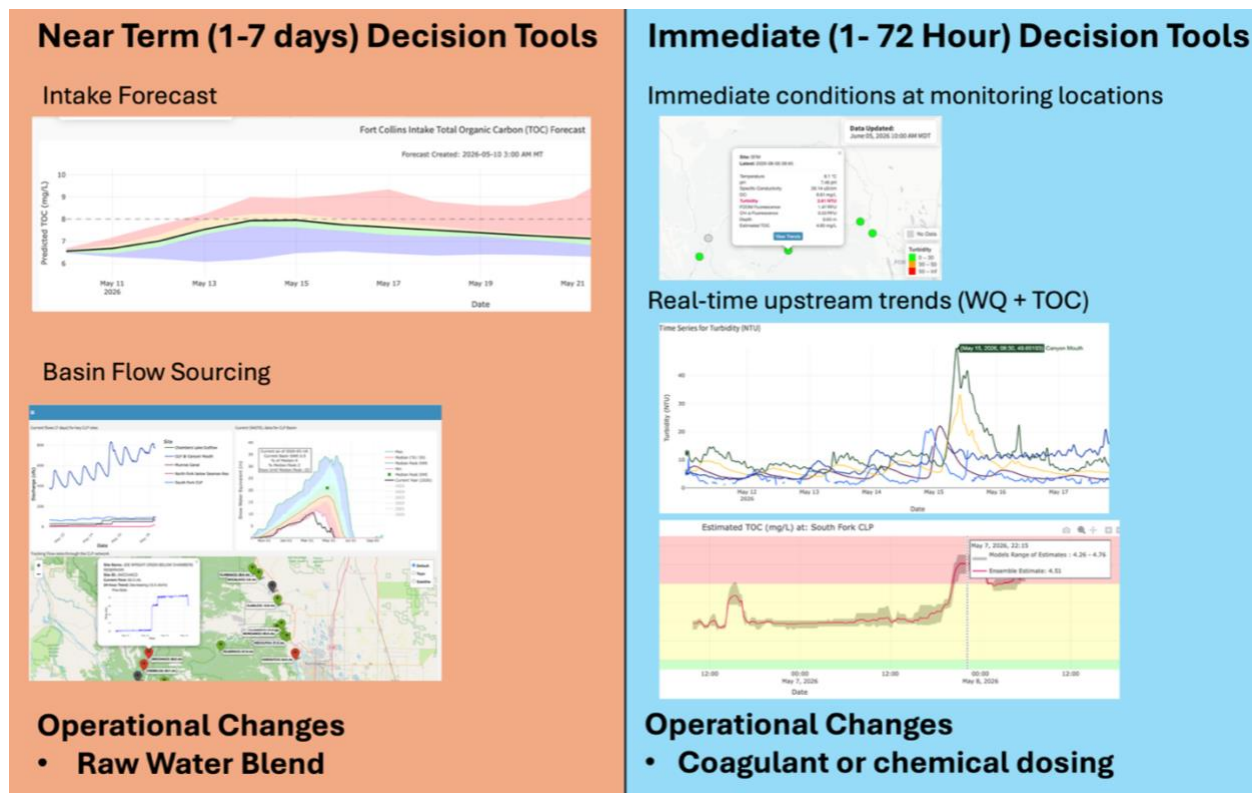


Figure 15: Operational decision support tools developed for municipal water treatment operators, organized by decision timescale. (Left, orange) Near-term tools (1–7 days) informing raw water blend adjustments: (1) a probabilistic 7-day TOC forecast at the Fort Collins Intake displaying the ensemble prediction range relative to treatment thresholds, and (2) a basin flow sourcing page showing discharge across the network. (Right, blue) Immediate tools (1–72 hours) informing coagulant and chemical dosing decisions: (1) a real-time network map displaying more recent status across all monitoring locations, and (2) time series views of upstream turbidity and real-time estimated TOC

For operators checking in during their daily workflow, speed of access to information was a priority. The Home page addresses this by displaying a cached snapshot of the most recent sensor observations on an interactive site map alongside the current TOC forecast, allowing users to assess immediate basin conditions without triggering a full API call. This design came directly from operator feedback: waiting approximately one minute for a page to load to retrieve an additional hour of data was seen as a barrier that could discourage regular use. Home page values are color-coded for each parameter using a green, yellow, and red framework; allowing operators to see exceedances of operational thresholds immediately.

Users who want to investigate conditions in greater depth can navigate to the Live WQ Data page, which initializes API calls to retrieve the full sensor record and displays time series of water quality parameters alongside real-time TOC model estimates. This page offers greater control over time periods, sites, and parameters, making it particularly useful during periods of change such as storm events or reservoir releases.

For near-term planning, the Home page also presents the most recent 7-day ensemble forecast, giving operators a forward-looking view of expected TOC concentrations at the intake. Supporting this, the Basin Conditions page aggregates streamflow data from CDWR and USGS gauges, SNOTEL SWE observations, and reservoir release records across the watershed, providing the hydrologic context operators need to anticipate raw water blending or treatment adjustments (Figure 15).

DISCUSSION

Dissolved organic carbon and total organic carbon represent growing concerns for water treatment providers due to the risk of disinfection byproduct formation during treatment (Cadee et al., 2025; Fernández-Pascual et al., 2023). This risk that is expected to intensify as increasing wildfire activity and subsequent mobilization elevates organic carbon in municipal water supplies, particularly across the western United States (Brucker et al., 2025; A. T. Chow et al., 2019; Rhoades et al., 2019). Additionally, DOC and TOC concentrations are expected to increase under increased climate change (Monteith et al., 2023), further compounding treatment challenges, particularly in areas sourcing from snowpack derived water resources (S. Xu et al., 2024).

This work focused on operationalizing existing modeling approaches to enable decision support for water treatment plant operators who are treat source waters with high TOC levels. Specifically, I built an XGBoost model with real-time sensor inputs for estimation of TOC throughout a river network, building off of methods in Demaree et al. (2026). In addition to this real-time work, we developed a forecast using a GAM with climate and seasonal forcing for forecasting, building off a similar approach to K. Wang et al. (2025), with the goal of transitioning these methods from research to operational decision support systems. This work was done entirely with our municipal partners in the loop, allowing us to identify modelling accuracy targets, iterate on dashboard design, and target model forecast horizons that were helpful at the treatment plant and for watershed supply planning. Municipal operators expressed a target accuracy of 0.5 mg L^{-1} RMSE for operational confidence; while this threshold was not fully achieved, the test set RMSE values of 0.9 mg L^{-1} for both methods demonstrate sufficient

accuracy to justify continued development and sample collection, and the cities of Greeley and Fort Collins are actively using the dashboard, with further development ongoing.

Throughout this process, we prioritized transparent communication of model limitations before asking operators to act on model outputs, an approach essential for building trust in the decision support tools (Houser et al., 2025; J. A. Olsson & Andersson, 2007). This was a learning experience in both directions: we developed a clearer ability to articulate the rationale behind cautious modeling choices, while operators developed a more grounded understanding of how these ML models work, performance they can reliably expect, and where they should exercise independent judgment.

The deployment of this sensor network and operational TOC model represents a step forward in both operational monitoring and scientific understanding of TOC dynamics in the Cache la Poudre watershed, similar to efforts in the Mackenzie River water supply basins (Carpenter et al., 2013). TOC concentrations are being measured and transmitted in real time across multiple mainstem locations, capturing storm and snowmelt-driven pulses commonly missed by grab sampling at daily and bi-weekly intervals (Akie et al., 2024; Clow et al., 2024; Hensley et al., 2022). Continuous sensors are increasingly deployed for real-time detection of harmful water quality parameters, including *E. coli* (Aulenbach & McKee, 2020; Knopp et al., 2026), bromide (Stone & Klager, 2023; T. J. Williams & Totzke, 2024), trace metals (Ellison et al., 2023; Morel et al., 2020), and nutrients (D. A. Burns et al., 2019; Pellerin et al., 2016). This growth has been driven by the increasing availability of lower-cost sensors (de Camargo et al., 2023; Ighalo et al., 2021) and methods (Dare et al., 2026; Pellerin et al., 2016) for translating continuous sensor readings into discrete, lab-equivalent parameter estimates.

Including lower watershed sites, where urban, agricultural, and municipal inputs create more diverse TOC dynamics, broadened the range of conditions captured by the XGBoost model. Greater training dataset diversity has been shown to improve transferability and accuracy in both hydrological and water quality ML models (Kratzert et al., 2019; Zhi et al., 2024). Tree-based ML models are well suited to this diversity, as they can handle additional complexity without sacrificing prediction accuracy (Appling et al., 2022). However, error in TOC estimates introduced by the non-fluorescent DOM fraction (Korak et al., 2014; Rosario-Ortiz & Korak, 2017) and other site-specific DOM composition (Downing et al., 2012; Saraceno et al., 2017; Watras et al., 2011) will likely persist without substantially larger and more diverse training datasets. Regardless, this sensor and modeling framework also offers a potentially more accessible and flexible alternative to frequent sampling or online TOC analyzers, potentially lowering the barrier to entry for utilities with limited capital budgets (A. T.-S. Chow et al., 2022).

While operational success was the primary motivation for this work, the dataset assembled across sites and years has created an opportunity to advance scientific understanding of carbon dynamics in the CLP. Analysis of the intake data reveal consistent differences in TOC concentrations between the rising and falling limbs of the hydrograph (Figure 1), consistent with work at other snowmelt watersheds (Hensley et al., 2022; Kelley et al., 2025). The early snowmelt, rising limb period is particularly challenging for operators, as water rights regulations and water resources teams encourage greater river water withdrawals during high flow periods, while rapidly shifting alkalinity conditions simultaneously increase treatment challenges (Heath & Thorp, 2023). Deeper scientific understanding of the processes driving TOC during this period, particularly interactions between snowmelt, soil moisture, and non-fluorescent DOM,

will be essential for improving forecast performance during this window (Boyer et al., 2000; M. A. Burns et al., 2016; Hensley et al., 2022; Hood et al., 2003). In a Montana headwater catchment, Nippgen et al. (2015) demonstrated that contributing areas expand during the rising limb of the hydrograph as storage thresholds are exceeded and lateral connectivity between hillslopes and the stream network increases, providing a mechanistic basis for the elevated and variable TOC fluxes that challenge model performance during snowmelt onset.

The GAM forecast model also offers a lens for understanding how anomalous hydrologic conditions influence TOC export, with particular relevance to future drought years. Water year 2026, characterized by low snowpack, early melt onset, and late-season storms that produced a bimodal TOC peak in early April and late May, provided an informative stress test of forecast performance under conditions outside the model's training conditions. The DOY + Q model performed poorest under these conditions, underpredicting during the early TOC peak and overpredicting after it receded, as the seasonal DOY signal no longer reflected the timing of observed dynamics (Figure 16). The SWE-based models exhibited similar DOY-driven errors but fit the data better overall across the seven-day horizon, with the strongest performance at the one- to three-day timestep. Beyond five days, however, the 14-day SWE model degraded below the DOY baseline in skill (Figure 16), suggesting that longer-term melt rate integration introduces compounding error when melt rates are dynamic and atypical.

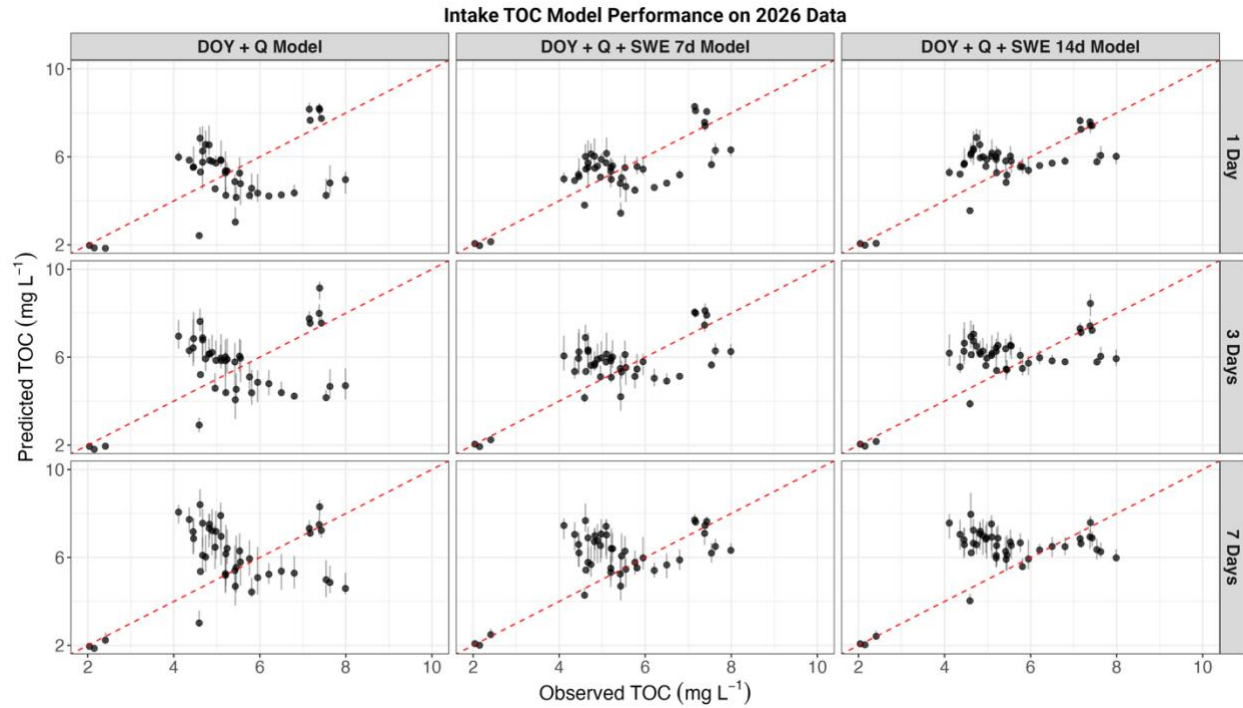


Figure 16: Evaluation of GAM performance for predicting daily TOC concentrations (mg L^{-1}) at the Poudre River intake using 2026 data. Observed vs. predicted TOC values are plotted across a 1-, 3- and 7-day forecasting horizon for three distinct model formulations.

Attribution of forecast error during this period further illustrates the relative contributions of model structure and forecast inputs (Figure 17). The DOY + Q model exhibited the highest RMSE at 1.6 mg L^{-1} , while the SWE-based models performed considerably better with RMSE values of 1.06 and 0.92 mg L^{-1} , respectively. HEFS flow inputs increased error across all models and horizons, driven in part by a consistent positive bias in HEFS seven-day forecasts identified across the 2023 to 2025 period (Figure A4), which propagates into TOC overprediction as discharge consistently increases predicted TOC. Notably, fixing SWE melt rates in the seven-day model reduced error metrics relative to baseline conditions, suggesting some hydrologic memory in the system whereby recent melt may persist on land surfaces before entering the stream as TOC. This error reduction was not observed in the 14-day model, indicating that fixing longer-term melt rates over extended forecast horizons may impose

unrealistic assumptions about sustained melt. HEFS forecast error dominates total model error at longer horizons, and addressing these flow forecast deficiencies represents the most impactful avenue for improving forecast skill across the seven-day window.

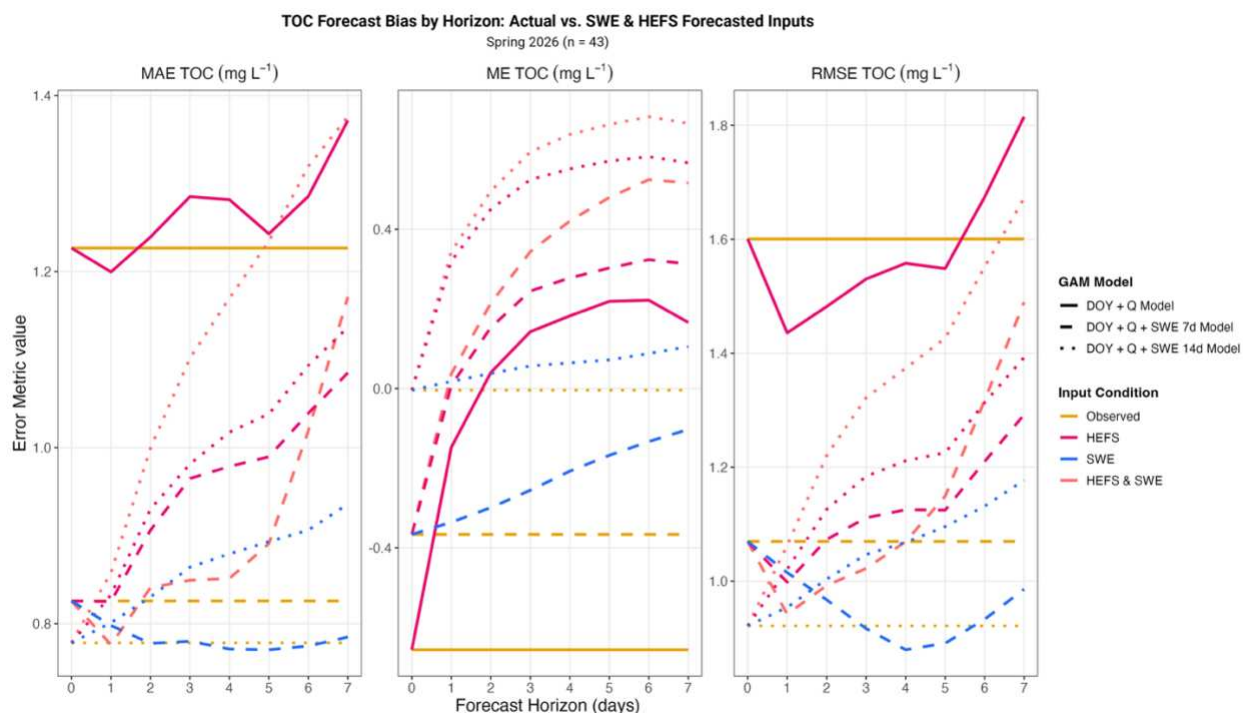


Figure 17: TOC forecast error metrics (MAE, ME, RMSE) propagated across a 1-to-7-day horizon for three GAM configurations during Spring 2026 ($n = 43$). Performance is evaluated under four distinct input conditions to isolate the independent and combined impacts of streamflow forecast (HEFS) and snowmelt assumption (SWE) uncertainty against a perfect-input baseline (Observed and Horizon 0) (See Forecasting Model Performance Evaluation 3.7. for details).

Study Strengths and Limitations 5.1

Real-Time Sensor Model 5.1.1

The real-time sensor model predicted TOC concentrations reasonably well across varying sites and TOC ranges, and adherence to rigorous cross-validation practices means that model performance limits are well characterized for our future deployments, even if overall accuracy is somewhat lower than comparable published work. The model also successfully captured TOC

spikes during summer storm events, which has direct value for immediate coagulant and chemical dosing decisions. However, several limitations constrain broader applicability. The model may not generalize well to basins with differing fDOM-TOC relationships, biofouling remains a known source of un-resolved error between sensor-based predictions and grab sample results, and model performance at high TOC concentrations, which are operationally the most consequential, remains an area for improvement. The inclusion of basin streamflow as a predictor improved model performance by capturing seasonal forcing but limits transferability to use in other watersheds, although comparable metrics could be computed for other basins. As the training dataset grows beyond its current size ($n = 414$) this feature could be replaced with a more transferable predictor such as DOY, which currently overfits due to limited sample volume and only two complete years of sampling. Despite these constraints, the sensor-based model was successfully integrated into an operational dashboard, and municipalities reported active use of the system during the 2026 snowmelt period.

Forecasting Model 5.1.2

The simplicity of the GAM framework allowed straightforward transition from a historical model to an operational forecast by substituting HEFS ensemble flow predictions and fixed SNOTEL melt rates, which may support transferability to other basins or municipal intakes given the broad regional coverage of the HEFS and SNOTEL systems. Hindcast evaluation across 2023 to 2025 provided a well-characterized picture of forecast skill and limitations that could be communicated directly to end users, and the inclusion of SWE melt rates meaningfully improved performance at high TOC concentrations where operational decisions are most critical.

Limitations became more apparent when the forecast was applied to preliminary spring 2026 data where inconsistent melt rates likely introduced error through the SWE melt rate term

rather than reducing it. Compounding this, the HEFS system exhibited deficiencies in forecasting Cache la Poudre flows during these anomalous conditions, and forecast error grows substantially with increasing horizon as a result. Together, these issues highlight that forecast skill is sensitive to both the hydrologic character of the year and the quality of the underlying flow forecast, and that the SWE component may behave poorly as atypical snowmelt conditions become more common under climate change.

Data Dashboard 5.1.3

The dashboard was successfully deployed ahead of the 2026 snowmelt season, and iterative stakeholder feedback has meaningfully improved its utility over time. However, several operational constraints remain. Two sites, CLP at Indian Meadows and CLP at Manners Bridge, do not currently provide livestreaming data, despite being key decision points for municipal operators, and filling these gaps would improve the capacity of the system. The application also lacks a dedicated server, with the GitHub Actions workflow and internal computation serving as a workaround that contributes to slower load times. Finally, the *Shiny* R-based framework, while effective for rapid development and deployment, imposed constraints on visualization flexibility and user interface customization that may limit future improvements.

Future Work 5.2

Municipal partners have committed to an additional year of funding to continue optimizing both the real-time and forecasting products. Once sufficient samples have been collected in 2026, real-time models will be retrained with the remaining 2025 data and tested on this new dataset. Near-term priorities include telemetry upgrades at Poudre at Manners Bridge and Poudre at Rustic to enable real-time TOC predictions at these key decision points, as well as

continued QAQC and dashboard improvements to build operator trust and sustained use. Stakeholders have also proposed two additions that would add meaningful value: a comment logging tool allowing field and water resources staff to provide contextual notes or photos alongside sensor data, and a transport time tool to predict when a sediment or TOC peak will arrive at the intake based on current flow conditions. Longer-term, tracking how operators actually engage with the system will be essential to guide iterative improvements. Lastly, assimilation of daily City-collected grab sample TOC data into the forecast model through a Kalman filter approach (Evensen, 2003; Kalman, 1960) may improve model accuracy during periods of rapid change or conditions outside of historical norms, an approach that has shown promise for improving operational water quality predictions and forecasting (Gao et al., 2025; Loos et al., 2020).

Transferability of the real-time model to other basins remains an open question, as the fDOM-TOC relationships and hydrologic dynamics of the Cache la Poudre may not be broadly representative. Continued testing of the modeling framework in other systems, including collaboration with parallel efforts such as (Demaree et al., 2026) in the Yampa River, will help identify inherent biases and boundary conditions for a regional model applicability. Water treatment managers in Loveland, Colorado have also indicated interest in applying a similar system to the Big Thompson River and Green Ridge Glade Reservoir, which will provide an opportunity to test model transferability in an adjacent but distinct system. Successful meta-transfer learning efforts in water quality contexts (Willard et al., 2021, 2023) may also offer a path toward adapting knowledge gained in this data-rich system to basins with more limited observational records.

CONCLUSION

TOC dynamics in the Cache la Poudre are tightly coupled to snowmelt, creating predictable but operationally challenging conditions that motivated this work. We developed an early warning system for TOC at municipal intakes, combining an upstream real-time sensor-based network with a seven-day probabilistic intake forecast to alert operators of anticipated elevated organic carbon conditions. We prioritized conservative and generalized performance in both models, and forecast skill was evaluated against a climatological baseline to ensure the forecast provides meaningful warning beyond what seasonal patterns alone would predict. Both tools were integrated into an operational dashboard actively used by municipal partners. While model accuracy fell short of the operator-defined target of 0.5 mg L^{-1} , iterative co-design with stakeholders produced a system that practitioners still trust and find value in. We suggest that this process, as much as the models themselves, represents a transferable framework for academic-municipal collaborations seeking to bring research tools into operational water quality management. Future work building on this dataset will advance understanding of carbon fluxes in this system and may extend this framework to other regional municipal intakes facing increasing organic carbon loads under a changing climate.

CONCLUSION

Western water supplies depend on interconnected networks of forested headwater catchments, reservoirs, transbasin diversions, and river mainstems that together make up raw water in municipal intakes (N. Liu et al., 2021; Simeone et al., 2024). These supplies face compounding pressures from warming temperatures (Petrie et al., 2017), declining snowpack (Barnard et al., 2023; Kampf et al., 2022), land use change (Theobald et al., 2011), and increasing wildfire activity (Alizadeh et al., 2021; Cunningham et al., 2024; Zhuang et al., 2021), all of which threaten both water availability and quality while driving up treatability concerns for providers who have historically relied on relatively pristine source waters (Abildtrup et al., 2013; N. Liu et al., 2022; Writer et al., 2014). As these stressors intensify under a changing climate, the burden on water resource managers will only grow, demanding not just better science, but science that is actionable.

The CLP watershed and 2020 Cameron Peak Fire illustrate these challenges. Municipalities faced elevated sediment and nutrient loads in the river mainstem (Heath & Thorp, 2023; Rhoades, et al., 2025), yet the fate of these impacts at high-elevation source water reservoirs, which supply the majority of late-summer flow (Barnard et al., 2023), remained poorly understood (Paul et al., 2022). Our reservoir work demonstrated that while no immediate shift in trophic status was observed following the fire, burned reservoirs exhibited measurable nutrient increases, and reservoirs exert localized but meaningful control on downstream Chl-*a* concentrations. Treatability risk in these systems is shaped not by any single factor, but by the intersection of reservoir characteristics, hydroclimatic conditions, and intake position within the watershed. This complexity underscores why bi-weekly grab sampling, while informative for

characterizing seasonal patterns, is insufficient to resolve the short-duration pulses of algae delivered during reservoir releases and storm events; precisely the conditions operators need to anticipate.

Recognizing this gap, we expanded our monitoring approach and worked directly with CLP municipal partners to co-design an operational early warning system for TOC, a common constituent in post-fire runoff, indicator of DBP precursors, and another primary treatment and regulatory concern for operators. Through an iterative, stakeholder-driven process, we developed a real-time upstream sensor network paired with a seven-day probabilistic intake forecast, both integrated into an operational dashboard for operators. Though our models did not fully meet operator-defined targets, practitioners trusted and acted on the system because they helped build it. This framework, grounded in open-source data products (HEFS and SNOTEL) and a generalizable modeling approach, offers a transferable model for other municipalities seeking to create a similar product for themselves.

These two efforts reflect a broader imperative: as western water systems face mounting climate-driven uncertainty, the academic community must prioritize building relationships with the practitioners managing these natural and built systems. Effective tools should be built iteratively, with and for the people using them (Baroni et al., 2014; Gregory et al., 2001), and designed to fit within the real operational and regulatory constraints resource managers navigate daily (Fogli & Guida, 2013). Looking forward, sustaining high-quality source waters will require moving beyond reactive management toward proactive stewardship, integrating the academic and institutional knowledge developed in studies like these into the design and protection of the ecosystems that our water supplies depend on (Ross et al., 2015).

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APPENDIX A: CHAPTER 1 SUPPLEMENTAL FIGURES

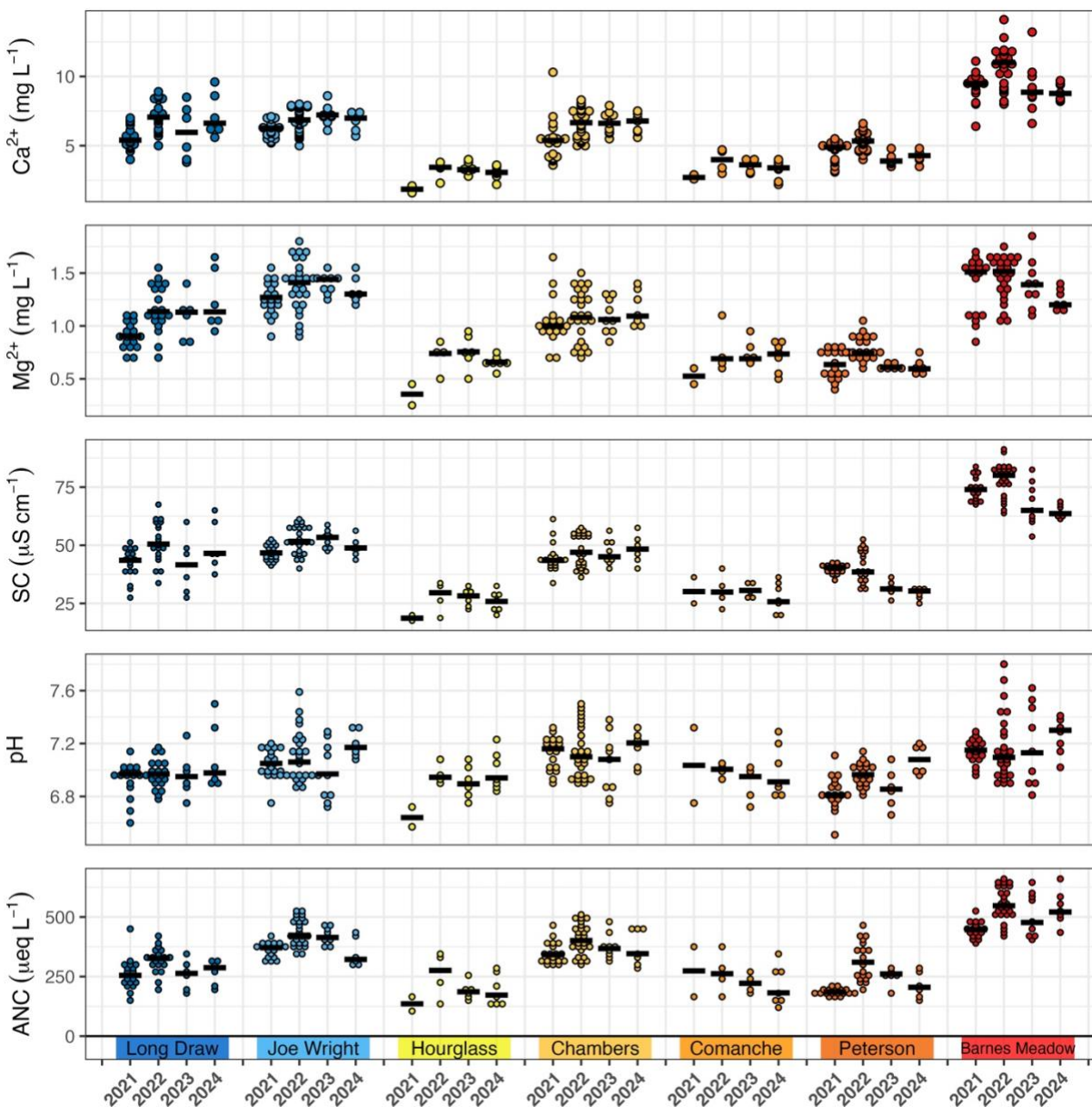
SI 1: Map of major transbasin water diversion structures entering the upper Cache la Poudre River (CLP) basin. Source boundaries for the Grand Ditch, Michigan Ditch, and Laramie River Tunnel are colored to match their respective delivery infrastructures and black lines indicate conveyance structures.



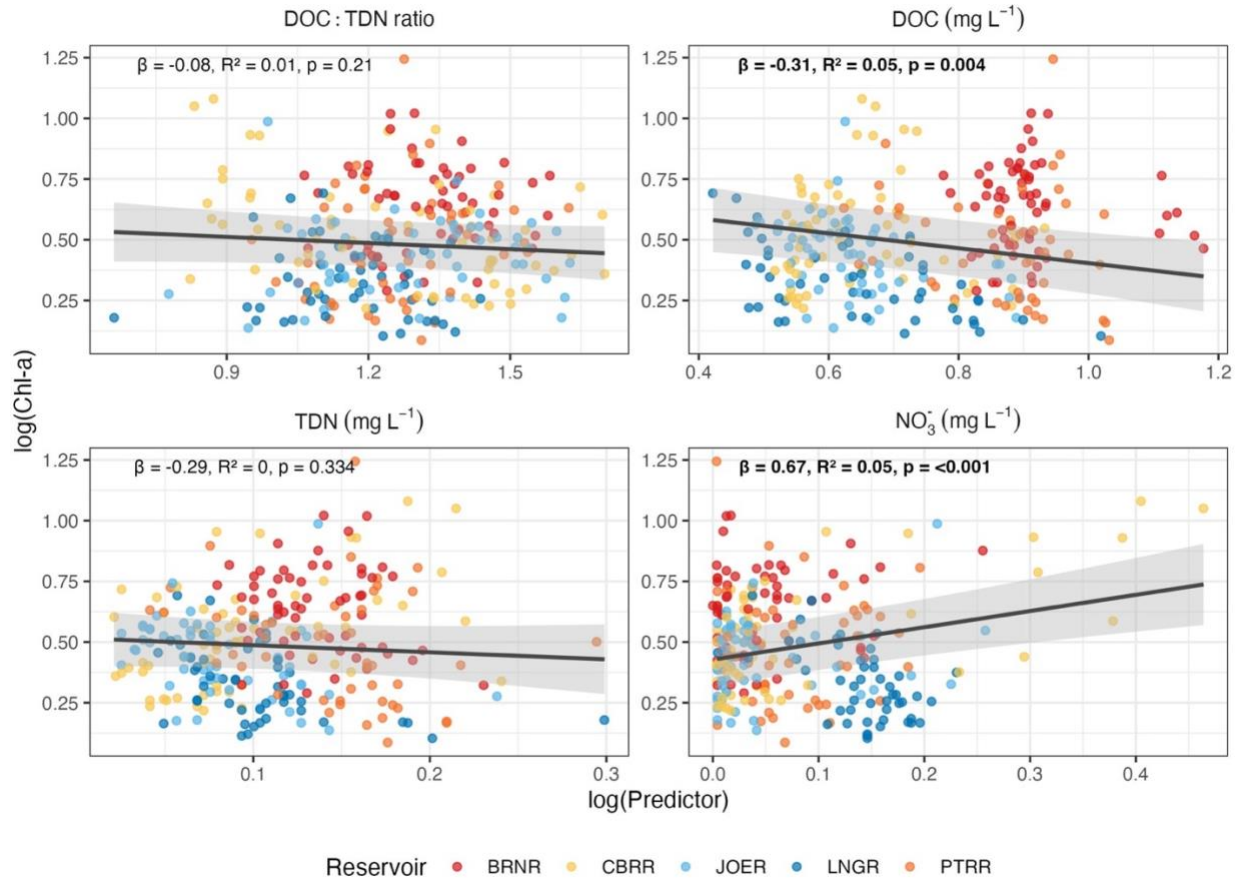
SI 2: Transbasin watershed areas (km²), average annual delivery volumes (Mm³) for transbasin diversion, and receiving Cache la Poudre watershed.

Transbasin Watershed	CLP Receiving Basin	Watershed Area (km ²)	Average Annual Flows (Mm ³)
Grand Ditch	La Poudre Pass Creek	49.8	21.3
Michigan Ditch	Joe Wright Creek	12.3	5.1
Laramie River Tunnel	Tunnel Creek	113.3	18.7

SI 3: Values and yearly medians (black bars) of additional constituents concentrations collected at reservoirs during study period (2021-2024). Sites are colored from blue to red (left to right) indicating watershed burn extent, see Table 1 for exact values.



SI 4: Relationships between chlorophyll-*a* and nutrient predictors across study reservoirs. Each panel shows the marginal fixed-effect model fit (black line) with 95% confidence interval (grey ribbon) from linear mixed-effects models with site and season as random effects. Text indicates fixed-effect slope estimate (β), marginal R^2 (R^2_m), and likelihood ratio test p-value for each parameter. Bold annotations indicate statistically significant relationships ($p < 0.05$). Points are colored by reservoir (BRNR, CBRR, JOER, LNGR, PTRR).



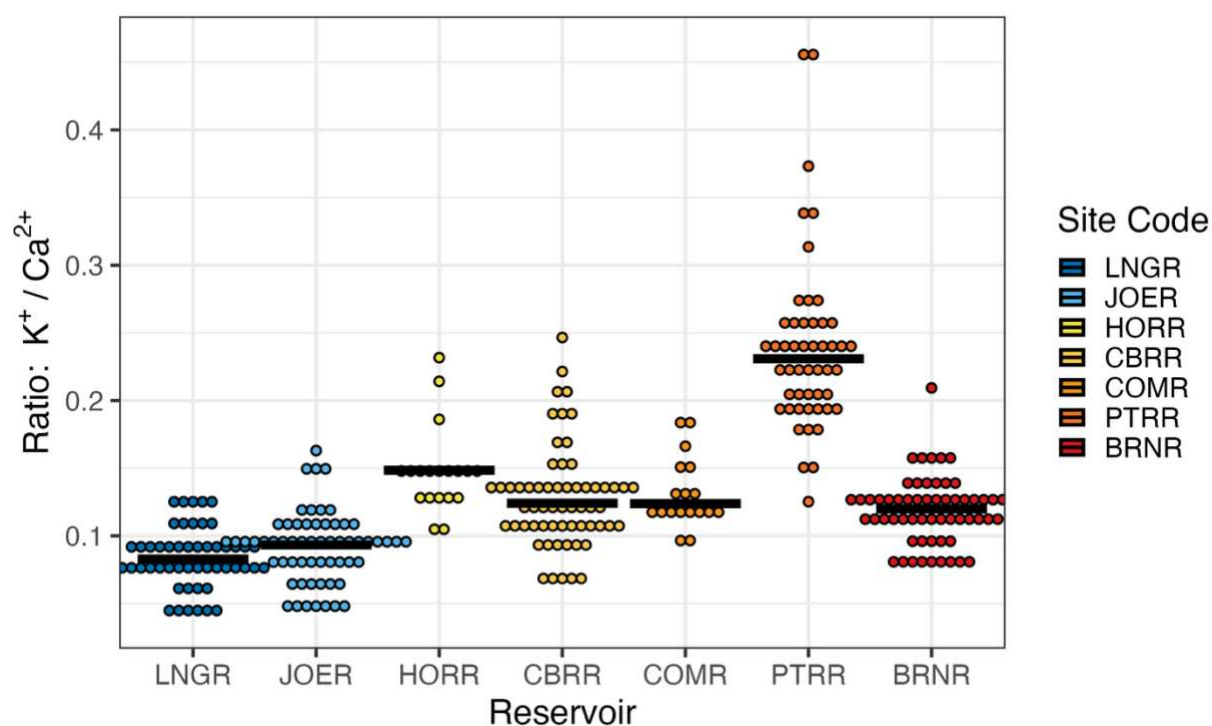
SI 5: Table of watershed attributes for study reservoirs. Elevation and slope are calculated from (Hollister, 2017), mean snow free date is from (Hammond, 2020) and landcover is from NLCD (United States Geological Survey, 2025). Reservoir Operators: G = City of Greeley, WSS = Water Supply and Storage, FC = City of Fort Collins

Site (site code)	Reservoir Elevation (m)	Max Watershed Elevation (m)	Reservoir Operator	Watershed Mean Snow Free Date	Mean Slope (degrees)	Pre-Fire Dominant Land Covers	Post-Fire Dominant Land Covers
Barnes Meadow Reservoir (BRNR)	2764	3156	G	May 15	11.93	Evergreen Forest (87.8 %) Grassland (5.2 %)	Grassland (80.6 %) Evergreen Forest (12.5 %)
Peterson Reservoir (PTRR)	2893	3305	G	June 5	10.57	Evergreen Forest (78.3 %) Grassland (7.2 %)	Grassland (51.2 %) Evergreen Forest (36.7 %)
Comanche Reservoir (COMR)	2859	3728	G	June 5	14.06	Evergreen Forest (56.9 %) Shrubland (31.1 %)	Grassland (48.2 %) Evergreen Forest (24.2 %)
Chambers Reservoir (CBRR)	2778	3942	WSS	June 3	14.52	Evergreen Forest (60.6 %) Shrubland (21 %)	Evergreen Forest (40.8 %) Grassland (29.4 %)
Hourglass Reservoir (HORR)	2852	3863	G	June 9	14.66	Evergreen Forest (52.4 %) Shrubland (30.7 %)	Evergreen Forest (31.8 %) Shrubland (30.2 %)
Joe Wright Reservoir (JOER)	3020	3814	FC	June 10	16.84	Evergreen Forest (60.9 %) Shrubland (19.5 %)	Evergreen Forest (57 %) Shrubland (19 %)
Long Draw Reservoir (LNGR)	3057	3918	WSS	May 29	19.36	Evergreen Forest (41.5 %) Barren (23 %)	Evergreen Forest (41.7 %) Barren (23 %)

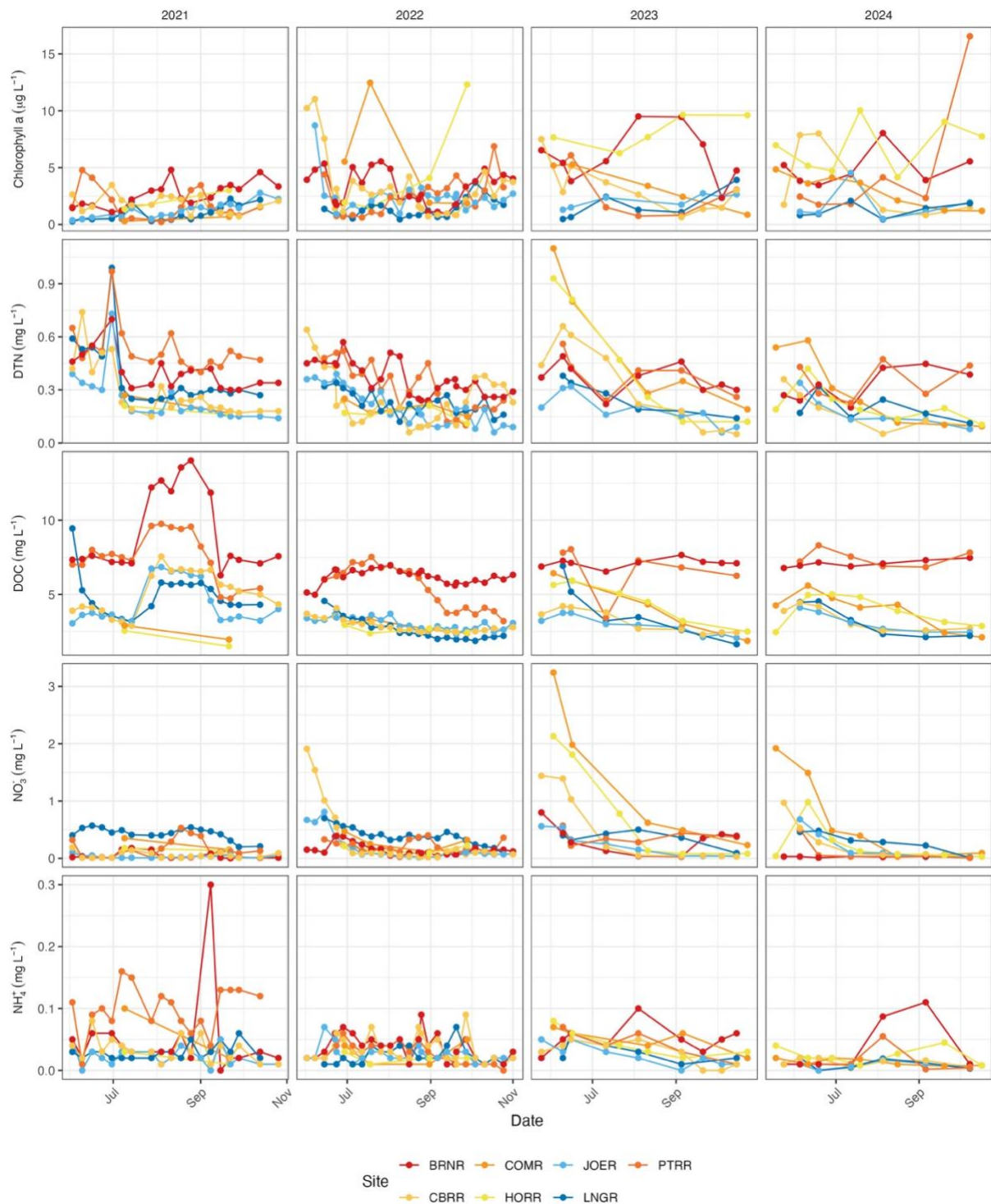
SI 6: Table of orthophosphate (PO_4^{3+}) detections at study sites. PO_4^{3+} detection limit is 0.01 mg L^{-1}

Site Type	Samples per Year				Percent above Detection Limit				Mean PO_4^{3+} (mg L^{-1}) Above Detection Limit			
	2021	2022	2023	2024	2021	2022	2023	2024	2021	2022	2023	2024
Reservoir	95	126	50	46	2.11	3.97	0.00	0.00	0.06	0.16	0.00	0.00
Outflow	95	96	46	59	6.32	7.29	2.17	0.00	0.18	0.14	0.02	0.00
Mainstem	77	103	76	127	12.99	2.91	5.26	0.00	0.13	0.23	0.13	0.00
Tributary	89	123	85	158	11.24	4.88	7.06	0.63	0.15	0.10	0.16	0.02

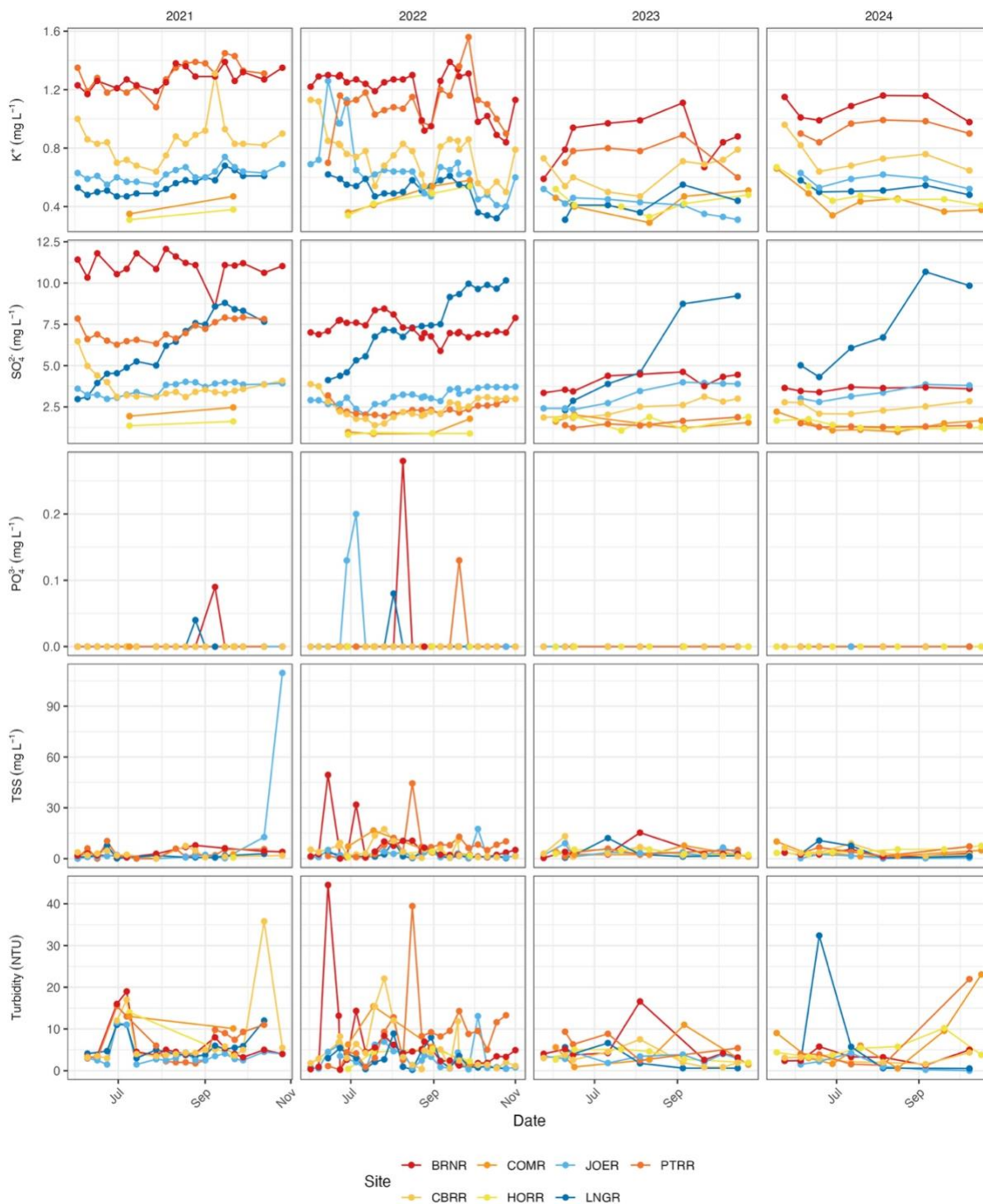
SI 7: Values and yearly medians (black bars) of K^+ and Ca^{2+} concentration ratios collected at reservoirs during study period (2021-2024). Sites are colored from blue to red (left to right) indicating watershed burn extent, see Table 1 for exact values.



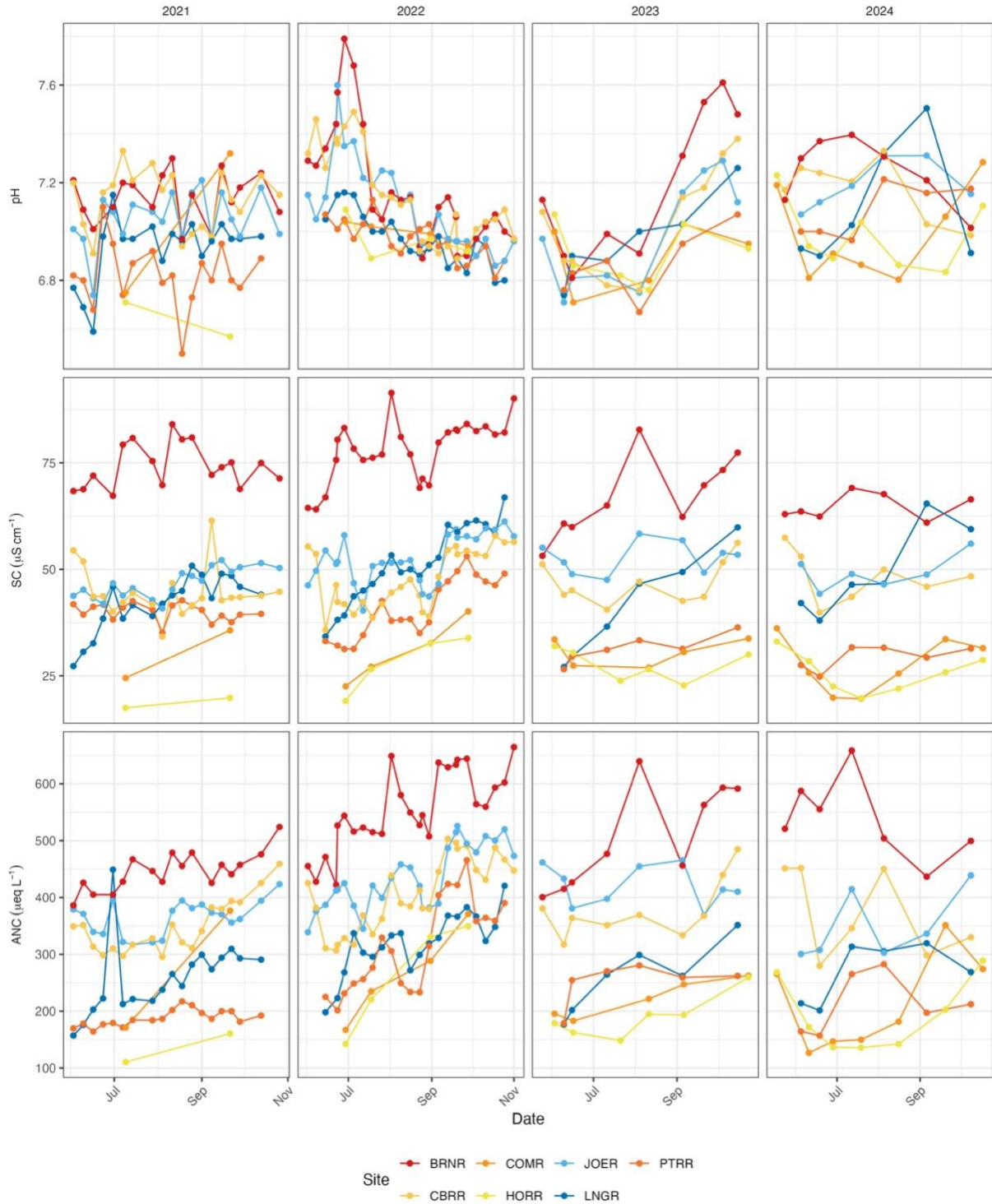
SI 8: Seasonal timelines of major carbon, nitrogen, and algal parameters across study reservoirs (2021–2024). Data points represent individual grab samples collected across seven distinct reservoir monitoring locations, color-coded by site code. Sites are colored from blue to red indicating watershed burn extent, see Table 1 for exact values.



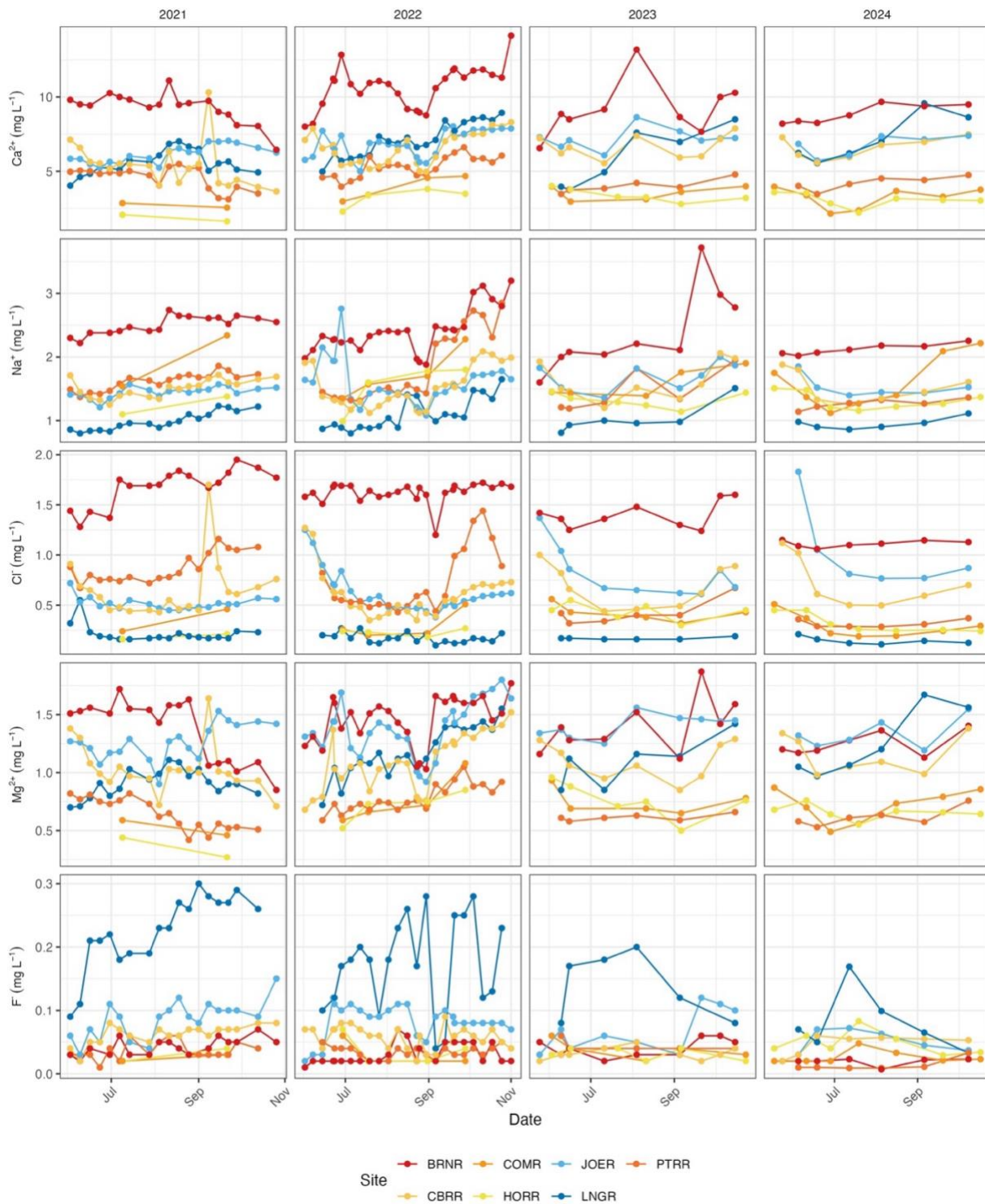
SI 9: Seasonal timelines of potassium, sulfate, orthophosphate, total suspended sediment and turbidity concentrations across study reservoirs (2021–2024). Data points represent individual grab samples collected across seven distinct reservoir monitoring locations, color-coded by site code. Sites are colored from blue to red indicating watershed burn extent, see Table 1 for exact values.



SI 10: Seasonal timelines of pH, specific conductance, and acid neutralization capacity concentrations across study reservoirs (2021–2024). Data points represent individual grab samples collected across seven distinct reservoir monitoring locations, color-coded by site code. Sites are colored from blue to red indicating watershed burn extent, see Table 1 for exact values.



SI 11: Seasonal timelines of calcium, sodium, magnesium and fluoride concentrations across study reservoirs (2021–2024). Data points represent individual grab samples collected across seven distinct reservoir monitoring locations, color-coded by site code. Sites are colored from blue to red indicating watershed burn extent, see Table 1 for exact values.



SI 12: Summary of linear mixed-effects models (LMM) used to evaluate water quality responses across analyses. NO_3^- was modeled using a Gamma GLMM with log link; all other parameters were log-transformed and fit with LMMs. All models were compared to a null model via likelihood ratio test to assess significance of fixed effects.

Category	Test	Parameters	Fixed Effects	Random Effects
Reservoir Chemistry	Burned vs. Unburned – Inference	Turbidity, TSS, DTN, NO_3 , DOC, SO_4 , K, Chl _a	burn_group	site_code
Reservoir Chemistry	Year-wise – All Sites – Inference	Turbidity, TSS, DTN, NO_3 , DOC, SO_4 , K, Chl _a	Year	site_code
Reservoir Chemistry	Year-wise – Burned Sites Only	Turbidity, TSS, DTN, NO_3 , DOC, SO_4 , K, Chl _a	Year	site_code
Reservoir Chemistry	Year-wise – Unburned Sites Only	Turbidity, TSS, DTN, NO_3 , DOC, SO_4 , K, Chl _a	Year	site_code
Reservoir Chemistry	Site × Year Interaction – Inference	Turbidity, TSS, DTN, NO_3 , DOC, SO_4 , K, Chl _a	Year + site_code	season
Reservoir Nutrient-Chl_a	Nutrient Predictor - Chl _a	NO_3 , DOC, DTN, C:N ratio	log(predictor)	site_code, season
Longitudinal – Joe Wright Reservoir	Site × Season – Inference	DTN, K, DOC, NO_3 , Chl _a	site_code + season	Year
Longitudinal – Chambers Reservoir	Site × Season – Inference	DTN, K, DOC, NO_3 , Chl _a	site_code + season	Year
Longitudinal – Chambers Outflow/ JWC	Site × Season – Inference	DTN, K, DOC, NO_3 , Chl _a	site_code + season	Year
CLP Mainstem	Site × Season – Inference	DTN, K, DOC, NO_3 , Chl _a	site_code	Year, season
South Fork	Location Effect – Unfilled Reservoirs	DTN, K, DOC, NO_3 , Chl _a	location	season
South Fork	Location Effect – Filled Reservoirs	DTN, K, DOC, NO_3 , Chl _a	location	season
South Fork	Location × Fill Status Interaction	DTN, K, DOC, NO_3 , Chl _a	location × fill_status	Year, season
Remote Sensing-SDD	Site × Fire Status – Secchi Depth	Secchi disk depth (mean_sdd)	site_code × fire_status	year
Remote Sensing-LST	Site × Fire Status – Surface Temperature	Lake surface temperature (med_surface_C)	site_code × fire_status	year

APPENDIX B: CHAPTER 2 SUPPLEMENTAL FIGURES

Table A 1: Summary table of site code, sensor locations, relevant flow gage and yearly deployment periods for each station.

Site Code	Latitude	Longitude	Site Description	Flow Gage	Deployment Periods
JOEI	40.540	-105.881	Joe Wright Creek Above Joe Wright Reservoir	USGS 6746095	2023-09-05 - 2023-10-10, 2024-05-23 - 2024-10-14, 2025-05-22 - 2025-10-01
CBRI	40.577	-105.857	Joe Wright Creek Below Joe Wright Reservoir	USGS 6746110	2023-09-05 - 2023-10-27, 2024-05-15 - 2024-10-23, 2025-05-01 - 2025-10-01
CHD	40.601	-105.842	Chambers Lake Outflow	DWR JWCCHACO	2023-09-07 - 2023-10-27, 2024-05-23 - 2024-10-23, 2025-05-01 - 2025-08-27
PFAL	40.651	-105.810	CLP River at HWY 14 downstream of Poudre Falls	Larimer County 11517	2024-05-02 - 2024-09-27, 2025-04-10 - 2025-10-27
PBR	40.700	-105.544	CLP River at HWY 14 downstream of Rustic		2025-04-08 - 2025-11-14
SFM	40.618	-105.525	South Fork CLP River at Pingree Park Road	DWR CLASRKCO	2023-10-24 - 2023-11-17, 2024-04-25 - 2024-11-13, 2025-04-08 - 2025-11-14
LBEA	40.623	-105.524	Little Beaver Creek		2024-04-30 - 2024-10-18
PENN	40.567	-105.549	Pennock Creek at Signal Mountain Trail		2024-04-30 - 2024-11-13
PMAN	40.696	-105.268	CLP River at Manner's Bridge		2025-04-11 - 2025-11-14
PBD	40.664	-105.224	CLP River at Canyon Mouth guage	DWR CLAFTCCO	2023-08-01 - 2023-11-16, 2024-04-16 - 2024-11-13, 2025-03-27 - 2025-11-14
salyer	40.600	-105.086	CLP River at Legacy Bridge in Slayer Natural Area		2023-08-01 - 2023-12-06,

					2024-03-12 - 2024-11-14, 2025-03-27 - 2025-11-17
udall	40.588	-105.069	CLP River at Lincoln St	USGS 06752260	2023-08-01 - 2023-12-06, 2024-03-18 - 2024-11-14, 2025-03-27 - 2025-11-17
riverbend	40.575	-105.033	CLP River at Timberline below Dry Creek		2023-08-01 - 2023-12-06, 2024-03-12 - 2024-11-14, 2025-03-27 - 2025-11-17
cottonwood	40.567	-105.027	CLP River below Spring Creek at Prospect		2023-08-01 - 2023-12-06, 2024-03-12 - 2024-11-14, 2025-03-27 - 2025-11-17
ELC	40.550	-105.008	CLP River above Boxelder Sanitation	USGS 06752280	2023-08-01 - 2023-12-06, 2024-03-22 - 2024-11-14, 2025-03-28 - 2025-11-17
archery	40.547	-105.001	CLP River below Boxelder Creek at Archery Range		2023-08-01 - 2023-12-06, 2024-03-12 - 2024-11-14, 2025-03-28 - 2025-11-17
riverbluffs	40.486	-104.961	CLP River below Fossil Creek Reservoir Inlet	DWR CLARIVCO	2023-08-03 - 2023-12-06, 2024-03-12 - 2024-11-14, 2025-03-28 - 2025-11-17

Table A 2: Multi-parameter sonde parameters, units, and calibration methods used in this study

Parameter	Units	Calibration Method
Specific Conductivity	$\mu\text{S}/\text{cm}$ at 25 °C	Monthly two-point with either DI (0.1 $\mu\text{S}/\text{cm}$) and 147 $\mu\text{S}/\text{cm}$ standard or 147 $\mu\text{S}/\text{cm}$ and 1413 $\mu\text{S}/\text{cm}$ depending on site range.
Temperature	degrees C	Annual Factory Calibration
pH	pH	Monthly three-point with 4,7,10 buffer standards
ORP	V	Monthly one-point calibration using Zobell's ORP/Redox Calibration Solution (229 mV at 25 degrees C)
RDO	mg/L	Monthly one-point 100% saturation in-air calibration using wetted sponge
Turbidity	NTU	Monthly two-point calibration using 10 NTU and 100 NTU standards
fDOM Fluorescence	RFU	Monthly one-point calibration using solid state calibration block (8.25 RFU)
Chl-a Fluorescence	RFU	Yearly two-point calibration of sensor using DI (0 RFU) and rhodamine dye (500 $\mu\text{g}/\text{L}$, 2.9 RFU)
Depth	m	If AquaTROLL only, depth is calibrated using onboard barometric pressure sensor to in-air pressure. If AquaTroll and Vulink are deployed together, VuLink Barometric Pressure compensation is applied

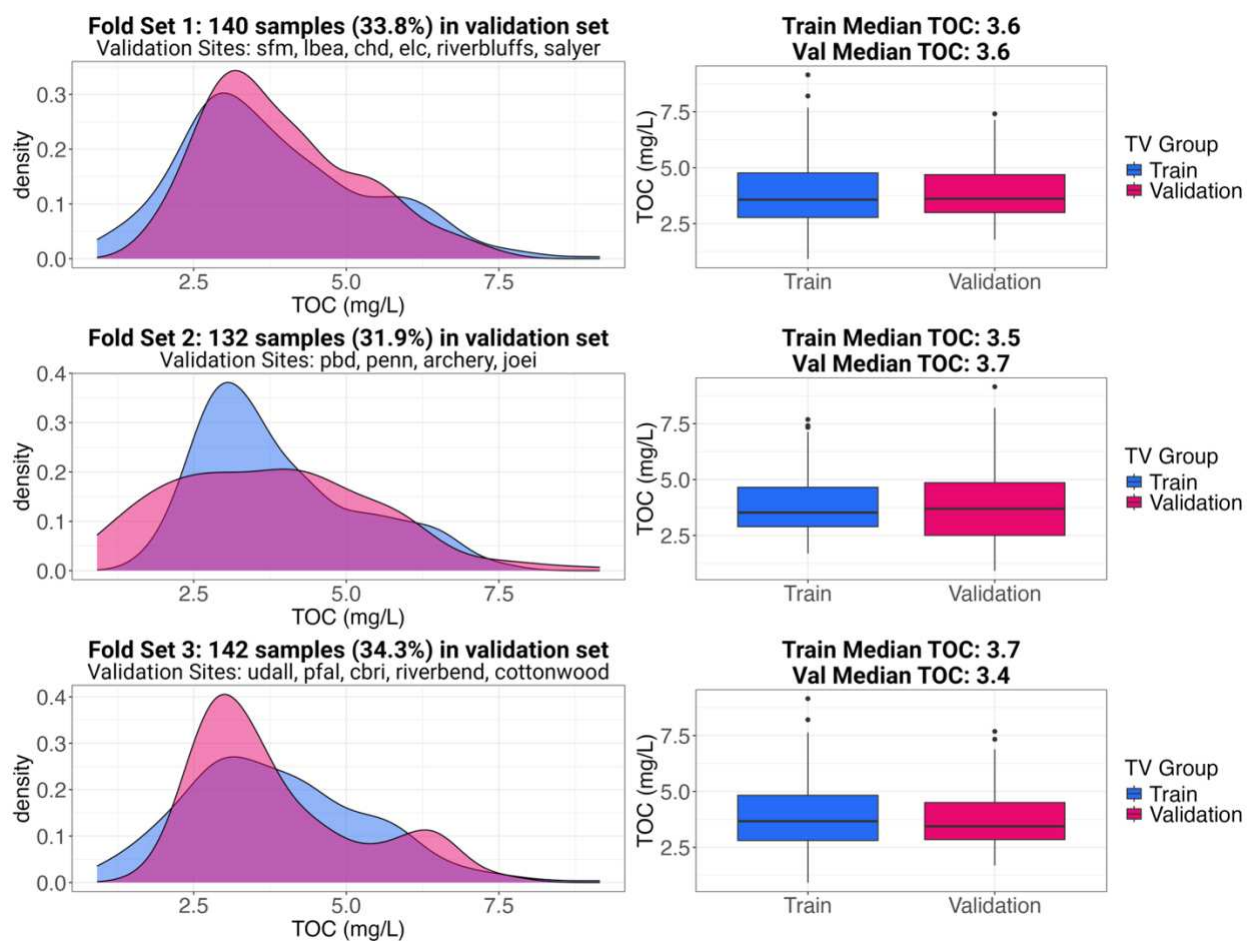


Figure A1: Distribution of Total Organic Carbon (TOC) across cross-validation folds. Density plots (left) and boxplots (right) illustrate the comparison of TOC (mg/L) concentrations between the training (blue) and validation (pink) sets for three distinct folds. Each fold panel details the number and percentage of validation samples, specific validation sampling sites, and median TOC values for both subsets to assess distribution balance.

Table A3: Hyperparameter grid space tuning parameters of the XGboost real-time TOC model. The table defines the objective of each hyperparameter, its corresponding test values within the grid search, and the specific parameter configurations selected by individual cross-validation training folds.

Hyperparameter	Goal of hyperparameter	Values in Grid Search	Fold Model Choices
max_depth	Controls the maximum depth of a tree. Deeper trees capture more complex interactions but significantly increase the risk of overfitting.	2,3,4	2, 4, 2
Learning Rate (eta)	Step-size shrinkage used during updates to prevent overfitting. Lower values make the model more robust but require more trees to converge.	0.01,0.05,0.1	0.05, 0.1, 0.05
gamma	The minimum loss reduction required to make a further partition on a leaf node, with larger values make the model more conservative.	0.8	0.8, 0.8, 0.8
Lambda	L2 regularization term on weights, higher values penalizes large weights and helps reduce model variance.	1,10	1, 10 10
Alpha	L1 regularization term on weights, can drive feature weights to absolute zero, encouraging sparsity in high-dimensional datasets.	0,1	1, 0, 1
colsample_bytree	The subsample ratio of columns (features) when constructing each tree. Subsampling prevents individual dominant features from completely dictating every split.	0.5,0.8	0.5, 0.5, 0.8
min_child_weight	Minimum sum of instance weight needed in a child leaf node. High values prevent the model from learning highly specific, isolated relationships.	2,4	2, 2, 4
subsample	The subsample ratio of the training instances. Collected randomly prior to growing trees each iteration to prevent overfitting and inject bagging-style randomness.	0.5,0.8	0.5, 0.8, 0.5

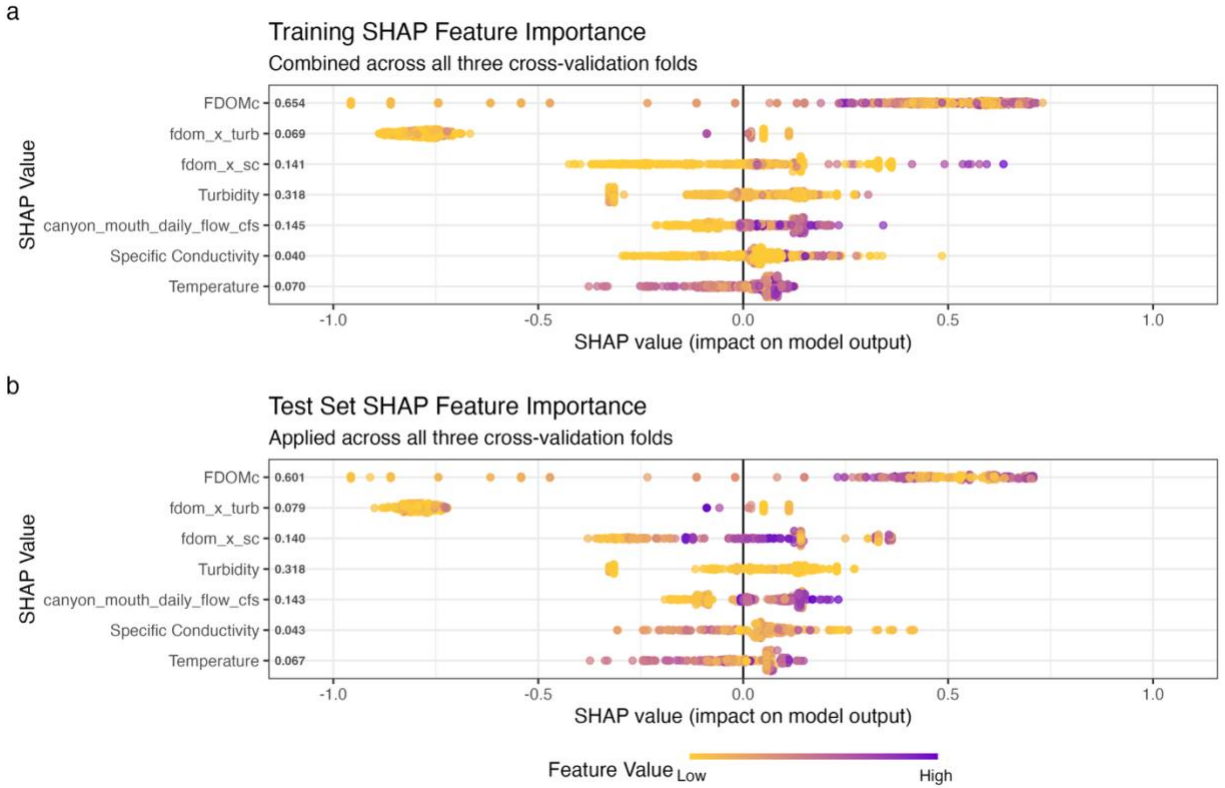


Figure A2: SHAP feature importance for the real-time XGBoost TOC model, combined across all three cross-validation folds. Each point represents a single observation, with position on the x-axis indicating the magnitude and direction of that feature's contribution to the TOC prediction (positive = increases predicted TOC, negative = decreases predicted TOC) and color indicating the relative feature value from low (yellow) to high (purple). Mean absolute SHAP values are shown for each feature to the right of the feature label. **(a)** SHAP values calculated on each fold's training data **(b)** SHAP values calculated on the withheld test set, reflecting feature behavior when applied to unseen sites and conditions.

CLP @ Lincoln St USGS Gage - Snowmelt 2025

Model Performance: Observed vs. Predicted TOC Pairings (Left) and Ensemble Timeseries Predictions (Right)

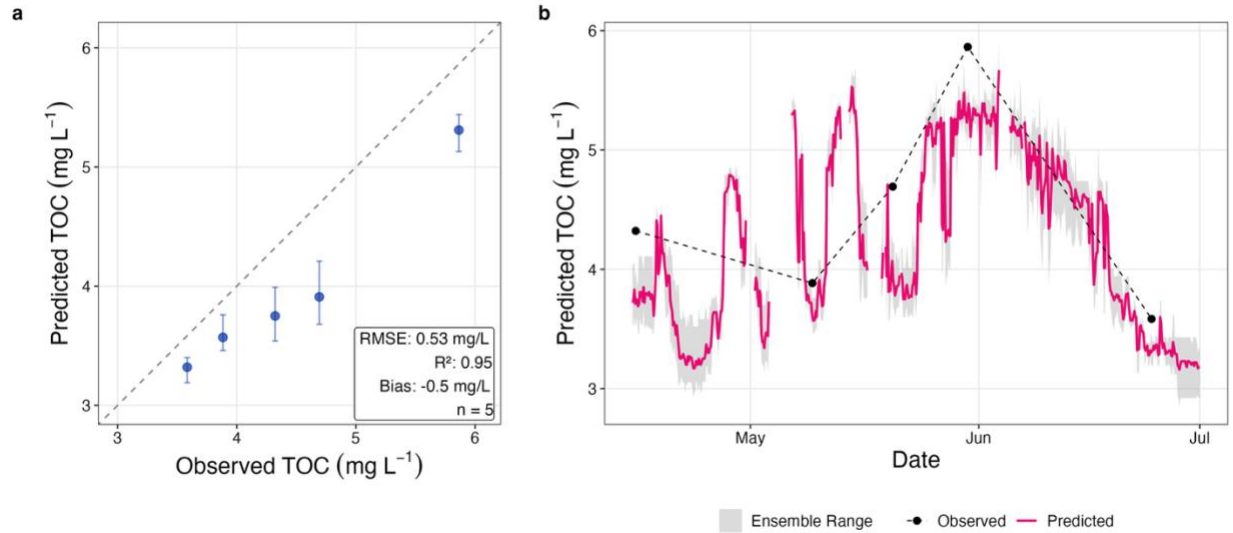


Figure A3: Real-time predicted total organic carbon (TOC) at the South Fork CLP site (SFM) during the 2025 snowmelt season using a three-member cross-validated XGBoost model trained on continuous sensor data. (a) Observed vs. predicted TOC for $n = 5$ sampling dates; error bars represent the range across ensemble members. The dashed 1:1 line and performance metrics (RMSE = 0.53 mg/L, $R^2 = 0.95$, Bias = -0.5 mg/L) are shown for reference. (b) Full ensemble timeseries from mid-April through July 2025. The pink line represents the median prediction, grey shading shows the full ensemble range, and black points indicate observed TOC.

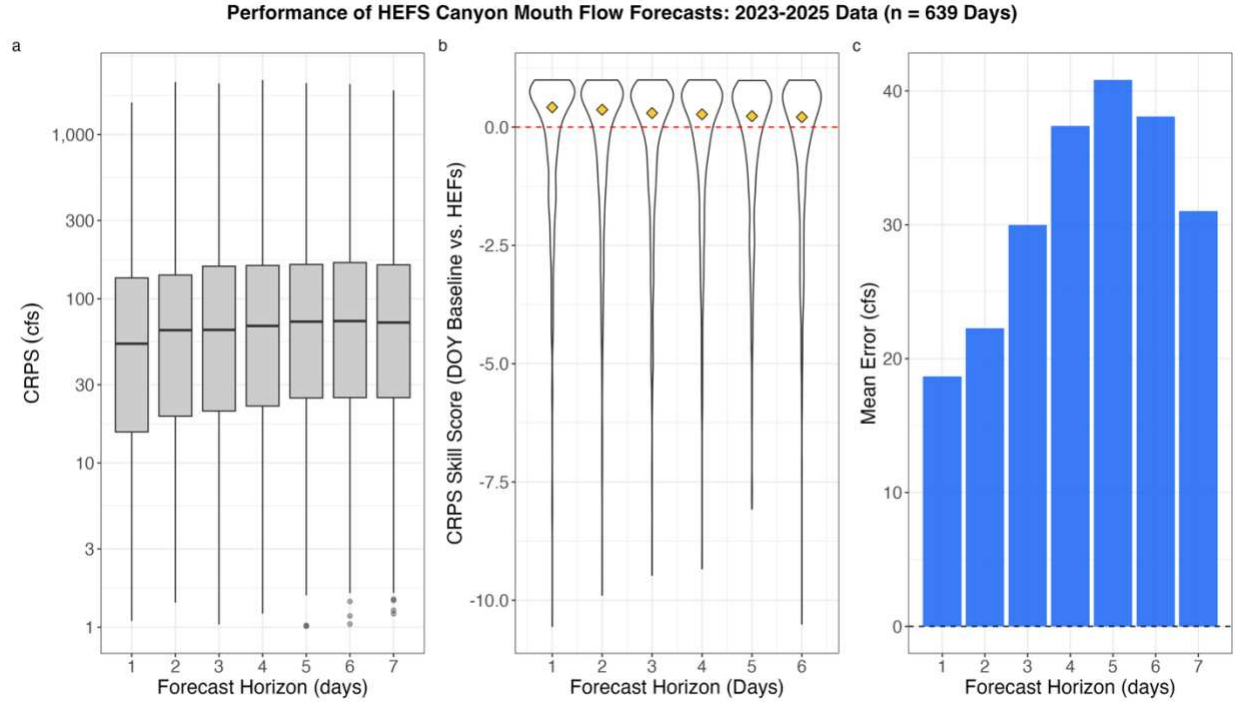


Figure A4: Probabilistic forecast performance of HEFS canyon mouth flow forecasts across lead times from 1 to 7 days (n = 639 forecast days, 2023–2025). (a) Continuous Ranked Probability Score (CRPS, cfs) by forecast horizon, where CRPS is analogous to mean absolute error but evaluated against the full ensemble distribution rather than a single deterministic prediction. Note the log scale on the y-axis. (b) CRPS Skill Score between DOY Baseline and HEFs Forecast. A positive value indicates that the model predicts better than baseline and a negative value indicates that it predicts worse. Orange diamonds represent median scores for each forecast horizon day. (c) Mean Error (ME, cfs) by forecast horizon, where positive values indicate the ensemble mean systematically overpredicts observed flow.

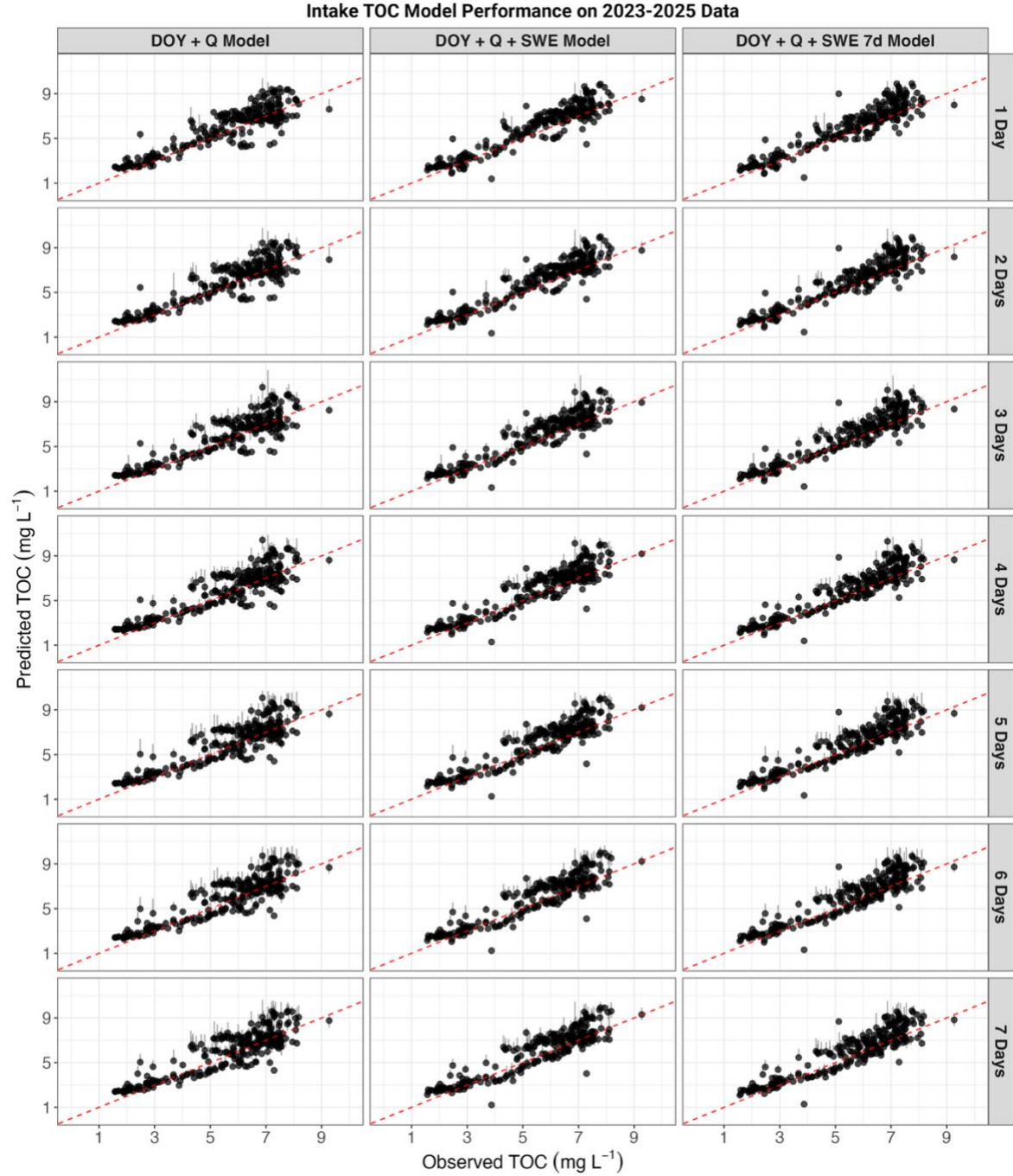


Figure A5: Evaluation of GAM performance for predicting daily TOC concentrations (mg L^{-1}) at the Poudre River intake using data collected from years 2023, 2024, and 2025. Observed vs. predicted TOC values are plotted across a 1-to-7-day forecasting horizon (rows) for three distinct model formulations (columns). The leftmost column displays predictions using a model built on day-of-year (DOY) and flow forecasts (Q) from the Hydrologic Ensemble Forecast System (HEFS). The center and right columns incorporate Snow Water Equivalent (SWE) melt rate (center: 14-day and right: 7-day) alongside DOY and HEFS flow. The dashed red line represents the 1:1 line of perfect agreement, and vertical error bars indicate the prediction uncertainty for each modeled data point.

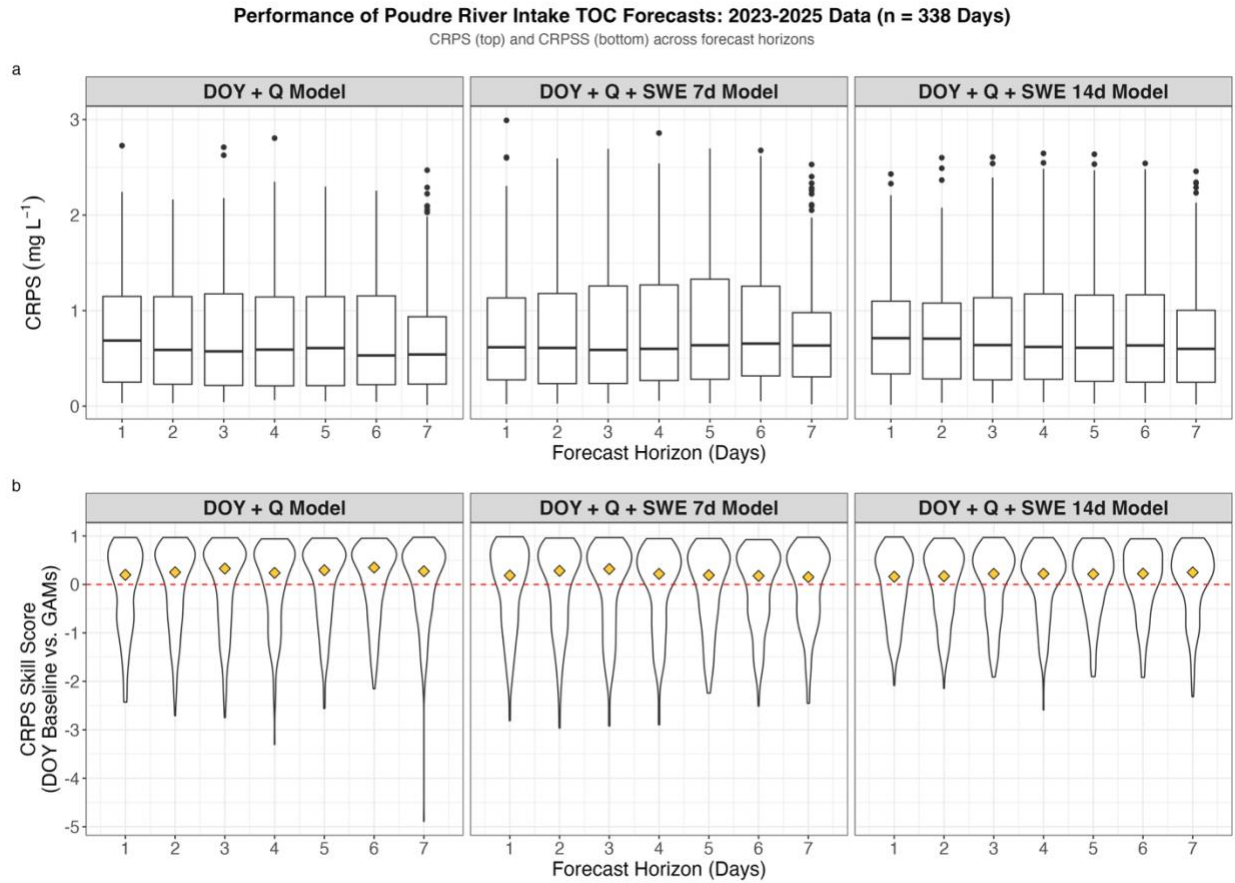


Figure A6: Performance evaluation of Poudre River Intake Total Organic Carbon (TOC) forecasts using 2023–2025 data ($n = 338$ days) across a 1-to-7-day forecast horizon. (a) Continuous Ranked Probability Score (CRPS mg L^{-1}) for three GAM formulations. (b) Distribution of CRPS Skill Scores (CRPSS), comparing the GAM models against a baseline day-of-year (DOY) model. In the violin plots, the dashed red line represents a skill score of zero, while the yellow diamonds indicate the median skill score for each horizon. Values above zero indicate that the inclusion of flow (Q) and Snow Water Equivalent (SWE) melt rate metrics (7-day and 14-day windows) improved predictive accuracy relative to the baseline.

Performance of Poudre River Intake TOC Forecasts: 2023-2025 June Data (n = 78 Days)

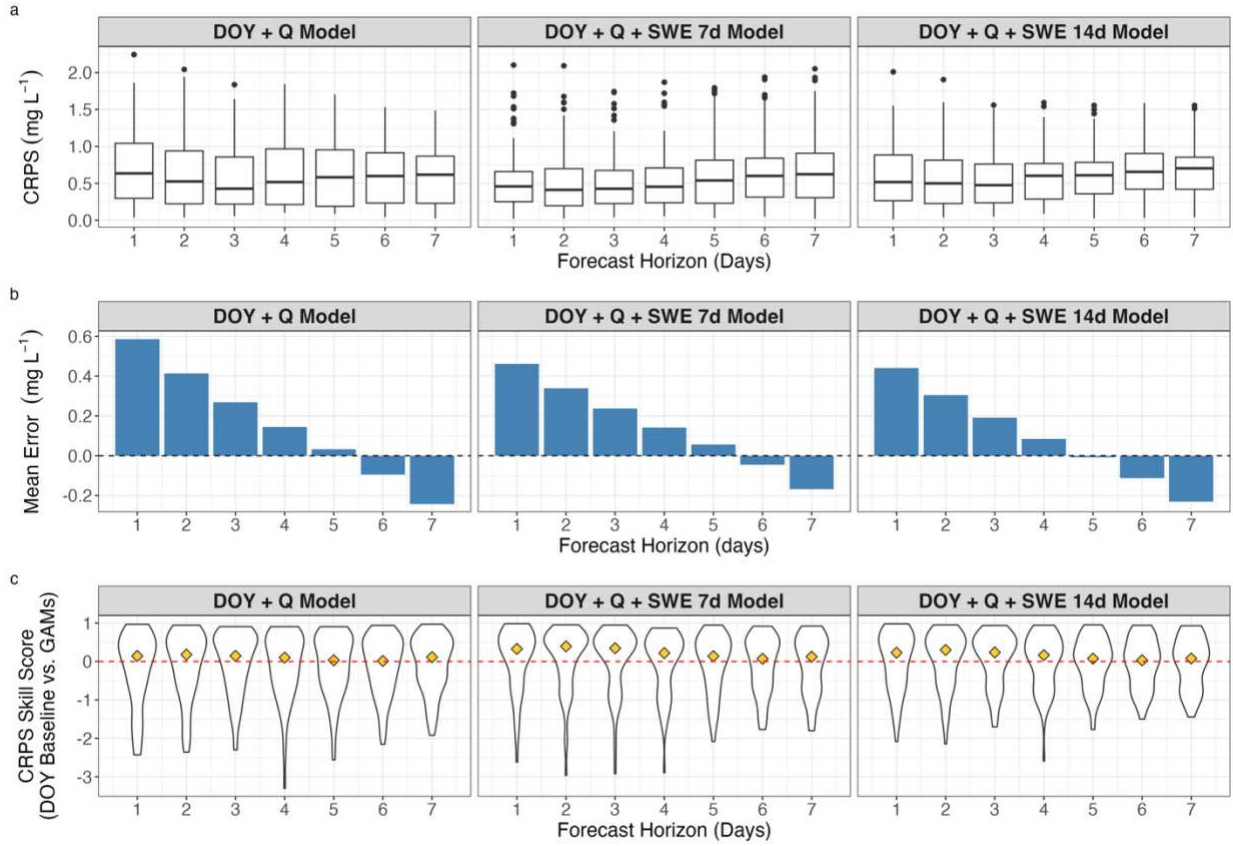


Figure A7: Performance of three GAM-based TOC forecast models at the Poudre River Intake across a 1–7 day forecast horizon, evaluated on June observations from 2023–2025 (n = 78 days). **(a)** CRPS by forecast horizon for each model. **(b)** Mean Error (ME) by horizon. **(c)** CRPS Skill Score (CRPSS) relative to a DOY-based climatological baseline, where values above zero (dashed red line) indicate the forecast outperforms the baseline and values below zero indicate poorer skill than climatological baseline; diamonds indicate the median CRPSS at each horizon.

Poudre River Intake TOC, SWE Melt Rate, and Canyon Mouth Flow in 2026

Compared to 2023-2025 conditions

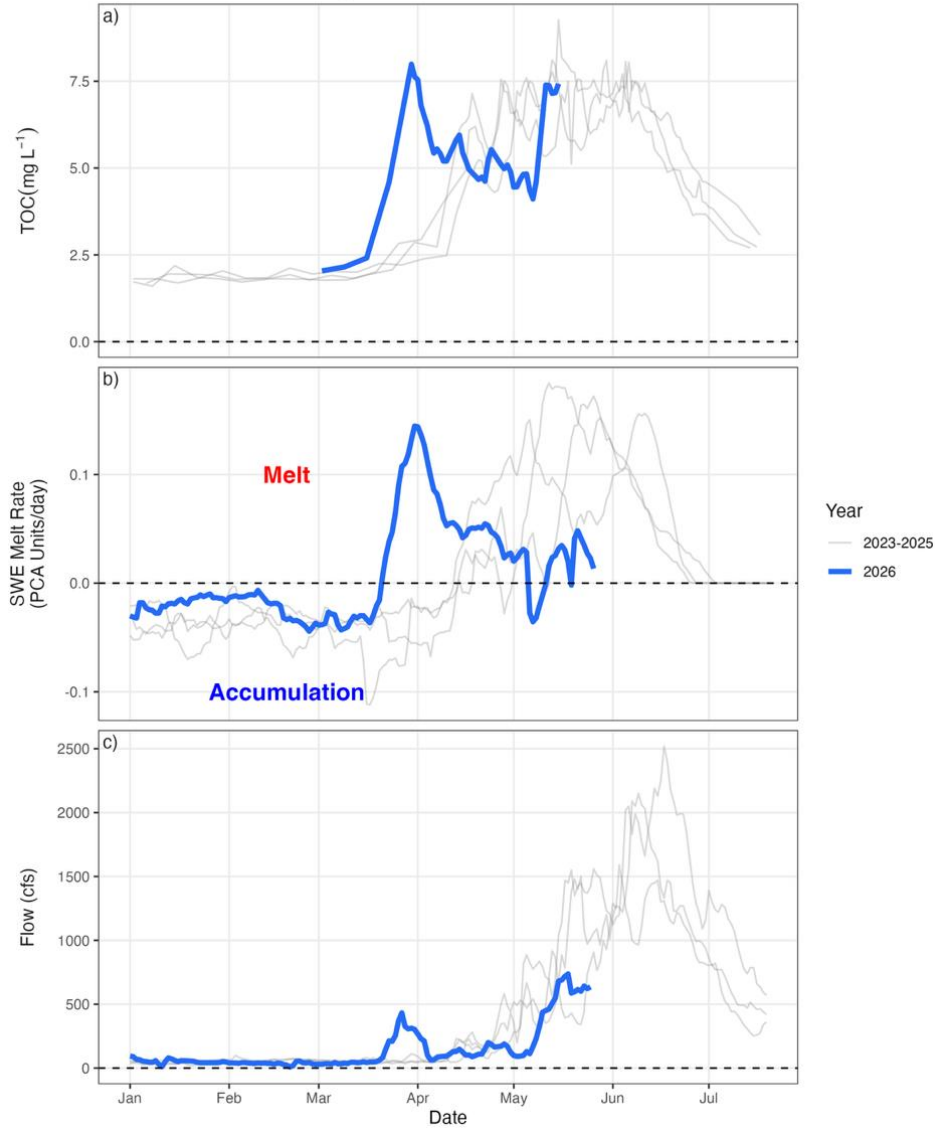


Figure A8: TOC, snowpack, and flow for the Cache la Poudre (CLP) River basin in spring 2026 compared to recent historical baselines (2023–2025). (a) Daily TOC concentrations captured at the Poudre River Intake, 2026 values (blue) against the 2023–2025 range (grey). (b) Basin-wide Snow Water Equivalent (SWE) 14-day melt rate dynamics derived via Principal Component Analysis (PCA Units/day), where the dashed horizontal line at $y = 0$ denotes a net-neutral melt rate to delineate periods of winter snow accumulation from active snowmelt. (c) Canyon Mouth river discharge measured in cubic feet per second (cfs) illustrating the timing and magnitude of the 2026 spring snowmelt

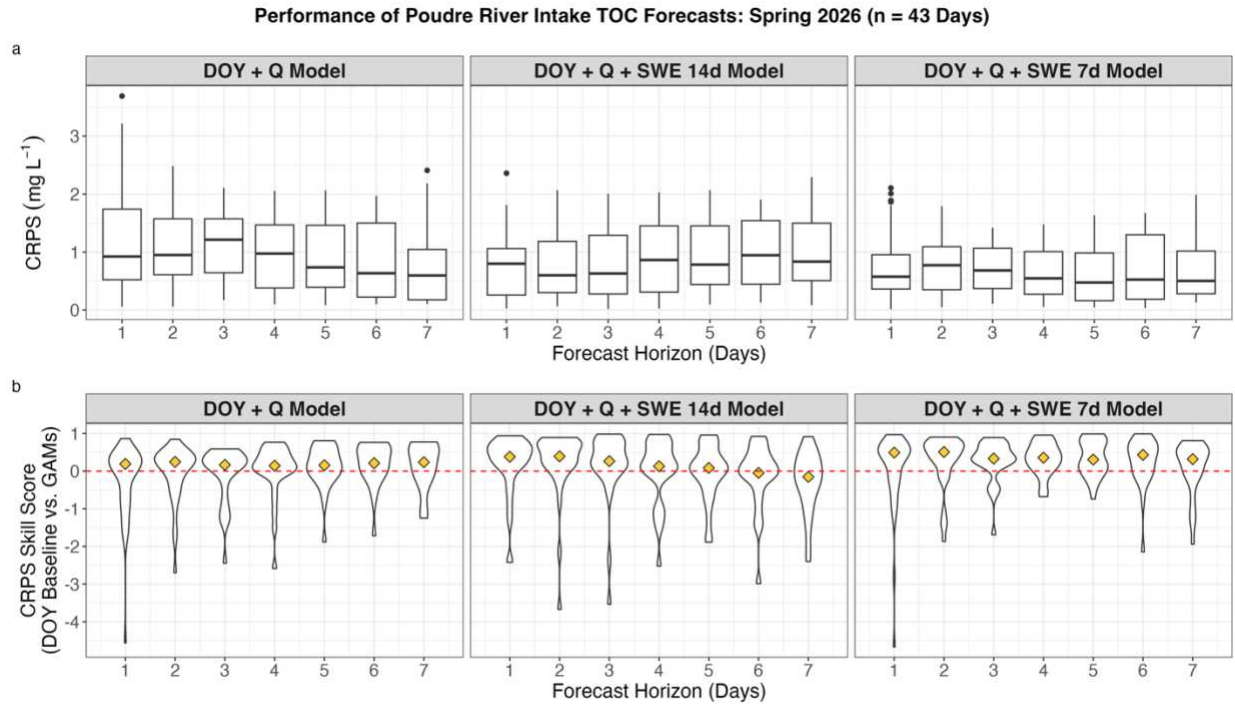


Figure A9: Performance evaluation of Poudre River Intake Total Organic Carbon (TOC) forecasts using March – May 2026 data (n = 43 days) across a 1-to-7-day forecast horizon. (a) Continuous Ranked Probability Score (CRPS mg L^{-1}) for three GAM formulations. (b) Distribution of CRPS Skill Scores (CRPSS), comparing the GAM models against a baseline DOY model. In the violin plots, the dashed red line represents a skill score of zero, while the yellow diamonds indicate the median skill score for each horizon. Values above zero indicate that the inclusion of Q and SWE melt rate metrics (7-day and 14-day windows) improved predictive accuracy relative to the baseline s