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Wildfires drive multi-year water quality degradation over the western United States

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Wildfires can dramatically alter water quality, resulting in severe implications for human and freshwater systems. However, regional-scale assessments of these impacts are often limited by data scarcity. Here, we unify observations from 1984–2021 in 245 burned watersheds across the western United States, comparing post-fire signals to baseline levels from 293 unburned basins. Organic carbon and phosphorus exhibit significantly elevated levels ($p \leq 0.05$) in the first 1–5 years post-fire, while nitrogen and sediment show significant increases up to 8 years post-fire. During peak post-fire response years, average carbon, nitrogen, and phosphorus concentrations are 3–103 times pre-fire levels, and sediment 19–286 times pre-fire concentrations. Higher responses are linked with greater forested and developed areas, which respectively explain up to 31 and 33% of inter-basin response variability. Overall, this analysis provides strong evidence of multi-year water quality degradation following wildfires in the western United States and highlights the influence of basin and wildfire features. These insights may aid water managers in preparation efforts, increasing resilience of water systems to wildfire impacts.

Forested watersheds provide high-quality water to nearly two-thirds of municipalities in the United States[1], making water treatment plants vulnerable to source water disturbances from wildfires[2]. Key contaminants important in water treatment process design—turbidity, sediment, dissolved organic matter (DOM), and nutrients[3]—are frequently reported to experience dramatic increases after wildfire events[4–10]. Increased sediment transportation and turbidity levels following wildfires are common due to the combined effects of burned vegetation and loss of root structure[11–13], as well as increased water repellency in burned soils producing higher runoff rates[13–15]. Post-fire DOM and nutrient concentrations are often elevated due to constituents released from burned soils, as well as leaching from increased stream sediment[10,16–20]. While recovery and return to pre-fire conditions often occur within a few months or years[9,21], lasting effects have been observed for decades following wildfires in several cases[10,22]. Numerous publications have observed these effects in in situ data on hillslope and watershed scales[7,9,18,23–26]. However, high natural variability between sites limits the transferability of watershed-scale findings to broad, regional trends. Scarcity of post-wildfire water quality data additionally hinders efforts to isolate wildfire effects from highly variable background drivers[22]. As wildfires have increased in both size and severity in the western United States in the past several decades[27–29], identification of trends in the magnitude and duration of post-burn water quality responses are necessary to inform water treatment plant preparedness and mitigation strategies.

Physical- and process-based models have been commonly used to assess post-wildfire water quality response[30]. However, these models require high temporal- and spatial-resolution datasets[22], limiting analyses to smaller domains with abundant data. As post-fire sedimentation rates have historically been more highly studied and monitored than DOM and nutrient responses[9,31], these models have also tended to focus on sediment and debris flows[30,32–37]. Data-driven approaches offer an alternative to physical models, with lower data requirements and a greater ability to capture multi-variate relationships with high adaptability. These features are well-suited for analyzing a wide range of complex post-wildfire responses[22], such as the runoff rates, landslide hazards, sedimentation, nutrients, and trace elements

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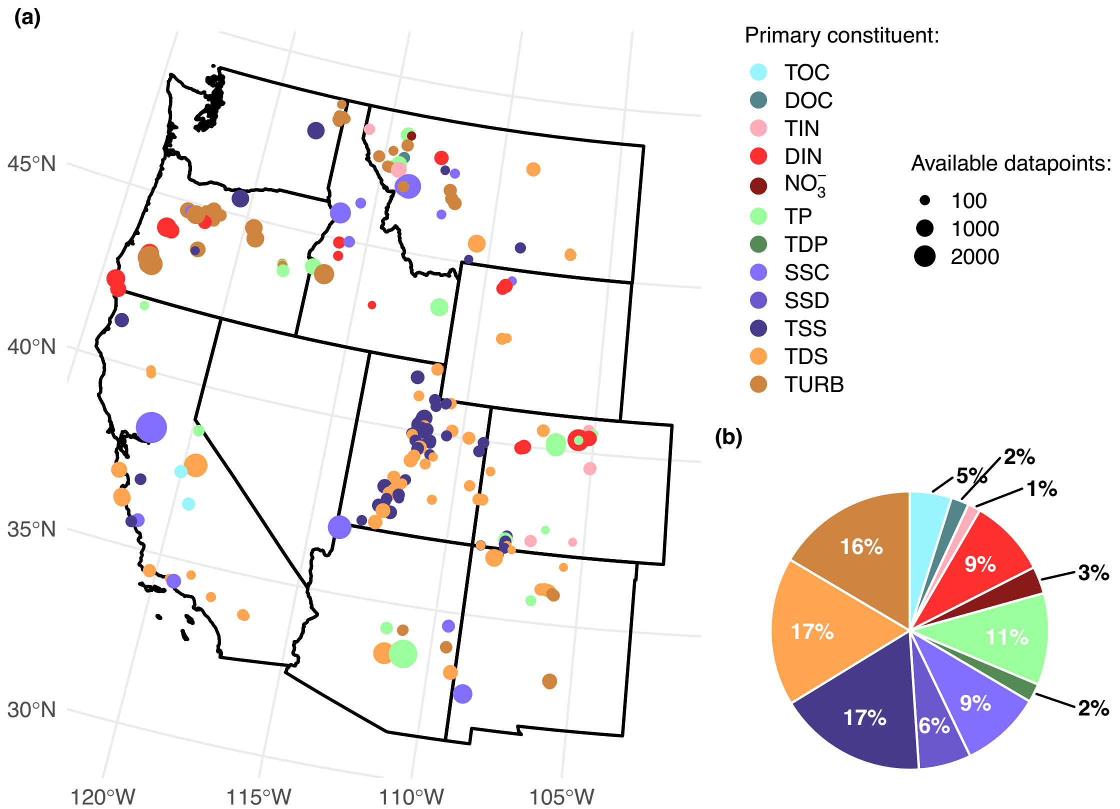

Fig. 1 | Water quality data availability in burned basins across the western United States. a Map of burned basins and available nutrient, DOM, and sediment water quality measurements from 1974–2022, with the color indicating the most numerous constituents at that site. **b** The proportion of each water quality variable relative to total data available. The 12 key constituents analyzed are abbreviated as follows: total organic carbon (TOC), dissolved organic carbon (DOC), total inorganic nitrogen (TIN), dissolved inorganic nitrogen (DIN), nitrate (NO_3^-), total phosphorus (TP), total dissolved phosphorus (TDP), suspended sediment concentration (SSC), suspended sediment discharge (SSD), total suspended solids (TSS), total dissolved solids (TDS), and turbidity (TURB).

assessed in previous data-driven studies[4,38–44]. Additionally, as data-driven analyses are not limited to individual watersheds or systems, these techniques have allowed for post-fire assessments across entire regions[39,44,45] and countries[41].

Using similar data-driven techniques, the goal of this study is to determine broad, long-term trends in post-fire water quality responses across the western United States. By focusing on both magnitude and duration of water quality changes, this study aims to inform water treatment plant planning and resilience efforts. We analyze a comprehensive set of sediment, DOM, and nutrient contaminants critical in water treatment process design over a large sample of watersheds to understand regional variability. Rust et al.[45] is the only post-fire study to previously analyze a similar set of contaminants over the western United States, using statistical tests to determine significant responses up to 5 years post-fire. However, our study uniquely incorporates a regression-based approach to isolate wildfire effects from background hydroclimatic drivers up to 8 years post-fire, following similar methods used in Williams et al.[44] and Beyene et al.[39] for analyzing post-fire runoff and trace elements, respectively. Additionally, to allow for this more robust analysis for a traditionally data-limited application, we used a custom-created dataset of 538 watersheds to maximize data availability—significantly more numerous than the 65 to 179 basins used in previous studies[39,44,45]. Using this framework, we quantified the duration and magnitude of impacts and identified predictors of inter-watershed variability.

Results

Unifying data across the western United States

In situ water quality data across the western United States were first collected and assessed across 245 burned basins, totaling 107,310 wildfire-affected water quality datapoints on a daily timestep. These were analyzed and compared to a set of 104,031 datapoints from 293 unburned basins. Data comprised measurements of carbon, nitrogen, phosphorus, sediment, and turbidity levels. As shown in Fig. 1, total suspended solids (TSS), total dissolved solids (TDS), and turbidity (TURB) had the largest sample sizes, with each making up roughly 17% of the total dataset. Dissolved organic carbon (DOC), total inorganic nitrogen (TIN), nitrate (NO_3^-), and total dissolved phosphorus (TDP) had the least availability, each comprising 3% or less of the total available water quality data. The rest of the constituents—total organic carbon (TOC), dissolved inorganic nitrogen (DIN), total phosphorus (TP), suspended sediment concentration (SSC), and suspended sediment discharge (SSD)—had moderate sample sizes, with each comprising 5–10% of the total dataset. Data collection, watershed delineation, and basin screening processes are described in Methods and further information on constituent data is in Supplementary Table 1.

Taken in aggregate across the entire western United States, post-wildfire water quality constituent levels generally increased, despite varying rates of significant changes within individual basins. When comparing constituent levels from eight years leading up to wildfire events in all burned basins to levels from two years after fire events (Supplementary Fig. 1), post-fire means were greater than pre-fire means for all constituents except SSD and TDS, which exhibited −16% and −3% changes in mean rates and concentrations, respectively. Mean levels of aggregated carbon characteristics showed up to a 462% increase post-fire, nitrogen and phosphorus characteristics showed up to a 224% increase, sediment characteristics showed up to a 254% increase, and turbidity showed up to a 4420% increase. Data from individual basins exhibited similar post-fire changes overall, though often lacking in statistical significance based on the Mann-Whitney

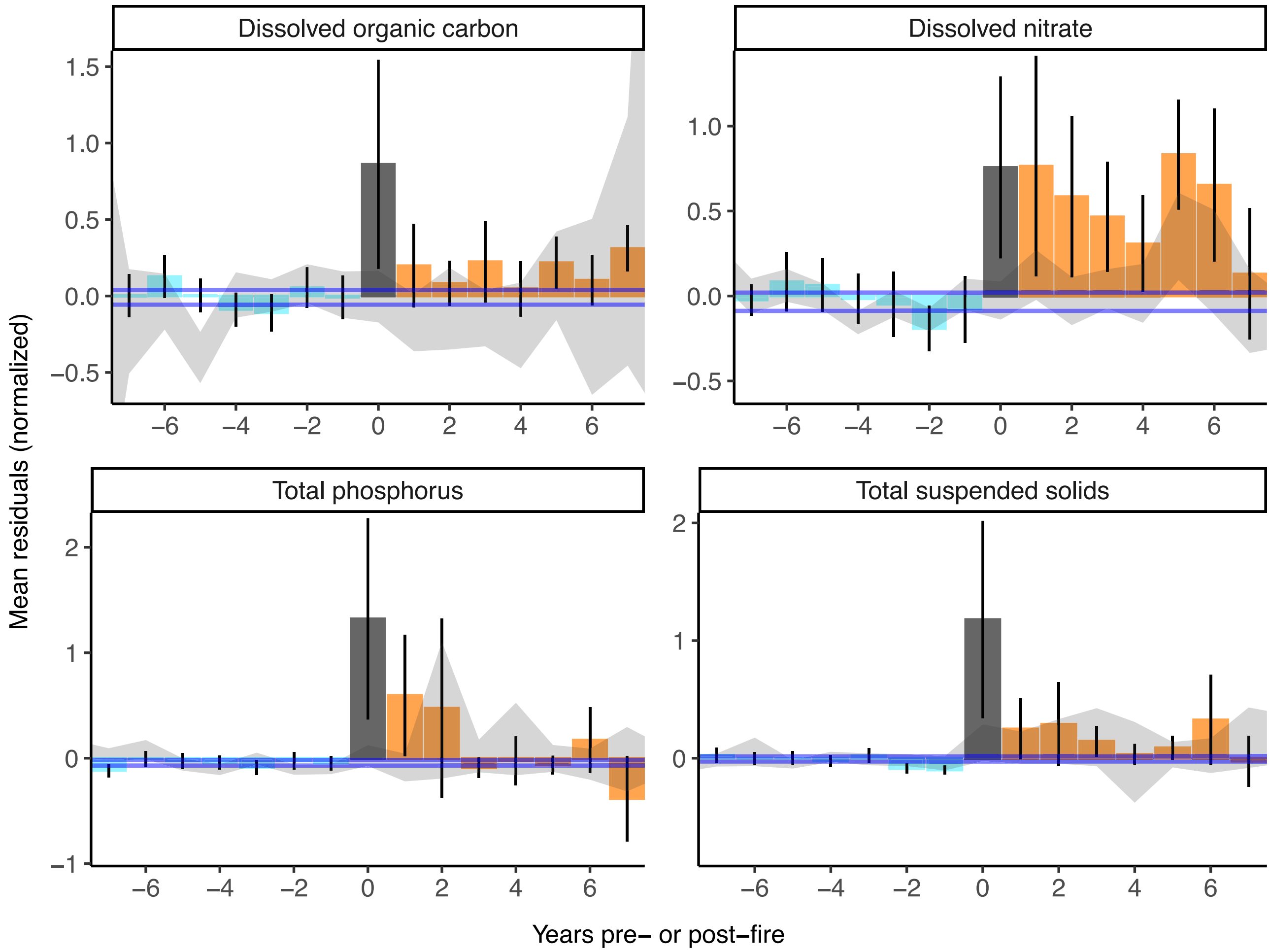

Fig. 2 | Constituent responses across eight post-fire years. Model residuals from all 538 burned and unburned basins for four key constituents representing the main water quality categories in this study: dissolved organic carbon, dissolved nitrate, total phosphorus, and total suspended solids. For burned basins ($n = 245$), mean residuals for each year are shown for seven years pre-fire (light blue bars), the year following wildfire events (grey bars), as well as the following seven years post-fire (orange bars). The black vertical lines on each bar represent 90% confidence intervals of burned basins' residuals for each year. Horizontal blue lines represent the overall 90% confidence interval bounds for all seven pre-fire years together, extended through the post-fire years to assess the significance of post-fire responses. To further assess post-fire response significance, the gray ribbons represent the residuals from unburned basins ($n = 293$), showing their 90% confidence intervals for each pre- and post-fire year.

U-tests. The percent of basins where post-fire changes were statistically significant ranged from 17% for TSS to 45% for DOC, with ~20–30% significance rates typical for most of the other constituents.

Broad changes in post-wildfire water quality

Linear models were built for each constituent in each basin to control for hydroclimatic variability across basins and through time, as described in Methods. Model covariates included total daily precipitation, potential evapotranspiration, maximum temperature, and estimated runoff, as these are prominent drivers of background water quality levels in streamflow[24,42,43]. Using these variables and water quality measurements for each basin, models were trained on pre-fire data to isolate burn impacts, characterized by residuals in post-fire periods. The framework used for these models is shown in the following equation (Eq. 1):

$$C = \sum_{i=1}^{n} \beta_i X_i + \beta_0 \tag{1}$$

where C is mean daily levels of a specific constituent, related to n hydroclimatic covariates specified by X. The coefficients β were calibrated over the pre-fire data before applying models to the entire period of record. Model performance metrics, tested using leave-one-out-cross-validation across pre-burn periods, generally indicated acceptable model accuracy for water quality modeling standards[39,46]. For each constituent, most models (i.e., greater than ~50%) had ratio of root mean squared error to standard deviation values less than 0.9, percent bias values in the range of −10% to 10%, and Nash-Sutcliffe efficiency values greater than 0.2. Models with extremely poor performance metrics were discarded to ensure accuracy of the analysis (discussed further in Methods).

Sharp, extended responses were observed after wildfire events for all 12 constituents (four of which are shown in Fig. 2)—consistent with post-fire trends observed on smaller scales[4,9]. Responses, or residuals, in each post-fire year were compared to constituents' natural variability, characterized by residuals from pre-burn periods and unburned basins. Significant ($p \leq 0.05$) increases in each post-fire year were determined when the means of residuals across all burned basins were above the upper 90% confidence bounds of both unburned basins' residuals for that same year, as well as burned basins' residuals from 8 years preceding wildfire events. Response magnitudes in each post-fire year were additionally determined by the difference in mean residuals from average pre-fire residuals.

Following this method, significant increases were observed in the first year post-fire for all constituents except TIN and TDP. Responses of TOC, DOC, TP, TSS, and TURB all peaked in the first post-fire year as well, with mean residuals increasing by 3213–28,570% compared with average pre-fire residuals. TIN, DIN, NO_3^-, TDP, and TDS had slightly delayed responses, peaking in the second- or third-year post-fire with residual increases of

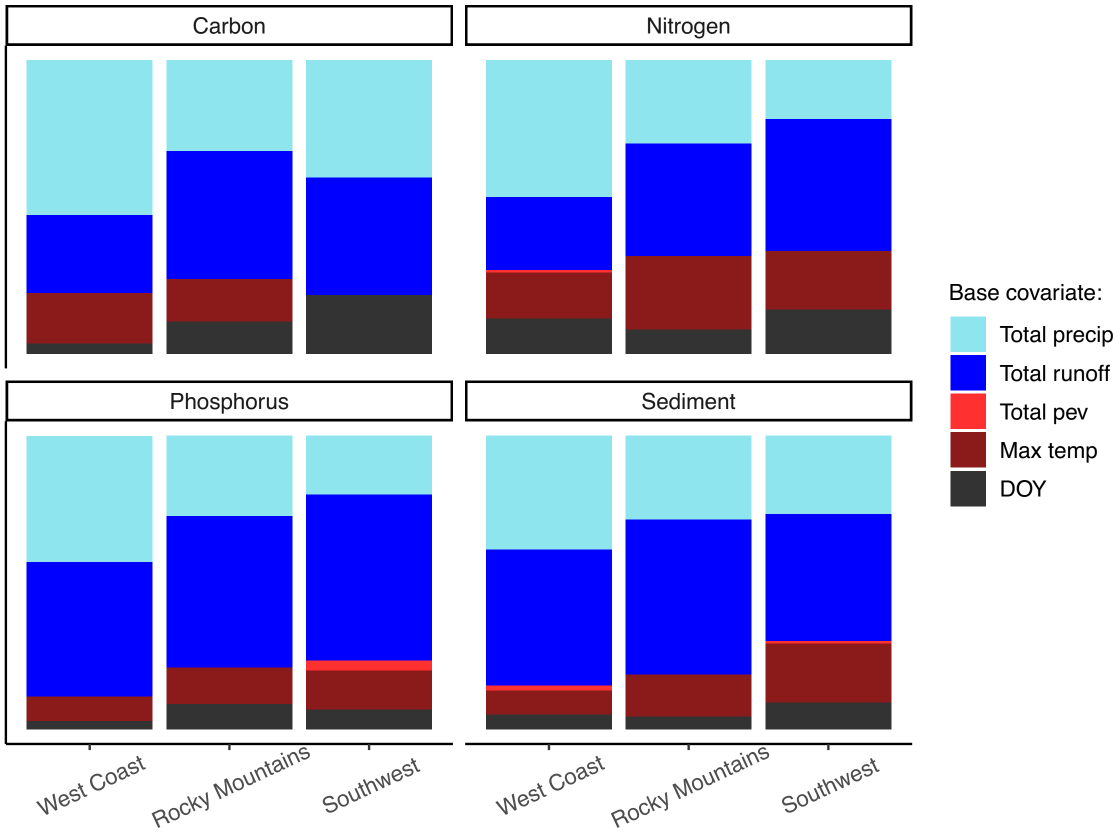

Fig. 3 | Covariates' influence on water quality by region and constituent type. Distribution of dominant covariates selected through the linear model building process for each constituent in each basin in the West Coast (OR, WA, and CA), Rocky Mountains (ID, MT, WY, UT, and CO), and Southwest (NV, AZ, and NM) regions of the western United States. Different covariates are represented by different colors, with temperature-related variables, total potential evaporation (pev) and max temperature (temp), in red colors and water-related variables, total precipitation (precip) and total runoff, in blue colors. "DOY" represents the day of the water year of the water quality measurement. Evaluated constituents are combined into organic carbon, nitrogen, phosphorus, and sediment categories.

253–27,852% compared with pre-fire residuals. These responses were all significant except for TDP, where mean residuals were significantly elevated compared to pre-fire data, but not compared to unburned basin responses. This confirms previous reports of the highest post-wildfire water quality responses within the first three years after a wildfire event[9,22,23,47]. However, SSC and SSD responses showed a longer delay, peaking in the fourth year post-fire with residual increases of 9829% and 1935%, respectively, compared with pre-fire residuals. Where TSS peaked in the first year post-fire, SSC and SSD responses are inversely proportional to streamflow and were likely smaller in the first few years due to elevated post-fire runoff rates[9]. Delayed spikes in sedimentation may have additionally been driven by shallow landslides which can occur in the years following wildfire events due to decaying roots from burned vegetation[14,21,40]. For nitrogen and phosphorus constituents, delays may have been due to variable vegetation recovery timelines influencing stream nutrient concentrations[43,48].

Responses of DOC, TIN, DIN, NO_3^-, TSS, TDS, and TURB were sustained for 5–8 years post-fire. Though these extended responses were not significant as compared with unburned basin responses in several cases, concentrations of DIN and NO_3^- were continually significantly elevated for 5 and 8 years, respectively. Long vegetation recovery periods[4,22,48] may have contributed to extended responses in nitrogen constituents, which are highly influenced by plant regrowth, as well as sediment constituents due to erosional effects from sparse vegetation[9,12,13].

Inter-basin variability

The selected covariates in the model-building process provided insight into drivers for each water quality constituent, which varied regionally as seen in Fig. 3. Water-related covariates (i.e., precipitation and runoff) were dominant for all constituents in all regions. However, the prevalence of temperature-related covariates (i.e., temperature and potential evaporation) and seasonal indicators (day of water year of the water quality measurement) varied across regions. For sediment, nitrogen, and phosphorus characteristics, temperature-related covariates had a greater influence in mountainous and plains regions as compared with coastal areas. This may be due to the effects of seasonal temperature fluctuations on vegetation regrowth in these regions—shown to have a strong influence on post-fire sediment and nutrient levels[14,48]. For carbon characteristics in a regional context, temperature covariates had slightly greater influence in coastal regions, with almost none in plains and deserts—potentially due to water being the limiting factor for constituent transport in these dryer regions. The day of water year when water quality measurements were taken was most explanatory in the Southwest for carbon, nitrogen, and sediment characteristics, and in mountainous regions for phosphorus. Similar to temperature covariates, this may be due to seasonal variations in vegetation growth in these regions. The spatial distribution of covariate influence across the western United States is shown in Supplementary Fig. 3.

Basin and fire characteristics influence

The relative forested and developed areas for each basin, as well as the distance of burn scars from basin outlets, showed strong correlations with post-fire responses for several constituents. Pearson's correlations between each constituent's residuals from the first two years post-fire and each physical variable are shown in Fig. 4, with significant values ($p \leq 0.05$) bolded. The forest coverage in each basin had significant, positive relationships (correlation > ~0.2) with TOC, DOC, NO_3^-, and SSC responses, explaining 14%, 31%, 13%, and 18% of their variance, respectively. This may

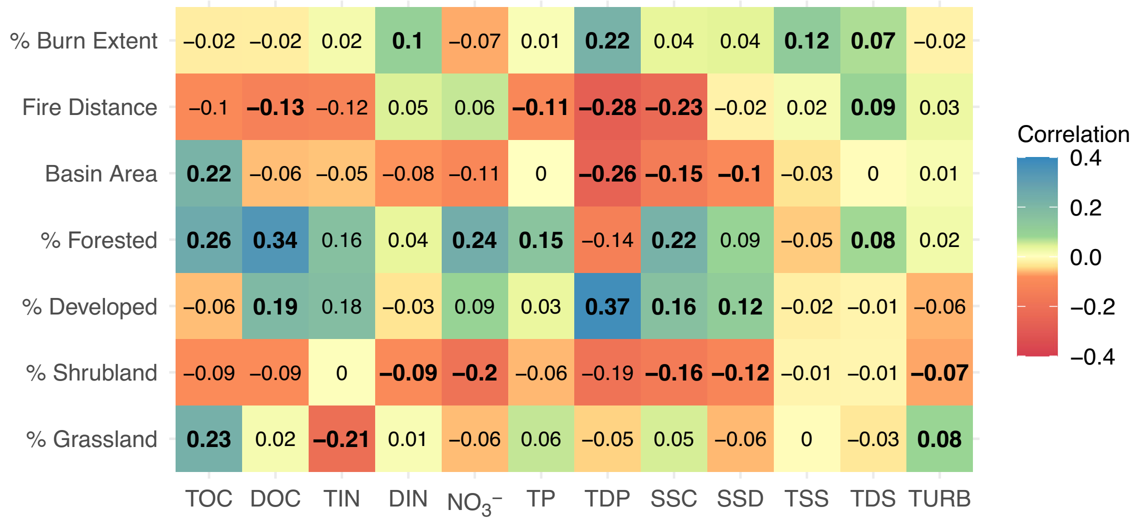

Fig. 4 | Relationships between post-fire constituent responses and watershed and fire characteristics. A correlation analysis using Pearson's correlations coefficients between model residuals from the first two years post-fire and watershed and fire variables. For each basin, "% Burn Extent" is the percent of basin area which lies within the associated fire perimeter, "Fire Distance" is the distance in km between its outlet and the closet edge of the associated fire perimeter, "Basin Area" is the area in km^2, % Forested, Developed, Shrubland, and Grassland are the percent of basin areas with land cover classified as forested, developed, shrub or scrub, and grassland, respectively. Significant ($p < 0.05$) correlations are bolded and slightly expanded.

be due to higher post-burn runoff rates as reported in more heavily forested watersheds in previous studies[44], resulting in increased constituent transport.

Developed area had significant, positive relationships with DOC and TDP, explaining 7% and 33% of their variability, respectively. This aligns with previous reports that showed proximity to urban locations strongly affects post-fire nutrient concentrations, likely due to the deposition of fossil fuel emissions[43]. The distances between fires and basins' outlets was significantly negatively correlated with TDP and SSC, explaining 9% and 15% of their variability, respectively. This may be due to diluting effects of additional unburned tributaries introduced downstream from burned areas.

Discussion

By leveraging several decades of water quality data aggregated from 538 burned and unburned basins across the western United States, this study provided evidence of distinct, wildfire-driven DOM, nutrient, and sedimentation increases lasting up to 8 years post-fire. In past research, the magnitude and duration of observed post-wildfire changes vary widely between studies and are often not significant within individual basins[9]—limiting the transferability of findings to other areas. Through maximizing data availability, a regional scope, and control of climatic factors' effects on water quality, this study's framework revealed significant signals in water quality in the western United States for multiple years post-fire. While previous studies have attempted more narrowly focused regional-scale analyses, incorporation of 245 burned basins here along with 293 unburned basins and over 200,000 combined datapoints was considerably more numerous than the 65 to 179 watersheds used in other studies[39,44,45].

Our findings provide strong evidence of multi-year persistence in significant water quality degradation driven by wildfires across the domain. While most previous wildfire studies have focused on short-term (~2–3 years) effects[9], our study is consistent with findings from the few studies which have analyzed long-term implications of wildfires on water quality[22,23,48,49]. This suggests that long-term post-wildfire water quality degradation is a common outcome. Here, we found that average post-fire organic carbon concentrations were elevated for 2–8 years, inorganic nitrogen concentrations were elevated for 5–8 years, phosphorus concentrations were elevated for 2–3 years, sedimentation was elevated for 4–8 years, and TDS and turbidity were elevated for 5–8 years, as compared with pre-fire levels. For most constituents, these trends were significantly greater than unburned basin responses in most years as well, though post-burn responses tended to lower in magnitude and fall below the level of significance after 2–5 years post-fire.

These longer-term effects suggest that wildfires on average impact deeper layers of soil, burn larger vegetative structures, and disrupt nutrient cycles to a greater extent than previously suspected. The slow return of nitrogen concentrations to pre-fire conditions was likely due to nutrients releasing from deep soil layers through combustion, then subsequently getting washed away through elevated runoff rates—resulting in long vegetation recovery periods following wildfires[48]. Similarly, DOM, sediment, and turbidity responses were likely elevated long-term due to lingering erosional forces from loss of tree canopies and root structure[14], resulting in soil instability which took years to recover through vegetative regrowth. This soil instability may have also driven the delayed responses observed in SSC and SSD, which likely peaked in the fourth year post-fire due to shallow landslides occurring years after runoff rates returned to pre-fire conditions. These years-long elevated concentrations and delays in responses support the importance of vigilant water quality monitoring for years following wildfire events.

Watersheds with higher forest coverage and larger developed areas tended to be associated with greater post-fire response magnitudes. Carbon, nitrogen, and sediment responses had strong correlations to basins' forested areas, potentially due to greater deposition of organic matter, nutrients, and ash from larger fuel sources, as well as increased transportation from higher post-fire runoff rates reported in more heavily forested watersheds[44]. These constituents were also correlated with larger developed areas in basins, potentially due to increased atmospheric deposition from burning fossil fuels[43]. Though the proximities of fires to sampling locations were negatively correlated with phosphorus and sediment, land cover characteristics overall had a greater influence on constituents than burn extent and proximity. This emphasizes the importance of the types of fuel available, versus area burned, in post-fire water quality response[43].

Though a high number of sites and datapoints were used in these analyses, results were still limited by spatial and temporal data scarcity. Analyzed watersheds were selected based on data quality criteria, meaning sites lacking access and infrastructure for water quality monitoring were less represented in results. Within the sites selected, irregular and infrequent water quality measurements resulted in a wide range of goodness-of-fit in linear models built. Due to limited data timespans, only 8 post-fire years

Table 1 | Summary of basin characteristics for burned and unburned basin subsets

Basin subset	Number of basins	Size (km^2)	Burn extent (%)	Fire-outlet dist. (km)	Forested extent (%)	Developed extent (%)
Burned	245	472.6 (5.1–63,407.8)	9.9 (5.0–100.0)	10.2 (0.0–97.4)	52.3 (25.0–91.5)	1.0 (0.0–5.0)
Unburned	293	470.7 (5.1–20,496.3)	N/A	N/A	58.6 (25.1–95.4)	1.5 (0.0–5.0)

Number of basins, area, percent burn extent, wildfire distance from basins' outlets, percent forested extent, and percent developed extent are displayed. Median values are shown, with min-max ranges displayed in parentheses.

were analyzed, whereas previous studies have suggested that wildfire effects may persist for decades[9,22]. Additionally, attribution of response magnitudes to basin and fire characteristics was limited for many constituents (e.g., sediment characteristics) due to low numbers of datapoints and high variability across sites. Future research may explore alternate modeling methods to increase model skill, examine longer response durations as additional years of data become available for recent wildfires, and incorporate additional covariates in assessment of inter-basin response variability. Normalized differenced vegetation index, soil information, and wildfire severity (i.e., burn extent represented by soil and vegetation characteristics) and intensity (i.e., burn temperature and duration), for example, have previously been shown to affect post-wildfire water quality[42,43,50] and may be more closely correlated with constituent response magnitudes.

Findings from this study may help inform wildfire planning and resilience efforts in the face of increasing wildfire threats[27,51]. In particular, water utilities may consider the longevity and magnitude of the post-fire responses identified in this study as possible benchmarks—preparing for 1–8 years of elevated constituent loads following a wildfire event, with the potential for dramatic increases in magnitude up to 300 times pre-fire levels. Additional mitigation, such as sedimentation basins, may be required to manage 8+ years of post-fire sediment, while shorter-term solutions such as increased coagulant dosages may be considered for DOM responses[3]. Another key finding is that variability in post-fire responses are partially explained by physiographic watershed features, which highlights the importance of localized assessments, depending on watersheds' local characteristics[3]. For example, more heavily forested watersheds may require expanded treatment capacity for DOM, nutrients, and sediment. Such planning efforts are expected to become increasingly important in the western United States in the coming decades, as wildfire hazards are projected to proliferate[27,51] with water resources already stressed by increasing drought driven by climate change[52].

Methods

Site selection

Beginning with a set of 51,101 custom-delineated basins with in situ stream water quality information from 1974–2022, burned and unburned basin subsets were filtered by burn extent, data availability, and land cover criteria. Initial data mining and basin delineation processes, including data sources, are discussed further in the Supplementary Methods and displayed in Supplementary Fig. 2. Using wildfire data from 1984–2021, basins were designated as burned when the perimeter from at least one individual fire overlapped with at least 5% of their total areas and unburned when no fires intersected with more than 0.5% of their areas—similar to criteria in previous studies[39,44,45]. Wildfires which affected an individual basin within the same water year were merged and considered as an individual fire event, with the date of ignition designated as the start date of the first fire. Where multiple fires affected the same basin outside of a single water year, events which occurred less than six years after a previous fire were discarded.

Basin subsets were then screened for data availability and land cover criteria. In an individual basin, each monitored constituent was required to have at least 20 days of pre-fire data and 10 days of post-fire data, as well as a period of record spanning more than 3 years before and after the date of fire ignition. Basins where these criteria were not met for any of their measured constituents were discarded. For each of the unburned basins, the ignition dates referenced for this filtering step were from fires affecting the closest burned basins. Though these sample sizes are low for model-building processes in individual basins, similar criteria were used by previous studies which aggregated water quality data in basins across the western United States[39,45]. Basins were further screened for those with greater than 25% forest coverage and less than 5% developed area (i.e., cities and residential areas) to maximize consistency in basins' geophysical characteristics—similar to thresholds used in Williams et al.[44], and Beyene et al.[39], respectively. As shown in Table 1, the attributes of the final 245 and 293 burned and unburned basins selected for analysis were similar between the two subsets.

Regression-based response analysis

Broad changes in water quality constituents were assessed for each post-fire year using a regression-based modeling approach, following similar methods as Beyene et al.[39] and Williams et al.[44]. Multivariate linear regression models were built for each basin to control for the influence of hydroclimatic variables on water quality levels, with the goal of isolating post-fire changes driven by wildfire activity. Natural variability in water quality was characterized by responses in pre-fire data, as well as unburned basins—compared to post-fire responses to assess their significance and magnitude outside of expected trends[22,44,53].

Hydroclimatic variables of precipitation, potential evapotranspiration, maximum temperature, and runoff were selected as candidate covariates for the modeling process due to their known impacts on background water quality levels in streamflow[24,42,43]. Precipitation, surface runoff, and streamflow are the primary driving mechanisms of sedimentation and turbidity, influencing erosional processes and heightened transportation rates[11,54]. Temperature and potential evapotranspiration are correlated with vegetation growth and stream temperatures, which control plant nutrient uptake and deposition and oxygen solubility, respectively—influencing nutrient and DOM concentrations[55,56]. A day of water year variable was additionally tested as a candidate covariate for each model to capture potential impacts of seasonality. While direct measurements of streamflow and stream temperature would have been ideal candidate covariates, these were only available for a small subset of the total basins. In an effort to maximize the number of candidate study locations, we elected to use reanalysis-based estimate for these quantities. While these lack in situ-level detail, they are observationally-driven and were continuous in both space and time.

As shown in Table 2, 49 candidate hydroclimatic covariates were prepared for building each model: Four variables at daily timesteps, additionally calculated for three moving average window widths and two transformations, plus the day of water year variable. First, gridded daily hydroclimatic variables were averaged across each basin, creating a singular time series for each. For each of these variables, 7-, 30-, and 90-day trailing moving average windows were then calculated for each day. These lag-times were evaluated to capture the time required for transport of constituents to basins' outlets, as well as the effects of longer-term shifts in hydroclimatic variables, e.g., a rainy season to a dry season, on constituent response[41]. Additional square- and log-transformations were calculated for each moving window size for each covariate, as variable distributions were mostly non-normal (assessed using density distributions and Q-Q plots). Sources and preprocessing steps for these covariates are discussed further in the Supplementary Methods.

Multivariate linear regression models were built for each constituent in each burned and unburned basin using key hydroclimatic covariates. These models were trained on pre-fire data to isolate the effects of hydroclimatic

Table 2 | Candidate covariates used in the model-building process

Type	Variable	Trailing moving average windows	Transformations
Climate	Total precipitation	7-, 30-, and 90-day	log and square
	Total potential evaporation		
	Max temperature		
Hydrologic	Surface runoff		
Seasonal	Day of water year	NA	NA

Hydroclimatic covariates used to build models for each basin and constituent combination. Additional trailing moving average window, log, and square transformations tested are shown. Sources of covariate data are described in the Supplementary Methods.

variables from burn effects. To improve inter-basin comparability, z-score normalization was first applied to water quality data for each basin using its pre-fire records. A correlation analysis was then completed for candidate covariates in each model-building process to reduce potential collinearity. The absolute maximum Pearson's correlation was calculated between all covariates, then those with a > 0.8 correlation with another covariate were removed, keeping the one more highly correlated with the water quality variable[57].

To build each model, covariates were selected using a forward stepwise approach, reducing potential overfitting due to high numbers of potential covariates and low sample sizes[39,44]. The covariate with the highest absolute Pearson's correlation with the response variable, i.e., pre-fire constituent data, was first used to condition a single-variable linear model. This initial model was evaluated using the Akaike information criterion with a bias correction for small sample sizes (AICc)[58], which penalizes complexity and is recommended when the ratio of sample datapoints to covariates is less than 40[59]. The model was then applied over the pre-fire training dataset, calculating residuals from the difference between observed and estimated constituent levels. From the remaining candidate covariates, the one most highly correlated to the previous model's residuals was then added to create a new model, calculating a new AICc. The additional covariate was retained if it lowered the AICc value by more than 2. This process was repeated until the addition of a new covariate did not satisfy the delta AICc requirement.

Performance metrics were calculated for each model using a leave-one-out cross-validation method applied to pre-fire data, similar to methods used by Beyene et al.[39], and McManus et al.[60]. Leave-one-out cross-validation involves first assigning one day of covariate and predictand variables as testing data, calibrating a model with data from the remaining days, then using that model to predict the response on the testing day. This process was repeated for each available day, then model performance metrics calculated from the full observed and predicted datasets. Metrics commonly used in water quality modeling were selected to evaluate each model[46]: the Nash-Sutcliffe efficiency[61], percent bias, and the ratio of the root mean squared error to standard deviation. These metrics describe, respectively, the model error relative to the total variation, the tendency of the model to overpredict or underpredict, and the goodness-of-fit of the model[39,62]. Models with low skill—or ratio of root mean squared error to standard deviation scores greater than 1—were discarded to ensure accuracy of results. An analysis exploring the influence of more strict filtering criteria is analyzed and discussed in Supplementary Fig. 4, Supplementary Fig. 5, and the Supplementary Discussion.

For each constituent, the mean and 90% confidence interval bounds were calculated for basins in the burned and unburned subsets for each pre- and post-fire year. Overall confidence bounds from all years of pre-fire residuals in burned basins were also calculated. Fire-related change in a post-fire year was then considered significant ($p \leq 0.05$) if the residual mean was outside both the confidence bounds for all pre-fire residuals in burned basins, as well as the bounds of the unburned basins' confidence interval for that year. Response magnitudes driven by burn effects were calculated as the percent difference between average pre-fire residuals and mean residuals for each post-fire year.

Inter-basin variability attribution

A correlation analysis was used to attribute differences in post-fire constituent responses to geophysical watershed and wildfire characteristics. Evaluated characteristics include percent forested, developed, shrubland, and grassland areas in each basin, as well as basins' areas, percent burn extent, and the distance of wildfire burn scars from their outlets—factors shown to be influential on water quality response in previous studies[39,42–44]. Similar to methods used in Williams et al.[44], model residuals averaged across the first two years post-fire in each burned basin were first plotted against each watershed and fire characteristic to visually assess their linear relationships. A best-fit linear model was applied to each combination, with an R^2 calculated to assess the strength of relationships. Correlations were then assessed by calculating Pearson's correlation coefficients between every response and factor combination, additionally calculating which were significant ($p \leq 0.05$).

Data availability

The burned and unburned basin datasets and associated water quality data used in the analyses in this paper are available at https://doi.org/10.5281/zenodo.10209088[63]. The data directly used in generating the plots in this manuscript and the Supplementary Information are also included in the published dataset. Additionally, the original water quality data used to create this dataset is available on the Water Quality Portal website (https://www.waterqualitydata.us/), wildfire information is available on the Monitoring Trends in Burn Severity website (https://www.mtbs.gov/), hydroclimatic data from the ERA5-Land reanalysis dataset are available on the Copernicus Climate Data Store website (https://cds.climate.copernicus.eu/cdsapp#!/dataset/reanalysis-era5-land), land cover information is available on the Multi-Resolution Land Characteristics Consortium website (https://www.mrlc.gov/), Shuttle Radar Topography Mission digital elevation model data are available through the USGS Earth Explorer portal (https://www.usgs.gov/tools/earthexplorer), and the National Hydrography Dataset streamlines are available on the Environmental Protection Agency website (https://www.epa.gov/waterdata/get-nhdplus-national-hydrography-dataset-plus-data).

Code availability

R programming scripts used to create watershed delineations, clean and analyze water quality data, and train linear models are available at https://doi.org/10.5281/zenodo.10209088[63]. R version 4.3.3 was used to develop and run these scripts.

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Author contributions
Carli P. Brucker designed the experiment, compiled and cleaned the datasets, developed methods and code to complete the analysis, created data visualizations and figures, and wrote and edited the manuscript; Ben Livneh and Fernando L. Rosario-Ortiz were co-lead supervisors of this work and both conceptualized and designed the experiment, guided the development of methods, and provided major feedback and edits to manuscript drafts; Fangfang Yao, A. Park Williams, William C. Becker, Stephanie K. Kampf, and Balaji Rajagopalan were all secondary supervisors of this work and provided feedback on the experimental methods and reviewed and edited manuscript drafts.

Competing interests
The authors declare no competing interests.

Additional information
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