

Evaluating the factors responsible for post-fire water quality response in forests of the western USA

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Abstract. Wildfires commonly increase nutrient, carbon, sediment and metal inputs to streams, yet the factors responsible for the type, magnitude and duration of water quality effects are poorly understood. Prior work by the current authors found increased nitrogen, phosphorus and cation exports were common the first 5 post-fire years from a synthesis of 159 wildfires across the western United States. In the current study, an analysis is undertaken to determine factors that best explain post-fire streamwater responses observed in those watersheds. Increased post-fire total nitrogen and phosphorus loading were proportional to the catchment extent of moderate and high burn severity. While post-fire dissolved metal concentrations were correlated with pre-fire soil organic matter. Total metal concentration increased where post-fire Normalised Difference Vegetation Index, a remote sensing indicator of live green vegetation, was low. When pre-fire soil field capacity exceeded 17%, there was a 750% median increase in total metals export to streams. Overall, the current analysis identified burn severity, post-fire vegetation cover and several soil properties as the key variables explaining extended post-fire water quality response across a broad range of conditions found in the western US.

Additional keywords: metals, nutrients, pre-fire soil, streams, vegetation recovery, wildfire.

Received 30 October 2018, accepted 6 July 2019, published online 3 September 2019

Introduction

The wildfire season has lengthened, and the frequency and extent of wildfires have increased in forested areas of western North America (Westerling *et al.* 2006; Morgan *et al.* 2008; Miller *et al.* 2009; Westerling *et al.* 2011). Under current climate projections, the mean area burned is predicted to increase 54% by 2050 in the region, with a similar increase globally (Spracklen *et al.* 2009; Pechony and Shindell 2010; Harvey 2016). Forest fires consume vegetation, expose soils to erosion and often interrupt or degrade drinking and irrigation water supply (Smith *et al.* 2011; Writer *et al.* 2012; Bladon *et al.* 2014). Given the increasing frequency of wildfires and their impact on water supply, an evaluation of water quality effects from fires across the diverse range of watershed and wildfire conditions is essential.

Wildfires commonly increase total suspended solids (Silins *et al.* 2009; Noske *et al.* 2010; Smith *et al.* 2011; Dahm *et al.* 2015), nutrients (Burke *et al.* 2005; Bladon *et al.* 2008; Mast and

Clow 2008; Rhoades *et al.* 2011; Writer *et al.* 2012) and metal export from burned catchments (Burke *et al.* 2013; Burton *et al.* 2016), though the degree and duration of responses vary widely. For example, ash inputs often increase stream pH, concentrations of nutrients and cations immediately after a wildfire, but these constituents then return to pre-fire conditions within months (Earl and Blinn 2003; Rhoades *et al.* 2011). In contrast, wildfire in Canadian boreal forests elevated dissolved and particulate phosphorus levels (Burke *et al.* 2005) and a severe wildfire in Colorado montane forests elevated nitrate and turbidity levels (Rhoades *et al.* 2011) for more than 4 years following these fires. In the Canadian Rockies, post-fire stream phosphorus concentrations remained elevated in some, but not other adjacent tributaries for 6 and 7 years after a fire (Emelko *et al.* 2016). Our previous assessment of wildfires in the western US documented altered post-fire water quality in 29% of burned watersheds the first 5 post-fire years (Rust *et al.* 2018). Although changes in post-fire water quality are commonly expected, the

factors that regulate the magnitude and duration of these changes remain poorly understood.

There are multiple factors that affect how wildfires alter the composition of streamwater and watershed exports. Wildfires combust vegetation and surface organic soil matter, exposing hillslopes and watersheds to post-fire erosion and nutrient losses (Certini 2005; Silins et al. 2009). Post-fire responses are closely linked to wildfire extent and severity (Riggan et al. 1994; Townsend and Douglas 2004; Arkle et al. 2010; Rhoades et al. 2011), but they are also influenced by catchment and soil conditions that regulate erosion, and climatic and ecological conditions that determine rates of vegetation recovery (Doerr et al. 2000; Dahm et al. 2015). For example, post-fire drought and slow recolonisation of severe wildfire patches can delay post-fire forest establishment (Abatzoglou and Williams 2016; Chambers et al. 2016; Wang and Zhang 2017; Stevens-Rumann et al. 2018) and prolong effects on watersheds and streams (Rhoades et al. 2018). Reduced plant nutrient and water demand increases nutrient export and stream discharge from burned watersheds (Kinoshita and Hogue 2011, 2015; Murphy et al. 2012; Saxe et al. 2018) and the rate of revegetation may influence post-fire watershed recovery. Proximity to urban air pollution sources has also been shown to influence post-fire nitrate and metal export (Riggan et al. 1994; Burke et al. 2013). Local and regional factors interact with wildfire severity in spatially and temporally complex ways to determine how fires alter water quality.

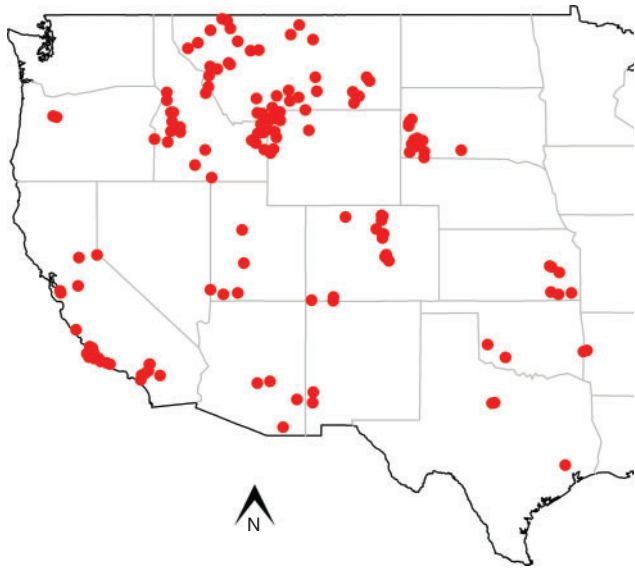


Fig. 1. Fire-impacted watersheds with ≥ 5 years of pre-fire and ≥ 10 years of post-fire water quality and stream discharge data ($n = 159$; Rust et al. 2018).

The goal of the current study is to identify climate, watershed and vegetation factors that influence post-fire water quality response and recovery on annual to decadal scales. This study aims to move beyond case studies on individual fires and evaluate a multitude of fires to more broadly identify these factors. The ability to anticipate post-fire water quality issues and identify their causes has emerged as a research priority (Moody et al. 2013; Nunes et al. 2018). A better understanding of which climate, watershed and vegetation factors drive water quality responses will help inform water treatment technologies, land management and post-fire restoration strategies, and confront challenges of increased frequency, size and severity of wildfires in the western US.

Methods

Wildfire, water quality and catchment data

The current study utilises data from 159 fires that burned between 1984 and 2012 within 153 watersheds in the western USA, constraining sites to those that had 5 years of pre-fire and 10 years of post-fire water quality and streamflow data (Fig. 1). All data used in this study are available through the U.S. Geological Survey (USGS) ScienceBase (Rust et al. 2019). Information about each fire was acquired from the Monitoring Trends in Burn Severity (MTBS) database (Eidenshink et al. 2007), and burned watersheds were delineated based on USGS stream gaging stations (U.S. Geological Survey 2019). Burned watersheds spanned 7 to 34 800 km² with 5 to 100% of the area burned (Table 1) and 0 to 84% high-severity wildfire (Table 1). The median and maximum distances between the closest point on the fire perimeter and stream sampling stations were 17 and 257 km respectively. Watersheds that burned more than once during the study period were excluded unless there was more than 10 years between fires. Out of the 153 watersheds selected, 6 had two fires within the watershed that were 14 to 24 years apart.

Physical and chemical water quality data were acquired from the following publicly available databases: the USGS National Water Information System database (U.S. Geological Survey 2019) and the Water Quality Portal, US Environmental Protection Agency 2019 (<https://waterqualitydata.us/>; accessed 16 January 2019). Sampling frequency varied for each site; some data were collected monthly, whereas other agencies collected data quarterly. We required a minimum of two samples per year for 5 years pre-fire and 10 years post fire to be included in this analysis. Data were plotted over time to confirm that sampling occurred throughout the 5-year pre- and 10-year post-fire time periods, and data below instrument detection limits were excluded from the dataset (Eaton et al. 1998; Rust et al. 2018). A total of 89 physical and chemical water quality parameters were evaluated as response variables (Appendix Table A1). The percentage change in median concentration and median loading rate (or flux)

Table 1. Information on the western United States forest fires that are the subject of the present study

Number of fires	Median size (ha)	Maximum size (ha)	Minimum size (ha)	Median % of watershed burned (range)	Median % moderate severity (range)	Median % high severity (range)
159	13 601	359 438	204	11 (5–100)	20 (0–66)	21 (0–84)

between pre- and post-fire conditions was calculated for dissolved (filtered through 0.45- μ m filter) and total (unfiltered) stream-water solutes. Mean daily flow data from USGS gages associated with water quality sampling points were used to calculate daily loading rates (flow-weighted mass/time; [Falcone 2011](#)). Where there were sufficient post-fire data, water quality recovery was examined for discrete post-fire periods (Year 1, Year 2, Years 3–5; Years 6–10).

Water quality responses were compared with the extent of a watershed burned, and the combined percentage of fire with moderate and high burn severity, conditions that consume nearly all vegetation and surface organic matter ([Keeley 2009](#)). The extent burned was calculated from wildfire perimeters overlaid on watershed areas defined by stream gauge locations ([Eidenshink et al. 2007](#); U.S. Geological Survey 2019). Fire severity was estimated with 30-m-spatial resolution Landsat imagery and the Differenced Normalized Burn Ratio (dNBR) ([Eidenshink et al. 2007](#)); remote burn severity classifications were not validated with on-site measurements. Mean elevation, latitude, slope, aspect and the distance from the perimeter of each wildfire to each respective water quality sampling location were estimated from a 30-m digital elevation model (*ArcMap 10.1*, [ESRI 2012](#)). The distance between water sampling locations and cities with >100 000 people that are potential sources of air pollution and water quality impairment was also estimated.

Edaphic variables

Soil properties that influence erosion, nutrient and metal export and post-fire recovery were averaged for each wildfire using publicly available data from the State Soil Geographic Database (STATSGO; [Schwartz and Alexander 1995](#); Soil Survey Staff, Natural Resources Conservation Service, USDA 2019). Although the STATSGO database contains dozens of edaphic variables, we selected soil properties that are known to affect water quality in streams and are used in watershed classification schemes ([Robertson et al. 2006](#)). Field capacity determines both plant water stress and soil oxidation–reduction conditions that regulate dissolved metal dynamics. We also included soil organic matter and calcium carbonate content and texture (percentage clay and silt). As an index of soil erodibility, we used the adjusted k-factor that considers rock fragments in surface soils that may mitigate pre-fire erosion ([Wischmeier and Smith 1965](#); [Schwartz and Alexander 1995](#); Soil Survey Staff, Natural Resources Conservation Service, USDA 2019).

Climatological factors and plant recovery

Climatic indices that may influence post-fire vegetation recovery were also evaluated. An aridity index (AI), defined as the ratio of mean annual precipitation to mean annual potential evapotranspiration, allows comparison of climate across the western USA ([www.cgiar-csi.org](#), accessed 25 July 2016). We also calculated solar energy available for vegetation regrowth at each burn area based on slope, latitude and aspect ([McCune and Keon 2002](#)).

The Normalised Difference Vegetation Index (NDVI) was used as an index of growing season greenness and vegetation recovery ([Deering et al. 1975](#); [Prince 1991](#); [Goward and Huemmrich 1992](#); [Prince and Goward 1995](#)). Data to calculate

NDVI before and after each fire were retrieved from the Landsat 5 and Landsat 7 satellites and processed in Google Earth Engine (USGS Earth Explorer, Google, Inc., <https://earthexplorer.usgs.gov/>; accessed 28 February 2017). Images with >30% cloud cover were excluded, and remaining images were processed with a cloud-masking algorithm. The maximum NDVI values measured every 16 days during the growing season (May through September) were composited for each pixel in the burn area. Pre-fire baseline conditions were calculated from 5 years of growing season NDVI. Post-fire NDVI was calculated for discrete time periods (Year 1, Year 2, Years 3–5; Years 6–10).

Statistical methods

Individual correlations among predictor variables, streamwater analyte concentrations and fluxes were analysed ([R Core Development Team 2018](#)). Statistical independence of each pair of variables and individual correlations between predictor and response variables were tested using Spearman's rank correlation coefficient ([Tamhane and Dunlop 2000](#)). Calculated Spearman's rho (r_s) values were compared with a chart of critical values for Spearman's rho, for a two-tailed hypothesis, where correlations were statistically significant if P -value was <0.05 ([Best and Roberts 1975](#)).

In addition to evaluating individual correlations, a conditional inference tree (CI tree) approach was used to define thresholds for predictor variables with the strongest association for a given water quality response variable ([Hothorn et al. 2006a, 2006b](#)). The non-parametric method does not assume independence among predictor variables or require assumptions of linearity, so it is effective at identifying thresholds where complex interactions exist ([Quinn and Keough 2002](#)). The CI tree method uses a chi-square test statistic to test the association between predictor and response variables and requires numerous (>5) observations; we required a minimum sample size of 20 watersheds in this CI tree analysis ([Das et al. 2009](#)). As individual monitoring stations did not all measure the same water quality analytes, individual cation or metal forms reported for each site were aggregated as one response variable in the CI tree. Each watershed was treated as an independent sample where the median of post-fire changes in individual cations or metals was aggregated and used to identify thresholds among predictor variables. An *a priori* P -value <0.05 was utilised to identify thresholds and partition the decision tree.

Results

Determinants of post-fire stream nitrogen and phosphorus Dissolved nitrogen

The percentage of the fire that burned at moderate and high severity was positively correlated with the percentage change in concentrations of dissolved nitrate and organic nitrogen ($r_s = 0.44$, $n = 32$, $P < 0.05$ and $r_s = 0.42$, $n = 40$, $P < 0.05$; [Fig. 2](#)). As post-fire NDVI increased over time, dissolved organic nitrogen declined ($r_s = -0.34$, $r_s = -0.41$, $r_s = -0.42$, $n = 40$, $P < 0.05$). The AI was positively correlated with concentrations of post-fire ammonia and nitrate ($r_s = 0.37$, $n = 61$, $P < 0.05$ and $r_s = 0.4$, $n = 32$, $P < 0.05$). The distance from a fire to a city was positively correlated with the concentration of ammonia in waters downstream from the fire, meaning

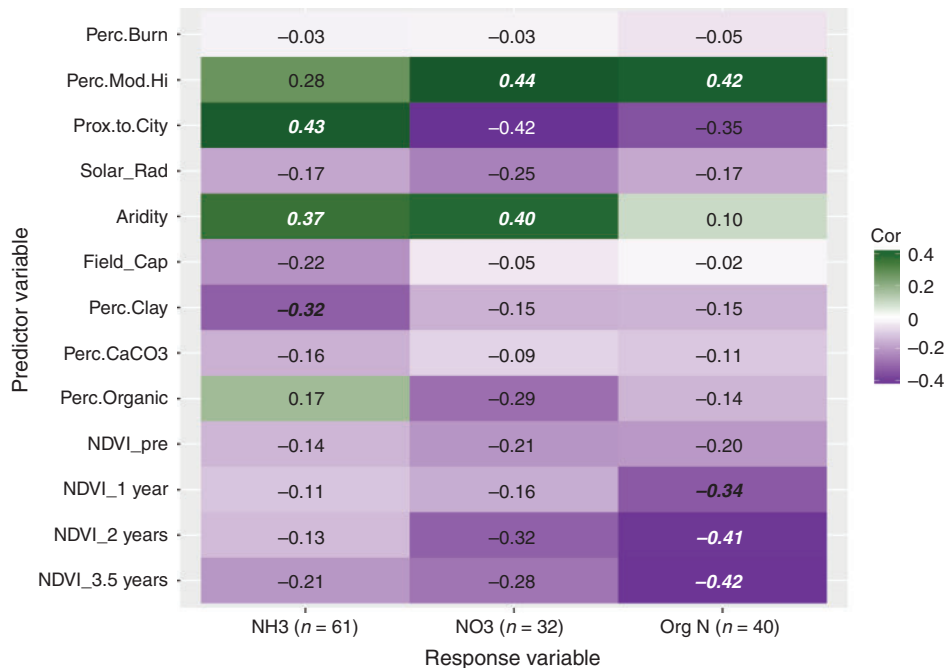


Fig. 2. Correlation (cor) between selected variables and median post-fire change in dissolved ammonia, nitrate and organic nitrogen concentrations in the first 5 years after fire. Spearman's correlation coefficients are typed within each box; significant correlations are shown in bold type where $P < 0.05$. The n values in parentheses by each constituent represent the number of watersheds included in the analysis.

the farther a fire was from a city, the greater the concentration of ammonia ($r_s = 0.43$, $n = 61$, $P < 0.05$). The percentage clay in the soil pre-fire was negatively correlated with post-fire concentrations of ammonia ($r_s = -0.32$, $n = 61$, $P < 0.05$).

Total nitrogen

Total nitrogen (TN) flux over all post-fire time periods was weakly correlated with most of the independent variables used in this study. Solar radiation was negatively correlated with nitrogen flux during the second year after fire ($r_s = -0.39$, $n = 30$, $P < 0.05$; Fig. 3). NDVI in the second year after fire was negatively correlated with TN 6 to 10 years after fire ($r_s = -0.58$, $n = 17$, $P < 0.05$).

Total phosphorus

Total phosphorus (TP) concentrations and fluxes were elevated during the first 5 post-fire years (Rust *et al.* 2018), but the CI tree technique did not identify a single responsible factor. However, there were significant correlations between post-fire change in stream TP loading rate and burn severity along with other watershed characteristics (Fig. 4). The proportion of a fire that burned at moderate and high severity was correlated with TP loading rate 3 to 5 years after fire ($r_s = 0.39$, $n = 46$, $P < 0.05$). There was a significant positive correlation between the soil field capacity and TP flux the first year and 6 to 10 years post fire ($r_s = 0.42$, $n = 44$, $P < 0.05$; and $r_s = 0.5$, $n = 20$, $P < 0.05$). TP flux was positively correlated with the pre-fire percentage clay in soil 6 to 10 years after fire ($r_s = 0.53$, $n = 20$, $P < 0.05$). TP flux 6 to 10 years after fire was negatively correlated with the NDVI values 2 years after fire ($r_s = -0.61$, $n = 20$, $P < 0.05$).

Base cations

The percentage of the fire that burned at moderate and high severity was positively correlated with the concentration of potassium in receiving streams ($r_s = 0.46$, $n = 46$, $P < 0.05$; Fig. 5). The higher the AI, the higher the concentration of calcium in streams the first 5 years after fire ($r_s = 0.41$, $n = 66$, $P < 0.05$; $r_s = 0.43$, $n = 52$, $P < 0.05$). Finally, the farther a fire was from a city, the greater the post-fire concentration of calcium, magnesium and sodium in sampled streams 5 years after fire ($r_s = 0.53$, $n = 66$, $P < 0.05$; $r_s = 0.48$, $n = 64$, $P < 0.05$; $r_s = 0.52$, $n = 52$, $P < 0.05$ respectively).

Determinants of heavy metal response

The CI tree method identified a threshold in post-fire aggregates of dissolved metal concentration associated with pre-fire soil organic matter (SOM) content ($P = 0.02$; Fig. 6). Where pre-fire SOM exceeded 2%, post-fire dissolved metal concentrations decreased relative to pre-fire conditions. There was a median of 0% change in dissolved metal concentrations in areas with $\leq 2\%$ SOM. Though the median percentage change was zero, the fourth quartile showed some streams with a 100% change in concentration; SOM of $\leq 2\%$ was correlated with a large positive change in dissolved metal concentrations.

Consistent with the CI tree results, there was a negative correlation between pre-fire SOM (Table 2) (Perc. Organic) and dissolved cadmium metal concentrations in receiving water ($r_s = -0.8$, $n = 11$, $P < 0.05$; Fig. 7). Solar radiation was negatively correlated with post-fire zinc concentrations ($r_s = -0.48$, $n = 20$, $P < 0.05$). Pre-fire NDVI values were positively correlated with post-fire zinc concentrations ($r_s = 0.5$,

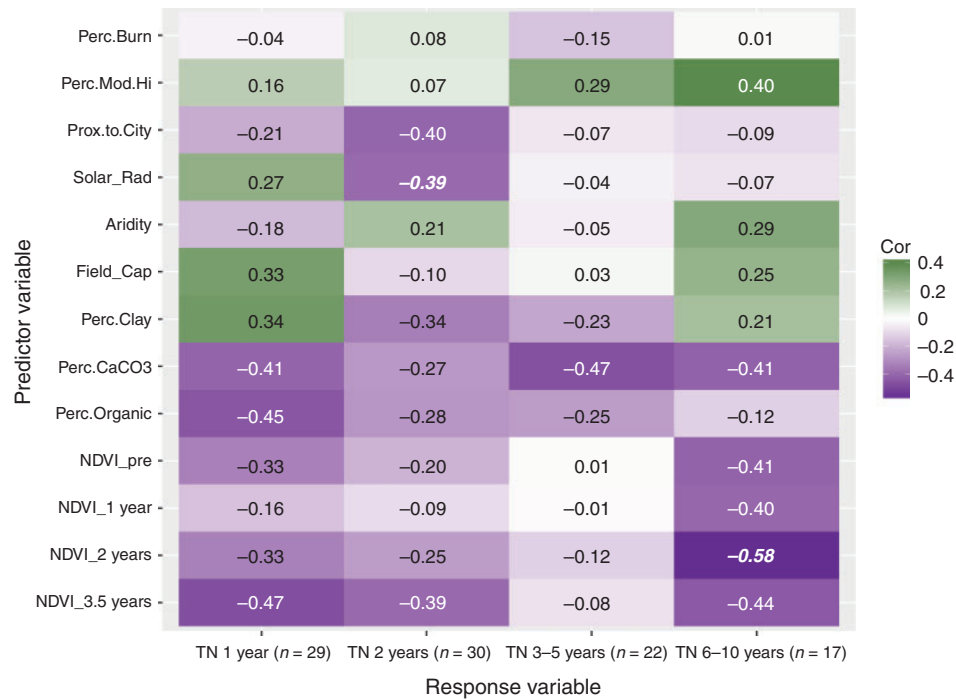


Fig. 3. Correlation (cor) between selected variables and median post-fire change in total nitrogen flux over different post-fire time periods. Spearman's correlation coefficients are typed within each box; significant correlations are shown in bold type where $P < 0.05$. The n values in parentheses by each constituent represent the number of watersheds included in the analysis.

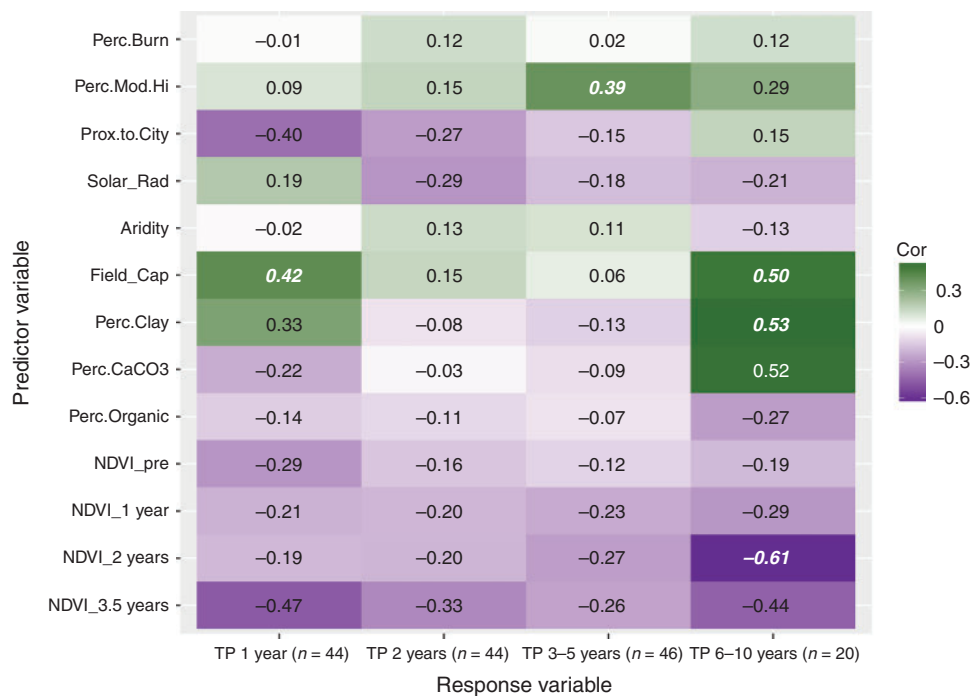


Fig. 4. Correlation (cor) between selected variables and median change in total phosphorus flux over different post-fire time periods. Spearman's correlation coefficients are typed within each box; significant correlations are shown in bold type where $P < 0.05$. The n values in parentheses by each constituent represent the number of watersheds included in the analysis.

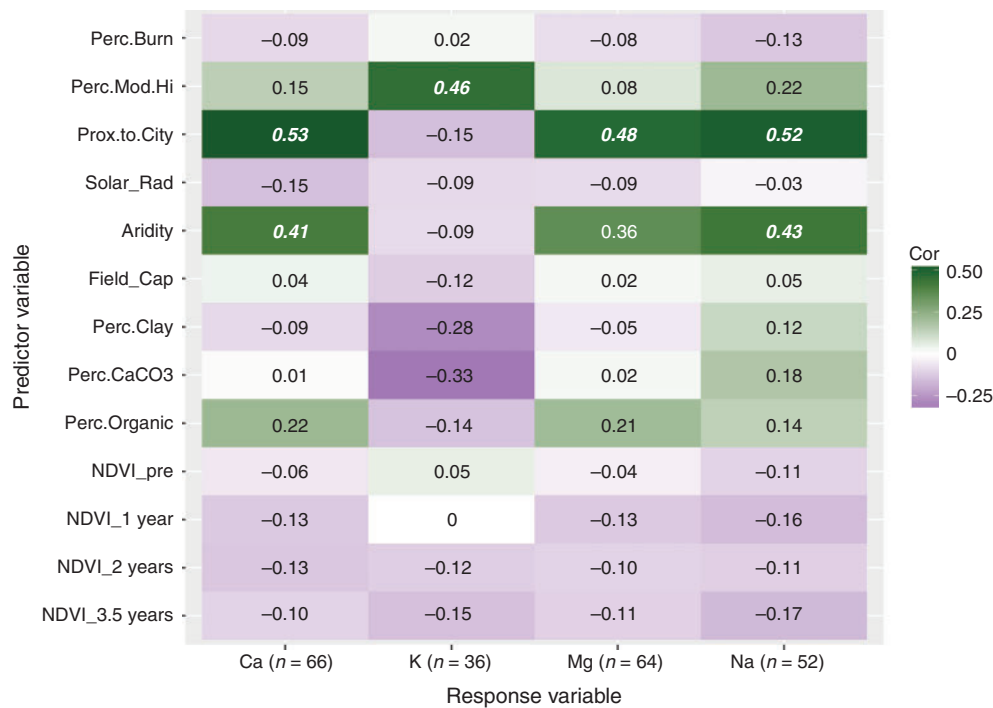


Fig. 5. Correlation (cor) between selected variables and median in the concentration of four major cations in the first 5 years after fire. Spearman’s correlation coefficients are typed within each box; significant correlations are shown in bold type where $P < 0.05$. The n values in parentheses by each constituent represent the number of watersheds included in the analysis.

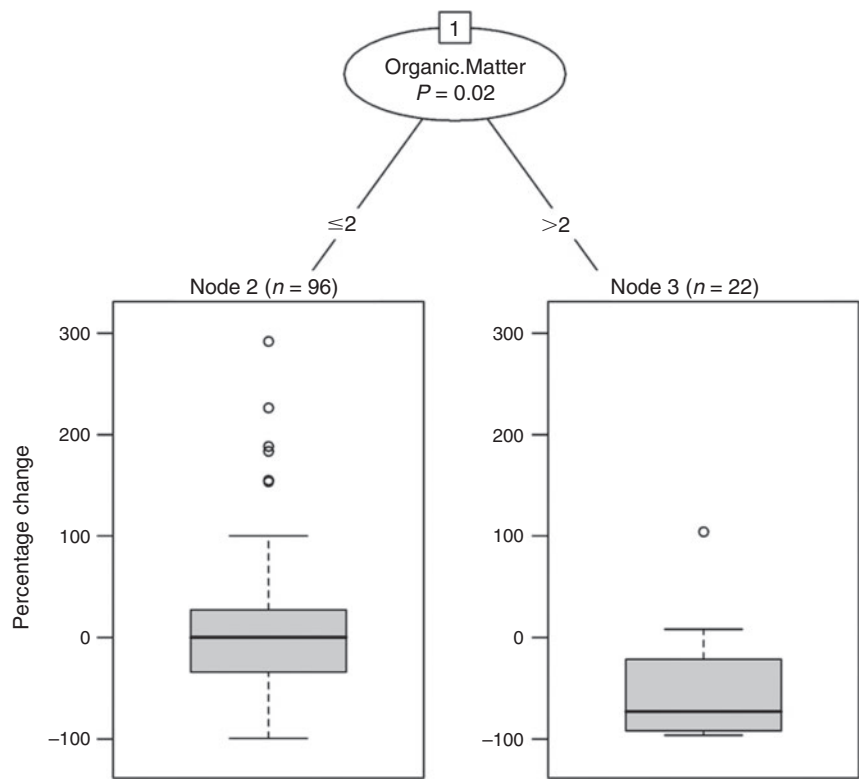


Fig. 6. Conditional inference tree results illustrating the significant relationship between the percentage of organic matter in the burn area soil and the median percentage change in dissolved metals concentration (Al, Ba, Cd, Cu, Mn, Pb and Zn) in the first 5 years after fire.

Table 2. Variables evaluated as potential drivers of observed post-fire water quality responses NDVI, normalised difference vegetation index

Parameter	Definition	Range
Fire and catchment conditions		
Percentage burn	Percentage of watershed burned	5–100
Percentage moderate burn severity	Percentage of fire that was moderate severity	0–65
Percentage high burn severity	Percentage of fire that was high severity	0–84
Percentage moderate and high burn severity	Percentage of fire that was moderate and high severity summed	0–93
Elevation (m)	Average elevation of burn area	13–2925
Latitude (radians)	Average latitude of burn area	0.5–0.85
Slope (%)	Average slope angle of burn area	0.3–17.6
Proximity to fire (km)	Distance from fire perimeter to water quality sampling site	0–257
Proximity to city (km)	Distance from fire perimeter to nearest city buffer	0–351
Climate factors		
Solar radiation ($\text{MJ cm}^{-2} \text{ year}^{-1}$)	Potential annual direct solar radiation	0.86–1.05
Aridity index	Ratio of mean annual precipitation to mean annual evapotranspiration	0.3–2.5
Edaphic factors		
Field capacity (inches water per inch soil) (Field Cap.)	Highest available water capacity	0–0.20
Silt (%)	Average percentage silt in soil	1.5–52
Clay (%)	Average percentage clay in soil	0.3–40
Calcium carbonate (%)	Average percentage calcium carbonate in soil	0–29
Soil k-factor	Erodibility factor	1 to 13
Soil organic matter (%)	Average percentage organic matter in soil	0.5–20
Vegetation cover		
NDVI pre-fire (5 years)	Maximum averaged 5 years pre-fire	0.14–0.76
NDVI post-fire Year 1	Ratio of the near-infrared (NIR) and visible radiances (VIS), maximum averaged 1 year post fire	0.21–0.79
NDVI post-fire Years 1–2	Maximum averaged 2 years post fire	0.17–0.81
NDVI post-fire Years 3–5	Maximum averaged 3–5 years post fire	0.28–0.77

$n = 20$, $P < 0.05$). Percentage calcium carbonate in the soil pre-fire was positively correlated with post-fire concentrations of manganese and zinc ($r_s = 0.62$, $n = 19$, $P < 0.05$ and $r_s = 0.55$, $n = 20$, and $P < 0.05$) but was negatively correlated with the post-fire concentrations of cadmium ($r_s = -0.69$, $n = 11$, $P < 0.05$).

Total metals

The CI tree identified drivers of both the change in concentration and loading rate of total metals in the 5 years after fire. The percentage change in the aggregate of total metal concentration was influenced by NDVI the first year after the fire ($P = 0.01$; Fig. 8). Where post-fire plant greenness was low ($\text{NDVI} \leq 0.4$), total metal concentrations increased (node 2). For sites with high NDVI (>0.4), incident solar radiation (node 3) influenced whether total metal concentrations increased or decreased in post-fire stream-water ($P = 0.02$). Where solar radiation was low (≤ 0.9) and vegetation greenness was high, there was a post-fire decrease in aggregate total metals concentration. Conversely, where NDVI was high (>0.4) and solar radiation was high (>0.9), there was no change in the aggregate of total metals concentration.

Similarly, post-fire plant cover and soil field capacity were related to the magnitude and direction of total metals loading rate (Fig. 9). The primary determinant of total metals loading rate was pre-fire soil field capacity ($P = 0.01$). When field capacity exceeded 17%, there was a 750% median increase in total metals loading rate in sampled streams (node 5, $P = 0.01$). For soils with $\leq 17\%$ field capacity and low post-fire plant cover ($\text{NDVI}_{1y} \leq 0.4$), there was a slight increase in median loading

rate (node 3, $P = 0.03$), and a 500% fourth quartile increase in flux of total metals in sampled waters. When first year post-fire NDVI was higher (>0.4), there was no change in total metals loading rate. In summary, soil field capacity was significantly correlated with the total metals loading rates, and slower vegetation recovery the first year after fire was correlated with increased loading rates of total metals.

There were several positive and negative correlations among the loading rates of individual total metals and predictor variables (Fig. 10). The AI was significantly negatively correlated with the loading rate of several metals including cadmium, chromium, iron and nickel (Fig. 10). Moderate and high burn severity was positively correlated with total copper ($r_s = 0.57$, $n = 16$, $P < 0.05$). The proximity of a fire to a large urban area was positively correlated with the loading rate of total iron ($r_s = 1$, $n = 9$, $P < 0.05$). Pre-fire SOM was negatively correlated with cadmium ($r_s = -0.9$, $n = 9$, $P < 0.05$). Finally, the pre-fire percentage of calcium carbonate in the soil was negatively correlated with the post-fire loading rate of iron ($r_s = -0.73$, $n = 9$, $P < 0.05$).

Discussion

This large compilation of publicly available data permitted a more expansive regional evaluation of factors that influence post-fire water quality responses than previously reported. The relations described in this study illuminate the physical, edaphic and biological characteristics that are correlated with different types of post-fire water quality responses. Broad themes emerged from this work: burn severity, post-fire vegetation greenness, soil

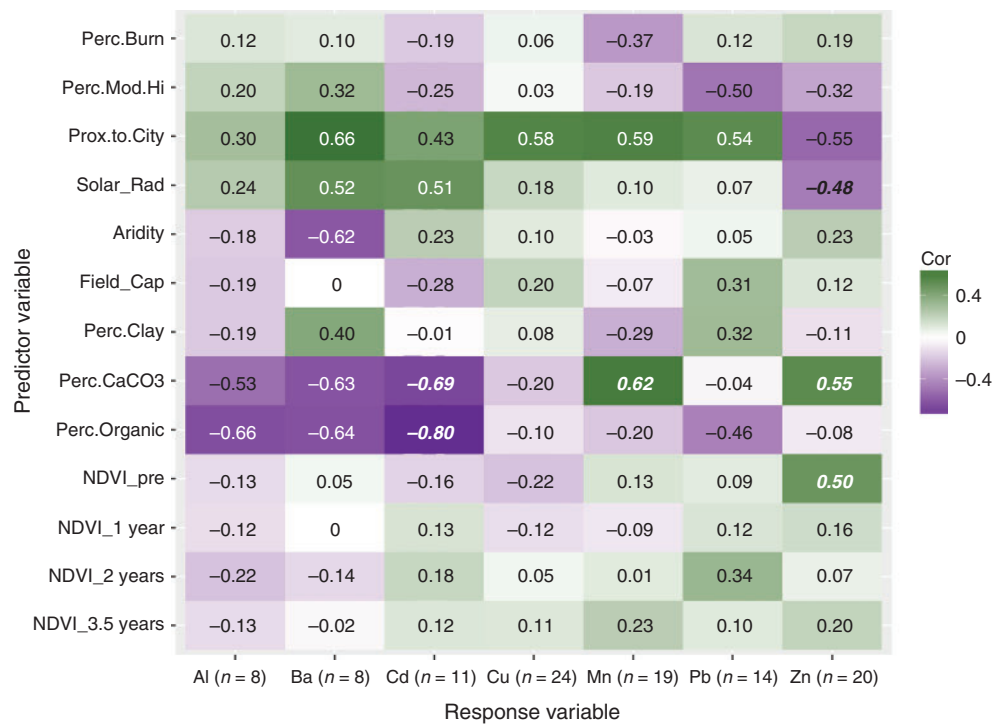


Fig. 7. Heatmap illustrating Spearman correlation coefficients among physical predictor variables and median change in dissolved metal concentrations in the first 5 years after fire. Spearman’s correlation coefficients are typed within each box; significant correlations are shown in bold type where $P < 0.05$. The n values in parentheses by each constituent represent the number of watersheds included in the analysis (cor, correlation).

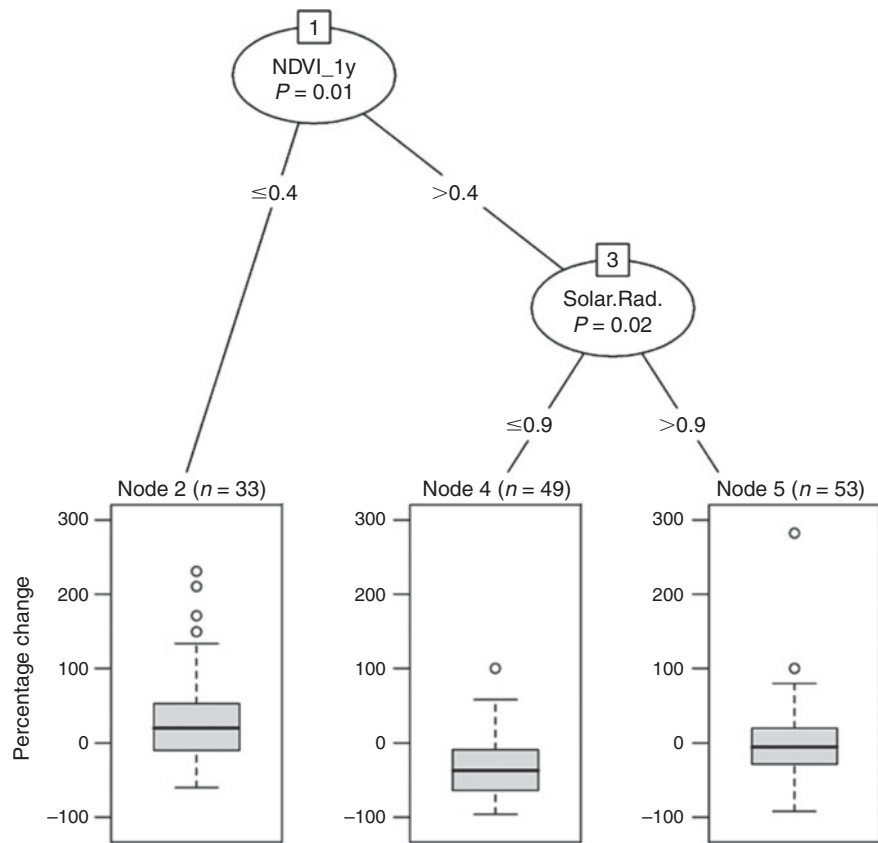


Fig. 8. Conditional inference tree results illustrating the significant relationship between the first year vegetation greenness (NDVI_1y), solar radiation and the median percentage change in total metals concentration (Ba, Cd, Cu, Fe, Mn, Ni, Pb, Se, Zn) in the first 5 years after fire.

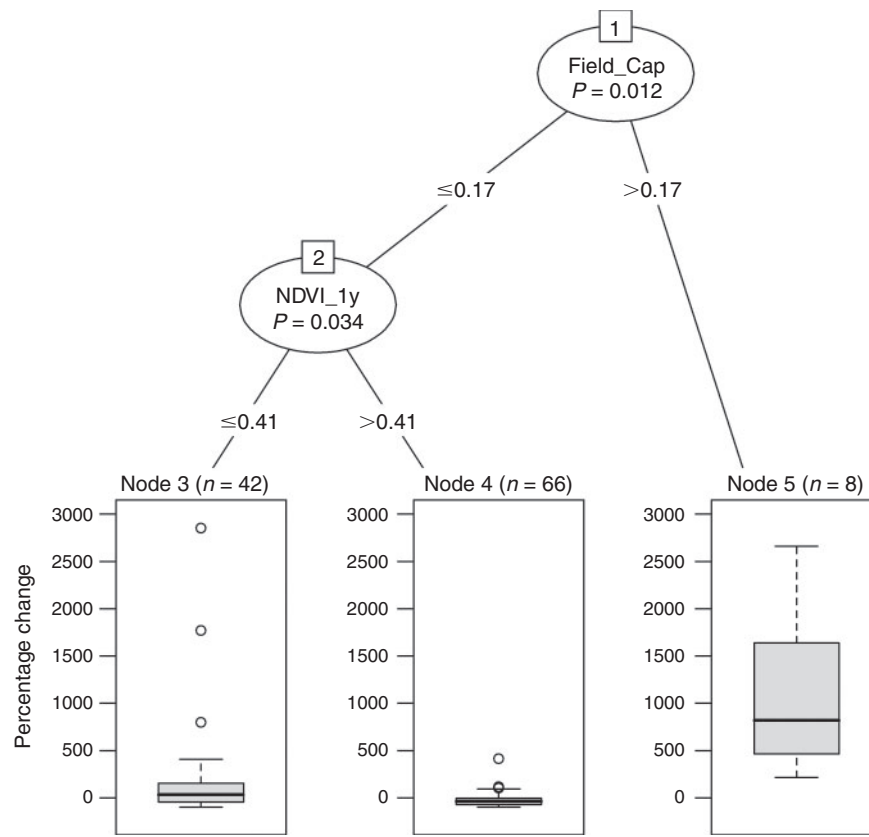


Fig. 9. Conditional inference tree results illustrating the significant relationship between the water content of the burn area soil, the first year vegetation greenness (NDVI_1y) and the median percentage change in total metals loading rate (Ba, Cd, Cu, Fe, Mn, Ni, Pb, Se, Zn) in the first 5 years after fire.

factors (pre-fire SOM, clay and field capacity) and the proximity of a fire to an urban area all affect the type and magnitude of water quality responses in fire-impacted watersheds. Previous studies have documented that wildfire severity influences stream chemistry response (Riggan *et al.* 1994; Rhoades *et al.* 2011; Rhoades *et al.* 2018) and that post-fire vegetation recovery influences stream nutrient and hydrologic responses and persistence in specific watersheds (Kinoshita and Hogue 2011, 2015; Rhoades *et al.* 2018). The current analysis confirms these findings at a regional scale and highlights the importance of edaphic conditions on post-fire water quality responses.

Whereas assigning each fire-impacted watershed a single number for the percentage clay, field capacity, or solar radiation required aggregating data from a small spatial scale to a large one, making broad inferences, significant correlations between pre-fire soil characteristics and post-fire water quality are worth considering. Edaphic characteristics and landscape-scale growing conditions are variables a watershed manager could easily assess after a fire to anticipate significant changes in water quality.

Of the broad list of physical, edaphic and biological predictor variables selected in this study, SOM influenced the response of dissolved metals in burned streams in the western US. Streams draining burned areas with $<2\%$ pre-fire SOM had a greater likelihood of increased dissolved metal concentrations. Dissolved metals bind and form immobile, stable complexes where SOM content is higher (Shaw 1989; Weng *et al.* 2002; Toribio

and Romanya 2006) and limit post-fire increases in stream metals. Lower dissolved metals concentrations in post-fire streams could help sensitive aquatic life because high concentrations of aqueous forms of zinc, copper, cadmium and other metals are lethal to rainbow trout (*Oncorhynchus mykiss*) (Hogstrand *et al.* 1994) and damaging to other aquatic biota in western US streams. Soil organic matter comes from accumulated needle and leaf litter and deadfall trees in western forests. Soil organic matter tends to be in higher concentrations in wetter, more productive climates than dry arid regions. Sensitive fish such as salmonids are present throughout wet and dry western forests. Forest managers should be encouraged to leave forest litter in place, especially in drier forests with less organic material, and view organic matter as a water quality mitigation tool rather than additional fuel load.

Wildfire severity influences post-fire water quality responses in the western US (Bladon *et al.* 2008). Moderate- and high-severity wildfires consume most of the organic surface layers (Keeley 2009; Parsons *et al.* 2010) and expose soils to increased erosion (Lane *et al.* 2006). We found that wildfire severity was significantly correlated with post-fire increases in dissolved and total nutrients, base cations and metals entering streams (Figs 3–5, 10). Specifically, streams below extensive moderate- and high-severity fires experience significant increases in dissolved nitrate, organic nitrogen, total phosphorus and total copper export.



Fig. 10. Heatmap illustrating Spearman correlation coefficients among selected physical predictor variables and median change in total metal loading rate the first 5 years after fire. Spearman's correlation coefficients are typed within each box; significant correlations are shown in bold type where $P < 0.05$. The n values in parentheses by each constituent represent the number of watersheds included in the analysis (cor, correlation).

Post-fire forest recovery is linked to fire severity (Turner *et al.* 1999). Plant and litter cover stabilise burned soils, reduce erosion rates and increase nutrient demand to limit sediment and nutrient losses (Pannkuk and Robichaud 2003; Certini 2005). Post-fire plant growth was correlated with post-fire dissolved organic nitrogen concentration and total metals concentrations and fluxes. Low post-fire plant cover (<0.4 NDVI) was associated with higher total metal concentrations and loading rates. Post-fire plant recovery, especially for herbaceous species, can be rapid under favourable climate and solar radiation conditions (Wittenberg *et al.* 2007; Wang and Zhang 2017; Fornwalt *et al.* 2018). Conversely, vegetation recovery can be slow after high-severity wildfires such as in California's chaparral systems or Wyoming's lodgepole pine systems (Turner *et al.* 1999; Kinoshita and Hogue 2011, 2015). As observed in the present study, the percentage of a fire burned at moderate and high severity was negatively correlated with post-fire NDVI ($r_s = -0.47$, $n = 160$, $P < 0.05$). Post-fire conifer regeneration was scarce in high-severity burn areas in multiple Colorado wildfires (Chambers *et al.* 2016). Only approximately half the pre-fire vegetation greenness recovered after 15 years in high-severity areas of Colorado's Hayman Fire (Rhoades *et al.* 2018). In this regional study of the western United States, burn severity was correlated with vegetation recovery and water quality response in streams impacted by fire.

Solar radiation, which relates hillslope, aspect and latitude to favourable growing conditions for vegetation, evaluated on this

spatial scale really represents differences in latitude and therefore growing season length in recovering watersheds. High NDVI and high solar radiation values were correlated with a neutral post-fire total metals flux; where vegetation recovered and conditions were favourable for vegetation, water quality response after fire was mitigated. Aridity index was used to identify the influence of climate on water quality response after fire. A higher AI reflects a more humid climate with more precipitation available to plants. Results show a correlation between a higher AI and a decrease in the loading rate of total metals. A climate with a higher AI would have higher mean annual precipitation, leading to higher runoff, and a more dilute load of total metals. Conversely, a higher AI was also correlated with higher concentrations of dissolved nutrients such as ammonia, nitrate and calcium, where higher mean annual precipitation carries dissolved constituents to the streams.

Other studies have observed high post-fire N and other constituents in proximity to urban areas (Riggan *et al.* 1994; Burke *et al.* 2013). In the current study, post-fire dissolved ammonia, calcium, magnesium, sodium concentrations and iron flux increased when large urban areas were farther away. In other words, proximity to urban areas was negatively correlated with the increase in these analyte concentrations and loading rates. Where fossil fuel combustion increases atmospheric nitrogen deposition on ecosystems surrounding large urban centres, wildfire then releases these constituents from upland vegetation and soils. Air pollution transport is dominated by

wind; in this broad regional study, wind direction was not included as a variable. It is possible that nitrogen and metals in air pollution are transported even farther by wind and have a greater influence on post-fire water quality that was not detected in this study.

Conclusions

The type, magnitude and persistence of water quality impacts after wildfire result from complex assortments of climate, vegetation and watershed conditions coupled with fire behaviour. This evaluation identified several factors that explain the lasting post-fire water quality responses across a broad range of conditions in the western US. Identifying determinants of post-fire water quality response, on a broad spatial and temporal scale, as in the current study, facilitates anticipation of water quality impacts following fire.

Overall, the proportion of SOM, wildfire severity and post-fire plant cover were strongly correlated with changes in post-fire water quality. Post-fire changes in stream dissolved metals were less for wildfires in watersheds with higher pre-fire SOM. Moderate- and high-severity wildfires increase organic N concentration and TP loading rates in downstream waters. High-severity wildfire reduced post-fire plant cover (NDVI) and elevated stream organic nitrogen, nitrate, and total metal concentrations and flux. This regional analysis confirms the findings of previous studies and concludes that post-fire vegetation cover regulates the response of numerous stream water quality constituents. With the large number of monitored watersheds and broad range of variability in the environmental data, these findings represent an important contribution to general understanding of the factors that influence post-fire water quality.

Conflicts of interest

The authors declare no conflicts of interest.

Acknowledgements

This work was supported by a Joint Fire Science Program (JFSP) grant (no. L14AC00165). Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

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Appendix

Table A1. Summary of physical and chemical water quality parameters and the percentage change in concentration and flux after fire
Rows where 25% or more watersheds changed significantly after fire are highlighted in light grey, 50% or more are highlighted in dark grey. Data utilised in present study and in Rust et al. 2018 are available in Rust et al. 2019 ANC, acid neutralising capacity; Turb., turbidity; TSS, total suspended solids; TDS, total dissolved solids; SAR, sodium adsorption ratio; OC, organic carbon; OP, orthophosphate

Analyte	Number of Fires with WQ data	Mean conc. pre-fire	Mean s.d. pre-fire	Mean flux pre-fire	Mean flux s.d. pre-fire	Mean conc. post-fire	Mean flux post-fire	Mean flux s.d. post-fire	Perc. change mean conc.	Mean flux post-fire	Perc. change mean flux	% Fires sig. change MWU
SpCuS/cm	145	648.2	188.8	NA	NA	437.8	705.1	NA	23.3	NA	NA	42.9
Temp_Water	152	12.2	6.1	NA	NA	5.9	12.0	NA	-0.4	NA	NA	13.2
pH	61	8.0	0.3	NA	NA	0.3	8.0	NA	0.3	NA	NA	26.6
ANC.mg/L*	12	146.8	26.5	270 098.2	164 755.6	130.6	69.6	24.2	-5.9	250 550.4	338.4	20.0
Alkalinity.mg/L	2	94.5	23.0	584.4	1740.6	10.2	255.1	17.6	-26.4	5365.7	818.1	100.0
DO.mg/L	46	9.6	1.5	21 510.9	21 637.1	9.8	104.4	1.1	3.0	23 239.1	127.4	17.2
DO.%.Sat	44	101.1	11.8	NA	NA	101.8	101.8	11.9	1.3	NA	NA	21.3
Hardness.mg/L	43	265.4	68.5	165 194.4	107 420.3	71.5	255.1	17.6	-3.4	157 303.4	171.0	32.9
HCO3.mg/L	5	112.6	16.7	726 130.3	474 442.1	104.4	104.4	17.6	-11.4	337 041.3	69.4	28.6
CO3.mg/L	2	1.4	2.5	13 297.0	3064.0	1.2	1.2	1.1	-36.9	1375.9	-32.5	0.0
CO2.unfilt.mg/L	35	3.2	2.4	6046.7	16 686.2	2.6	2.6	1.5	-7.5	3022.5	460.0	22.4
Turb.NTU*	12	12.8	22.4	NA	NA	702.9	702.9	1354.4	2350.4	NA	NA	15.8
TSS mg/L*	3	2.8	4.0	4216.4	21 890.7	12.9	226.8	20.4	244.6	78 831.0	89.3	25.0
TDS mg/L *	3	257.9	56.9	NA	NA	51.5	226.8	51.5	-7.0	NA	NA	0.0
Ca.filt.mg/L	47	60.3	15.0	44 237.5	28 944.2	56.3	56.3	15.1	-3.5	42 015.5	193.6	26.1
Cl.filt.mg/L	41	67.9	29.0	36 630.5	25 887.7	67.8	67.8	34.0	-1.3	39 821.4	176.8	21.4
Mg.mg/L	42	57.1	21.1	22 020.3	20 031.5	33.7	33.7	12.0	25.8	19 010.4	358.6	28.2
Na.filt.mg/L	35	82.1	34.5	35 525.8	24 357.0	83.0	83.0	34.6	5.9	43 403.1	225.8	28.8
Na.fraction.cations%	31	30.8	3.0	NA	NA	30.1	30.1	3.0	-2.2	NA	NA	24.1
SAR *	34	1.8	0.5	NA	NA	1.8	1.8	0.6	-6.0	NA	NA	24.2
K.filt.mg/L	31	4.1	1.0	3723.3	2618.1	4.1	4.1	1.0	2.4	4616.5	924.7	30.5
SO4.filt.mg/L	40	176.6	63.7	53 560.1	34 249.4	173.9	173.9	66.3	0.4	53 302.0	187.8	30.4
OC.filt.mg/L*	4	5.2	2.2	11 275.6	17 813.2	5.3	5.3	3.7	23.3	13 697.7	32.3	16.7
OC.unfilt.mg/L	5	6.6	2.7	13 883.2	20 749.2	8.4	8.4	3.2	42.9	13 021.9	164.8	28.6
Org.N.filt.mg/L	7	0.4	0.1	629.2	980.0	0.3	0.3	0.1	-6.7	404.6	75.6	37.5
Org.N.unfilt.mg/L	39	0.6	0.5	1422.5	2154.2	1.6	1.6	2.8	150.2	4582.6	1056.2	34.0

46	NH3.filt.mg/L.N	0.1	0.1	110.6	147.5	0.1	0.1	84.1	108.6	2.9	216.9	45.2
13	NH3.unfilt.mg/L	0.1	0.1	130.5	160.8	0.1	0.1	154.1	262.7	66.9	438.8	22.2
7	NH3plusOrgN.filt.mg/L	0.4	0.2	676.4	1050.0	0.3	0.1	459.6	813.0	-4.3	97.8	25.0
28	NH3plusOrg.N.unfilt.mg/L	0.6	0.4	1835.8	2654.7	0.8	1.0	2220.4	3669.3	43.2	182.7	38.2
25	NO2.filt.mg/L.N	0.0	0.0	22.5	22.9	0.0	0.0	25.6	29.0	1.0	176.4	23.4
26	NO3.filt.mg/L.N	0.5	0.3	507.6	345.2	0.5	0.4	578.5	558.8	75.5	406.9	24.5
39	NO3plusNO2.filt.mg/L	0.6	0.3	524.6	426.7	0.7	0.4	735.3	701.5	63.6	3554.4	33.3
4	NO3plusNO2.unfilt.mg/L	0.7	0.3	850.2	699.2	0.6	0.5	227.8	381.4	502.3	451.8	28.6
7	TN.filt.mg/L	1.7	0.6	1453.9	1682.3	1.2	0.5	730.3	1145.9	-5.8	75.4	37.5
29	TN.unfilt.mg/L	1.4	1.3	3071.5	5021.9	1.4	1.1	2921.9	3880.1	35.8	150.0	34.2
40	OP.filt.mg/L*	0.3	0.2	247.7	241.5	0.3	0.2	294.3	300.5	32.2	3872.4	36.4
39	PO4.unfilt.mg/L.P	0.6	0.3	798.5	375.4	NA	NA	NA	NA	NA	NA	0.0
18	P.filt.mg/L	0.1	0.1	155.3	179.0	0.1	0.1	165.1	200.3	5.9	197.1	18.2
46	P.unfilt.mg/L	0.3	0.4	396.5	716.0	0.5	1.1	600.5	1705.9	265.8	257.6	34.6
14	Ag.filt.ug/L	0.8	0.1	3.2	2.9	0.7	0.0	3.3	3.3	-26.6	33.4	15.8
4	Ag.unfilt.ug/L	0.6	0.2	0.5	0.6	0.4	0.1	0.3	0.3	-43.8	-55.6	50.0
14	Al.filt.ug/L	36.0	69.5	109.2	197.4	24.0	25.7	69.0	103.0	69.4	266.1	27.3
20	As.filt.ug/L	4.2	1.6	11	7	4.9	2.5	11	7	0.1	83.9	28.1
19	As.unfilt.ug/L	29.0	12.3	45.8	21.0	30.4	18.3	47.2	26.7	50.9	149.1	33.3
14	Ba.filt.ug/L	44.4	12.9	141.9	108.4	43.7	12.1	98.0	80.4	1.7	99.5	30.0
7	Ba.unfilt.ug/L	102.7	90.0	112.4	118.2	158.0	235.3	157.6	382.6	100.5	281.3	33.3
12	Be.filt.ug/L	0.7	0.5	2.2	2.6	0.2	0.1	1.4	1.5	-48.6	-2.4	62.5
13	Bo.filt.ug/L	223.0	59.4	29.9	30.5	199.0	55.1	33.5	38.8	-4.9	428.2	25.0
8	Bo.unfilt.ug/L	102.1	39.9	77.7	55.7	102.6	62.2	108.6	130.1	17.5	208.4	18.2
15	Cd.filt.ug/L	0.6	0.2	3.0	3.4	0.4	0.0	2.2	2.5	-15.0	53.2	44.4
11	Cd.unfilt.ug/L	0.5	0.2	1.4	1.6	0.2	0.3	0.3	0.6	-28.2	72.8	60.0
14	Cr.filt.ug/L	2.1	1.2	4.2	5.3	1.0	0.7	6.1	11.0	-3.5	90.5	20.8
12	Cr.unfilt.ug/L	4.5	4.5	6.0	7.9	4.1	7.3	4.2	8.3	40.4	9.9	46.7
8	Co.filt.ug/L	3.0	0.5	15.3	12.6	2.3	0.2	14.0	13.9	-22.7	-8.5	20.0
26	Cu.filt.ug/L	2.9	2.2	10.3	18.6	2.2	1.4	7.2	10.7	-1.9	68.4	30.6
17	Cu.unfilt.ug/L	10.8	12.9	16.4	23.8	15.6	31.1	21.0	52.8	79.0	228.3	40.9
38	F.filt.mg/L	0.5	0.1	556.5	365.5	0.5	0.1	602.3	583.4	-0.2	257.1	23.8
26	Fe.filt.ug/L	42.0	74.1	63.5	120.1	41.5	27.8	46.6	60.2	77.0	9076.7	19.1
11	Fe.unfilt.ug/L	2222.6	2604.6	2360.4	3739.0	3165.1	5773.2	2684.7	5099.7	179.2	244.0	23.8
8	Li.filt.ug/L	32.5	8.4	147.5	66.0	34.6	8.4	107.8	56.0	-8.4	150.4	15.4

(Continued)

Table A1. (Continued)

Analyte	Number of Fires with WQ data	Mean conc. pre-fire	Mean s.d. pre-fire	Mean flux pre-fire	Mean flux s.d. pre-fire	Mean conc. post-fire	Mean flux post-fire	Mean flux s.d. post-fire	Perc. change mean conc.	Perc. change mean flux	% Fires sig. change MWU
Mo.filt.ug/L	9	8.4	1.2	46.9	39.5	7.3	42.6	42.3	-10.5	-6.9	18.2
Mn.filt.ug/L	28	40.2	28.0	20.6	22.5	28.8	12.9	14.8	37.1	182.7	34.6
Mn.unfilt.ug/L	19	209.8	290.3	191.2	301.3	1463.4	966.0	2331.2	497.1	5089.4	20.0
Ni.filt.ug/L	18	6.4	6.3	9.8	17.7	3.3	4.8	7.3	-14.7	63.6	11.1
Ni.unfilt.ug/L	15	7.2	7.9	6.1	8.7	12.1	11.4	23.8	117.1	203.5	22.2
Pb.filt.ug/L	17	2.5	2.3	8.2	12.4	0.7	3.0	4.0	-26.7	26.0	50.0
Pb.unfilt.ug/L	15	17.8	25.1	12.6	25.0	50.3	39.7	120.5	227.6	633.4	32.0
Se.filt.ug/L	23	1.3	0.5	2.0	2.0	1.2	2.0	2.1	-2.8	130.0	28.6
Se.unfilt.ug/L	19	1.4	0.7	0.8	1.0	1.3	0.7	1.3	8.0	86.6	38.1
Si.filt.mg/L	28	16.0	6.7	22467.3	19473.3	15.1	22133.3	21209.2	-1.6	354.5	16.4
Sr.filt.ug/L	7	442.6	98.0	1172.7	641.2	561.4	922.2	606.3	-2.5	234.4	27.3
Zn.filt.ug/L	24	10.3	9.0	35.9	53.2	6.5	20.0	29.1	-2.1	Inf	17.1
Zn.unfilt.ug/L	16	40.5	55.5	44.2	62.1	88.6	71.7	199.0	85.1	262.8	24.0