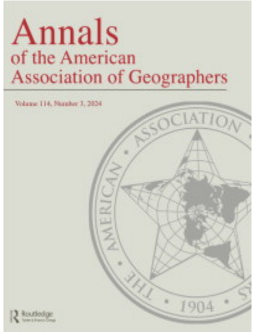
1-2024

Scales of Connectivity within Stream Temperature Networks of the Clackamas River Basin, Oregon

Michael Krochta
Portland State University, mkrochta@pdx.edu

Heejun Chang
Portland State University, changh@pdx.edu

Citation Details
Michael Krochta & Heejun Chang (19 Jan 2024): Scales of Connectivity within Stream Temperature Networks of the Clackamas River Basin, Oregon, Annals of the American Association of Geographers, DOI: 10.1080/24694452.2023.2289981



Taylor & Francis
Taylor & Francis Group

Annals of the American Association of Geographers

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/raag21

Scales of Connectivity within Stream Temperature Networks of the Clackamas River Basin, Oregon

Michael Krochta & Heejun Chang

To cite this article: Michael Krochta & Heejun Chang (19 Jan 2024): Scales of Connectivity within Stream Temperature Networks of the Clackamas River Basin, Oregon, Annals of the American Association of Geographers, DOI: 10.1080/24694452.2023.2289981

To link to this article: https://doi.org/10.1080/24694452.2023.2289981

Published online: 19 Jan 2024.

ANNALS OF THE AMERICAN ASSOCIATION OF GEOGRAPHERS
https://doi.org/10.1080/24694452.2023.2289981

Scales of Connectivity within Stream Temperature Networks of the Clackamas River Basin, Oregon

Michael Krochta and Heejun Chang

Department of Geography, Portland State University, USA

Water quality varies along the stream network; thus, considering the directional, dendritic nature of stream networks with surrounding landscape variables is essential in explaining spatial variations of water quality. Using a spatially extensive stream temperature monitoring effort in the Clackamas River Basin in the United States, we first compare spatial scales of analysis of atmospheric, landscape, and in-stream explanatory variables through their correlation with summer stream temperatures. We then derive a predictive stream temperature model with factors representing the spatial variation of local climate, recent wildfire effects, and discharge. Finally, we compare nonspatial multiple linear regression to a spatial stream network (SSN) model to assess the combined importance of the spatial scale of analysis and flow-connected stream distance in explaining total variation in stream temperatures. Most explanatory variables show the most highly significant relationships to stream temperature when derived as a percentage of the total upstream area above observation sites. Elevation and vegetation cover, however, were most significantly correlated to stream temperature at the riparian buffer area scale and the local reach contributing area scale, respectively. Multiple regression analysis using total upstream burned area, total upstream area with underlying High Cascades geology, and the elevation within the 100-m-wide riparian area explained 81 percent of variation in stream temperature. SSN outperformed this nonspatial statistical model, however, in explaining the total variation in stream temperature. These comparisons of scaled data sets demonstrate both the local and cumulative upstream effects on stream temperature, providing a spatial network-informed framework to those prioritizing watershed restoration and wildfire recovery activities. *Key Words: scale, spatial stream network, stream temperature, water quality.*

Stream temperature is a barometer of water quality of great influence to the overall health of aquatic ecosystems (Poole and Berman 2001). The temperature of water determines rates of both physical and biochemical processes in streams, setting the geographic distribution of native fish and other aquatic organisms adapted to a specific range of temperatures (Richter and Kolmes 2005; Caissie 2006; McCullough et al. 2009). In particular, summer stream temperatures are highly important for cold-water fisheries in the Pacific Northwest of North America. Cold-water salmonid species have cultural importance to native tribes who have relied on these fish species for food and spiritual rituals. Warming trends due to climate change are threatening the viability of cold-water salmonid species' habitats and efforts to conserve them in many areas (Isaak et al. 2012; Chang, Watson, and Strecker 2018).

An understanding of water temperature fluxes within a stream requires consideration of stream energy processes as well as the variables on the landscape that influence these processes. Stream temperature changes occur in direct proportion to heat gained or lost through (1) water surface energy exchanges related to solar and long-wave radiation, sensible and latent heat (Brown 1969); (2) streambed exchanges related to streambed conduction, hyporheic exchange, and friction (Caissie and Luce 2017); and (3) advective exchanges through hydrologic processes such as surface and groundwater inflows, and in-channel flows (Leach et al. 2023). These processes vary in their relative influence based on a stream's position on the landscape and its surroundings, with small headwater streams' temperatures likely associated with advection from subsurface inflows, whereas large

ARTICLE HISTORY
Initial submission, December 2022; revised submissions, July and September 2023; final acceptance, October 2023

CORRESPONDING AUTHOR Heejun Chang changh@pdx.edu

rivers' temperatures are more likely associated with incoming solar radiation (Webb and Zhang 1997; Leach et al. 2023).

Although many researchers have investigated the various influences on stream heat dynamics and subsequent temperature fluctuations, quantifying influential variables still poses challenges to those seeking to understand their relative importance from location to location (Webb et al. 2008; Ficklin, Stewart, and Maurer 2013; Booth, Kraseski, and Jackson 2014). Influences on stream temperatures are closely related to the energy fluxes discussed earlier and have generally been divided into four groups: (1) atmospheric (e.g., air temperature, precipitation), (2) topography (e.g., shade from vegetation, geology, elevation), (3) discharge (e.g., groundwater input), and (4) streambed related (e.g., slope) (Caissie 2006). These variables work together but ostensibly at different spatial scales, confounding efforts to understand how modifying them might influence future stream temperatures from place to place. For example, previous studies indicate that near-stream conditions (e.g., riparian vegetation) could influence stream temperatures more than cumulative upstream land-cover conditions, but this effect varies by the riparian buffer size, stream channel width, aspect, upland topography, and distance from the monitoring station (Isaak et al. 2010; Janisch, Wondzell, and Ehinger 2012; Zhou, Wu, and Peng 2012; Chang and Psaris 2013; Chen and Chang 2021; Leach et al. 2023). Thus, landscape variables vary in importance depending on the location and spatial scale used for analysis.

Several innovative methods have been used to relate landscape variables to stream temperature across space (Mainali, Chang, and Chun 2019). A promising geostatistical approach to deriving explanatory variables and predicting stream temperatures at large scales is spatial stream network (SSN) modeling. SSNs draw on the concept of spatial autocorrelation (which assumes greater similarity between objects close together compared to further apart) based on flow-connected hydrologic distances within stream networks, accounting for spatial effects beyond the explanatory variables alone (Ver Hoef, Peterson, and Theobald 2006; Ver Hoef and Peterson 2010; Isaak et al. 2014). Indeed, SSNs incorporate the flow directionality, distance, and accumulation inherent in the dendritic network structure of rivers to make predictions throughout stream networks (Isaak et al. 2017).

SSN models typically integrate explanatory variables calculated at a mix of spatial scales (e.g., a land-cover percentage of the total upstream area vs. immediately adjacent to the stream), based on the study hypotheses, data type, and availability (Steel, Sowder, and Peterson 2016; Isaak et al. 2017; Gendaszek et al. 2020). Past modeling efforts, though, rarely provide an explicit comparison between spatial units of analysis used to derive explanatory variable data sets. To fill this gap, this study uses data from a large stream temperature monitoring effort in the Clackamas River Basin (CRB) in Oregon, United States, to (1) compare scales of analysis related to calculating a novel pool of explanatory data sets through their correlation with observed stream temperatures; (2) derive a predictive stream temperature model with factors representing the spatial variation of local climate, recent wildfire effects, and stream discharge; and (3) compare nonspatial multiple linear regression (MLR) analysis to an SSN model to assess the combined importance of the spatial scale of analysis and flow-connected stream distance in explaining total variation in stream temperatures.

Data and Methods

Study Area

With a contributing drainage of 2,435 km^2, the Clackamas River in Oregon flows 133 km from its headwaters to its confluence with the Willamette River. The basin consists of approximately 5 percent developed area, 10 percent agricultural lands, and 85 percent forested and shrub lands (Dewitz and U.S. Geological Survey 2021; Figure 1). Urban development and agricultural lands are concentrated in the lower watershed, with primarily forested lands in the middle and upper watershed. Approximately 72 percent of the CRB is managed by the Mt. Hood National Forest, with an additional 25 percent privately owned and 3 percent tribally managed. Forest management practices to protect aquatic resources vary across land ownerships, with federal lands managed under the Mt. Hood National Forest Land and Resource Management Plan (U.S. Forest Service [USFS] 1990) having the most protective regulations

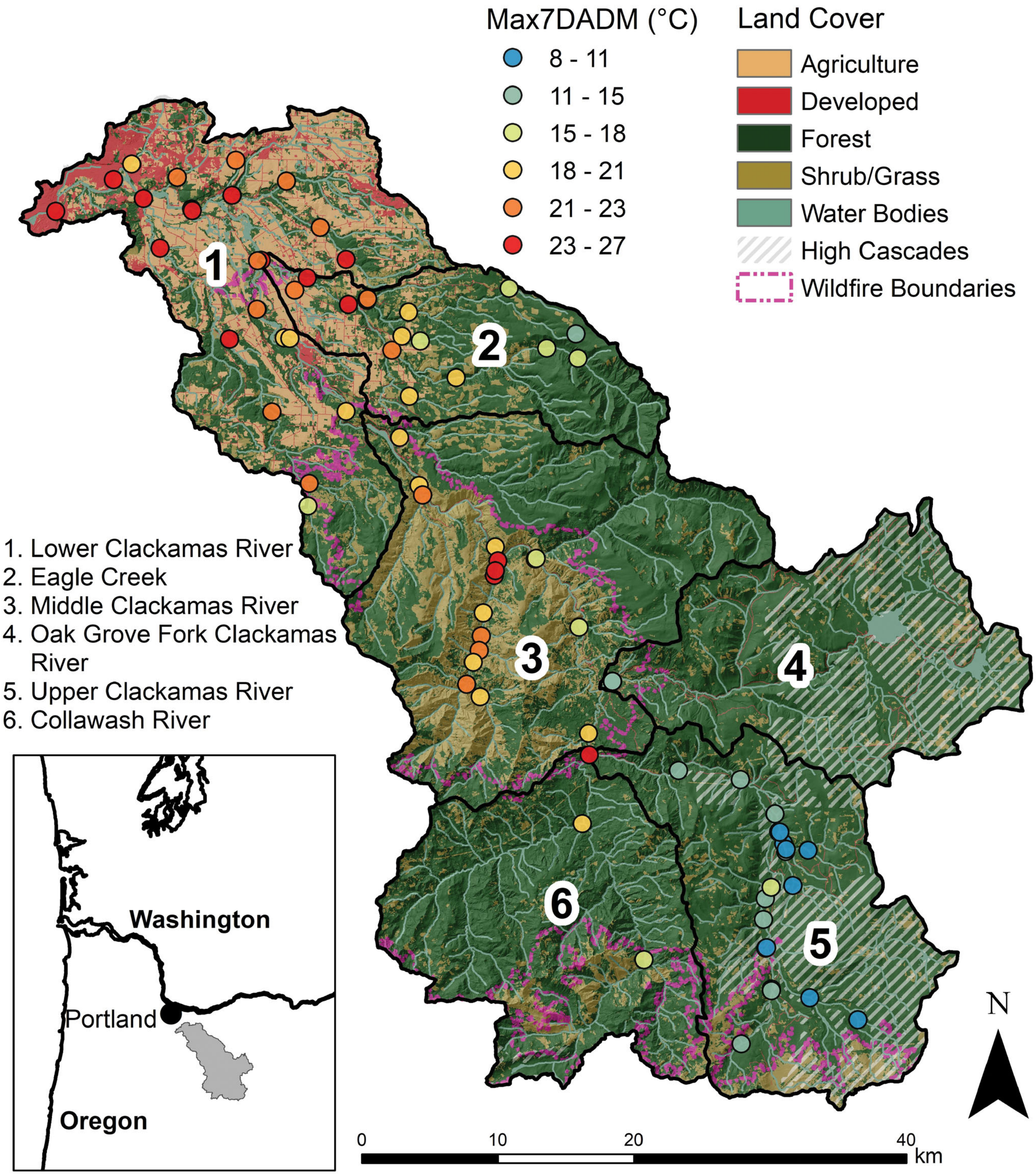


Figure 1. Clackamas River Basin study area with observed site locations and corresponding maximum seven-day average daily maximum temperature (Max7DADMs). Also shown are land-cover types and locations of subwatersheds (numbered) within the basin. Wildfire boundaries includes areas burned between 2020 and 2021. Shrub/grass includes areas of both high-severity burns and openings created by past forest management.

for streams (e.g., relatively large no-harvest riparian buffers of over 70 m in total width for streams with listed fish habitat; USFS 2020), and private lands managed under the Oregon Forest Practices Act having the least protective regulations for streams (Lorensen, Andrus, and Runyon 1994). Notably, in 2020 and 2021, wildfires collectively burned 23 percent of the CRB, resulting in 55,785 ha burned with 20,900 ha (9 percent of the total watershed; Figure 1) burning at high severity. The 2020 wildfires were not found to have substantial impacts on peak flows, though (Long and Chang 2022).

The CRB has a Mediterranean climate, characterized by cool, wet winters and warm, dry summers (Oregon Climate Service 2005). Mean annual air temperature varies spatially from 5.5 °C to 12.3 °C. The average precipitation from 1991 to 2020 across the basin varies spatially from 1,109 to 3,041 mm (PRISM 2021), with most of this precipitation occurring during the winter months. In general, relatively cooler temperatures and larger amounts of precipitation occur annually at higher elevations within the basin (PRISM 2021). Elevation in the basin ranges from 3 m to 2,200 m, with a mean elevation of 828 m. With rising temperatures, 1 April snow water equivalent, which has a substantial impact on summer low flows, has declined in recent decades and this trend is projected to continue throughout the twenty-first century (Chen and Chang 2023).

The hydrology of the CRB is tightly coupled with its underlying geology. The geology of the basin is primarily Western Cascades volcanics, with the lower watershed including Willamette Valley alluvium deposits, and the upper watershed including High Cascades geology. Geologically young High Cascades volcanic terrains in high elevations (Figure 1) have relatively high amounts of cold groundwater inputs compared to the Western Cascades, where older geology in low elevations has lower permeability and greater runoff relative to base flows (Tague et al. 2007).

There are four major CRB hydropower projects, including one tributary and three main stem developments, regulated under the Federal Clean Water Act with total maximum daily load (TMDL) for stream temperature. Due to a combination of large inflows of groundwater surrounding the tributary development, deep water release downstream of dams, and minimal water residence times and stratification at reservoirs, the projects are believed to have minor influence on changes water temperatures downstream of the dams (Oregon Department of Environmental Quality [ODEQ] 2009; Portland General Electric Company [PGE] 2013).

The CRB supports significant runs of cold-water-dependent anadromous salmon. Being home to the last run of wild late winter Coho in the Columbia Basin, the CRB also includes one of only two remaining runs of spring Chinook in the Willamette Basin. In addition, it supports a significant population of winter steelhead (Clackamas River Basin Council) 2005), and a recent bull trout reintroduction project has taken place in the Upper Clackamas subwatershed (Starcevich 2021). Four stream segments in the basin have been included on the Oregon 303(d) list for temperature, however (lower Clackamas River, Eagle Creek, Fish Creek, and Cow Creek; ODEQ 2006).

Stream Temperature Data Collection

Stream temperature data were collected for eighty-one sample sites distributed across the CRB. The sampling occurred between June and October 2021 with all sites having complete temperature data for August. In-stream temperature probes were deployed by the USFS, U.S. Geological Survey (USGS), U.S. Fish and Wildlife Service, Oregon Department of Fish and Wildlife, PGE, Clackamas Water Environmental Services, and one individual landowner. The vast majority of sensors were Onset HOBO or TidbiT data loggers, with the remainder being YSI Sonde loggers. Monitoring sites were chosen to minimize any human and natural disturbances, such as vandalism or major fluctuations of water levels. To safeguard data loggers in the field, they were encased in protective housings, which were then secured to immobile objects (e.g., submerged rocks or large wood) in the stream. Each site location was recorded with a Global Positioning System to ensure the logger could be found at a later date. All stream temperature data collection by the individual landowner followed a rigorous deployment and retrieval protocol though an ODEQ approved sampling and analysis plan (Bugni 2021), and data collection by public entities followed their individual agency's stream temperature data quality standards. All temperature sensors used were found to be accurate to ± 0.5 °C.

Following data collection, a data quality assurance process was undertaken to ensure no erroneous data were analyzed (Dunham 2005; Wagner et al. 2006; Sowder and Steel 2012; Stamp et al. 2014). Examples of data cleaning included removing data suspected to be collected during dewatering events (based on comparisons to interpolated local air temperature; PRISM 2021). Stream temperature was then summarized at each site by deriving the maximum seven-day average daily maximum temperature (Max7DADM; Figure 1), a metric used by the U.S. Environmental Protection Agency and the ODEQ for setting protective thermal criteria (including TMDL) for salmonids during the summer under the Federal Clean Water Act (U.S. Environmental Protection Agency 2003; PGE 2013). Max7DADM describes the maximum temperatures in a stream that fish are exposed to without being overly influenced by temperatures on individual days. Thus, although this metric does not capture acute effects, it does account for cumulative thermal exposure experienced by fish over a course of a week (U.S. Environmental Protection Agency 2003).

Building the Landscape Network

Much of the process for creating the spatial architecture required for SSN analysis was carried out using the Spatial Tools for Analysis of River Systems (STARS) tool set, Version 2.0.7, for ArcMap (Peterson and Ver Hoef 2014). A total of eighty-one stream temperature observations, along with a total of 17,274 prediction points spaced 100 m apart that would later include modeled stream temperature estimates, were created and added to a network consisting of stream segments and corresponding relationship tables containing its distance to the watershed outlet. Reach contributing areas (RCAs) and 100-m-wide buffer polygons were created for each stream reach, so that explanatory variables could be calculated as areal means or proportions within them. Table 1 summarizes the data sources, rationales, and supporting literature for the variables initially chosen. These included land cover, topography, local atmospheric data (i.e., precipitation and air temperature), geology, and recent wildfire burn perimeters. Although some of the data sets were assumed to be related, one purpose of this exercise was to assess the relative influences of these variables, which were each intentionally selected based on a review of the literature, on stream temperature. As a basic requirement, all data sets we included spanned the entire basin with values that could be associated with every stream reach. In general, land cover and condition variables fell into three spatial categories, depending on how they were calculated, using either (1) the 100-m-wide riparian buffer scale, (2) stream catchment (i.e., RCA) scale, or (3) total upstream watershed area scale (see Figure 2). The buffer width of 100 m was chosen due to the comparatively large mean size of RCAs in the CRB ($2.4\,\text{km}^2$), and because most previous studies have found significant relationships between explanatory variables within riparian buffer areas and stream temperature (Isaak et al. 2010; Janisch, Wondzell, and Ehinger 2012; Zhou, Wu, and Peng 2012; Chang and Psaris 2013). In-stream variables were collected and assigned at the stream reach scale, including base flow index (BFI; the component of streamflow that can be attributed to groundwater discharge into streams) and stream channel slope.

Nonspatial Correlation and Multiple Linear Regression Models

To assess individual variables' scales of influence on stream temperatures, nonparametric Spearman's rank correlation coefficients were calculated for each of the explanatory variables included in Table 1 by using values derived for each of the eighty-one observation sites. To analyze the combined effects of variables associated with local climate (e.g., precipitation, air temperature), increased natural disturbance (e.g., wildfire), and discharge (e.g., groundwater inputs) on stream temperatures basin-wide, MLR analysis was run using elevation, percentage of high-severity burn area, and percentage of High Cascades variables at scales found to be most correlated with the observed stream temperatures. In addition to drawing on Spearman's rank correlation coefficients of these three variables, we tested for nonspatial multicollinearity among them through calculations of variance inflation factors in an ordinary least squares regression analysis (Belsley, Kuh, and Welsch 2005).

SSN Model Fitting

A stream distance matrix was created using R's SSN package (Ver Hoef and Peterson 2020) using flow-connected distance, which is measured between

Table 1. Summary of explanatory data sets used for this study

Variables	Scales	Data source	Expected relationship	References
Atmospheric variables				
Maximum air temperature	RCA	PRISM (2021)	Positive	Gendaszek et al. (2020), Luce et al. (2014)
Mean summer air temperature	RCA	PRISM (2021)	Positive	Gendaszek et al. (2020), Luce et al. (2014)
Mean monthly maximum air temperature	RCA	PRISM (2021)	Positive	Gendaszek et al. (2020), Luce et al. (2014)
Annual precipitation	RCA	PRISM (2021)	Negative	Chang and Psaris (2013)
Summer precipitation	RCA	PRISM (2021)	Negative	Chang and Psaris (2013)
Wet season precipitation	RCA	PRISM (2021)	Negative	Chang and Psaris (2013)
In-stream variables				
Base flow index	Stream reach	U.S. Geological Survey (2012)	Negative	Mayer (2012)
Slope	Stream reach	U.S. Geological Survey (2012)	Negative	Grabowski, Watson, and Chang (2016), Mayer (2012)
Landscape variables				
Percentage canopy cover	Buffer; RCA; Total upstream	LANDFIRE (2021)	Negative	Caissie (2006), Isaak et al. (2017)
Vegetation height	Buffer; RCA; Total upstream	LANDFIRE (2021)	Negative	Caissie (2006), Isaak et al. (2017)
Percent burn area	Buffer; RCA; Total upstream	U.S. Geological Survey, U.S. Forest Service, and Nelson (2022)	Positive	Chen and Chang (2021)
Percent agriculture area	Buffer; RCA; Total upstream	Dewitz and U.S. Geological Survey (2021)	Positive	Chang and Psaris (2013)
Percent developed area	Buffer; RCA; Total upstream	Dewitz and U.S. Geological Survey (2021)	Positive	Watson and Chang (2018)
Percent wetlands area	Buffer; RCA; Total upstream	U.S. Fish and Wildlife Service (2021)	Positive	Isaak et al. (2017), Chang and Psaris (2013)
Percent open water area	Buffer; RCA; Total upstream	U.S. Fish and Wildlife Service (2021)	Positive	Isaak et al. (2017)
Percent High Cascades area	Buffer; RCA; Total upstream	Oregon Department of Geology and Mineral Industries (2020)	Negative	Tague et al. (2007)
Road density	Buffer; RCA; Total upstream	Clackamas County (2021)	Positive	Watson and Chang (2018)
Elevation	Buffer; RCA; Total upstream	Oregon Department of Geology and Mineral Industries (2020)	Positive	Chang and Psaris (2013), Grabowski, Watson, and Chang (2016)
Other landscape variables				
Total upstream area	Total upstream	Derived using ArcGIS	Positive	Isaak et al. (2014), Peterson and Ver Hoef (2014)

Note: Buffer = area within 100-m buffer surrounding each stream reach; RCA = reach contributing area, that is, the area within each stream's catchment; Total upstream = total area of all upstream catchments of all flow-connected stream reaches.

points with an upstream-to-downstream connection (Isaak et al. 2014; Peterson and Ver Hoef 2014). SSN models based on hydrologic distance include several variations of structures that allow for autocorrelation based on flow-connected or flow-unconnected observations (Ver Hoef et al. 2014). The

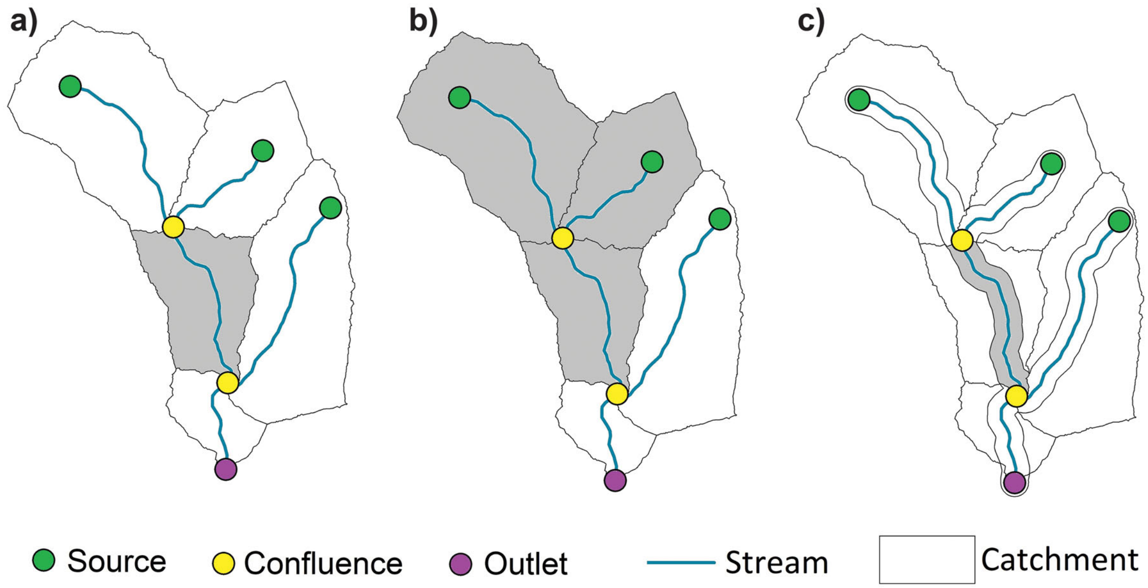


Figure 2. Conceptual diagram of three spatial scales used to calculate landscape variables associated with stream temperature. These scales of calculation, which relate to a stream reach and associated catchment, include (A) stream reach contributing area scale, (B) total upstream area scale, and (C) a set buffer scale of 100 m on each side of each stream reach.

flow-connected model with the lowest Akaike's information criterion (AIC; indicating the best overall model fit) and root mean square prediction error (indicating the least uncertainty) was selected for use in predictive mapping of stream temperature (Isaak et al. 2017; Ver Hoef and Peterson 2020; Rhea et al. 2022).

Following model selection, SSN model performance was further quantified through leave-one-out cross-validation (Ver Hoef et al. 2014). This process removed observations one at a time and the resulting model was used to predict each of the removed values and its predicted standard error (Ver Hoef and Peterson 2020). Finally, predicted Max7DADM values were generated for each of the 17,274 prediction points created for the basin. These predictions, along with their associated standard error values, were joined to the original stream network for uncertainty visualization.

Results

Spearman's Correlation Coefficients

Results from nonparametric Spearman's correlation coefficients (ρ) calculated for each of the explanatory variables are summarized in Figure 3. In-stream explanatory variables, BFI, which represents the component of streamflow that can be attributed to groundwater discharge into streams (ρ = −0.78, $p < 0.001$), and stream channel slope (ρ = −0.49, $p < 0.01$) were negatively correlated with Max7DADM. Of atmospheric variables, summer mean air temperature ($\rho = 0.58$, $p < 0.001$) and wet season precipitation (ρ = −0.52, $p < 0.01$) were the most significantly correlated with Max7DADM.

Of the explanatory variables calculated at multiple scales, those resulting in the most significant correlations in their corresponding calculated scales were High Cascades geology, calculated as a total upstream watershed percentage (ρ = −0.62, $p < 0.001$); vegetative cover, calculated as an average percentage at the RCA scale (ρ = −0.66, $p < 0.001$); vegetation height, calculated as an average percentage at the total upstream scale (ρ = −0.65, $p < 0.001$); percentage agriculture land cover at the total upstream scale ($\rho = 0.66$, $p < 0.001$); percentage developed land cover at the total upstream scale ($\rho = 0.63$, $p < 0.001$); and elevation, calculated as an average at the buffer scale (ρ = −0.78, $p < 0.001$). Other scaled variables (burned area, road density, wetland area, open water area) did not result in significant correlation coefficients greater than 0.4 or less than −0.4.

Multiple Linear Regression Model Selection and Results

The nonspatial MLR analysis described earlier resulted in a model that included (1) percentage upstream watershed area burned ($p < 0.001$), (2)

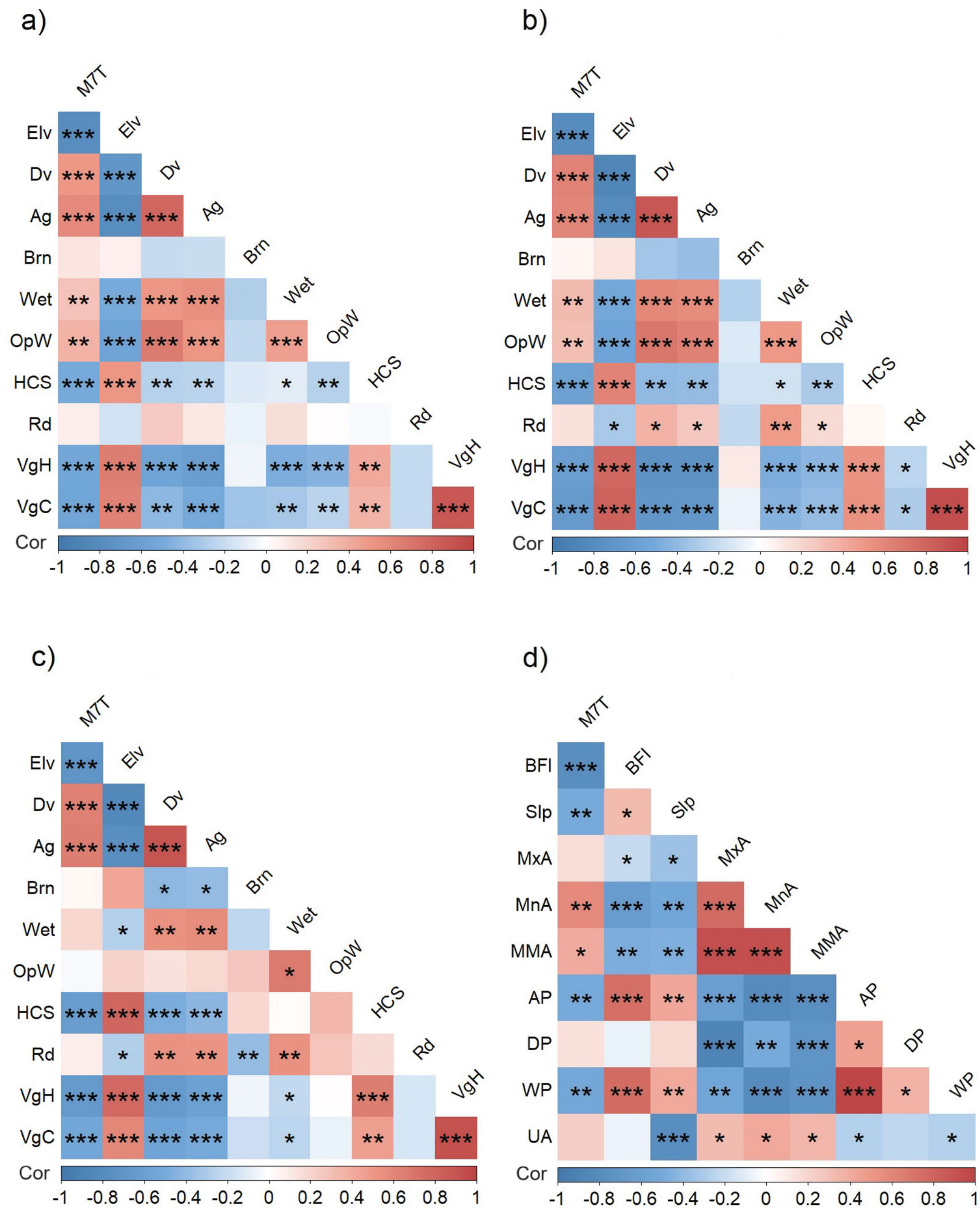


Figure 3. Spearman correlation matrices of investigated predictor variables and stream temperature (maximum seven-day average daily maximum temperature: (A) derived at the 100-m buffer area scale; (B) derived at the reach contributing area scale; (C) derived at the total upstream area scale; and (D) single-scale variables related to in-stream and atmospheric conditions, along with total upstream area as a stand-alone covariate. Statistical significance of predictor variables: $^*p < 0.05$. $^{**}p < 0.01$. $^{***}p < 0.001$. M7T = Max7DADM; Elv = elevation; Dv = developed; Ag = agriculture; Brn = burned area; Wet = wetland; OpW = open water; HCS = High Cascades; Rd = road density; VgH = vegetation height; VgC = vegetation cover; BFI = base flow index; Slp = slope; MxA = maximum air temperature; MnA = mean air temperature; MMA = monthly mean maximum air temperature; AP = annual precipitation; DP = dry season precipitation; WP = wet season precipitation; UA = upstream area; Cor = Spearman correlation coefficient.

elevation at the buffer scale ($p < 0.001$), and (3) percentage upstream watershed area with underlying High Cascades geology ($p < 0.001$). This combination of variables resulted in an R^2 value of 0.81, a leave-one-out cross-validation R^2 value of 0.80, and an AIC value of 362.8 (Table 2).

Table 2. Summary of spatial stream network (SSN) and multiple linear regression (MLR) models that explain stream temperature

		Model type	
		MLR	SSN
Parameter estimates	Upstream burned %	0.06***	0.07***
	Elevation, buffer scale	−0.01***	−0.01***
	Upstream High Cascades %	−0.07***	−0.06***
Variance components (%)	Explanatory variables	81.2	68.6
	Flow-connected distance	0	25.9
	Total explained	81.2	94.4
	Total unexplained	18.8	5.6
Model performance	Akaike's information criteria	362.8	325.6
	Leave-one-out cross validation R^2	0.80	0.93

Note: Parameter estimates represent the regression coefficient, which equals change in the stream temperature based on a 1-unit change in the predictor variable with all other variables being constant. Variance components assign variance in stream temperature to explanatory variables, flow-connected stream distance, and unexplained variance.
$^{*}p < 0.05$.
$^{**}p < 0.01$.
$^{***}p < 0.001$.

SSN Model Selection and Results

The SSN model, which used the same set of three explanatory variables as that in the nonspatial MLR, resulted in a lower AIC value of 325.6, indicating a better overall model fit than the nonspatial model. A linear regression model of observed versus cross-validated predictions resulted in an R^2 value of 0.93, further confirming a good model fit.

Variance components were calculated for explanatory variables and autocovariance structures within the SSN model, with 68.6 percent explained by explanatory variables, and an additional 25.9 percent explained by spatial autocorrelation of flow-connected observations alone (Table 2). The prediction points along the landscape network showed Max7DADM values ranging from 1.10 °C to 27.54 °C (Figure 4). Standard errors for each prediction point ranged from 0.44 to 2.69. These prediction errors increase with distance from observed stream temperature values, and along stream reaches that are associated with values of explanatory variables lacking observed counterparts (e.g., a prediction of stream temperature in a severely burned reach within a modeled watershed without a direct observation of stream temperature in a similarly burned reach).

Discussion

The highly negative correlations of elevation and High Cascades geology with stream temperature indicate that the CRB's stream temperatures are highly regulated by these factors, as shown in cold temperatures in the groundwater-rich upper subwatersheds of the Upper Clackamas and Oak Grove Fork of the Clackamas (Figure 1). High Cascades geology was most negatively correlated with stream temperature as an accumulated watershed percentage; cold groundwater is accumulated as the stream network passes through porous geology containing cold water springs (Tague and Grant 2004). Indeed, predicted stream temperatures across the basin (Figure 4) indicate that subwatersheds with underlying High Cascades geology are carrying cooled water downstream, and on their confluence with warmer tributaries with underlying Western Cascades geology and lower base flow contributions, have a cooling effect on the mainstem Clackamas River. For example, when observed Max7DADM Collawash River (upstream Western Cascades geology) temperatures of 25 °C (67.5 BFI) near its outlet meet the groundwater-dominated Upper Clackamas subwatershed (with predicted Max7DADM temperatures of 16 °C just above its outlet, 69.9 BFI), the resulting predicted temperature of the downstream mainstem Clackamas drops to 21 °C (68.48 BFI). This and other examples demonstrate a downstream directional network connectivity throughout the basin as it relates to porous groundwater source areas upstream.

High-severity burn area effects were included in MLR and SSN models as a highly significant explanatory variable independent of elevation and geology

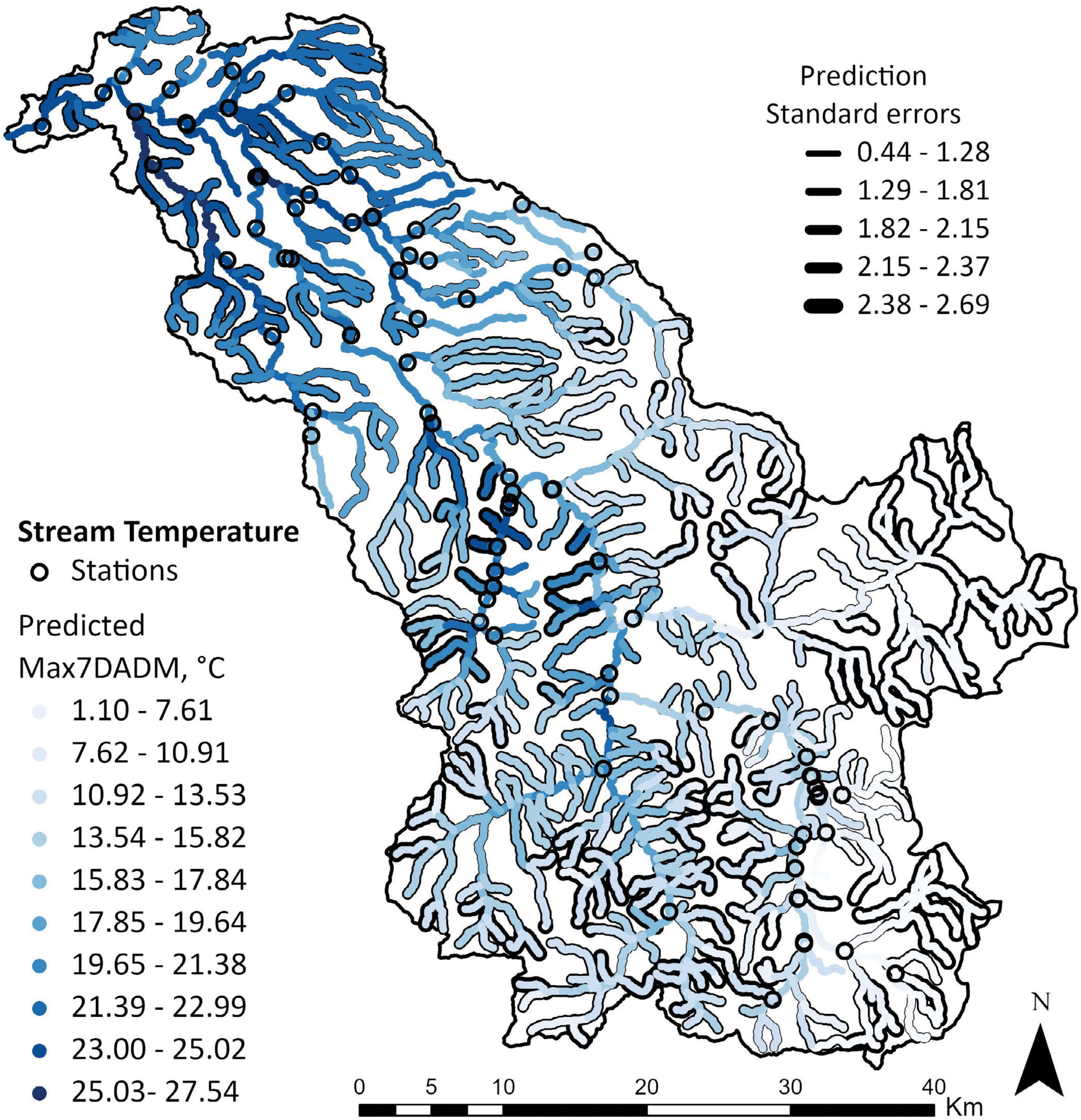


Figure 4. Basin-wide, continuous predicted stream temperatures with standard errors. The size of the gray line below each prediction indicates the prediction standard errors; thicker lines have higher prediction standard errors, thus the less confidence in a point, the more it stands out in the graphic. Standard errors range from 0.4 to 2.7. Max7DADM = maximum seven-day average daily maximum temperature.

(see Figure 3). This variable, in addition to percentage tree mortality, includes metrics such as soil burn severity in its definitions of wildfire burn severity (Eidenshink et al. 2007). An increase in summer stream temperatures has been reported downstream of and following high-severity wildfire, lasting for up to several years depending on watershed characteristics and local climate (Dunham et al. 2007; Chen and Chang 2023), although some maximum temperatures lessened once deciduous vegetation reestablished (Mahlum et al. 2011). Furthermore, increased aridity and frequency of wildfire events under climate change in the Pacific Northwest could contribute to prolonged periods between riparian forest canopy reestablishment in the future, with possible ecosystem shifts toward lower density patches of vegetation (Busby, Moffett, and Holz 2020). Research investigating the impact of wildfires on watershed flow regimes, however, has found temporary increases in base flow following wildfires in some areas, which could contribute to cold water observations during parts of the summer months (Saxe, Hogue, and Hay 2018). With subsequent years of stream monitoring data being available in the future, further investigation of the rate of change in wildfire effects on stream temperatures, including vegetation recovery and changes in base flow, will be possible.

Our results add to the growing body of literature demonstrating the utility of a spatial network approach in explaining the variation of stream temperature. Incorporating SSN models' realistic covariance structures associated with stream distance, flow accumulation, and flow direction decreases the bias of stream temperature observations that are often clustered and nonrandom, such as ours. When the same explanatory variables were included in the SSN model that considered stream temperature variation explained by flow-connected distance between observations, a much higher amount of variation was explained (94.4 percent vs. 81.2 percent in nonspatial model; see Table 2). Mapping of maximum stream temperatures illustrates thermal cold spots and hot spots that can be flagged for further study or management activities. Additionally, mapped standard errors identify potential future monitoring sites in areas with higher uncertainty of predicted stream temperatures (e.g., the upper Oak Grove Fork Clackamas River).

These results include management implications and will inform future SSN modeling using stream temperature data, contributing to a knowledge gap in the literature regarding scale-dependent performance of variables used in SSN models and their applications. These implications include the potential benefit of upland forest restoration (i.e., maintaining or increasing tree cover while retaining tall trees) on reducing downstream temperatures. Wildfire suppression or recovery efforts in the areas of thermal concern could also lower future downstream water temperatures through activities focused on maintaining shade or increasing postfire shade during the summer months. As others have noted (e.g., Isaak et al. 2010), however, wildfire suppression in riparian areas as a strategy to reduce stream temperature increases must also be weighed against long-term benefits to stream habitat and diversity resulting from wildfires (Pettit and Naiman 2007). Predictions of stream temperature in response to changes in land use and climate inform management of cultural values such as tribal fisheries and the distribution of recreation infrastructure adjacent to streams such as parks and campgrounds. They also inform an adaptive approach to economically driven management actions within the basin and across the region, including timber harvest and hydropower development.

Finally, ecologically driven initiatives such as in-stream habitat restoration will be most viable when prerestoration stream temperature conditions are integrated into project prioritization, planning, and monitoring of compliance with water quality standards (e.g., TMDLs). The spatially continuous stream temperature predictions generated by SSNs showcase the spatial extent of both cold water refugia and more thermally sensitive reaches, potentially guiding strategic planning efforts by agencies and interest groups determining appropriate site-specific approaches to watershed restoration (Clackamas Partnership 2018), as well as aquatic species conservation and recovery plans and designations of critical habitat. For example, both warm and cold stream reaches might be lacking structural habitat components required by salmonids (e.g., large wood, spawning gravel), but persistent cold-water areas identified by SSN analysis could have a higher likelihood of successfully creating viable habitat in the long term, even if additional shade is added to the comparatively warmer reaches before restoring in-stream structure.

Conclusions

This study leveraged a stream temperature monitoring effort in the CRB to (1) compare scales of analysis related to calculating a novel pool of explanatory data sets through their correlation with observed stream temperatures; (2) derive a predictive stream temperature model with factors representing the spatial variation of local climate, recent wildfire, and stream discharge; and (3) compare nonspatial MLR analysis to an SSN model to assess the combined importance of the spatial scale of analysis and flow-connected stream distance in explaining total variation in stream temperatures.

The results of this study demonstrated the relative importance of certain explanatory variables, the scale of analysis, and network connectivity. Of explanatory variables that were calculated at multiple scales, most of the significant relationships derived by correlation were at the total upstream area scale. The strongest correlation between elevation and stream temperature, however, was derived at the buffer area scale, and vegetative cover was most correlated with stream temperature at the reach contributing area scale. The nonspatial MLR model including explanatory variables of total upstream burned area, total upstream area with underlying High Cascades geology, and the elevation of the 100-m riparian area was outperformed by SSN modeling that used flow-connected stream network in its calculation of spatial effects.

Future investigations of stream networks in the CRB could benefit from including more stream temperature metrics, such as thermal flashiness and days above a biologically significant temperature threshold (Grabowski, Watson, and Chang 2016), or sensitivity to air temperature (Chang and Psaris 2013). This last metric in particular could aid in explaining spatial variation in the effects of extreme air temperatures resulting from 2021s historic heat dome event on stream temperatures in the CRB. Given that Oregon's forestry laws related to stream temperature center around protective riparian buffer areas (Lorensen, Andrus, and Runyon 1994), further investigation could shed light on the spatial mechanisms of stream cooling by vegetation at the accumulated RCA versus buffer scales by adding a scale of analysis defined by smaller (e.g., 30 m) buffer widths or the total upstream riparian buffer area from each monitoring site. Furthermore, future work could include a hybrid SSN–geographically weighted regression model (e.g., Mainali, Chang, and Parajuli 2023), which could reveal more spatially explicit hydrological processes within different parts of the basin. Additionally, integrating historic atmospheric and stream temperature data into the model, along with projected climate change scenarios, could provide more locally relevant estimations of future stream temperatures than are currently available through regional databases such as NorWeST (Isaak et al. 2017). Such endeavors undoubtedly inform watershed managers preparing adaptive management strategies in response to a changing climate.

Acknowledgments

We thank three anonymous reviewers whose comments improved the article. We also thank David Bugni and Steve Starcevich for reviewing earlier versions of the article. This study was made possible through the coordinated stream temperature data collection efforts, which included Dave Bugni, Clackamas Water Environment Services, Oregon Department of Fish and Wildlife, Portland General Electric, U.S. Forest Service, U.S. Fish and Wildlife Service, and U.S. Geological Survey.

Disclosure Statement

No potential conflict of interest was reported by the authors.

Funding

This material is based on work supported by the Clackamas River Basin Council, Clackamas River Water Providers, and Clackamas Water Environment Services. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of these sponsoring agencies.

References

Belsley, D. A., E. Kuh, and R. E. Welsch. 2005. *Regression diagnostics: Identifying influential data and sources of collinearity*. New York: Wiley.

Booth, D. B., K. A. Kraseski, and R. C. Jackson. 2014. Local-scale and watershed-scale determinants of summertime urban stream temperatures. *Hydrological Processes* 28 (4):2427–38. doi: 10.1002/hyp.9810.

Brown, G. 1969. Predicting temperatures of small streams. *Water Resources Research* 5 (1):68–75. doi: 10.1029/WR005i001p00068.

Bugni, D. 2021. Sampling and analysis plan: Clackamas River Basin water temperature study. MAS21-VOL-0044-SAP. Portland: Oregon Department of Environmental Quality.

Busby, S. U., K. B. Moffett, and A. Holz. 2020. High-severity and short-interval wildfires limit forest recovery in the central Cascade Range. *Ecosphere* 11 (9):e03247. doi: 10.1002/ecs2.3247.

Caissie, D. 2006. The thermal regime of rivers: A review. *Freshwater Biology* 51 (8):1389–1406. doi: 10.1111/j.1365-2427.2006.01597.x.

Caissie, D., and C. H. Luce. 2017. Quantifying streambed advection and conduction heat fluxes. *Water Resources Research* 53 (2):1595–1624. doi: 10.1002/2016WR019813.

Chang, H., and M. Psaris. 2013. Local landscape predictors of maximum stream temperature and thermal sensitivity in the Columbia River basin, USA. *The Science of the Total Environment* 461–462:587–600. doi: 10.1016/j.scitotenv.2013.05.033.

Chang, H., E. Watson, and A. Strecker. 2018. Climate change and stream temperature in the Willamette River basin: Implications for fish habitat. In *Bridging science and policy implication for managing climate extremes*, ed. H. Jung and B. Wang, 119–32. Hackensack, NJ: World Scientific. doi: 10.1142/9789813235663_0008.

Chen, J., and H. Chang. 2021. Relative impacts of climate change and land cover change on streamflow using SWAT in the Clackamas River Watershed, USA. *Journal of Water and Climate Change* 12 (5):1454–70. doi: 10.2166/wcc.2020.123.

Chen, J., and H. Chang. 2023. A review of wildfire impacts on stream temperature and turbidity across scales. *Progress in Physical Geography: Earth and Environment* 47 (3):369–94. doi: 10.1177/03091333221118363.

Clackamas County. 2022. Streets data layer. Clackamas County GIS data portal. Accessed September 2022. https://www.clackamas.us/gis/data-portal.

Clackamas Partnership. 2018. Watershed restoration for native fish populations: Clackamas partnership strategic restoration action plan. Accessed September 2021. https://conservationdistrict.org/?wpfbdl=649.

Clackamas River Basin Council. 2005. Clackamas Basin summary: Watershed overview. Accessed September 2021. https://clackamasriver.org/wp-content/uploads/2019/09/Clackamas_Overview_6-01-2005.pdf.

Dewitz, J., and U.S. Geological Survey. 2021. National Land Cover Database (NLCD) 2019 products (version 2.0, June 2021): U.S. Geological Survey data release. doi: 10.5066/P9KZCM54.

Dunham, J. 2005. *Measuring stream temperature with digital data loggers: A user's guide*. Fort Collins, CO: U.S. Department of Agriculture, Forest Service, Rocky Mountain Research Station. doi: 10.2737/RMRS-GTR-150.

Dunham, J. B., A. E. Rosenberger, C. H. Luce, and B. E. Rieman. 2007. Influences of wildfire and channel reorganization on spatial and temporal variation in stream temperature and the distribution of fish and amphibians. *Ecosystems* 10 (2):335–346. doi: 10.1007/s10021-007-9029-8.

Eidenshink, J., B. Schwind, K. Brewer, Z. L. Zhu, B. Quayle, and S. Howard. 2007. A project for monitoring trends in burn severity. *Fire Ecology* 3 (1):3–21. doi: 10.4996/fireecology.0301003.

Ficklin, D. L., I. T. Stewart, and E. P. Maurer. 2013. Effects of climate change on stream temperature, dissolved oxygen, and sediment concentration in the Sierra Nevada in California. *Water Resources Research* 49 (5):2765–82. doi: 10.1002/wrcr.20248.

Gendaszek, A. S., J. B. Dunham, C. E. Torgersen, D. P. Hockman-Wert, M. P. Heck, J. Thorson, J. Mintz, and T. Allai. 2020. Land-cover and climatic controls on water temperature, flow permanence, and fragmentation of Great Basin stream networks. *Water* 12 (7):1962. doi: 10.3390/w12071962.

Grabowski, Z. J., E. Watson, and H. Chang. 2016. Using spatially explicit indicators to investigate watershed characteristics and stream temperature relationships. *The Science of the Total Environment* 551–552:376–86. doi: 10.1016/j.scitotenv.2016.02.042.

Isaak, D. J., C. H. Luce, B. E. Rieman, D. E. Nagel, E. E. Peterson, D. L. Horan, S. Parkes, and G. L. Chandler. 2010. Effects of climate change and wildfire on stream temperatures and salmonid thermal habitat in a mountain river network. *Ecological Applications: A Publication of the Ecological Society of America* 20 (5):1350–71. doi: 10.1890/09-0822.1.

Isaak, D. J., E. E. Peterson, J. M. Ver Hoef, S. J. Wenger, J. A. Falke, C. E. Torgersen, C. Sowder, E. A. Steel, M. Fortin, C. E. Jordan, et al. 2014. Applications of spatial statistical network models to stream data. *WIREs Water* 1 (3):277–94. doi: 10.1002/wat2.1023.

Isaak, D. J., S. J. Wenger, E. E. Peterson, J. M. Ver Hoef, D. E. Nagel, C. H. Luce, S. W. Hostetler, J. B. Dunham, B. B. Roper, S. P. Wollrab, et al. 2017. The NorWeST summer stream temperature model and scenarios for the western US: A crowd-sourced database and new geospatial tools foster a user community and predict broad climate warming of rivers and streams. *Water Resources Research* 53 (11):9181–9205. doi: 10.1002/2017WR020969.

Isaak, D. J., S. P. Wollrab, D. Horan, and G. L. Chandler. 2012. Climate change effects on stream and river temperatures across the northwest US from 1980–2009 and implications for salmonid fishes. *Climatic Change* 113 (2):499–524. doi: 10.1007/s10584-011-0326-z.

Janisch, J., E. S. M. Wondzell, and W. J. Ehinger. 2012. Headwater stream temperature: Interpreting response after logging, with and without riparian buffers, Washington, USA. *Forest Ecology and Management* 270:302–13. doi: 10.1016/j.foreco.2011.12.035.

LANDFIRE. 2021. Existing vegetation cover layer, LANDFIRE 2.0.0. U.S. Department of the Interior, Geological Survey, and U.S. Department of Agriculture. Accessed September 2021. http://www.landfire/viewer.

Leach, J. A., C. Kelleher, B. L. Kurylyk, R. D. Moore, and B. T. Neilson. 2023. A primer on stream temperature processes. *Wiley Interdisciplinary Reviews: Water*:e1643. doi: 10.1002/wat2.1643.

Long, W. B., and H. Chang. 2022. Event scale analysis of streamflow response to wildfire in Oregon, 2020. *Hydrology* 9 (9):157. doi: 10.3390/hydrology9090157.
Lorensen, T., C. Andrus, and J. Runyon. 1994. *The Oregon Forest Practices Act water protection rules: Scientific and policy considerations*. Forest Practices Policy Unit, Oregon Department of Forestry. Accessed September 2021. https://www.oregon.gov/odf/Documents/workingforests/monitoring-technical-report-01.pdf.
Luce, C., B. Staab, M. Kramer, S. Wenger, D. Isaak, and C. McConnell. 2014. Sensitivity of summer stream temperatures to climate variability in the Pacific Northwest. *Water Resources Research* 50 (4):3428–43. doi: 10.1002/2013WR014329.
Mahlum, S. K., L. A. Eby, M. K. Young, C. G. Clancy, and M. Jakober. 2011. Effects of wildfire on stream temperatures in the Bitterroot River Basin, Montana. *International Journal of Wildland Fire* 20 (2):240–47. doi: 10.1071/WF09132.
Mainali, J., H. Chang, and Y. Chun. 2019. A review of spatial statistical approaches to modeling water quality. *Progress in Physical Geography: Earth and Environment* 43 (6):801–26. doi: 10.1177/0309133319852003.
Mainali, J., H. Chang, and R. Parajuli. 2023. Stream distance-based geographically weighted regression for exploring watershed characteristics and water quality relationships. *Annals of the American Association of Geographers* 113 (2):390–408. doi: 10.1080/24694452.2022.2107478.
Mayer, T. D. 2012. Controls of summer stream temperature in the Pacific Northwest. *Journal of Hydrology* 475:323–35. doi: 10.1016/j.jhydrol.2012.10.012.
McCullough, D. A., J. M. Bartholow, H. I. Jager, R. L. Beschta, E. F. Cheslak, M. L. Deas, J. L. Ebersole, J. S. Foott, S. L. Johnson, K. R. Marine, et al. 2009. Research in thermal biology: Burning questions for coldwater stream fishes. *Reviews in Fisheries Science* 17 (1):90–115. doi: 10.1080/10641260802590152.
Oregon Climate Service. 2005. *General descriptions of Oregon's climatic zones*. Corvallis: Oregon Climate Service, Oregon State University. Accessed September 2021. www.ocs.oregonstate.edu/index.html.
Oregon Department of Environmental Quality (ODEQ). 2006. *Willamette basin total maximum daily load (TMDL)*. Salem: Oregon Department of Environmental Quality.
Oregon Department of Environmental Quality (ODEQ). 2009. Evaluation and findings report on the application for certification pursuant to Section 401 of the Federal Clean Water Act. Submitted by Portland General Electric Company for the Clackamas Hydroelectric Project (FERC No. 2195), Oregon Department of Environmental Quality Water Quality Division, Salem, OR.
Oregon Department of Geology and Mineral Industries. 2020. *Oregon geologic data compilation, release 7*. Portland: Oregon Department of Geology and Mineral Industries. Accessed September 2021. https://www.oregongeology.org/pubs/dds/p-OGDC-7.htm.
Peterson, E., and J. Ver Hoef. 2014. STARS: An ArcGIS toolset used to calculate the spatial information needed to fit spatial statistical models to stream network data. *Journal of Statistical Software* 56 (2):1–17. doi: 10.18637/jss.v056.i02.
Pettit, N. E., and R. J. Naiman. 2007. Fire in the riparian zone: Characteristics and ecological consequences. *Ecosystems* 10 (5):673–87. doi: 10.1007/s10021-007-9048-5.
Poole, G. C., and C. H. Berman. 2001. An ecological perspective on in-stream temperature: Natural heat dynamics and mechanisms of human-caused thermal degradation. *Environmental Management* 27 (6):787–802. doi: 10.1007/s002670010188.
Portland General Electric Company (PGE). 2013. Clackamas River project water quality management and monitoring plan: Clackamas River hydroelectric project. FERC No. 2195. https://www.oregon.gov/deq/FilterDocs/PGEC2195wqmmprev13.pdf.
PRISM. 2021. Explorer. Oregon State University. Accessed July 2021. https://prism.oregonstate.edu/explorer/.
Rhea, A. E., T. P. Covino, C. C. Rhoades, and A. C. Brooks. 2022. Use of geostatistical models to evaluate landscape and stream network controls on post-fire stream nitrate concentrations. *Hydrological Processes* 36 (9):e14689. doi: 10.1002/hyp.14689.
Richter, A., and S. A. Kolmes. 2005. Maximum temperature limits for Chinook, coho, and chum salmon, and steelhead trout in the Pacific Northwest. *Reviews in Fisheries Science* 13 (1):23–49. doi: 10.1080/10641260590885861.
Saxe, S., T. S. Hogue, and L. Hay. 2018. Characterization and evaluation of controls on post-fire streamflow response across western US watersheds. *Hydrology and Earth System Sciences* 22 (2):1221–37. doi: 10.5194/hess-22-1221-2018.
Sowder, C., and E. A. Steel. 2012. A note on the collection and cleaning of water temperature data. *Water* 4 (3):597–606. doi: 10.3390/w4030597.
Stamp, J., A. Hamilton, M. Craddock, L. Parker, A. Roy, D. Isaak, Z. Holden, M. Passmore, and B. Bierwagen. 2014. Best practices for continuous monitoring of temperature and flow in wadeable streams. EPA/600/R-13 F, 170, Global Change Research Program, National Center for Environmental Assessment, Washington, DC. Accessed September 2021. https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P100LOD6.TXT.
Starcevich, S. J. 2021. *Clackamas River Bull Trout Reintroduction Project: Characterizing status, trends, and thermal habitat suitability in 2020. Science Bulletin 2021-09*. Corvallis: Oregon Department of Fish and Wildlife, Native Fish Investigations Program. Accessed January 2022. https://odfwnfi.forestry.oregonstate.edu/reports.
Steel, E. A., C. Sowder, and E. E. Peterson. 2016. Spatial and temporal variation of water temperature regimes on the Snoqualmie River network. *JAWRA: Journal of the American Water Resources Association* 52 (3):769–87. doi: 10.1111/1752-1688.12423.

Tague, C., M. Farrell, G. Grant, S. Lewis, and S. Rey. 2007. Hydrogeologic controls on summer stream temperatures in the McKenzie River basin, Oregon. *Hydrological Processes* 21 (24):3288–300. doi: 10.1002/hyp.6538.

Tague, C., and G. E. Grant. 2004. A geological framework for interpreting the low-flow regimes of Cascade streams, Willamette River Basin, Oregon. *Water Resources Research* 40: W04303. doi: 10.1029/2003WR002629.

U.S. Environmental Protection Agency. 2003. EPA region 10 guidance for Pacific Northwest State and tribal temperature water quality standards. EPA 910-B-03-002, Region 10 Office of Water, Seattle, WA. Accessed September 2021. https://nepis.epa.gov/Exe/ZyPURL.cgi?Dockey=P1004IUI.TXT.

U.S. Fish and Wildlife Service. 2021. *National wetlands inventory*. Washington, DC: U.S. Fish and Wildlife Service. https://www.fws.gov/program/national-wetlands-inventory.

U.S. Forest Service (USFS). 1990. *Mt. Hood National Forest land and resource management plan*. Portland: Forest Service Pacific Northwest Region, U.S. Department of Agriculture, Portland, Oregon.

U.S. Forest Service (USFS). 2020. *Zigzag integrated resource project design criteria*. Sandy, OR: Mt. Hood National Forest. https://www.fs.usda.gov/project/mthood/?project=57109.

U.S. Geological Survey (USGS). 2012. NHDPlus version 2. Accessed August 2021. https://nhdplus.com/NHDPlus/.

U.S. Geological Survey (USGS), U.S. Forest Service (USFS), and K. Nelson. 2022. Monitoring trends in burn severity: U.S. Geological Survey data release. doi: 10.5066/P9IED7RZ.

Ver Hoef, J., and E. E. Peterson. 2010. A moving average approach for spatial statistical models of stream networks. *Journal of the American Statistical Association* 105 (489):6–18. doi: 10.1198/jasa.2009.ap08248.

Ver Hoef, J., and E. E. Peterson. 2020. SSN. R package version 1.1.15. Accessed August 2021. https://cran.r-project.org/web/packages/SSN/SSN.pdf.

Ver Hoef, J., E. E. Peterson, D. Clifford, and R. Shah. 2014. SSN: An R package for spatial statistical modeling on stream networks. *Journal of Statistical Software* 56 (3):1–45. doi: 10.18637/jss.v056.i03.

Ver Hoef, J., E. E. Peterson, and D. Theobald. 2006. Spatial statistical models that use flow and stream distance. *Environmental and Ecological Statistics* 13 (4):449–64. doi: 10.1007/s10651-006-0022-8.

Wagner, R. J., R. W. Boulger, Jr., C. J. Oblinger, and B. A. Smith. 2006. Guidelines and standard procedures for continuous water-quality monitors—Station operation, record computation, and data reporting: U.S. Geological Survey Techniques and Methods 1–D3. Accessed June 15, 2022. http://pubs.water.usgs.gov/tm1d.

Watson, E. C., and H. Chang. 2018. Relation between stream temperature and landscape characteristics using distance weighted metrics. *Water Resources Management* 32 (3):1167–92. doi: 10.1007/s11269-017-1861-9.

Webb, B. W., D. M. Hannah, R. D. Moore, L. E. Brown, and F. Nobilis. 2008. Recent advances in stream and river temperature research. *Hydrological Processes* 22 (7):902–18. doi: 10.1002/hyp.6994.

Webb, B., and Y. Zhang. 1997. Spatial and seasonal variability in the components of the river heat budget. *Hydrological Processes* 11 (1):79–101. doi: 10.1002/(SICI)1099-1085(199701)11:1 ≤ 79::AID-HYP404 ≥ 3.0.CO;2-N.

Zhou, T., J. Wu, and S. Peng. 2012. Assessing the effects of landscape pattern on river water quality at multiple scales: A case study of the Dongjiang River watershed, China. *Ecological Indicators* 23:166–75. doi: 10.1016/j.ecolind.2012.03.013.

MICHAEL KROCHTA is a PhD Student in the Department of Geography, Portland State University, Portland, OR 97201. E-mail: mkrochta@pdx.edu. His research interests include the combined effects of climatic and landscape variability on hydrology and water quality at multiple scales.

HEEJUN CHANG is a Professor in the Department of Geography at Portland State University, Portland, OR 97201. E-mail: changh@pdx.edu. His research interests include combined impacts of climate change, urbanization, and restoration on water-related ecosystem services using process-based models and spatial statistical analysis.