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RESEARCH ARTICLE

Spatial and temporal variability in stream thermal regime drivers for three river networks during the summer growing season

Matthew R. Fuller[1] | **Naomi E. Detenbeck**[2] | **Peter Leinenbach**[3] | **Rochelle Labiosa**[3] | **Daniel Isaak**[4]

[1]Oak Ridge Institute for Science and Education Postdoc at the Atlantic Coastal Environmental Sciences Division, U.S. Environmental Protection Agency, Narragansett, Rhode Island, USA

[2]Atlantic Coastal Environmental Sciences Division, U.S. Environmental Protection Agency, Narragansett, Rhode Island, USA

[3]Region 10, U.S. Environmental Protection Agency, Seattle, Washington, USA

[4]Rocky Mountain Research Station, U.S. Forest Service, Boise, Idaho, USA

Correspondence
Matthew R. Fuller, Oak Ridge Institute for Science and Education Postdoc at the Atlantic Coastal Environmental Sciences Division, U.S. Environmental Protection Agency, Narragansett, RI, USA.
Email: matthew.fuller@usda.gov

Present address
Matthew R. Fuller, Northern Research Station, U.S. Forest Service, Amherst, Massachusetts, USA

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Abstract

Many cold water-dependent aquatic organisms are experiencing habitat and population declines from increasing water temperatures. Identifying mechanisms which drive local and regional stream thermal regimes facilitates restoration at ecologically relevant scales. Stream temperatures vary spatially and temporally both within and among river basins. We developed a modeling process to identify statistical relationships between drivers of stream temperature and covariates representing landscape, climate, and management-related processes. The modeling process was tested in three study areas of the Pacific Northwest United States during the growing season (May [start], August [warmest], September [end]). Across all months and study systems, covariates with the highest relative importance represented the physical landscape (elevation [1st], catchment area [3rd], main channel slope [5th]) and climate covariates (mean monthly air temperature [2nd] and discharge [4th]). Two management covariates (groundwater use [6th] and riparian shade [7th]) also had high relative importance. Across the growing season (for all basins), local reach slope had high relative importance in May, but transitioned to a regional main channel slope covariate in August and September. This modeling process identified regionally similar and locally unique relationships among drivers of stream temperature. High relative importance of management-related covariates suggested potential restoration actions for each system.

KEYWORDS
covariate relative importance, information criterion, model selection, Pacific Northwest, United States, restoration, river networks, spatial stream network model, temperature, water resources management, water quality

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Research Impact Statement

Determining the relative importance of mechanisms controlling stream temperature helps manage future habitat availability. Some mechanisms are important across watersheds/time, while others vary.

1 | INTRODUCTION

Stream temperatures vary over space and time due to multiscale interactions among climate, geomorphic, and vegetation-related variables (Caissie, 2006; Maheu et al., 2016). Understanding the spatiotemporal patterns of temperature in river networks helps predict ecosystem process rates, organismal life-history patterns, and animal behavior because of the strong temperature dependence of lotic communities (Caissie, 2006; Magnuson et al., 1979; Webb, 1996). This is especially true of species that require cold water temperatures such as salmon, trout, and char which are undergoing net global declines in thermally suitable habitats across southerly range extents (Isaak & Young, 2023).

Cold water species have evolved life-history strategies that depend on environments with sustained, episodic, or seasonal cold water habitat during key life cycle periods (Dahlke et al., 2020; Magnuson et al., 1979). Their dependence on cold water habitats puts them at higher risk of population decline as climate-induced warming continues (Isaak et al., 2018; Keefer et al., 2018). Pacific salmonids are species adapted to cold water habitat that have already suffered habitat loss and population decline where warming has exceeded their thermal tolerance threshold (Crozier et al., 2019; Keefer et al., 2018). Identifying the mechanisms driving local and regional stream temperature, therefore, can help target cold water habitat restoration and management activities.

The management of cold water habitat takes many forms. Local site-based restoration directly influences known problem reaches (McKergow et al., 2016; Osborne & Kovacic, 1993). Alternatively, restoration can be indirect in the form of distant management activities that, for example, focus on keeping more water in the river network by reducing withdrawals from surface waters or upland groundwater aquifers that would otherwise supply baseflow to targeted stream reaches (Poole & Berman, 2001). The large spatial extents encompassed by these indirect restoration activities are difficult to study through experimentation or calibration of data-intensive mechanistic water temperature models. However, statistical models can be used to simultaneously assess the marginal effects of multiple covariates across a range of spatiotemporal scales to investigate the importance of indirect effects on stream temperature. The usefulness and potential of indirect management options for cold water habitat restoration can then be compared with direct management activities that have been empirically tested (e.g., shading and channel morphology modifications [Johnson (2004) and Merriam and Petty (2019), respectively]).

Stream temperature models generally fall into two major categories; process-based or statistical models. Process-based temperature models employ a physics-based heat-budget approach that quantifies the processes which add or remove heat from streams based on energy exchanges at both the air–water and channel surface–subsurface boundaries (Dugdale et al., 2017). These models often require extensive calibration and validation (e.g., Heat Source—Boyd & Kasper, 2003) which usually limits their application to river reaches rather than the entirety of river networks. Once established, however, process-based models can provide detailed simulations of stream temperature responses to factors that alter boundary conditions and affect heat budgets.

Statistical models predicting stream temperature take many forms (Laanaya et al., 2017), from nonlinear models (Mohseni et al., 1998) for individual sites to linear mixed models (Peterson & Ver Hoef, 2010) or generalized additive models (Georges et al., 2021; Jackson et al., 2018; Laanaya et al., 2017; Siegel & Volk, 2019) that are applied to networks. Another distinction among statistical models is whether spatial autocorrelation is addressed. Results from models which are fit to large datasets derived from dense monitoring arrays can be biased by the redundancy that autocorrelation causes among observations. This has led to the development of spatial models for stream networks which address both landscape and network proximity and topology (Peterson & Ver Hoef, 2010; Ver Hoef et al., 2006). A primary advantage of statistical models compared to process-based models is that covariates may be easily derived from broadly available geospatial and climate models that serve as proxies for heat budget processes. This enables statistical models to be developed and applied with large stream datasets at broad spatial extents (Isaak, Wenger, et al., 2017; Jackson et al., 2016; Jackson, Hannah, et al., 2017).

The ability to quickly develop statistical models for large spatial extents provides a convenient first step in determining similarities or differences between regional or temporal attributes affecting stream temperature (Isaak, Wenger, et al., 2017; Jackson et al., 2016; Jackson, Fryer, et al., 2017). Furthermore, the ability to rapidly build statistical stream temperature models for new locations means a standardized model development process can be used to provide a consistent baseline for regional comparisons. This baseline process can also be used in the same location for different time periods to evaluate temporal shifts in attributes affecting stream temperature.

Statistical stream temperature models have used a range of covariates to derive relationships between stream temperature and the physical landscape, climate, or hydrologic processes (Caissie, 2006; Ouellet et al., 2020; Webb, 1996; Webb et al., 2008). We leveraged the rich literature on stream temperature to select covariates which included common parameters like air temperature, discharge, elevation, latitude, and solar radiation. In addition to these common covariates, we also explored more novel covariates. For example, we tested several covariates that represent hydrologic surface–subsurface water exchange processes. We also reimagined the way riparian shade is often incorporated in temperature models by developing an estimate of riparian shade condition that integrates across upstream reach distances or travel times rather than just at the site of a temperature observation. Additionally, we explored various interaction terms that explore processes as more than just the sum of the two parts (e.g., interactions between slope and surface–subsurface exchange process covariates or interactions between shade and discharge), which is a less common practice in statistical stream temperature models. Finally, stream temperature management-related covariates (e.g., consumptive water use from surface or groundwater extraction) were included to allow our final models the ability to make predictions based on implementation of related management activities (e.g., reduced water extraction from surface or groundwater sources) for a more direct translation of our modeling process and products for environmental managers.

We used spatial stream network (SSN) models (Peterson & Ver Hoef, 2010) in the model development process we produced. SSN models are specifically designed to address spatial autocorrelation among dense sets of observations in stream networks by including a residual error term that accounts for network topology, flow direction, and the distances over which observation values are spatially correlated. Previous work has identified reliable goodness of fit and prediction accuracy of SSN temperature models across large spatial extents and for different study areas (Detenbeck et al., 2016; Isaak, Wenger, et al., 2017). Furthermore, the explicit incorporation of spatial autocorrelation by SSN models yields unbiased parameter estimates and enables accurate temperature predictions in stream reaches and tributaries with little or no observation data. While our study focuses on stream temperature, SSN models have been used with a range of other response variables (e.g., baseflow sources [Segura et al., 2019], conductivity [McManus et al., 2020], ecosystem metabolism [Kaylor et al., 2019], fish abundance/presence [Isaak, Ver Hoef, et al., 2017], and nutrient concentrations [French et al., 2020]) which highlights potential flexibility in using our SSN model development process for other restoration purposes.

Our first goal was to develop a flexible statistical model selection process that builds models with high predictive accuracy across stream networks. This process is standardized for use in different study systems for direct comparisons of covariate importance between study systems or different time periods within a system. The model selection procedure allowed selective competition among covariates representing similar processes (e.g., surface–subsurface exchange or solar energy inputs) to determine which best fit observed data patterns and produce the best prediction models. The second goal was to use our model development process to build stream temperature models which compare the relative importance of covariates in three study networks during periods of the growing season (May [start], August [warmest], and September [end]) that are important for Pacific salmon life-history stages in the northwestern United States (U.S>). Finally, we assessed the relative importance of stream temperature covariates that may be affected by management actions compared to those that represent landscape and climatic processes.

2 | METHODS

2.1 | Study basins

Our three study areas in the Pacific Northwest, U.S., included the Middle Fork John Day River (MFJD), South Fork Nooksack River (SFNR), and Wind River (WR) (Figure 1). There are previously issued TMDLs for temperature for all three basins (Butcher et al., 2010; Kennedy & Butcher, 2012; Pelletier, 2002) with detailed system characterizations. Briefly, the three study areas occupy a range of climate and physical landscape conditions (Table 1) that we expect to result in different local drivers of stream temperature.

The three study regions have more than 50% of their area forested according to the 2016 National Landcover Database (NLCD; Yang et al., 2018). The WR had 50% forested land cover while the MFJD was 54% and SFNR 72%. There was also little development in each study region with 4% or less of the area classified as developed by the NLCD (MFJD: 1%, SFNR: 2%, WR: 4%). The shrubland cover in each basin ranged from 11% in the SFNR to 20% in the WR and the MFJD at 18%. The SFNR did not have as much grassland land cover (4%) as the MFJD (26%) and the WR was somewhere between (12%). The WR included the most agricultural/cultivated land cover at 12%, while the SFNR (1%) and MFJD (0.1%) had much lower areas associated with these land classifications.

2.2 | Temperature data

Observed temperature data were from the NorWeST database (https://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html) for all three study catchments. We also included data from the Integrated Status and Effectiveness Project (ISEMP) online database (Northwest Fisheries Science Center, 2017) covering the MFJD. The number of observation sites ranged from 44 to 310 among the three study catchments depending on the month and catchment (Table 2). Some observation sites had multiple years of data, but only a random year was selected to be used at a site.

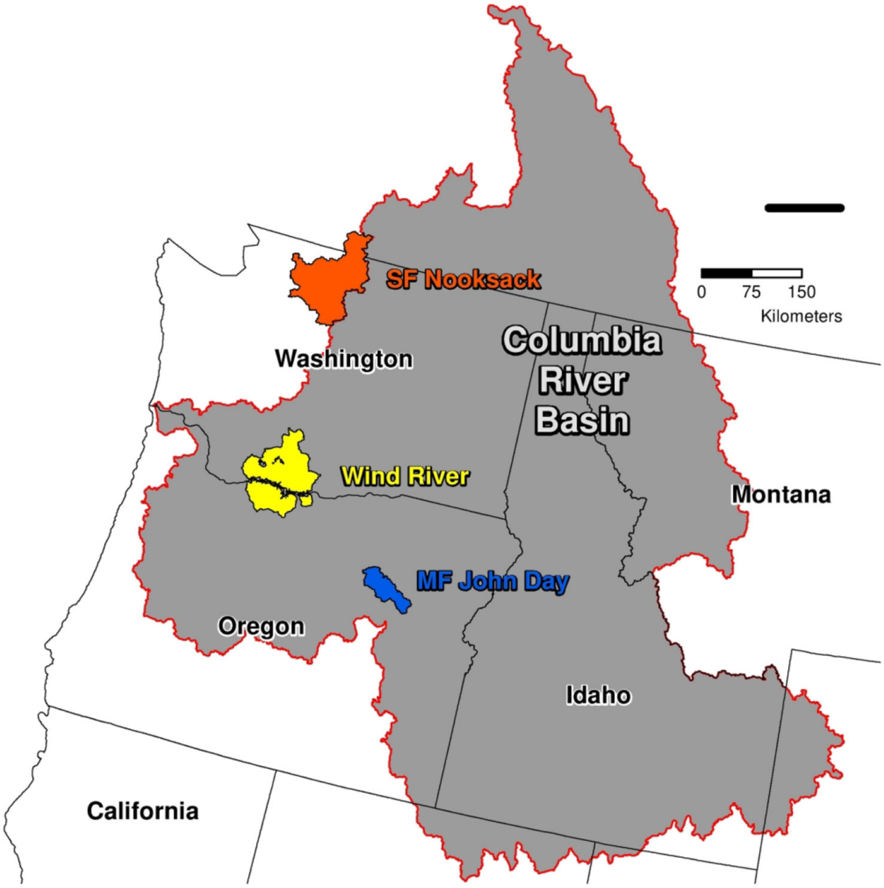

FIGURE 1 Three study areas in the Pacific Northwest, United States with Columbia River Basin for reference.

TABLE 1 Study area characteristics for the networks where temperature models were fit to observed site (Obs. Sites) data and predictions (Preds Sites) were made across the network.

Study area	Drainage area (km^2)	Prediction river network length (km)	Study area elevation (m) [min–mean–max]	Mean annual precipitation range (mm)	Mean annual air temperature (°C)[a] [min–mean–max]	Obs. Sites (*n*)	Preds Sites (*n*)
MFJD	2051	1581	666–1379–2477	350–1000	4.4–6.4–9.1	278	1394
SFNR	7988	1157	11–1049–3284	1125–3500	1.4–6.3–10.2	89	1443
WR	9033	3812	19–779–3746	275–3250	1.5–7.5–11.6	319	3343

Abbreviations: MFJD, Middle Fork John Day; SFNR, South Fork Nooksack River; WR, Wind River.
[a]McKay et al. (2012).

All temperature observation sites needed 95% of the regular temperature measurements for a given day and for the days in each month to be included in our dataset. For missing data during a day or month, a linear interpolation was conducted using the "zoo" R package (Zeileis & Grothendieck, 2005) to fill the missing value and complete the time series. Using the complete monthly time series of mean daily temperatures, a mean monthly temperature was calculated for each observation site. These mean monthly temperatures for each observation site were the response variables in our models.

2.3 | Site attribute development

For each temperature observation site, we derived several model covariates from site attributes that have a known relationship with stream temperature. These site attributes were organized into categories consisting of attributes that represent the physical landscape, climate, shade and solar radiation, and management (covariates that could be manipulated by managers in the study areas [e.g., water use, irrigated crop water

TABLE 2 Summary statistics for model suites.

Study area	Month	Model suite #	Obs. site #	Gen. R^2 (±SD)	RMSPE (°C) (±SD)
MFJD	May	13	52	0.90 (±0.003)	0.67 (±0.060)
	August	53	207	0.66 (±0.002)	1.02 (±0.008)
	September	15	173	0.75 (±0.014)	0.82 (±0.009)
SFNR	August	24	67	0.55 (±0.048)	1.44 (±0.212)
	September	14	44	0.92 (±0.017)	0.84 (±0.041)
WR	May	16	87	0.80 (±0.004)	0.89 (±0.010)
	August	20	310	0.49 (±0.020)	1.28 (±0.017)
	September	13	251	0.57 (±0.007)	1.17 (±0.006)

Note: "Model suite #" indicates the number of models retained by the model selection process and "Obs. site #" indicates the number of temperature observation sites used for fitting models in each study area/month. Model suite mean (±SD) diagnostics (Generalized R^2 and root mean square prediction error—RMSPE) among all models for a given study area and month.

Abbreviations: MFJD, Middle Fork John Day; SFNR, South Fork Nooksack River; WR, Wind River.

losses; see Table 3]). Data S1 describes in detail how each covariate was developed and Data S2 provides a comprehensive evaluation of the correlations among these covariates to detect evidence of potential multicollinearity issues.

We provide a brief overview of the shade covariate development here with more details in the supplementary files. Often, shade is estimated locally at the observation site by looking at canopy density above the channel center or averaged along a study reach (Isaak, Wenger, et al., 2017). We took an integrated approach and estimated reach shade for sites as the average riparian shade condition upstream of a site. We call these integrated shade estimates "upstream shade buffers" since they average the riparian shade condition along the upstream channel. We used arbitrary distances upstream and average travel times for a parcel of water to delineate how far an upstream buffer extended up the channel network. Data S3 includes a protocol and sample data for delineating these upstream buffers in the MFJD study area. Data analyses, figure plotting, and model fitting procedures were conducted within the statistical software R v4 (R Core Team, 2020) using the following packages: "circlize" (Gu et al., 2014), "corrplot" (Wei et al., 2017), "SSN" (Ver Hoef et al., 2014; Ver Hoef & Peterson, 2010), and "tidyverse" (Wickham et al., 2019). See Data Availability section for access to example code.

2.4 | Spatial stream network (SSN) models

We developed SSN models (Peterson & Ver Hoef, 2010) for mean monthly stream temperature (May, August, September) within each study area. SSN models are linear mixed models that include autocovariance functions as random effects to address the spatial autocorrelation across a river network (Peterson & Ver Hoef, 2010; Ver Hoef et al., 2006). The autocovariance functions can take three primary forms: (1) Euclidean, (2) tail-up, or (3) tail-down (Ver Hoef & Peterson, 2010). Euclidean autocorrelation is measured along the shortest straight-line distance between two points (Turner & Gardner, 2015). Tail-up autocorrelation represents a moving-average autocorrelation function for only flow-connected relationships between sites along stream reaches. Tail-down autocorrelation, however, provides model autocorrelation to address both flow-connected and flow-unconnected sites along stream reaches (Peterson & Ver Hoef, 2010; Ver Hoef et al., 2006; Ver Hoef & Peterson, 2010). Each of these three types of autocovariance in the SSN model can take on different shapes (e.g., exponential, spherical, linear with sill, or Mariah) (Ver Hoef et al., 2006). In addition to these autocovariance functions being used as random effects, we varied the site attributes described earlier to develop fixed-effect model structures.

2.5 | SSN model structure selection process

To select among fixed effect covariates and identify the best fixed effect covariate model structure for the observed temperature data, we compared SSN model fits using a combination of exhaustive model selection and stepwise regression procedures in four distinct steps. At the end of each step, we used Akaike's information criterion (AIC) to determine which subset of the models in each step had the best fit to the observed data (models with AIC values within three AIC units of the lowest AIC value are considered to have an equally good fit to the data [Burnham & Anderson, 2002]). Those best fit models were then used as the starting models moving forward in the following step.

The first step in our model selection process develops an initial list of models from a variety of covariate combinations that are eventually all compared using AIC. We began developing this list of models using different combinations of the original NorWeST covariates, but including mean annual air temperature and canopy cover in all models for two reasons. First, air temperature provides a stochastic variable

TABLE 3 List of all covariates used during the model selection process, their ID name used in figures and tables, the units for the covariate, its classification (Class.) into one of four groups, what step (Steps 1–4) the covariate entered (In) the model selection process, and the first stage at which the covariate could be dropped (Out) from models.

Covariate	ID	Units	Class.	In	Out
Start covariates from NorWeST model					
Site elevation	elevation	m	Landscape	1	1
Mean annual precipitation (historical average 1970–2000)	precipitation	mm	Climate	1	1
Lake area as proportion of catchment area	prop. lake	prop.	Landscape	1	1
Site catchment area	catchment area	km^2	Landscape	1	1
Site location latitude as northing	latitude	M	Landscape	1	1
NLCD reach canopy cover	canopy cover	Percent	Shade	1	2
Proportion of catchment area covered by glaciers	glacier	prop.	Landscape	1	1
Mean monthly air temperature over site's catchment	air temp.	deg. C	Climate	1	3
Mean monthly discharge[1]	Q	cms	Climate	1	1
Baseflow index[1]	BFI	Percent	Landscape	1	1
Local reach slope[1]	slope	Unitless	Landscape	1	1
Discharge-related covariates					
Mean monthly discharge[1]	Q	Cms	Climate	1	1
Discharge volume adjusted by SW use and wastewater returns	stream flow	cms/km^2	Climate	1	1
Mean monthly discharge divided by catchment area	area-norm. Q	cms/km^2	Climate	1	1
Surface–subsurface exchange process covariates					
Baseflow index[1]	BFI	percent	Landscape	1	1
Cold spring abundance in catchment per unit area	cold springs	$\#/km^2$	Landscape	1	1
Proportion of catchment classified as high hydraulic conductivity class	prop. high HC	prop.	Landscape	1	1
Average hydraulic conductivity of surficial sediments across catchment	avg hydraulic cond.	m/day	Landscape	1	1
Average baseflow recession coefficient (*k*)	avg baseflow rec. coef.		Landscape	1	1
Proportion of catchment that contains geothermal activity and/or hot springs	geothermal	prop.	Landscape	1	1
Gradient covariates					
Local reach slope[1]	slope	unitless	Landscape	1	1
Main channel slope	mc slope	unitless	Landscape	1	1
Interaction terms between gradient and surface–subsurface exchange process covariates					
[not all listed due to large number; see Data S1]		NA	Landscape	1	1
Upstream shade buffers by distance					
Distance buffers for 1–5, and 10 km	shade-##km	percent	Shade	2	2
Entire upstream watershed	shade-wdhr	percent	Shade	2	2
Upstream shade buffers by travel time					
Travel time buffers for 1–6, 12, and 24 h	shade-##hr	percent	Shade	2	2
Solar radiation inputs averaged across a site's upstream subcatchment					
Clear sky Direct Normal Irradiance or Global Horizontal Irradiance	clear DNI or clear GHI	$watt/m^2$	Shade	2	2
Cloudy sky Direct Normal Irradiance or Global Horizontal Irradiance	cloud DNI or cloud GHI	$watt/m^2$	Shade	2	2
Solar radiation difference for DNI or GHI sky conditions (clear sky–cloudy)	DNId or GHId	$watt/m^2$	Shade	2	2
Solar radiation ratio for DNI or GHI sky conditions (cloudy/clear sky)	DNIr or GHIr	NA	Shade	2	2

TABLE 3 (Continued)

Covariate	ID	Units	Class.	In	Out
Joint upstream shade buffer and average solar radiation input covariates					
[not all listed due to large number; see Data S1]	shade-clearDNI##km	watt/m^2	Shade	2	2
Interaction terms between shade-classified and discharge-related covariates					
[not all listed due to large number; see Data S1]		NA	Shade	2	2
Air temperature and discharge-related covariates interaction terms					
Air temp. vs. (Q, area-norm. Q, or streamflow	air temp.:Q	NA	Climate	3	3
Management covariates					
Irrigated crop water loss from evapotranspiration	crop H_2O loss		Management	4	4
Wastewater treatment plant surface water returns	wastewater returns		Management	4	4
Surface water extraction for municipal use	SW use		Management	4	4
Groundwater extraction for municipal use	GW use		Management	4	4
H_2O balance from SW use, GW use, wastewater returns, and crop H_2O loss	net water loss		Management	4	4

Note: Development of each covariate detailed in Data S1. Covariates with a superscript "1" indicate a NorWeST SSN model covariates listed in more than one category to note their membership in NorWeST and substitution groups in the model selection process.

related to interannual variability in stream temperature. Second, canopy cover was a covariate for which we developed alternate reach shade covariates that we wished to substitute in later model structures within our model selection process. Consequently, we did not want either of these covariates to have the option to be dropped from the models this early on in the selection process. From these models, we substituted alternative covariates for reach slope, baseflow index, and discharge.

We selected each model that included a reach slope covariate and substituted main channel slope in its place. These models were added to the starting list of models as competing model hypotheses. This same substitution process was completed for all models that included the baseflow index covariate, representing channel surface-subsurface exchange processes (Table 3).

We followed Detenbeck et al. (2016) by including an interaction term between a slope covariate and a surface–subsurface exchange process covariate. These interactions (as were all other interaction terms described in the modeling process steps) were allowed to stand alone (no independent slope or surface–subsurface exchange process covariates included) or be combined with one or both slope and surface–subsurface exchange process covariates in the model structure. All additional models with this interaction term were again added to the list of competing models in step one.

For the list of competing models from step one, alternate discharge covariates, including area-normalized discharge and the stream volume water budget covariates, were also substituted for mean monthly discharge. Models with these substitutions were also added to the step one list and make up the final set of models competing against each other in step one of this model selection process. From step one's fitted SSN models, we identified and retained only those that were within three AIC units of the model with the lowest AIC value.

In the second step, we took the retained models from step one and created a new list of models to compare by focusing on covariate substitutions in those models for solar energy inputs to streams. We substituted the NorWeST's canopy cover covariate (previously forced into all models in step one) with alternate reach shade and solar radiation energy covariates. At this stage, the NorWeST canopy cover and our representations of solar radiation and shade were allowed to drop out of the model structure. There were 79 alternate shade covariates that represented upstream buffers by distance and time, raw solar radiation (clear sky and with clouds) across upstream catchments, and the multiplication of the reach shade buffer percent times the average solar radiation inputs identifying how much energy was intercepted by shade (Data S1). Additionally, we allowed the interaction of any discharge-related covariate in the model with the shade covariate. AIC was again used to select the best models to retain and move to the next step.

In the third step, we introduced interaction terms between the air temperature covariate and any discharge-related covariate into the models from step two. In this step, air temperature is allowed to drop out of the model despite it being forced into all models fit in steps one and two. AIC was again used to retain models for step four.

In the fourth and final step of the fixed effect covariate model structure selection process, we focused on management-related covariates. Here, we added individual and combinations of management-related covariates to the models retained from step three to see if they improved (or did not negatively affect) the model fit (AIC). This step allows management-derived covariates to potentially be used for scenario planning when using the fitted models to predict how altering the system (e.g., through riparian shade restoration or water use regulation) could change stream temperatures. We again compared these models using AIC and retained a final set of models which we refer to as the "suite of best fit models" for a given temperature dataset (monthly data for a given basin).

Selection of a suite of best fit models was chosen over selecting one final "best" model for a few reasons. First, selecting a suite of models with similar levels of support (e.g., models within three AIC units of the lowest AIC model) incorporates the various alternate hypotheses these distinct model structures represent in the final selection (Burnham & Anderson, 2002). In contrast, selecting a single model only highlights the one hypothesis represented by that model structure's combination of covariates and potentially misses other important covariate combinations. Second, selecting a single model does not incorporate the model selection uncertainty when using information theoretic criteria like AIC in model selection (Grueber et al., 2011). Third, a suite of best fit models can leverage model averaging for predictions which reduces the bias of the predictions when compared with a single "best" model (Burnham & Anderson, 2002).

During these fixed effect model selection steps, we used a maximum likelihood (ML) estimation method while holding the random effects (autocovariance functions) constant. We used the recommended starting forms of the autocovariance functions (exponential tail-up, exponential tail-down, and exponential Euclidean) for these initial steps before proceeding with the final fixed effect model structures to determine the best autocovariance functions for each basin and month suite of best fit models (Peterson & Ver Hoef, 2010).

2.6 | Autocovariance function selection

We used an exhaustive model selection process for identifying the best autocovariance function types (Euclidean, tail-up, tail-down) and shapes (exponential, linear with sill, Mariah, spherical) to include in our models. For each suite of best fit models, we fit each model within the suite with all possible combinations of the autocovariance function types and shapes using a restricted maximum likelihood (REML) estimation method. REML is best used to compare models with variation in random effects (autocovariance functions) when the fixed effect covariates are held constant (Ver Hoef & Peterson, 2010).

Alternate autocovariance structures were compared for each model in the suite of best models using AIC to select autocovariance function types and shapes for each model in the suite. Since each model within a suite of best fit models did not have the exact same set of function types and shapes, we selected the most common combination of autocovariance types and shapes from among the suite of best fit models.

2.7 | Relative importance of covariates

We evaluated the covariates used in each suite of best fit models using a relative importance metric based on the AIC values of each model within each suite of best fit models. These relative importance values ranged from 0 (not important or absent from a model) to 1 (very important) and were calculated for each covariate retained in a model within a suite of best models (Burnham & Anderson, 2002). When a covariate's relative importance value equals 1 for a suite of models, then the covariate is present in all models within the suite of best fit models. We can also average these relative importance values across months or basins to determine temporal or regional variation in covariate relative importance for stream temperature.

2.8 | Standardized model coefficient estimates

We used AIC-weighted model-averaging processes (Burnham & Anderson, 2002) to derive AIC-weighted mean standardized coefficient estimates for all covariates included in each model suite. These mean AIC-weighted standardized coefficient estimate values are directly comparable within a suite of models. The larger the absolute estimate value (difference from zero), the more influence that covariate has on stream temperature predictions when using the suite of models to predict stream temperature. Therefore, covariates with the largest estimate values are indicators of what would be most likely to impart stream temperature change when manipulated in the system (e.g., riparian shade or surface water extraction volumes) to help manage stream temperature.

3 | RESULTS

The model selection process produced different and varying numbers of models for each suite of best fit models in each basin and month (Table 2). The MFJD suites of best fit models for May, August, and September included 13, 53, and 15 models each for 3 months, respectively. The SFNR did not have enough observed temperature data for May, so suites of models were only generated for August and September (24 and 14 models, respectively). The WR had 16, 20, and 13 models in its suites for May, August, and September, respectively.

The suites of models had average root mean square prediction errors (RMSPE) ranging from 0.67 to 1.44°C and average model R^2 ranging from 0.49 to 0.92 across all models in a suite of best fit models for a given study area and month (Table 2). Suites of models for

August had the highest average RMSPE and lowest R^2 values in each study area and were also fit to the largest observation datasets in each study area. The May suite of models in the MFJD and WR had the smallest RMSPE and highest R^2 values indicating the best model suite fit to the data in these study areas across the 3 months (May, August, and September). The SFNR did not have enough observation site data to fit models for May, but the September suite of models had lower RMSPE and higher R^2 values than the August suite of models in this study area.

3.1 | Similar covariates among suites of models

Among the eight suites of best fit models, a total of 26 site attribute covariates were retained. Some of these 26 covariates were also included in interaction terms (18 different interaction terms used some combination of two of the 26 covariates) in the model leading to 44 total unique fixed effect terms being retained in the eight suites of models. Among all the site attribute covariates tested in our model selection procedure, elevation was the only covariate that was ubiquitous and appeared in all the models selected within our eight suites of best fit models. For the three MFJD suites of models, elevation was the only covariate retained in all models (Figure 2). The two SFNR suites of models included three covariates in all its models (catchment area, elevation, and discharge) (Figure 3). The three WR suites of models included air temperature and elevation in all its models (Figure 4).

Several covariates were retained in all eight suites of best fit models but may not have been used in every model within a given suite of best fit models (Table 4). These covariates are air temperature and groundwater extraction use for public supply. Catchment area and main channel slope were covariates that were present in seven of the eight suites of best fit models. The next most common covariates appearing among the eight suites of best fit models were discharge, surface water extraction use, irrigated crop water loss, the proportion of upstream catchment area covered in lakes, and the interaction term between discharge and mean August air temperature, which were present in five of the eight suites of best fit models.

In addition to the individual covariate terms that were common across all suites of models, there were alternative covariates within a class of site attributes that were present across all suites of models. All suites of models included some version of stream discharge (i.e., discharge, upstream catchment area-normalized discharge, or area-normalized discharge adjusted by surface water use withdrawals and wastewater

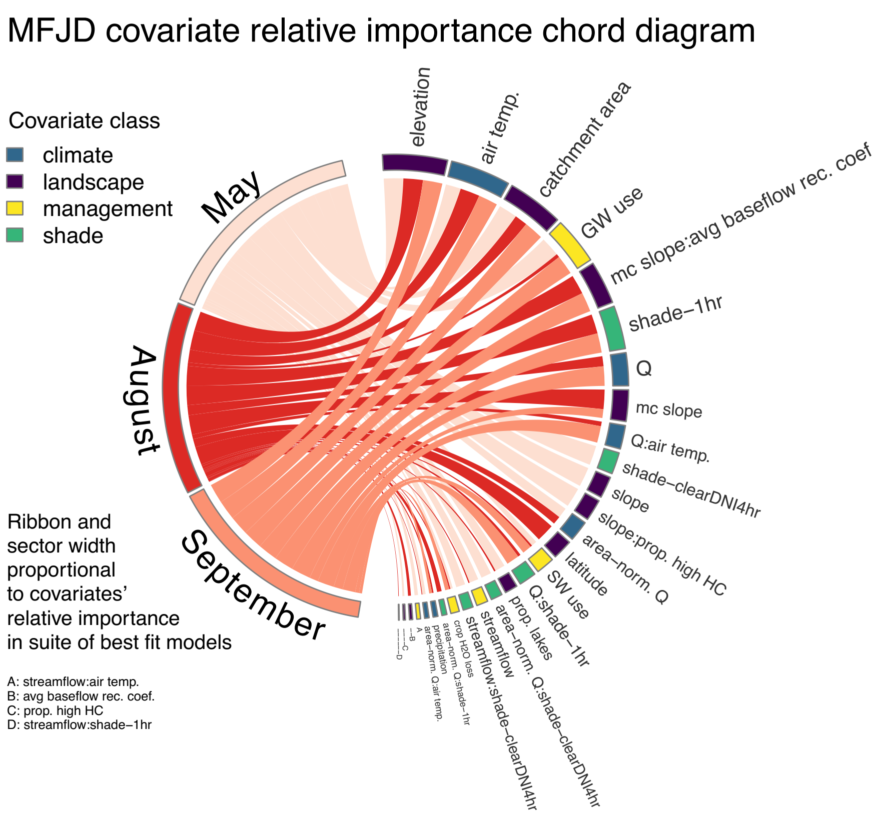

FIGURE 2 Chord diagram demonstrating the relative importance of covariates between months for the suites of models for the Middle Fork John Day (MFJD) study area. Covariate names as in Table 3.

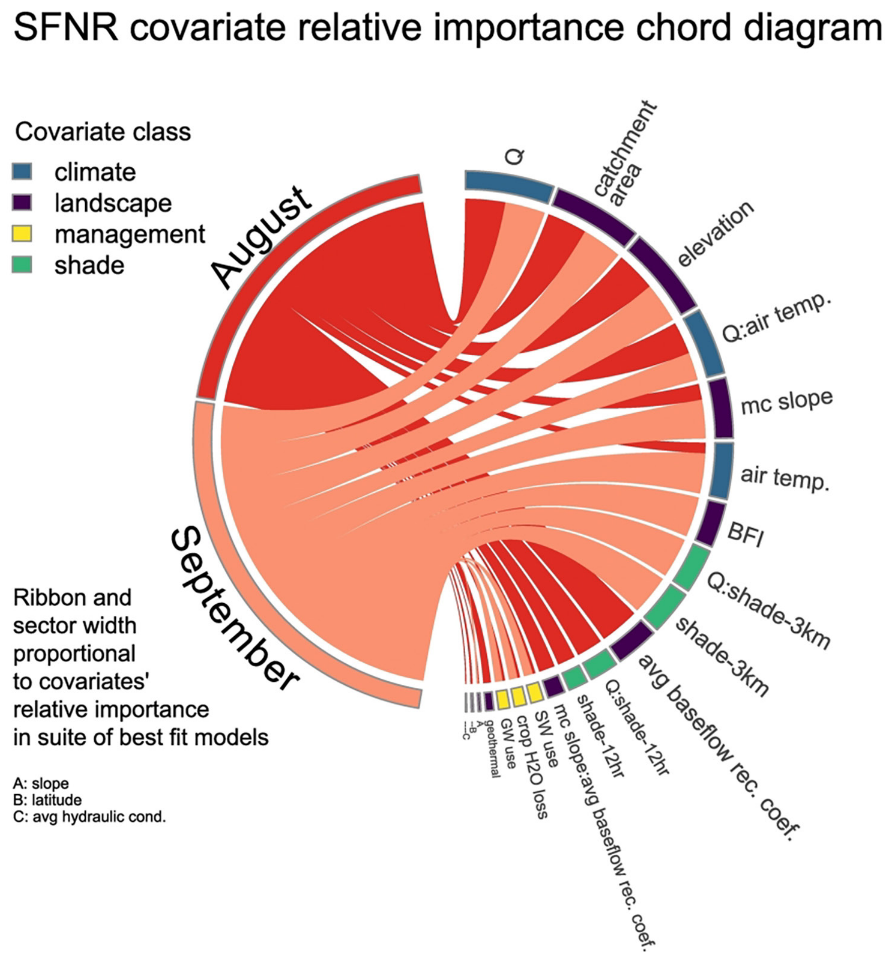

FIGURE 3 Chord diagram demonstrating the relative importance of covariates between months for the suites of models for the South Fork Nooksack River (SFNR) study area. Covariate names as in Table 3.

treatment plant returns) and some version of reach shade or solar energy inputs. The individual covariate for each of these differed between the basins and the months for each suite of models (Figures 2–4; Table 4). This was also observed for some interaction terms. The interaction between one of the three discharge covariates and air temperature was present in all eight suites of models. Interaction terms between gradient (reach slope or main channel slope) and surface–subsurface process covariates (e.g., baseflow index, average baseflow recession coefficient, or average hydraulic conductivity of surficial sediments) were also common across most model suites.

3.2 | Covariates unique to or missing from study area model suites

Some covariates were missing from all suites of models for a given study area but retained in the others. Geothermal activity and hot spring presence were retained in both the SFNR and WR August model suites, but absent from the MFJD, as expected since the MFJD did not include any geothermal activity or hot springs within its boundaries. Additionally, in the WR, geothermal activity or hot spring presence was also retained as an interaction term with main channel slope. The SFNR did not retain mean annual precipitation or proportion of the upstream catchment covered by lakes in any of its suites of models, while both of these covariates were retained in the MFJD and WR study areas. The WR study area lacked two management-related covariates (irrigated crop water loss and surface water extraction use for public supply) in its suites of models that were both retained in the MFJD and SFNR suites of models.

3.3 | Shade and solar radiation covariates

Shade and solar radiation covariates were nearly ubiquitous in the study (retained in almost all models in all eight suites of models) despite being allowed to fall out of models during the third step of the model structure selection process. The primary difference between retained

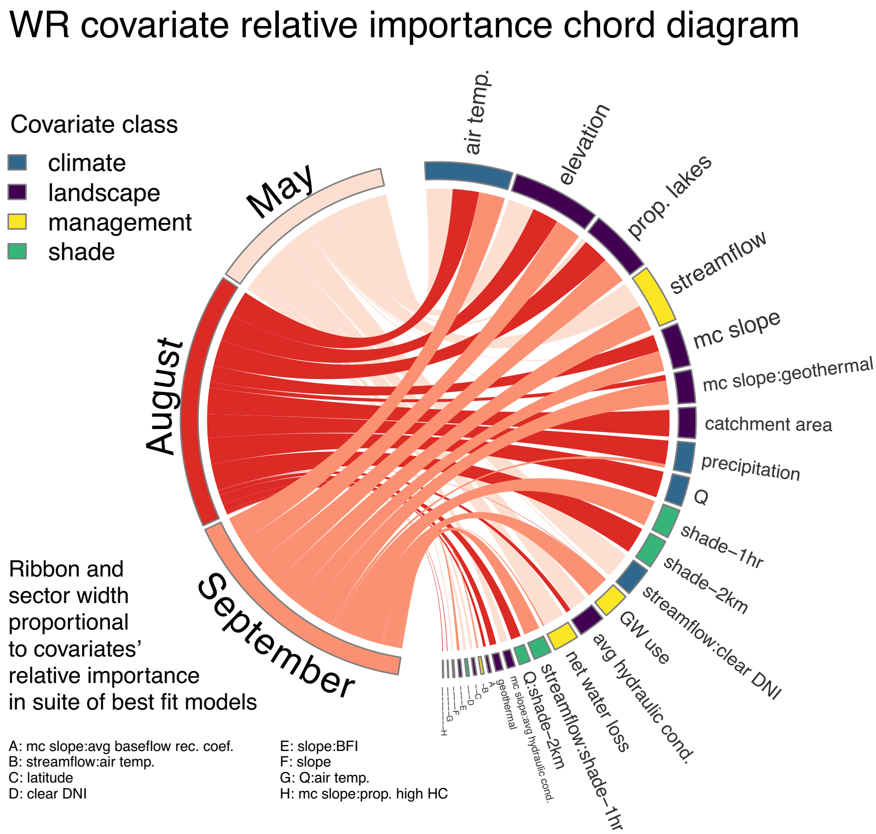

FIGURE 4 Chord diagram demonstrating the relative importance of covariates between months for the suites of models for the Wind River (WR) study area. Covariate names as in Table 3.

shade covariates from one suite of model to the next was the version of shade or solar radiation covariate. In the MFJD suites of models, travel time shade buffers were retained for each month (Figure 2). The travel time upstream shade buffers also differed between the months within the MFJD with the overall travel time shortening from 4 h in May to 1 h in August and September. The SFNR suites of models retained both travel time (August: 12 h) and upstream distance (September: 3 km) shade buffer covariates (Figure 3). The WR May suite of models was the only suite to retain a pure solar radiation covariate (clear-sky DNI) rather than a riparian shade-derived covariate. The August and September suites for the WR used upstream shade buffers that included a distance (August: 2 km) and travel time (September: 1 h) upstream buffer.

There were instances where some models were removed from a suite of best fit models when models were identical except for their shade covariate. The decision to arbitrarily remove models from the final suite of models was only made when the shade covariates among the suite of models appeared to be selecting a single upstream buffer integration metric (distance or travel time), but could not discern between variants of the shade covariate that all used that upstream buffer integration metric.

3.4 | Mean relative importance of covariates

Among all eight suites of models, the most important covariate was elevation (mean relative importance [±1SD] is 1 ± 0) (Figure 5). The next highest mean relative importance covariates across all eight suites of models were air temperature (0.88 ± 0.27), catchment area (0.63 ± 0.46), main channel slope (0.54 ± 0.40), and discharge (0.50 ± 0.53). Air temperature had a higher mean relative importance in the WR than in the MFJD or SFNR (Figure 5). The high relative importance of catchment area, main channel slope, and discharge in the SFNR helped retain these covariates in the top five most important covariates in this study across the three study areas (Figure 5). Among months, air temperature was most important in the September model suites followed by May and then August (Figure 5). Catchment area, main channel slope, and discharge were all approximately equally important to the model suites fit to August and September temperature data but were less important for May model suites (Figure 5).

TABLE 4 Relative importance of covariates for each suite of models and by mean values calculated for all eight suites, by study area basin, and by month.

	Individual suite relative importance								Mean relative importance						
	MFJD			SFNR		WR			All eight suites	By basin			By month		
Covariate	May	August	September	August	September	May	August	September		MFJD	SFNR	WR	May	August	September
air temp.	0.782	1	1	0.266	1	1	1	1	0.881	0.927	0.633	1.000	0.891	0.755	1.000
area-norm. Q	0.53	0.422	0	0	0	0	0	0	0.119	0.317			0.265	0.141	
area-norm. Q:air temp.	0.17	0.035	0	0	0	0	0	0	0.026	0.068			0.085	0.012	
area-norm. Q:shade-1hr	0	0.233	0	0	0	0	0	0	0.029	0.078				0.078	
area-norm. Q:shade-clearDNI4hr	0.53	0	0	0	0	0	0	0	0.066	0.177			0.265		
avg baseflow rec. coef.	0	0.147	0	0.976	0	0	0	0	0.140	0.049	0.488			0.374	
avg hydraulic cond.	0	0	0	0.024	0	0.727	0.183	0	0.117		0.012	0.303	0.364	0.069	
BFI	0	0	0	0	1	0	0	0	0.125		0.500				0.333
catchment area	0.953	0.655	1	1	1	0.06	1	0	0.709	0.870	1.000	0.353	0.506	0.885	0.667
clear DNI	0	0	0	0	0	0.097	0	0	0.012			0.032	0.048		
elevation	1	1	1	1	1	1	1	1	1.000	1.000	1.000	1.000	1.000	1.000	1.000
geothermal	0	0	0	0.185	0	0	0.253	0	0.055		0.093	0.084		0.146	
GW use	1	0.18	1	0.066	0.185	0.051	0.021	0.845	0.418	0.727	0.125	0.306	0.525	0.089	0.677
crop H_2O loss	0.123	0.067	0.207	0.069	0.205	0	0	0	0.084	0.133	0.137		0.062	0.046	0.137
latitude	0	0.927	0	0.049	0	0.099	0	0	0.134	0.309	0.025	0.033	0.049	0.325	
mc slope	0	1	0.452	0.398	0.963	0.063	0.64	0.771	0.536	0.484	0.680	0.491	0.032	0.679	0.729
mc slope:avg baseflow rec. coef.	0	1	1	0.398	0	0	0.102	0	0.312	0.667	0.199	0.034		0.500	0.333
mc slope:avg hydraulic cond.	0	0	0	0	0	0.273	0	0	0.034			0.091	0.136		
mc slope:geothermal	0	0	0	0	0	0	0.218	0.905	0.140			0.374		0.073	0.302
mc slope:prop. high HC	0	0	0	0	0	0	0.022	0	0.003			0.007		0.007	
net water loss	0	0	0	0	0	0.813	0	0.059	0.109			0.291	0.406		0.020
precipitation	0	0.079	0.144	0	0	0	0.901	0.134	0.157	0.074		0.345		0.327	0.093
prop. high HC	0.1	0	0	0	0	0	0	0	0.012	0.033			0.050		
prop. lakes	0.516	0.08	0	0	0	0.182	1	1	0.347	0.199		0.727	0.349	0.360	0.333
Q	0	0.518	1	1	1	0	1	0	0.565	0.506	1.000	0.333		0.839	0.667
Q:air temp.	0	0.239	0.852	0.813	0.693	0	0.023	0	0.327	0.364	0.753	0.008		0.358	0.515

TABLE 4 (Continued)

	Individual suite relative importance								Mean relative importance						
	MFJD			SFNR		WR			All eight suites	By basin			By month		
Covariate	May	August	September	August	September	May	August	September		MFJD	SFNR	WR	May	August	September
Q:shade-12hr	0	0	0	0.646	0	0	0	0	0.081		0.323			0.215	
Q:shade-1hr	0	0.145	0.653	0	0	0	0	0	0.100	0.266				0.048	0.218
Q:shade-2km	0	0	0	0	0	0	0.385	0	0.048			0.128		0.128	
Q:shade-3km	0	0	0	0	1	0	0	0	0.125		0.500				0.333
slope	1	0	0	0.023	0.037	0.054	0	0	0.139	0.333	0.030	0.018	0.527	0.008	0.012
slope:BFI	0	0	0	0	0	0	0	0.095	0.012			0.032			0.032
slope:prop. high HC	1	0	0	0	0	0	0	0	0.125	0.333			0.500		
shade-12hr	0	0	0	0.441	0	0	0	0	0.055		0.221			0.147	
shade-1hr	0	1	1	0	0	0	0	1	0.375	0.667				0.333	0.667
shade-2km	0	0	0	0	0	0	1	0	0.125			0.333			0.000
shade-3km	0	0	0	0	1	0	0	0	0.125			0.000		0.000	
shade-clearDNI4hr	1	0	0	0	0	0	0	0	0.125		0.000				0.000
stream flow	0.47	0.06	0	0	0	1	0	1	0.316	0.177			0.735		
stream flow:air temp.	0.176	0	0	0	0	0.048	0	0.051	0.034	0.059		0.033	0.112	0.000	0.017
stream flow:clear DNI	0	0	0	0	0	1	0	0	0.125	0.000		0.333	0.500		0.000
stream flow:shade-1hr	0	0.025	0	0	0	0	0	0.612	0.080			0.204	0.000		
stream flow:shade-clearDNI4hr	0.47	0	0	0	0	0	0	0	0.059	0.157				0.000	
SW use	0.283	0.097	0.47	0.071	0.217	0	0	0	0.142			0.000			0.229

Note: Relative importance values range from 0 to 1 with 1 being the most important and 0 the least. Mean values use 0 for covariates absent in a suite of models. Table covariates are sorted alphabetically and described in Table 3.

Abbreviations: MFJD, Middle Fork John Day; SFNR, South Fork Nooksack River; WR, Wind River.

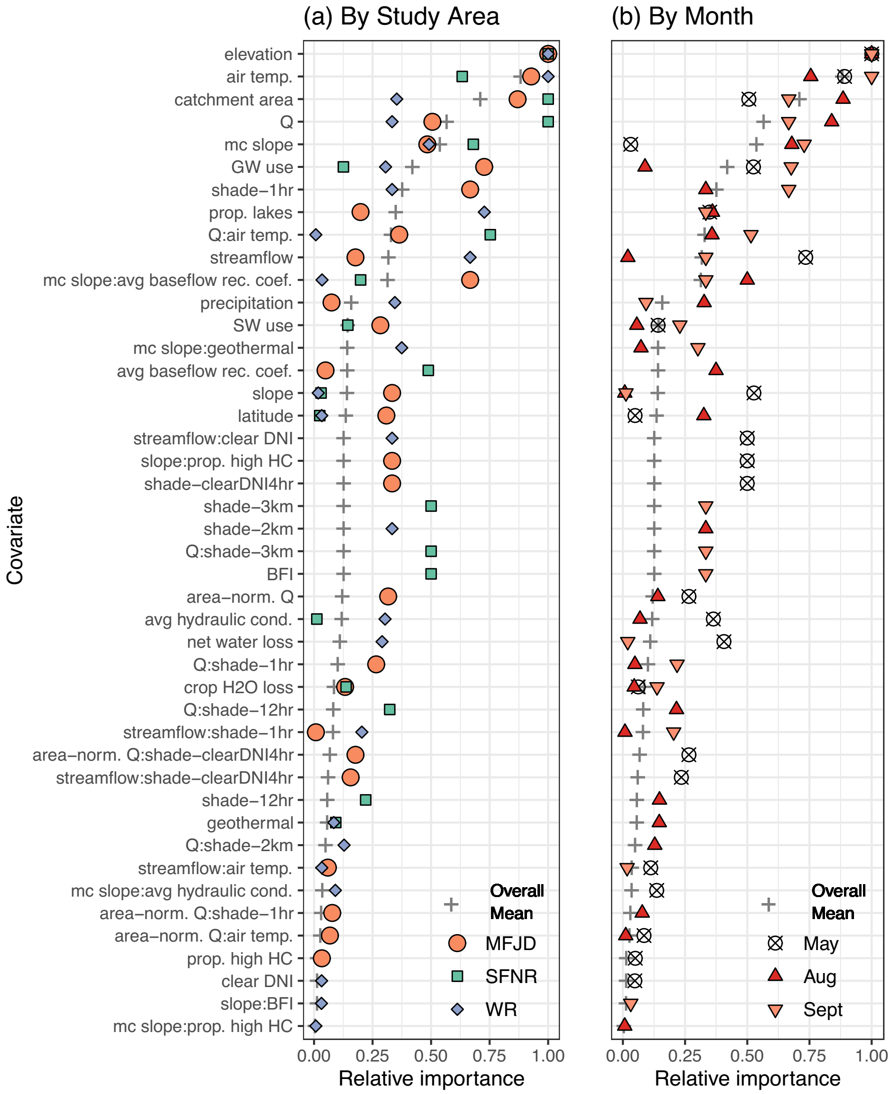

FIGURE 5 Mean relative importance for each covariate across all eight suites of best fit monthly models (Overall mean = +). The mean relative importance for covariates across suites of models for each study area (a) and by month (b). For means, Middle Fork John Day (MFJD): *n* = 3, South Fork Nooksack River (SFNR): *n* = 2, Wind River (WR): *n* = 3, May: *n* = 2, August: *n* = 3, September *n* = 3. Covariates defined in Table 3 are ordered by relative importance of overall mean (+).

3.5 | Standardized model coefficient estimates

Each suite of models had different covariates with the largest absolute value for an AIC-weighted mean standardized coefficient estimate (Table 5). In the MFJD, the interaction between reach slope and the proportion of the upstream catchment within a "high" hydraulic conductivity class was the largest followed by suite of models' retained shade covariate and the groundwater extraction use. The August MFJD covariate with the largest absolute mean standardized coefficient estimate was elevation. This was followed by the interaction between the main channel slope and average baseflow recession coefficient, and the retained shade covariate. Catchment area was the largest absolute mean standardized coefficient estimate in the September MFJD suite of models followed by elevation and then groundwater extraction use. In the SFNR August and September model suites, catchment area had the largest absolute standardized coefficient estimate followed by discharge. In the WR May suite of models, the streamflow volume covariate had the largest absolute value standardized coefficient value followed by the interaction of streamflow with the suite of models' retained shade covariate and the independent shade covariate retained for the model suite. The August WR suite of models had elevation followed by discharge as the two covariates with the largest absolute values for mean standardized coefficient estimates. Elevation was also the covariate with the largest standardized coefficient estimate in the WR Sept model suite, but the second largest coefficient estimate belonged to the suite's shade covariate.

TABLE 5 Covariate AIC-weighted mean standardized coefficient estimates for all eight suites of best fit models.

	MFJD			SFNR		WR		
Covariate	**May**	**August**	**September**	**August**	**September**	**May**	**August**	**September**
air temp.	0.030	0.021	0.065	−0.0002	0.011	0.078	0.068	0.046
area-norm. Q	−0.058	−0.005						
area-norm. Q:air temp.	0.004	−0.00004						
area-norm. Q:shade-1hr		0.002						
area-norm. Q:shade-clearDNI4hr	−0.078							
avg baseflow rec. coef.		−0.001		−0.052				
avg hydraulic cond.				−0.001		0.014	−0.005	
BFI					−0.014			
catchment area	−0.144	0.012	0.190	0.575	0.212	0.0005	0.074	
clear DNI						−0.187		
elevation	−0.118	−0.040	−0.129	−0.094	−0.063	−0.081	−0.133	−0.183
geothermal				−0.025			0.005	
GW use	0.1668	−0.001	−0.112	−0.0004	−0.017	0.00002	−0.00003	−0.023
crop H_2O loss	−0.009	0.0001	−0.005	0.004	0.007			
latitude		0.010		0.001		−0.001		
mc slope		−0.021	−0.003	0.007	−0.0004	−0.0001	−0.015	−0.004
mc slope:avg baseflow rec. coef.		−0.033	−0.091	−0.014			0.004	
mc slope:avg hydraulic cond.						−0.030		
mc slope:geothermal							−0.019	−0.130
mc slope:prop. high HC							−0.0004	
net water loss						−0.009		−0.019
precipitation		0.0002	−0.003				−0.039	−0.001
prop. high HC	0.002							
prop. lakes	−0.003	−0.0002				0.0002	0.038	0.044
Q		−0.008	−0.042	−0.463	0.089		−0.127	
Q:air temp.		−0.002	−0.045	−0.067	0.072		−0.0003	
Q:shade-12hr				0.111				
Q:shade-1hr		0.002	0.013					
Q:shade-2km							−0.017	
Q:shade-3km					−0.087			
slope	−0.049			0.0003	0.001	−0.0002		
slope:BFI								0.015
slope:prop. high HC	−0.261							
shade-12hr				−0.008				
shade-1hr		−0.031	−0.091					−0.134
shade-2km							−0.061	
shade-3km					0.002			
shade-clearDNI4hr	0.1675							
stream flow	−0.053	−0.001				−0.281		−0.088

(Continues)

TABLE 5 (Continued)

	MFJD			SFNR		WR		
Covariate	May	August	September	August	September	May	August	September
stream flow:air temp.	0.002					−0.004		−0.005
stream flow:clear DNI						0.198		
stream flow:shade-1hr		0.0003						−0.001
stream flow:shade-clearDNI4hr	−0.064							
SW use	0.010	−0.0003	0.023	−0.002	0.002			

Note: Larger absolute values indicate greater influence on predicted stream temperature values within a model suite (within a column). Values not directly comparable between model suites (among columns). The largest three absolute value magnitude coefficient estimates are highlighted in shades of gray. The darkest gray is the largest absolute magnitude estimate value in the model suite and the slightly lighter shades of gray are the second and third largest absolute magnitude values, respectively. Covariate names as described in Table 3.
Abbreviations: MFJD, Middle Fork John Day; SFNR, South Fork Nooksack River; WR, Wind River.

4 | DISCUSSION

The models developed in this study identified regional (similar across study areas) and local (unique to each study area) relationships between site attributes and stream temperature. Changes in the model structure among months also provided a quantitative evaluation for how site attributes relate to stream temperature through time within a study area. Our inclusion of management-related covariates in the model development process was compared in terms of their relative importance in the model suites to the non-management-derived site attributes. Furthermore, these management covariates could be used to directly inform and compare alternative management and restoration activities in the future.

4.1 | Retained covariates and their use in other temperature models

The common covariates retained in all (or nearly all) eight suites of models, spanning study area and month, indicate their relationships to stream temperature may be independent of location and time. Elevation was the only ubiquitous covariate. For decades, elevation (or altitude) has been used as a predictor or classification metric for characterizing stream temperature/thermal regimes (Hynes, 1960; Smith, 1972). The next five most important covariates across all suites of models in this study were air temperature, catchment area, main channel slope, discharge, and groundwater extraction use. These covariates (and elevation) are all factors Caissie (2006) identified as influencing stream temperature. Air temperature, catchment area, and discharge are common covariates used in stream temperature models (Detenbeck et al., 2016; Figary et al., 2021; Isaak, Wenger, et al., 2017; Jackson et al., 2018).

Air temperature is regularly used in statistical stream temperature models as a stochastic parameter to predict stream temperature (Caissie, 2006) and this is how air temperature functioned in our SSN models. Consequently, air temperature predictions for alternate climate scenarios (e.g., Intergovernmental Panel on Climate Change future air temperature predictions [Collins et al., 2013]) can be used to make predictions for stream temperature under those same alternate climate scenarios (e.g., Isaak, Wenger, et al., 2017). These predictions can help identify potential habitat loss or habitat at higher risk of being lost (based on upper thermal tolerances) in future decades (Fuller et al., 2022; Isaak et al., 2018).

Our discharge covariate also functioned as a stochastic parameter. The Miller et al. (2018) dataset provides spatially explicit estimates of discharge for each flow line or stream reach in the NHDPlus V2 hydrography network and covers the historical period of 1950–2015. This provides more precise (in both space and time) discharge estimates for our observation sites than previous SSN models that did not have access to spatially explicit discharge data in ungauged basins and generalized across a study area (Detenbeck et al., 2016; Isaak, Wenger, et al., 2017).

The model selection process in our study retained different shade and solar radiation covariates among the model suites that suggests local variation in how shade affects stream temperature. For example, the MFJD study area retained three different shade covariate derivations for the suites of models in May, August, and September (Figure 2; Table 4). The difference in shade covariates retained through time from May to August to September (travel time upstream shade buffers of 4, 1, and 1 h, respectively) might suggest that the upstream influence and integration of shade upstream contracts through the growing season. Further investigation would be necessary to tease out why shade integration upstream changes between the months, but this is largely consistent with the thermal inertia relationship between temperature, discharge, and depth in streams (Gu et al., 1998), and could also be influenced by seasonal changes in canopy cover not reflected in vegetation assessments from a single point in time. There are additional management options to explore related to riparian buffer widths (and their regulation) that may affect how upstream shade integration is related to stream temperatures.

The upstream extent of riparian shade's influence on stream temperature has been evaluated in Europe (Kalny et al., 2017) and North America (Figary et al., 2021), but more often shade is only measured or estimated at the point of temperature observation (Wawrzyniak et al., 2017). Our use of upstream shade buffers is an attempt to look at the integration of conditions that parcels of water encounter prior to mixing and being measured at an observation point. The travel time upstream shade buffer metric specifically incorporates hydrology into the solar energy input covariates. This contrasts with just using an arbitrary upstream distance which ignores the timing of different pathways a parcel of water might take prior to reaching an observation site (i.e., coming from a side tributary or from the mainstem upstream). The influence of many factors including water residence time or flow velocity plays important roles in how far upstream different parcels of water come from when integrating upstream via travel time.

We tested and used the same upstream buffer shade integration process as Figary et al. (2021) who also found different upstream buffer integration metrics across months in their eastern North America study system. The difference in upstream buffer metrics (distances or travel times) likely reflects the different study system characteristics and would also prescribe different management activities. With longer travel time buffers explaining more of the variation in stream temperature, we would expect that management of that system would require focusing riparian vegetation management farther upstream than in locations with shorter travel time shade buffers. Additionally, an upstream buffer distance or travel time could shift temporally and be seasonally dependent. These types of details provide managers with more reasonable expectations for whether riparian management should expand or contract upstream from a restoration site.

4.2 | Relatively important interaction terms

Several interaction terms were important across models which included the interaction of (1) main channel slope with baseflow recession coefficient and (2) discharge with air temperature. The main channel slope by baseflow recession coefficient interaction provides a link between the residence time of water in the river channel (main channel slope effect) and the permeability of surficial sediments in the upstream catchment of a site. Main channel slope has also been described as characterizing the relative vertical gradients that run parallel to the reach (Rosgen & Silvey, 1996). The importance of the interaction between the baseflow recession coefficient and main channel slope, therefore, reflects how the influence of the overall gradient of an upstream catchment also depends on surface–subsurface exchange rates in the surficial sediments (what the baseflow recession coefficient represents in these systems [Janisch et al., 2012; Thomas et al., 2013; Vogel & Kroll, 1992]). The interaction between main channel slope and baseflow recession coefficient has been retained in other SSN temperature models (Detenbeck et al., 2016; Figary et al., 2021).

The air temperature to discharge interaction term can be characterized as a moderating parameter explaining the influence of air temperature on stream temperature in terms of the relative thermal capacity of a stream as a result of changing discharge magnitude. For instance, air temperature is more likely to have a thermal influence on stream temperature when the discharge is small because there is less water and therefore a smaller thermal capacity to change. Other statistical temperature modeling efforts have tested this interaction term but have not found it to be as important or significant a predictor as in this study (Figary et al., 2021; Isaak et al., 2012).

4.3 | Management-related covariates

From a management perspective, our results indicate that shade- and discharge-related restoration activities will likely have the largest impact on stream temperatures. Shade- and discharge-associated covariates were among the three largest standardized coefficient estimates in seven of the eight model suites. When making predictions using these suites of models, small changes to these discharge and shade covariates will impart greater changes to stream temperature than most of the remaining covariates in the suites of models. Therefore, our model selection process and this interpretation of the AIC-weighted mean standardized coefficient estimates can point toward which covariates are most sensitive to changing stream temperature in each basin and between months within a basin. For example, in the MFJD May and August model suites included shade covariates among the top three largest standardized coefficient estimates but September's suite of models did not. This could be an indication that shade restoration would provide a larger impact on stream temperature in May and August than in September. An alternative interpretation would be that another parameter becomes more influential in September than shade that has low relative importance during the other months. In the MFJD September model groundwater extraction for public supply use is among the three covariates with the largest coefficient estimates and therefore may be more important for stream temperatures in September than shade. Our model selection process, therefore, can help determine what type of impact different restoration activities may provide and when implementing them could be most influential in the study system. For the MFJD, these results might indicate that reducing groundwater extraction in September is a useful management activity to explore at the end of the growing season.

Irrigated cropland water loss was a management covariate retained by five of the eight model suites but had neither a high relative importance nor large absolute magnitude mean standardized coefficient estimate value. This result could be due to uncertainty with the covariates estimated values from their development or an artifact of how this management covariate was incorporated into the modeling process. Additionally, there may not have been an adequate coverage of irrigated cropland in each basin to derive a meaningful relationship with stream temperature in our study areas.

We introduced management-related covariates (except shade) at the end of the model selection process (step four). This allowed management covariates to be retained when they may have provided only a little explanatory power to the model, but also did not hurt the model fit. This allows the final suite of models the ability to make predictions that might reflect temperature changes when different management actions are taken. We wanted our model selection process to retain as many management-related covariates as possible in our model suites, which is why we chose to incorporate them last in the model selection process. This final step for management covariates could be skipped or blended into earlier steps in future adaptations of this model selection process if predictions for management activities are not a specific goal of the study.

4.4 | Future use of our modeling process

Our modeling process could be used in a few ways. First, the specific models for temperature we developed in this study could be used to make temperature predictions of various management actions in our study areas. Second, these predictions could be compared to the process-based models that exist for the same study areas' mainstem reaches so see how they compare. Third, the modeling process as a whole, could be reused with a different response variable besides temperature in stream networks with other water quality management concerns. We elaborate on these three future research pathways below.

Our model selection process is one of the first applications of SSN models using a full scope of predictors for restored temperature simulation and watershed-scale covariate derivation (but see Marsha et al., 2021 for another recent example). The suites of models for our study systems could be used to make model-averaged predictions (Burnham & Anderson, 2002) to generate continuous stream network temperature predictions for each study system. Predictions could then be used alongside scenario planning to explore stream temperatures under different management or restoration activities based on the management covariates retained in our model selection process. Management activities that could be explored are channel width restoration, cropland irrigation water loss reduction, reduced groundwater extraction, or riparian vegetation shade restoration (all activities identified in temperature TMDLs for the three study basins [Butcher et al., 2010; Kennedy & Butcher, 2012; Pelletier, 2002]). Scenario planning could also include combined management activities when two or more actions are considered. These scenario predictions could help assess the restoration potential of each individual or combined management option to meet essential fish habitat state water quality thermal criteria (Fuller et al., 2022). We have provided example R scripts and datasets for a study area and month (see Data Availability section) to support future research along these lines.

A second potentially productive future research pursuit could compare and combine model-averaging predictions with process-based model predictions within the same study system. Each of our study areas have temperature TMDLs with mechanistic models for the mainstem reaches. Comparing predictions from the mechanistic model with that of the model-averaged SSN suite of models will show how and where each model type excels and struggles (Lee et al., 2020). For example, the mainstem mechanistic models used in the TMDLs have a spatial resolution focused at the 100-m reach scale and a temporal resolution of 1 h, while SSN models are often set to a 1-km reach scale and monthly time step. Despite the finer spatial and temporal resolution of the mechanistic models, they are only built for the mainstem reaches, which limits their spatial coverage in the system and ignores tributaries. The SSN predictions across the network could inform the tributary boundary conditions for the mainstem mechanistic models and offer a means for the two model types to work together. Combining the two model types would provide additional support for tracking fine spatial and temporal scale cold water habitat along the mainstem and spatially extensive cold water habitat across the network.

A third use of our modeling process could apply the model selection process to new study areas. If the same set of site attribute covariates are used as in this study, direct comparison with our three study areas could extend the temperature evaluation of regionally and locally important covariates. This would be a straightforward research pursuit when using the R scripts we developed and provide on EPA's ScienceHub (a publicly accessible dataset and code site for EPA products—see Data Availability section) following publication. Alternatively, the new study areas for comparison could use a subset, entirely new set, or combination of covariates in the model selection process steps to tailor suites of models to their specific study systems and relevant management activities.

4.5 | Modeling process considerations

The modeling process we have developed includes some potential limitations to consider when reusing our steps or modifying them for a new purpose. One important consideration is SSN models require large observed temperature datasets ($n > 50$) to maintain adequate statistical

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power to include autocovariance functions and several fixed effect covariates (Isaak et al., 2014). In our study, the SFNR month of May was absent because we did not have the suggested minimum number of observed temperature sites for us to confidently fit models with our process. For the remaining study basins, we were able to increase our observed temperature data by expanding the spatial coverage of our models to include adjacent tributary networks until a suitable dataset existed. This extent expansion was still unsuccessful in the SFNR in May. Other studies have increased observed data availability by including multiple years of data at a single site location by using "site" and "year" as random effects in their SSN model structures (Isaak, Wenger, et al., 2017). We chose not to take this approach in our study. Therefore, available observed data should be an important consideration for small or sparsely monitored systems before building SSN temperature models.

Model selection processes such as stepwise regression or exhaustive model/best subsets selection are often criticized for (1) their unguided thought process (i.e., letting the data identify patterns instead hypothesizing a priori model structures to test), (2) the best selected model's tendency to have inflated R^2 values, (3) potential multicollinearity effects (i.e., model parameter estimates/standard error instability), and (4) over parameterization of models (Burnham & Anderson, 2002; Harrell, 2001; Rencher & Pun, 1980). While our model selection process employs aspects of stepwise regression and best subsets analysis, we made careful decisions in developing our model selection process to address and minimize these potential criticisms. First, rather than selecting an individual "best" model from our selection process, we arrive at a final suite of best models that use model averaging for predictions and multimodel inference statistics to evaluate covariate relationships to the response variable. Model averaging is best suited when prediction is a primary goal of a model selection process (as in this study) (Burnham & Anderson, 2002). However, multimodel inference is still possible with a suite of models and leverages the weight of evidence for each covariate present in the suite of models rather than relying on the presence–absence dichotomy for covariates when using a single model (Burnham & Anderson, 2002). These advantages are limited, though, when multicollinearity exists within the covariate set (Cade, 2015). A thorough correlation analysis of the covariates tested in our model selection process for each basin and month is provided in the supplementary files (Data S5) to detect potential collinear covariates used in our model selection process. Covariates with high correlations ($r > 0.7$) and potentially indicative of multicollinearity presence (Dormann et al., 2013) were present, but rare among our covariate set. These limitations from multicollinearity are not extended to the model-averaged predictions, however, only their coefficient estimate interpretation (Harrell, 2001).

One caveat to the temporal comparisons in our modeling process to consider is the variation in observation sites from month to month. Because SSN models assess and account for spatial autocorrelation based on observation site relationships, if you have different sets of observation sites from 1 month to another, it is possible for covariates to have slightly different relationships with temperature due to the site-based autocorrelation relationships. Therefore, the best way to assess temporal change would be to use the exact same set of sites across all time points (monthly models in this study).

Another consideration to make with the modeling process surrounds how covariates are developed for the model fitting process. Depending on the process being linked to stream temperature, capturing that process or relationship in a covariate for the model can range from simple to complex. Indirect relationships (e.g., the effect on stream temperature from water loss off irrigated cropland) are likely more difficult to capture in a covariate than direct relationships (e.g., the effect of direct solar radiation on the stream water surface). This also extends to relationships that are more or less heavily investigated in the literature and therefore more tightly or loosely linked. Part of the modeling process experimentation is testing new and alternate ways to characterize these relationships. Our methods for evaluating the influence of shade integrated across upstream distances and travel times are one means for exploring new covariate developments for this parameter which is often only considered at the local observation site. Additionally, this type of covariate development provides more direct management advice since it suggests the range of upstream riparian shade condition that is relevant for maintaining a stream temperature for a given study reach.

5 | CONCLUSIONS

This study has produced a model selection process that provides directly comparable suites of models for different study areas and times of year that can be used with a variety of response variables. In testing the process among three study areas, site attributes were identified that had strong relationships with stream temperature that were location independent. Relationships between study area shade attributes were also determined, and these relationships were shown to shift through time. The inclusion of management-related covariates allowed us to explore the relative importance of restoration activities in each study system and provides a means for evaluating the theoretical stream temperature response from modifying one or more of those activities in our study areas. Finally, potential future research ideas were provided for the modeling process and for the specific suites of models developed during model selection process test. These future research avenues could (1) apply this model selection process in new study areas to investigate stream temperature (or other response variables that SSN models may be used to predict), (2) further tease out relationships between site attributes and stream temperature within these three study areas, (3) begin scenario planning for future restoration and management activities, or (4) make comparisons between statistical temperature models developed during this process with mechanistic models previously developed for these three study basins.

AUTHOR CONTRIBUTIONS

Matthew Fuller: Conceptualization; data curation; formal analysis; methodology; project administration; software; validation; visualization; writing – original draft; writing – review and editing. **Naomi Detenbeck:** Conceptualization; data curation; formal analysis; funding acquisition; methodology; project administration; resources; software; supervision; writing – original draft; writing – review and editing. **Peter Leinenbach:** Conceptualization; data curation; formal analysis; methodology; validation; writing – review and editing. **Rochelle Labiosa:** Conceptualization; funding acquisition; project administration; supervision; writing – review and editing. **Dan Isaak:** Data curation; methodology; writing – review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest relevant to this study.

DATA AVAILABILITY STATEMENT

Data and R scripts used in this work will be available via U.S. EPA's ScienceHub (permanent DOI: https://doi.org/10.23719/1524755) once EPA's data release review process is complete.

ORCID

Matthew R. Fuller https://orcid.org/0000-0002-9147-5110
Naomi E. Detenbeck https://orcid.org/0000-0002-9868-0475
Daniel Isaak https://orcid.org/0000-0002-8137-325X

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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