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ARTICLE

A Simple Prioritization Tool to Diagnose Impairment of Stream Temperature for Coldwater Fishes in the Great Basin

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Abstract
We provide a simple framework for diagnosing the impairment of stream water temperature for coldwater fishes across broad spatial extents based on a weight-of-evidence approach that integrates biological criteria, species distribution models, and geostatistical models of stream temperature. As a test case, we applied our approach to identify stream reaches most likely to be thermally impaired for Lahontan Cutthroat Trout *Oncorhynchus clarkii henshawi* in the upper Reese River, located in the northern Great Basin, Nevada. We first evaluated the capability of stream thermal regime descriptors to explain variation across 170 sites, and we found that the 7-d moving average of daily maximum stream temperatures (7DADM) provided minimal among-descriptor redundancy and, based on an upper threshold of 20°C, was also a good indicator of acute and chronic thermal stress. Next, we quantified the range of Lahontan Cutthroat Trout within our study area using a geographic distribution model. Finally, we used a geostatistical model to assess spatial variation in 7DADM and predict potential thermal impairment at the stream reach scale. We found that whereas 38% of reaches in our study area exceeded a 7DADM of 20°C and 35% were significantly warmer than predicted, only 17% both exceeded the biological criterion and were significantly warmer than predicted. This filtering allowed us to identify locations where physical *and* biological impairment were most likely within the network and that would represent the highest management priorities. Although our approach lacks the precision of more comprehensive approaches, it provides a broader context for diagnosing impairment and is a useful means of identifying priorities for more detailed evaluations across broad and heterogeneous stream networks.

The human-caused warming of temperature in stream ecosystems is widespread and viewed as a major threat to coldwater fishes (Poole and Berman 2001; Olden and Naiman 2010). The impairment of stream water quality owing to excessive warming is often diagnosed by applying biological temperature criteria, typically based on thresholds linked to physiological stress or decreased survival associated with increased temperature (e.g., Brungs and Jones 1977; Armour 1991). For example, when formerly cold streams warm to exceed values specified by biological temperature criteria we can expect a greater probability of physiological stress or mortality for coldwater biota. Although this approach to diagnosing water quality impairment appears sensible enough and is relatively straightforward to apply, further examination has

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revealed several important shortcomings. First, a single biological criterion or limited set of criteria may not fully protect the range of temperatures that fish require (McCullough et al. 2009). Compounding this issue is the diversity of conditions represented by thermal regimes (Arismendi et al. 2013) and the likelihood that the application of overly simplistic criteria will misdiagnose water quality impairment (Poole et al. 2004). Finally, there is the problem of identifying locations where species protected by biological temperature criteria should be expected to be present, as this dictates where criteria are applied.

Biological temperature criteria are difficult to specify for stream fishes because most species require a variety of habitats in which to spawn, rear, and take refuge from harsh environmental conditions, including variable temperature (Schlosser and Angermeier 1995; Falke and Fausch 2010). The effects of temperature can be specified in terms of acute or chronic exposure. Acute exposure to brief excursions of temperature outside of the species' physiological range can lead to immediate stress or death. Over longer time frames, chronic exposure to temperature with sublethal effects on behavior, growth, disease resistance, or a variety of other responses (McCullough et al. 2009) can be a concern. Therefore, it may be unreasonable to expect that a single criterion or limited set of criteria could successfully ensure that thermal requirements are met across habitat types and life stages. Compounding this issue is the vast number of ways in which thermal regimes can be described, which include the magnitude, frequency, duration, and timing of temperature across seasons and throughout the year (Arismendi et al. 2013). Failure to consider such patterns of thermal variability may have obvious biological consequences (Poole et al. 2004; Olden and Naiman 2010), but important physical consequences are likely as well. For example, the application of point estimate biological criteria alone could (legally) allow cold streams to be warmed even if the criteria are not exceeded or could misdiagnose streams that are not naturally cold as impaired (Poole and Berman 2001; Poole et al. 2004). Identifying where biological temperature criteria should be applied is yet another challenge, but in many cases reliable maps or models of species distributions are available and can be useful in this regard. Given the considerations discussed here, it is clear that approaches that seek to address more than just biological temperature criteria are more likely to lead to satisfactory management outcomes (see also Poole et al. 2004; McCullough 2010).

Our overall objective in this study was to develop a practical approach for diagnosing the impairment of stream water temperature for coldwater fishes across broad spatial extents by recognizing that multiple lines of evidence, not solely biological criteria, may be most useful. To do so, we considered three lines of evidence. The first step in diagnosing impairment is to consider the likelihood that the observed water temperature is causing physiological stress to the species of interest. This involves the evaluation and application of biological temperature criteria. With this template in place, our next step was to define where a species could be found (i.e., geographic range) and what temperatures should be expected to occur within that area to support the species of interest. In our application, this involved mapping the potential range of our focal species. The final step was to provide a means of evaluating the likelihood that stream temperature was warmer than expected, relative to some baseline. Ideally, such an evaluation would involve the use of a fully parameterized heat budget model (e.g., Cox and Bolte 2007; Diabat et al. 2012), but this approach is impractical when considering many sites across a broad extent; statistical models of stream temperature may prove more useful (Isaak et al. 2010; Falke et al. 2013; Jones et al. 2014). Together, these lines of evidence were combined to diagnose the impairment of stream temperature for aquatic biota (Figure 1).

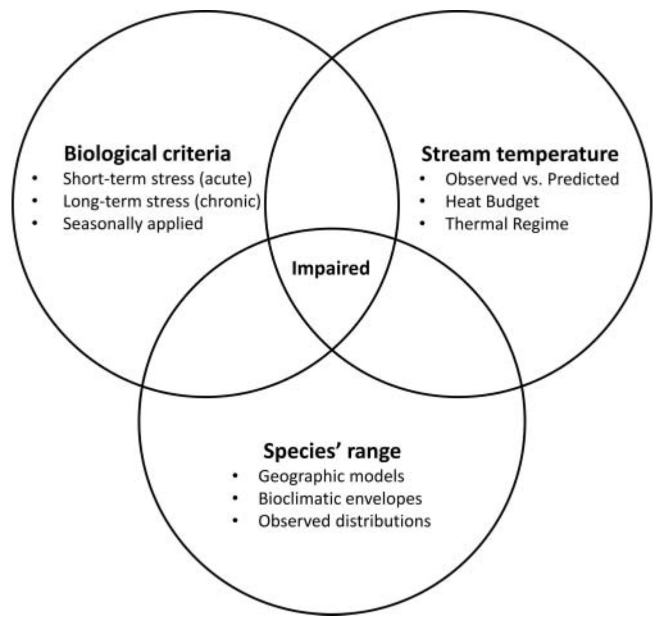

FIGURE 1. Illustration of the three lines of evidence used to diagnose impairment of stream temperature. Biological criteria refer to thresholds based on physiological responses of fish to temperature. These can be specified as short-term or acute exposures (≤1 d) or chronic (≥7 d) exposures to temperature (e.g., minimum, maximum, mean, or other). Biological criteria can apply to different seasons of the year to cover different uses or life stages of fish. Stream temperature refers to spatial or temporal patterns of temperature as related to factors that influence the heat budget of streams or statistical associations with factors linked to heat budgets (e.g., elevation). Species' range refers to the potential extent of a species distribution in the absence of thermal impairment or other local constraints (e.g., movement barriers, nonnative fishes). Intersections between two of the three lines of evidence indicate questions related to uncertainty about the third. For example, if biological criteria are satisfied and observed and predicted temperatures are similar, then questions remain regarding whether a given location is actually within a species' range. For sites within a species' range, attainment of biological criteria leaves questions about thermal potential, whereas attainment of thermal potential leaves questions about meeting biological criteria. In concert, all three lines of evidence provide the strongest inference for evaluating the likelihood of impairment of stream temperature.

We evaluated the case of Lahontan Cutthroat Trout *Oncorhynchus clarkii henshawi* in the northern Great Basin of the western USA to provide an example of our proposed approach for diagnosing patterns of stream temperature impairment (Figure 1). This region represents a vast and remote landscape, where the range of native salmonids is constrained by topographic and geographic gradients and associated in-stream conditions (temperature and desiccation; Platts and Nelson 1989; Dunham et al. 1999; Warren et al. 2014). To address these constraints, we first considered existing biological temperature criteria developed specifically for Lahontan Cutthroat Trout to evaluate thermal impairment. Next, we applied an existing model (Warren et al. 2014) to identify streams that occurred within the expected range of the species and modeled spatial patterns of temperature within these streams using a geostatistical model (Peterson et al. 2013; Isaak et al. 2014) with elevation as the covariate to account for longitudinal patterns of warming. This allowed us to track longitudinal changes in temperature, with a positive difference between the observed–predicted temperatures indicating potential instances of localized warming. Finally, we combined the three lines of evidence resulting from these analyses to diagnose patterns of potential impairment across a Great Basin riverscape in central Nevada.

METHODS

*Study area.—*The Great Basin includes a large arid region in the western USA comprised of several distinctive endorheic basins (i.e., basins which have no current outlet to the sea; Grayson 2011). To evaluate biological criteria for our study species, we focused on streams in the eastern Lahontan portion of the Great Basin (Hubbs and Miller 1948), which comprises the native range of Lahontan Cutthroat Trout, with additional sites in the nearby Jarbidge River basin (Figure 2). Lahontan Cutthroat Trout is listed as a threatened species under the U.S. Endangered Species Act (USFWS 2008).

The application development portion of our study was centered on the upper Reese River basin (Figure 2 inset), which comprises the southern edge of the distribution of Lahontan Cutthroat Trout in the eastern Lahontan basin. This network of streams originates high in the federally protected Arc Dome Wilderness (3,591 m in elevation), the largest natural area within the state of Nevada (U.S. Forest Service, Humboldt National Forest). From their headwaters, these streams flow down into lower-elevation federal lands managed for multiple uses (U.S. Forest Service and Bureau of Land Management) and through parcels of land under tribal and private ownership. Accordingly, this network represents a gradient of thermal conditions and land management.

Within the upper Reese River basin, Lahontan Cutthroat Trout have been extirpated from all but the upstream-most reaches of a major tributary, Stewart Creek (USFWS 2008). Despite native Lahontan Cutthroat Trout being mostly extirpated, the basin represents a potential opportunity for species recovery and currently supports nonnative Rainbow Trout *O. mykiss*, Brook Trout *Salvelinus fontinalis*, and Brown Trout *Salmo trutta*.

*Biological criteria evaluation.—*Our first step was to consider the likelihood that observed water temperature might cause physiological stress to Lahontan Cutthroat Trout. Our evaluation of biological criteria focused on two key questions: (1) which individual stream temperature descriptors account for the most variation in summer water temperature? and (2) can a single descriptor ensure that other criteria are not exceeded? For the latter question, we compared descriptors describing acute versus chronic and summer versus winter thermal regimes.

Stream temperature data from across the northern Great Basin and the Jarbidge River basin in Nevada were obtained from the Nevada Division of Environmental Protection (NDEP) for 1997–2012 and via our own sampling in the upper Reese River basin in 2012 and the Oregon Lakes region in 2012–2013 (Figure 2). These data represented a broad range of variability in climate, elevation, and watershed physiography. Sites suspected to have dried or become intermittent were removed from the analysis, resulting in a total of 219 sites (119 for the NDEP, 51 in the upper Reese River basin, and 49 in the Oregon Lakes region) included in our biological criteria evaluation. All analyses were based on data collected at hourly intervals.

Within the upper Reese River basin, we collected continuous stream temperature data during summer and early fall 2012 (June–October; Figure 2). Hourly temperature was recorded using HOBO Water Temp Pro v2 loggers (Onset, Bourne, Massachusetts). Water temperature loggers were deployed at 51 sites: 28 in the upper Reese River, 21 in Stewart Creek, and 1 logger each was placed a short distance upstream of the confluences of two small tributaries to the upper Reese River, Big Sawmill Creek, and Little Sawmill Creek. Year-round temperature data were collected from 49 sites in the Oregon Lakes region during 2009–2011. Calibration and field deployment of temperature loggers in the upper Reese River basin and Oregon Lakes region datasets followed guidelines outlined in Dunham et al. (2005).

*Summer thermal regime variability.—*Next, we evaluated the capability of a variety of stream thermal regime descriptors to explain variation. We identified descriptors commonly used to characterize the thermal regimes of streams during summer months that represent five aspects of a stream's thermal regime: magnitude, variation, frequency, duration, and timing (Arismendi et al. 2013). Subsequently, summer water temperature descriptors were calculated for the NDEP and upper Reese River basin sites (Figure 2; $n = 170$) using a custom script in Program R (R Core Team 2012). Based on an initial examination of the data, the period of July 1 through August 30 was chosen as the period of analysis (hereafter referred to as summer). See Supplementary Table S.1 in the online

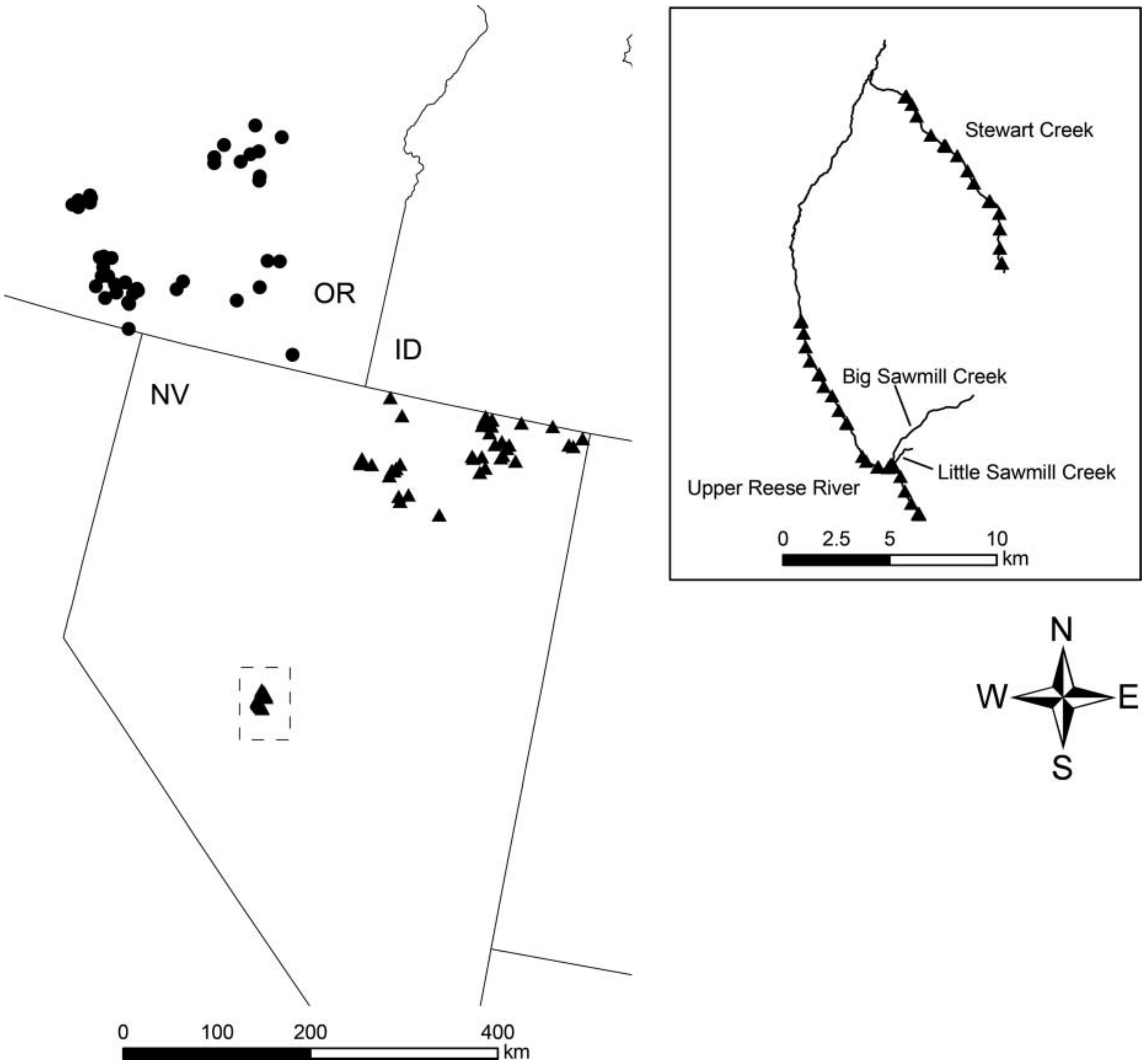

FIGURE 2. Map of the locations of all the sites sampled for stream temperature in the northern Great Basin, with symbols indicating the sites used in the analysis of summer (July–August) versus nonsummer 7-d moving average of daily maximum stream temperatures (October–May; circles) and of summer chronic and acute criteria and among-descriptor redundancy (triangles). Sites in the upper Reese River and Stewart Creek that were included in the spatial stream network model are shown in the inset.

version of this article for a list of descriptor definitions and how the descriptors were calculated.

Principal components analysis (PCA) was performed on the correlation matrix of water temperature descriptors calculated for each site to examine dominant patterns of intercorrelation and describe the major sources of variation while minimizing redundancy among the descriptors.

The correlation rather than the covariance matrix was used for this study because the descriptors themselves, not the sites, were the focus of the analysis, and this method ensured that all descriptors contributed equally to the PCA and were scale-independent (Legendre and Legendre 1998). The statistical significance of PCA axes was evaluated using the broken-stick method, for which observed eigenvalues are compared with randomly generated values (Jackson 1993). Descriptors were ranked by thermal regime aspect (see above) for each significant axis. Descriptors with the highest loadings were considered to explain the dominant pattern of variation in thermal regimes.

Descriptor exceedance likelihood.—Because specific temperature criteria for Lahontan Cutthroat Trout do not currently exist for Nevada, we used criteria developed by the state of Oregon (State of Oregon 2015; Table S.2) to evaluate whether a single biological temperature criterion could act to ensure that other criteria were not exceeded. The Oregon criterion specifies that temperature to support Lahontan Cutthroat Trout shall not exceed 20°C at any time of the year, as indicated by the 7-d moving average of daily maximum temperatures

(7DADM). As used here, 7DADM refers to the warmest 7-d average of daily maximum temperatures observed for a defined span of time (e.g., a month, season, or year). This quantity is calculated with slightly different methods in the different states that use this descriptor. For example, in Idaho the weekly mean of daily maximum temperatures is calculated over a consecutive 7-d period ending on the day of calculation, whereas in Washington the weekly mean of daily maximum temperatures is calculated using 3 d preceding and 3 d following the day of calculation included in the weekly summary (Table S.2). We used the latter method here.

We next evaluated whether a single descriptor could ensure that other criteria were not exceeded through an assessment of chronic versus acute criteria applied during the summer (defined herein as July–August) and during the reproductive season (October–May; Todd et al. 2008). We used logistic regression to predict the probability during summer of exceeding an acute thermal stress descriptor, the daily maximum temperature (DM), conditional on the 7DADM, to evaluate if the 7DADM prevents unacceptable exceedance of DM temperatures of 20, 22, 24, and 26°C. This analysis was conducted on the NDEP and upper Reese River basin datasets (total $n = 170$ sites).

We also used logistic regression to model the probability of exceeding a 7DADM of 12, 13, 14, or 15°C from October–May as a function of the maximum 7DADM in the same water year (October–September) to evaluate if the summer (July–August) 7DADM is protective of the water temperature required during the reproductive season for salmonids. These thresholds cover the range of criteria considered by some states to be protective of salmonid spawning (Table S.2). This analysis was based on the Oregon Lakes region ($n = 49$ sites) dataset.

Species range.—The next step in our prioritization process was to determine the range of Lahontan Cutthroat Trout within our study area. We applied a geographic distribution model of species' range developed by Warren et al. (2014) to evaluate the potential range of salmonids within the Reese River basin. This model predicts the lower elevation of salmonid distributions in stream networks based on latitude and longitude. The model was parameterized using empirical, georeferenced surveys of fishes conducted over several decades (1953–2010), reflecting a broad spectrum of spatial and temporal hydroclimatic conditions in the northern Great Basin. Predictions from this model represent downstream elevations above which 95% of salmonid presence would occur in warmer months (July 1 to September 30; Warren et al. 2014). For the purpose of this study, we applied the distribution model corresponding to Lahontan Cutthroat Trout.

Stream temperature.—We assessed spatial variation in the upper Reese River basin dataset to evaluate the likelihood that stream temperature is warmer than expected, relative to some baseline, using a spatial stream network model (SSN; Ver Hoef et al. 2006; Peterson and Ver Hoef 2010; Ver Hoef and Peterson 2010). This spatial linear-mixed model allows for relaxation of the assumption of independence among observations (i.e., spatial dependency) and spatial autocorrelation in the errors. Thus local (i.e., at a site) deviations in the response from the overall mean are modeled using the covariance between nearby sites, based on the stream distance (i.e., hydrologic distance along the stream) separating them. This approach ensures that parameter estimates reflect the appropriate amount of uncertainty and, by incorporating spatial relationships (i.e., autocorrelation), allows for improved local predictions and uncertainty estimates at unsampled locations (Cressie 1993; Peterson et al. 2013; Isaak et al. 2014). An SSN model of 7DADM (July 1 to August 30, as above) as the response variable and elevation (m) as a fixed-effect covariate was fit using data from the 51 sites sampled within the upper Reese River. Elevation for each site was taken from a 10-m digital elevation model for the region (Dollison 2010).

Hydrologic distances (km) were estimated based on a digital stream network created using the Functional Linkage of Waterbasins and Streams (FLoWS) toolbox (Theobald et al. 2006) for ArcGIS version 9.3 (ESRI 2009) based on the 1:100,000 scale National Hydrography Dataset (NHDPlus) digital hydrography (McKay et al. 2012). Spatial weights were based on upstream watershed areas (km^2) for each stream reach in the network taken from the NHDPlus and incorporated into the SSN object using the Spatial Tools for the Analysis of River Systems (STARS) version 9.3.1 geoprocessing toolbox. Preliminary analysis based on Akaike information criterion model selection (Akaike 1973; Burnham and Anderson 2002) indicated that a two-tailed (i.e., tail-up and tail-down) linear-with-sill moving-average autocovariance function best fit the data (see Ver Hoef and Peterson 2010 for examples). The SSN model was fit using the SSN package (Ver Hoef and Peterson 2013) in Program R (R Core Team 2012). The FLoWS, STARS, and SSN packages are freely available (USFS 2015).

Diagnosis of potential impairment.—We evaluated the potential impairment of stream temperature in the Reese River–Stewart Creek network (upper Reese River basin) based on the framework proposed herein (Figure 1). First, we evaluated the potential for sites to support salmonids based on species distribution models (Dunham et al. 2002; Warren et al. 2014). Sites within the potential range of salmonids were evaluated with respect to (1) their expected and observed temperatures, based on predictions of the SSN model, and (2) conformance to biological temperature criteria (≤20°C 7DADM; see Results). Stream temperature at each observed site was evaluated using a leave-one-out cross validation (LOOCV), whereby a single site was excluded from the dataset and the SSN model was fit with the remaining data (Wenger and Olden 2012). Predictions from this resulting model were applied to the excluded site and the resulting difference between the predicted and observed temperature was calculated. If the observed temperature was warmer than predicted, we interpreted this as a potential case of excessive warming or impairment that would require further investigation (e.g., an evaluation of site conditions that could contribute to warming). We defined a site as significantly warmer than predicted if the difference between the predicted and observed 7DADM exceeded the range of associated prediction error (defined by root mean square prediction error). Similarly, sites with temperatures exceeding the thresholds specified by biological temperature criteria were considered as potentially impaired. Finally, we used the SSN model to predict 7DADM every 0.5 km throughout the upper Reese River and Stewart Creek study area. We then broke the network into reaches that corresponded with the range parameter (i.e., length of stream for which estimates are spatially redundant) estimated by the SSN model and classified each of these reaches with respect to evidence indicating potential impairment (Figure 1).

RESULTS

Summer Thermal Regime Variability

Four principal component axes were statistically significant and explained 81.0% of the variation in summer water temperature descriptors (Table 1). The strength of the PCA is the ability to identify individual descriptors that explain nonredundant variation in summer thermal regimes. The first axis (PC I; 51% of variation explained) represented a gradient in maximum or high temperature descriptors, whereas PC II (13%) represented a gradient in minimum temperature descriptors. In terms of overall variation explained, summer temperature descriptors describing minima, variability in minimum temperatures, frequency of moderate temperatures, and timing of maximum temperatures were ranked highest. The 7DADM descriptor used for this study ranked highly among descriptors describing the magnitude component of a thermal regime. This result indicates that among the descriptors we considered that described the magnitude of thermal variation at a site, 7DADM provides the least among-descriptor redundancy.

Descriptor Exceedance Likelihood

For 170 sites across the Great Basin and Jarbidge River basin, our descriptor representing acute stress during summer (DM) ranged from 16.61°C to 38.17°C (mean = 23.74°C, SD = 4.17) and our descriptor representing chronic stress (7DADM) ranged from 15.71°C to 33.86°C (mean = 22.51°C, SD = 3.83). The summer 7DADM was a nearly perfect predictor of DM during the same time period (simple linear regression, $F = 11{,}670.00$, $P < 0.001$, $r^2 = 0.985$), and the slope and intercept of this relationship were not significantly different than 1 or 0, respectively ($t = 0.6$, $P = 0.41$; $t = -1.78$, $P = 0.09$). All four logistic regressions were highly significant (all $P < 0.002$) indicating that for the range of DM thresholds

TABLE 1. Top three stream temperature descriptors with the largest absolute loadings for each significant principal component (PC I – PC IV) by category. Descriptors with the largest absolute loadings across all four principal components are also presented (Overall column). The eigenvalues and percentage of variance are shown for each significant principal component and the total. See Table S.1 for the definitions of descriptor abbreviations.

Category	PC I	PC II	PC III	PC IV	Overall
Magnitude	WMT95	OVER_MIN	MMAX	OVER_MIN	MMIN
	MWMT	MMIN	WMT5	WMT5	OVER_MIN
	7DADM	WMT5	MMIN	WMT25	7DADM
Variation	RNG	CV_MIN	CV_MN	CV_MIN	SIGMA_MIN
	DELTA_MAX	CV_MN	SIGMA_MN	SIGMA_MIN	SIGMA_MN
	SIGMA_MIN	CV_MAX	CV_MAX	CV_MN	DELTA_MAX
Frequency	SUM_18	SUM_14	WEEK_18	SUM_14	SUM_14
	SUM_22	SUM_22	SUM_22	WEEK_18	SUM_22
	WEEK22	WEEK22	WEEK_14	SUM_22	WEEK_18
Duration	PG15	PG10	DMAX10	DMOV15	DMAX15
	DMAX20	PG5	DMOV10	DMAX15	DMOV15
	PG20	PG15	DMOV20	DMAX10	PG10
Timing	MDMT_DATE	MDMT_DATE	MIN_DATE	MDMT_DATE	MDMT_DATE
	MDMT_ ROLL	MDMT_ ROLL	MIN_ ROLL	MDMT_ ROLL	MDMT_ ROLL
	MIN_DATE	MIN_DATE	MDMT_DATE	MIN_DATE	MIN_DATE
Eigenvalue	23.15	6.07	4.53	2.68	
Percent variance	51.44	13.48	10.07	5.96	81.0

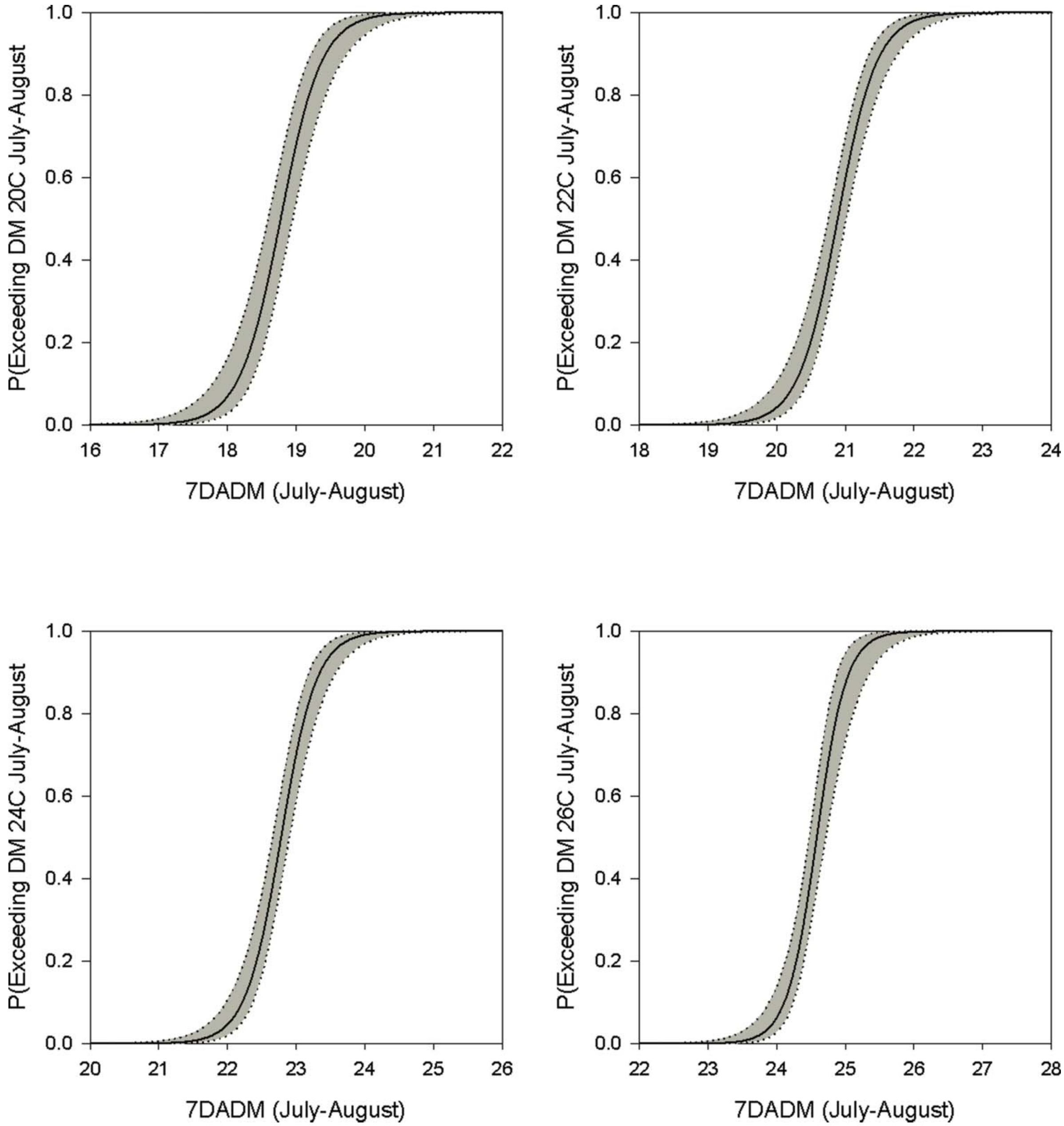

FIGURE 3. Summer (July 1 to August 30) 7-d moving average of daily maximum stream temperatures (7DADM;°C) in relation to the probability of exceeding a summer daily maximum stream temperature (DM) of 20, 22, 24, and 26 °C at 170 sites sampled across the Great Basin and Jarbidge River basin (Figure 2). See the text for the calculation of the 7DADM and DM descriptorKHs. The gray shading represents the 95% confidence interval.

that we analyzed (20–26°C), if 7DADM exceeds that value, the DM will almost certainly as well (Figure 3; Table 2). Therefore, for the range of thermal regimes we analyzed, the 7DADM descriptor is a good indicator of both chronic and acute thermal stress.

The observed summer 7DADM in streams across the Oregon Lakes basins dataset ranged from 11.78°C to 26.38°C (mean = 19.54°C, SD = 3.73), whereas for winter the descriptor ranged from 7.60°C to 16.85°C (mean = 11.55°C, SD = 2.09). Summer (July–August) 7DADM was a significant (all $P < 0.05$) predictor of winter (October–May) 7DADM thresholds set at 12, 13, 14, and 15°C (Figure 4; Table 3). Based upon Oregon's summer criteria for Lahontan Cutthroat Trout (7DADM = 20°C), the likelihoods of exceeding winter 7DADMs of 14°C and 15°C were low (<0.2, including the upper 95% confidence limit; Figure 4), but increased for 12°C and 13°C, with a maximum probability of 0.46 (upper 95% confidence limit) to exceed 12°C. Thus for the dataset we analyzed, the ability of a summer chronic water temperature descriptor to predict winter conditions was dependent on the

TABLE 2. Parameters from the logistic regression models used to predict the probability of exceeding a daily maximum stream temperature of 20, 22, 24, or 26 °C from July 1 to August 31 as a function of the 7-d moving average of daily maximum temperatures (7DADM; see text for calculation) in the same time period (July–August). Data were from 170 sites sampled across the Great Basin and Jarbidge River basin (Figure 2).

July–August 7DADM (°C)	Coefficient	Estimate	SE	z	P-value
20	Intercept	−63.096	18.172	−3.472	<0.001
	7DADM	3.361	0.966	3.479	<0.001
22	Intercept	−73.279	19.745	−3.711	<0.001
	7DADM	3.508	0.943	3.720	<0.001
24	Intercept	−88.735	23.031	−3.853	<0.001
	7DADM	3.895	1.011	3.852	<0.001
26	Intercept	−114.491	37.645	−3.041	0.002
	7DADM	4.657	1.538	3.029	0.002

selected winter threshold. In other words, attaining a suitably cold 7DADM in summer does not guarantee sufficiently cold temperatures in the nonsummer reproductive seasons. For example, under the natural thermal regimes we studied it may be difficult to meet the lowest winter standard (12°C) with a summer 7DADM of 20°C.

Stream Temperature and Species Range

Based on model predictions from Warren et al. (2014), all 51 sites we sampled in the upper Reese River and Stewart Creek were located within a designated habitat patch for Lahontan Cutthroat Trout (Figure 5), indicating that thermal and/or flow conditions in these streams should be expected to potentially support this species. However, based on our observed data and the criterion we applied (7DADM < 20°C), we found that temperatures were exceeded at 29 of the 51 sites (57%); these sites would be classified as impaired if only biological criteria were considered. None of these sites were in Stewart Creek. The SSN model predicted 7DADM as a function of elevation ($t = -2.012$, $P = 0.037$; Table 4). Diagnostics from the LOOCV indicated results of the SSN model had near-zero bias (the mean of observed–predicted values was −0.07, with a 1:1 relationship; Figure 6). Prediction error was estimated to be less than 0.5°C (root mean square prediction error = 0.44). As expected, error in the predictions increased with distance from the observed sites (Figure 5).

Implementation of Prioritization Tool

In the context of our framework for diagnosing potential impairment of stream temperature, 29 of the 51 sampled sites located predominantly in the upper Reese River would be classified as impaired based solely on biological criteria. Of these, 25 were substantially warmer (>2°C) than our selected maximum criterion (7DADM < 20°C). Based on LOOCV, 8 of the 51 sites (16%) were significantly (>0.44°C) warmer than predicted. Combining evidence from both of these lines (since all sites were within the expected range of Lahontan Cutthroat Trout; Figure 5) we found that 3 of the 51 (6%) sites exceeded the biological criteria of 20°C *and* were warmer than predicted, thus providing the strongest evidence for thermal impairment.

We further refined our classification of impairment by applying interpolated 7DADM values from the SSN model. Based on the range parameter estimate from the SSN model, which indicated that 7DADM estimates were redundant to within about 1.5 km of a given site (Table 4), we broke up the stream network into 20 reaches of approximately 1.5 km and categorized each by evidence for impairment, calculating the total length of stream in each of the potential impairment categories (Figure 5). Within the 29.15 km comprising the upper Reese River and Stewart Creek study area, 11.20 km (38%) exceeded the biological criteria of 20°C, and 10.06 km (35%) were significantly warmer than predicted. Overall, 4.90 km (17%) exceeded the biological criteria and were significantly warmer than predicted.

DISCUSSION

Although the prioritization tool we propose here is simple in concept, we found it provides a rapid and relatively low-cost assessment of the potential for the impairment of stream temperature across a stream network. Such approaches are a practical necessity given the vast and remote expanse of the Great Basin and the limited resources available to sample fish or stream temperature. We suspect that the case of the Great Basin is not unique and that there are many areas facing similar challenges with respect to assessing stream temperature. Each of the three lines of evidence we evaluated is limited when considered independently, but applied together each can act as a filter to identify or prioritize the most important sites needing further evaluation for evidence of impairment. Below we discuss the advantages and limitations of the approach we applied here with respect to each of the three lines of evidence.

In our case study, the first line of evidence, the distribution of Lahontan Cutthroat Trout, was not by itself useful as

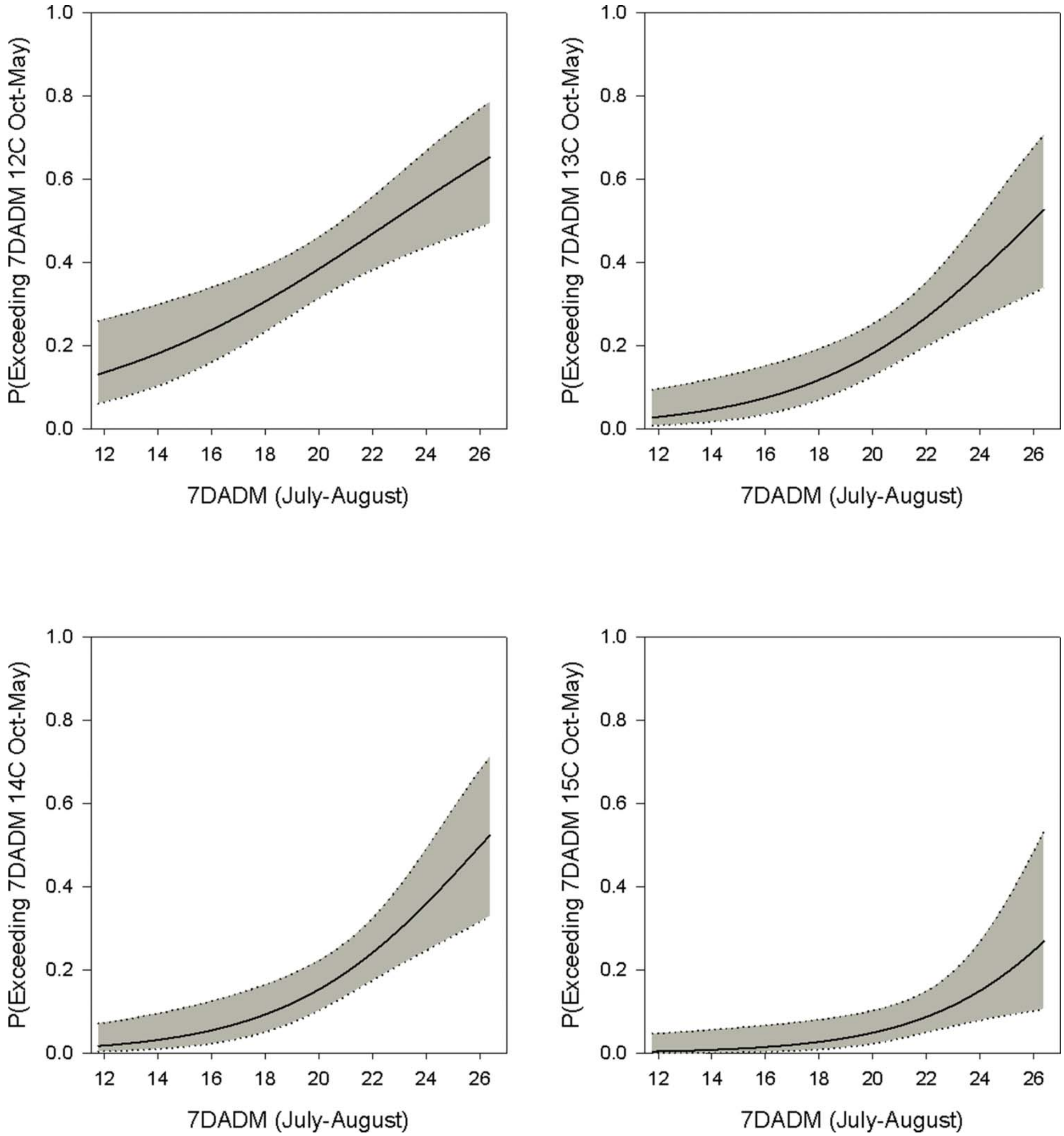

FIGURE 4. Summer (July 1 to August 30) 7-d moving average of daily maximum stream temperatures (7DADM;°C) in relation to the probability of exceeding a nonsummer (October 1 to May 31) 7DADM of 12, 13, 14, and 15°C at 49 sites sampled in the northern Great Basin (Figure 2). The gray shading represents the 95% confidence interval.

a means of prioritization because all the sites that we sampled were located within the species' range. More generally this would not be the case as the range of salmonids in the Great Basin in general is limited to colder portions of stream networks (Warren et al. 2014). Accordingly, if our method was applied more broadly across the Great Basin, or in other locations, we would expect the species' range to serve as a useful means of prioritizing sites for diagnosis of impairment. This is important because the most recently updated summary of water quality impairment in the United States provided by the U.S. Environmental Protection Agency (USEPA 2013) indicates over 3,100 instances of thermal impairment of streams, with a total of over 1,400 km of streams listed as impaired for temperature in the state of Nevada alone (NDEP 2014).

Our second line of evidence, biological criteria, indicated that 38% of the stream network that we studied was potentially impaired with respect to the thermal tolerance of Lahontan

TABLE 3. Parameters from the logistic regression models used to predict the probability of exceeding the 7-d moving average of daily maximum temperatures (7DADM; see text for calculation) of 12, 13, 14, or 15 °C from October–May as a function of the maximum 7DADM in the same water year (October–September). Data were from 49 sites in the Oregon Lakes region (Figure 2).

October–May 7DADM (°C)	Coefficient	Estimate	SE	z	P-value
12	Intercept	−3.9279	2.0311	−2.321	0.020
	7DADM	0.17276	0.0952	1.815	0.008
13	Intercept	−6.5564	2.8803	−2.276	0.023
	7DADM	0.2524	0.1341	2.651	0.041
14	Intercept	−7.3724	3.2059	−2.300	0.022
	7DADM	0.2830	0.1476	2.199	0.028
15	Intercept	−9.1030	3.6430	−2.252	0.024
	7DADM	0.3071	0.1687	2.023	0.041

Cutthroat Trout. Although biological criteria can diagnose naturally warm reaches of streams as impaired for coldwater use (Poole et al. 2004), applying our criterion to the network of streams we considered herein provided a useful means of prioritizing sites for further consideration. Our third and final line of evidence, a statistical model of stream temperature, indicated that 35% of the stream network that we considered was warmer than predicted, but only 17% of the network was too warm for Lahontan Cutthroat Trout *and* warmer than predicted. This filtering allowed us to identify locations where physical *and* biological impairment were most likely within the network that we studied. These locations likely represent the highest priorities from a management perspective, but it is important to note that warming in streams that do not exceed biological criteria is also a concern and a limitation of relying too strongly on biological criteria alone as a means of diagnosing impairment (Poole et al. 2004). In our example, the reaches with the strongest evidence of impairment were located downstream of protected areas (i.e., designated wilderness) or associated with natural features that can heat streams (e.g., beaver ponds; Kemp et al. 2012; Figure 3).

Given that we relied heavily on a simple geostatistical model in our example, it is worth discussing the advantages and limitations of this specific approach in more detail. Our model predicted 7DADM only as a function of elevation, which for this situation was statistically precise. This approach is useful for the system we studied because higher elevations are located in a designated wilderness area with relatively minimal human impacts. Similar models in other systems where human impacts are more prevalent could be improved by including additional temporal (e.g., streamflow or climatic conditions) and spatial (e.g., shade, riparian or instream habitat condition) covariates in the SSN model (Isaak et al. 2010) or by adopting a more causal modeling approach (Irvine et al. 2015). Any selected covariates should be carefully considered with respect to how reliably they represent the processes driving natural or human-caused changes in stream temperature (Poole and Berman 2001; Irvine et al. 2015). In cases where greater resolution is needed, the application of more mechanistic models of heat budgets (Cox and Bolte 2007; Diabat et al. 2012) may be warranted, but these approaches are more intensive and costly than our approach and thus unlikely to be feasible across broad extents, such as we have considered herein. In this regard, the application of the SSN model also highlighted its value in cases where temperature records are missing. The site at Little Sawmill Creek that dried (not included in the SSN model) had an observed 7DADM of 33.9°C (a measure of local air temperature since this site had dried). Using the SSN model to predict this missing observation resulted in a predicted 7DADM of 16.7°C (SE, 2.9), which is closer to what would be expected if the site on this small tributary had not dried and highlights that interpolation can be made quite accurately using these methods.

Finally, it is worth considering the climatic context in which our case study occurred. The widespread pattern of warm (>20°C) temperature in our network of streams could be attributed in part to the fact that the year we sampled (2012) was above-average warm and dry. For example, the Palmer drought severity index, which incorporates air temperature, precipitation, and soil moisture into an index representing wet or dry conditions, indicated that for the Reese River basin, conditions ranged from moderately to extremely dry throughout 2012 (NOAA 2014). However, in many cases water temperature was well above (e.g., 7DADM > 20°C) our criteria, suggesting that even in a typical climate year temperatures would be relatively warm in the system. Clearly, consideration of the spatial and temporal context within which a system is set should be taken into consideration with respect to management decisions. Flexible prioritization tools such as the one we have developed should be useful in this situation.

Management Implications

In conclusion, by considering biological criteria in the context of other lines of evidence, we were able to more efficiently diagnose the reaches of streams most likely to be

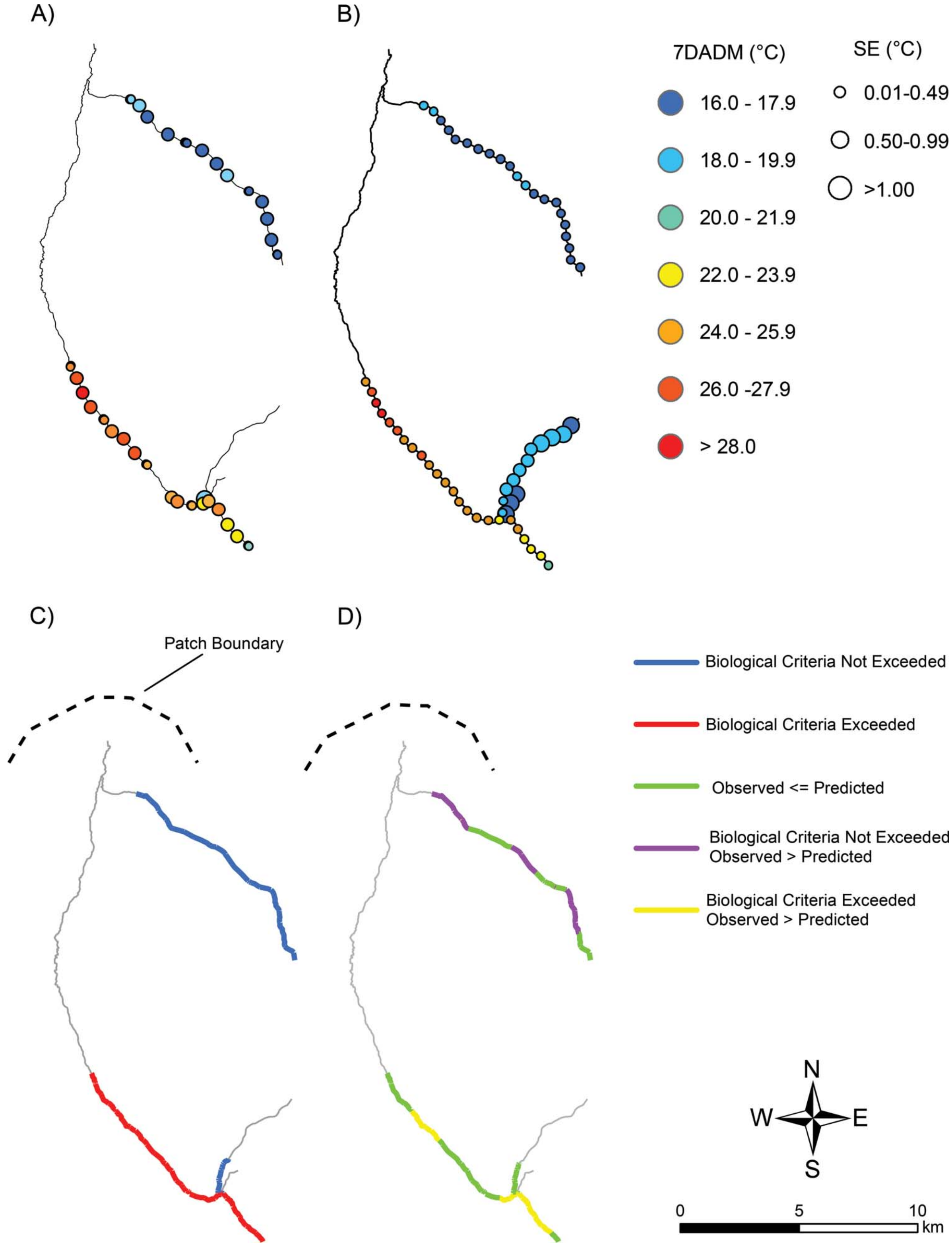

FIGURE 5. Predictions of 7-d moving average of daily maximum stream temperatures (7DADM) for 51 sites in the upper Reese River–Stewart Creek network in Nevada (see Figure 2 inset) from a spatial stream network model. The map shows **(A)** values for observed sites and **(B)** predictions made every 0.5 km along each stream. The size of each point reflects the standard error of the estimate. Reaches were categorized **(C)** based on exceedance of biological temperature criteria (7DADM > 20°C) or **(D)** by both biological temperature criteria and observed versus expected temperatures following the methods suggested in the text and Figure 1. Unsampled reaches (gray lines) were not categorized.

TABLE 4. Parameters from a spatial stream network model with a mixed-model linear-with-sill autocovariance function used to predict the 7-d moving average of daily maximum temperatures (7DADM) from July 1 to August 30 as a function of elevation (m) for 51 sites in the Reese River basin, Nevada (Figure 2). The partial sill is equal to the sill minus the nugget effect.

Predictor	Autocovariance function	*b*(SE)	*P*-value	*t*
Intercept		34.404 (15.27)	0.029	2.251
Elevation (m)		−0.006 (0.003)	0.037	−2.012
Autocovariance component				
Partial sill	tail-up	12.89		
Range (km)	tail-up	0.16		
Partial sill	tail-down	3.67		
Range (km)	tail-down	1.49		
Nugget		0.07		

thermally impaired. Many approaches to evaluating thermal impairment for coldwater fishes rely heavily on specifying biological criteria, which can become a very involved process (e.g., Todd et al. 2008; McCullough 2010) and risk the misdiagnosis of streams that are not naturally cold as impaired (Poole et al. 2004). The approach we applied here considers biological criteria but also provides a more integrated approach to diagnosing impairment and a useful means of identifying priorities for more detailed evaluations across a broad network of stream reaches. Moreover, previous methods used to diagnose thermal impairment in streams are limited because they require the availability of data in a particular stream reach. As we have shown here, improved statistical methods for modeling and mapping species distributions and stream temperature, and perhaps as important the uncertainty surrounding those predictions (see also Isaak et al. 2010; Ruesch et al. 2012; Falke et al. 2013), provide the capability for accurate diagnosis of thermal conditions and potential thermal impairment throughout stream networks. Such capabilities promise to extend our view beyond local instances of impairment to stream network and regional extents that are more broadly relevant for considering the future of coldwater fishes in the context of changing land use and climate.

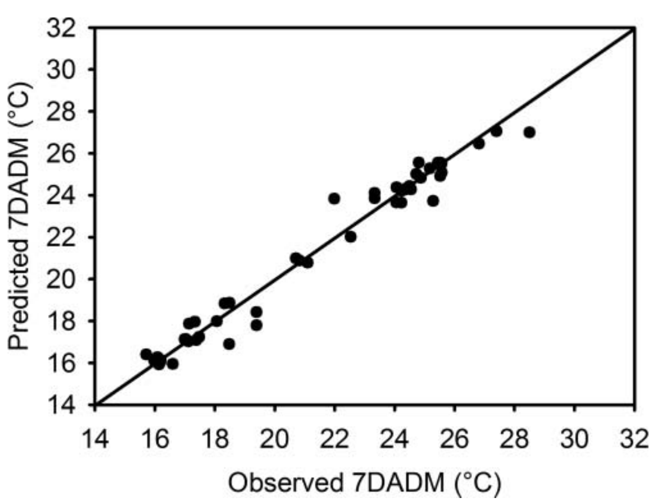

FIGURE 6. Observed (*x*-axis) versus leave-one-out cross-validated predicted values (*y*-axis) from a spatial stream network model predicting the 7-d moving average of daily maximum stream temperatures (7DADM) for sites in the upper Reese River and Stewart Creek, Nevada, as a function of elevation. A 1:1 line is shown for comparison.

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