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Original Articles

Monitoring riverine thermal regimes on stream networks: Insights into spatial sampling designs from the Snoqualmie River, WA

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ABSTRACT

Understanding, predicting, and managing the spatiotemporal complexity of stream thermal regimes requires monitoring strategies designed specifically to make inference about spatiotemporal variability on the whole stream network. Moreover, monitoring can be tailored to capture particular facets of this complex thermal landscape that may be important indicators for species and life stages of management concern. We applied spatial stream network models (SSNMs) to an empirical dataset of water temperature from the Snoqualmie River watershed, WA, and use results to provide guidance with respect to necessary sample size, location of new sites, and selection of a modeling approach. As expected, increasing the number of monitoring stations improved both predictive precision and the ability to estimate covariates of stream temperature; however, even relatively small numbers of monitoring stations, n = 20, did an adequate job when well-distributed and when used to build models with only a few covariates. In general, winter data were easier to model and, across seasons, mean temperatures were easier to model than summer maximums, winter minimums, or variance. Adding new sites was advantageous but we did not observe major differences in model performance for particular new site locations. Adding sites from parts of the river network with thermal regimes which differed from the rest of the network, and which were therefore highly influential, improved nearby predictions but reduced model-estimated precision of predictions in the rest of the network. Lastly, using models which accounted for the network-based spatial correlation between observations made it much more likely that estimated prediction confidence intervals covered the true parameter; the exact form of the spatial correlation made little difference. By incorporating spatial structure between observations, SSNMs are particularly valuable for accurate estimation of prediction uncertainty at unmeasured locations. Based on our results, we make the following suggestions for designing water temperature monitoring arrays: (1) make use of pilot data when possible; (2) maintain a distribution of monitors across the stream network (i.e., over space and across the full range of covariates); (3) maintain multiple spatial clusters for more accurately estimating correlation of nearby sites; (4) if sites are to be added, prioritize capturing a range of covariates over adding new tributaries; (5) maintain a sensor array in winter; and (6) expect reduced accuracy and precision when predicting metrics other than means.

1. Introduction

Understanding, predicting, and managing the spatiotemporal complexity of stream thermal regimes on entire stream networks requires carefully designed monitoring strategies. Water temperature regimes on stream networks, influenced by incoming solar radiation, groundwater and atmospheric inputs, as well as a wide range of landscape features such as elevation, human development, riparian vegetation, and geomorphology (Caissie, 2006; Webb et al., 2008), vary within a day and across seasons. These temporal patterns are distributed spatially, with some tributaries experiencing, for example, large daily fluctuations in water temperature during summer and other tributaries experiencing dramatic annual fluctuations (Steel et al., 2016). Capturing the fine-scale temporal variability in temperature at many discrete locations on one stream network is possible using relatively inexpensive in-stream sensors. Site-based measurements can then be used to interpolate particular facets of the thermal regime, e.g., mean summer temperature, to unsampled parts of the network as well as to estimate the effect of variables believed to control water temperature. These models of thermal regimes on stream networks can help identify suitable habitats,

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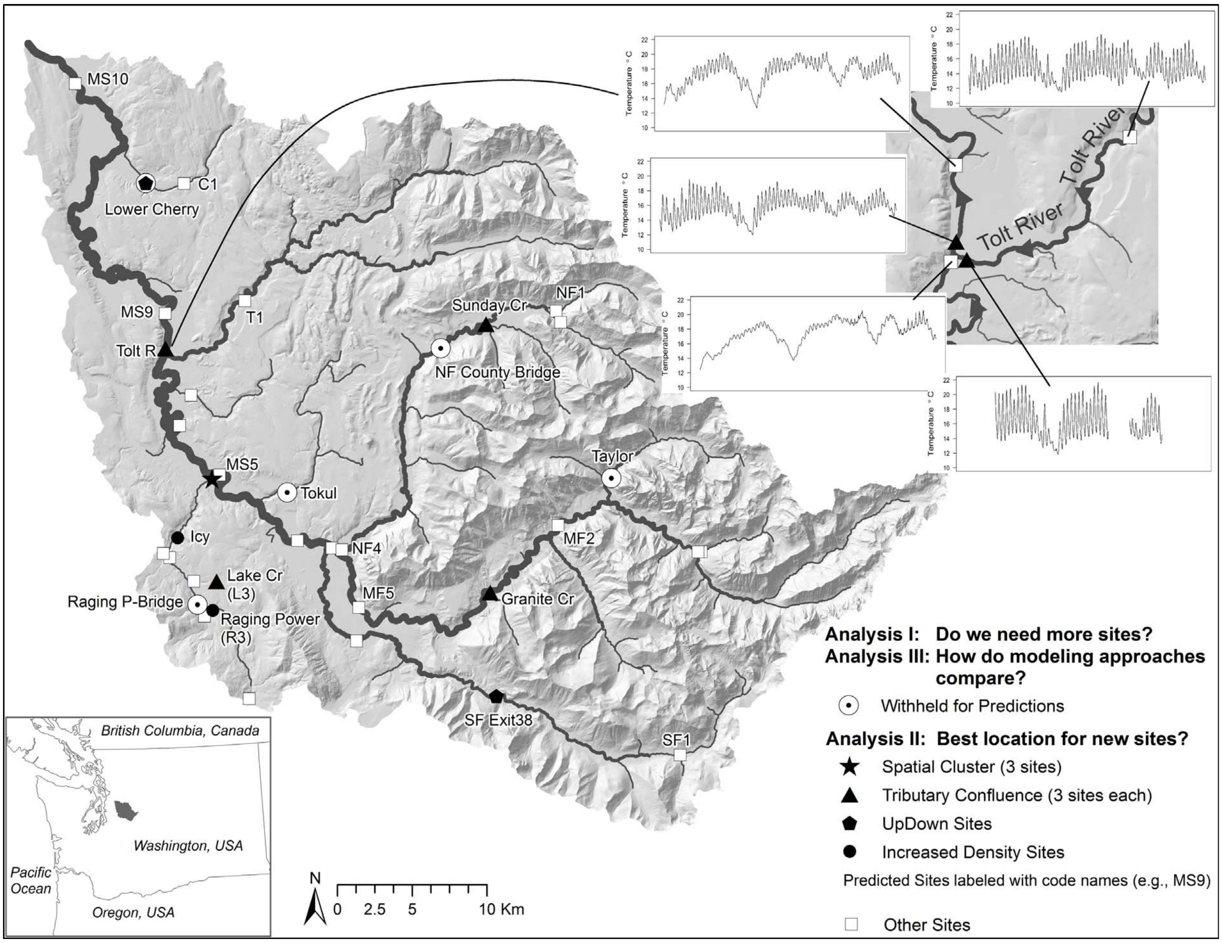

Fig. 1. Map of Snoqualmie River, Washington, USA. Sites withheld to test predictive accuracy in resampling analyses, evaluating effect of sample size, and comparing modeling approaches (Analysis I and III; Table 1; Fig. 2) are identified with an inner dot. Sites systematically added to explore how the addition of particular sets of sites affects model performance (Analysis II; Table 1) are identified with solid symbols: star, triangles, pentagons, circles. Sites in which model performance was evaluated in Analysis II are labeled with a short site name which is also used in Fig. 5 and Fig. 6. Time series of temperature data for five sites associated with the confluence of the Tolt and Snoqualmie Rivers are inset to display differences in data for nearby sites. The two sites added in Analysis II (Table 1, Fig. 5, and Fig. 6) for the Tolt River confluence are identified as solid triangles in inset which, unlike the triangles in the main figure, represent just one site each.

prioritize management actions, estimate compliance with legal regulations, and indicate relationships between watershed and instream condition.

As budgets for research, management, and conservation efforts remain limited, new guidance is needed for designing efficient monitoring arrays (a set of spatially distributed monitoring sensors) that capture the spatiotemporal complexity of thermal regimes on the stream network. Moreover, practitioners may wish to understand and predict one or more specific indicators that are of importance for target species and life stages or for protecting thermal regimes through regulatory thresholds. For instance, summer maximum temperatures at least partly determine growth and survival of juvenile salmonids (Satterthwaite et al., 2009) and upriver migration success for returning adults (Martins et al., 2011). These relatively well-understood physiological relationships have ensured that summer maximum temperature is one of the most commonly evaluated facets of water temperature regimes. However, other facets of the thermal regime may be equally important for species viability. For example, daily fluctuations in winter temperature, when salmonid eggs are incubating in the gravel, are correlated with fry emergence phenology (Steel et al., 2012). Without data on winter variance, ecologists and managers may not be able to account for (or even question) its effect on later life stages. Future monitoring designs may need to be tailored to specifically capture particular facets of the thermal regime and seasons or time windows of interest.

Spatial stream network models (SSNMs) can be fit from water temperature data that were originally collected for other purposes (e.g., Isaak et al., 2011) and not necessarily designed purposefully for building models of water temperature across entire networks. However, ad hoc datasets may not adequately represent spatiotemporal variation in thermal regimes at appropriate scales for managing thermally sensitive species and water uses. Researchers therefore need guidance on necessary sample sizes and best locations for placing additional loggers that will improve predictions and/or estimation of model parameters. Using toy and simulated stream networks, Som et al. (2014) suggest that effective sampling designs should include sites along the full range of important environmental gradients, in major tributaries, in spatial clusters of sites, and at the outlet and headwaters of the stream network. Li (2009) and Zimmerman (2006) found that clustered designs and a mix of space-filling and clustered designs were optimal for similar situations. Falk et al. (2014), using a combination of simulated data on simulated networks and empirical data from the Lake Eacham basin in Queensland, Australia, found that optimal designs for prediction were distributed fairly evenly over the network but that optimal designs for parameter estimation were somewhat clustered.

In this paper, we use empirical data to expand on the work conducted by Som et al. (2014) and others. We provide practical guidance on the design of monitoring arrays for accurately modeling and predicting particular indicators within complex thermal landscapes. We assess predictive accuracy and estimation of covariate effects from