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Local landscape predictors of maximum stream temperature and thermal sensitivity in the Columbia River Basin, USA

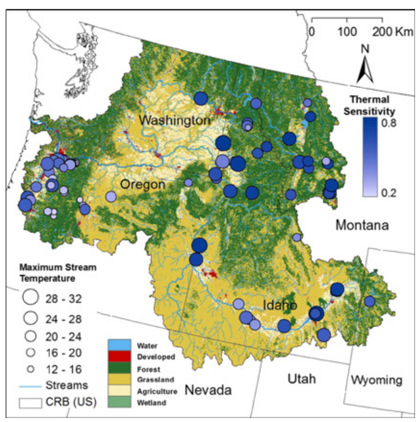
Heejun Chang *, Mike Psaris

Department of Geography, Portland State University, 1721 SW Broadway, Portland, OR 97201, United States

HIGHLIGHTS

- Thermal sensitivity is largely explained by distance to coast, baseflow index, and area.
- Maximum stream temperature (Tmax) is controlled by baseflow index, percent forest cover, and stream order.
- The relative importance of landscape predictors for TS and Tmax changes by the scale of analysis.
- Geographically weighted regression better explains the spatial variation of TS and Tmax than OLS estimated regression.

GRAPHICAL ABSTRACT



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ABSTRACT

Stream temperature regimes are important determinants of the health of lotic ecosystems, and a proper understanding of the landscape factors affecting stream temperatures is needed for water managers to make informed decisions. We analyzed spatial patterns of thermal sensitivity (response of stream temperature to changes in air temperature) and maximum stream temperature for 74 stations in the Columbia River basin, to identify landscape factors affecting these two indices of stream temperature regimes. Thermal sensitivity (TS) is largely controlled by distance to the Pacific Coast, base flow index, and contributing area. Maximum stream temperature (Tmax) is mainly controlled by base flow index, percent forest land cover, and stream order. The analysis of four different spatial scales – relative contributing area (RCA) scale, RCA buffered scale, 1 km upstream RCA scale, and 1 km upstream buffer scale – yield different significant factors, with topographic factors such as slope becoming more important at the buffer scale analysis for TS. Geographically weighted regression (GWR), which takes into account spatial non-stationary processes, better predicts the spatial variations of TS and Tmax with higher R^2 and lower residual values than ordinary least squares (OLS) estimates. With different coefficient values over space, GWR models explain approximately up to 62% of the variation in TS and Tmax. Percent forest land cover coefficients had both positive and negative values, suggesting that the relative importance of forest changes over space. Such spatially varying GWR coefficients are associated with land cover, hydroclimate, and topographic variables. OLS estimated regression residuals are positively autocorrelated over space at the RCA scale, while the GWR residuals exhibit no spatial autocorrelation at all scales. GWR models provide useful additional information on the spatial processes generating

* Corresponding author. Tel.: +1 503 725 3162.
E-mail address: changh@pdx.edu (H. Chang).

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the variations of TS and Tmax, potentially serving as a useful tool for managing stream temperature across multiple scales.

1. Introduction

Lotic ecosystems depend on stable hydrologic temperature regimes in order to remain viable. Dissolved oxygen levels, rates of chemical reactivity, and salmon and trout's ability to survive and reproduce are all significantly influenced by stream temperatures (Naiman et al., 2005, Hannah et al., 2008; Richter and Kolmes, 2005; Davie, 2008; Mantua et al., 2010). Stream temperatures, in turn, are determined by the stream's local heat budget. The local heat budget is influenced by the amount of receiving solar radiation, amount of flow, and groundwater input. Streams around the world have seen significant changes to their natural heat budgets as a result of landscape modification and global climate change. Therefore, identifying temperature-sensitive streams has become an important area of research in freshwater ecology and fisheries management (Webb and Walling, 1993; Nelitz et al., 2007).

There are a number of anthropogenic landscape changes that cause increased stream temperatures. Decreases in forest lands and land compaction resulting from logging, mining or agricultural practices accelerate runoff and reduce subsurface flows which typically attenuate a stream's water temperature response to air temperature (Naiman et al., 2005, Hannah et al., 2008). Surfaces less pervious than natural lands (e.g., urban parking lots) reduce infiltration and warm surface flows before they reach stream channels, providing additional heat to the water bodies (Nelson and Palmer, 2007). Finally, the elimination of riparian zones remove stream shading, which in turn increases exposure to diurnal radiation (Poole and Berman, 2001; Johnson, 2004).

Global climate change will have varying hydrologic effects throughout the world. The Pacific Northwest is a snowmelt dominated region, so increases in global temperatures are projected to cause earlier springtime runnoff, which in turn will reduce summer flows and decrease the thermal capacity of streams, which would otherwise act as a buffer to increases in stream temperature (Mohseni et al., 1999; Chang and Jung, 2010; Arismendi et al., 2013). A study of 157 river temperature stations worldwide has shown that increases in daily air temperatures of 2, 4, and 6 °C induce an increase in stream temperatures of 1.3, 2.6, and 3.8 °C, respectively (Van Vliet et al., 2011). Decreases in daily mean discharge of 20% and 40% from these rivers could increase annual mean water temperatures by 0.3 °C and 0.8 °C on average. In an urbanized watershed, the combined effects of air temperature rise and discharge decrease could further exacerbate thermal pollution (Chang and Lawler, 2011). While innovative water management strategies such as releasing water from the bottom of reservoirs where the water is cooler, can reduce monthly mean stream temperatures (Risley et al., 2010), counteracting the combined warming effects of anthropogenic activities remains a challenge (Hester and Doyle, 2011).

The importance of stream temperatures in stream health has prompted academics and water managers to develop predictive modeling techniques to aid in their work to mitigate climate change and anthropogenic impacts (Caissie, 2006; Webb et al., 2008). These models fall into three general categories: stochastic, process based, and statistical. Stochastic models attempt to mimic the semi-random nature of environmental data in order to properly model stream temperatures (Risley et al., 2003). In contrast, process based models, also called deterministic models, attempt to account for the entire heat budget of a stream in order to derive highly accurate models. These models require numerous inputs, such as air temperature, relative humidity, solar radiation, and stream channel morphology. Given the complexity of these physically based models, they can be of limited use due to the lack of measurements at a local scale for calibrating the model. Statistical techniques use historic data to derive a regression model of stream temperature from environmental characteristics such as air temperature and landscape attributes. These environmental characteristics are often times easier to collect and analyze, and so regression-based models are a popular alternative to physically based models (Isaak and Hubert, 2001; Isaak et al., 2010; Hrachowitz et al., 2010). For these reasons, we use regression models for our analysis. However, it is important to note that regression models have their limitations too. They do not fully capture biophysical processes that affect stream temperature, and while regression techniques are good at interpolation, extrapolating beyond the study area and time period may be problematic.

There are three main objectives of this paper. First, we identify hydrologic landscape factors affecting the spatial variations of maximum stream temperature (Tmax) and the response of stream temperature change to air temperature change (defined as thermal sensitivity = TS, Crisp and Howson, 1982; Mohseni and Stefan, 1999; Kelleher et al., 2012) in a large river basin. We chose these two indices because maximum stream temperature is associated with critical limits for the life cycle of salmonids (Ebersole et al., 2001; Hrachowitz et al., 2010), and TS summarizes the cumulative buffering effects of local landscape characteristics on stream temperatures and it can be used for quantifying the sensitivity of stream ecology to future climate change (Kelleher et al., 2012).

The second objective is to compare the relative contributing area (RCA) scale and the buffer scale analysis at the whole RCA and 1 km upstream scales. Previous studies show that stream temperature is affected more by local land cover conditions (e.g., 1 km upstream) than landscape conditions further upstream (Isaak et al., 2010), while others report landscape variables within the whole mainstem riparian buffer zone explain more variations in stream temperature than those within the 1 km buffer zone (Scott et al., 2002). We also investigate whether landscape factors determining the variations of Tmax and TS vary across scales.

The third objective of this article is to compare two regression approaches — OLS estimates and geographically weighted regression (GWR; Fotheringham and Charlton, 1998). We identify where spatial variability in the influence of landscape factors on thermal sensitivity and maximum stream temperature exists, and compare OLS regression estimates with GWR model estimates in order to investigate whether there is significant improvement in model predictability. Previous studies show that GWR improved model performance compared to OLS in identifying the relationship between landscape factors and hydrology (Brown et al., 2012) and water quality (Tu and Xia, 2008; Pratt and Chang, 2012).

2. Study area

The Columbia River Basin (CRB) (Fig. 1) is one of the largest basins in North America. It spans the states of Washington, Oregon, Idaho, Montana, Wyoming, Nevada, Utah, and a portion of the Canadian province of British Columbia. The basin is contained by the Rocky Mountains to the East, includes the Cascade and Coastal Ranges in the west, and drains into the Pacific Ocean at Astoria, OR. The Cascade Range runs north to south, dividing the basin into two distinctly different climates. East of the Cascades is dominated by warm summer continental climates, while the climate west of the Cascades is mostly Mediterranean (NRC, 2004; Chang et al., 2013). Hydrologic regimes vary throughout the basin, however. Due to a winter wet season which results in significant snow accumulation, peak flows typically occur in late spring or early summer as snow melts, and low flows