**Using spatially explicit indicators to investigate watershed characteristics and
stream temperature relationships**

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ABSTRACT: We generate a series of novel indicators of spatially explicit watershed permeability and runoff characteristics to examine the relationship between land cover and water temperature parameters in a rapidly urbanizing watershed. Our framework provides a readily adaptable method to examine the thermal sensitivity of streams based upon the underlying geomorphological and surface characteristics of drainage basins. Using four model groups each using a different landscape characteristic weighting scheme (Model Group 1: areal averages; Model Group 2: inverse distance by total flow length; Model Group 3: overland distance to stream network and distance squared; Model Group 4: proportional flow accumulation), we examined the predictive capacity of 19 variables, including combinations of simplified land cover, elevation, slope, and flow accumulation, on five stream thermal properties: seven day moving average of daily minimum and maximum, seasonal mean temperature, a novel metric of thermal ‘flashiness’, and total days with maximum temperature exceeding 17.8 °C. We find that the use of spatially explicit landscape indicators combining watershed processes improves the performance of regressions for predicting a number of ecologically relevant stream temperature variables. Improved indicators of watershed condition lend themselves for rapid investigation of the relationship between stream thermal conditions and landscape characteristics in watersheds modified by human land uses, ultimately providing a more hydrologically meaningful indicator for the impacts of landscape change.

Key words: stream temperature; landscape; distance-weighted; geographic information system; spatial analysis; urban ecosystem

1. Introduction

Stream ecosystems around the world face increasing threats from climate change and land use change (Döll and Zhang 2010, Penaluna et al. 2015, Santos et al., 2015). This tends to be amplified in areas affected by land use conflicts (Valle Junior et al., 2015). The thermal regimes of streams fundamentally influence their suitability as habitat for stream biota both directly and indirectly by altering in stream biogeochemical processes, as well as determining the suitability of stream for a wide range of human uses. Summer stream temperature is particularly critical for cold water salmonid species in temperate climates. Salmon abundance has been reduced within much of their historical ranges across the U.S., where considerable resources are invested in restoring aquatic habitats to support wild populations (Yeakley et al. 2014). Yet, streams in the region remain vulnerable to climate and land use changes. especially by reductions in riparian forest cover, agricultural intensification, urban development and increased thermal loading from industry and wastewater treatment (Hrachowitz et al. 2010, Isaak et al. 2012, Chang and Psaris 2013, Selbig 2015, Hannah and Garner 2015).

In order to disentangle these impacts so that we may plan mitigation actions effectively, we require a better understanding of the landscape scale factors affecting seasonal aggregate stream properties as well as indicators of stream temperature variability. Different modes of forest harvesting, riparian vegetation removal (Mitchell 1998) or shading (Johnson 2004), built development (Nelson and Palmer 2007, Kaushal et al. 2010), and agricultural land management (Simmons et al. 2014) all have the potential to influence stream temperature by increasing long wave radiation into the

1 stream and by reducing or increasing air flows over the stream surface. Land uses also
2 modify surface routing and groundwater recharge by altering soil permeability (Webb et
3 al. 2008). All of these impacts of land uses on stream properties are scale dependent
4 (Allan and Johnson 1997, Allan 2004, Vondracek et al. 2005), and attempting to model
5 their impacts on stream temperatures at the watershed scale has taken many forms
6 (Gallic et al. 2015, Sun et al. 2015, Daraio et al. 2014, Vatland et al 2015).

7 Part of such an endeavor requires the creation and landscape scale indicators
8 (Hill et al. 2016), which represent key physical processes (Wente 2000, Peterson et al.
9 2010). Peterson et al.'s (2010) hydrologically active inverse distance weighted (HA-
10 IDW) metrics account for the spatial distribution of land uses with variable flow
11 accumulation relative to either the stream network itself or a defined sampling point.
12 These approaches weight watershed properties based on their proximity to the entirety
13 of the stream network, simultaneously representing important buffering processes
14 (Sweeney and Newbold 2014) and catchment scale properties (Sawicz et al 2014).

15 Yet, we can go farther in characterizing physical processes of water movement in
16 the landscape. In particular, the HA-IDW metrics (Peterson et al. 2010) assume that all
17 flow is above ground flow and do not provide a means for evaluating the relative
18 influence of parcels with different soil permeability and slope. Existing methods, such as
19 the runoff curve number method (Cronshey 1986), a 'mature' and robust method for
20 estimating relative permeability of soil hydrologic types under different land uses (Ponce
21 and Hawkins 1996), can be adapted to be more spatially explicit watershed runoff
22 characteristics that provide a relative indicator of per-cell permeability. Combining this
23 approach with metrics characterizing the spatial distribution of slopes and flow

1 accumulation, we should be able to provide spatially explicit classification of the basin
2 scale runoff characteristics.

3 With these considerations in mind, we created a series of novel watershed scale
4 metrics that take into account the spatial distribution and flow accumulation interaction
5 of key watershed characteristics relative to both the stream network and sampling
6 points. We test the utility of these metrics in simplifying complex watershed scale
7 properties for examining summertime stream thermal regimes. Our hypotheses are that
8 (1) models that include distance-weighted watershed parameters that take into account
9 some watershed physical processes can better predict thermal properties of streams
10 than basin average watershed parameters, but (2) the degree of model predictability
11 depends on specific stream temperature indicator used in analysis.

13 **2. The Tualatin Basin Study Area**

14 The Tualatin River Basin (TRB), west of Portland OR, USA, covers 1,844 km² of
15 herbaceous (17%), forested (31%), agricultural (27%) and rapidly growing urban areas
16 (~22%) (see Fig. 1a). The Tualatin River originates in the Oregonian Coast range,
17 characterized by high winter rainfall with a notable prolonged dry season (Chang 2007),
18 and summer river flows are augmented by water release from Hagg Lake dam and
19 inter-basin water transfer from Barney reservoir from the western slope of the Oregon
20 Coast range. Although most of the basin lies in extensive lowland flat plains, steep
21 basin edges create an interesting elevation gradient and precipitation rates tend follow
22 this elevation gradient (Fig.1b - DEM). The lower section of the Tualatin has been
23 subject to severe stream temperature problems (Chang and Lawler 2011). Climate

change and ongoing urban development are likely to exacerbate existing water quality problems in the basin (Praskievicz and Chang 2009, 2011), although some best management practices and the extensive restoration of riparian vegetation may offset those impacts (Hoyer and Chang 2014, Psaris and Chang 2014). Thus, the basin is the site of an ambitious and experimental program of complying with Thermal TMDLs under Clean Water Act regulations through extensive riparian tree planting projects (Cochran and Logue 2011), which contribute to other natural area conservation measures in the region (EPA 2007). Historically, the Tualatin basin has also experienced extensive wetlands loss due to drainage, infilling and reductions in beaver (*Castor canadensis*), which has prompted interest in re-establishing wetland areas to improve groundwater infiltration and potentially improve a number of water quality issues (Taft and Haig, 2003).

4. Data and Methods

4.1 Stream Temperature Indices

We obtained continuous hourly temperature data from Clean Water Services (CWS) in the Tualatin Basin from all available sites (n = 33) in the year 2011 (CWS 2015). The year 2011 was chosen because land cover data for the same year were available. Examining hydrographs and temperature distributions for the basin, we selected a period of relatively stable flow bounding a four-month summer period from June 1st to September 30th, 2011. We also used 29 sites that have continuous stream temperature data in summer 2010 for model validation. Examination of the hydrograph for this period found it to be typical of summertime flow conditions in the Tualatin basin,

with no anomalous high flow events. Preliminary data treatment examined the normality of hourly temperature data using Shapiro-Wilkes, as well as examining statistically significant differences between all sites using Mann Whitney tests. Given that significant differences existed between sites, and their seasonal hourly temperature values were normally distributed, we calculated five dependent variables. First, we calculated average daily mean temperature for representing average stream conditions for each station. Second and third, we computed the seven day daily moving average for minimum and maximum temperatures (7DADMin or 7DADMax) as reliable indicators of buffered minima and maxima of stream temperature. A fourth metric, the total number of days with 7DADMax exceeding the regulatory threshold of 17.8 °C, was examined as Salmonids prefer temperature ranges of 12.8 (incubation) up to 17.8 (rearing) °C, and extended periods of exposure to above 17.8 °C are known to cause stress and increase fish mortality (OR DEQ, 2001). Finally, we calculated a novel metric of inter-daily thermal variability, a modification of the Richard's Baker flashiness equation (Baker et al 2004) with the following form:

$$\text{Thermal Flashiness, for all } i, = \text{SUM}(T_i - T_{i-1}) / \text{SUM}(T_i) \quad (1)$$

Where T_i = Daily mean temperature for day i and T_{i-1} = daily mean temperature at day $i-1$, a metric aggregating the inter-daily range of mean stream temperatures. Such a metric avoids the bias inherent in choosing the maximum or minimum inter-daily ranges as a metric of variability, as well as generalized indicators of the coefficient of variation, as it examines the time dependent step changes in thermal regime.

4.2 Derivation of explanatory variables: GIS analysis

We constructed explanatory variables of land use characteristics using ArcGIS 10.1.

While the majority of our catchments are independent headwater drainages, for the few that are nested, distance metrics utilizing the total overland and in stream flow distance were used to compute catchment scale indicators of watershed transmissivity. For Indicators utilizing distance to stream metrics, nested catchments are not truly independent of each other, as areas of overlap have the same pixel values of to the stream distance. However, since they aggregate a larger area they still provide a comparable calculation of watershed characteristics to the observed temperature profiles. Given a main purpose of this study is to test scale dependence of landscape properties, we included nested catchments within our regression equations.

We first utilized a 30m DEM (Gesch et al. 2002) for the study basin. Using hydrotools in ArcGIS 10.2 (ESRI 2013), we derived flow accumulation and flow direction for each pixel in the TRB, and divided the basin into sub-basins based upon our continuous temperature gage locations (using a snap distance of 100m given our fairly flat topography in many stream areas). Using these delineated watersheds, we calculated the total flow length from each pixel in a sub-basin to its respective temperature monitoring point. Overland flow lengths were derived by subtracting out stream lengths from the total flow distances using the flow length tool in the Spatial Analyst Extension (ESRI, 2013). We then extracted a calculated curve number (following Cronshey 1986 using NLCD 2011 Land Use Data and Soils data from

SSURGO) raster for the sub-basin, the per pixel slopes in degrees (Jin et al. 2013; Soil Survey Staff 2013), and the elevation values for each individual pixel (Fig. 2, Table 1).

Using these rasters singly and in combination, we calculated values for 19 watershed characteristics using per pixel values (see Table 2 for a complete list and description) in four model groups. The first model group was comprised of areal statistics for watershed curve number, slope and elevation calculated by summing their per pixel values in a given watershed, and dividing by the watershed's number of pixels. Our second and third model groups used the same characteristics of slope, elevation and curve number, but weighted them singly and in combination using pixel total flow distance and overland flow distance to the sampling point, respectively. Distance weighted metrics were constructed with general form of equation:

$$IDW-K_j = \text{SUM}[k_{i,j}/FL_{i,j}]/\text{SUM}(1/FL_{i,j}) \quad (2)$$

where the Inverse Distance Weighted (IDW) metric for the product of k parameters for pixel i in vector K, in watershed j, is divided by the flow length (FL). Flow length is then either total flow distance (D) to the outlet, or the overland flow distance to the stream (O), all of which is divided by the sum of inverse distance weights in order to normalize metrics across watersheds. An example, taking into account the Curve Number (CN) and slope (SL), has the form:

$$IDW_CN_SL_j = \text{SUM}(CN_{i,j} * SL_{i,j} / D_{i,j}) / \text{SUM}(1 / D_{i,j}) \quad (3)$$

where $CN_{i,j}$ is the Curve Number of pixel i in watershed j , $SL_{i,j}$ is the slope of pixel i in watershed j , and $D_{i,j}$ is the total flow distance of pixel i in watershed j to the sampling point. We also utilized inverse squared distance metrics in order to examine non-linearities in distance relationships utilizing the general form:

$$IDW2-K_j = \text{SUM}(k_{i,j} / D_{i,j}^2) / \text{SUM}(1 / D_{i,j}^2) \quad (4)$$

Within the custom-built ArcGIS tool, these calculations are all performed using map algebra on raster arrays (Fig. 3). This method allows the calculations to be performed on all values within a layer simultaneously, rather than having to iterate through each individual pixel. Our fourth model consisted of the collection of attributes created by weighting pixel properties (Slope, Curve Number, Elevation) by their proportional flow accumulation, defined as the normalized distribution of flow accumulations of each pixel by the maximum flow accumulation in the watershed. Such an approach allows for direct comparisons between watersheds of different size to estimate the influence of per pixel weighted by the proportion of the watershed drained by each pixel.

4.3 Multiple Regression Analysis

We split our constructed indices of watershed condition into four model groups to evaluate the relative performance of the covariate types discussed above using multiple regression analysis. Using a combination of coefficient significance testing and an information in a two way stepwise selection criteria, we evaluated subsets of our novel

landscape metrics in four models to capture variance in temperature indices while eliminating variables not significant at $p > 0.05$, minimizing the Aikake Information Criterion (AIC) (using stepAIC from the package 'MASS' in R 3.1.2, Venables and Ripley 2002), and excluding variables with a Variance Inflation Factor higher than 3. Each model tested a comparable iteration of the distance weighting of our metrics, except for the proportional flow accumulation model group. Model Group 1 was composed of our non-inverse distance weighted metrics, Model Group 2 was our inverse distance total flow length variable set, Model Group 3 was the overland distance and distance squared set, and Model Group 4 was the proportional flow accumulation set. We also included basin size, proxy for stream order, computed as the product number of pixels in the watershed and the pixel area, in each model group, because stream order has been identified as a driver of stream temperature (Chang and Psaris 2013).

5. Results

5.1 Exploratory data analysis

Spatial variation in our temperature variables was quite high (Fig. 4). As expected, high seasonal minimum 7DADmin, maximum 7DADmax, average 7DADmean, and the total number of days with daily temperature exceeding 17.8 °C are concentrated in the eastern part of the basin, mostly within urban areas. The spatial pattern of flashiness of daily mean temperatures appears to be associated with stream order, with higher thermal flashiness found in peripheral upstream areas.

Examining basic correlations between landscape and stream temperature variables yielded many significant correlations. Average elevation and slope are negatively associated with mean 7DADmean temperature, while CN is negatively related to mean 7DADmean temperature. The combined variable of size and CN is strongly positively correlated to mean 7DADmean temperature, while the combined variable of CN and slope is negatively related (Fig. 5).

5.2 Regression model results

Full model results are summarized in Table 3, grouped by dependent temperature variable in each column, with bolded representing best performance models, defined as having the highest adjusted R^2 value and lowest in group AIC.

In general, models utilizing variables representing the distribution of flow accumulation throughout the watershed (Model Group 4) performed better than others in explaining variance of derived temperature indices. In terms of distance weighting, overland flow weighted variables (Model Group 3) outperformed total flow length variables (Model Group 2), which is not surprising as the weight of a given pixel is more likely to be represented by its distance to the stream, as in-stream processes aggregate drainage basin influences. These results indicate that including information on the spatial configuration of watershed characteristics, rather than area weighted averaged statistics, using relatively simple GIS tools, will greatly improve analytical and predictive performance of models relating in stream properties to landscape characteristics.

Model residuals became smaller once we included distance-weighted variables (Fig. 6). Interestingly, higher residuals are typically found in more developed urban

areas, meaning that human alteration of the hydroscape and routing pathways may make generalizable landscape predictors less useful, meaning that higher resolution data on anthropic flowpaths such as ditches, storm and waste water systems and drainage technology may be necessary to improve predictions (Fig. 7) as has been found in other urbanized catchments (Nelson and Palmer, 2007). All models displayed no significant ($\alpha = 0.05$) spatial autocorrelation (results not shown). A more detailed discussion of the results of regression model groups on each thermal property is below.

5.2.1. Seven Day Average Daily Minimum (7DADMin)

Seasonal seven day average minimum temperature was best estimated by a combination of non-distance weighted variables, the average elevation of the basin and its size, consistent with results elsewhere (Webb and Walling, 1986, Chang and Psaris 2013). This is the only exception to the general observations described above. All other models also found elevation to be the main driver of 7DADMin, with negative association with the overland distance weighted curve number x slope (IDW_CN_SL_OL) also significant (as reported in model 3). This result is not surprising given that slope corresponds largely with water velocity, and in a watershed such as the Tualatin, lower elevation areas that have lower slope reaches, have sluggish water flow of higher volume, which cools more slowly than smaller basins at higher elevation. Such interpretation is based on a slight reversal of the dominant logic surrounding stream thermal regimes, as we emphasize cooling processes rather than warming processes. Following this logic, another consideration is that convective heat transfer may also be occurring. Although air temperature plays a minimal role in the heating of streams due

to the nature of the thermal gradient, convective heat transfer can occur when air temperatures cool below stream temperatures. This can take place at night in higher elevation basins, which is exacerbated by topographies promoting col-air-pooling, such as those with steeper slopes and local basins represented by our metrics (Vosper et al. 2014)). This dynamic has been observed in small stratified lakes (MacIntyre et al. 2010) but remains largely underexplored in streams and rivers.

5.2.2. Seven Day Average Daily Maximum (7DADMax)

The proportional flow accumulation and slope (PFAW_CN) served as the best predictor for 7DADMax as report in Model 4. Its negative relationship indicates that as higher slope areas drain increasing portions of the watershed, lower maximum temperatures result. Conversely, watersheds with a higher proportion of their drainage areas in low slope areas, have higher maximum temperatures. Additionally, since the stream itself has the highest proportional flow accumulation, these results may indicate the impact of stream slope, a proxy for water velocity, on maximum temperatures, with higher stream slopes corresponding to lower maximum water temperatures. However, since this model has a relative low Adjusted R^2 value of 0.34, these results should be interpreted with caution. In general, it was more difficult for our model groups to capture variance in 7DADMax across sites than minimum temperatures. This indicates that the thermal loading of given segments that should drive daily maxima may not be well captured by such landscape scale metrics – rather, the dynamics of and thermal loading of water draining into stream reaches are represented by other landscape variables (e.g.

groundwater inputs vs. surface water inputs from wetlands and ponds, the degree of riparian shading of shorter reaches around temperature monitoring points).

5.2.3. Seasonal Mean Hourly Temperature (SMHT)

The single best predictor of SMHT was the inverse overland distance weighted slope (IDW_SL_OL), which had similar overall performance to a model utilizing the proportional flow and slope (PFAW_SL) (both having adjusted R^2 of 0.68, and AIC of -9.35 vs -8.49, respectively). This is a highly promising result as it may provide some generalizable insight into the relationship of distributed overland flow distances and a key thermal regime variable. In essence, given the negative relationship between IDW_SL_OL and SMHT, we can infer that the closer higher slopes are to the stream throughout its drainage, the lower its mean temperature will be, as well as the inverse in that the lower slopes are adjacent to the stream, the higher its mean temperatures will be. Since overland flow takes into account slopes relative to the entire stream network above the monitoring point, this makes sense as it is a coarse estimate of the aggregated topographic shading of the entire stream network.

5.2.4. Flashiness of Daily Means (FDM)

The FDM, a metric of the aggregate seasonal inter-daily temperature change of a given location, indicates the overall seasonal thermal sensitivity of the network stream at the sampling point more robustly than choosing an arbitrary daily maximum range as it is less sensitive to extreme events (Laszewski 2013). Model Group 4's Elevations x Proportional Flow metric (PFAW_EL) was a positively associated single predictor with

adjusted R^2 of 0.39 and AIC of -360.38, Our results that higher elevation streams have higher flashiness corroborates work indicating that lower volume, upper catchment streams have greater diurnal and inter-daily variation (Webb 2008), despite other observations to the contrary (Caissie, 2006). While results from model groups 3 and 4 indicated that elevation indeed was the main driver of variation in flashiness, model groups 1 and 2 indicated that curve number may play a role in thermal flashiness as has been found for hydrologic flashiness more generally. This indicates that the transmissivity of the watershed, characterized by the distribution of inverse distance squared weighted curve number is negatively related to FDM. While seemingly counterintuitive, this may represent that lower curve numbers, resulting from forested areas, which generally have steeper slopes, may be related to higher stream flashiness, concurrent with results from model groups 3 and 4. Such a finding runs somewhat contrary to what would be expected from previous studies which link flashiness of stream conditions to more developed areas (Walsh et al. 2005), in that higher curve number areas do not result in higher flashiness, which may reflect the influence of stabilizing discharges from waste water treatment facilities. However, given the low performance of our model, those two separate processes may compete against each other, and it may be more appropriate to investigate higher curve number areas separately for the relative influence of topography. The distribution of sampling points in more forested upper catchment areas may also affect our results as the two characteristics are separated in space (higher elevation areas are less developed for built and agricultural uses).

5.2.5. Total days with 7DADMax exceeding 17.8 °C

The total days exceeding the regulatory and biological threshold of 17.8 °C was best explained by spatially weighted metrics. Specifically, model groups 3 and 4 performed equally as well in terms of both R^2 and AIC values (Adjusted R^2 of 0.49, AIC of 218.73). Significant improvements in efficiency measures were observed, particularly between Model 1 and Models 3 & 4. The outperformance of spatial metrics, especially those calculated with overland or proportional flow accumulation, demonstrates the potential benefits of weighting landscape variables according to hydrologic distances. In model group 3, similar to 7DADMin and 7DADMax, overland flow inverse distance weighted slope multiplied by curve number variable (IDW_CN_SL_OL) alone explains approximately half of variation in Total days with 7DADMax exceeding 17.8 °C. In model group 4, proportional flow accumulation weighted slope variable (PFAW_SL) explains about 50% of variation.

6. DISCUSSION and CONCLUSIONS:

Our simple inverse distance weighted metrics provide significantly more accurate predictions of a range of stream temperature conditions. Areal averaged metrics appeared to provide a better estimate of minimum 7DADmin temperatures than distance and flow weighted metrics, similar to results found in other studies of broad patterns of spatial variation in stream temperature (Webb and Walling, 1986, Webb et al. 2008). Our results from Model Group 2 mirror those found in other studies of improved model performance including more spatially explicit information in connecting landscape characteristics with stream properties (Wente 2000, Peterson et al. 2011).

1 However, we provide a more direct measure of 'proximity' than Wentz (2000) by
2 examining the effects of overland and total flow distance directly rather than utilizing the
3 proxy of flow accumulation. In line with Wentz (2000) and Peterson et al.'s (2011)
4 findings, flow accumulation is a powerful predictor variable, if corrected for by
5 calculating a proportional flow accumulation metric due to the abstract nature by which
6 flow accumulation is otherwise calculated (the relative number of pixels draining into
7 any given pixel in the watershed, which scales non-linearly as you approach the stream
8 network).

9 In general, our approach seeks to combine intuitive and theoretical information
10 on the physical relationship between landscape properties and stream properties and
11 represent them with reproducible and less computationally intensive statistical
12 indicators. Such work is part of a broader effort to include physical process information
13 in statistical models (Mohseni and Stefan 1999, Gallice et al. 2015). These metrics
14 could be readily generated and evaluated across a much broader study region using
15 existing land use, soil, and topographic databases, provided that comparative stream
16 temperature data is available. Including specific land uses via distance weighted means
17 was shown to improve predictive regression performance using stepwise AIC in
18 Australia (Peterson et al. 2011), and may be repeatable across study regions
19 elsewhere. We provide a means by which the overall transmissivity of a watershed can
20 be more tightly defined by examining the spatial distribution of transmissivity, which may
21 provide utility in understanding landscape scale relationships with stream temperatures
22 in climate change studies.

However, model refinement or improvements could be made in several ways. First, our distance-weighted landscape variables indirectly consider spatial autocorrelation between upstream and downstream stations if they are nested along the same hydrologic network. Given that such spatial autocorrelation has been more directly taken into account by Ver Hoef et al. (2014), it would be interesting to compare the result of our study with the one using Ver Hoef et al.'s model to see if parameter estimates are improved. Second, our model is tested using one season for one watershed that has relatively homogenous climate. Although our model validation results are stable between the years we examined, our model could be further tested for other basins for other seasons. Using a publically available stream temperature database such as NorWeST (<http://www.fs.fed.us/rm/boise/AWAE/projects/NorWeST.html>) may offer such new opportunities. Third, our model could be refined by introducing additional predictors. While our initial focus was landscape variables that do not vary over time, using time series hydrometeorological variables such as precipitation, solar radiation, humidity, and soil moisture are likely to improve our model fit. The stable assumption of soil moisture during the summer when calculating CN could be further modified to better reflect changes in soil moisture over time. Additionally, considering relatively high residuals in more developed areas than the other parts of the basin, infrastructure variables such as storm pipes and wastewater treatment plants can be included to potentially increase a predictive power of our model.

Overall, we provide an improved rationale for including spatially explicit metrics in predictive regressions seeking to link terrestrial and stream processes. Improvements

upon this work will increase our ability to predict the outcomes of landscape scale riparian restoration programs altering terrestrial infiltration properties, as well as water and land managers for potential impacts of climate change. In order to improve the utility of this work, we welcome reproducible studies utilizing similar approaches, especially those investigating the changes over time of stream thermal properties and landscape characteristics. By understanding how landscape – stream relationships modulate climatic drivers of stream thermal regime, we can improve the integrated management of anthropic hydrosapes to protect, maintain, and enhance them for current and future generations.

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Table 1. Stream temperature and landscape data used in analysis

Data	Resolution	Derived variables	Source
Stream temperature	Hourly		Clean Water Services (2015)
Stream network	10m	Subbasin boundary Flow length Basin size	US Geological Survey/US Environmental Protection Agency, National hydrological database (2015)
Digital elevation model	30m	Slope Overland flow distance Proportional flow accumulation	US Geological Survey, National Elevation data set (2002)
Land use/land cover	30m	% land cover curve number	US Geological Survey, National land cover data (2011)
Soil	30m	% hydrologic soil group curve number	US Department of Agriculture, Web soil survey (2015)

Table 2. Non-distance and distance weighted landscape variables used in regression analysis

VARIABLE NAME		DESCRIPTION	EQUATION
Area_CN		mean subcatchment curve number	$SUM(CN_{i,j})/n_{i,j}$
AvgElev		mean subcatchment elevation	$SUM(EL_{i,j})/n_{i,j}$
AvgSlope		mean subcatchment slope	$SUM(SL_{i,j})/n_{i,j}$
CN_SL		Mean curve number * slope	$SUM(CN_{i,j} * S_{i,j}) / n_{i,j}$
Size		subcatchment size in sq m	$n_{i,j} * 30m^2$
IDW_CN		total flow length inverse distance weighted curve number	$SUM(CN_{i,j} / D_{i,j}) / SUM(1 / D_{i,j})$
IDW_SL		total flow length inverse distance weighted slope	$SUM(SL_{i,j} / D_{i,j}) / SUM(1 / D_{i,j})$
IDW_CN_SL		total flow length inverse distance weighted slope*curve number	$SUM(CN_{i,j} * SL_{i,j} / D_{i,j}) / SUM(1 / D_{i,j})$
IDW_EL		total flow length inverse distance weighted elevation	$SUM(EL_{i,j} / D_{i,j}) / SUM(1 / D_{i,j})$
IDW2_CN		total flow length inverse squared distance weighted curve number	$SUM(CN_{i,j} / D_{i,j}^2) / SUM(1 / D_{i,j}^2)$
IDW2_SL		total flow length inverse squared distance weighted slope number	$SUM(SL_{i,j} / D_{i,j}^2) / SUM(1 / D_{i,j}^2)$
IDW2_CN_SL		total flow length inverse squared distance weighted slope*curve number	$SUM(CN_{i,j} * S_{i,j} / D_{i,j}^2) / SUM(1 / D_{i,j}^2)$
IDW2_EL		total flow length inverse squared distance weighted elevation	$SUM(E_{i,j} / D_{i,j}^2) / SUM(1 / D_{i,j}^2)$
IDW_CN_OL		overland flow inverse distance weighted curve number	$SUM(CN_{i,j} / O_{i,j}) / SUM(1 / O_{i,j})$
IDW_SL_OL		overland flow inverse distance weighted slope	$SUM(SL_{i,j} / O_{i,j}) / SUM(1 / O_{i,j})$
IDW_CN_SL_OL		overland flow inverse distance weighted slope*curve number	$SUM(CN_{i,j} * S_{i,j} / O_{i,j}) / SUM(1 / O_{i,j})$
IDW_EL_OL		overland flow inverse distance weighted elevation	$SUM(EL_{i,j} / O_{i,j}) / SUM(1 / O_{i,j})$
IDW2_CN_OL		overland flow inverse squared distance weighted curve number	$SUM(CN_{i,j} / O_{i,j}^2) / SUM(1 / O_{i,j}^2)$
IDW2_SL_OL		overland flow inverse squared distance weighted slope	$SUM(SL_{i,j} / O_{i,j}^2) / SUM(1 / O_{i,j}^2)$
IDW2_CN_SL_OL		overland flow inverse squared distance weighted slope*curve number	$SUM(CN_{i,j} * S_{i,j} / O_{i,j}^2) / SUM(1 / O_{i,j}^2)$
IDW2_EL_OL		overland flow inverse squared distance weighted elevation	$SUM(E_{i,j} / O_{i,j}^2) / SUM(1 / O_{i,j}^2)$
PFAW_CN		Proportional flow accumulation weighted curve number	$SUM(CN_{i,j} * (FA_{i,j}/FA_{max})) / SUM(FA_{i,j}/FA_{max})$
PFAW_SL		Proportional flow accumulation weighted slope	$SUM(SL_{i,j} * (FA_{i,j}/FA_{max})) / SUM(FA_{i,j}/FA_{max})$
PFAW_CN_SL		Proportional flow accumulation weighted slope*curve number	$SUM(CN_{i,j} * (FA_{i,j}/FA_{max})) / SUM(FA_{i,j}/FA_{max})$
PFAW_EL		Proportional flow accumulation weighted elevation	$SUM(E_{i,j} * (FA_{i,j}/FA_{max})) / SUM(FA_{i,j}/FA_{max})$

For each pixel *i* in sub-watershed *j*, CN = curve number, E = elevation in meters, S = slope in degrees, D is the distance from the pixel to the monitoring point, O = distance from the pixel to the stream network, FA = the flow accumulation, or number of pixels draining to pixel *i,j*

Table 3. Four regression model groups and beta coefficients for significant variables for five temperature indices. (Model Group 1: areal averages; Model Group 2: inverse distance by total flow length; Model Group 3: overland distance to stream network and distance squared; Model Group 4: proportional flow accumulation) Adjusted R^2 is based on calibrated data for 2011 and evaluation R^2 is based on validation data for 2010.

Model	Variable, R^2 , AIC	7DADMin	7DADMax	SMHT	FDM	>17.8°C
Model 1	Area_CN					
	AvgElev	(-0.956) ***		(-0.845) ***		
	AvgSlope					
	CN_SL		(-0.408) **		(+0.500) ***	(-0.587) ***
	Size	(+0.173) **		(+0.271) **		
	Adjusted R^2	0.83	0.14	0.63	0.23	0.32
	AIC	-25.76	43.79	-2.95	-352.69	227.90
	Evaluation R^2	0.85	0.25	0.62	0.14	0.59
Model 2	IDW_CN					
	IDW2_CN				(-0.541) ***	
	IDW_SL					
	IDW_CN_SL		(-0.456) ***	(-0.779) ***		(-0.616) ***
	IDW_EL	(-0.874) ***				
	IDW2_CN_SL					
	Adjusted R^2	0.76	0.18	0.60	0.27	0.36
	AIC	-13.96	42.11	-1.06	-354.63	226.11
	Evaluation R^2	0.81	0.28	0.58	0.25	0.62
Model 3	IDW_CN_OL					
	IDW2_CN_OL					
	IDW_SL_OL			(-0.833) ***	(+0.582) ***	
	IDW2_SL_OL					
	IDW_CN_SL_OL	(-0.606) **	(-0.592) ***			(-0.710) ***
	IDW_EL_OL	(-0.315) ***				
	Adjusted R^2	0.75	0.33	0.68	0.32	0.49
	AIC	-12.02	1.71	-9.35	-356.88	218.73
	Evaluation R^2	0.80	0.46	0.68	0.20	0.71
Model 4	Size					
	PFAW_CN					
	PFAW_SL		(-0.601) ***	(-0.828) ***		(-0.709) ***
	PFAW_CN_SL					
	PFAW_EL	(-0.881)			(+0.637)	

		***			***	
	Adjusted R ²	0.77	0.34	0.68	0.39	0.49
	AIC	-15.80	0.13	-8.49	-360.38	174.73
	Evaluation R ²	0.78	0.45	0.66	0.23	0.71

Note: Variable descriptions are the same in Table 2. Significance level: *** <0.001, ** <0.01
Numbers in parenthesis are VIF values.
The best model is shown in bold.

Fig 1 (a) land cover characteristics of the study area and (b) location of stream temperature monitoring stations with elevation as background

Fig. 2. Land Cover and Soil Combine to calculate soil conservation service Curve Number

Weighting Landscape Variables

— Stream Line

[Number] = Value by Cell

Curve Number

Flow Distance

Weights

IDW Curve Number

Fig. 3. A schematic depicting how inverse distance weighting modifies landscape characteristic variable values.

Fig. 4. Spatial Variation in our five stream temperature variables in the Tualatin river basin based on summer 2011 data.

Fig. 5. Relation between seasonal mean temperatures and areal average landscape

variables. Pearson correlation coefficient and p-values are reported in each scatterplot.

Model 1: Areal Average Metrics

Model 3: IDW Overland Metrics

Model 4: Flow Accumulation Weighted

Fig. 6. Residual maps of mean temperature, thermal flashiness and days 7-day moving average of daily maximum stream temperature exceeding 17.8 °C. for model group 1 (areal average), 3 (overland distance to stream network and distance weighted) and 4 (flow accumulation weighted).