Journal of Environmental Management 118 (2013) 170–176

Contents lists available at SciVerse ScienceDirect

Journal of Environmental Management

journal homepage: www.elsevier.com/locate/jenvman

Linking landscape variables to cold water refugia in rivers

Wendy A. Monk[a], Nathan M. Wilbur[a], R. Allen Curry[a,*], Rolland Gagnon[b], Russell N. Faux[c]

[a] Canadian Rivers Institute, P.O. Box 4400, 10 Bailey Drive, University of New Brunswick, Fredericton, New Brunswick E3B 5A3, Canada
[b] J.D. Irving, Ltd., P.O. Box 5777, 300 Union Street, Saint John, New Brunswick E2L 4M3, Canada
[c] Watershed Sciences, Inc., 517 SW 2nd Street, Suite 400, Corvallis, OR 97333, USA

ARTICLE INFO

Article history:
Received 20 February 2012
Received in revised form
21 December 2012
Accepted 26 December 2012
Available online

Keywords:
Thermal infrared imagery (TIR)
Thermal refugia
Landscape variables
Tributaries
PLS regression

ABSTRACT

The protection of coldwater refugia within aquatic systems requires the identification of thermal habitats in rivers. These refugia provide critical thermal habitats for brook trout (*Salvelinus fontinalis*) and Atlantic salmon (*Salmo salar*) during periods of thermal stress, for example during summer high temperature events. This study aims to model these refugia using georeferenced thermal infrared images collected during late July 2008 and 2009 for a reach of the Cains River, New Brunswick, Canada. These images were paired with geospatial catchment variables to identify the driving factors for coldwater refugia located within tributaries to the main channel. Using Partial Least Square (PLS) Regression, results suggest that median temperatures of tributary catchments are driven by their position within the landscape including slope in addition to the density of wetlands and mixed forest within the upstream catchment. Similar results are presented when PLS models were developed to predict the magnitude of the cold water refugia (i.e. the difference between the mainstem water temperature and the thermal refugia). These results suggest that thermal infrared images can be used to predict critical summer habitats for coldwater fishes.

1. Introduction

Aquatic communities are highly adapted to their physical environments and thus, temperature plays a critical role in defining adaptations and distributions because survival is ultimately based in chemical reactions within living cells (reviewed for coldwater fishes by McCullough et al., 2009). For example, coldwater species such as the Atlantic salmon (*Salmo salar*) and brook trout (*Salvelinus fontinalis*) have physiological thermal optima at 10 °C to 20 °C (e.g., Jonsson et al., 2001; Xu et al., 2010). Fish and invertebrates in the fresh waters of cold climate regions must survive extended periods of extreme cold and accumulations of ice in winter followed by summer periods where air temperatures can exceed their maximum thermal tolerances for extended periods. To deal with the temperature stress and survive, these poikilothermic biota have evolved physiological adaptations as well as the behaviour of moving to thermal refugia to escape high temperatures in summer or cold water and ice accumulations in winter (Sutton et al., 2007; Breau et al., 2007; Linnansaari et al., 2008) and for some populations, anomalies sustain reproductive habitats (Curry et al., 1995; Baxter and Hauer, 2000). For some coldwater species, their thermal optima are already being exceeded during high temperature events in summer across their native eastern North American range when water temperatures are increasingly exceeding 24 °C in late July and August (e.g., Monk and Curry, 2009). With recent and projected future climate warming, there is a clear impact facing coldwater biota. Recent research predicts a future significant loss of suitable and accessible coldwater habitats with clear negative effects on poikilothermic fish (Rahel et al., 1996; Battin et al., 2007; Jonsson and Jonsson, 2009). Therefore, predicting the occurrence and persistence of such critical thermal habitats has become paramount for resource managers (Battin et al., 2007; McCullough et al., 2009).

Within rivers in eastern North America, the summer, coldwater sources are determined primarily by flows from baseflow or groundwater (Alexander and Caissie, 2003; Mellina et al., 2002), hyporheic flow (Poole et al., 2008), and tributary streams that remain cooler because of forest cover in their catchments (Story et al., 2003), i.e., landscape scale characteristics can control the local, reach scale habitats driving the location and characteristics of thermal refugia. However, anthropogenic development can alter these landscape patterns, for example through deforestation, mineral extraction, urban development, and this can have a direct influence on ground and surface water temperatures (see Webb et al., 2008 for a comprehensive review). Therefore, the

* Corresponding author. Tel.: +1 506 452 6208; fax: +1 506 453 3583.
E-mail address: racurry@unb.ca (R. Allen Curry).

0301-4797/$ – see front matter © 2013 Elsevier Ltd. All rights reserved.
http://dx.doi.org/10.1016/j.jenvman.2012.12.024

development of a tool to predict the occurrence and characteristics of thermal refugia based on understanding and measuring landscape scale characteristics that impact the hydrological processes controlling water temperatures would contribute to sustainable river management. This tool combined with regional climate patterns would then predict how land use and potential future climate change may affect critical, coldwater thermal habitats.

The study of river ecosystems at the landscape scale is the foundation of the emerging field of ecohydrology (Poole, 2010; Johnson and Host, 2010). In the ~25 years since the introduction of Geographic Information Systems (GIS) that produced the computational ability to handle and analyse the overwhelming amounts spatial data generated from remote sensing (see summary by Johnson and Gage, 1997), there has been a continuous push to extend our studies of river ecosystems from the scale of sites, reaches, and catchments to landscapes. This rapid expansion of technology and advances in statistical computing power has allowed us to begin exploring the complexity of interconnectedness in the ecosystem that the pioneers in river science established, including the impacts of human activities on landscapes (e.g., Leopold and Maddock, 1953; Hynes, 1975; Vannote et al., 1980). Thermal infrared (TIR) imagery has been shown to be effective in mapping spatial patterns of temperature in rivers (e.g., Banks et al., 1996; Belknap and Naiman, 1998; Torgersen et al., 2001; Danielescu et al., 2009). Combining geospatial data with TIR imagery and focussing on tributaries that may create coldwater, thermal refugia, we aim to (i) identify temperature variations at tributary discharge points; (ii) quantify the relationship between geospatial landscape descriptors and temperature in this mixing zone; and (iii) develop an approach to model the landscape scale characteristics that best predict the quantity of these potential coldwater refugia in rivers.

2. Methods

2.1. Study area

The Cains River (1399 km^2 catchment) is a major tributary of the southwest branch of the Miramichi system (Fig. 1). The Miramichi River watershed is located in the central-eastern region of New Brunswick and drains 13,800 km^2 of the central area of the province. The regional climate is typically continental with cold winters and warm, dry summers when July air temperatures regularly exceed 25 °C (Environment Canada, 2010). The watershed was glacier covered until ~10,000 years before present (Curry, 2007) and the present landscape has gentle topography (small, rolling hills) with shallow ablational till (Rees et al., 1992). The mean annual temperature is 4.8 °C (1971–2000 average for Doaktown, NB – Environment Canada, 2010). The average annual precipitation from 1971 to 2000 measured 1150 mm (863 mm of rainfall and 287 mm of snowfall) with most rainfall occurring throughout the summer and autumn months (Environment Canada, 2010). The hydrological regimes of the region reflect a typical Atlantic Maritime hydrological regime with a dominant spring freshet following snowmelt and secondary peak during the fall because of rainfall (Monk et al., 2011).

In the Cains River catchment, 96% of the land is forested (6% hardwood forest, 73% softwood forest, 17% mixed forest and 4% non-forest) with very few seasonal residences (New Brunswick Department of Natural Resources Forest Management Branch, 2005). Within the catchment, the greatest anthropogenic activity is forestry operations (26% of the area has experienced forestry operations in last 25 years). The Cains River is well known for its brook trout and Atlantic salmon populations and the recreational fisheries they support.

2.2. Thermal infrared mapping

The thermal images were collected in collaboration with Watershed Sciences, Inc. (www.watershedscience.com). A TIR sensor (FLIR Systems SC3000 LWIR) was housed in a gyro-stabilized mount and attached to the underside of a helicopter. The TIR sensors measure the thermal energy emitted at the water's surface which can accurately represent bulk water temperatures where the water column is thoroughly mixed. Although thermal stratification can occur in reaches with little or no mixing (e.g. in some pools), stratification is not likely during to naturally turbulent flow and can be detected in the imagery. We assessed mixing and found this river to be of uniform temperature across the water column (Wilbur, 2012). The sensor captured single band images (8–9.5 μm) of the stream channel while the helicopter was flown longitudinally along the river corridor at ~400 m height above the river. The main stem channel is open with generally unobstructed line of sight between the water and the airborne remote sensor. The flight altitude was selected in order to optimize resolution (pixel resolution = 0.44 m) while providing an image ground footprint wide enough to capture the active channel (129 m). The TIR sensor was set to acquire images at a rate of 1 image every second resulting in 40–70% vertical overlap between images. Each pixel contained a measured energy value that was converted to radiant temperatures. Although variable water surface conditions or changes in viewing aspect can result in differences in the calculated radiant temperatures, the apparent temperature variability is generally less than 0.5 °C (Torgersen et al., 2001). Therefore, apparent stream temperature of less than 0.5 °C is not considered significant unless they are associated with a known surface inflow, for example tributaries or seeps.

Data from continuous temperature probes set in the river during flights were used to calibrate the conversion parameters so that radiant temperatures represented actual river, i.e., kinetic temperatures. This adjustment was performed to correct for path length attenuation and the emissivity of natural water. All imagery was geo-rectified at a 60 cm pixel size in order to maintain consistency in the final mosaics. The difference between radiant and kinetic temperatures ranged from 0 to 0.1 °C (±0.2 °C), except for the downstream sensor, which showed a difference of 1.9 °C. The cause of this difference could not be determined but variable weather conditions near the downstream section likely contributed (R.A. Curry, unpublished data).

Once calibrated, the images were analysed in a Geographical Information System (GIS) (ArcGIS, version 9.3, ESRI, 2008) by interpreting spatial temperature patterns and querying radiant temperatures (pixel values) from the center of the stream channel and saving the median value of a ten-point cell sample to a GIS database file. In addition, using the same approach, water temperatures of easily detectable surface inflows (i.e. tributaries) were sampled at the point where they entered the mainstem channel (see example in Fig. 2).

2.3. Geospatial landscape information

A 3 arc-second continuous Shuttle Radar Topography Mission Digital Terrain Model (SRTM-DTM) was used for watershed delineation (Jarvis et al., 2006). The SRTM-DTM was processed at a 10 m resolution to remove all depressions through a combination of filling and breaching and the stream and waterbodies network from the National Hydro Network were used to identify the flow network. Upstream sub-catchments for each of the tributaries were delineated using the Spatial Analyst Hydrology toolset in ArcGIS version 9.3 (ESRI, 2008). For each delineated tributary sub-catchment, geospatial variables were extracted by intersecting with environmental data available at an appropriate spatial and

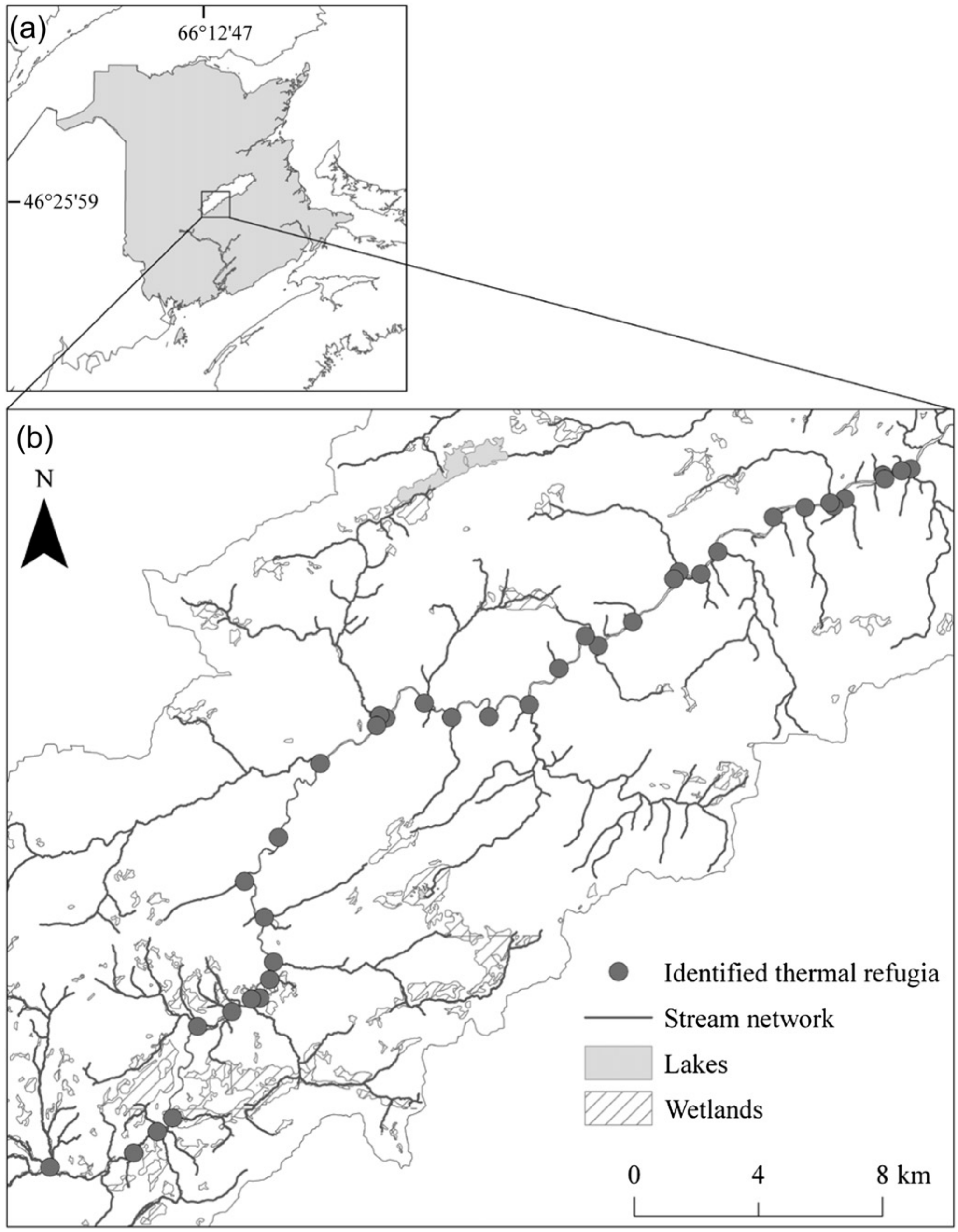

Fig. 1. Location of the (a) Cains River catchment and (b) identified tributaries where surface water temperatures (at mouth – grey circles) were compared to adjacent mainstem temperatures using thermal infrared images.

temporal scale (Table 1). Environmental variables included local climatic variables, landscape factors (for example surficial and bedrock geology, forestry and wetlands), anthropogenic variables (for example road presence within the sub-catchment and recent forestry activities) and stream network descriptors (for example distance of tributary along mainstem network and total tributary stream length) (Table 1). Extracted environmental variables were summarised as raw values or relative area and transformed using $\log_{10}(x + 1)$ or arcsine ($\sqrt{x}$), where appropriate.

2.4. Statistical analyses

Using the median of adjacent pixels, the temperature data (°C) were summarised as median temperature at the mouth of the tributary and the difference between the tributary and channel temperature (Fig. 2). Prior to analyses, the environmental variables were assessed to comply with the assumptions of partial least squares (PLSs) regression (Legendre and Legendre, 1998; Tabachnick and Fidell, 2001). Water temperature variables were transformed using $\log_{10}$ transformation. Data preparation and analysis were undertaken using Microsoft Excel, Statistical Package for Social Sciences (SPSS 17; SPSS Inc., 2008) and R (version 2.12.0, R Development Core Team, 2010).

PLS analysis was performed using the PLS package (version 2.1, Mevik and Wehrens, 2007) within the R software to quantify how well one data set (the *X*-data set or predictor, landscape variables) reflected variation in second data set (the *Y*-data set or response, water temperature). This method allows statistical exploration of data whilst enabling the user to identify the variables contributing to the patterns. PLS reduces the predictor and dependent variables

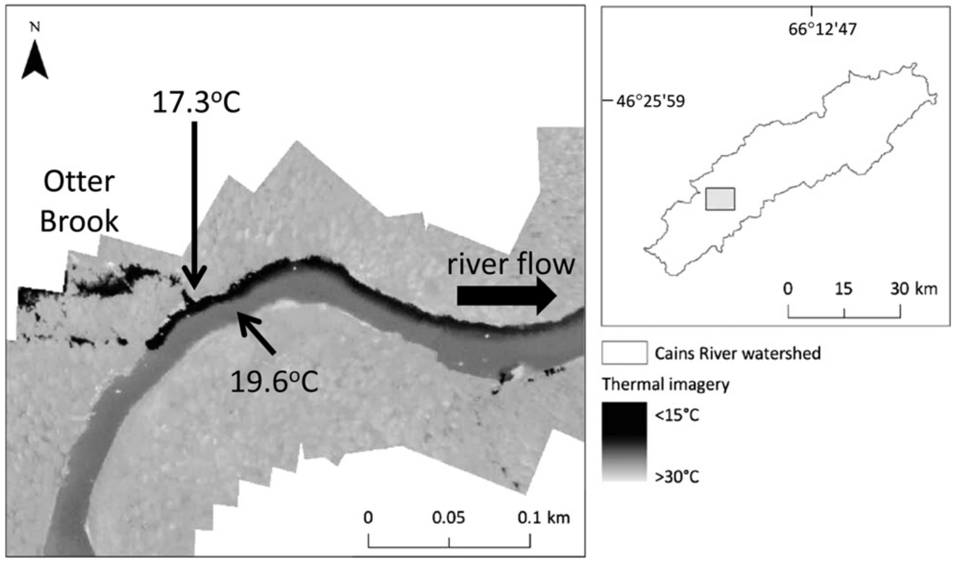

Fig. 2. Example thermal image from a reach of Cains River showing Otter Brook (median temperature = 17.3 °C) entering the main stem of the river (19.6 °C) and the resulting coldwater plume along the north bank of the main stem.

to principal components meaning that the predictor components are orthogonal and thus overcoming the problem of multi-collinearity of environmental variables. In addition, PLS is robust with data noise and missing data, which are restrictions for conventional linear regression (Eriksson et al., 1995; Wold et al., 2001).

The performance of a PLS model is expressed in the terms r^2_X, r^2_Y and Q^2_Y. Two of the model statistics, r^2_X and r^2_Y are the fractions of the modelled *X*-variation and *Y*-variation, respectively. A leave-one-out cross validation method was performed to select the number of significant components through the calculation of Q^2_Y (i.e. the cross-validated r^2_Y, 1-predicted residual sum of squares). The critical value for a single component was set as $Q^2_Y < 0.097$, which corresponds to a $p < 0.05$, with components excluded if they fall below this value (Eriksson et al., 1995). Following the initial model run, variables that were not significant ($p > 0.05$) were excluded and the model was re-run with the smaller subset. The Variable Influence on Projection (VIP) was used to assess the statistical importance of each predictor variable (landscape variables), taking into account the amount of *Y*-variance explained by each latent variable. VIP values >1 are the most statistically important in explaining the variation in the dependent variables, values >0.7 are considered moderately influential, while values <0.7 are deemed less influential (Eriksson et al., 1995).

Models were assessed by three measures of error using the observed and predicted values: the cross validation statistics; root mean square error of prediction (RMSEP); and the Nash–Sutcliffe coefficient (NSC). The Nash–Sutcliffe coefficient determines the relative magnitude of the residential variable compared with the measure data variance (Nash and Sutcliffe, 1970). The Nash–Sutcliffe coefficient varies between $-\infty$ and 1.0, where 1 is the optimum value but values <0 indicate that the mean observed value is a better predictor than the simulated value (Moriasi et al., 2007). Predominant in the hydrological literature, it is suggested that a Nash–Sutcliffe value >0.75 is very good, >0.65 is good, >0.50 is satisfactory while a value <0.50 is unsatisfactory (Saleh et al., 2000; Moriasi et al., 2007).

Table 1
List of geospatial landscape variables with data sources.

Group	Variables	Data layer	Data source
Stream morphology	Catchment area (km^2) Stream density in catchment (km/km^2) Mean/maximum/minimum elevation in catchment (m) Mean/maximum/minimum slope in catchment (%) Stream length (km) Distance along stream network (km)	Digital elevation model (re-sampled to 10 m resolution)	NASA Shuttle Radar Topography Mission (SRTM)
Climate	Total July 2008/2009 precipitation (mm) Mean July 2008/2009 air temperature (°C)	Climate (precipitation and temperature)	CANGRID – Meteorological Service of Canada
Geology	Categories of soils Categories of bedrock geology	Soil type Bedrock geology	NB Soil Survey Geological Survey of Canada
Land use	Forest type Land use	Forest inventory Non-forest inventory	NB Department of Natural Resources Forest Management Branch
Road presence	Road density in catchment (km/km^2)	Provincial road layer (includes primary, secondary and forestry roads)	NB Department of Natural Resources Forest Management Branch
Anthropogenic disturbance	Area of catchment disturbed through forestry activity in previous 25 years	Forest inventory	NB Department of Natural Resources Forest Management Branch

3. Results and discussion

3.1. River temperature characteristics

The remote sensing technology used in this project generated georeferenced spatial distributions of very accurate surface water temperatures in rivers which allows us to explore how landscapes control river temperatures and ultimately, develop models to predict spatial patterns of river temperatures (Webb et al., 2008). Approximately 75 km of the Cains River was surveyed in late July 2008 and 2009 ($\approx$1500 h). In 2008, bulk water temperatures were stable showing only a 2 °C (18.8 °C–20.8 °C) fluctuation along this reach. The TIR survey detected 99 thermal habitats including 15 names streams along the Cains river with a large number of additional seeps that were too small for accurate sampling. Ninety four of these inflows provided colder water than the main channel. For the sub-reach studied, 38 inflows from tributaries were identified with catchment areas ranging from 0.07 km^2 to 67.00 km^2 (1 standard deviation [S.D.] = 17.64 km^2). The median temperature of all measured tributaries ranged from 12.8 °C to 20.0 °C (S.D. = 1.77 °C). In 2009, thermal image surveys were re-sampled and an additional 22.5 km was added. The median main channel water temperatures were stable (21.2 °C–22.2 °C) while the inflows to the system ranged between 17.9 °C and 21.4 °C (S.D. = 0.99 °C). For both survey years, the differences between the radiant and kinetic temperatures were within the target accuracy of $\pm$0.5 °C. Overall, water temperatures were warmer in 2009 due to weather conditions in the preceding weeks.

3.2. Median tributary temperatures

The initial PLS model with one significant component for median tributary temperature as the dependent variable explained 23.9% of the independent landscape variables (r_x^2) and 67.0% of the variance in the dependent variable (r_y^2). The total variation explained by the model as quantified by the Q_Y^2 statistic was 55.0%. One PLS component was selected because it minimised the RMSEP and the value was below the critical cut-off value. Several landscape variables did not significantly contribute to the PLS model and were removed from the model, which also minimized the potential for model overfitting. Therefore, the PLS model was re-run using the reduced subset of 13 landscape variables, which were significant at $p < 0.05$.

The final PLS model with one significant component explained 39.3% of the independent landscape variables (r_x^2), 70.2% of the dependent variable (r_y^2) while the cross-validated statistic, Q_y^2, was 65.5%. The NSC value was 0.72 suggesting a good fit between the observed and predicted data while the RMSEP was 1.07 °C. Six of the 13 variables demonstrated a VIP score greater than 1 suggesting that they were statistically important in explaining the variance in the median temperature: distance downstream along the stream network, elevation at tributary mouth, total precipitation and average temperature for the preceding month, and % wetlands and % mixed forest within the tributary catchment (Fig. 3). An additional six variables had a VIP > 0.7 suggesting moderate influence and two additional variables (minimum and maximum slope) did not strongly contribute to the model (Fig. 3). The variable with the highest VIP score (VIP = 1.42) was distance downstream along the stream network suggesting that spatial position was important in determining median water temperatures. The final PLS model variables included catchment-scale metrics which reflect hydrological control parameters associated with groundwater contributions to baseflow. Slope and wetlands are parameters positively linked to hydraulic head potential (e.g., Winter, 1999), and forest cover is positively linked to solar insulation and shallower water table levels (e.g., Smerdon et al., 2009). With the known relationship between air temperature and stream temperature in addition to the moderating influence of precipitation, it is perhaps unsurprising that these variables were identified as significant in the final PLS model. The importance of spatial position along the stream network may reflect varying contributions in groundwater along the channel. For the Cains River, the upstream headwaters of the main stem are primary wetlands and downstream areas have the only defined topographic relief. The suggestion is that topographic relief is important for generating cooler water, i.e., via shallow groundwater potentials, and wetland size and location can have impacts that are both positive (e.g., tributary temperatures) and negative (e.g., distance from upstream wetland complex).

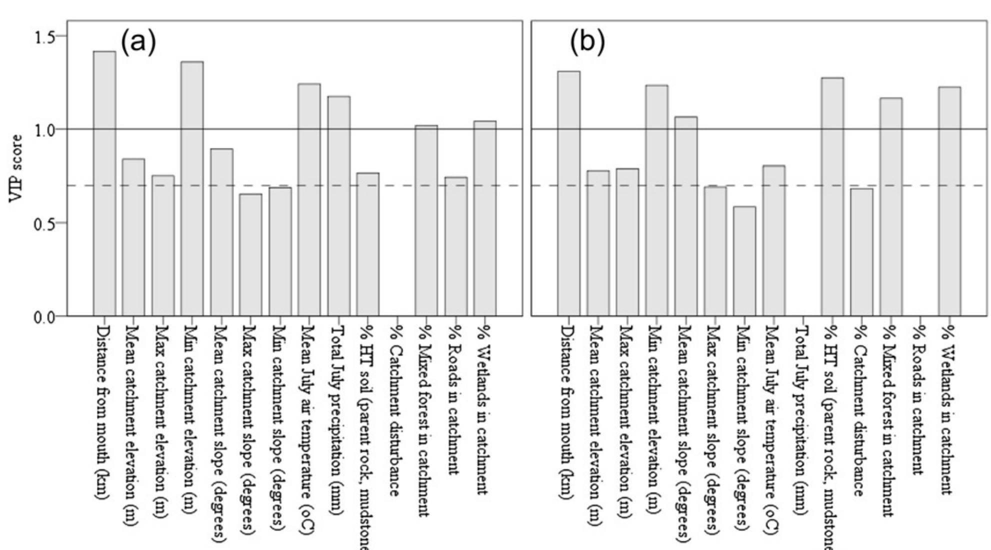

Fig. 3. Summary of the VIP values from the calculated PLS regression models using (a) median tributary temperature and (b) difference between tributary and main channel temperature as the dependent variable. Variables above the solid line (VIP > 1) are considered highly influential, variables above the dashed line (>0.7 VIP < 1) are considered moderately influential while variables below the dashed line (VIP < 0.7) are considered less influential in explaining the variation in the dependent variable. Only variables retained in the final models are shown in the figure.

3.3. Magnitude of thermal refugia

The PLS model with one significant component for quantifying the magnitude of the thermal refugia (i.e. difference in median tributary and main channel water temperature) as the dependent variable explained 24.1% of the independent landscape variables (r_x^2) and 47.8% of the variance in the dependent variable (r_y^2). The total variation explained by the model, as quantified by the Q_Y^2 statistic, was 31.7%. One PLS component was selected because it minimised the RMSEP and the value was below the critical cut-off value. Several landscape variables were excluded from the initial model following examination of the statistical significance of the landscape variables contributing to the PLS model. Therefore, the PLS model was re-run using the reduced subset of 12 landscape variables, which were significant at $p < 0.1$.

The final reduced PLS model explained 41.6% of the independent landscape variables (r_x^2), 47.1% of the dependent variable (r_y^2) while the cross-validated statistic, Q_y^2, was 36.1%. The NSC was 0.32 suggesting a good fit between the observed and predicted data while the RMSEP is 1.81 °C. The model demonstrated a lower level of precision and explained variance when compared with the first PLS model developed to predict the median tributary water temperature at mouth. Six of the 12 landscape variables demonstrated a VIP score greater than 1 suggesting that they were statistically important in explaining the variance in the median temperature (Fig. 3). These highly influential variables reflected distance downstream along the stream network, catchment descriptors, and % forest type, soils and wetlands within the catchment. An additional three variables reflecting catchment descriptors and preceding month air temperature had a VIP > 0.7 suggesting moderate influence while three variables (catchment disturbance and slope) were not strongly contributing to the model (Fig. 3). As with the PLS model exploring median tributary temperature, the variable with the highest VIP score was distance downstream along the stream network.

The relatively low level of accuracy in the model predictions of the difference in a one-time temperature measure between tributaries and the main stem may reflect the complex and diverse mixing zones at their confluences that are temporally dynamic. This is in part due to the nature of TIR data which captures only the surface temperature <1 cm deep (Torgersen et al., 2001). In summer, colder water entering a river without mixing has the potential to be isolated under the warmer, less dense surface water (Kay and Jay, 2003) and thus impacts interpretation of infrared data in the mainstem. However, Wilbur (2012) examined water column mixing in the Cains River and found that temperatures were uniform (average depth = 36 cm).

3.4. Next phase of modelling

While our models are only first glimpses at these very complex spatial data sets, the level of accuracy of prediction and inclusion of metrics we would *a priori* predict for inclusion, i.e., parameters of base flow contributions and climate, indicate the potential promise of the approach. As the present study begins to demonstrate, we can now move beyond basic studies that examined correlations between the physical state of a landscape and biological components of river ecosystems to begin the search for causation of patterns, i.e., how physical/hydrological processes influence/regulate biological structures and processes (e.g., Benda et al., 2004), how landuse can alter these processes (e.g., Johnson and Host, 2010), and how current trends in climate warming will potentially alter riverine habitats (e.g., Monk and Curry, 2009).

These are our first demonstrations of the management potential of the emerging TIR, GIS, and statistical analytical techniques and approaches. We have yet to explore all the facets of the watershed, but we are developing metrics of riverscape features as presented and discussed in Benda et al. (2004) such as temperature variability from hyporheic flow (Poole et al., 2008), characteristics of upstream water mass pathways (e.g., sinuosity, pool-riffle-run configurations, slope-velocity, friction heating), and the influences of solar radiation on upstream river temperatures (Webb and Zhang, 1997). We have developed a preliminary statistical model to explore the relationship between landscape scale variables and temperature of both the mouth of tributaries and the temperature difference between tributaries and the main channel. We plan to expand our analytical approach to additional rivers to allow the development of a generic regional model. Our future goal is to develop management maps to allow the protection of these important cold water refugia within the region using existing GIS variables.

4. Conclusions

We used TIR and PLS regression analysis to demonstrate that relative to the mainstem of a river, temperatures of tributaries are reasonably predicted by their location in the river network (distance downstream in this watershed) and the amount of mixed forest, specific soil type, and wetlands within the catchment. Not included in models were catchment disturbance (by human activity) or average slope. The models were statistically significant, but additional refinement of parameters will be necessary to improve accuracy and thus determine causation of catchment-scale patterns and the implications for management.

Acknowledgements

The authors wish to thank NSERC, New Brunswick's Environmental Trust Fund and Wildlife Trust Fund, Miramichi Salmon Association, and J.D. Irving, Limited for funding support. M. Gautreau and staff of J.D. Irving, Limited and Watershed Sciences, Limited provided logistic support. Geospatial information was provided through the Atlas of Canada, Geobase, New Brunswick Aquatic Data Warehouse and New Brunswick Department of Natural Resources Forest Management Branch. Upstream catchment delineation for each tributary was completed by Mark Castonguay (UNB).

References

Alexander, M.D., Caissie, D., 2003. Variability and comparison of hyporheic water temperatures and seepage fluxes in a small Atlantic salmon stream. Ground Water 41, 72–82.
Banks, W.S., Paylor, R.L., Hughes, W.B., 1996. Using thermal-infrared imagery to delineate groundwater discharge. Ground Water 34, 434–443.
Battin, J., Wiley, M.W., Ruckelshaus, M.H., Palmer, R.N., Korb, E., Bartz, K.K., Imaki, H., 2007. Projected impacts of climate change on salmon habitat restoration. Proceedings of the National Academy of Sciences of the United States of America 104, 6720–6725.
Baxter, C.V., Hauer, F.R., 2000. Geomorphology, hyporheic exchange, and selection of spawning habitat by bull trout (Salvelinus confluentus). Canadian Journal of Fisheries and Aquatic Sciences 57, 1470–1481.
Belknap, W., Naiman, R.J., 1998. A GIS and TIR procedure to detect and map wall-base channels in western Washington. Journal of Environmental Management 52, 147–160.
Benda, L., Poff, N.L., Miller, D., Dunne, T., Reeves, G., Pess, G., Pollock, M., 2004. The network dynamics hypothesis: how channel networks structure riverine habitats. Bioscience 54, 413–427.
Breau, C., Cunjak, R.A., Bremset, G., 2007. Age-specific aggregation of wild juvenile Atlantic salmon, *Salmo salar*, at cool water sources during high temperature events. Journal of Fish Biology 71, 1179–1191.
Curry, R.A., 2007. Late glacial impacts on dispersal and colonization of Atlantic Canada and Maine by freshwater fishes. Quarternary Research 67, 225–233.
Curry, R.A., Noakes, D.L.G., Morgan, G.E., 1995. Groundwater and the incubation and emergence of Brook trout (Salvelinus fontinalis). Canadian Journal of Fisheries and Aquatic Sciences 52, 1741–1749.
Danielescu, S., MacQuarrie, K.T., Faux, R.N., 2009. The integration of thermal infrared imaging, discharge measurements and numerical simulations to quantify the relative contributions of freshwater inflows to small estuaries in Atlantic Canada. Hydrological Processes 23, 2847–2859.

Environment Canada, 2010. Canadian climate normals for Doaktown 1971–2000. http://climate.weatheroffice.gc.ca/climate_normals/index_e.html. 14-4-2010.
Eriksson, L., Hermens, J.L., Johansson, E., Verhaar, H.J., Wold, S., 1995. Multivariate analysis of aquatic toxicity data with PLS. Aquatic Sciences 57, 217–241.
ESRI, 2008. ArcMap. Version 9.3. ESRI, Redland, CA.
Hynes, H.B.N., 1975. The stream and its valley. Verhandlungen der Internationalen Vereinigung für Theoretische und Angewandte Limnologie 19, 1–15.
Jarvis, Reuter, Nelson, Guevara, 2006. Hole-filled SRTM for the Globe, Version 3. CGIAR-CSI SRTM 90m.
Johnson, L.B., Gage, S.H., 1997. Landscape approaches to the analysis of aquatic ecosystems. Freshwater Biology 37, 113–132.
Johnson, L.B., Host, G.E., 2010. Recent developments in landscape approaches for the study of aquatic ecosystems. Journal of the North American Benthological Society 29, 41–66.
Jonsson, B., Jonsson, N., 2009. A review of the likely effects of climate change on anadromous Atlantic salmon, *Salmo salar*, and brown trout, *Salmo trutta*, with particular reference to water temperature and flow. Journal of Fish Biology 75, 2381–2447.
Jonsson, B., Forseth, T., Jensen, A.J., Næsje, F., 2001. Performance of Juvenile Atlantic Salon, Salmo salar L. Functional Ecology 15 (6), 701–711.
Kay, D.J., Jay, D.A., 2003. Interfacial mixing in a highly stratified estuary – 1. Characteristics of mixing. Journal of Geophysical Research – Oceans 108, 3072.
Legendre, P., Legendre, L., 1998. Numerical ecology. Numerical Ecology 20, 1–895.
Leopold, L.B., Maddock, T. Jr., 1953. The Hydraulic Geometry of Stream Channels and Some Physiographic Implications. U.S. Geological Survey Professional Paper 252, 56p.
Linnansaari, T., Cunjak, R.A., Newbury, R., 2008. Winter behaviour of juvenile Atlantic salmon, Salmo salar L., in experimental stream channels: effect of substratum size and full ice cover on spatial distribution and activity pattern. Journal of Fish Biology 72, 2518–2533.
McCullough, D.A., Bartholow, J.M., Jager, H.I., Beschta, R.L., Cheslak, E.F., Deas, M.L., Ebersole, J.L., Foott, J.S., Johnson, S.L., Marine, K.R., Mesa, M.G., Petersen, J.H., Souchon, Y., Tiffan, K.F., Wurtsbaugh, W.A., 2009. Research in thermal biology: burning questions for coldwater stream fishes. Reviews in Fisheries Science 17, 90–115.
Mellina, E., Moore, R.D., Hinch, S.G., MacDonald, J.S., Pearson, G., 2002. Stream temperature responses to clearcut logging in British Columbia: the moderating influences of groundwater and headwater lakes. Canadian Journal of Fisheries and Aquatic Sciences 59, 1886–1900.
Mevik, B.-H., Wehrens, R., 2007. The PLS package: principal component and partial least squares regression in R. Journal of Statistical Software 18, 1–24.
Monk, W.A., Curry, R.A., 2009. Models of past, present and future stream temperatures for selected Atlantic salmon rivers in Northeastern North America. In: Haro, A., et al. (Eds.), International Symposium on Challenges for Diadromous Fishes in a Dynamic Global Environment. American Fisheries Society, Bethesda, MD, pp. 215–230.
Monk, W.A., Peters, D.L., Baird, D.J., Curry, R.A., 2011. Trends in indicator hydrological variables for Canadian Rivers. Hydrological Processes 25, 3086–3100.
Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. Transactions of the ASABE 50, 885–900.
Nash, J.E., Sutcliffe, J.V., 1970. River flow forecasting through conceptual models. Part I – A discussion of principles. Journal of Hydrology 10, 282–290.
New Brunswick Department of Natural Resources Forest Management Branch, 2005. New Brunswick Forestry Data.
Poole, G.C., 2010. Stream hydrogeomorphology as a physical science basis for advances in stream ecology. Journal of the North American Benthological Society 29, 12–25.
Poole, G.C., O'Daniel, S.J., Jones, K.L., Woessner, W.W., Bernhardt, E.S., Helton, A.M., Stanford, J.A., Boer, B.R., Beechie, T.J., 2008. Hydrologic spiralling: the role of multiple interactive flow paths in stream ecosystems. River Research and Applications 24, 1018–1031.
R Development Core Team, 2010. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria.
Rahel, F.J., Keleher, C.J., Anderson, J.L., 1996. Potential habitat loss and population fragmentation for cold water fish in the north platte river drainage of the Rocky Mountains: response to climate warming. Limnology and Oceanography 41, 1116–1123.
Rees, H.W., Langmaid, K.K., Losier, J.G., Veer, C., Wang, C., Wells, R.E., Fahmy, S.H., 1992. Soils of the Chipman-Minto-Harcourt Region of New Brunswick. New Brunswick Soil Survey Report No. 11. Research Branch, Agriculture Canada, Ottawa, Ontario.
Saleh, A., Arnold, J.G., Gassman, P.W., Hauck, L.M., Rosenthal, W.D., Williams, J.R., McFarland, A.M.S., 2000. Application of SWAT for the upper north Bosque river watershed. Transactions of the ASAE 43, 1077–1087.
Smerdon, B.D., Redding, T.E., Beckers, J., 2009. An overview of the effects of forest management on groundwater hydrology. BC Journal of Ecosystems and Management 10, 22–44.
SPSS Inc, 2008. Statistical Package for the Social Sciences. Version 17.0, Chicago, Illinois.
Story, A., Moore, R.D., MacDonald, J.S., 2003. Stream temperatures in two shaded reaches below cutbacks and logging roads: downstream cooling linked to subsurface hydrology. Canadian Journal of Forest Research 33, 1383–1396.
Sutton, R.J., Deas, M.L., Tanaka, S.K., Soto, T., Corum, R.A., 2007. Salmonid observations at a Klamath River thermal refuge under various hydrological and meteorological conditions. River Research and Applications 23, 775–785.
Tabachnick, B.G., Fidell, L.S., 2001. Using Multivariate Statistics, fourth ed. Allyn and Bacon, Needham Heights, MA.
Torgersen, C.E., Faux, R.N., McIntosh, B.A., Poage, N.J., Norton, D.J., 2001. Airbourne thermal remote sensing for water temperature assessment in rivers and streams. Remote Sensing of Environment 76, 386–398.
Vannote, R.L., Minshall, G.W., Cummins, K.W., Sedell, J.R., Cushing, C.E., 1980. River continuum concept. Canadian Journal of Fisheries and Aquatic Sciences 37, 130–137.
Webb, B.W., Zhang, Y., 1997. Spatial and seasonal variability in the components of the river heat budget. Hydrological Processes 11, 79–101.
Webb, B.W., Hannah, D.M., Moore, R.D., Brown, L.E., Nobilis, F., 2008. Recent advances in stream and river temperature research. Hydrological Processes 22, 902–918.
Wilbur, N., 2012. Characterizing thermal refugia for brook trout (*Salvelinus fontinalis*) and Atlantic salmon (*Salmo salar*) in the Cains River, New Brunswick, Canada. MSc CE thesis, University of New Brunswick, Fredericton, Canada.
Winter, T.C., 1999. Relation of streams, lakes, and wetlands to groundwater flow systems. Hydrogeology Journal 7, 28–45.
Wold, S., Sjöström, M., Eriksson, L., 2001. PLS-regression: a basic tool of chemometrics. Chemometrics and Intelligent Laboratory Systems 58, 109–130.
Xu, C., Letcher, B.H., Nislow, K.H., 2010. Context-specific influence of water temperatures on brook trout growth rates in the field. Freshwater Biology 55, 2253–2264.