Assessing the Landscape Drivers of Cold-Water Temperatures at Tributary Confluence Plumes: A Multi-Spatial Analysis

by

Hannah S. Green

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Supervisors:	Charles Sacobie, PhD, Biology
	Jae Ogilvie, MSc, RPF, Forestry and Environmental Management
Examining Board:	Janet Blackadar, MScF, Forestry and Environmental Management, Chair
	Alexa Alexander-Trusiak, PhD, Biology, HRA

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Abstract

The impact of climate change and human disturbances affects the thermal regime of rivers, increasing the need for conservation of thermal refuges. Tributary confluence plumes are a classification of thermal refuges on the Restigouche River watershed. The objectives of this thesis were to use landscape attributes to predict water temperatures at tributary confluence plumes at two spatial scales (global and reach-specific) and identify how landscape drivers vary at the sub-catchment. Model 3D explored three variables, and a second model (12D) included the addition of nine other variables. We increased global variability explained between model 3D ($R^2 = 0.07$) and model 12D ($R^2 = 0.88$). We classified reach-scale models under three categories of high relative importance: bedrock, climate and canopy cover. We recommend that the Kedgwick (canopy), Restigouche and Upsalquitch Southeast (climate) tributaries be of high priority for protection, while continuing exploration into the effects of geomorphology on the watershed.

Dedication

I would like to dedicate this to my parents, Shayne and Lisa. Thank you for everything. I love you.

Acknowledgements

I would like to start this off by acknowledging my co-supervisors, Dr. Charles Sacobie and Jae Ogilvie. Charles, thank you for your support since day one. Without you, I would have never done an honours thesis, let alone this graduate work. Thank you for all your support during my athletic and academic career; your support has made this process the most enjoyable academic experience I will ever have, and for that I cannot thank you enough. To Jae, thank you for always taking the time to guide me in the right direction, to deal with my impromptu visits to your office for updates, and for letting my brain wander and speak aloud without judgment. I would like to thank my supervisory committee: Michelle Gray. Thank you for the time you have dedicated to guiding me through this process, editing, commenting, and reviewing. And thank you for catching the small things I would have never seen otherwise!

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To the West Coast and to my family, Lisa, Shayne, Jenna, Mike, and Phil. Thank you for always being there for me through my undergraduate and graduate work. All of you have shown me nothing but unwavering support and love, and I miss you all every day (almost as much as I miss the mountains). Thank you to my parents and to Mike specifically for nurturing my love and curiosity for the forest, and all that it brings.

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List of Symbols, Nomenclature, or Abbreviations

CHR – Canopy Height Raster

CV – Coefficient of Variation

DEM – Digital Elevation Model

ECA – Equivalent Cut Areas

FA – Flow Accumulation

FCBR – Forest-Based Classification and Regression

GINU - Gespe'gewa'gi Institute of Natural Understanding

GIS – Geographic Information Systems

GPS – Global Positioning System

ha – Hectare

km – kilometer

LiDAR – Light Detecting and Radar

LMEM – Linear Mixed Effects Models

MFRN – Ministère des Forêts et Ressources Naturelles

MSE – Mean standard error

MTT – Mean Transit Time

Mya – Millions of Years Ago

NB – New Brunswick

NBDNR – New Brunswick Department of Natural Resources

NSC – Nash-Sutcliffe Coefficient

QC – Québec

RRCE - Regressive Rate of the Cut Effect

RRWMC – Restigouche River Watershed Management Council

RSS – Residual sum of squares

SE – Standard Error

SD – Standard Deviation

TCP – Tributary Confluence Plume

TIR – Thermal Infrared Imagery

UNB – University of New Brunswick

VIF – Variance Inflation Factor

WTR – Water Table Ratio

1.0 Introduction

1.1 Water Temperature

Water temperature is a determining factor in the survival capability of many aquatic species, and often influences their behaviours (Caissie, 2006; Hudon et al., 2010). For salmonid species such as Atlantic Salmon (*Salmo salar*), temperatures above 24.8°C pushed salmon to aggregate within cold-water patches within the Ouelette River, Québec due to experiencing the beginnings of thermal stress (Dugdale et al., 2016). While there is debate over what the exact temperature values, typically, temperatures above 17°C are what cause Atlantic Salmon to experience thermal stress, while sustained temperatures exceeding 23°C can lead to mortality (Wilbur et al., 2020; Quilbé et al., 2023). For Atlantic Salmon, water temperature also plays a key factor in rate of food intake, growth, reproductive rate, and influences the probability of individual presence on a mainstem river or tributary (DeWeber & Wagner, 2015; Santiago et al., 2017).

1.2 Thermal Refuges

Cold-water refuges are areas of thermal variance where poikilotherms aggregate to find temporary thermoregulation (Sullivan et al., 2021). The term ‘thermal refuge’ has been used differently among researchers, with disagreements on its definition. The terms 'thermal refuge', 'thermal refugia' and 'cold-water refuge' have been used to define the same concept in different research contexts. Hydrologists and biologists define the term differently, making a universal term definition difficult to achieve. Hydrologists describe a thermal refuge as a 'thermal anomaly' where distinct water temperature mixing occurs (Sullivan et al., 2021). However, the term 'thermal anomaly' does not exclusively define the mixing between cold and warm, but simply a general temperature difference between the two. This is like the definition of a 'thermal refuge', which can be classified as cold-water or warm-water refuges. Biologists and ecologists define the term 'thermal refuge' as being a cold-water patch utilized by organisms to achieve favourable physiological conditions (Sullivan et al., 2021). In the context of this thesis, the classification of thermal refuges is exclusively cold-water. The definition of a cold-water patch comparative to a cold-water refuge is dependent on the biological lens. Cold-water patches are areas of cool water temperatures at least three degrees Celsius cooler than the mainstem river, while cold-water refuges are cold-water patches that pertain to the physiological requirement of poikilotherms to avoid high water temperatures (Sullivan et al., 2021). A cold-water patch may not be utilized as a cold-water refuge if the biological requirements for reproductive success, increased growth rates, and prey availability are inadequate (Ritter, 2020; Sullivan et al., 2021; Wilbur, 2020).

There are seven classifications of thermal refuges: cold alcove, cold side channel, hyporheic upwelling, lateral seep, springbrook, tributary confluence plume, and wall-based channel (Table 1).

Table 1. List of thermal refuge classifications and definitions. Modified from Dugdale (2014), Dugdale et al. (2015) and Torgersen et al. (2012).

Classification	Definition	Reference
Cold Alcove	Floodplain/gravel bar groundwater extends to downstream end of floodplain into main channel	Ebersole et al., 2003a
Cold Side Channel	A secondary cold-water channel along the mainstem river	Dugdale et al., 2015
Hyporheic Upwelling	A resurgence found downstream from meanders, bars, and riffles	Brunke & Gonser, 1997; Dugdale et al., 2015
Lateral Seep	Active channel disrupts groundwater flow through slope, alluvial fan, or terrace	Torgersen et al., 2012
Springbrook	Steady flow emerging from floodplain depressions	Ebersole et al., 2003a
Tributary Confluence Plume	Tributary inputs intersect with mainstem and create a plume of cold water	Dugdale, 2014; Torgersen et al., 2012
Wall-based Channel	Cold channels characterized by runoff from a terrace or valley wall	Dugdale et al., 2015; Torgersen et al., 2012

1.2.1 Tributary Confluence Plumes

A tributary confluence plume (TCP) is a cold-water plume found at the mouth of tributaries that flow into the mainstem, where there is a discharge of cold-water that mixes with warmer mainstem flow (Dugdale et al., 2013; Dugdale et al., 2015). Tributary confluence plumes are typically more frequent than that of other refuge classifications due to their locations at tributary and main flow intersections (Dugdale et al., 2013). Dugdale (2014) found that plumes were more temporally persistent, with 69.9% observed on more than one occasion. The repeat observation of confluence plumes suggested that they are also less likely to be affected by seasonal variations in groundwater than other classifications such as lateral seeps (Dugdale, 2014). This may be due to the stability of the refuge, where the cold-water plumes are more stable than refuges that depend on other landscape variables for cold water patches, such as boulder deflections (Dugdale, 2014).

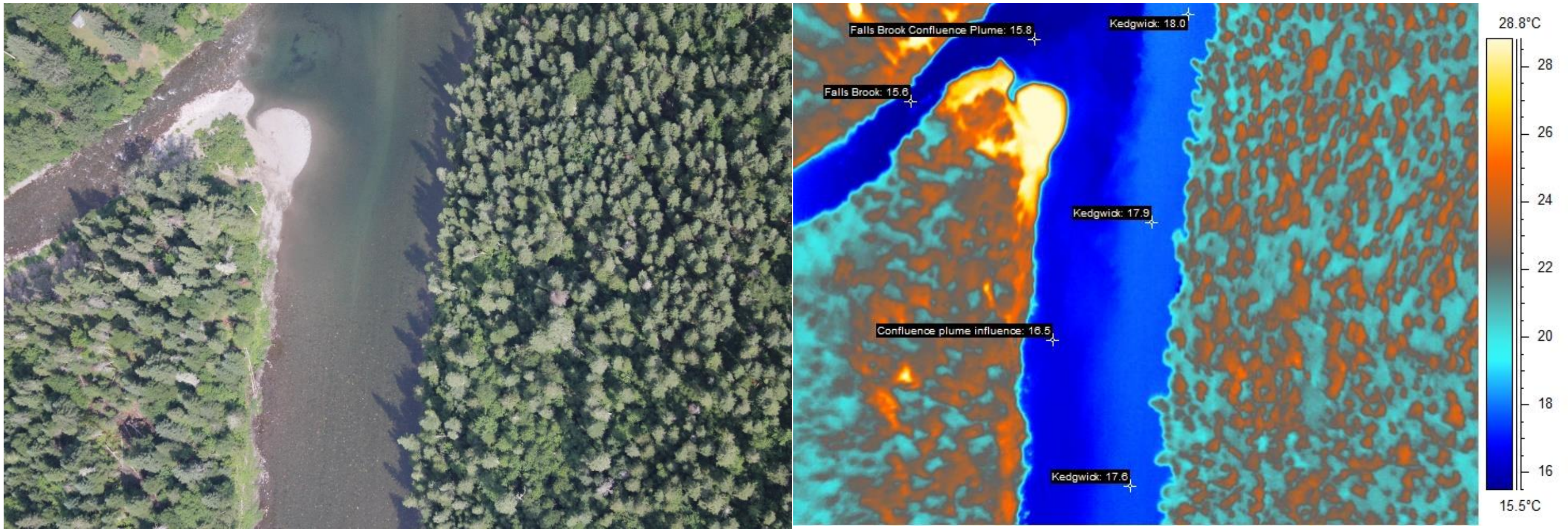

Figure 1. Side by side comparison of orthoimagery (left) and thermal imagery (right) of a tributary confluence plume located on the Kedgwick tributary at Falls Brook. Modified by Gillis (2024).

1.3 Landscape Drivers of Water Temperature

Cold-water tributary temperatures are an accumulation of factors in the structure, function, and spatial scale of the drainage system. At the watershed (global) scale, drivers of TCPs differ from those at the sub-catchment (reach-level) or at the microhabitat level (Torgersen et al., 2012). This is primarily due to the variance of landscape effects at different spatial scales. Variables such as slope and aspect experience minimal variation at the microhabitat scale (10^{-1}-10^{0} m^2) compared to the basin scale (10^{2}-10^{3} km^2). A study by Monk et al. (2013) explored the effects of landscape drivers contributing to cold-water temperatures of TCPs at the watershed-level and found there was a significant relationship between cold-water temperatures and landscape variables such as elevation, soil type, forest type, refuge position and the presence of wetlands in the delineated catchment on the Cains River in New Brunswick. Similarly, Torgersen et al., (2012) suggested that at the watershed level, thermal refuge water temperatures were driven by the relationship between topography, hydrogeology, and land cover composition. His findings are comparable to other previous literature on the drivers of thermal refuge temperatures (Ebersole et al., 2003a; Sullivan et al., 2021; Timm et al., 2017).

1.3.1 Canopy Cover

Riparian cover contributes to shading at the sub-catchment level, where tributary level shading can influence water temperature greater than at the watershed level (Aas et al., 2010). The influence of canopy cover depends on the width and water volume of the streams (Johnson & Wilby, 2015), and in general, a tributary will experience higher canopy cover than a river's mainstem. Forest cover adjacent to waterways influence surface water temperatures by reducing incoming solar radiation (Kurylyk et al., 2015). A channel with minimal to no canopy cover will receive more solar radiation, increasing the amount of solar radiation that hits the stream and/or mainstem river. Johnson and Wilby (2015) found one of the channels of their study location in England, the Dove, received 1.54 x 10^6 MJ/km of direct solar energy with no tree canopy present, while the section with trees present received 0.39 x 10^6 MJ/km (25%) direct solar energy. Canopy cover is a natural protection from soil erosion, reducing the amount of runoff entering the tributary system (Kurylyk et al., 2015). This can have a positive or negative effect on water temperature depending on the nature of the rest of the tributary system.

1.3.2. Landscape Topography and Lithology

Soil drainage and slope have a strong relationship due to the nature of groundwater movement. Soil drainage is characterized by lithology and has strong influence on the percolation rate of water in a watershed (Shaban et al., 2016). Typically, coarse textured soil with larger grain sizes and shallow depths on the landscape reduce the storage time of groundwater, and allows for faster discharge (Briggs et al., 2017; Huggenberger et al., 1988; O'Sullivan, 2021; Shaban et al., 2016). We would expect to see that a well-drained soil connected with a high average slope percentage would be important drivers of cool-water temperatures, as a higher rate of flow decreases the time in which groundwater is stagnant, and surface water is heated through solar radiation (Monk et al., 2013). This statement is supported in cases such as in Québec, where thermal refuges were associated with well-drained alluvial soils (Fakhari et al., 2022).

Landscape topography influences the structure of tributaries, groundwater movement, and surface water flowpaths (Leibowitz et al., 2018). The direction of the slope face is also a factor in water temperature cooling or warming, as south facing slopes receive more solar radiation than north-facing slopes and will experience a greater variability in temperatures (Furze et al., 2021).

1.3.3. Wetlands

Wetlands facilitate surface and groundwater interactions with the landscape and are important contributors to water temperature in watersheds (Winter, 1998). They contribute to recharge and discharge within watersheds (Price et al., 2005), as the connectivity between wetlands and tributaries facilitates groundwater movement (Leibowitz et al., 2018). Groundwater connectivity directly affects the ability of wetlands to influence thermal regimes, as wetlands can be characterized as a recharge, discharge, or flow through (Winter, 1998). The contribution from wetlands to groundwater systems is influenced by their position on the watershed, as well as contributions from soil and geologic underlay (Price et al., 2005).

1.3.4 Bedrock Geology and Groundwater

Groundwater has been described as an important driver in tributary water temperatures (Caissie, 2006; Fakhari et al., 2019). Typically, thermal refuges are driven by groundwater, however, watersheds are complex, dynamic systems, wherein thermal refuges can be informed by other landscape drivers (Wawrzyniak et al., 2016). Within the watershed, groundwater functions as a connector between wetlands and streams (Leibowitz et al., 2018). For example, the presence of an isolated wetland on the watershed may still contribute to streams disconnected from wetlands by way of a deep groundwater aquifer, which recharges the wetland through groundwater flow or surface-water flow (Leibowitz et al., 2018).

The type of exposed bedrock significantly affects groundwater recharge (Shaban et al., 2006), showing that bedrock type may be correlated to water temperature depending on permeability, bedrock age, and mean travel time for groundwater. The connection between bedrock geology and groundwater is described by Hale et al. (2016), where their study found that the mean transit time (MTT) of groundwater was longer in catchments underlaid with permeable and weathered sandstone compared to catchments with volcanic bedrock. O'Sullivan et al. (2019) found that the underlaying coarse textured glaciofluvial material, which is permeable and typically associated with groundwater discharge, was a significant variable in water temperature predictions in Clearwater Brook, New Brunswick. They concluded that older bedrock is more permeable than younger bedrock, which, coupled with a greater volume of surficial deposits, lead to cooler groundwater inflow in the Cains River, New Brunswick (O'Sullivan et al., 2019).

1.4 Threats to Thermal Refuges

The removal of forest cover for forest harvesting, agriculture or urban expansion can have drastic effects on tributary water temperatures (Stott & Marks, 2000; Quilbé et al., 2023). Forest harvesting affects other landscape metrics that directly inform water temperatures, such as groundwater levels, soil drainage, and surface runoff (Brewer et al., 2013; Moore et al., 2005; Shaban et al., 2006). Paul and Meyer (2001) found that on an altered landscape, the loss of riparian vegetation increased stream temperatures through increased solar radiation levels, and surface runoff through vegetation removal at stream banks (Quilbé et al., 2023). The removal of canopy cover at the catchment level may increase groundwater temperatures upstream of the tributary, with or without the presence of a riparian buffer (Kurylyk et al., 2013).

Groundwater levels can be altered and decreased through anthropogenic interventions such as the draining of aquifers for agricultural or urban use, flow manipulations such as dams, and aggregate extraction (Quilbé et al., 2023; Wu et al., 2020). In areas of high agricultural activity, draining of wetlands can lead to loss of biological and functional activity, as direct and indirect wetland connection to the stream network contributes to water levels (Leibowitz et al., 2018; Wu et al., 2020). Drainage of wetlands may also decrease groundwater recharge availability by lowering the water table (Leibowitz et al., 2018).

1.5 Challenges in Thermal Refuge Management

The impact of climate change is dependent on the landscape scale as well as the characteristics of the watershed (Arnell & Reynard, 1996). Wang (2020) describes the correlation between the increase in air temperature to increasing stream temperatures, as well as the following negative effects caused by said warming such as decreased inflow, increased evaporation, and a shift from snowmelt-to-rainfall-dominated flow regimes on thermal refuges. Similarly, Wilbur (2020) discusses how climate factors such as increased heat events will almost guarantee an expected decrease in flow events during summer months.

The study of thermal refuges and what drives water temperatures is complicated by spatial and temporal variations at the stream level, as well as the many influential landscape factors that interact with each other. A study conducted by Bogan et al (2003) on USGS stream gauging stations in the eastern and central United States found that climate controlled water temperatures on 22% of the total 596 streams while groundwater and other variables influenced water temperatures in the remaining reaches. Similarly, Loinaz et al. (2013) used simulations on data collected from Silver Creek, Idaho that by reducing groundwater flow by 10% to the Silver Creek stream reach increased water temperatures by an average of 0.3°C and a maximum of 1.5°C. Statements that water temperatures are heavily influenced by climate may not be accurate without accounting for the spatial and temporal aspects.

The connection between the atmosphere and landscape makes managing TCPs difficult, and there are knowledge gaps that have been identified when it comes to thermal refuge research. The need for statistical models at different spatial integrations has been documented as a knowledge gap (Mejia et al., 2023; Ouellet et al., 2020), as well as identifying anthropogenic interactions at different spatial scales that affect the aquatic environment (Gillis et al., 2023; Mejia et al., 2023; Ouellet et al., 2020).

1.6 Research Aim and Layout

The primary aim of this research is to explore knowledge gaps through introducing spatially predictive models for thermal refuge temperatures in the Restigouche River watershed**.** The complexity of water temperature drivers varies at different spatial scales, making it difficult to identify commonalities. With the development of a global and reach-specific models, we can use overall predictor variables at a both scales to help identify the differences between variable importance at both scales. A secondary aim is to create accessible statistical models at the global and reach-specific scales that are applicable to seventh streams on other watersheds. The models can then be used to predict TCP locations on a watershed based on associated landscape variables and identify anthropogenic effects and manageable characteristics at the reach-level.

My research question was: what are the landscape-level drivers of water temperatures at tributary confluence plumes (TCPs) on the Restigouche River watershed? **Objective 1** is to use models to predict water temperatures at TCP's based on twelve landscape variables at the watershed (global) and tributary (reach-specific) levels through the creation of Forest Based Classification and Regression and multiple linear regression models. **Objective 2** is to determine how landscape level drivers vary in terms of driving strength at the reach scale.

2.0 Methods

2.1 Study Area

The Restigouche River watershed crosses the provincial boundaries of New Brunswick and Québec, with a total area of 660,000 hectares (ha) and a total drainage basin of 12,800 km^2 (Quilbé et al., 2023). The watershed is located on the unceded territory of the Mi'gmaq of Gespe’gewa’gi, and is stewarded by the Listiguj, Ugpi'ganjig (Eel River Bar) and Oinpegitjoig (Pabineau) communities (Jeannotte et al., 2007). Within New Brunswick, there are seven major tributaries (sub-catchments): Matapegiag (Matapédia), Patapegiag (Patapédia), Metamgetjuig (Kedgwick), Getnig (Restigouche), Little Main Restigouche, Apse’tgwejg (Upsalquitch) Northwest, Apse’tgwejg (Upsalquitch) Southeast and Apse’tgwejg (Upsalquitch) (Figure 3). These tributaries intersect the mainstem Restigouche and empty into the Mawi Paqtapegigtug (Baie des Chaleurs) (Jeannotte et al., 2007; Simard & Clowater, 2006).

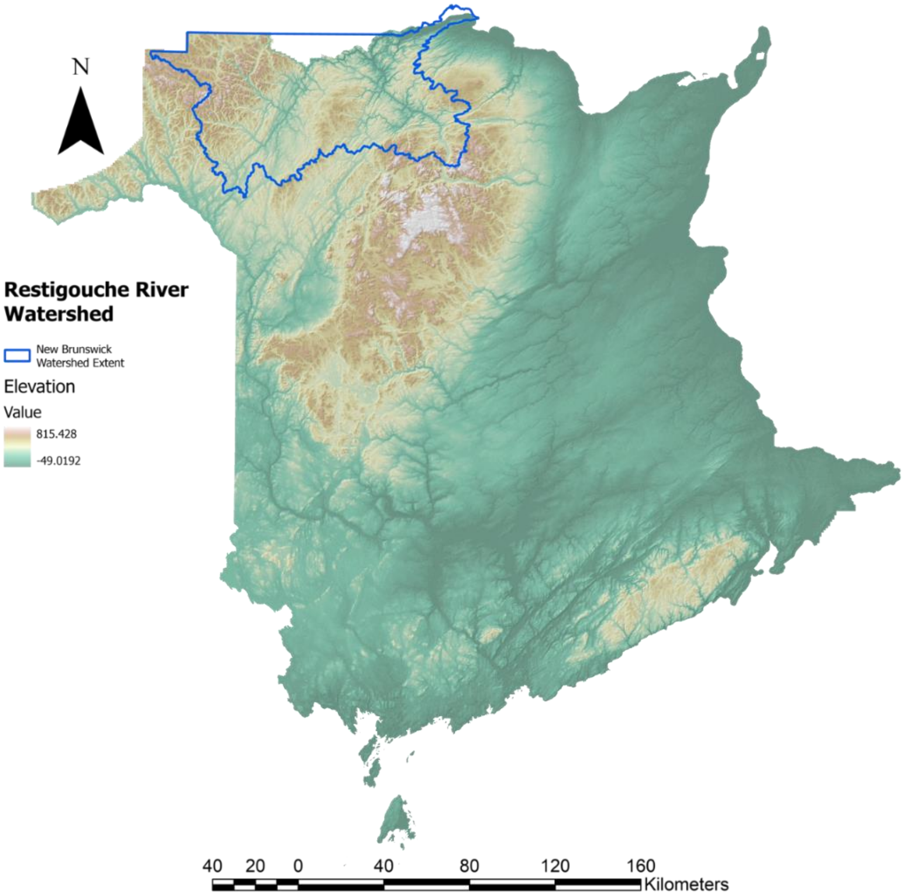

Figure 2. Location of the Restigouche River watershed study area relative to the extent of the New Brunswick provincial limit. The watershed is in the northernmost part of the province, outlined in blue. The study extent of the project extends into the southern tip of the province of Québec but does not include the remainder of the watershed extent.

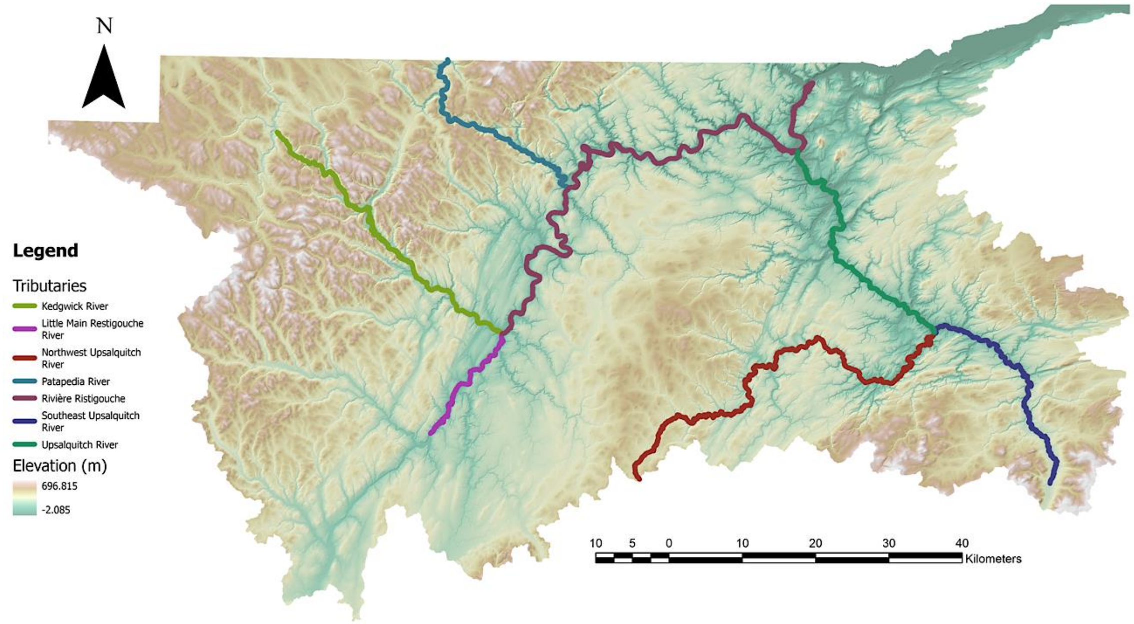

Figure 3. Delineated study area of the Restigouche River watershed and the locations of the tributaries.

2.2 Watershed Characteristics

The New Brunswick section of the watershed is located within the Atlantic Maritimes region with three intersecting ecoregions: The Central Uplands (25%), Highlands (27%), and Northern Uplands (48%) (Wilson, 2006). The lithological classifications of the landscape include the Edmundston Highlands, Miramichi Highlands, and the Chaleur Uplands, and is comprised of glacial deposits of till-covered and exposed bedrock of limestone, slate, and calcareous shale (Aas et al., 2010; Curry, 2002; Wilson, 2006). The watershed is dominated by forest cover (93%), with approximately 4% urbanized area (Quilbé et al., 2015). Agricultural land accounts for less than 2% due to the high percentage of steep slopes > 25% (Dugdale, 2014; Simard & Clowater, 2006). Softwood tree species dominate the watershed, followed by hardwood stands, then mixedwood stands (Simard & Clowater, 2006). Species of common occurrence within the region include coniferous species such as white spruce (Picea glauca), balsam fir (Abies balsamea), red pine (Pinus resinosa) and white pine (Pinus strobus). Deciduous species include yellow birch (Betula alleghaniensis), sugar maple (Acer saccharum), and white birch (Betula papyrifera) (Zelazny et al., 2007). Wetlands within the watershed are mainly categorized as open water and marsh wetlands fed by rain, snowmelt, and flooding (NWWG, 1987; Zelazny et al., 2007).

2.3 Data Collection

Observed water temperature data was provided by the Gespe'gewa'gi Institute of Natural Understanding (GINU) and was released through a data sharing agreement. Water temperature acquisition was performed by GINU and Dugdale (2014) between 2011-13 to include the total watershed extent in both provinces, with the total New Brunswick survey length completed in 308km. Imagery was taken during the months of July and August between the hours of 11:00 and 16:00, when temperature variability between tributaries and the mainstem river were highest and more easily observable from remote sensed imagery. Optical and thermal infrared imagery (TIR) were collected with a digital SLR and TIR camera respectively, while GPS coordinates were identified by a Garmin GPS76 CSx unit. Stable river discharge ensured the accuracy of TIR imagery to avoid decreasing the temperature signal in the river, which can occur following rainfall events where flow from tributaries may increase depending on the rate of incoming rainfall (Dugdale, 2014). Optical imagery required warm, sunny days for the best results, as the high sun positioning avoided image blurring, and the absence of clouds ensured minimal reflections that would have been difficult to view beneath the water surface (Dugdale, 2014). Four temperature loggers were placed in the tributary thermal refuges to record in-situ measurements to confirm the accuracy of TIR water temperature values. Refuge locations were defined through the methodology outlined in Dugdale (2014). In total, 222 tributary confluence plumes (TCP) were identified on the New Brunswick portion of the Restigouche River watershed (Figure 4). The shapefile created included attributes such as a unique point identifier, GPS coordinates, observed temperatures, refuge classification, tributary location, and original data source (Leblanc et al., 2012).

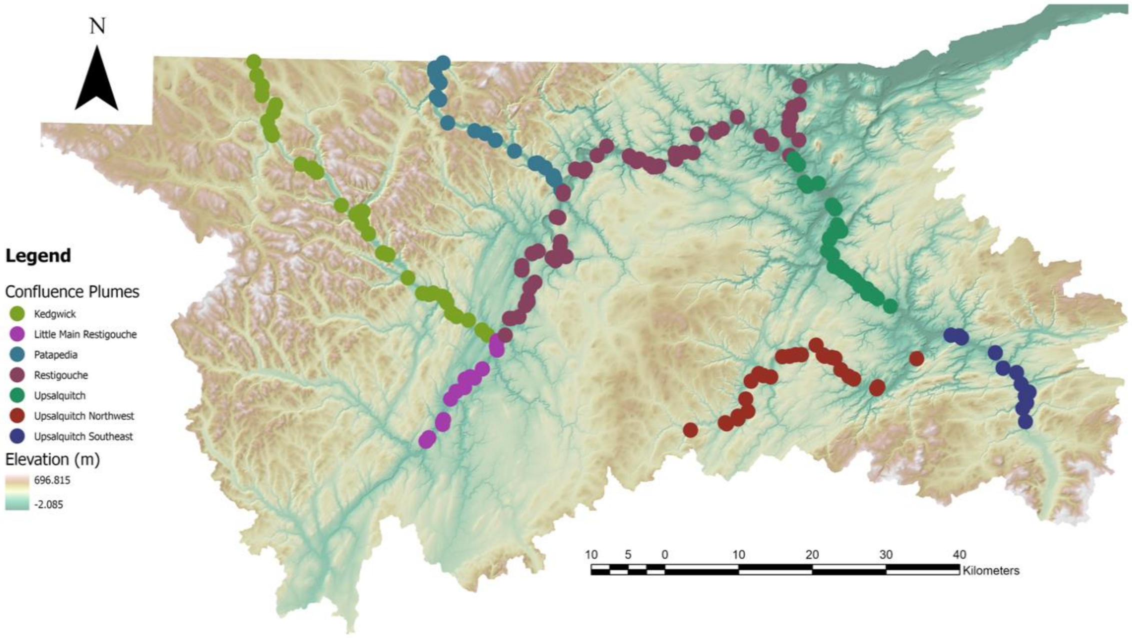

Figure 4. Dispersion of tributary confluence plumes (TCPs) within sub-tributaries of the Restigouche River watershed (NB extent). A total of 195 TCPs is present on the sub-tributaries: Kedgwick (n = 33), Little Main Restigouche (n = 15), Restigouche (n = 56), Patapédia (n = 21), Upsalquitch (n = 31), Upsalquitch Northwest (n = 26), Upsalquitch Southeast (n = 12).

2.4 Geospatial Data Availability

LiDAR data for the province of New Brunswick was accessed through the University of New Brunswick (UNB) and included digital elevation model (DEM) at 1m resolution, a hillshade raster at 2m resolution, and a canopy height raster at 1m resolution. LiDAR for the province of Québec was acquired through ForêtOuvert (Ministère des Forêts et Ressources Naturelles, 2023), which included a DEM at 1m resolution, a hillshade raster at 2m resolution and a canopy height raster at 1m resolution. The province of New Brunswick acquired LiDAR data in 2017, while the province of Québec acquired their LiDAR data in 2020. Data analysis was conducted in ArcGIS Pro Version 3.0 (2022). Acquisition of provincial data was done through open data sources, which include GeoNB and Ministère des Forêts et Ressources Naturelles (see Appendix A).

2.5 Sub-Catchment Delineation

The Hydrology toolset in ArcGIS Pro was used to create sub-catchments for each TCP by utilizing the clipped watershed DEM at 2m resolution and to create a D8 flow direction integer raster, which identifies the steepest downslope neighbour by determining the direction of steepest descent in each cell (Jenson & Domingue, 1988). In conjunction with the flow direction raster, a flow accumulation raster was created to identify the highest flow points, where the associated tributary met the mainstem river.

TCP points were snapped to match an associated flow accumulation point symbolized by the dark blue colour. It must also be noted that the original GPS coordinates had an error of ± 200m of their original location. In some cases, points were located on an incorrect bank, in the middle of the mainstem, or opposite of the correct flow point. To identify the tributary associated with the TCP, orthoimagery and hillshade rasters were used to evaluate the accuracy and likelihood of TCP location at the mainstem intersections. Orthoimagery and hillshade rasters allowed for the identification of culverts, slopes, valleys, and roads that may impact the correct location of the TCP (Lidberg et al., 2017; Paul et al., 2017).

TCP points were snapped to the corresponding flow accumulation cell with the snap pour point tool, snapping the points to the closest cell of highest flow accumulation within a neighbouring distance of 2.9m. The watershed tool, with the snap pour point and flow direction rasters, concluded the hydrological analysis, with individual sub-catchments for each TCP created to visualize the total drainage areas. While we acknowledge that TCPs require the account of influence from upstream drivers, in the case of this study, individual tributaries located at the mainstem intersection and variables contributing within the unique catchment areas were of primary interest. A total of 194 sub-catchments were delineated for analysis (Figure 6). Delineated sub catchments ranged in size from 0.06km^2 to 255.8km^2, with the smallest sub catchment located in the Upsalquitch and the largest in the Restigouche (Figure 5).

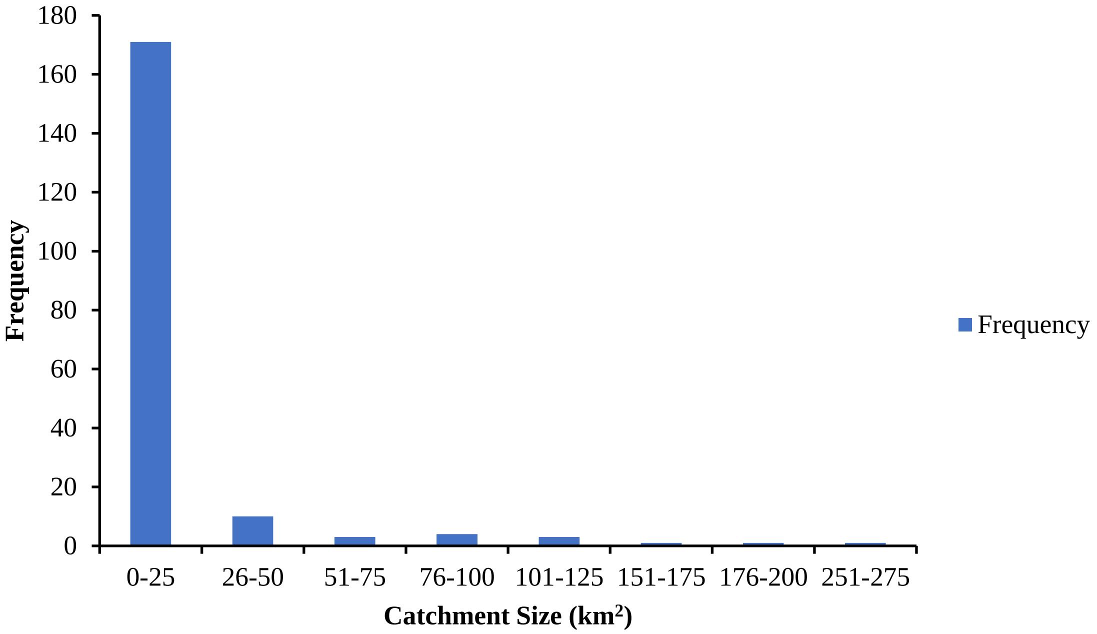

Figure 5. Frequency of sub-catchment sizes in the Restigouche River watershed delineated from the TCP sub-catchments created from total drainage area associated with their snapped flow accumulation points (n = 194).

2.6 Variable Acquisition and Definitions

Raster data was resampled to 2m resolutions with the exceptions of slope and aspect rasters, where resampling was done at 2m, 10m and 20m resolutions to determine how differences at spatial scales affect modelled temperature predictions. Aspect was classified based on eastness to determine locations of high radiation contact, calculated using the sin function in Raster Calculator at 2m, 10m and 20m resolution using the following equation: *Sin (Aspect*3.14/180).*

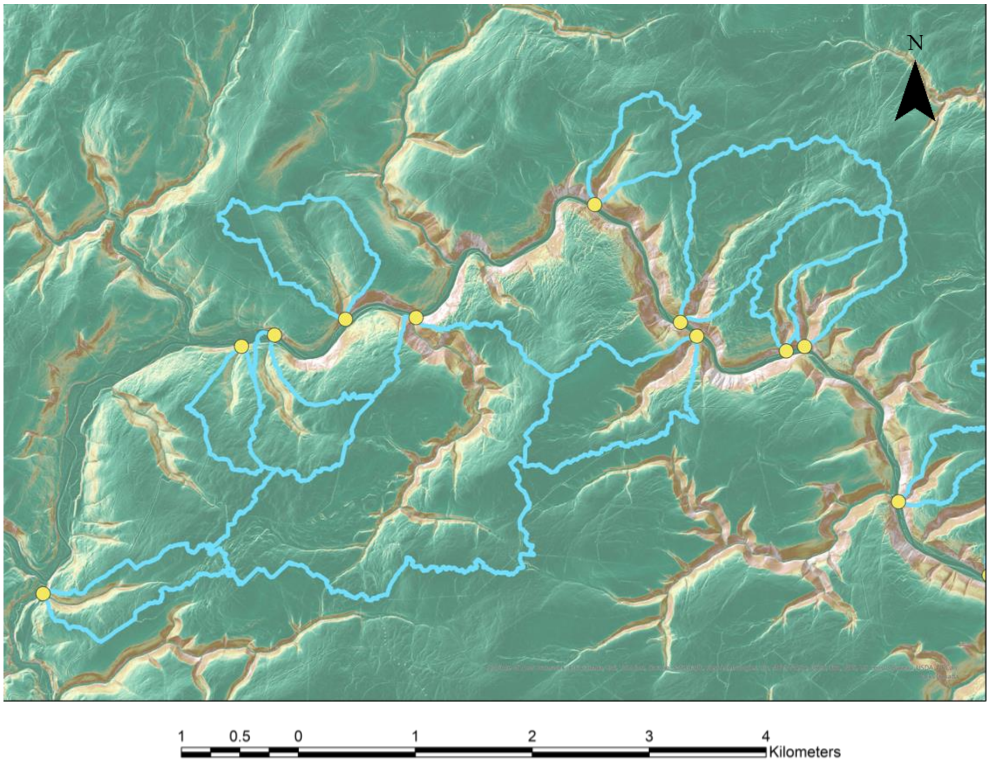

Figure 6. Sample of delineated sub-catchment areas on the Upsalquitch Northwest tributary. Yellow points show locations of tributary confluence plumes. The light blue outlines show the delineated drainage areas of each point. The map is underlaid by a slope raster at 20m resolution, with a gradient from low slope (blue) to high slope (light brown).

Canopy cover data were obtained from the canopy height raster (CHR) from provincial datasets and masked to exclude buildings by using a building footprint layer (Figure 7). Canopy values were extracted from 30m stream buffers created using the Euclidean Distance tool, then defined as values ≤ 30m (Figure 8). Stream buffers were delineated at 30m to abide by the Province of New Brunswick's Watercourse and Wetlands Alteration Technical Guidelines (New Brunswick Department of Environment, 2012).

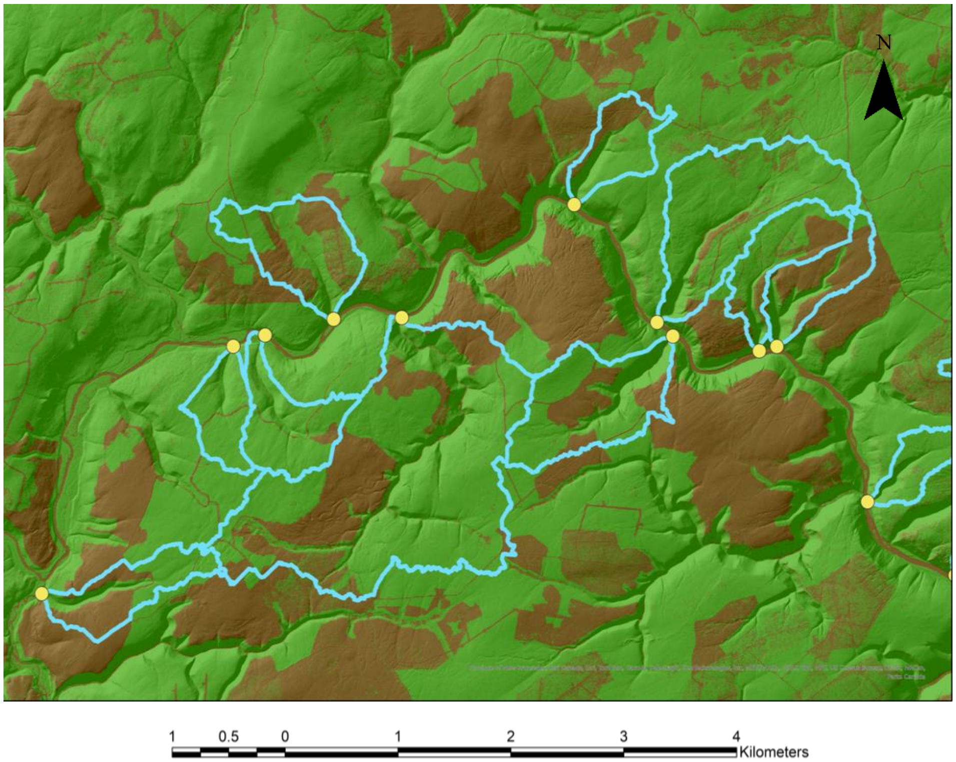

Figure 7. Canopy cover classified as ≥3m (green) and <3m (brown). Canopy height was calculated through the percentage of forest and non-forest values in raster calculator using the equation *Forested / (Forested + Non-Forested) *100*

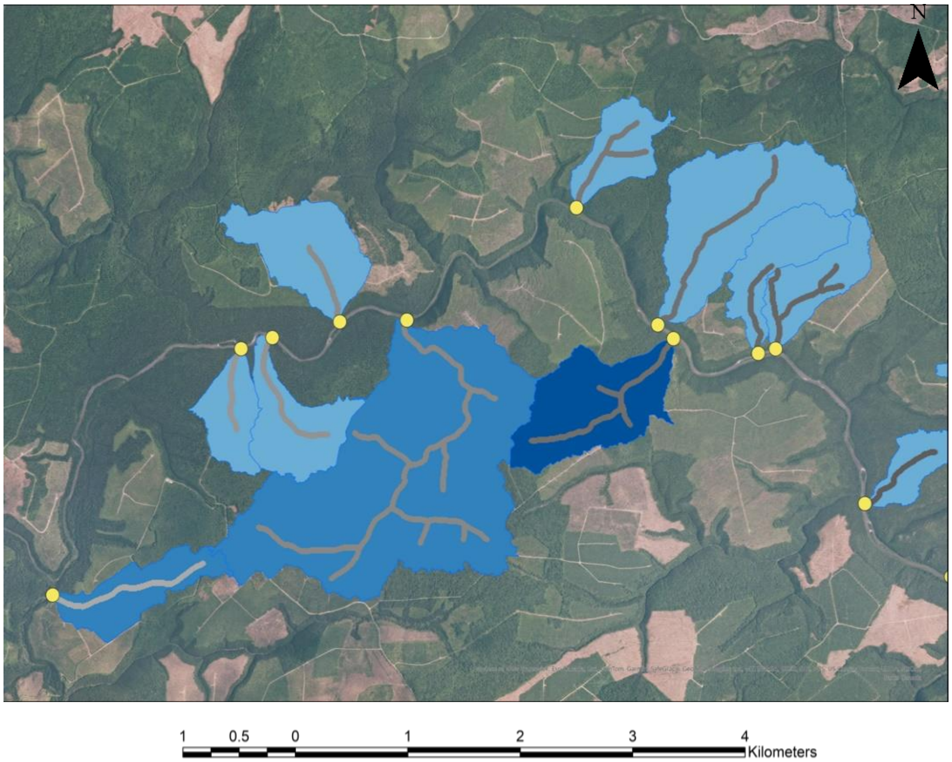

Figure 8. Delineated 30m riparian buffer zones (grey) depicted within the sub-catchments along streams. Riparian buffers were calculated using the raster calculator by inputting the following equation: *Con (“EucDisRastert ≤ 30, WatershedRaster”).*

Geological data were extracted from provincial datasets from New Brunswick and Québec and categorized based on the average age in millions of years ago (Mya) of the geological period: Cambrian (541-485.5Mya), Ordovician (485-443.8 Mya), Silurian (443.9-419.2 Mya), and Devonian (419.2-358.9 Mya) (Wilson, 2006). Average geological ages were calculated by taking the time period range of the geological time period and identifying the median age (Wilson, 2006). Soil drainage classifications were delineated from the GeoNB Forest Soils layer and corrected to account for wetlands and waterbody occurrences within the provincial data (Furze et al., 2021). Classifications were grouped into six classifications to determine overall drainage capability of underlying soil, where 0 is defined as poorly drained, and 6 is classified as very-well drained soils (Table 2). The wet areas mapping (WAM) raster was masked using the raster calculator to delineate wet areas with a value of 1, and remaining areas with a value of 0 (Murphy et al., 2008; Murphy et al., 2009; Murphy et al., 2011; White et al., 2012).

Table 2. Soil drainage classifications delineated based on the depth of wet areas. Classes were calculated using the raster calculator on the WAM raster, where WAM.MN represents the average depth of wet areas (White et al., 2012).

Soil Drainage Class	**Drainage Classification**	**WAM Parameters**
0	Very Poor	WAM.MN > 10
1	Poor	WAM.MN ≥ 5 and WAM.MN ≤ 10
2	Imperfect	WAM.MN ≥ 1 and WAM.MN ≤ 5
3	Moderately Well	WAM.MN ≥ 0.5 and WAM.MN ≤ 1
4	Well	WAM.MN ≥ 0.25 and WAM.MN ≤ 0.5
5	Rapid	WAM.MN ≥ 0.1 and WAM.MN ≤ 0.25
6	Very Rapid	WAM.MN ≥ 0 and WAM.MN ≤ 0.1

Forest cover type was extracted from provincial datasets, and stand types were harmonized with Québec definitions. Stand types were identified as softwood, mixed wood or hardwood stands based on the provided attributes and the top three species by density found within each stand. Forest harvesting data were provided by GINU by equivalent cut areas (ECA). ECA is defined as the sum of area of all harvesting or natural clearing multiplied by the regressive rate of the cut effect (RRCE), with the calculated ECA value divided by the total basin area (Leblanc et al., 2012). The RRCE was calculated based on the intensity of the cut occurring on the watershed. For example, a partial cut is defined as a less intense disturbance than a clear-cut, and these differences are accounted for through the weighted value of the RRCE and includes the last thirty-five years of forest harvesting defined by New Brunswick forestry (Leblanc et al., 2012). Roads and agricultural locations were obtained through the provincial data sources of GeoNB and ForêtOuvert and were classified as presence or absence within the watershed.

The water-table ratio (WTR) was sourced from Cuthbert et al. (2019) and is defined as the fullness of the subsurface and its interaction to the landscape. The WTR identifies areas of the landscape where groundwater is controlled topographically (WTR >1) or by recharge (WTR <1) (Cuthbert et al., 2019).

2.7 Variable Extraction

Variable extraction within sub-catchment rasters was categorically divided into raster and vector data and extracted using two tools for consistency (Table 3). The Tabulate Areas tool was used for vector data as the tool summarizes the total sum of values that intersect the delineated sub-catchment. For example, canopy cover percentage was calculated by dividing the total forested area by the catchment area and expressed as a percentage ((Forested Area/Catchment Area) *100). Zonal Statistics were used for raster data to determine statistical values such as the average, maximum and minimum values through cross calculating the raster with the sub-catchment area. Extracted data were compiled in aspatial tables and joined to the confluence plumes attribute table by their associated sub-catchment ID number.

Table 3. List of predictor variables and their associated variable measurements used in the global and reach-specific models. Italicized variables were identified as being used in preliminary analysis.

Summary Tool	**Variable**	**Variable Measurement**	**Reference**
Zonal Statistics (Raster Data)	*Slope (2m, 10m, 20m)*	Mean/Max/Min	Moore et al. (2005); Vidon & Hill (2004)
	Aspect (2m, 10m, 20m)	Mean	Furze et al. (2021)
	Wet Areas	Max/Mean	Leibowitz et al. (2018)
	Water Table Ratio	Max/Mean	Winter (1998)
	Canopy Cover	Percent	Kurylyk et al. (2015); Wilby (2015)
	Bedrock Age	Mean	O’Sullivan et al. (2019)
Tabulate Area (Vector Data)	*Soil Drainage*	Percent	Briggs et al. (2017); Huggenberger et al. (1988)
	Forest Stand Type	Percent	Garner et al. (2014)
	Agriculture	Presence/Absence	Leibowitz et al. (2018)
	Road Presence	Presence/Absence	Torgersen et al. (2012)
	Loss Year Equivalent Cut Areas	Percent	Moore et al. (2015)

2.8 Model 3D

Multiple linear regression was computed in Excel for the global and reach-specific predictions of water temperature. The preliminary model was restricted to three continuous variables within the multiple regression, being named the 3D model to describe the inclusion of the three variables. Soil drainage class, slope percentage and canopy cover percentage were used due to their use in previous research in relationship to water temperature (Ebersole et al., 2013; Johnson et al., 2015; Leibowitz et al., 2018 Monk et al., 2013). Analysis was divided into watershed (global) and tributary (reach-specific) level models to review model performance at different spatial scales. The Québec section of the watershed was not included in this analysis due to lack of data availability. At the global and reach-specific scales, three landscape variables of interest were included as model parameters: total canopy cover percentage, well-drained soil classes (0-6), and average slope at 2m, 10m and 20m resolutions.

2.9 12D Model

2.9.1 Global Model

A secondary global model was created to explore whether the addition of more variables would increase the effectiveness of temperature predictions at a the global scale, with nine additional variables unaccounted for in the 3D model. Forest-Based Classification and Regression (FBCR) is a statistical analysis tool which outputs a prediction raster, or features based on categorical and continuous input variables. The tool outputs multiple tables for analysis, including a variable importance table, which calculates the influence of individual variables based on the total sum of Gini coefficients. The tool outputs validation R^2 values based on the number of validation runs. Alongside output tables, two feature class outputs were created: a temperature prediction feature class as well as a standardized residual feature class to depict the over and underpredictions of the model to the observed values. Global model inputs were conducted with identical overall parameters: a classification tree number of 150, a mean tree depth of 11 using 100% of the available training data, and 11 randomly sampled variables. The models by the FBCR included the total number of inputs to total n = 35 predictor variables (Table 4).

Table 4. Legend of model abbreviations and associated model variable definitions.

Model Abbreviation	**Variable**
Y	Latitude
MEAN_WTR	Water Table Ratio
VALUE_469	Average Bedrock Age (469Mya)
AECCOLLEC	Equivalent Cut Area
LOSSYR	Forest Extent Change (2012-2023)
VALUE_390	Average Bedrock Age (390Mya)
PROP_WET	Proportion of Wet Areas
CANOPY	Non-Buffered Canopy Cover Percentage
MEAN_S10	Average Slope (10m)
VALUE_430	Average Bedrock Age (430Mya)
MEAN_S20	Average Slope (20m)
MEAN_S2	Average Slope (2m)
MAX_S2	Max Slope (2m)
MAX_S20	Max Slope (20m)
MEAN_E2	Average Aspect (2m)
MIN_S20	Min Slope (20m)
MAX_S10	Max Slope (10m)
A_1	Poor Soil Drainage
MEAN_E20	Average Aspect (20m)
F	Hardwood Stand
MIN_S2	Min Slope (2m)
MEAN_E10	Average Aspect (10m)
A_2	Imperfect Soil Drainage
A_0	Very Poor Soil Drainage
M	Mixedwood Stand
R	Hardwood Stand
ROADP_1	Road Presence
MIN_S10	Min Slope (10m)
A_6	Very Rapid Soil Drainage
A_3	Moderately Well Soil Drainage
A_5	Well Soil Drainage
A_4	Rapid Soil Drainage
AGRI	Agricultural Presence

Global FBCR models were separated to view the impact of canopy on temperature, specifically to determine if canopy cover is important at different intensities within the sub catchments. The “No Buffer” FBCR model depicts catchments where canopy cover is used as a predictor for the entire sub-catchment. The “Buffer” FBCR model restricts canopy cover to the provincially legislated 30m buffer distance around high flow ephemeral streams located within the sub-catchments. The performance of the FBCR models were measured using the Nash-Sutcliffe Coefficient (NSC), a measure of model fit (Nash & Sutcliffe, 1970). An NSC value of 1.0 depicts a perfect-fit model (Jain & Sudheer, 2008).

2.9.2 Reach-Specific Model

Reach-specific analysis was conducted using a multiple regression R script by Monk (2018) in RStudio (v4.3.1). Data were scaled and transformed using the “dplyr” package. In the reach-specific models, I wanted to identify how the top drivers of the global model fair at the different reach levels for management purposes. Reach-specific model inputs were determined based on the results of the FBCR models, where the top statistically relevant variables were included, in conjunction with their variable strength within the models. Reach-specific models were divided into a buffered and non-buffered version for each tributary to explore the differences between canopy cover at the 30m riparian buffer level versus canopy cover at the catchment level. The differences in canopy cover were the only variations of the reach-specific models, leaving the remaining variable inputs identical. Correlation tests were run to remove related variables, where variables with a perfect correlation of 1.0 were removed. Tests for collinearity (at the tributary level) were run to view the variance inflation factor (VIF). Variables with a VIF > 24 signifies a high level of collinearity. To avoid overfitting, models were reduced using the avsPlots function in conjunction with the stepANOVA function in R. Outliers were identified and removed by viewing residual vs fitted plots to confirm points did not cross or closely approach Cook's D contours, which identifies observation values that are far removed from the remaining observations (Dhakal et al., 2017).

3.0 Results

3.1 3D Model

3.1.1 Global 3D Model

The global model temperatures (n = 194) ranged from 13°C to 21°C, with most values ranging from 17 °C to 19 °C (Figure 9). The global model performed poorly under statistical analysis, producing an R^2 value of 0.07 and a standard error of 2.0°C. This result did not account for reach-specific differences. The average temperatures for the global prediction model showed a range of values from 17°C – 20°C.

3.1.2 Reach-Specific 3D Model

Residual graphs depict the difference between the observed value and mean value that the model predicted for the observation (Figures 10, 11). Positive residuals mean that there was an under prediction while a negative residual mean there was an over prediction of values. The R^2 value describes the variance between the outcome and the predicted variables that were input in the regression model. We would expect to see an R^2 value close to 1.0 which would mean that the variance is almost 100% described by the predictors that were input into the model.

At the reach level, temperature predictions were condensed depending on the tributary, with the warmest values located in the Restigouche (19°C – 21°C), and the coolest values located in the Upsalquitch Southeast (13°C – 15°C). These inter-tributary differences account for the high standard error within the global model (Figure 9).

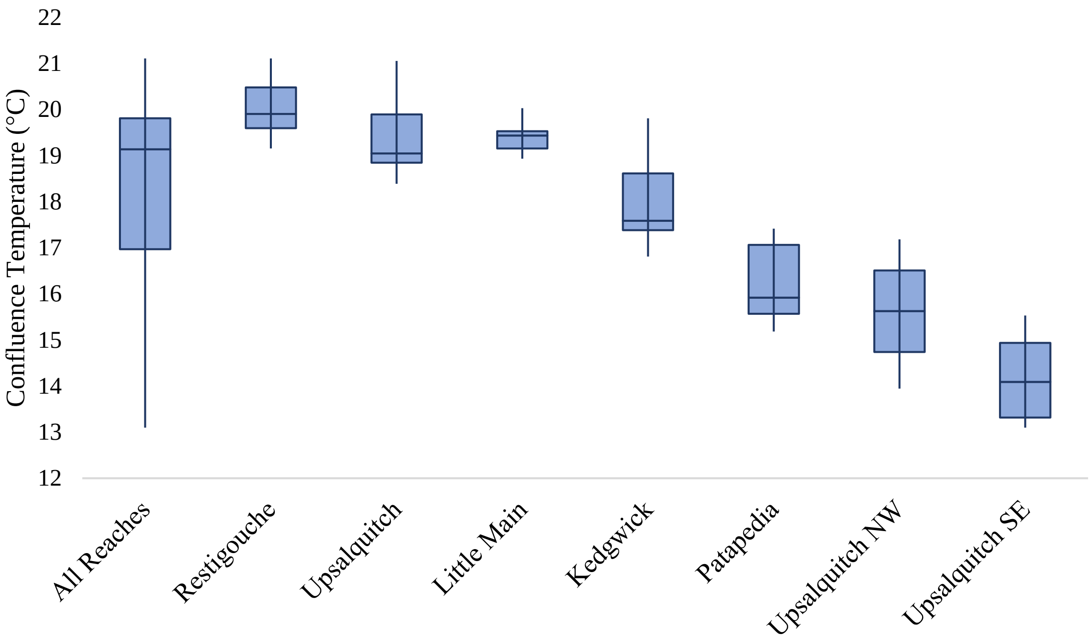

Figure 9. Global model (all reaches) and reach-specific modelled mean ± standard error (SE) tributary confluence plume (TCP) water temperature in order from warmest to coldest average tributary (n = 194).

Reach-specific models provided more variability explained than the global model, with standard errors (SE) between 0.2°C and 0.8°C. This observation was expected during the initial analysis to occur due to the spatial variation at the global scale. The Little Main Restigouche (n = 15) showed one of the highest R^2 (Figure 10) and standard error (0.2) values and showed the lowest CV (1.6%). In comparison, the Upsalquitch Southeast, with a comparable sample size (n = 12), had the highest CV of predicted temperatures for the reach specific results (6.6%), but also the highest R^2 (0.91). Similarly, the Upsalquitch (n= 31) and the Restigouche (n = 75) tributaries both demonstrated CV values of 4.0% and 2.7%, respectively. However, both models performed poorly in terms of temperature predictions, with R^2 values of 0.19 and 0.27, respectively (Figure 10).

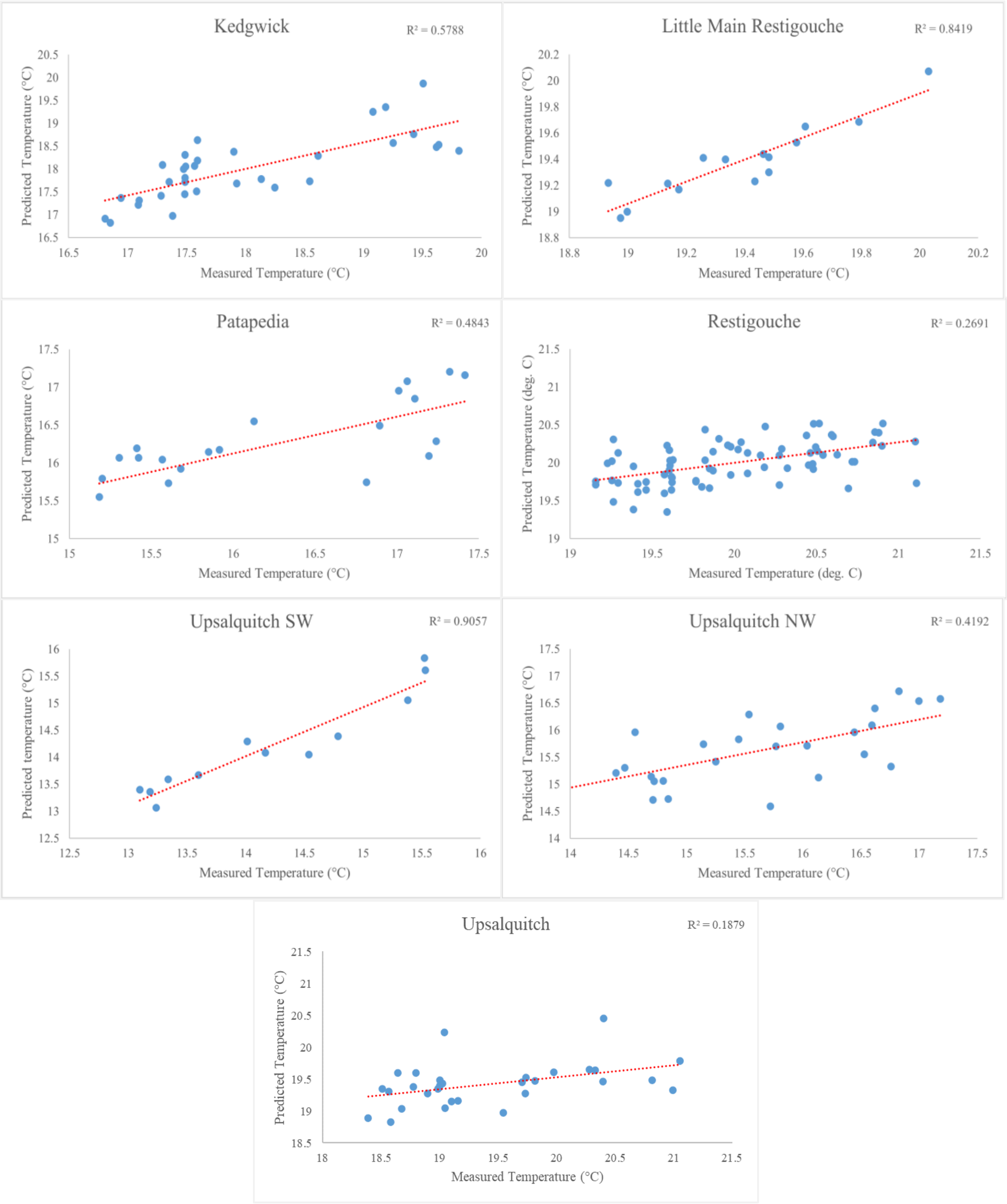

Figure 10. Measured vs. predicted temperatures (°C) of reach-scale water temperatures and associated R^2 values at the seven tributaries (n=194).

Model residuals inform the results of predicted tributary confluence water temperatures (Figure 11). Similar to the R^2 results from the Upsalquitch SE and the Little Main Restigouche, the observed versus predicted water temperature graphs depict minimal ranges in over and under predictions of water temperature values. Under suitable circumstances, the predicted temperature residual values would sit along the x-axis to show the difference between the predicted and observed values.

In the Upsalquitch SE and the Little Main Restigouche tributaries, respective residuals sit closest to the x-axis compared with remaining tributary extents (Figure 11). These results infer that the parameters included within these two reach-specific models may be strong drivers to modelling tributary confluence plume temperatures on the Upsalquitch SE and Little Main Restigouche. However, these same parameters used in the poorly performing models of the Restigouche and Upsalquitch may not be the dominant drivers of tributary confluence water temperatures at these tributaries.

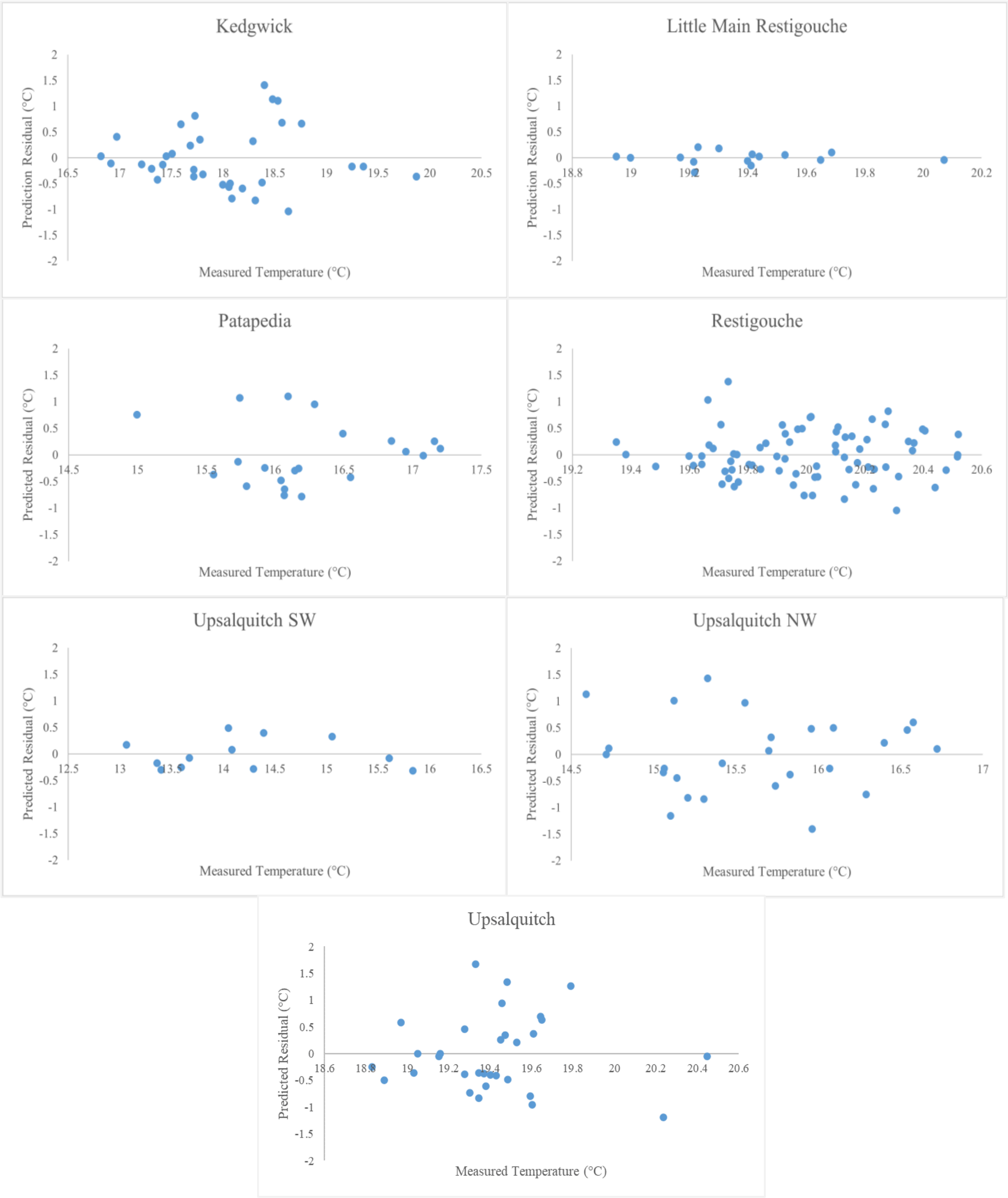

Figure 11. Residual graphs of measured vs predicted temperatures (°C) of the seven tributaries.

3.2 12D Model

3.2.1 Global 12D Model

The global models yielded a total of 195 tributary confluence points (Table 5). Both canopy model variations exhibited identical model parameters, with 10% training data, 150 trees tested with the input variables, a tree size of 5, a tree depth range between 8 and 18, and an average tree depth of 11.

Table 5. Total sample sizes of tributary confluence points within the seven tributaries used in the global model analysis.

Tributary	**Sample Size (n)**
Kedgwick	33
Little Main Restigouche	15
Patapédia	21
Restigouche	56
Upsalquitch	31
Upsalquitch Northwest	26
Upsalquitch Southeast	12

Predicted temperature results of the buffered FBCR global model (n=195) showed a range of values from 14.3°C – 20.5°C, with an average predicted temperature of 18.1°C. The Upsalquitch Southeast exhibited the coolest mean predicted temperature of 15.6°C with an SE of 0.2°C, while the Restigouche exhibited the warmest mean predicted temperature of 19.2°C with an SE of 0.1°C. These results were comparable to the 2012 TIR measured temperatures, which found the Upsalquitch Southeast as the coolest tributary with an average temperature of 14.7°C with an SE of 0.3°C, and Restigouche with the warmest mean temperatures at 20.1°C with an SE of 0.1°C. The final buffered model produced a validation R^2 of 0.81 and a standard error of 0.089. The out-of-bag errors produced a mean squared error (MSE) of 1.92, with 55.3% of the variation explained. Model variable strength was calculated by calculating the percentage of Gini coefficients compared to the total coefficients of the model. Based on the associated variable Gini coefficients, four variables accounted for 50% of the model strength, while nine variables

accounted for 75% of the model strength (Table 6). There is a considerable decrease in model strength after the top three variables in both models, where there is a drop of approximately 4.5% in variable importance (Figures 12 and 13).

Table 6. Percentage of variable model strength of variables included under the buffered and non-buffered models. See Appendix E for comprehensive list of variable Gini strength.

Regression Variables		
	Gini Strength (%)	
Variable	**Non-Buffered**	**Buffered**
Latitude	18.56	17.36
Water Table Ratio	15.69	17.57
Bedrock 469	11.57	11.19
ECA Value	6.03	6.75
Loss Year	5.70	5.25
Bedrock 390	5.23	5.45
Wet Areas	3.47	3.21
Canopy Cover	3.25	3.31
Bedrock 430	2.69	1.93

The “No Buffer” FBCR global model (n = 195) resulted in temperature predictions ranging from 13.9°C to 20.6°C, with the Upsalquitch Southeast and Restigouche having the mean coolest (15.0°C and SE of 0.2°C) and warmest (19.8°C and SE of 0.1°C) temperatures, respectively. The mean predicted temperature was calculated at 18.6°C with an SE of 0.1°C. These results are like that of the "Buffer" model, where the coolest and warmest tributaries are consistent. The validation R^2 value was greater than that of the Buffered model, sitting at 0.88. The standard error of the model shows a value of 0.097. Model out-of-bag error outputs showed the model had an MSE of 1.90, with 56.1% of the variation explained.

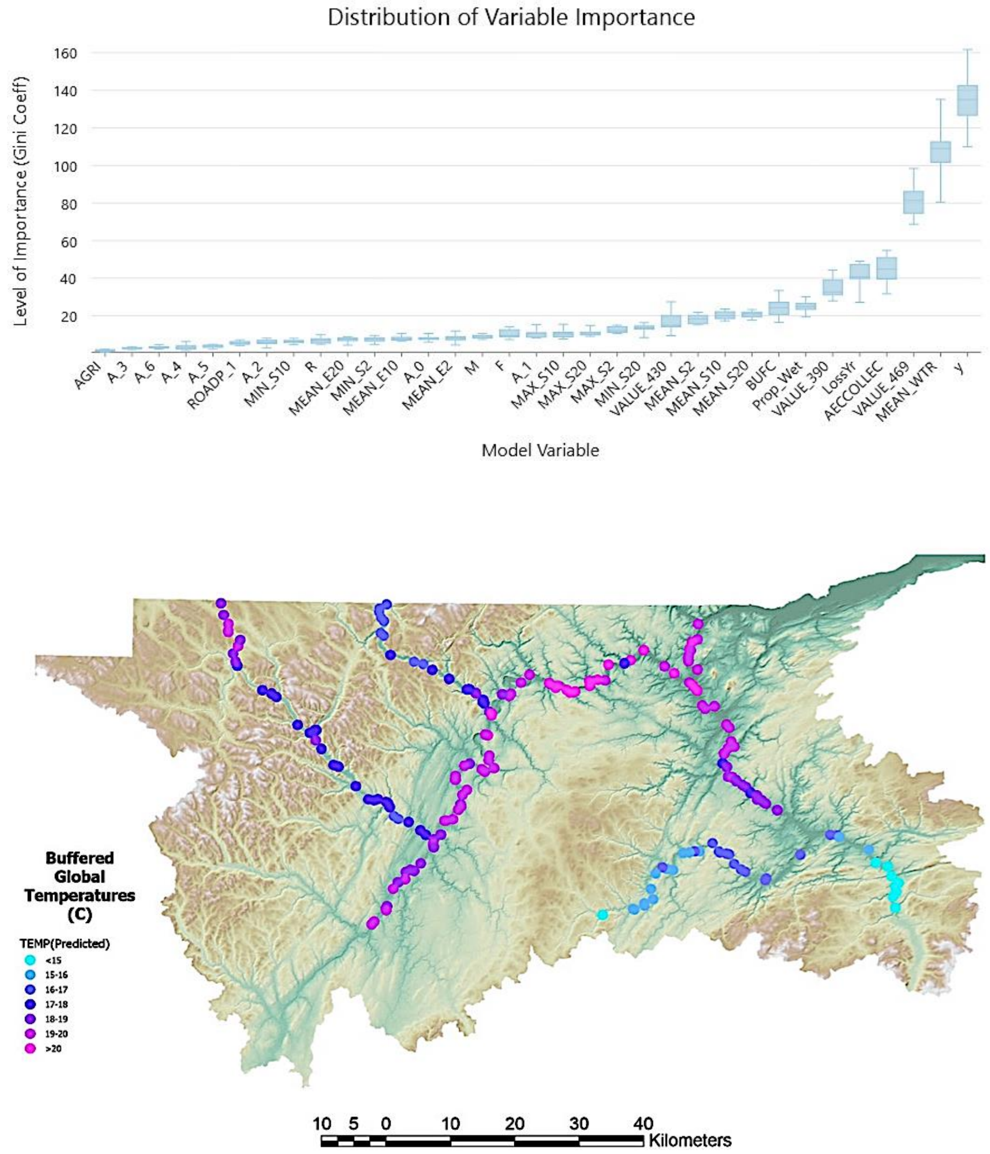

Figure 12. Distribution of variable importance based on total Gini Coefficients for the global "buffered" model and associated predicted water temperature values. A drop in Gini Coefficient strength occurs at canopy cover (BUFC), with the highest variable of importance being latitude (Y). Variables that contributed to 75% of the model strength (Gini Coefficient > 3) were used for reach-specific models.

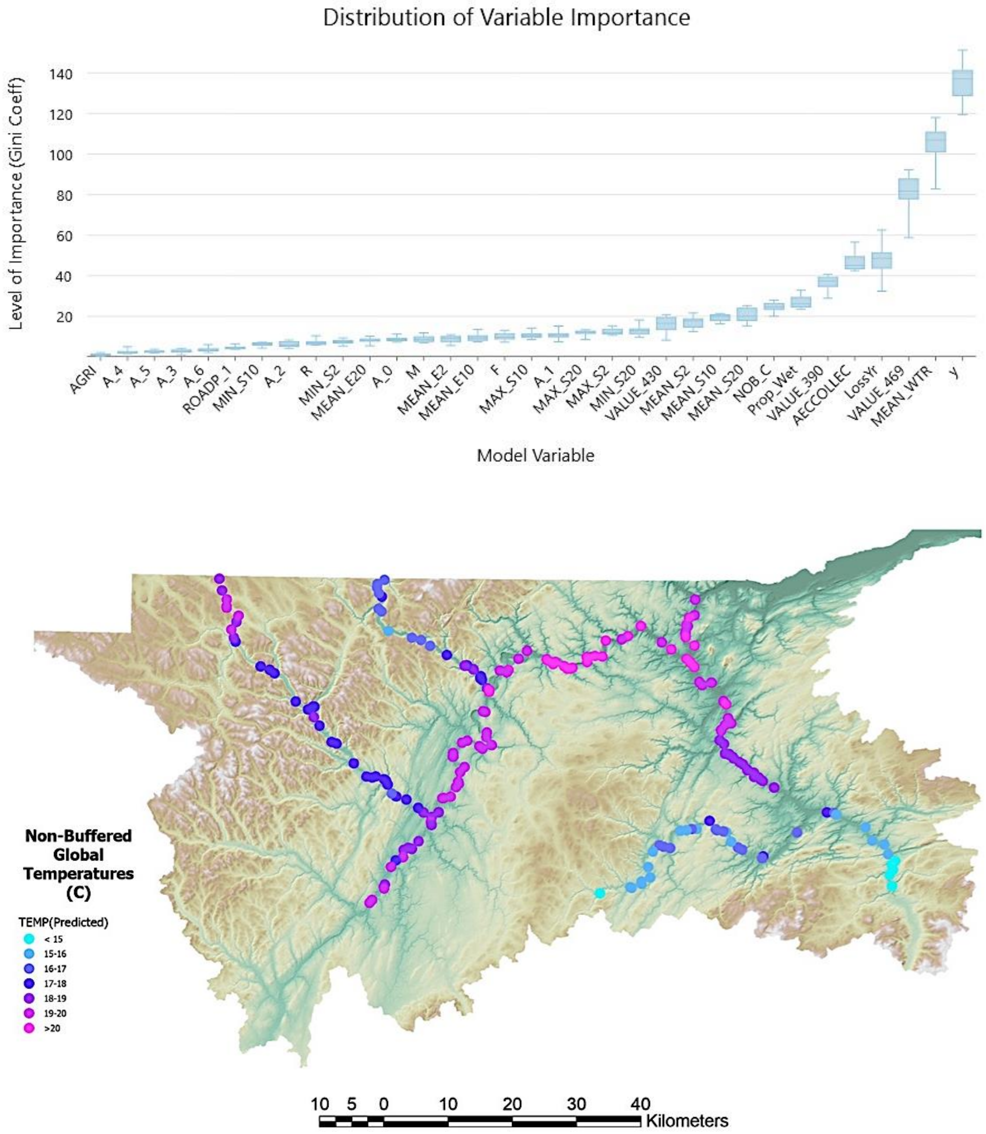

Figure 13. Distribution of variable importance based on total Gini coefficients for the global "non-buffered" model and associated predicted water temperature values. A drop in variable strength occurs at average bedrock age 390 (VALUE_390), with the highest variable of importance being latitude (Y). Variables that contributed to 75% of the model strength (Gini Coefficient >3 were used for reach-specific models.

We expected to see minimal change when comparing the canopy models under the 12D model parameters against each other due to the minimal changes in values. In both global models, four variables accounted for 50% of the total model strength for predicting tributary water temperature. These variables included the latitude (Y), water table ratio (MEAN_WTR), bedrock at an average age of 469 Mya (VALUE_469), and the equivalent cut areas (ECA). In model 12D, there were spatial patterns within the prediction abilities of the model at different reaches. Under both models, the Patapédia, Little Main Restigouche, Restigouche and Upsalquitch temperature predictions fell within -0.5 to 1.5 standard deviations, while the Upsalquitch Northwest, Upsalquitch Southeast and Kedgwick predictions fell within -1.5 to > 2.5 standard deviations.

As I aimed to compare the differences in canopy cover within the models, canopy cover contributed to 3.25% and 3.31% of the model strength for the non-buffered and buffered models, respectively. The Nash-Sutcliffe coefficient calculation was conducted for the "Buffer" and "No Buffer" models respectively, and the resulting values were compared to each other to determine which model was more effective. The resulting NSC values in both circumstances were comparable, with the "Buffer" model with an NSC of 0.908, and the "No Buffer" model with an NSC of 0.912. Both models explain the variance in the data to an almost perfect-fit regardless of catchment-wide canopy cover or 30m riparian cover as an NSC value of 1.0 depicts a perfect-fit model (Jain & Sudheer, 2008). However, the "No Buffer" model was a slightly better fit than that of the "Buffer" model in terms of model fit to the data.

3.2.3 Reach-Specific 12D Model

Reach-specific results were divided into two regression analyses to explore the differences between buffered riparian zones and total canopy cover (non-buffered). We used the results of the global model to inform the model variable parameters by taking the number of variables that added to 75% of the total model strength and using them at the reach-level. The inputs of the reach-specific models included latitude, water table ratio, bedrock at 469Mya, 390Mya and 430Mya, canopy cover, loss year, ECA and wet areas.

In the case of all tributaries, no variables indicated high collinearity (VIF > 5). Results of the model reductions produced variable results, with the Patapédia being reduced to one variable, while the Upsalquitch Southeast was reduced to six variables for the largest amount of model variables to remain. One outlier was removed from the Restigouche tributary and from all prior analyses, where a negative average water table ratio caused distortion in the results in crossing Cook’s D contours.

A model ANOVA comparison was run with the final reduced models to determine which 12D canopy cover model was a better fit based on the residual sum of squares (RSS). The results showed that the Kedgwick and Restigouche tributaries performed better under the buffered model, while the Upsalquitch Southeast and Upsalquitch Northwest performed better under the non-buffered model. The Patapédia, Little Main Restigouche, and Upsalquitch tributaries did not have canopy cover in the final reduced model (Table 7).

Buffered canopy cover (2/7 models), average bedrock age (5/7 models), and forest harvesting intensity (2/7 models) were common variables occurring within the reduced models (Table 7). No significant trends in variable presence were observed in the final models, as there was no spatial relationship between the number of final variables and the location of the tributaries. One interesting observation was the range in variables depending on latitude, seen in the reduced models of the Patapédia and Kedgwick compared to those of the Upsalquitch Forks. The tributaries at higher latitudes had ≤ 2 variables, while the tributaries at lower latitudes had ≥ 3 variables.

Table 7. Final reduced models of the reach-specific models. See Appendix C for standardized model coefficients.

Tributary	**Reduced Model**
Kedgwick	OBSERVED ~ Y + BUFC
Little Main	OBSERVED ~ AECCOLLEC + PROP_WET + PROP_469
Patapédia	OBSERVED ~ PROP_390
Restigouche	OBSERVED ~ Y + BUFC + MEAN_WTR + LOSSYR
Upsalquitch	OBSERVED ~ AECCOLLEC + LOSSYR + PROP_WET + PROP_469
Upsalquitch NW	OBSERVED ~ NOB_C + MEAN_WTR + PROP_469
Upsalquitch SE	OBSERVED ~ Y + NOB_C + MEAN_WTR + AECCOLLEC + PROP_WET + PROP_390

Models that performed the strongest were characterized as models showing an R^2 value ≥ 0.75; Upsalquitch Southeast (R^2 = 0.96), Patapédia (R^2 = 0.86), and the Upsalquitch (R^2 = 0.75). A similar R^2 result in both model 3D and model 12D was identified, with the Upsalquitch Southeast having an R^2 value of 0.96 and 0.91 in models 1 and 2, respectively.

Models that performed moderately well were defined as models with R^2 values between 0.50 and 0.75; Little Main Restigouche ($R^2 = 0.63$), Kedgwick ($R^2 = 0.58$), and the Restigouche ($R^2 = 0.51$). These models showed a trend of forest harvesting and canopy cover being important drivers among the three tributaries, however, compared to the Kedgwick and Little Main Restigouche, the Restigouche did not contain a variation of bedrock age as a driving variable. The Kedgwick and Restigouche tributaries both showed that latitude was a driving factor in the reduced models, but not for the Little Main Restigouche. The Kedgwick tributary showed an identical R^2 value under both model 3D and model 12D parameters. Contrastingly, the values of the R^2 for the Kedgwick and Restigouche tributaries decreased and increased, respectively.

One model that underperformed was characterized with an R^2 value of below 0.50: Upsalquitch Northwest ($R^2 = 0.39$). The Upsalquitch Northwest showed a similar trend under both models, with an R^2 of 0.42 in the 3D model. There was a decrease in the number of poorly performing tributaries under 12D model variables, as the Restigouche and Upsalquitch performed poorly under model 3D but increased under the 12D model parameters (Table 8).

Table 8. Descriptive statistics for the final reduced models of reach-specific 12D model results.

Tributary	**n**	***p*-value**	**R^2**	**F-statistic**	**Standard Error**
Kedgwick	33	<0.001	0.78	59.33	0.42
Little Main	15	0.003	0.63	8.955	0.19
Patapédia	21	<0.001	0.86	113.7	0.32
Restigouche	56	<0.001	0.51	14.52	0.37
Upsalquitch	31	<0.001	0.75	23.68	0.39
Upsalquitch NW	26	0.003	0.39	6.453	0.73
Upsalquitch SE	12	<0.001	0.97	79.67	0.14

4.0 Discussion

4.1 3D Model

4.1.1 Global

The global watershed level model under the 3D model parameters failed to explain an adequate amount of variation ($R^2 = 0.07$). Further analysis at the global scale was not conducted.

4.1.2 Reach-Specific

The variables in the 3D model best fit the Upsalquitch Southeast and the Little Main Restigouche tributaries; the difference between the TIR measured and predicted water temperatures was minimal as seen in the R^2 values of both tributaries. Respectively, 91% and 85% of the variation at these tributaries could be predicted from the drivers of the 3D model. We can infer that under the restraints of the 3D model, the Upsalquitch Southeast and the Little Main Restigouche are primarily driven by slope, canopy cover, and well-drained soil and water temperature can be estimated without the addition of other parameters. For the Upsalquitch and Restigouche tributaries, 19% and 27% of the variation was predicted from the drivers of the model. In these cases, the model was not a reliable predictor of water temperatures and requires a more extensive model to inform predictions.

In the 3D model, several landscape variables were unaccounted for that may have affected the amount of variation able to be explained at the reach-scale. TCP water temperatures are driven by groundwater and provide a stable input to the plume in summer months when temperature variation is highest and are less susceptible to changes in temperature as they receive stable water inputs compared to other thermal refuge classifications (Dugdale, 2014; Wawrzyniak et al., 2016). Measured temperature data were collected during the summer months of 2011-2013 when variation in water temperatures were highest. The temporal variation between the observed data and geospatial data used in the analysis may have contributed to unexplained variation within the model.

We expected to see that well-drained soil with a high average slope would strongly contribute to cold-water temperatures at the reach-scale, as soil permeability informs recharge rates and water percolation (Leibowitz et al., 2018; Shaban et al., 2006). The reach models did not indicate a strong relationship between soil drainage and TCP water temperatures. The Upsalquitch Southeast, a strongly predicted tributary, showed a well-drained soil average of 75%, while the Restigouche tributary, one of the poorly predicted tributaries, averaged a soil drainage of 72%. Soil drainage may not have been one of the strong driving predictors, as there was no relationship between a high average well drained soil to strong performing tributary models, which could be due to the reduction of variability across the reaches during the initial drainage classification process.

As stated in the literature, the greater the slope, the less time groundwater and surface water sources are able to saturate the soil or remain stagnant (Monk et al., 2013; Leibowitz et al., 2018; Vidon & Kill, 2004). We can infer that it could be a driving factor in tributaries such as the Upsalquitch Southeast, as this tributary has the highest average area of steep slopes ≥ 25% at 18% total area (Simard & Clowater, 2006). Similarly, the Restigouche tributary stands at a total of 8% total steep slope landscape.

Canopy cover decreases the amount of solar radiation that contacts tributary surface waters (Kurylyk et al., 2015), and has an indirect relationship to water temperatures as it does not cool the water but creates a cooling gradient along the tributary under the canopy (Garner et al., 2014). This would also be the similar process occurring at the mouth of the tributary to the mainstem, where canopy cover would provide shade to the plume. In total, 85% of the watershed was identified as having canopy cover >3m in height, with over half of the watershed characterized as old forest habitat (Simard & Clowater, 2006). Forest cover at the Little Main Restigouche, Upsalquitch Southeast, Restigouche and Upsalquitch tributaries demonstrated a collective average catchment canopy cover of 84%. However, the Restigouche and Upsalquitch tributaries did not perform well under the reach models. We can infer that the sources of water flow to these tributaries may not be affected by the cooling gradient of canopy cover.

4.2 12D Model

4.2.1 Global

The results of the global watershed model under the 12D model parameters showed that water temperature predictions responded to the same variables regardless of the presence or absence of a buffered riparian canopy (Table 9). The buffered and non-buffered global models showed that the amount of variation explained through the input variables was 55% and 56%, respectively.

Table 9. Descriptive statistics of the global buffered and non-buffered models.

Model	**Mean Temp**	**Median R^2**	**Validation R^2**	***p*-value**	**Standard error**	**MSE**	**% variance explained**
Non-Buffered	18.60	0.70	0.88	<0.001	0.097	1.896	56.10
Buffered	18.10	0.71	0.81	<0.001	0.089	1.915	55.25

This result was expected, as the global model variables were exclusively landscape variables, and discounted the variance that could be explained through other variables, such as air temperature, stream morphology, precipitation, snowpack and other detailed hydrological processes (Torgersen et al., 2012; O'Sullivan et al., 2022; Pander et al., 2024; Wiley et al., 2006). The consistency in variable importance between both global models informs Objective 1 of determining if there was a relationship between landscape drivers and TCP water temperatures at the global scale.

We identified variation between the observed and predicted temperature results at the reach-specific level, meaning that not all models demonstrated identical variable selection for predicting water temperature at each tributary. While the global model is useful in informing drivers across the watershed level, landscape level drivers are variable in order of importance at the tributary level, which could inform management procedures through the lens of protecting tributary confluence plumes. The watershed-level global model can be used as a proxy for identifying landscape variables and informing the inputs of the reach-specific prediction models. We expected to see that certain variables would not contribute to the global model, as their spatial scales were inadequate at the global scale. Variables such as agriculture, road presence, and soil drainage are stronger predictors at the reach-scale as their processes are more effective or impactful at the smaller scale (Leibowitz et al., 2018; Wilbur et al., 2020). Similarly, forest cover type was statistically unimportant at the global scale, as forest cover types inform water temperatures through indirect processes such as through evapotranspiration (Garner et al., 2014). This process is not a strong driver at the global scale, however, a previous study identified summer stream temperatures under deciduous forest cover being warmer than under coniferous forest cover (Dugdale et al., 2018). Although this study did note that while forest cover type was not the sole factor driving summer stream temperatures, further studies into forest cover type as a factor in the cooling of water temperatures may be more effective at the reach-scale to inform tree species selection during restoration efforts (Quilbé et al., 2023).

4.2.2 Reach-Specific

Comparing the results of model 3D and model 12D, there was a significant increase in the amount of variance explained with the addition of variables. The reach-specific model results informed objective 2 of determining the variation of importance of landscape drivers at the tributary level, and to identify sub-catchments for provincial level protection based on the variables of importance. The reduced models of each tributary showed that the variables of importance at the tributary level were not identical, informing objective 2. The relative importance of the variables was identified, where we found that variables could be classified into three broader categories: canopy, bedrock, and climate.

4.2.3 Canopy

Canopy cover was the driver of highest relative importance at the Kedgwick tributary, specifically at the 30m buffer level of cover (see Appendix D). The reduced model showed a negative relationship between buffered canopy cover and water temperatures, supporting previous studies that found canopy cover at the tributary level influences water temperature (Aas et al., 2010; Drake et al., 2010; Johnson et al., 2015). A suggestion for the strength of the “buffered canopy” model attribute for the Kedgwick tributary may be attributed to the high slopes on the sub-catchments. The Kedgwick tributary does not experience prominent levels of forest harvesting compared to that of other tributaries such as the Upsalquitch Forks, presumably due to low accessibility due to high slopes. As the Kedgwick tributary exhibits high average slopes in comparison to other tributaries on the watershed and low levels of forest harvesting, this could be reducing the amount of solar radiation coming into contact with the tributary.

We recommend that the Kedgwick tributary be of high importance to managers in terms of protection, as canopy cover is a manageable landscape variable. We recommend that the tributary and its TCP catchment areas be covered at minimum a 30m riparian buffer under the New Brunswick provincial regulation guidelines, but preferably protect canopy cover at the catchment scale or to explore the use of variable-width buffers to accommodate for spatial differences at the reach-scale, where a 30m protective riparian buffer may not suffice. Specifically following the recommendations of GINU, where recommendations are to restore and manage shaded buffer zones along the stream network and reducing forest harvesting to limit clearcutting and managing the forest to prioritize planting of indigenous tree species as well as species forecasted to thrive under future climate scenarios (Quilbé et al., 2023).

4.2.4 Bedrock

The average bedrock age was the driver of highest relative importance at the Little Main Restigouche, Patapédia, Upsalquitch and Upsalquitch Northwest tributaries (see Appendix D). We identified literature stating that bedrock and local geomorphology influences the thermal regime of tributaries, as the bedrock influences groundwater movement through deep geological fractures and high soil permeability levels (Aas et al., 2010; Jolly et al., 2008; O'Sullivan, 2021; Price et al., 2005; Vidon and Kill, 2004). Interestingly, we identified positive and negative relationships between tributary water temperatures and bedrock. Typically, the older the bedrock, the cooler the water inputs

(O'Sullivan, 2021) due to the higher level of permeability and bedrock depth. Our results showed that there was no relationship between the older bedrock to water temperature specifically, where the warmest water temperatures from the Little Main Restigouche tributary is located on the oldest average bedrock age (469Mya). Conversely, the Patapédia tributary had cooler water temperatures on the youngest average bedrock age (390Mya). We can infer there may be other processes occurring at the catchment level, or variables not considered here, contradicting the findings of O'Sullivan (2021). Further exploration into the geomorphology of the Restigouche River watershed in terms of geological depth and permeability of the bedrock would be of interest as these characteristics of the bedrock have been documented to be significant variables within other predictive models (O'Sullivan et al., 2019).

4.2.5 Climate

The relative importance of latitude, or the position of the tributary on the watershed, was highest for the Restigouche and the Upsalquitch Southeast (see Appendix D). These tributaries have been identified as tributaries that could be most susceptible to climate change due to the high relative importance of latitude as a model variable. At the Restigouche and Upsalquitch Southeast, there is a positive relationship between latitude and tributary water temperatures, where an increase in latitude at both tributaries predicts an increase in water temperature by 0.61ºC and 0.92ºC, respectively. While there is no physical process that can allow for latitude to be managed on a watershed, identifying these tributaries as more susceptible to a warming climate, we recommend that the Restigouche and Upsalquitch Southeast be of highest importance of protection under the climate category due to its greater possible sensitivity to temperature increases as a function of their regional location on the watershed.

4.3 Restrictions

The dynamic nature of riverine systems makes predicting water temperatures an imperfect exercise, as statistical models and data analyses fail to account for the spatial and temporal variance in favourable circumstances. The global and reach-specific models exclusively include landscape-specific parameters, excluding other driving variables such as air temperature, snowmelt, stream morphology, variation in climate, precipitation, and water movement (Caissie et al., 2007; Torgersen et al., 2012).

The tributary confluence plume temperature measurements used in our models were collected between 2011 and 2013 leaving a 10-year gap between initial collection and the current analysis. Canopy cover data were derived from LiDAR data collected in New Brunswick during 2021, and Québec in 2020, which has invariably changed over the past decade, plausibly due to natural forest clearing and the continuation of forest harvesting.

There remains a level of uncertainty regarding the precise locations of tributary confluence plumes in model 3D. This level of uncertainty was decreased through the addition of the Québec portion of the watershed and compared against previously created catchments by GINU. However, the hydrological flow accumulation rasters are still subject to human manipulation and must be confirmed in the field for accuracy purposes.

The inconsistencies in the importance of canopy cover can be attributed to the secondary link between canopy cover and TCP temperatures, as well as other factors on the watershed where canopy cover affects other processes. Wetlands may connect directly to the stream network and experience high hydrological connectivity to downstream waters, however, wetlands located further upstream may still contribute to hydrological connectivity depending on the nature of other landscape variables (Leibowitz et al., 2018). Standing wetlands on the watershed may be indirectly connected hydrologically to the river system and may be subjected to elevated levels of solar radiation with the absence of canopy cover. Without forest cover to reduce solar radiation at wetlands, groundwater connections between wetlands and the tributaries may be subject to increased warm water inputs (O'Sullivan et al., 2019). In cases such as the Little Main Restigouche and Upsalquitch tributaries, where canopy cover was not included in the reduced models, but wetlands were, ensuring that wetlands are covered by forest may aid in providing cooler water inputs indirectly.

The inability of the models to explain some variation at tributaries such as the Little Main Restigouche may be due to anthropogenic influences which were disregarded at this scale. The relationship between agriculture, urban expansion, and road presence is greater at the reach-scale than at the global scale (Torgersen et al., 2012). Agriculture and roads were not included at the reach-scale.

4.4 Future Implications for Management

Future research into predictive models should be explored at a variety of different spatiotemporal scales and the variability of the landscape drivers between them. Small-scale landscape variables, such as agricultural land use may be better used in small-scale models than larger scale models as agricultural land is typically spatially smaller than other variables such as catchment-wide canopy cover. The spatial scale of predictive models is crucial to identify before choosing landscape variables. Variables with minimal spatial variation, such as average bedrock age, are better used in larger models. Similar to spatial variation, acquiring high resolution data is important for predictive models, as the higher the resolution, the greater the data accuracy, which aids in creating a more realistic depiction of the landscape.

Our reach-level models were successful in explaining a substantial proportion of variance, however, there remained unexplained variance that if captured, would contribute to the success of the models. A recommendation for future predictive models would be to add additional parameters that are not classified as landscape variables to identify the remaining variation. For example, channel configuration and structure has been seen to influence water temperature patterns and storage (Ebersole et al., 2003), while the classification and depth of the bedrock may explain the lack of consistency between bedrock age in our models (Hale et al., 2016). Some additional variables of interest stated in literature include water velocity, stream morphology, channel configuration, and bedrock type (Briggs et al., 2018; O'Sullivan et al.,2022)

Another recommendation when developing models would be to account for changes in climate, as it is a given that river and tributary water temperatures will increase, making the effects of climate change a key area of research (Gillis et al., 2023). When creating water temperature prediction models, the addition of air temperature, snowmelt, solar radiation, and precipitation will be of importance (O'Sullivan et al., 2022; Westhoff & Paaukert, 2014; Wiley et al., 2007).

The headwaters of streams and rivers play a significant role in water temperature, due to its contribution through surface and subsurface water, and its sensitivity to changes on the landscape through forest harvesting and land use (Acreman et al., 2019; Johnson et al., 2015; Quilbé et al., 2023). This is due to the connective nature of the riverine systems, described as the Waterscape Continuum Concept, in which O’Sullivan et al. (2022) describes how landscape variables connect holistically, and all contribute on a continuum to ecosystem success. The continuous success of the riverine system extends far beyond the river. Acreman et al. (2019) described the importance of longitudinal, lateral, vertical, and temporal connectivity at river systems in its biological success and informs the presence of thermal refuges. When the system is altered through human disturbances, the biological processes of the watershed are affected (Abell et al., 2006; Acreman et al., 2019; Hansen & DeFries, 2007). A recommendation for management would be to move towards catchment-wide protection of TCPs to ensure total landscape connection, not only for cold-water temperatures, but for other biological processes that occur on the watershed (Abell et al., 2006; Acreman et al., 2019; Bower et al., 2017).

While some of the tributaries showed no statistical significance favouring the reduced non-buffered models, we argue that not only does canopy cover act as a buffer to solar radiation, but also contributes to other ecological services that help the success of thermal refuges, such as nutrient inputs and decreasing perceived risk of predation of salmonids (Gibson, 1978; Rimmer, Paim & Saunders, 1984). We identified that seven tributary models had a variation of forest harvesting or canopy cover as a variable of importance. Forest harvesting on the Upsalquitch, Little Main Restigouche, Restigouche, and Upsalquitch Southeast tributaries informed water temperature predictions, and were not influenced by temporal variation in the datasets. Canopy cover was of importance at the global and reach-scales. When a catchment experiences forest harvesting, specifically a clearcut, groundwater temperatures may increase regardless of the presence of a stream buffer as the canopy cover influences ground and surface water temperatures through atmospheric exchanges (Kurylyk et al., 2015). Currently, the Restigouche River watershed is managed by private companies at 24%, while the remaining 76% is managed by the Crown (Simard & Clowater, 2006). On crown lands, avoiding clearcutting within catchment areas while favouring less intensive harvesting techniques would be preferable. Our recommendation for catchment-wide management is in favour of converting TCP catchment areas to protected natural areas status under the New Brunswick Protected Natural Areas Act.

5.0 Conclusion

This thesis aimed to determine the drivers of TCP cold-water temperatures at different spatial scales in the Restigouche River watershed. The objective of model 3D was to determine if soil drainage, slope percentage and canopy cover could be used as predictor variables at the global and reach-specific level for tributary confluence plume water temperatures. The 3D model global fit concluded that the drivers did not provide enough variability to inform predictions. There was a strong relationship between the 3D model parameters at certain tributaries, specifically at the Upsalquitch Southeast and the Little Main Restigouche. However, it failed to explain most variability for the Restigouche and Upsalquitch tributaries, and provided limited explanations for the Patapédia, Upsalquitch Northwest and Kedgwick tributaries. The 12D model contained nine landscape variables in addition to the three variables of model 3D to create a stronger prediction model at the global and reach-scales. We identified similar landscape drivers at both spatial scales of the model 12D as being informative drivers of tributary water temperatures through Forest-Based Classification and Regression (global) and multiple regression (reach-specific). Additional variables included average bedrock age, aspect, groundwater, wet areas, forest cover type, forest harvesting, agriculture, and road presence. We identified comparable model fits between the global buffered model (NSC = 0.908) and the non-buffered model (NSC = 0.913). However, the non-buffered model (R^2= 0.88) explained more variance than that of the buffered model (R^2 = 0.81). We identified variables to be used at the reach-scale through the results of the global model based off Gini coefficient strength and identified three variable classifications of importance at the reach-level: bedrock, climate, and canopy cover. Recommendations for management at the reach-scale included the catchment-wide protection of tributary confluence plumes, as previous studies have identified catchment-wide protection as the most effective in terms of protecting and enhancing thermal refuges in watersheds.

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Appendix A

Descriptive List of Model Landscape Variables, Descriptions, and Sources

Variable	Attribute	Variable Description	Data Source
Landscape Attributes	Aspect		GeoNB, MDFERN
	Latitude	Digital Elevation Model (resampled to 2m, 10m, 20m-	
	Slope		GeoNB, MDFERN
Geology	Soil Drainage	Poor to well-drained soil classifications 0 -6	GeoNB, MDFERN
Geology Land Composition	Bedrock Age	Median age of geological time period	GeoNB, MDFERN
	Canopy Cover	Total percentage of cover in 30m buffered stream lengths within unique catchment areas	GeoNB, MDFERN
Land Composition	Forest Type	Hardwood, mixedwood, softwood stand types	GeoNB, MDFERN
	Wet Areas	Proportion of wet areas compared to total catchment area	White et al., 2012
	Water Table Ratio	Logarithm of linearly water table ratio	Cuthbert et al., 2019
	Road Presence	Provincial road layer for NB and QC (primary, secondary and forestry roads)	GeoNB, MDFERN
	Agriculture	Locational agriculture in NB and QC	GeoNB, MDFERN
Forest Harvesting	Equivalent Cut Areas (ECA)	Sum of forest disturbances multiplied by the regressive rate of the cut effect (RRCE) divided by the sum of the sub-catchment area	Leblanc et al., 2012
	Loss Year	Forest extent and change from 2012 - 2023	Global Forest Watch

Appendix B

Model 3D Descriptive Statistics

	Descriptive Statistics				Regression Prediction	
	n	Mean Temp (ºC)	St. Dev. (ºC)	CV (%)	R^2	Standard Error (ºC)
Global	194	18.3	2.0	11.1%	0.07	2.0
Restigouche	75	20.0	0.5	2.7%	0.27	0.5
Upsalquitch	31	19.4	0.8	4.0%	0.19	0.8
Little Main Restigouche	15	19.4	0.3	1.6%	0.84	0.2
Kedgwick	33	18.0	0.9	5.1%	0.58	0.7
Patapédia	21	16.2	0.8	5.0%	0.49	0.7
Upsalquitch NW	26	15.6	0.9	6.0%	0.42	0.8
Upsalquitch SW	12	14.2	0.9	6.6%	0.91	0.4

Appendix C

Model 12D Standardized Coefficients

	Kedgwick	Little Main Restigouche	Patapedia	Restigouche	Upsalquitch	Upsalquitch NW	Upsalquitch SE
Y	0.7336254	x	x	0.6113968	x	x	0.9211534
Canopy (buffer)	-0.3611122	x	x	-0.248467	x	x	x
Canopy (No buffer)	x	x	x	x	x	0.262128	0.1323955
Bedrock 469	x	0.9999513	x	x	0.6211239	-0.5948365	x
Bedrock 390	x	x	-0.9256235	x	x	x	0.1971054
Bedrock 430	x	x	x	x	x	x	x
Water Table Ratio	x	x	x	-0.143255	x	-0.2949849	-0.0660487
Wet Areas	x	0.6063354	x	x	0.2405809	x	0.1004729
Loss Year	x	x	x	-0.208638	-0.2299861	x	x
ECA	x	0.9642322	x	x	-0.2134168	x	-0.3055845

Appendix D

Model 12D Reach-Specific Relative Importance

	Kedgwick	Little Main Restigouche	Patapedia	Restigouche	Upsalquitch	Upsalquitch NW	Upsalquitch SE
Y	0.25			0.68			0.7
Canopy (Buffer)	0.75			0.04			
Canopy (No Buffer)						0.16	0.06
Bedrock 469		0.42			0.53	0.75	
Bedrock 390			1				0.02
Water Table Ratio				0.13		0.09	0.03
Wet Areas		0.22			0.05		0.02
Loss Year					0.24		
ECA		0.36		0.15	0.18		0.17

Appendix E

Global 12D Model Variable Importance (%)

Variable	Non-Buffered	Buffered
Y	18.56	17.36
MEAN_WTR	15.69	17.57
VALUE_469	11.57	11.19
AECCOLLEC	6.03	6.75
LOSSYR	5.70	5.25
VALUE_390	5.23	5.45
PROP_WET	3.47	3.21
CANOPY	3.25	3.31
MEAN_S10	2.69	2.47
VALUE_430	2.69	1.93
MEAN_S20	2.59	2.77
MEAN_S2	2.40	2.01
MAX_S2	1.98	1.42
MAX_S20	1.44	1.21
MEAN_E2	1.43	1.15
MIN_S20	1.43	1.77
MAX_S10	1.38	1.10
A_1	1.30	1.41
MEAN_E20	1.16	1.06
F	1.16	1.01
MIN_S2	1.06	1.22
MEAN_E10	1.06	1.38
A_2	1.02	0.68
A_0	0.97	1.38
M	0.93	1.37
R	0.92	0.85
ROADP_1	0.65	0.60
MIN_S10	0.65	0.75
A_6	0.45	0.39
A_3	0.41	0.40
A_5	0.30	0.63
A_4	0.28	0.67
AGRI	0.13	0.28

Curriculum Vitae

Candidate's Full Name: Hannah Stephanie Green
Universities Attended:
MSc. Environmental Management. University of New Brunswick, Fredericton, NB, 2023-2024
BSc. Environment and Natural Resources (Honours). University of New Brunswick, Fredericton, NB, 2018-2023

Conference Presentations:

Green, H.S., Sacobie, C. F. D., & Ogilvie, J. J. February 2023. Predicting the drivers of cold-water temperatures at tributary confluence plumes [Conference Presentation]. Restigouche River Watershed Science Advisory Committee Chapter (Campbellton, NB).

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