2023

Assessment of Stream Metabolism and Associated Environmental Drivers in the Greiner Lake Watershed, Nunavut, Canada

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by

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B.Sc. (Env.), University of Western Ontario, 2019

THESIS

Submitted to the Department of Integrative Biology
Faculty of Science
In partial fulfillment of the requirements for the
Master of Science in Integrative Biology
Wilfrid Laurier University
2023

ABSTRACT

Stream metabolism is an ecological process that can be monitored to assess carbon cycling and productivity within a stream ecosystem. GPP (gross primary productivity) is measured as oxygen produced by autotrophs and ER (ecosystem respiration), which is measured by oxygen depleted by all living organisms. Complications arise when estimating GPP and ER in the Arctic because most methods require a period of darkness when GPP ceases, however, summer regimes of photosynthetically active radiation (PAR) do not reach zero. Furthermore, natural diffusion of oxygen from the atmosphere (k) must be accounted for but this requires extensive field work, thus posing problems for remote locations. Few studies have assessed how stream metabolism is influenced by the surrounding environment, even though it is well established that stream metabolism in other biomes is affected by key environmental variables.

The thesis assesses methods that are appropriate for estimating stream metabolism in the Arctic and determines stream metabolism and associated environmental variables in the Greiner Lake Watershed, Nunavut. Stream metabolism was estimated using streamMetabolizer and empirical methods. These methods were compared based on values expected for low productivity streams, and model diagnostics (process and observation error) for Bayesian statistics. StreamMetabolizer produced biologically possible days with realistic average values and ranges of GPP and ER.

Estimates of GPP and ER from streamMetabolizer were used in a partial least square regression analysis (PLSR) with environmental variables measured at each site (water chemistry, channel form, land cover type and surrounding waterbodies). I discovered that GPP was positively related to median substrate particle size (D_{50}), and ER was positively related to the area of upstream lakes and stream width. D_{50} may have been providing ideal habitats for primary

producers, and lakes may have been impacting downstream controls of ER. Overall, streamMetabolizer is a useful method for determining stream metabolism in Arctic environments that are remote and have limited periods of darkness in the summer. Moreover, this research contributes to a growing data base of stream metabolism in the Arctic and indicates key environmental variables influencing stream metabolism in the Arctic.

ACKNOWLEDGEMENTS

I owe the following people my thanks and appreciation:

My thesis supervisors, Dr. Joseph Culp and Dr. Jordan Musetta-Lambert for their unwavering patience, and consistently constructive advice. I owe virtually everything I know about conducting scientific research thanks to their counsel. They also taught me to feel comfortable to reach out for help, and to seek accommodation. This is a skill I will be grateful for indefinitely. I would also like to thank my committee Dr. Adam Yates, Dr. Michael Power and Dr. Derek Gray for their swift editing under a significant time crunch. None of this would have been possible without your understanding, compromise, and constructive feedback.

The Stream Lab at UWO. First, Dr. Adam Yates for being my undergraduate supervisor, for recommending me for this project, and introducing me to the dynamic world of river ecology. As well, Dr. Nolan Pearce for helping me to understand stream metabolism and teaching me R throughout my graduate studies and my undergraduate studies. I also thank you for your patience to my extensive amount of questioning which likely seemed rudimentary to an experienced and intelligent scientist. I also thank you for providing me with an R script that helped me explore different modelling types for stream metabolism. Much of this thesis is built upon your extensive knowledge and ideas.

To all those who made accommodations for me, such as Dr. Michael Wilkie, as I underwent the process of obtaining my master's despite the worsening of my epilepsy. I would also like to thank my family, who supported my every decision (even on the days I was certain I had to give up) throughout this process.

TABLE OF CONTENTS

LIST OF FIGURES AND ILLUSTRATIONS

LIST OF TABLES

CHAPTER 1: INTRODUCTION

1.1 Introduction

Average Arctic temperatures have increased at almost twice the global average rate in the past 100 years (IPCC, 2007) with the increase being notably pronounced in the Canadian Arctic where freshwater ecosystems are particularly vulnerable to environmental change (Rouse et al., 1997). Warming will have a significant impact on the terrestrial cryosphere, landscape vegetation, hydrologic regimes, aquatic species abundance and composition, and biological productivity (Wrona et al. 2006). These environmental changes will have cascading effects on freshwater ecosystems processes such as ecosystem metabolism that are affected by alterations to the cryosphere and the surrounding environment. Specifically, changes to the chemical properties of stream water, air and water temperature, precipitation patterns, and hydrological regimes can alter the physicochemical parameters controlling ecosystem metabolism (Prowse et al, 2006a).

Net ecosystem metabolism (NEP) is an ecological process defined by Woodwell and Whittaker (1968) that is comprised of gross primary productivity (GPP) and ecosystem respiration (ER). GPP is the primary production of algae and aquatic plants, and ER is the respiration of all organisms. Therefore, ecosystem metabolism permits inferences about the use of organic resources by biotic communities (Bott et al., 2006; Odum, 1956; Young et al., 2008). Moreover, metabolism is affected by environmental factors such as nutrient concentration and water temperature making it an especially relevant process for bioassessment of Arctic rivers (Yvon-Durocher et al., 2010). Changes in dissolved oxygen in freshwater occurs due to the interrelationship of GPP, ER and reaeration, making oxygen fluctuations a good indicator of

ecosystem metabolism (Dodds & Cole, 2007; Hoellein, Bruesewitz & Richardson, 2013; Young et al., 2008). Increased light is associated with higher photosynthetic rates that cause an increase in dissolved oxygen, whereas respiration consumes oxygen regardless of light levels (Bernot et al., 2010; Izagirre et al., 2008; Mulholland et al., 2001). The differences between daytime increases in dissolved oxygen and nighttime decreases in dissolved oxygen can provide information on the rates of GPP and ER if reaeration rates can be accounted for (Holtgrieve et al., 2010).

Gathering baseline data on stream metabolism in the Arctic will aid in the assessment of how stream ecosystem functions are affected by their environment and can help detect and predict future change in these freshwaters. Stream metabolism is an ideal candidate for monitoring stream changes due to its sensitivity to factors such as atmospheric and water temperature, nutrients, and ice phenology (Bernot et al., 2010; Mulholland et al., 2001). A basic understanding of which environmental factors have the greatest influence on metabolic rates, therefore, is required. My study aims to begin developing an understanding ecosystem metabolism in Arctic rivers and the environmental variables and spatial scales that are potential drivers of stream metabolism.

1.2 Environmental factors that affect stream metabolism

Frissell et al., (1986) indicated that there are patterns in biological processes, such as ecosystem metabolism, that are associated with specific morphological features of a stream. Thus, they proposed the delineation of different morphological features into categories of hierarchical spatial scales; microhabitats, pool/riffle reaches, segments and systems, all of increasing sizes and nested within each other. Large scale characteristics include geology,

geomorphological structures, and climate, which can be similar for hundreds of kilometers. Smaller-scale characteristics, which are typically only similar over hundreds of meters include conditions such as temperature, canopy cover, nutrient concentrations, substrate composition, water depth, etc. Thus, morphological features of fluvial channels and landscape characteristics may be developed as indicators for understanding changes in the biological function of streams. Furthermore, there are dynamic nested hierarchies of habitat characteristics that also must be considered to understand stream processes. To my knowledge, few studies have been conducted where subcatchment conditions are compared to stream scale characteristics to determine the factors that control GPP and ER in Arctic biomes. Streams may be more affected by proximal features (i.e., riparian environmental variables), and these features may overwhelm any potential for a large-scale environmental variation to control stream metabolic rates. For instance, large rivers and floodplain lakes can deplete nutrients nitrogen (N) and phosphorus (P) (Wrona et al., 2006), and may reduce downstream flooding (Leach & Laudon, 2019).

1.3 Subcatchment scale variables

Furthering the understanding of how functional processes, such as metabolism, are associated with the surrounding environmental conditions is important for determining how climate change might impact streams and describing the feedback mechanisms by which streams could exacerbate climate change (Prowse et al., 2006b). Whether the immediate surrounding environment (reach scale), or the larger scale environment (subcatchment scale) controls metabolic rate may vary among systems. Streams receive a significant amount of carbon from surrounding ecosystems and inland flow. Organic matter (OM) entering a stream (allochthony) is incorporated into the food web and can greatly outweigh energy produced instream

(autochthony) through photosynthesis. The relative importance of allochthony and autocthony depends on which factors (nutrients, temperature, light availability, etc.) limit productivity (Allan & Castillo, 2007).

Several factors that can affect allochthony and autocthony in freshwaters may change because of climate warming (Yvon-Durocher et al., 2010) with such changes potentially impacting instream environments as well as other ecosystems. For instance, increased warming may result in an increased amount of carbon and nutrients transported to stream ecosystems from terrestrial environments (Battin et al., 2009). Increases in overland flow, permafrost thaw, groundwater inputs, and increases in atmospheric temperature can result in streams becoming a carbon source (Michel & Van Everdingen, 1994; Woo, Lewkowicz & Rouse, 1992; Zolkos et al., 2022). For example, researchers found that in the Kuparuk River, Alaska, there was a flux of $1.4x10^5$ mol of CO_2 to the atmosphere per year and they predicted this could increase as temperatures warmed and raised temperature-dependent respiration rates (Kling, Kipphut & Miller, 1991). In contrast, there is conflicting evidence that as the climate warms, Arctic rivers will act as carbon sinks due to increases in P (Demars et al., 2011; Drake et al., 2018; McGuire et al., 2009). Changes to Arctic stream functions can also significantly impact ocean ecosystems, which can have implications for ocean ecosystem function and for global climate systems (CliC/AMAP/ISAC, 2016). This is because Arctic rivers can carry a significant amount of nutrients and organic matter to the ocean (Parmentier et al., 2017). Under climate change, increases in terrestrial tundra runoff due to thermokarst activity will supplement the transfer of organic matter, and/or nutrients to the Arctic ocean, due to streams switching from heterotrophic ($P:R<1$) to autotrophic ($P:R>1$) (Kling, Kipphut & Miller, 1991; McGuire et al., 2009).

1.4 Reach scale variables

Stream metabolism is a holistic measure of stream function and health and is affected by numerous factors including light levels and water temperature. Light reaching primary producers is one of the most important factors controlling GPP (Mulholland, 2001; Young, Matthaei & Townsend, 2008; Bott et al., 1985) and has been shown to affect enzyme activity in periphytic microbial communities (Kuehn, 2014). In addition, many studies have shown that increases in temperature are associated with increases in GPP and ER (Yates et al., 2013; Bott et al., 1985).

Nutrients can limit stream metabolism, with higher nutrient concentrations leading to increased rates of GPP and ER (Bott et al., 1985; Fuss & Smock, 1996; Bowden et al., 1992). In addition, substrate chemistry (nutrient poor vs. nutrient rich) can influence metabolic rates (dos Reis Oliveira et al., 2019). Lastly, pH can influence stream metabolism as increasing acidification can increase both the chlorophyll *a* standing crop and filamentous algae (Allard & Moreau, 1987; Collier et al., 1990).

GPP and ER are also affected by stream gradient and morphology, current velocity, and substrate composition. For example, GPP has been shown to be negatively correlated with gradient (Lamberti & Steinman, 1997), and high-water velocity can reduce vegetation, subsequently decreasing primary production due to scouring (Kurz et al., 2017). In contrast, ER appears to be more resistant to flood events which involve increased flow (Qasem et al., 2019). Total production and respiration were observed to be higher in pools than riffles, as algae accumulates more easily in pools, while riffles scour algae away (Bowden et al.,1992). Different substrates tend to support different pigment densities, due to the different rates of sedimentation, bedload movement and scouring (Tett et al., 1978). Furthermore, larger substrate sizes are positively correlated with greater rates of metabolism and biofilm formation (Cardinale et al.,

2002). Stream metabolism is also associated with stream order, with studies having shown that streams have higher rates of GPP and become more autotrophic as order increases (Anglier, 2003; Bott et al, 1985; Naiman & Seddel, 1980).

1.5 Defining the research problem

Metabolism has been widely used as a bioassessment tool for understanding the impacts of anthropogenic and natural disturbances on ecological function in streams (Bunn, Davies & Mosisch,1999; Li, Zheng & Liu., 2010; Young Matthaei & Twonsend, 2008). However, there is a notable lack of research conducted on these functions in Arctic streams. Most of the research conducted on the connection between metabolism and environmental factors has focused on temperate environments (Appling et al., 2018a; Izigairre et al., 2008; Mulholland et al., 2001; Pastor et al., 2017) where conditions such as seasonality are significantly different than in northern rivers. Furthermore, studies often do not account for the nested hierarchical nature of stream environments. Streams can be affected both by their proximal environment (stream reach scale) and by the features of their watershed, and which is more significant varies between streams (Lento et al., 2013; Schneider, 2001; Yates et al., 2013). Therefore, this hierarchy must be considered when attempting to define the relationship between stream metabolism and environmental variables.

Further research on ecosystem functions in Arctic streams is vital to understanding the impacts of climate change within stream ecosystems and their interactions with their surrounding ecosystems. Gathering data about how Arctic stream ecosystems are affected by their environment will help establish a baseline useful for determining the significance of monitored future changes in stream ecosystem function. Stream metabolism is an ideal candidate for monitoring stream changes, due to its sensitivity to variations in atmospheric and water

temperature, nutrients, and ice phenology (Demars et al., 2011; Fuß et al., 2017; Prowse and Culp, 2003; Yvon-Durocher et al., 2012) However, a basic understanding of which environmental factors have the greatest influence on metabolic rates is required. Also required is an understanding of the importance of scale. Therefore, my study seeks to develop an understanding of which environmental variables, measured at which scales, are most closely correlated with measures of stream metabolism in the Arctic. In the future, understanding these interactions may help improve biomonitoring techniques and management strategies aiming to sustain the environment and protect the vital functions of Arctic streams.

1.6 Objectives

This thesis aims to: 1) determine the most effective method for measuring Arctic stream metabolism by using the streamMetabolizer model and empirical equations model (ER-Interpolation, linear regression, and mass balance equation) (Chapter 2), and 2) applying the most effective method to determine if there are any spatial or temporal patterns in daily GPP and ER rates, and which environmental variables are most important determinants of daily GPP and ER rates (Chapter 3). In Chapter 2, methods for measuring Arctic stream metabolism are assessed by comparing the range and magnitude of the predicted values to determine which approach produces GPP and ER rates more appropriate for characterizing an Arctic stream. Extremely high or low values of GPP and ER are considered very unlikely in these streams due to harsh conditions in the Arctic (flooding regimes, low temperatures, low nutrient levels). Thus, higher variability in the predicted values will likely indicate a poorly performing method. The most appropriate method for measuring Arctic stream metabolism will be selected and refined as needed to move forward to Chapter 3. Chapter 3 assesses changes in stream metabolism through

space and time to determine if: (i) average daily GPP and ER at the study sites differed significantly across the watershed; (ii) sites showed consistent temporal patterns throughout the study period; and (iii) if there were environmental variables that were significantly associated with changes in average daily GPP and ER.

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CHAPTER 2: DETERMINING A VIABLE MODEL FOR ESTIMATING STREAM METABOLISM

2.1 Introduction

Stream metabolism (or net ecosystem productivity, NEP) refers to the combined processes of primary productivity by autotrophs and secondary productivity by heterotrophs which are referred to as GPP and ER respectively. (Riley & Dodds, 2013). Researchers commonly use the single station method, where O_2 sensors are placed in a well-mixed portion of the stream to measure daily oxygen levels. Measuring stream metabolism through diel variation in dissolved oxygen (DO) concentration in a stream is based on the premise that changes in DO concentrations are the results of GPP, ER and the natural diffusion of oxygen between the air-water interface, referred to a reaeration (k) or a reaeration coefficient (K600). The instantaneous change in dissolved oxygen can be calculated by Equation 1 (Grace & Imberger, 2006).

$$\text{Equation 1: } \triangle DO = GPP - ER \pm k$$

During darkness, it is assumed that GPP is equal to 0 and any changes in oxygen levels are due to k and ER (a nighttime method). k is determined by Equation 2, where K_{O2} is the reaeration constant and D is the oxygen deficit – the difference between the measured DO concentration and the 100% saturation value (which is dependent on water temperature) (Grace & Imberger, 2006).

$$\text{Equation 2: } k = K_{O2} \text{ x } D$$

Stream metabolism should be a useful tool for monitoring and understanding carbon cycling in Arctic streams, however, the standard night-time calculations (when GPP is assumed to be 0 in the dark) for estimating NEP are complicated by the fact that, during the summer in Arctic streams (e.g., Greiner Lake Watershed) light levels of 0 may be observed only for limited

time or not at all (Mesa et al., 2017). Therefore, additional techniques must be applied, or night-time methods need to be modified to calculate ER and k.

The overall goal of this chapter is to select a model that can produce suitable results for developing a baseline of stream metabolism data for streams in the Greiner Lake Watershed. The first approach assessed was streamMetabolizer, which is a software uses daily oxygen levels and Bayesian statistics to measure stream metabolism and does not require hands on measurements of reaeration (Appling et al., 2018b). The second approach used reaeration values calculated based on channel morphology measurements, three separate ER estimation methods, and a standard mass balance equation model to measure daily metabolic rates. These approaches were used at four sites in the Greiner Lake Watershed and were compared to determine which was most effective.

2.2 Methods

2.2.1 Approach for Model Selection

The streamMetabolizer and the stream hydraulics models were applied using continuous measurements of DO (mg/L), PAR ($\mu mol\ m^{-2}\ s^{-1}$) depth (m) and temperature (°C) measurements taken from 16 sites in early July to mid-August of 2019 in the Greiner Lake Watershed **(Figure 2.1).** For streamMetabolizer, light levels were of most concern due to the nature of GPP being calculated linearly with light and requiring a period of darkness (PAR = 0) to determine ER (Hall et al., 2016). Therefore, to evaluate model sensitivity to PAR inputs, a range of adjustments were made to the PAR data to determine if the quality of the results would improve and remain steady, regardless of the changes in PAR levels. If there are significant changes between the adjustments made to the values taken from the same site, the models are sensitive to PAR changes and could

represent a shortcoming in the metabolism calculation, making it imperative to reassess the use of streamMetabolizer.

For the ER-Interpolation using linear regression and the stream hydraulics mass balance equation, k was determined by using reaeration coefficients discussed by Raymond et al. 2012, using values of width, depth, and velocity from each stream. Because I did not adjust light levels, the number of days input were based on when each site began experiencing darkness, an approach that would also change which values of width, depth and velocity used given that flow decreased throughout the study period. Any inconsistencies between overlapping dates would likely be indicative of a poorly performing model, or inaccurate calculations of reaeration (which could be due to sampling errors).

Although there are few metabolism studies available for Arctic streams, there are fundamental expectations for stream metabolism based on the specifics of study period and location. The first expectation was GPP, ER and K600 would not show excessive daily variation (e.g., $3gO_2^{-1}$ to 40 gO_2-^{1} GPP) since the study period is relatively short, and that Arctic streams do not experience significant weather events throughout the summer (Myrstener et al, 2021; Rocher-Ros, 2019). The second expectation is that streams would not be highly productive as this trend is what has been found for other studies of Arctic streams (~15 gO_2-^{1}) (Myrstener et al, 2021; Rocher-Ros, 2019). Third, ER O_2 cannot be positive, GPP O_2 cannot be negative, and K600 cannot be negative (Appling, 2018b).

2.2.2 Data Collection

Stream metabolism was estimated between July 9th to August 12th in 2019 using the open single station method, which determines how the DO (dissolved oxygen) in the stream changes as a function of time by using measurements from loggers positioned at a single location in the

stream. The method is ideal for use in streams with an open canopy (Grace & Imberger, 2006) such as these tundra systems, and is used to calculate GPP, ER and NEP. A key assumption of the method is that DO concentration is uniform throughout a study reach (Grace & Imberger, 2006). Oxygen concentration measurements were taken every 15 min over the period of the study using D-Opto loggers measuring temperature, DO mg/L, %DO, and DO ppm continuously. Depth (m) and temperature (°C) were also measured every 15 min using HOBO loggers. Both D-Opto and HOBO data loggers were attached to rebar embedded vertically into the substrate at the end of each reach in a well-mixed area within the main flow, approximately 5 cm above the substrate so that loggers remained underwater throughout the entire sampling period. The positioning in the water column was required to obtain accurate measurements of dissolved oxygen, and to protect sonde membranes from sedimentation (Grace & Imberger, 2006). PAR was measured every 5 minutes using the Odyssey® Waterproof Photosynthetic Active Radiation Logger, which was attached to the top of the rebar with the optical sensor head pointing upwards. This summarized PAR of the reach since light availability remained relatively the same.

2.2.3 Calculating Stream Metabolism

The following section describes the different sets of models used to calculate stream metabolism. The first model is streamMetabolizer, which uses continuous oxygen data to estimate ER, GPP and K600 simultaneously. The second method estimates stream metabolism from the oxygen data by incorporating three additional methods of determining GPP and ER, and one single method of determining K600.

2.2.3.1 Stream Classification

Each stream was placed into 1 of 3 different categories: 1. Narrow, 2. Wide, and 3. very wide, such that the width to depth ratios were <20 for narrow streams, ≥20-50 for wide streams, and ≥50 for very wide streams. Narrow streams included sites: ER03, ER04, CB14, CB29, CB24 CB26, CB28, CB21 and CB25. Wide streams included streams: CB15, CB16, CB20 and CB22. Very wide streams included sites: CB27, CB05, CB06 and CB04 **(Table 3.6)**. The watershed was summarized based on the sizes of streams because morphology can directly effect reaeration rates (Raymond et al., 2012). Although decreased stream width may be associated with lower light levels due to riparian cover in temperate streams, this was not the case in the Greiner Lake Watershed where vegetation is low-lying shrub tundra (NASA, 2015). Therefore, different sizes would represent the diversity of conditions in the watershed.

2.2.3.2 streamMetabolizer Method

The model employs Bayesian statistics to simultaneously calculate GPP, ER and K600 using data trends previously observed in other stream systems. In the initial application of the streamMetabolizer method (Appling et al., 2018b), there were no alterations made to the default settings of the streamMetabolizer model, and the "Bayes" model within the streamMetabolizer package was applied. Of the several different options for algorithms that can be used via the streamMetabolizer package, the trapezoid numerical algorithm was applied to model dissolved oxygen data because it is more accurate compared to the other algorithm options (Appling et al., 2018b). Additionally, process and observation error were included in the model to help distinguish errors attributable to the data collection process, or due to a shortcoming of the model. Lastly, K600 was set to "normal", meaning that the model will not pool K600 based on

any previously inserted values as there were only 2 measurements of discharge available through this study.

2.2.3.3 Stream Hydraulics, ER Determination Alternatives and Mass Balance Methods

This section explains how stream reaeration was calculated from hydraulic components of each stream site, the various equations used to calculate ER, and then their application to a mass balance equation. The equations used included a mass balance equation when PAR = 0 μmols^{-1}, an ER interpolation equation when PAR >0 μmols^{-1}, or the use of the lowest PAR values to calculate ER when ER interpolation was poor (i.e., produced positive ER values).

First, the reaeration coefficient (K normalized to a schmidt number of 600) was calculated based on equations found to be most effective for small streams in a study of 256 streams in the USA (Raymond et al., 2012), where several different equations were applied to calculate reaeration rates. The equation used in that case was:

$$Equation\ 3\text{: } K_{600} = (VS)^{0.89 \pm 0.0.020} \text{x } D^{0.54 \pm 0.030} \text{x } 5037 \pm 604$$

Where k_{600} is O_2 normalized to a temperature between 17.5 and 20.0 °C, D is depth (m), V is velocity (m/s), and S is slope (m/m). Then, to determine reaeration from the coefficient of reaeration the following equation was used:

$$Equation\ 4\text{: } K_{O2} = \frac{K_{600}}{(600\ /Sc_{O2})^{-0.5}}$$

Where S is the Schmidt number, C_{O2} is the concentration of dissolved O_2, and k_{O2} is the reaeration coefficient.

When PAR = 0 μmols^{-1} at some point throughout the day, a standard night-time regression equation to determine GPP and ER can be applied. Since Arctic streams at latitude 69°N usually

experience a small amount of time in darkness (1-2 hours), the instantaneous ER is averaged over the time steps with 0 $\mu mols^{-1}$ PAR. This value is used to estimate daily ER following temperature correction. When PAR>0 $\mu mols^{-1}$ for the entirety of the night, the instantaneous ER at 0 $\mu mols^{-1}$ PAR is interpolated through linear regression (Cappelletti, 2006). The value is then used to estimate daily ER following temperature correction. The model extrapolates ER based on the temperature of the water when PAR=0 $\mu mols^{-1}$, and then is extrapolated backwards assuming ER changes with temperature by 10-fold with natural logarithms (Cappelletti, 2006). Lastly, when PAR > 0 $\mu mols^{-1}$ but interpolation is poor (ER is greater than 0 $gm^{-2}d^{-1}$) the instantaneous ER at the minimum PAR is used to estimate daily ER following temperature correction. The k value is then calculated based on coefficients recommended by Raymond et al., 2012 using measures of stream width, depth, velocity, and slope. The calculated k value is then incorporated into the mass balance equation as described by Grace & Imberger (2006) **(Figure 2.2)**.

2.2.4. Testing Differences Between Model Results Based on Input Data/Parameters

Subsets of the data were used to test different adjustments of the data that were applied to improve model estimates of metabolism. Determination of data to be used in streamMetabolizer was based upon several considerations including the minimum levels of 1) PAR used, since streamMetabolizer is directly impacted by light levels, and 2) dates used, since the number of days varied in lights level throughout the night. For the empirical stream hydraulics and mass balance model, data were input based on depth levels, as depth levels are related to stream hydraulics. The first set of data modifications to streamMetabolizer is labeled SMOD (StreamMetabolizer MODifications), where light levels were adjusted minimally. The second data modification to streamMetabolizer was labeled SMOD2, where additional light level

adjustments were applied for the dates included and threshold PAR values used. The third data adjustment used data from the beginning, or the end of the study period based on water depths levels was labeled EMOD (i.e., Empirical MODification), as depth is highly related to reaeration rates in streams and varies considerably over the study period. The empirical modifications refer to the Raymond, ER interpolation and mass balance equation methods and how they are used (Cappelletti, 2006; Grace & Imberger, 2006; Raymond et al., 2012;). The following sections provide a detailed description of the model and data adjustments.

2.2.4.1 SMOD

Because light levels do not reach zero at this latitude during early summer, I adjusted the PAR input data to create varying periods of darkness where GPP was hypothesized to be at a minimum. I created periods of darkness by adjusting PAR values ≤ 15 $\mu mols^{-1}$ to 0 $\mu mols^{-1}$ (SMOD15), and secondly PAR values ≤ 20 to 0 $\mu mols^{-1}$ (SMOD20). These adjusted periods of darkness began on days where there were at least 12, 3-h intervals of complete darkness (PAR = 0). This modification allowed determination of diel light curves with adequate darkness for metabolism calculation.

2.2.4.2 SMOD2

Next, more dates were included to determine if creating these thresholds and altering the data set would produce more satisfactory results. SMOD2 constitutes more substantial changes to dates and light values than SMOD. Because the number of values being set to PAR=0 $\mu mols^{-1}$ increased, the number of dates without PAR=0 $\mu mols^{-1}$ was less of a concern, since PAR values as high as 100 $\mu mols^{-1}$ would be set to 0 $\mu mols^{-1}$ and be used in the model. Specifically, dates were selected where PAR would reach 0 $\mu mols^{-1}$ for at least one 15 min interval. This set of results is referred to as SMOD-2 and includes versions that were modified from the original data

set. PAR was set to 0 at PAR<15 μmols^{-1} (SMOD2-15), PAR<20 μmols^{-1}, (SMOD2-20), PAR<50 μmols^{-1} (SMOD2-50) and PAR<100 μmols^{-1} (SMOD2-100) to see the sensitivity of the model **(Figure 2.3)**.

2.2.4.3 EMOD

Two different data adjustments were evaluated to determine how metabolism estimates changed with input data used for water depth and stream hydraulics. This model addresses dark periods by switching between equations that require darkness and those that can estimate ER regardless of darkness. First, metabolism was calculated using E-UNMOD (Empirical Unmodified) that used the average measurements of stream hydraulics (width, depth, velocity, discharge, slope) taken at the beginning of the study period during deployment, and then from the end of the study period during extraction.

Second, the EMOD only used stream hydraulic values taken at the end of the study when depth values were stable. In theory, because depth is highly correlated with reaeration rates, once depth remains constant reaeration rates will be constant. This usually took place beginning in August and was done with the intention of improving the accuracy of reaeration rate estimates. Depth was deemed stable based on visual inspection of the depth curve as the point when there was no further large (i.e., > 10 cm change) increases or decreases in depth.

2.2.4.4 streamMetabolizer Final Modifications

Although streamMetabolizer was the ideal model, it produced output that occasionally was impossible (i.e., days where ER > 0 gm^{-2}d^{-1} or GPP < 0 gm^{-2}d^{-1}). In response to this, additional changes to light levels and days used were made, and a specific alteration to the streamMetabolizer settings was implemented. Three data set adjustments were used to remedy this error. The first set used was unchanged in any way (UNMOD). Next, the entire data set was

used, and any PAR<1000 μmols^{-1} were set to 0 μmols^{-1} (PAR 1000). Moreover, only data from August was used, and PAR levels remained unaltered (AUG). Next, only data from August were used, and all values less than 1000 μmols^{-1} were set to 0 μmols^{-1}. Lastly, the final modification included the entire data set, unchanged, however, an altered version of streamMetabolizer was employed where it was set so that ER could not be greater than 0 gm^{-2}d^{-1}, and GPP could not be less than 0 gm^{-2}d^{-1} (ER.GPP) **(Figure 2.3)**.

2.3. Statistical Analysis

2.3.1 Kernel Density Estimate and ANOVA

A bivariate Kernel density estimation was used to display the paired values of ER and GPP produced by the various models and sensitivity tests. The purpose of the bivariate kernel density estimation is to make inferences about the underlying probability density function everywhere. The different levels of the plot are representative of how much data are expected to fall within a certain range. To conduct a bivariate kernel density estimation, the stat_density_2d argument was used in ggplot2 (Wickham, 2016) to simultaneously conduct the kde, using the MASS:kde2 package, and display the results graphically. Bivariate kernel density plots were performed for K600, ER and GPP for one site in every morphology class, with the assumption that sites in the same class would have similar distributions. Lastly, an ANOVA and Tukey-HSD test were performed to determine if there were significant differences between the modifications (dates and PAR thresholds used) within each model (SMOD vs SMOD2 and EMOD vs EMOD2) and between the models (SMOD vs. EMOD).

2.3.2 Analyzing Model Diagnostics (Markov chain Monte Carlo (MCMC) and Bayesian Statistics

The streamMetabolizer uses the Bayesian modeling software Stan via the rstan R interface combined with Markov chain Monte Carlo (MCMC) to explore the posterior distribution (Stan Development Team, 2016). This model incorporates a Bayes' algorithm that bases predictions on initial information given to the model, usually based on information from previous studies (i.e., “priors”) and a distribution resulting from providing the model with additional data. MCMC is commonly used in tandem with Bayes' theorem to assist in reducing complicated computations when there are non-normalised distributions. In this package, the process error and observation error will be analyzed and reported as *rhat* values, with an acceptable *rhat* value being ≤1.1. and these terms will be used to assess how accurate the model is (van Ravenzwaaij, Cassey & Brown., 2018). The more the models converge (i.e., how well the observed data fits with the modelled data), the more the model consistently predicts similar results from the sample distribution, i.e., the metabolism data. Accurate predictions of the sample distribution are essential to determining if the Bayesian model is adequately predicting these values. However, *rhat* is not the only means of determining model convergence, and model convergence does not necessarily mean they are accurately representing real-life data (Taboga, 2021). Therefore, model convergence will be considered, but will also be used in tandem with common sense to interpret results.

2.3.3 Covariance

Pearson correlation was used to determine if there was any significant correlation between ER and K600 between each day at each site (cor_test in R) (R Core Team, 2018). When calculating stream metabolism, it is imperative to correctly attribute changes in oxygen levels at night to either ER or K600. As these values are calculated simultaneously in streamMetabolizer, it is important to ensure that the models can distinguish between changes in oxygen due to reaeration and changes due to ecosystem respiration. If correlation between these two variables is consistently high (above 0.6) between these two variables, it may suggest the model was unable to draw a distinction between the fluxes. This is especially important when streamMetabolizer is altered so that values of ER and K600 values cannot be greater than 0, and there is a lack of data used for K600 pooling.

2.4 Results

2.4.1 Comparison of SMOD, SMOD2, EMOD and EMOD2 models using Kernel Density Estimates

For the narrow stream type (CB29), changes to lower thresholds of PAR and the number of dates used in streamMetabolizer calculations produced minimal differences in ER, GPP and K600 as observed through kernel density estimates (kde) **(Figures 2.4 - 2.8)**. These plots indicate that the highest density (i.e., relative probability) falls in the same range for all SMOD and SMOD2 models. Highest SMOD densities estimates of GPP for CB29 were between ~0.5 - 1.5 g $O_2\,m^{-2}\,d^{-1}$, while ER was between -1 to 1 g $O_2\,m^{-2}\,d^{-1}$**(Figure 2.4a)**. In the SMOD2 model variation, where more days were included in the estimate calculation, a second cluster of high density is evident **(Figure 2.4b)**. Reaeration values also remained similar between SMOD and SMOD2 **(Figure 2.5a-b.)**, with values ranging between 5 - 14 K_{600} day^{-1} for CB29. In contrast,

KDEs showed that empirical methods differed greatly between EMOD and EMOD2 **(Figure 2.4c)** such that estimates of ER and GPP for the two models did not overlap and EMOD2 values did not cluster together. For example, EMOD the GPP and ER estimates were 0 to 5 g O_2 m^{-2} d^{-1} and 0 to 2 g O_2 m^{-2} d^{-1}, respectively, while EMOD2 estimates ranged from 10 to 20 g O_2 m^{-2} d^{-1} for GPP, and -5 to 4 g O_2 m^{-2} d^{-1} for ER. Furthermore, K_{600} was 46.7 K_{600} day^{-1} for EMOD and 59.6 K_{600} day^{-1} for EMOD2.

There was a greater range in streamMetabolizer estimates for the wide stream type (CB20) compared to CB29. However, GPP and ER estimates were again more consistent than those of the empirical methods. SMOD and SMOD2 produced the highest densities in a similar range as for CB29, with GPP and ER estimates of -2 to 0 g O_2 m^{-2} d^{-1} and 4 to 10 g O_2 m^{-2} d^{-1}, respectively **(Figure 2.6a-b)**. For reaeration, SMOD to SMOD2 produced estimates of 18 to 15 K_{600} day^{-1}, respectively **(Figure 2.7a-b)**. As observed for CB29, EMOD and EMOD2 estimates were dissimilar, showing minimal overlap in ER and GPP values. EMOD values of GPP ranged from 0 to 7 $gm^{-2}d^{-1}$ while ER was between 0 to -10 g O_2 m^{-2} d^{-1} **(Figure 2.6c)**. In contrast, EMOD2 produced GPP values between 0 to 20 g O_2 m^{-2} d^{-1} and ER values ranging from- 17 to 0 g O_2 m^{-2} d^{-1}. For K_{600} values, EMOD values were lower at 7.3 K_{600} day^{-1} relative to the much higher EMOD2 estimates at 23.3 K_{600} day^{-1}.

Lastly, for the very wide stream type (CB27), SMOD and SMOD2 produced the highest densities within a similar range for ER and GPP, with GPP consistently falling between 1 to 2 g O_2 m^{-2} d^{-1}, and ER between -1 to 0 g O_2 m^{-2} d^{-1} **(Figure 2.8a-b.)** However, reaeration varied more than at other sites, with values ranging from 7 to 12 K_{600} day^{-1} for SMOD and 10 to 22 K_{600} day^{-1} for SMOD2 **(Figure 2.9a-b.)**. EMOD and EMOD2 presented a large variation in densities and showed little overlap. EMOD produced ER estimates ranging from 0 to -8 g O_2 m^{-2} d^{-1} and

GPP from 0 to 9 g O_2 m^{-2} d^{-1} , while EMOD2 estimated GPP ranging from 0 to 3 g O_2 m^{-2} d^{-1}, and ER from -3 to 0 g O_2 m^{-2} d^{-1} **(Figure 2.8c)**. Reaeration estimates of EMOD1 and EMOD2 varied greatly, with EMOD1 being higher at 17.0 K_{600} day^{-1} compared to the lower value of 5.5 K_{600} day^{-1} for EMOD2.

2.4.2 Comparison of Metabolism Estimates From SMOD, SMOD2 and EMOD, EMOD2 Using Boxplots and ANOVA

Boxplots show that in most cases, the various versions of the SMOD model produced similar values of GPP, ER and K600 when data from all sites was combined **(Figures 2.10 – 2.12)**. For SMOD-15 to SMOD2-100, GPP average values were between 0 to 2.5 g O_2 m^{-2} d^{-1} **(Figure 2.10)**, ER values were between 0 to -1 g O_2 m^{-2} d^{-1} **(Figure 2.11)**, while reaeration values ranged between 7 - 8 K_{600} day^{-1} **(Figure 2.12)**. SMOD-15 is the only visible outlier for GPP values, with a slightly higher range of GPP values compared to all other models. In contrast, EMOD and EMOD2 showed much more variable results such that GPP averages for EMOD2 and EMOD were 2.5 and 2 g O_2 m^{-2} d^{-1}, respectively. However, the range of these estimates was greater than the SMOD model variations, with GPP estimates reaching of 60 g O_2 m^{-2} d^{-1} for EMOD2, and approximately 30 g O_2 m^{-2} d^{-1} for EMOD **(Figure 2.10)**. While EMOD and EMOD2 ER averages were between -2 to -2.5 g O_2 m^{-2} d^{-1} and like the SMOD results, some values were exceptionally high ranging from -45 g O_2 m^{-2} d^{-1} for EMOD2, and -30 g O_2 m^{-2} d^{-1} **(Figure 2.11)** for EMOD. EMOD and EMOD2 average reaeration values were between 18 - 19 K_{600} day^{-1} however, outliers reached values of 60 K_{600} day^{-1} for EMOD2, and 50 K_{600} day^{-1} for EMOD **(Figure 2.12)**. Furthermore, ANOVA tests demonstrated that there were no significant differences in GPP, ER and K600 between streamMetabolizer versions (SMOD15 vs SMOD20, and SMOD2-0 to SMOD2-100). However, an ANOVA did reveal a significant difference

(p=0.001) between EMOD and EMOD2, as well as EMOD and EMOD2 and all SMOD and SMOD2 values of GPP, ER and K600.

2.4.3 Analysis of Markov Chain Monte Carlo (MCMC), Pearson Correlation Values and Barplots

MCMC is a statistical modelling technique that creates a series of chains of potential predictions, and the model tests itself by seeing how often the model successfully predicts values based on actual data collected. The level of convergence helps assess whether these chains end up predicting the same values. Convergence is represented by *rhat* and is considered successful when (*rhat* = <1.1). When analysing streamMetabolizer modifications of AUG, AUG.1000, ER.GPP, NO.MOD and PAR.1000, there was a mix of converging (*rhat* = <1.1) and non-converging results between models, and between sites **(Tables 2.2 – 2.6)**. Sites CB04, CB05, CB15, CB16, CB26, CB27, CB29 and ER04 all produced at least 1 model that had an acceptable value of *rhat*. Furthermore, most sites had significant correlations between K600 and ER, with certain sites having high correlations and some sites having low correlations, and some with insignificant correlations. Sites that had at least 1 model that produced insignificant correlation (p<0.05) were CB06, CB05, CB15, CB20, CB21, CB22, CB26 and ER04. The models that produced correlations of r-values <0.6, and acceptable MCMC values (*rhat* = <1.1), were greatest for ER.GPP and AUG. Successful ER.GPP sites included CB04, CB05, CB15 and CB29 and ER04, and sites that were successful for AUG included CB05, CB16, CB20, CB26 and ER04 **(Tables 2.1 - 2.5)**. In terms of analyzing values of ER.GPP, models were forced not to produce any values less than 0 g O_2 m^{-2} d^{-1} for GPP and there were no sites with ER > 0 g O_2 m^{-2} d^{-1}, however, averages did not differ visibly from between the models **(Figure 2.13)**. All other versions produced values of GPP less than 0 g O_2 m^{-2} d^{-1}, and ER values greater than 0 g

$O_2\ m^{-2}\ d^{-1}$. Although PAR.1000 and NO.MOD had lower correlation values, they had a higher percent of days with ER that were biologically impossible. ER.GPP was better in every other measure of model success as it produced the most reliable results in terms of lowest process error, observation error and highest biologically possible days **(Table 2.6)**. Therefore, I concluded that ER.GPP was most successful, and would be used moving forward into Chapter 3 for environmental analysis.

2.5 Discussion

Stream metabolism is frequently used to evaluate carbon flow in temperate stream ecosystems (Ferreira et al., 2020). In Arctic streams, metabolism has seldom been assessed because these ecosystems are understudied due to their remoteness, and sensors for measuring dissolved oxygen have only recently become available. To address this deficiency, I evaluated whether the standard model for estimating stream metabolism, namely streamMetabolizer (Appling et al., 2018b), could be improved for application in the Arctic by raising the lower limit of PAR thresholds, thereby extending the daily period and the number of days over which ER could be estimated reliably. In addition, I evaluated empirical models that used multiple ER calculation methods (ER interpolation or ER regression based on PAR levels) combined with reaeration coefficients to calculate K600, which were then used in a mass balance equation model which also was designed to eliminate complications due to a lack of darkness. Empirical models did not provide consistently reasonable values. In contrast, application of the ER.GPP model, where streamMetabolizer was altered to produce biologically possible days (GPP≥0 and ER≤0), produced values of GPP and ER values that were deemed reasonable (i.e., within the

expected range for Arctic streams), and most sites had adequate model diagnostics (process or observation error ≤1.1).

2.5.1 Effect of Changing PAR Thresholds on ER and GPP Estimates

Increasing the lower limit of PAR thresholds produced longer periods of darkness but did not improve ER estimates for the different model versions (i.e., SMOD, SMOD2, PAR.1000, AUG.1000, AUG), and continued to produce biologically impossible days. In contrast, model versions ER.GPP, and AUG produced biologically possible results for each day as these modifications to streamMetabolizer require ER to be less than or equal to 0, and GPP to be greater than or equal to 0. While there is the risk that changing these parameters within streamMetabolizer could produce inaccurate estimates, ER and K600 were not correlated meaning that the model was able to discriminate between changes in oxygen due to respiration or reaeration (Appling et al., 2018b). Furthermore, model diagnostics indicated that the ER.GPP version produced acceptable values of *rhat* (i.e., accurate predictions of GPP, ER, and K600), and improved predictions of daily values of GPP, ER and K600. In summary, the increased amounts of biologically possible days, the low correlation values, and the adequate *rhat* values showed that ER.GPP was the best model for estimating ER and GPP in these Arctic streams.

Modification of PAR thresholds used in the streamMetabolizer model has not been tested previously, thus an important finding was that increasing the lower PAR thresholds for ER estimation did not affect the performance of streamMetabolizer. GPP in these Arctic streams appears to be insensitive to changes in PAR between 0 to 1000 μmol m^{-2} indicating that it is unlikely PAR values below 1000 μmol m^{-2} (1.7 μmol m^{-2} s^{-1}) do not provide enough energy for substantial photosynthesis to occur. It is often the case that even within the PAR spectrum,

different levels of light have different efficiencies for varying species of photosynthesizes (Hill., 1995). While light is a main contributing factor to stream metabolism (Trimmer et al. 2012), primary producers also may be limited by other factors including nutrients and temperature such that PAR levels may need to exceed 1000 μmol m^{-2} to increase primary production in Arctic streams (Singh & Singh, 2015). In this study, changes to streamMetabolizer also indicated that the addition of model parameters (the requirement that ER is ≤ 0, and GPP is ≥ 0) can increase the number of usable days for GPP and ER estimates without compromising model performance. Based on the use of continuous measurements values of DO, PAR, temperature, and depth alone, streamMetabolizer was able to distinguish between ER and K600, showing that streamMetabolizer is a low sample effort option for use in remote streams where data needed for calculating K600 cannot be collected from repeated field sampling visits throughout the study period. Finally, the ER.GPP model performed better than unmodified models in terms of model diagnostics and produced biologically feasible estimates.

2.5.2 Complicating Factors of Empirical Models (EMOD, EMOD2)

The lack of success for EMOD and EMOD2 may be related to a need for repeated measurements of stream geometry and hydrology data that could improve estimates of K600. Because of the remote location of the study sites, discharge could only be measured twice during the summer. Given that discharge decreased throughout the summer, reaeration estimates were likely affected by decreases in critical parameters of stream hydraulics (e.g., stream width, depth, velocity) which would affect the results of the coefficient calculation (Raymond et al., 2012). Lastly, there may have been issues with the methods of ER calculations. The empirical models are likely affected by equifinality (Appling et al., 2018b), that is the phenomena of having

consistent NEP values but higher variability in GPP, ER and K600 values. Moreover, when the diel oxygen change is limited as it is in these Arctic streams, high or low values of GPP, ER and K600 can create the same NEP value (Appling et al., 2018b). The empirical models had more unreasonable results because there was no way to assess and reduce equifinality. It is likely that streamMetabolizer was more successful due to the Bayesian statistics that reduce this phenomenon (Appling et al., 2018b).

2.5.3 Limitations of Metabolism Methods and Future Improvements

Several sampling limitations may have affected the metabolism calculations. First, improved estimates from streamMetabolizer can be obtained by measuring velocity consistently throughout the summer (Appling et al., 2018b), however, this was logistically impractical. Secondly, the study was undertaken in an area with no available information on GPP, ER and K600 that could be used as a reference values (i.e., priors) for Bayesian calculations in streamMetabolizer. Future studies in this geographic region will benefit from data collected in my study, as well as more recent stream metabolism research in the Arctic (Myrstener et al., 2021: Rocher-Ros et al., 2019). Moreover, there were no reaeration values that could be used for K600 pooling method in streamMetabolizer. In addition, the results show that most sites had low GPP and ER values, which made interpreting results particularly difficult, and risked equifinality even when using streamMetabolizer (Appling et al., 2018b). In conclusion, the proposed changes to PAR thresholds did not produce changes to daily values of GPP, ER and K600 and, still produced biologically impossible days. Furthermore, empirical models would have required greater sampling effort and models that relied on stream hydraulics were not successful, likely due to inadequate sampling (which is not reasonable for remote Arctic streams) or equifinality. The

most successful approach was adding extra parameters to streamMetabolizer that created only biologically possible values of GPP, ER and K600. Model's that require minimal sampling will make tracking changes in carbon and nutrient cycling in streams more feasible, which is especially useful as we expect many changes to these ecosystems in the onset of climate change.

2.6 CHAPTER 2 REFERENCES

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2.7 CHAPTER 2 FIGURES

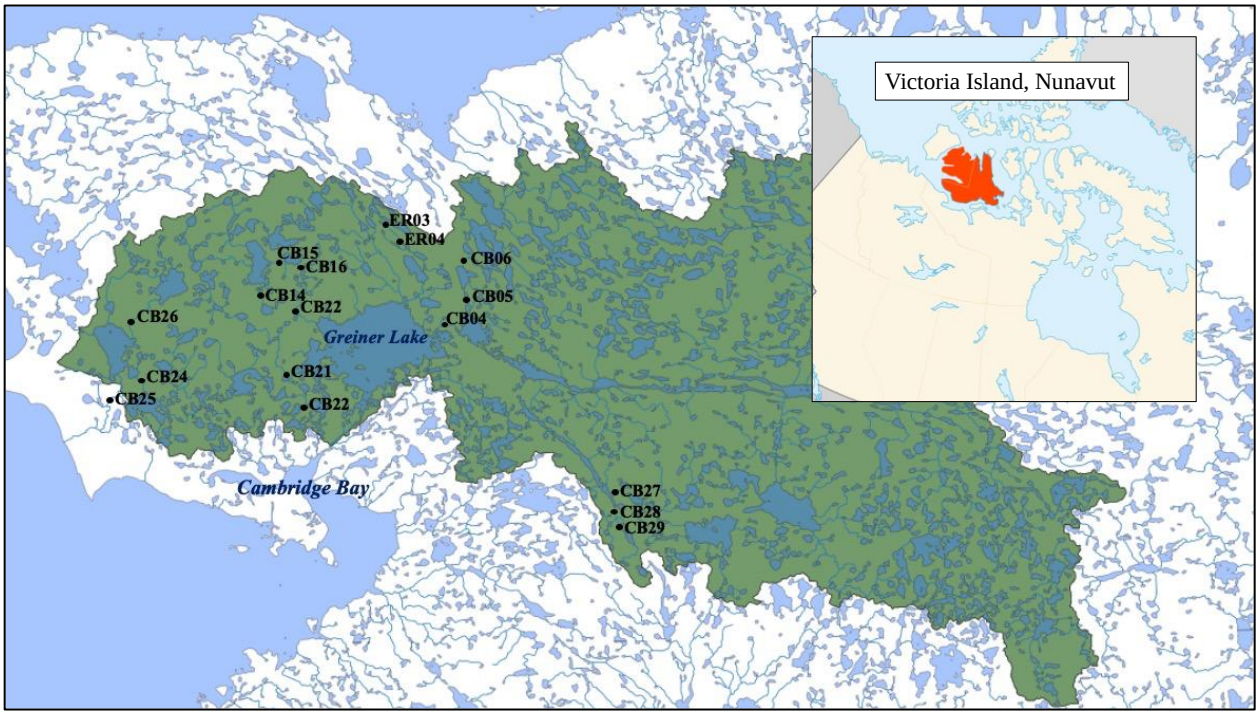

Figure 2.1: Map of the Greiner Lake Watershed and Sample Sites. The Greiner Lake Watershed is located on Victoria Island, Nunavut, Canada latitude 69°N and a longitude of 105°W.

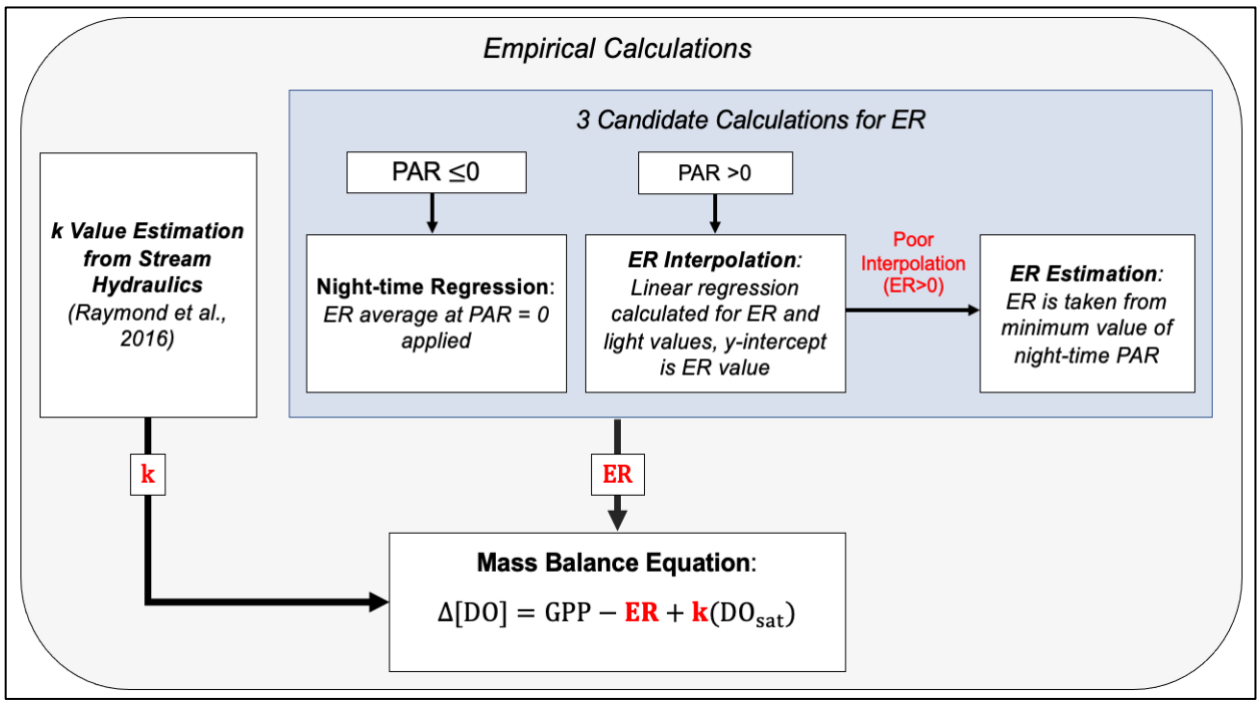

Figure 2.2: Diagram of the Determination of Each Empirical Calculation Used. K (reaeration values) remained the same for all 3 methods of ER calculation. Boxes shown in blue explain the choice of ER estimation methods based on the levels of PAR experienced throughout the night, and then through the success of the interpolation method. k and ER are then applied to the mass balance equation shown where in conjunction with O_2 measurements can calculate GPP.

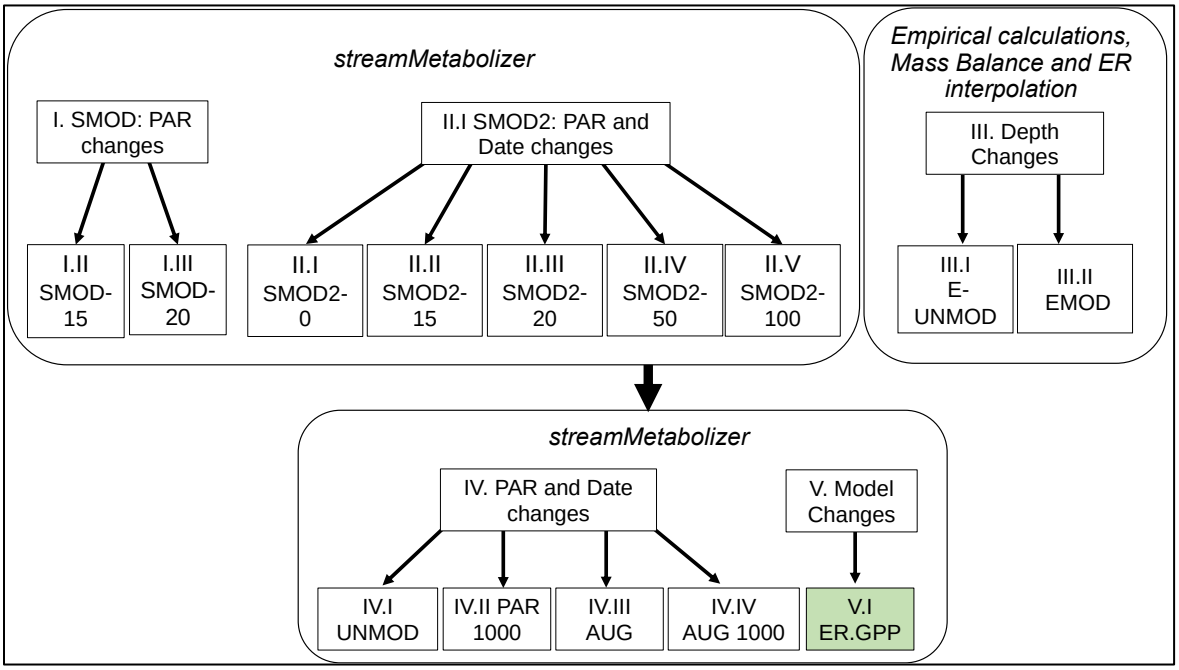

Figure 2.3: Summary of Data Adjustments for Testing Model Performance. This diagram depicts the different categories of models and the different parameters used to estimate stream productivity. I. S-MOD represents the first set of data, where only days with 12, 3-h intervals of PAR=0 were used. Data adjustment 1.1 represents PAR=0 when PAR≤ 15, 1.2 represents PAR=0 when PAR≤ 2. 1. II. S-MOD2 represents the second data set, where days with at least one value of PAR=0 were used. II.I represents unaltered data, II.II represents PAR=0 if PAR≤ 15, II.III represents PAR=0 if PAR≤ 20, II.IV represents PAR=0 if PAR≤ 50, II.V represents PAR=0 if PAR=100. III.I E-UNMOD represents the entire data set used, with the calculations of reaeration taken from the beginning and end of the study period III.II EMOD Uses the second half of the data set after depth starts to decline, and measure reaeration based on values determined at the end of the study period

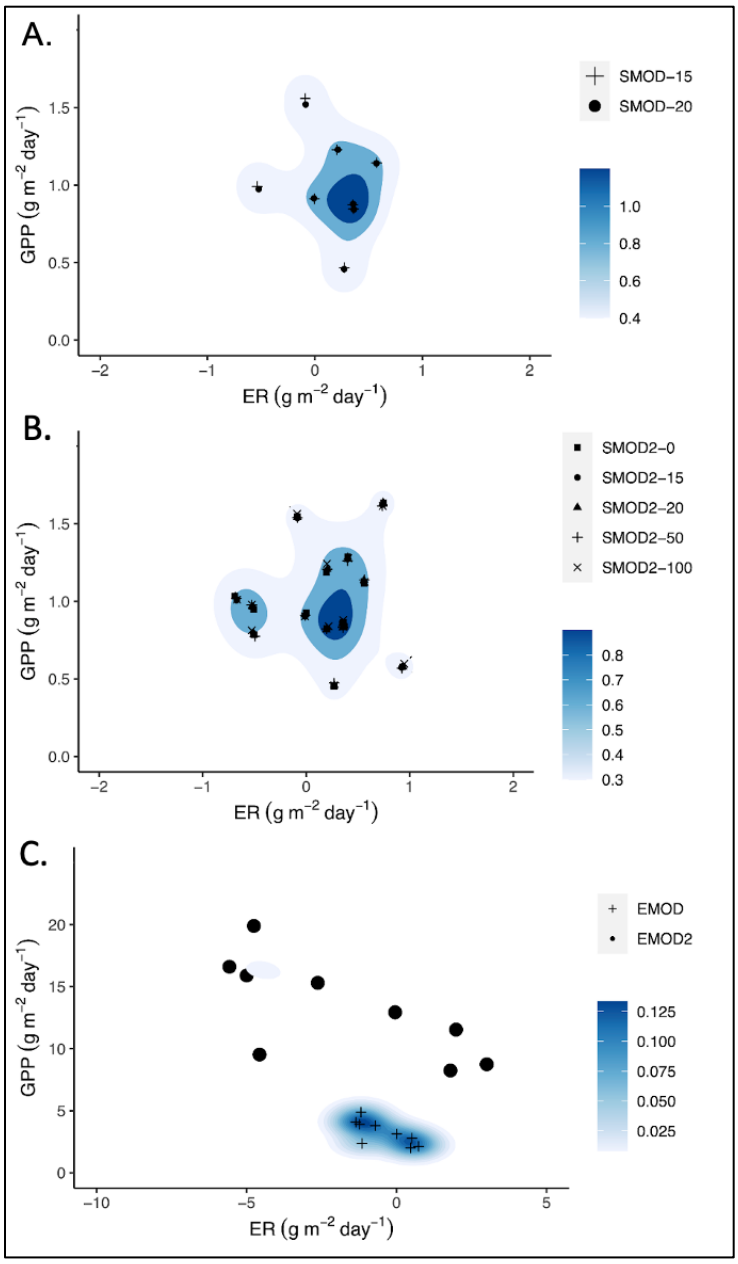

Figure 2.4: Kernel Density Estimates Representative of Narrow Streams (CB29). KDE showing *relative*, *non-parametric* probabilities of a random sample of GPP and ER values based on previously gathered data of GPP and ER values observed throughout summer of 2019 in the Greiner Lake Watershed. Darkest blue values represent areas with greatest volumes beneath, i.e., 2 dimensional (x = ER and y = GPP being the dimensions) ranges of values where a random sample would be most likely to fall. Points represent actual values of GPP and ER observed throughout the study period, with the various shapes representing different version, whereas the colour gradient shows the probability of where a new a new observation may fall. Variations in PAR and dates used vary by model where A. SMOD15 and SMOD20 uses dates with at least 12 timesteps of darkness (PAR=0) throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. B. used SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 which also uses streamMetabolizer but increases the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20,

>50, >100 $\mu mols^{-1}$ are all set to 0. C. EMOD uses empirical methods, combing mass balance equations, ER regression and ER interpolation paired with coefficients proposed by Raymond et al., 2012 to calculate reaeration values based on discharge, velocity, width, depth and slope of stream channels. EMOD uses total average values of the reaeration values calculated at the beginning and end of the study EMOD (46.67 K_{600}) and end of the study EMOD-2 (59.64 K_{600}).

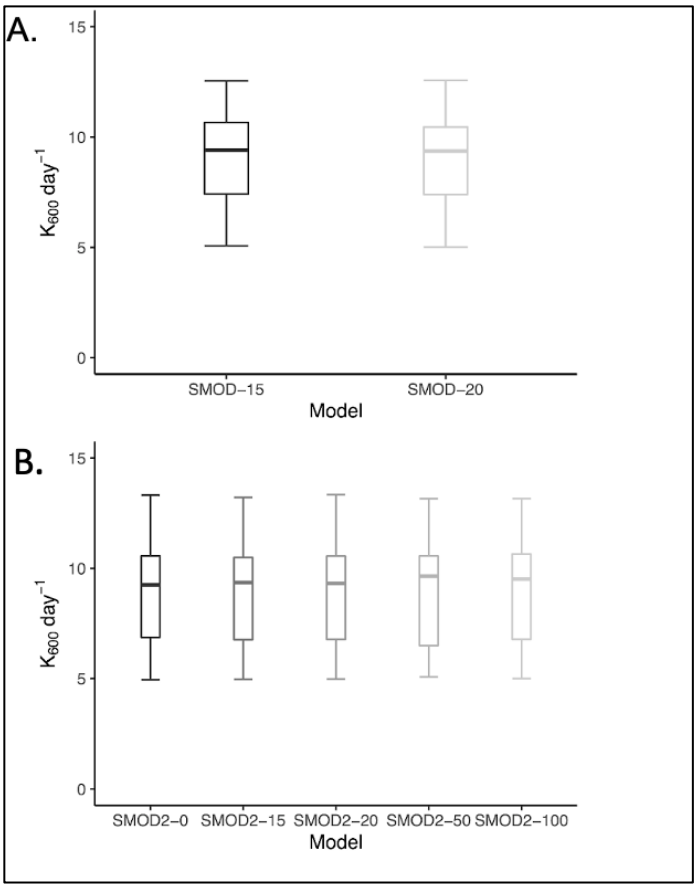

Figure 2.5: Boxplots Demonstrating Reaerations Values of a Narrow Stream (CB29).Boxplot where the top line represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, and the bottom line represents the smallest value within 1.5x below the 25TH percentile. SMOD15 and SMOD20 (A.) used dates with at least 12 timesteps of darkness (Photosynthetically active radiation (PAR)) = 0 throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 (B.) also used streamMetabolizer but increased the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 $\mu mols^{-1}$ are all set to 0.

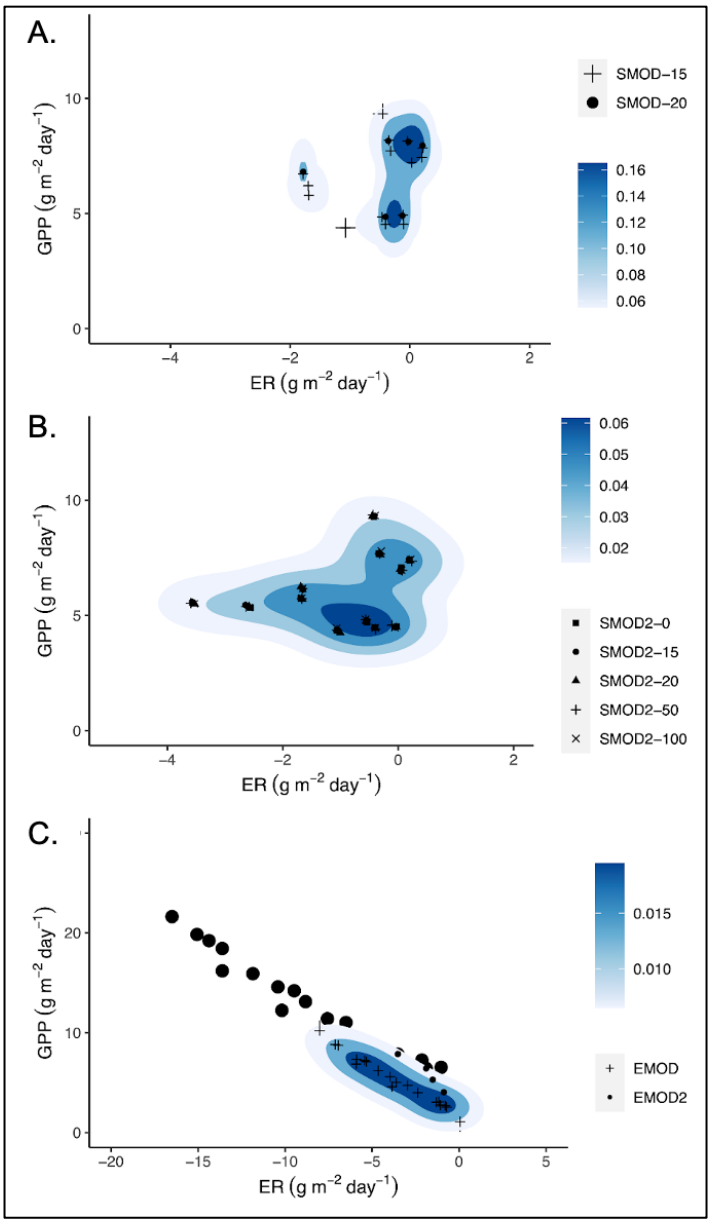

Figure 2.6: Kernel Density Estimates Representative of Wide Streams (CB20). KDE showing the *relative*, *non-parametric* probabilities of a random sample of GPP and ER values based on previously gathered data of GPP and ER values observed throughout summer of 2019 in the Greiner Lake Watershed. Darkest blue values represent areas with greatest volumes beneath, i.e., 2 dimensional (x = ER and y= GPP being the dimensions) ranges of values where a random sample would be most likely to fall. Points represent actual values of GPP and ER observed throughout the study period, with the various shapes representing different version, whereas the colour gradient shows the probability of where a new a new observation may fall. A. SMOD15 and SMOD20 uses dates with at least 12 timesteps of darkness (PAR=0) throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. B. uses SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 which also uses streamMetabolizer but increases the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 $\mu mols^{-1}$ are all set to 0. C. EMOD uses empirical methods, combing mass balance equations, ER regression and ER interpolation parried with coefficients

proposed by Raymond et al., 2012 to calculate reaeration values based on discharge, velocity, width, depth and slope of stream channels. EMOD uses total average values of the reaeration values calculated at the beginning and end of the study EMOD (7.3 K_{600}) and end of the study EMOD-2 (23.3 K_{600}).

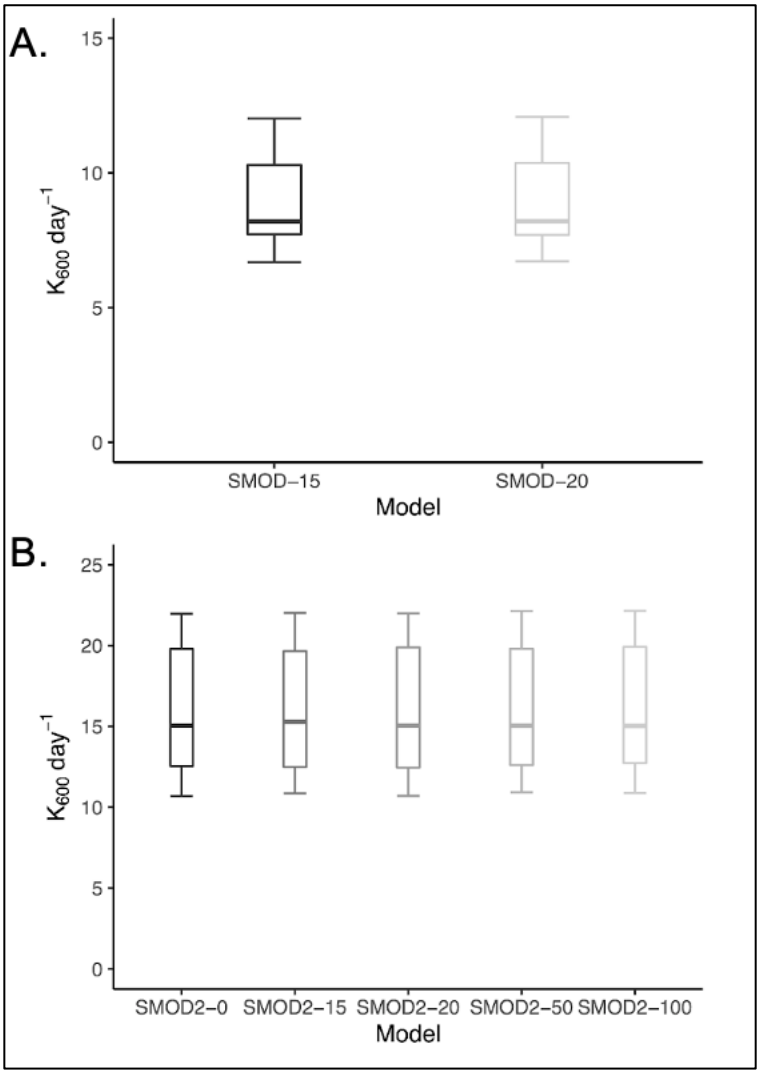

Figure 2.7: Boxplots Demonstrating Reaerations Values of a Wide Stream (CB20). Boxplot where the top line represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, and the bottom line represents the smallest value within 1.5x below the 25TH percentile. SMOD15 and SMOD20 (A.) used dates with at least 12 timesteps of darkness (Photosynthetically active radiation (PAR)) = 0 throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 (B.) also used streamMetabolizer but increased the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 $\mu mols^{-1}$ are all set to 0.

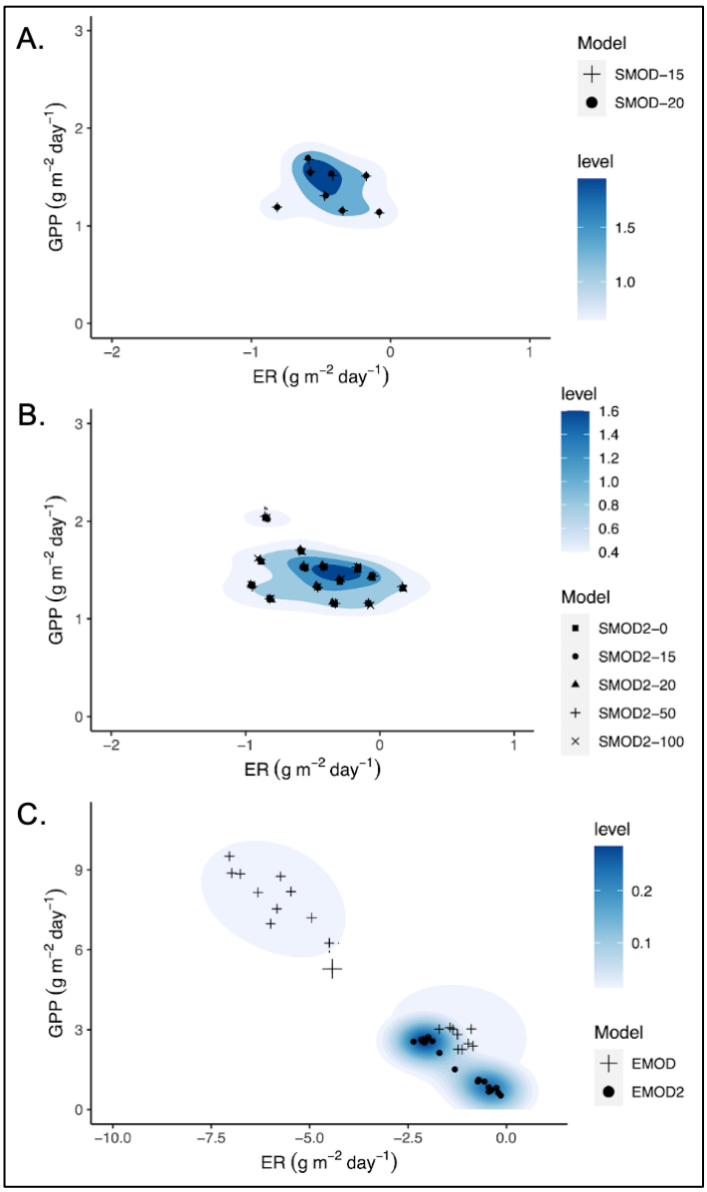

Figure 2.8: Kernel Density Estimates Representative of a Very Wide Stream (CB27). KDE showing the*relative*, *non-parametric* probabilities of a random sample of GPP and ER values based on previously gathered data of GPP and ER values observed throughout summer of 2019 in the Greiner Lake Watershed. Darkest blue values represent areas with greatest volumes beneath, i.e., 2 dimensional (x = ER and y= GPP being the dimensions) ranges of values where a random sample would be most likely to fall. Points represent actual values of GPP and ER observed throughout the study period, with the various shapes representing different version, whereas the colour gradient shows the probability of where a new a new observation may fall. SMOD15 and SMOD20 (A.) used dates with at least 12 timesteps of darkness (PAR=0) throughout the night, and all values <15 and <20 μmols^{-1} are changed to 0 respectively. SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 (B.) also used streamMetabolizer but increases the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 μmols^{-1} are all set to 0. C. EMOD uses empirical methods, combing mass balance equations, ER regression and ER interpolation parried with coefficients proposed by Raymond et al., 2012 to calculate reaeration values based on discharge, velocity, width, depth and slope of stream channels. EMOD uses total average values of the reaeration values calculated at the beginning and end of the study EMOD (17 K_{600}) and end of the study EMOD-2 (5.5 K_{600}).

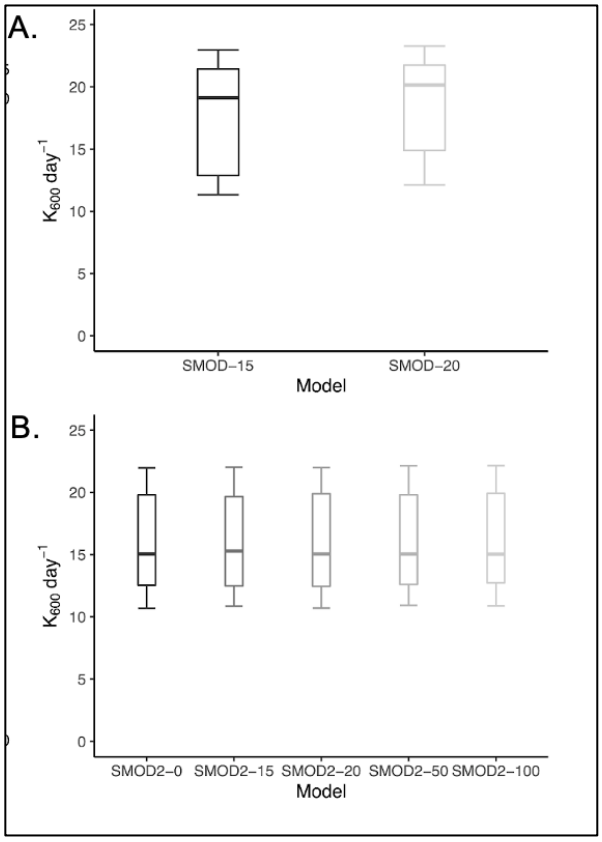

Figure 2.9: Boxplots Demonstrating Reaerations Values of a Very Wide Stream (CB27). Boxplot with the top line represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, and the bottom line represents the smallest value within 1.5x below the 25TH percentile. SMOD15 and SMOD20 used dates with at least 12 timesteps of darkness (Photosynthetically active radiation (PAR)) = 0 throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 also used streamMetabolizer but increased the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 $\mu mols^{-1}$ are all set to 0.

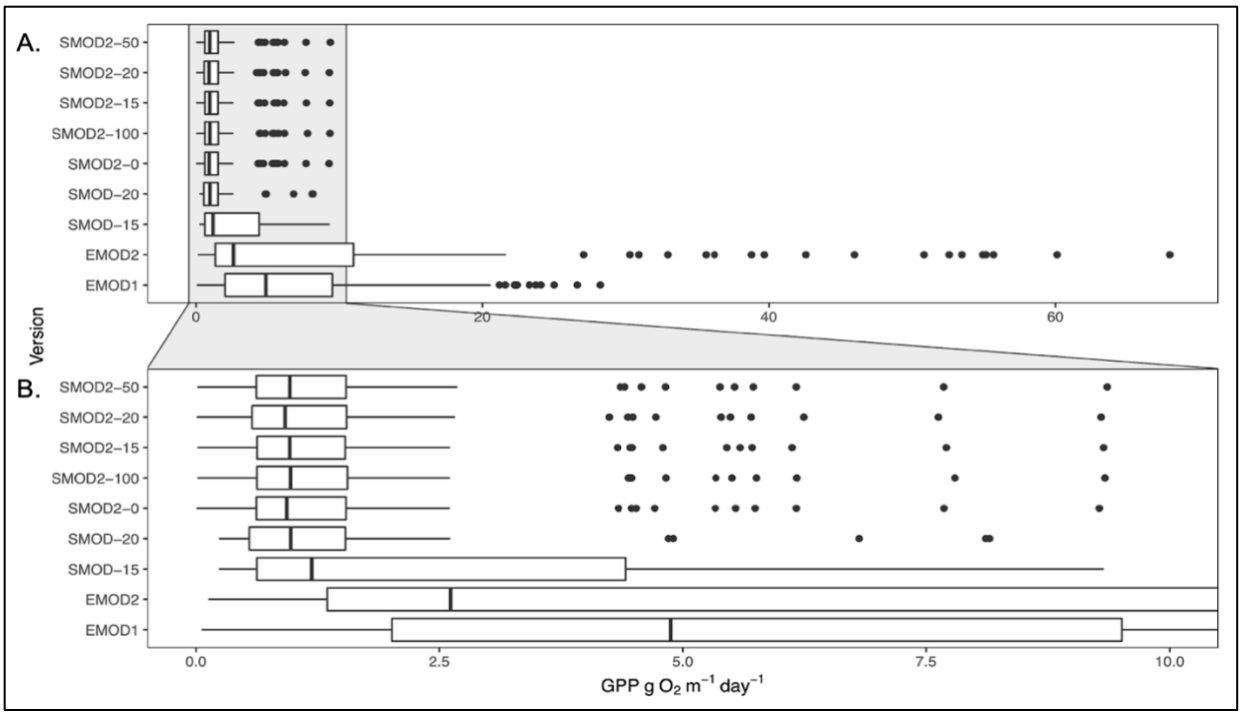

Figure 2.10: Boxplots Representing Combined GPP Data. Boxplots represent all 16 sites across the study period in order to demonstrate the changes to values when using different versions of the model. The line to the left represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, the line to the right represents the smallest value within 1.5x below the 25TH percentile and the dots are values that or greater than or less than the 1.5x IQR value. SMOD15 and SMOD20 used dates with at least 12 timesteps of darkness (Photosynthetically active radiation (PAR)) = 0 throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 also used streamMetabolizer but increased the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 $\mu mols^{-1}$ are all set to 0. EMOD used empirical methods, combing mass balance equations, ER regression and ER interpolation paired with coefficients proposed by Raymond et al., 2012 to calculate reaeration values based on discharge, velocity, width, depth and slope of stream channels. EMOD uses total average values of the reaeration values calculated at the beginning and end of the study EMOD and end of the study EMOD-2. The figure was divided into 2 parts in order to accentuate differences between streamMetabolizer models, as EMOD models had higher values making distinctions difficult to observe when the full scale was observed. A. shows the total scale of values observed throughout the study, and B. shows a range with increased focus on the range of the different version of the streamMetabolizer model.

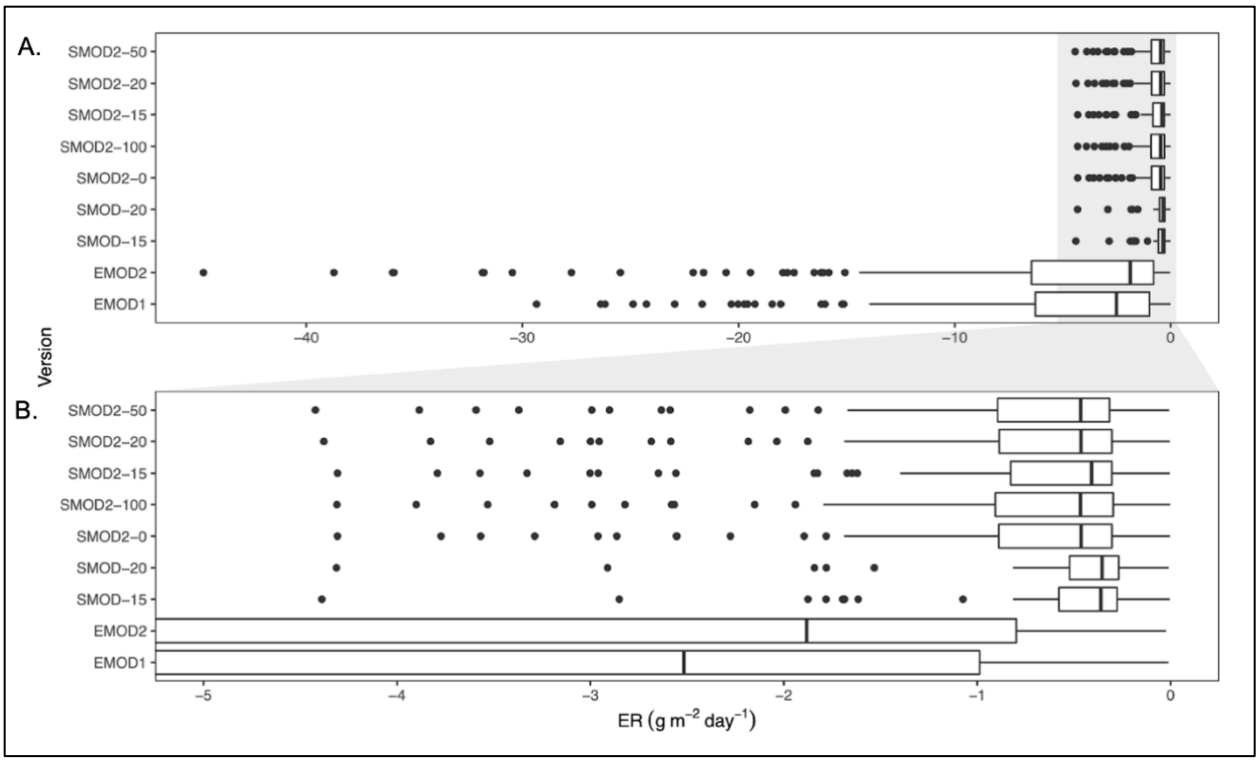

Figure 2.11: Boxplots Representing Combined ER Data. Boxplots representing combined ER across all 16 sites across the study period in order to demonstrate the changes to values when using different versions of the model. The line to the left represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, the line to the right represents the smallest value within 1.5x below the 25TH percentile and the dots are values that or greater than or less than the 1.5x IQR value. SMOD15 and SMOD20 used dates with at least 12 timesteps of darkness (Photosynthetically active radiation (PAR)) = 0 throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 $\mu mols^{-1}$ also used streamMetabolizer but increased the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 $\mu mols^{-1}$ are all set to 0. EMOD used empirical methods, combing mass balance equations, ER regression and ER interpolation paired with coefficients proposed by Raymond et al., 2012 to calculate reaeration values based on discharge, velocity, width, depth and slope of stream channels. EMOD uses total average values of the reaeration values calculated at the beginning and end of the study EMOD and end of the study EMOD-2. The figure was divided into 2 parts in order to accentuate differences between streamMetabolizer models, as EMOD models had higher values making distinctions difficult to observe when the full scale was observed. A. shows the total scale of values observed throughout the study, and B. shows a range with increased focus on the range of the different version of the streamMetabolizer model.

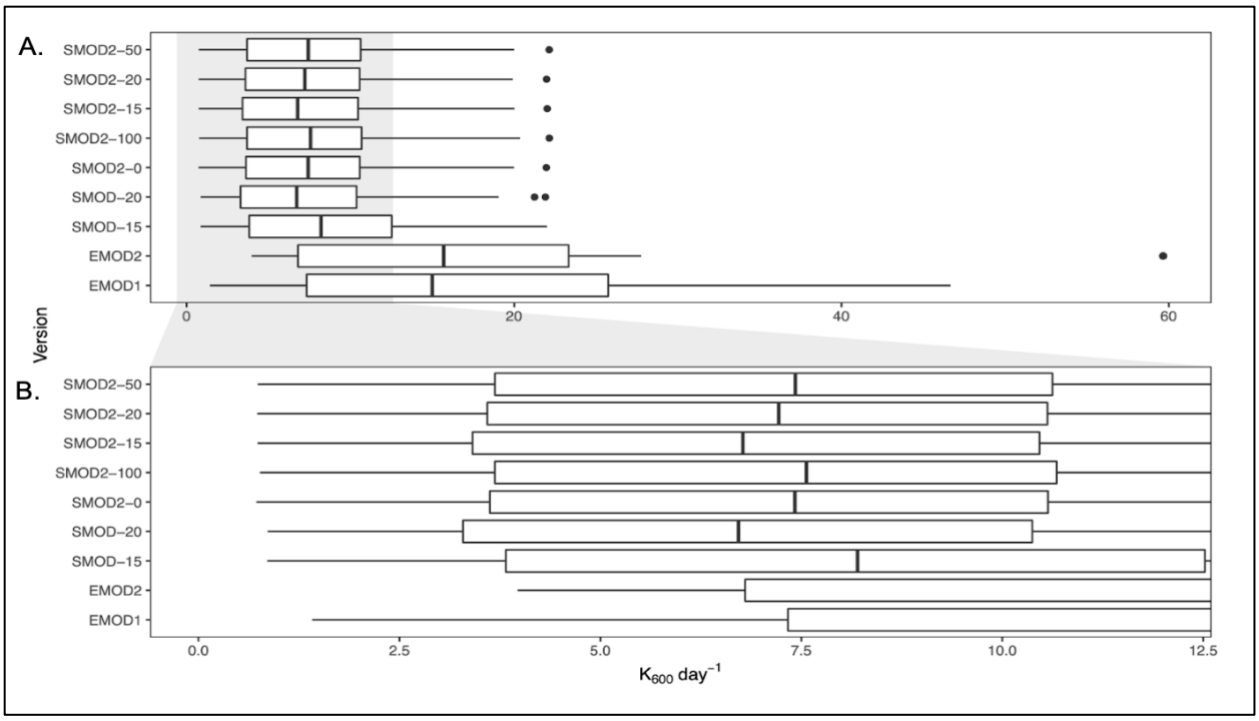

Figure 2.12: Boxplots Representing Combined K_{600} Data. Boxplots representing combined GPP across all 16 sites across the study period in order to demonstrate the changes to values when using different versions of the model. The line to the left represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, the line to the right represents the smallest value within 1.5x below the 25TH percentile and the dots are values that or greater than or less than the 1.5x IQR value. SMOD15 and SMOD20 used dates with at least 12 timesteps of darkness (Photosynthetically active radiation (PAR)) = 0 $\mu mols^{-1}$ throughout the night, and all values <15 and <20 $\mu mols^{-1}$ are changed to 0 respectively. SMOD2-0, SMOD2-15, SMOD2-20, SMOD2-50 and SMOD2-100 also used streamMetabolizer but increased the number of days used by including dates with at least 1 period of darkness, i.e., 1 time step of PAR=0, and values >15, >20, >50, >100 $\mu mols^{-1}$ are all set to 0. EMOD used empirical methods, combing mass balance equations, ER regression and ER interpolation paired with coefficients proposed by Raymond et al., 2012 to calculate reaeration values based on discharge, velocity, width, depth and slope of stream channels. EMOD uses total average values of the reaeration values calculated at the beginning and end of the study EMOD and end of the study EMOD-2. The figure was divided into 2 parts to accentuate differences between streamMetabolizer models, as EMOD models had higher values making distinctions difficult to observe when the full scale was observed. A. shows the total scale of values observed throughout the study, and B. shows a range with increased focus on the range of the different version of the streamMetabolizer model.

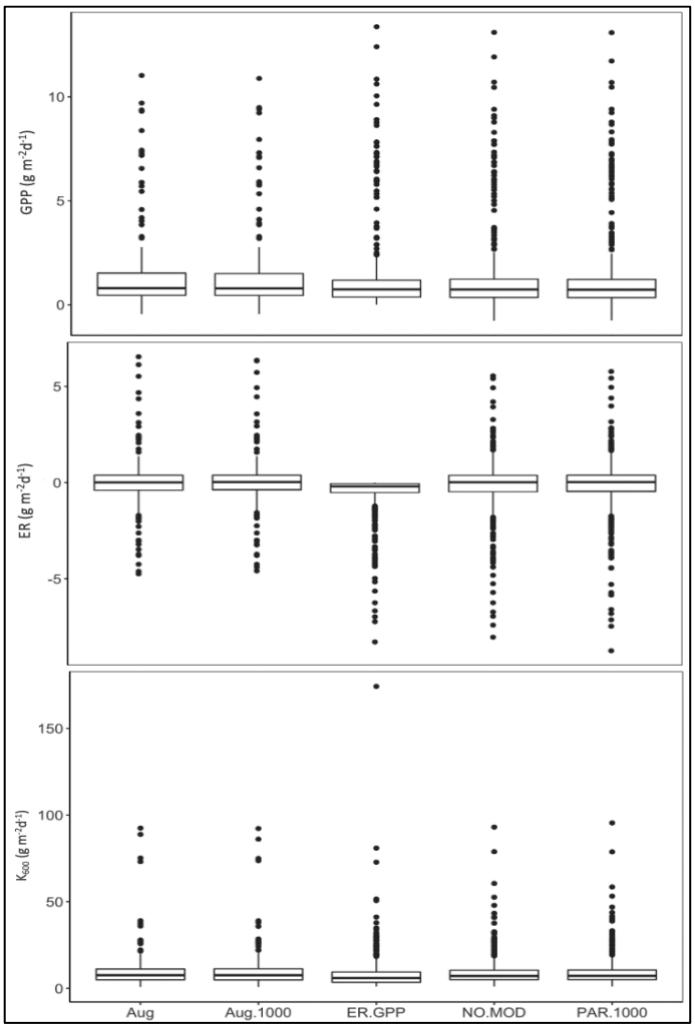

Figure 2.13: Boxplots Representing the Second Part of Changes Made to the streamMetabolizer Input Variations Including AUG, AUG.1000, ER.GPP, NO.MOD and PAR.1000a and the range of GPP, ER and K600 values. The top line represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, the bottom line represents the smallest value within 1.5x below the 25TH percentile and the dots are values that or greater than or less than the 1.5x IQR value. The first data set used was unchanged in any way (UNMOD). Next, the entire data set was used, and any PAR<1000 μmols^{-1} was set to 0 μmols^{-1} (PAR 1000). Moreover, only data from August was used, and PAR levels remained unaltered (AUG). Next, only data from August was used, and all values less than 1000 μmols^{-1} were set to 0 μmols^{-1}. Lastly, the final modification included the entire data set, unchanged, however, an altered version of streamMetabolizer was employed where it was set so that ER could not be greater than 0 gm^{-2}d^{-1}, and GPP could not be less than 0 gm^{-2}d^{-1} (ER.GPP)**.**

2.8 CHAPTER 2 TABLES

Table 2.1: Model Diagnostics of AUG. Model diagnostics were used to determine the effectiveness of the Bayesian models to measure AUG stream metabolism values via the streamMetabolizer package in R, across all 16 sites, including all observations made in the month of August. Model diagnostics included observing MCMC values when process error and observation error. Observation errors are caused by errors in the actual measurement of daily [O_2] values, whereas process errors represent mistakes in the modelling process. Values greater than > 1.1 show a lack of convergence between actual observations of stream metabolism and modelled values/estimates. Pearson correlation assessed the relationship of ER and K_{600} to ensure streamMetabolizer could distinguish the difference between ER and K_{600} when modelling GPP, ER and K_{600} values. High levels of correlation could show a lack of ability to distinguish between the two values.

Site	Width Depth Ratio	Start	End	Observation Error	Process Error	Correlation
CB04	Very Wide	19/06/07	19/13/08	1.82	1.02	r(11)=0.82, p =0.001
CB06	Very Wide	19/06/07	19/13/08	2.46	1.17	r(11)=0.72, p =0.006
CB05	Very Wide	19/06/07	19/13/08	1.03	1.02	r(11)=0.5, p =0.079
CB14	Wide	19/06/07	19/15/08	1.28	1.01	r(13)=-0.96, p =0.001
CB15	Wide	19/06/07	19/17/08	2.87	1.64	r(41)=-0.28, p =0.074
CB16	Wide	19/06/07	19/15/08	1.00	1.04	r(13)=-0.67, p =0.006
CB20	Wide	19/08/07	19/14/08	1.00	1.01	r(12)=0.06, p =0.839
CB21	Narrow	19/07/07	19/14/08	1.74	1.19	r(12)=-0.01, p =0.977
CB22	Narrow	19/07/07	19/14/08	1.91	1.08	r(12)=0.36, p =0.211
CB24	Narrow	19/07/07	19/17/08	1.90	1.12	r(15)=-0.53, p =0.028
CB26	Narrow	19/07/07	19/17/08	1.02	1.01	r(15)=0.34, p =0.184
CB27	Wide	19/07/07	19/16/08	3.61	1.13	r(14)=-0.09, p =0.743
CB29	Narrow	19/07/08	19/16/08	1.60	1.24	r(11)=-0.74, p =0.004
ER03	Narrow	19/06/07	19/13/08	1.28	1.14	r(11)=-0.74, p =0.004
ER04	Narrow	19/06/07	19/13/08	1.00	1.00	r(11)=-0.37, p=0.213

Table 2.2: Model Diagnostics of AUG.1000. Model diagnostics were used to determine the effectiveness of the Bayesian models to measure stream metabolism using the AUG.1000 version via the streamMetabolizer package in R, across all 16 sites, including all observations made in the month of August. However, all PAR (photosynthetically active radiation values) that were < 1000 were set to 0. Model diagnostics included observing MCMC values when process error and observation error. Observation errors are caused by errors in the actual measurement of daily [O_2] values, whereas process errors represent mistakes in the modelling process. Values greater than > 1.1 show a lack of convergence between actual observations of stream metabolism and modelled values/estimates. Pearson correlation assessed the relationship of ER and K_{600} in order to ensure streamMetabolizer could distinguish the difference between ER and K_{600} when modelling GPP, ER and K_{600} values. High levels of correlation could show a lack of ability to distinguish between the two values.

Site	Width Depth Ratio	Start	End	Observation Error	Process Error	Correlation
CB04	Very Wide	19/06/07	19/13/08	1.56	1.01	r(11)=0.83, p =0.000
CB06	Very Wide	19/06/07	19/13/08	1.51	1.14	r(11)=0.74, p =0.004
CB05	Very Wide	19/06/07	19/13/08	1.73	1.12	r(11)=0.5, p =0.079
CB14	Wide	19/06/07	19/15/08	1.66	1.00	r(13)=-0.96, p =0
CB15	Wide	19/06/07	19/17/08	1.87	1.24	r(41)=0.17, p =0.287
CB16	Wide	19/06/07	19/15/08	1.00	1.00	r(13)=-0.66, p =0.008
CB20	Wide	19/08/07	19/14/08	1.03	1.04	r(12)=0.09, p =0.751
CB21	Narrow	19/07/07	19/14/08	2.82	1.36	r(12)=-0.02, p =0.956
CB22	Narrow	19/07/07	19/14/08	1.30	1.05	r(12)=0.36, p =0.211
CB24	Narrow	19/07/07	19/17/08	1.52	1.09	r(15)=-0.53, p =0.028
CB26	Narrow	19/07/07	19/17/08	1.01	1.00	r(15)=0.35, p =0.165
CB27	Wide	19/07/07	19/16/08	2.31	1.02	r(14)=-0.06, p =0.826
CB29	Narrow	19/07/08	19/16/08	1.64	1.23	r(11)=-0.58, p =0.039
ER03	Narrow	19/06/07	19/13/08	1.32	1.16	r(11)=-0.58, p =0.039
ER04	Narrow	19/06/07	19/13/08	1.01	1.01	r(11)=-0.37, p=0.214

Table 2.3: Model Diagnostics of ER.GPP. Model diagnostics were used to determine the effectiveness of the Bayesian models of ER.GPP to measure stream metabolism via the streamMetabolizer package in R, across all 16 sites, including all observations made in the month of August. However, an extra requirement was added to the original model used for determining stream metabolism using streamMetabolizer. The model was required to only produce "biologically possible" values, meaning GPP > 0, and ER < 0. Model diagnostics included observing MCMC values when process error and observation error. Observation errors are caused by errors in the actual measurement of daily $[O_2]$ values, whereas process errors represent mistakes in the modelling process. Values greater than > 1.1 show a lack of convergence between actual observations of stream metabolism and modelled values/estimates. Pearson correlation assessed the relationship of ER and K_{600} to ensure streamMetabolizer could distinguish the difference between ER and K_{600} when modelling GPP, ER and K_{600} values. High levels of correlation could show a lac of ability to distinguish between the two values.

Site	Width Depth Ratio	Start	End	Observation Error	Process Error	Correlation
CB04	Very Wide	19/06/07	19/13/08	1.03	1.00	r(37)=-0.30, p =0.064
CB06	Very Wide	19/06/07	19/13/08	3.17	1.08	r(37)=0.25, p =0.120
CB05	Very Wide	19/06/07	19/13/08	1.07	1.04	r(37)=0.19, p =0.254
CB14	Wide	19/06/07	19/15/08	2.73	1.01	r(38)=-0.77, p =0
CB15	Wide	19/06/07	19/17/08	1.01	1.00	r(15)=0.14, p =0.584
CB16	Wide	19/06/07	19/15/08	1.00	1.02	r(39)=-0.53, p =0
CB20	Wide	19/08/07	19/14/08	1.05	1.35	r(36)=-0.55, p =0
CB21	Narrow	19/07/07	19/14/08	2.25	1.10	r(37)=-0.68, p =0
CB22	Narrow	19/07/07	19/14/08	1.81	1.03	r(37)=0.04, p =0.828
CB24	Narrow	19/07/07	19/17/08	2.01	1.04	r(40)=-0.87, p =0
CB26	Narrow	19/07/07	19/17/08	1.00	1.01	r(40)=-0.69, p =0
CB27	Wide	19/07/07	19/16/08	1.03	1.02	r(38)=-0.63, p =0
CB29	Narrow	19/07/08	19/16/08	1.03	1.00	r(37)=-0.47, p =0.002
ER03	Narrow	19/06/07	19/13/08	2.32	1.42	r(37)=-0.47, p =0.002
ER04	Narrow	19/06/07	19/13/08	1.01	1.00	r(37)=-0.37, p=0.022

Table 2.4: Model Diagnostics of NO.MOD. Model diagnostics were used to determine the effectiveness of the Bayesian models of NO.MOD to measure stream metabolism via the streamMetabolizer package in R, across all 16 sites, including all observations made throughout the study. diagnostics included observing MCMC values when process error and observation error. Observation errors are caused by errors in the actual measurement of daily [O_2] values, whereas process errors represent mistakes in the modelling process. Values greater than > 1.1 show a lack of convergence between actual observations of stream metabolism and modelled values/estimates. Pearson correlation assessed the relationship of ER and K_{600} to ensure streamMetabolizer could distinguish the difference between ER and K_{600} when modelling GPP, ER and K_{600} values. High levels of correlation could show a lac of ability to distinguish between the two values.

Site	Width Depth Ratio	Start	End	Observation Error	Process Error	Correlation
CB04	Very Wide	19/06/07	19/13/08	1.01	1.01	r(37)=0.61, p =0
CB06	Very Wide	19/06/07	19/13/08	3.17	1.08	r(37)=0.47, p =0.002
CB05	Very Wide	19/06/07	19/13/08	1.02	1.01	r(37)=0.39, p =0.014
CB14	Wide	19/06/07	19/15/08	2.05	1.01	r(38)=-0.8, p =0
CB15	Wide	19/06/07	19/17/08	1.02	1.01	r(15)=0.18, p =0.494
CB16	Wide	19/06/07	19/15/08	1.01	1.09	r(39)=-0.53, p =0
CB20	Wide	19/08/07	19/14/08	1.02	1.32	r(36)=-0.47, p =0.003
CB21	Narrow	19/07/07	19/14/08	2.29	1.24	r(37)=0.22, p =0.172
CB22	Narrow	19/07/07	19/14/08	2.48	1.04	r(37)=0.19, p =0.237
CB24	Narrow	19/07/07	19/17/08	1.75	1.00	r(40)=-0.87, p =0
CB26	Narrow	19/07/07	19/17/08	1.00	1.01	r(40)=-0.6, p =0
CB27	Wide	19/07/07	19/16/08	1.03	1.02	r(38)=-0.28, p =0.077
CB29	Narrow	19/07/08	19/16/08	1.20	1.09	r(37)=-0.35, p =0.03
ER03	Narrow	19/06/07	19/13/08	1.87	1.35	r(37)=-0.35, p =0.03
ER04	Narrow	19/06/07	19/13/08	1.01	1.01	r(37)=-0.46, p=0.005

Table 2.5: Model Diagnostics of PAR.1000. Model diagnostics were used to determine the effectiveness of the Bayesian models to measure stream metabolism using the PAR.1000 version via the streamMetabolizer package in R, across all 16 sites, including all observations made throughout the study. However, all PAR (photosynthetically active radiation values) that were < 1000 were set to 0. Model diagnostics included observing MCMC values when process error and observation error. Observation errors are caused by errors in the actual measurement of daily [O_2] values, whereas process errors represent mistakes in the modelling process. Values greater than > 1.1 show a lack of convergence between actual observations of stream metabolism and modelled values/estimates. Pearson correlation assessed the relationship of ER and K_{600} to ensure streamMetabolizer could distinguish the difference between ER and K_{600} when modelling GPP, ER and K_{600} values. High levels of correlation could show a lack of ability to distinguish between the two values.

Site	Width Depth Ratio	Start	End	Observation Error	Process Error	Correlation
CB04	Very Wide	19/06/07	19/13/08	1.04	1.00	r(37)=0.61, p =0
CB06	Very Wide	19/06/07	19/13/08	1.51	1.14	r(37)=0.49, p =0.002
CB05	Very Wide	19/06/07	19/13/08	1.03	1.01	r(37)=0.4, p =0.012
CB14	Wide	19/06/07	19/15/08	1.88	1.00	r(38)=-0.82, p =0
CB15	Wide	19/06/07	19/17/08	1.04	1.01	r(41)=0.16, p =0.317
CB16	Wide	19/06/07	19/15/08	1.00	1.04	r(39)=-0.52, p =0
CB20	Wide	19/08/07	19/14/08	1.05	1.24	r(36)=-0.45, p =0.004
CB21	Narrow	19/07/07	19/14/08	2.00	1.17	r(37)=0.22, p =0.178
CB22	Narrow	19/07/07	19/14/08	2.15	1.02	r(37)=0.17, p =0.306
CB24	Narrow	19/07/07	19/17/08	2.07	1.02	r(40)=-0.87, p =0
CB26	Narrow	19/07/07	19/17/08	1.00	1.02	r(40)=-0.6, p =0
CB27	Wide	19/07/07	19/16/08	1.04	1.02	r(38)=-0.27, p =0.091
CB29	Narrow	19/07/08	19/16/08	1.28	1.12	-r(37)=0.33, p =0.038
ER03	Narrow	19/06/07	19/13/08	2.13	1.45	r(37)=-0.33, p =0.038
ER04	Narrow	19/06/07	19/13/08	1.01	1.01	r(37)=-0.44, p=0.005

Table 2.6: Percent Success of Each Model Based on Model Diagnostics. Results of model diagnostics including the successful values of observation and process errors determined by streamMetabolizer and the biologically possible values of GPP (≥ 0) and ER (≤ 0).

Method	**% Success of Observation Error (≥1.1)**	**% Success of Process Error (≥1.1)**	**% Success Correlation Values (r<0.6)**	**% Biologically Possible Days (GPP) (≥0)**	**% Biologically Possible Days (ER) (≤0)**
ER.GPP	56	81	63	100	100
AUG	31	44	56	42	50
AUG.1000	30	56	63	87	100
PAR.1000	50	63	80	95	49
NO.MOD	50	80	69	94	49

CHAPTER 3: ASSESSMENT OF ENVIRONMENTAL DRIVERS OF STREAM METABOLISM IN THE GREINER LAKE WATERSHED, NU

3.1 Introduction

Streams play an essential role in carbon cycling by transporting organic carbon across the landscape to the ocean and releasing carbon dioxide to the atmosphere (Lundin et al., 2016; Stackpoole et al., 2017). In Arctic tundra streams, there is a clear link between stream metabolism and CO_2 evasion, with stream metabolism being a key driver of the fate of inorganic and organic matter across the landscape (Rocher-Ros, 2019). Therefore, it is critical to understand associations between stream metabolism in Arctic streams and key environmental factors (e.g., hydrological regimes, land cover type, precipitation patterns). Although stream metabolism is an effective biomonitoring technique to study environmental changes (Bernot et al., 2010; Mulholland et al., 2001) , most of the research conducted on stream metabolism and its connections to the surrounding environment has focused on alpine and temperate environments (Staehr et al., 2012; Tank et al., 2010; Young, Matthaei & Townsend., 2008) where conditions, such as seasonality, are substantially different (Huryn, Benstead & Parker, 2014). Therefore, the goal of this study was to develop a baseline understanding of how Arctic tundra streams are affected by the current features of their environment.

Research on stream metabolism from well-studied eco-regions has uncovered a wide range of temporal patterns and environmental variables that can strongly influence GPP and ER. Land-use, vegetation, stream order, underlying geology, subcatchment size and climate (dos Reis Oliveira et al., 2019; Frey, Siegel & Smith, 2007; Mosher & Finlay, 2011; Pearce et al., 2020; Rodríguez-Castillo et al., 2019) can all play a role in affecting stream metabolism via nutrient cycling dynamics, hydrology, channel form (stream width and depth), substrate size and type,

light availability and temperature (Bott et al., 1985 ; Bowden et al., 1992; Fuss & Smock, 1996; Kurz et al., 2017; Mulholland et al., 2001). However, the primary environmental drivers of GPP and ER tend to differ in most eco-regions; GPP being most affected by light availability, nutrient availability, and a stable habitat for autotrophs to flourish (Hill, Ryon & Schilling, 1995; Mulholland et al., 2001), whereas ER is driven by organic matter availability and temperature (Bott et al. 1985; Hill et al. 2000). In contrast, stream metabolism in Arctic ecosystems is poorly understood, and little is known about how GPP and ER are affected by unique the environmental features of the Arctic. Key factors that separate the Arctic from more thoroughly researched biomes (e.g., temperate) include constant summer daylight (for early summer, PAR ≥ 0 at all times through a 24-hr period), low nutrient levels and differences in landscape and substrate composition (Prowse et al., 2006b). The unique environment and remoteness of many locations creates difficulty in measuring and calculating stream metabolism, as most methods require periods of complete darkness to estimate ER (Grace & Imberger et al., 2006). However, advances in how to measure metabolism offer an alternative to traditional methods. The streamMetabolizer package allows GPP to be scaled linearly with light and K600 to be determined without prior measurements, thereby requiring minimal work to be conducted in remote areas (Appling et al., 2018b). This method allows scientists to further research the key associations between environmental factors and GPP or ER in Arctic stream ecosystems that are required to monitor changes to Arctic ecosystems.

To better understand the relationship among environmental variables and the metabolism of Arctic streams, the objectives of this study are to: 1) develop a baseline understanding of spatial and temporal variation in stream metabolism, and 2) investigate the environmental drivers

of stream metabolism in the Arctic streams of the Greiner Lake Watershed during the summer months, the time when Arctic streams are generally most productive.

The Greiner Lake Watershed is an ideal location to investigate variation in stream metabolism and environmental drivers associated with these patterns as multiple sub-watersheds are available for study within a localized area. Furthermore, the Greiner Lake Watershed is a focal study area for the Canadian High Arctic Research Station (CHARS) where additional information about the watershed is available for an investigation of the importance of environmental drivers for stream metabolism.

These objectives were investigated across 16 streams during the summer of 2019 by continuously measuring dissolved oxygen, photosynthetically active radiation (PAR) and water depth. Continuous data collection is necessary to estimate stream metabolism via streamMetabolizer (Appling et al., 2018b) and for calculation of daily average GPP and ER. I predicted that daily average GPP and ER would not vary significantly over time as the observation times were relatively short in comparison to other studies on Arctic streams that witnessed minimal changes (Myrstener et al., 2021). Furthermore, I do not expect many differences in ER and GPP across spatially across the watershed as the Greiner Lake Watershed has relatively uniform geomorphic features (NASA et al., 2015) and Arctic biomes in general have low biodiversity due to the harshness of the climate (Roxburgh & Noble, 2001). Lastly, I predicted that streams in the watershed would be limited by nutrient levels more than any other factor, as has been observed for many other Arctic freshwater streams (Myrstener et al., 2021).

3.2 Methods

3.2.1 Environmental Variables

Study reaches were approximately 50 – 100m and were selected in attempt to be representative of all stream types within the Greiner Lake Watershed. Nutrients were collected in grab samples during the deployment and retrieval at each site of water monitoring equipment. Water chemistry analysis was completed at the Burlington-National Lab for Environmental Testing (NLET), where water was tested for nutrients including DOC (mg L^{-1}), DOIC (mg L^{-1}), TN (mg L^{-1}) and TDP (mg L^{-1}). All methods followed those described in the 2020-21 NLET methods Descriptions Manual V1.0 (Environment and Climate Change Canada, 2018). DOC and DIC were measured using method 1021, which was fully automated and used a UV-persulfate TOC Analyzer (Shimadzu TOC-Vwp), which had an analytical range for organic carbon up to 15 mg L^{-1} and concentrations of inorganic carbon up to 30 mg L^{-1}. TN was determined using method 1151, using the Alkaline Persulfate Oxidation, Automated Flow Injection Analyzer (FIA), Hydrazine Reduction, Azo Dye Photometric Method, and reported TN concentrations up to 1.50 N mg L^{-1}. TP and TDP were determined using method 1191, using the Unfiltered, Acidic Persulphate Oxidation, CFA, Ascorbic Acid, Molybdenum Blue, Colorimetric Method, which had an analytic range up to 0.5 P mg L^{-1} (Environment and Climate Change Canada, 2018).

Temperature (°C) and light μmols^{-1} were measured continuously throughout the study. Temperature was determined as the average measured using deployed monitoring equipment (see *2.2.2 Data Collection*). Channel form was determined using cross-section measurements of width and depth taken at each site. At each site, depending on the size of the site, 3-5 transects were taken. Wetted width (m) was measured across the stream, and depth (cm) measurements were taken every 2-3 metres, with a maximum of 10 measurements. However, depth measurements were taken more than every 2-3 m at sites with greater wetted widths. The average

wetted width and depth from all transects at the sites will be used. Substrate size was determined using the Wolman pebble count method, combined with the zig zag method. The pebble count method involved measuring the b' axis of 100 randomly chosen pebbles from the substrate of the stream, moving in a zigzag pattern upstream (Bevenger, 1995; Wolman, 1954). Substrate particle size was represented by D50, which was determined by finding the median of all pebbles recorded using the Wolman pebble count. Gradient (slope) was measured at each site using a Nikon Forestry Pro., digital clinometer units **(Table 3.1 – 3.3)**

Upstream water bodies were characterized relative to each site using geospatial techniques implement via ArcGIS (10.8.2, 2020) and included the total area of the subcatchment (Ha), the total amount of area in the subcatchment covered in any type of surface water (Ha), distance to the nearest up stream lake (km), area of the nearest upstream lake (Ha), depth class of the nearest upstream lake (rated 1 – 4), and the number of ponds upstream of the site **(Table 3.1)**. Following the 4 land categories depicted in tundra ecosystem maps produced by Ponomarenko et al., 2019, the composition of the subcatchment was defined by the percent vegetative coverage (land including Productive Mesic - Subhygric Communities, Turfy Mountain Avens, Lythic Mountain Avens and Shrubs), wetland coverage (land including seasonal ponds, Hygric Sedge Fen, sedge Fen, Riparian Moss, Productive sedge fen and Subhygric communities) bare soil coverage (including sparsely vegetated areas, unvegetated areas and beaches) and/or surface water (water bodies between 1 to greater than 4 metres deep). The sub watershed was defined as all the land area above the site (i.e., all land area draining to that site is considered a subcatchment) **(Table 3.4).**

3.2.2 Site and Temporal Differences

To determine the differences in stream metabolism across the watershed, a One-way ANOVA was used where the stream was the factor, and daily measurements of GPP, ER were the replicates within the stream. To account for daily differences, a block was added to the one-way ANOVA. Furthermore, a Tukey test was then conducted to determine which sites differed significantly. To determine if there were any patterns in GPP and ER across time in the watershed, the study time was divided into 4 separate periods consisting of 8 days. The total daily average of GPP and ER for each of the 8-day periods was calculated and used for comparison. Each subsection included 8 days. Week 1 represents July 9 -August 17th, week two represents July 18 – 26, week 3 represents July 27th – August 4th and week 3 represents August 5th – August 13th. The average daily GPP, and the average ER, were taken for each week, and displayed graphically.

3.2.3. Environmental Drivers of GPP and ER

To assess the environmental drivers of stream GPP and ER, a partial least square regression analysis (PLSR) was used in the statistical software XLSTAT which performs many of the standard tests used for interpreting a PLSR. PLSR is an effective technique to reduce multidimensionality where 1) there is likely a high amount of covariance between predictor variables and 2) the amount of predictor variables is high relative to the response variables (Abdi, 2010). In this study, a PLSR was chosen due to the ratio of predictor variables to response variables (Carrascal et al. 2009). The goal of a PLSR is similar to a PCA, however, a PLSR searches for components called latent vectors, that perform a simultaneous analysis of X and Y with the constraint that the components explain as much as possible of the covariance between X and Y (Abdi, 2010).

First, using leave-one-out for (LOO) cross validation and 4 fixed components, using a confidence of 90%. XLSTAT helps to assess the important environmental drivers by reporting model quality indices Q2 (cum), R2 Y(cum) and R2 X(cum) parameters, which help indicate the most stable models, as a function of the number of components. The most stable models have values close to 1 and Q2 (cum), R2 Y(cum) are within 20% of each other (Eriksson et al., 1995). Furthermore, XLSTAT shows the VIPs (Variable Importance for the Projection) for each explanatory variable. VIP variables explain which variables contribute the most to the models, with values greater than 1 being considered the most important. A model goodness of fit is then reported via R^2 and SD values. Lastly, XLSTAT performs a test for potential outliers, which can be identified via dModx and DModY values over their critical values (DCritX and DCritY). These values represent how the predicted X and Y values deviate from the model (AddinSoft, 2017). Then, using only sites with a significant VIP value, a Pearson correlation analysis was run in R using log transformed values of GPP and ER.

Next, average daily GPP and ER (log transformed), were divided into 4 subsections to include the most recent measurements of stream characteristics for the respective GPP and ER values. The analyses included July GPP, July ER, August GPP and August ER. The dependent variables consist of two different data sets: measurements taken at the beginning and end of the study period (Water Quality and Channel Form), and measurements only taken once (Subwatershed Characteristics and Waterbodies). July uses observations of water quality and channel form taken at the beginning of the study period (between July 5^{th} – 7^{th}) and August uses the observations from the end of the study period (August 14^{th} – 19^{th}) with the date depending on the site **(Figure 3.1)**. These data were combined with the single observations of subwatershed

characteristics and waterbodies to use in PSLR to assess environmental drivers of the dependent variables (GPP and ER).

3.3 Results

3.3.1 Differences between sites

Average GPP and ER daily values observed during the study period showed little noticeable variation and remained relatively low **(Figure 3.2).** Total daily average GPP between all sites was 1.203 gO_2m^3 (SD=1.770) and had a range of 0.010 to 13.371 gO_2m^3. Most sites have a higher daily GPP value than their respective ER value, except for CB24 and CB14. A one-way ANOVA showed a significant difference in average GPP ($F_{14,525}$=213.8, $p<0.001$). A TukeyHSD demonstrated that sites with the highest GPP values, CB20 and CB14, were significantly different from each-other and all other sites ($p<0.05$).

The total average daily ER for all sites across the study period had a mean value of -0.580 gO_2m^3 (SD=1.040), with a range of -8.230 to -0.090 gO_2m^3. Furthermore, daily average ER estimates throughout the study period were significantly different ($F_{14,525}$)=55.99, $p\leq0.001$. A Tukey HSD demonstrated that the significantly different sites were limited primarily to sites with lower daily averages of ER, including CB14 and CB20, which were significantly different from all other sites including each other ($p<0.05$). Sites generally had similar and low magnitude averages, generally falling below -2 gO_2m^3, many of which were not significantly different. CB24 was an exception, as it greater than -2 gO_2m^3, but still was significantly different ($p<0.05$) from some of the lower magnitude sites including CB04, CB06, CB15, CB29 and CB05. CB16 was also an exception, as it was significantly different ($p<0.05$) than CB04, CB06 and CB15.

3.3.2 Temporal Differences

Average GPP across the study period showed mixed results for site differences among weeks 1, 2, 3 and 4, with most sites only reaching a value of ~2.5 gO_2m^3, and without a clear increase or decrease in values. CB20 was the only exception to this rule, as it reached values of ~13 gO_2m^2 **(Figure 3.3)**. A two-way ANOVA was performed to compare the main effects of week period and site, and their interaction, on daily average GPP. The site and time interaction for GPP was significant ($F_{42,480}$=2.436, $p \leq 0.001$).

ER rates generally decreased for almost all sites across weeks 1, 2, 3 and 4, with most sites reaching negligible daily averages (0 gO_2m^3) by week 4. For example, sites CB20 and site CB14 which had the highest ER rates of all the sites in the study, decreased from a maximum average daily value of ~-7.5 gO_2m^3 to -3gO_2m^3 per day, and ~-6 gO_2m^3 to -2.5 gO_2m^3 respectively, however, most sites did not reach rates less than ~-2.5 gO_2m^3 at any point **(Figure 3.3).** A two-way ANOVA was performed to compare the main effects of week and site, and their interaction, on daily average ER. The time period and site interaction was significant ($F_{42,480}$=4.424).

3.3.3 Environmental drivers of stream metabolism

3.3.3.1 August GPP

The initial PLSR was of poor model quality as Q^2(cum) was not within 20% of R^2Y(cum). Four outlier sites with high values of dModX and dModY were identified (CB16, CB20, CB26 and CB29), indicating that these sites were not accurately represented by the model. A subsequent PLSR of GPP that excluded these sites resulted in the fourth component with a R^2Y(cum) within 20% of Q^2(cum). Model quality indices showed Q^2(cum), R^2Y(cum), and R^2X(cum) parameters of 0.889, 0.995, and 0.755, **(Figure 3.4.a)** Based on the Q^2 quality index, the quality of components assessed through leave one out (LOO) showed that the fourth

component (Q^2 =0.646) was significant (Q^2 limit > 0.097, corresponding to $p < 0.05$). Furthermore, GPP was accurately predicted by the model (R^2 =0.995, SD = 0.034). The VIPs (Variable Importance for the Projection) for the fourth component demonstrated that D_{50}, Area of the watershed, surface water in the watershed, percent vegetation in the watershed, stream width and TDP were all significant (greater than 1) (**Figure 3.5.d, Table 3.5.)**. Lastly, a Pearson correlation analysis was run for all the variables that were VIPS and average daily GPP across all sites and the only significant relationship was D_{50} ($r(13)=.68$, $p<0.01$)), which had a strong, positive correlation.

3.3.3.2 August ER

The first PLSR was of poor model quality as Q^2(cum) was not within 20% of R^2Y(cum). Sites CB 14 and CB 29 were identified as outliers. A subsequent PLSR of ER with outlier excluded showed that the third and fourth components were interpretable. Model quality indices for the third component were Q^2(cum), R^2Y(cum), and R^2X(cum) parameters of, 0.889, 0.992, and 0.601 **(Figure 3.4.b)**. Based on the Q^2 quality index, the quality of components assessed through leave one out (LOO) showed that component 3 (Q^2 =0.819) was significant (Q^2 limit > 0.097, corresponding to $p < 0.05$). Furthermore, GPP was accurately predicted by the model (R^2 =0.997, SD =0.037). The VIPs for the third component showed that area of the nearest upstream lake, depth class of nearest upstream lake, width of the stream, percent of bare land in the subcatchment, DOC were all significant (greater than 1) **(Figure 3.6.c, Table 3.6)**. Lastly, a Pearson correlation analysis was run for all the VIPs. This allowed for further confirmation of the significance of these variables with the addition of outliers that were removed in the PLSR. It was found that log average ER had a strong, negative relationship between the area of the upstream lake ($r(13)=-0.68$, $p\leq.01$) and stream width ($r(13)=-0.62$, $p=0.042$) and a positive

relationship with percent bare area in the subcatchment (r(13)=0.53, p=0.042). For ER data, negative data was converted to positive by multiplying all values by negative one, to be able to log transform the data. Therefore, there was a strong positive correlation between the area of upstream lakes, and stream width, with ER.

3.3.3.3 July GPP and ER

The PLSR analyses of July GPP and ER were not interpretable as the Q^2(cum) was not within 20% of R^2Y(cum) **(Figure 3.4.c-d.)** despite the removal of outliers (CB16, CB27, CB29 for GPP and CB14, CB22 for ER). Therefore, further analysis of the results was not warranted.

3.4 Discussion

Stream metabolism within the Greiner Lake Watershed was remarkably similar in space and time at most sites during July and August, 2019 with GPP below 2.5 and ER above -2.5 $gO_2m^2d^{-1}$. In August the environmental drivers of GPP were correlated with the substrate variable (D_{50}), while ER was positively correlated with the area of the upstream lake and stream width. Streams in the Greiner Lake Watershed were associated more with D_{50} and the amount of upstream lake area in the watershed than seen in other Arctic or temperate streams where nutrient levels, light availability and temperature constrain stream productivity (Myrstener et al., 2021; Rocher-Ros et al., 2019). While low variation in GPP and ER over space and time has been observed elsewhere in Arctic stream ecosystems (Myrstener et al., 2021), the relationships with D_{50} as an important driver of GPP, and the area of upstream lakes for ER, were previously unknown. Such relationships between downstream stream reaches and upstream lakes have been observed for temperate streams where lake outflow is thought to create transitory environments downstream that have both different nutrient concentrations (Schmadel et al., 2018) and species

composition (Crump et al., 2007) compared with other stream reaches. Similarly, a connection between D_{50} and productivity has been noted in temperate systems as D50 provides greater surface area for attached biofilms (Cardinale et al., 2002; Tett et al., 1978).

3.4.1 Spatial and Temporal Trends in GPP and ER

Mean GPP at 80% of streams in the Greiner Lake Watershed was below 2.5 $gO_2m^2d^{-1}$ (excluding CB20 which was an outlier), and are comparable but somewhat higher than values measured in other Arctic tundra streams at similar latitudes and biomes, such as the Miellajokka catchment, Sweden (GPP 0.57 $g\ O_2\ m^{-2}\ d^{-1}$), and the Kapuruk and the Toolik rivers, Alaska ($0.456 \pm 0.2531\ g\ O_2\ m^{-2}\ d^{-1}$ and $0.09 \pm 0.2531\ gO_2m^2d^{-1}$, respectively) (Myrstener et al., 2021; Rocher-Ros et al., 2019). Potential factors that may lead to these differences across the circumpolar Arctic include temperature, lake area in the watershed and watershed topography. First, the temperature regimes of streams in the Greiner Lake Watershed were much warmer than that of the Miellajokka Catchment, with Greiner Lake watershed's temperatures ranging between 10 – 12 °C and the Miellajokka system ranging between 5.4 – 6.9°C. However, the Kaparuk's watershed had temperatures more comparable to Greiner Lake, as they were greater than 5 °C between July 7th and August 2nd and consistently had values between 10 and 11°C. Another potential factor is the spatial distribution of lakes and ponds, as lakes and pond abundance can substantially change organic matter cycling downstream (Larson et al., 2007; Wang et al., 2018). The Greiner Lake watershed consists of numerous lakes and ponds, with most streams having a lake within 1 km as well as many other streams have ponds interconnected among lakes and streams (NASA, 2015). In contrast, the Miellajokka Catchment only has 2 lakes within its boundary with these lakes well upstream of the same site and more than 1 km from the stream

channel. However, it should be noted these streams are fed by glaciers and snowpack, which may cause discrepancies in metabolic rates between streams (Holdar et al., 1959). Finally, small topographic changes across the tundra landscape can affect the biochemistry of a stream, and there are more significant elevation changes in the Miellajokka catchment that could be causing variation between average daily average GPP (Larson et al., 2007). Although total yearly average GPP is much higher in temperate streams given the limited Arctic open water period and growing season, summer values in Arctic streams as those in the Greiner watershed and the above examples for Alaska and Sweden are quite comparable to temperate streams. For instance, in a study on Walker Branch, Tennessee, a first order stream in a deciduous forest, daily rates of GPP fell below 1 g O_2 m^{-2} d^{-1} between July and August, when in the spring before leaf growth, rates were above ~6 - 11 g O_2 m^{-2} d^{-1} (Roberts, Mulholland, & 2007). However, it would be incorrect to conclude that Arctic streams have similar productivity rates to temperate streams, as their growing seasons are generally limited compared to other biomes. Although productivity is controlled by a stream's reach scale variables (vegetation, nutrients/or hydrology), a stream will also be affected by temporal variables such as nutrient synchrony, canopy cover, light availability, temperature and/or precipitation, and these temporal variables will be different across different biomes and latitudes (Mulholland et al., 2001). Therefore, comparing just summer GPP and ER in streams of the Greiner Lake Watershed to temperate streams is insufficient to draw conclusions about how productive the respective systems as a whole.

Daily mean value of ER was -0.27± 0.37 $gO_2m^2d^{-1}$ with a range of -0.089 - 4.0924 $gO_2m^2d^{-1}$, excluding the outlier sites CB14 and CB20. These estimates are lower than in other tundra catchments such as in the Miellajokka (mean of -4.22 $gO_2m^2d^{-1}$), Toolik River (-2.40±0.176 O_2 m^{-2} d^{-1}), and Kapuruk River, (-8.42±1.63) (Rocher-Ros., 2021). As proposed for GPP, these

difference among tundra rivers may be related temperature regimes, lake influence or catchment topography. Although not assessed in these studies, respiration may increase due to an influx of organic matter into streams (Hill et al., 2000) providing more nutrients for secondary producers to accumulate biomass. This organic matter can come from sources such as thawing permafrost (Wang et al., 2018), which could result in spatial differences in stream metabolism across a watershed. Such differences in organic matter input may be why differences in ER are noticeable, but GPP was not. In terms of other biomes, daily mean ER in the Greiner Lake Watershed was lower than values noted by Bernot et al. (2010) across multiple biomes in Europe and the USA that included grasslands, forests (deciduous, coniferous, tropical), deserts, and mountains.

There was no consistent increase or decrease in ER or GPP during the study period, which has been observed previously in Arctic streams. For example, Myrstener et al., (2021) found that there were no distinct temporal patterns in GPP during the ice-free season (May to October) in two tundra streams in the Miellajokka catchment, a catchment 200 km north of the Arctic circle in Sweden. This is likely due to the same reason that sites across the catchment were the same – a harsh environment. Any significant temporal patterns would likely be due to environmental variables that allow productivity to bounce back faster after a disturbance, which was not assessed in this study as measurements began after spring flooding and ice break up.

3.4.2 Environmental Drivers

The main variable affecting GPP was D_{50}, which showed a strong positive correlation with log daily average. This positive relationship has been observed in Europe. Pastor et al., (2017) found D_{50} to be more important to GPP than many other associated environmental variables including nutrient concentrations, temperature regime, light regime (including canopy

cover). Furthermore, it is well established that coarser substrates assist in facilitating the growth of autotrophic biofilms, algae, and microbial colonization (Johnson, Tank & Dodds, 2009). This may be because increased surface area of rocks provides more habitat suitable for algal and microbial colonization (Johnson, Tank & Dodds, 2009). Specifically, larger rocks can produce sheltered areas of low velocity and low sheer stress, thereby reducing the scour of primary producers (Cardinale et al., 2002). Furthermore, larger rocks provide greater surface area and heterogeneous microhabitats for colonization as opposed to fine sediments. Fine sediments are more mobile, and are easily moved during flooding events, whereas larger rocks remain stable (Tett et al., 1978) thus providing a more consistent habitat for biofilm growth.

There were strong positive relationships between the daily rates of ER and the area of upstream lakes and stream width. There are numerous reasons how a lake may affect a downstream environment. First, shallow lakes have accelerated primary production, compared to deeper lakes, as light can reach the bottom of the lake where biofilms and macrophytes can flourish (Vadeboncoeur, 2008). Shallow lakes will also warm faster during the summer months, thereby increasing productivity (Rautio et al., 2011). Both factors will contribute to productivity, which will in turn affect carbon and nutrient cycling. Primary producers can convert inorganic nutrients (N and P) to organic nutrients to fuel ecosystem respiration in lake-connected streams (Baker et al., 2016). In addition, upstream lakes can directly influence ER through flow regulation, increasing water temperature, and altering taxonomic composition in connected streams (Baker et al., 2016; Huziy & Sushama, 2017; Jones et al., 2010; Lamberti, Chaloner & Hershey et al., 2010; Robinson & Minshall, 1990). The surrounding terrestrial environment is a primary driver of organic matter dynamics. Stream ecosystems receive nutrients from soil organic matter or eroding peat, which affects substrate type and chemistry, by increasing organic

matter and vital nutrients for respiration (dos-Ros Oliveira et al., 2019; Reynolds & Tenhunen, 1996; Webster & Meyer, 1997). Furthermore, wider streams may have more available surface area for microbes relative to the free-flowing water volume (Mulholland et al., 2001), as many of the wide streams in this study are also shallow. However, most studies focus on the effects of terrestrial environments in temperate environments where leaf litter decay dominates organic matter cycling in many streams (Fenoy et al., 2016). Little is known about the role surrounding tundra vegetation will play on carbon and nutrient cycling in Arctic streams.

Overall, GPP and ER estimates for streams in this study were relatively homogenous across the watershed, and through the study period. This pattern is likely controlled by the the homogeneity across streams in the Greiner Lake watershed which likely results from the harshness of the Canadian Arctic that including seasonal spring flooding, cold winter temperatures, and ice in the winter limiting or eliminating primary and secondary production and after the spring pulse of flow. While others have documented strong connections between nutrients and GPP, my study showed that such relationships can be outweighed by geomorphological features. GPP was highly correlated with D_{50}, most likely due to the relationship between grain size and disturbance. Specifically, larger rocks could provide more surface area for algal and microbial community growth and were more stable during periods of high flow (e.g., spring snow melt). ER was positively associated with the area of upstream lakes and stream width, which may be due to how lakes transport nutrients and regulate the environments of downstream rivers. However, these results once again show the potential linkages between geomorphological features (stream width) and stream metabolism in nutrient deficient Arctic streams. In the future, the effects of flood and associated streambed stability on GPP should be explored to help predict the impact that the expected changes to hydrology will

have on GPP. Furthermore, understanding nutrient cycling in Arctic lakes throughout complex lake-stream networks may help to predict the changes to ER in rivers downstream of lakes in the watershed. Additionally, understanding the importance of stream geometry, hydraulics, and nutrient cycling, can help predict how ER may respond to a changing environment. This study demonstrates that there is a need for improved mechanistic understanding of the drivers of stream metabolism to better forecast how climate warming could modify ecological function in vulnerable Arctic freshwaters.

3.7 CHAPTER 3 REFERENCES

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3.6 CHAPTER 3 FIGURES

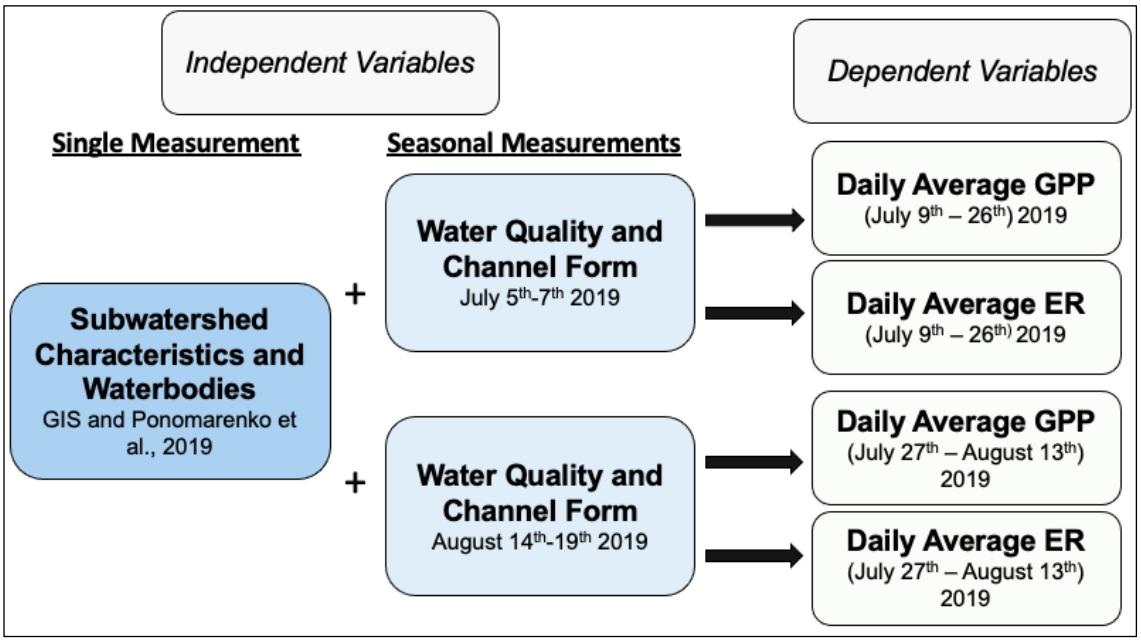

Figure 3.1: Subwatershed and Channel Form/Water Quality Data Collection. Single observations of subwatershed characteristics taken from GIS and data from Ponomarenko et al., 2019, and observed reach scale characteristics measured at each site, once at the beginning and once at the end of the study period.

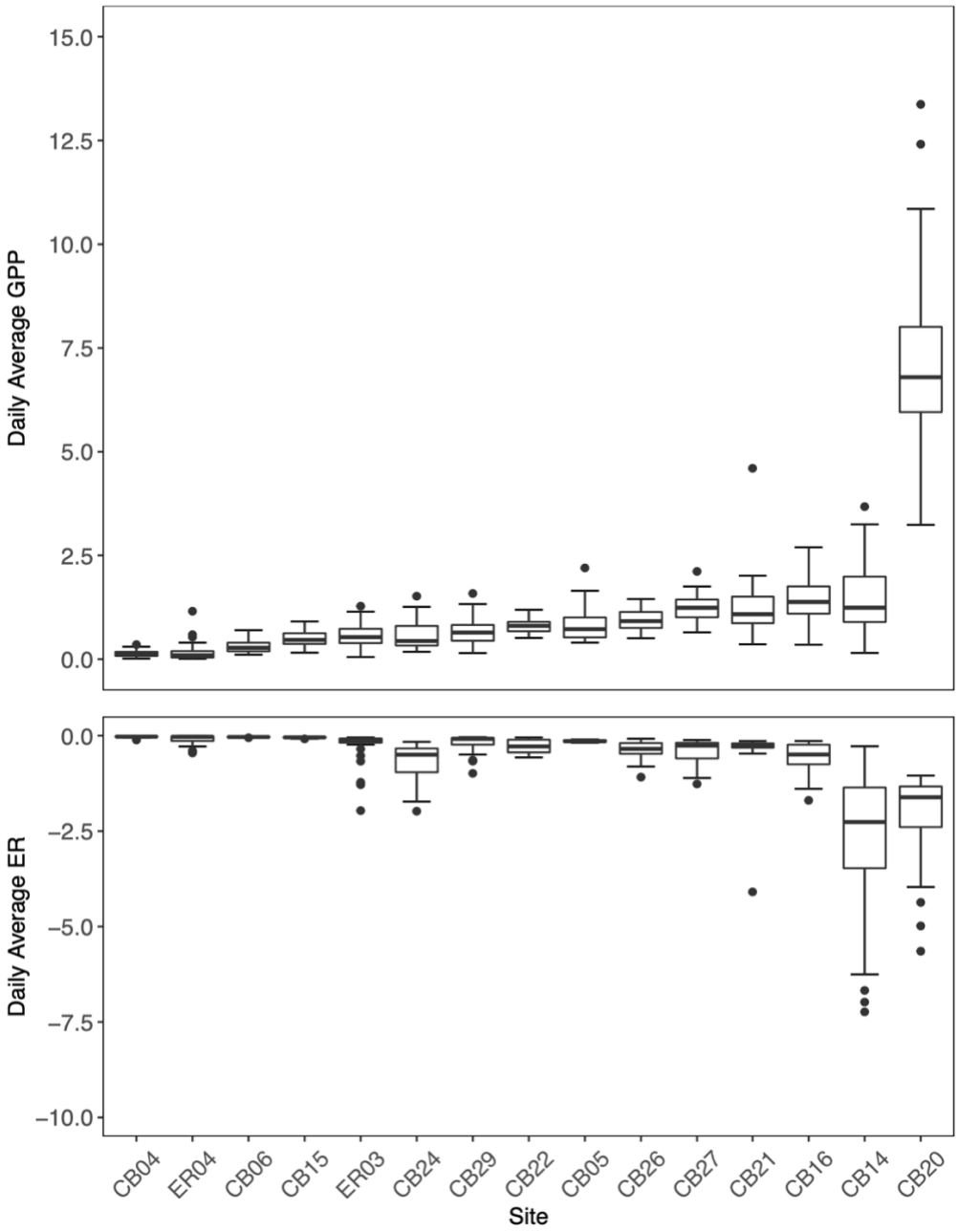

Figure 3.2: Boxplots of Average Values of Daily GPP and ER Rates. Boxplots from the entire study period in ascending Daily rates of GPP and ER (July 9th – August 13th). The top line represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, the bottom line represents the smallest value within 1.5x below the 25TH percentile and the dots are values that or greater than or less than the 1.5x IQR value.

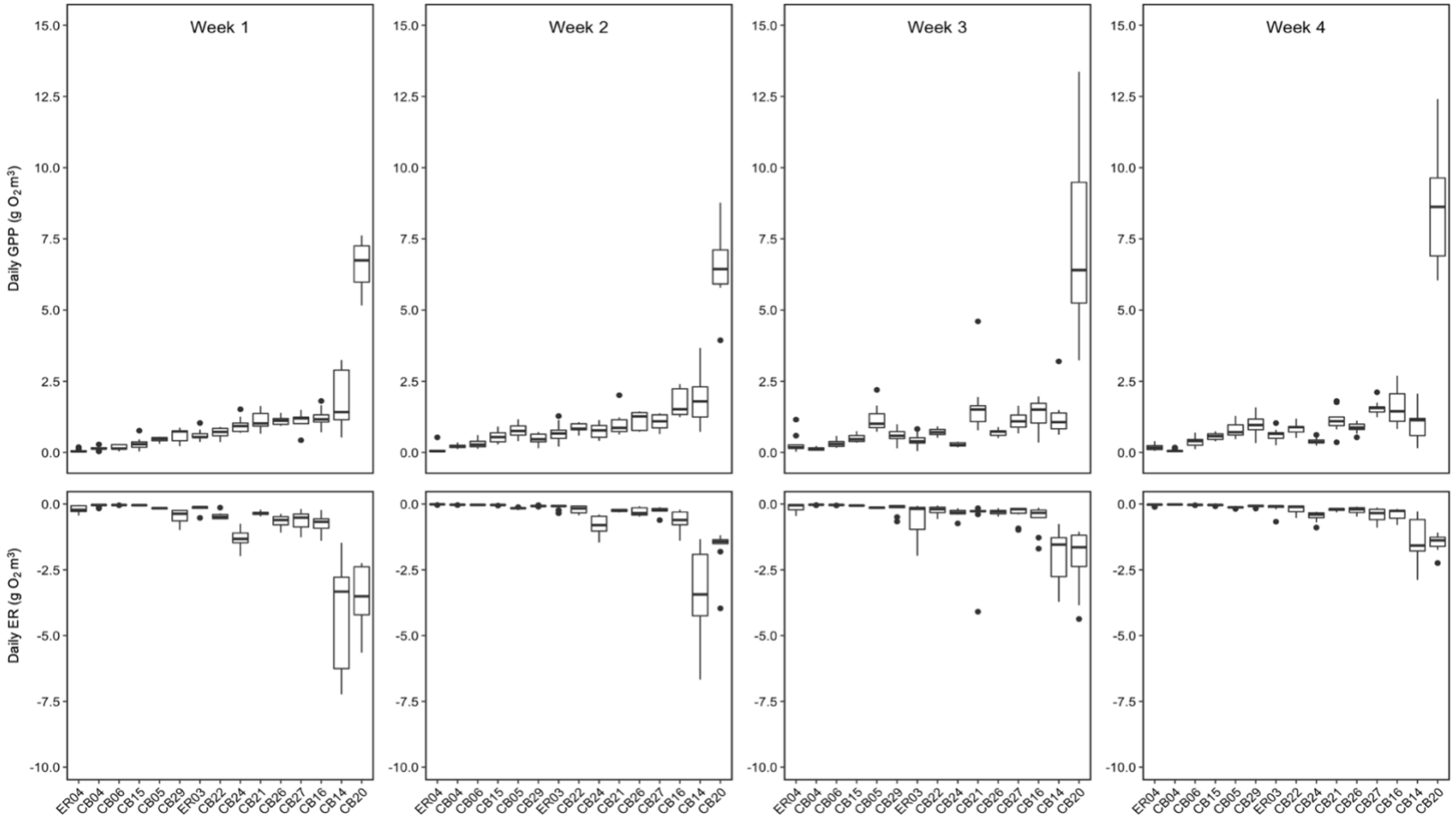

Figure 3.3: Boxplots Representing Temporal Variability in Stream Metabolism Across All Sites. Temporal variability in stream metabolism, including ER and GPP throughout the study period across all study sites in the summer of 2019. Week 1 represents July 9 -August 26th, week two represents July 18 – 26, week 3 represents July 27th – August 4th and week 3 represents August 5th – August 13th. The top line represents the largest values within 1.5x interquartile range (IQR) above the 75th percentile, the box represents the 75th – 25th percentile range with the median in the middle, the bottom line represents the smallest value within 1.5x below the 25TH percentile and the dots are values that or greater than or less than the 1.5x IQR value.

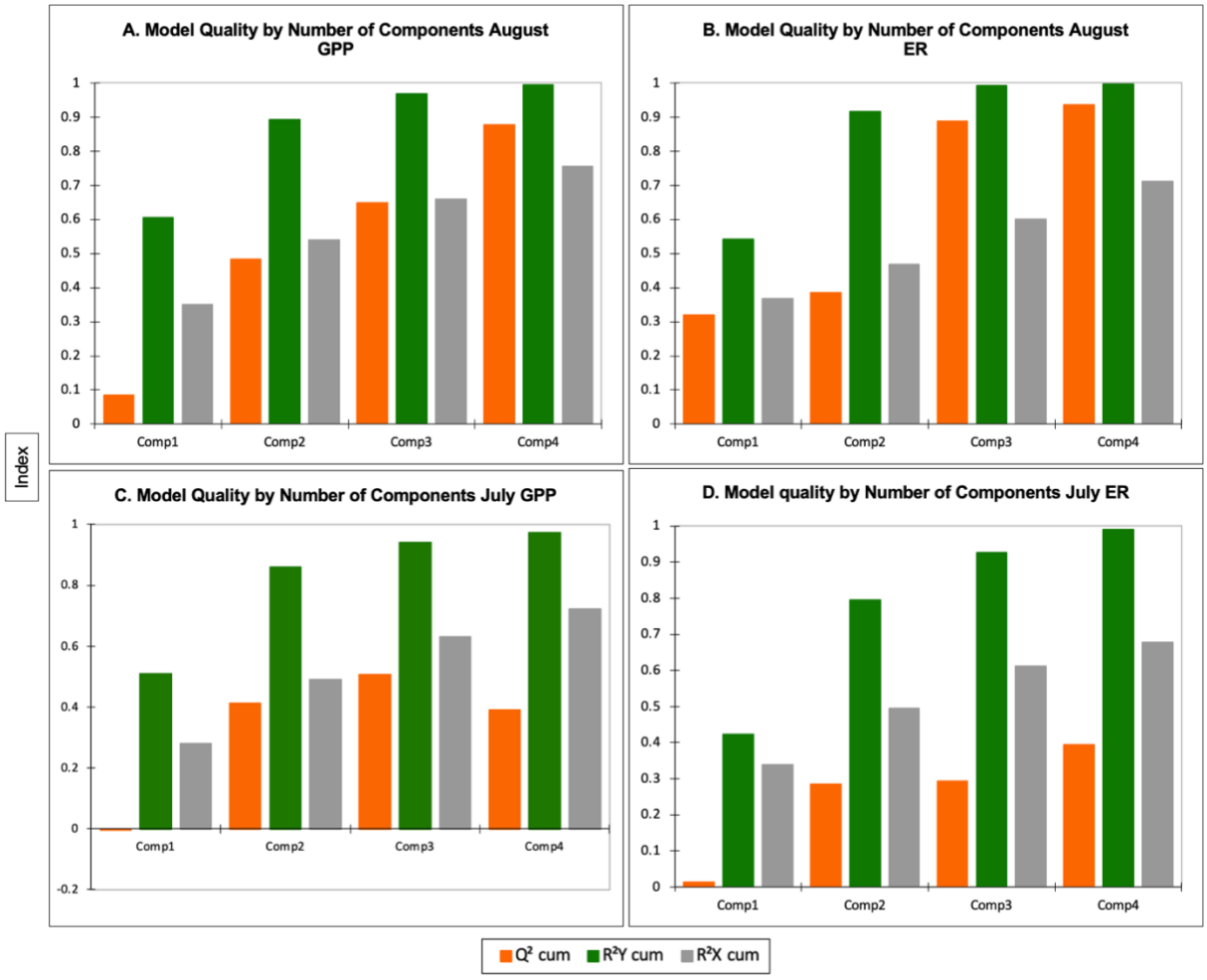

Figure 3.4: Model Quality Indexes of PLSR Components. The quality corresponds to the contribution of the component to the indexes. The Q2 cumulated index (Q2 cum) measures the global contribution of the component to the predictive quality of the model.

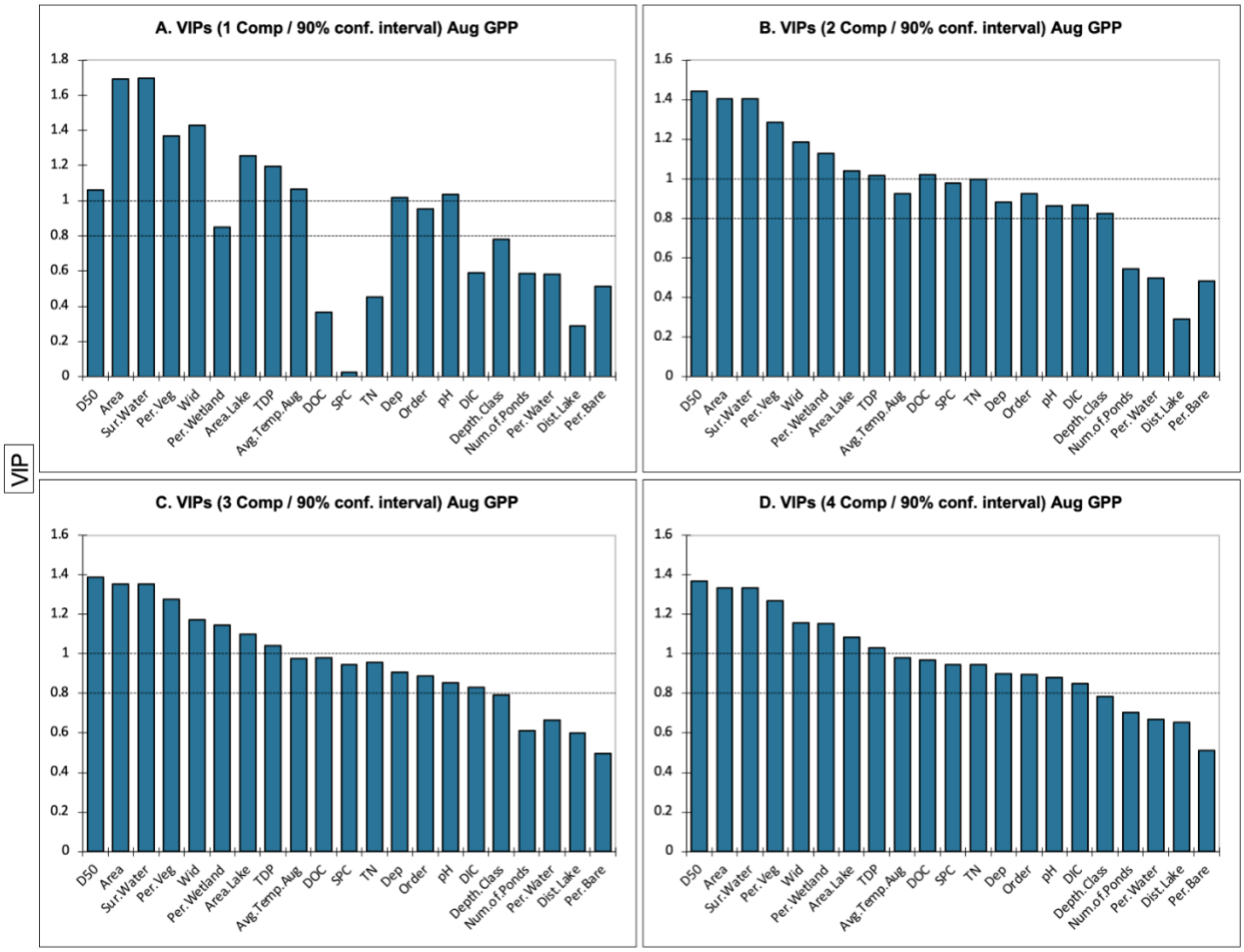

Figure 3.5: Environmental VIPs of August GPP Barplot. VIPS for each explanatory variables of the first component to the fourth component. All values above 1 are considered highly influential variables, and values above 0.8 are considered moderately influential. Only the third and fourth components were considered having a significant impact on the log of daily average GPP.

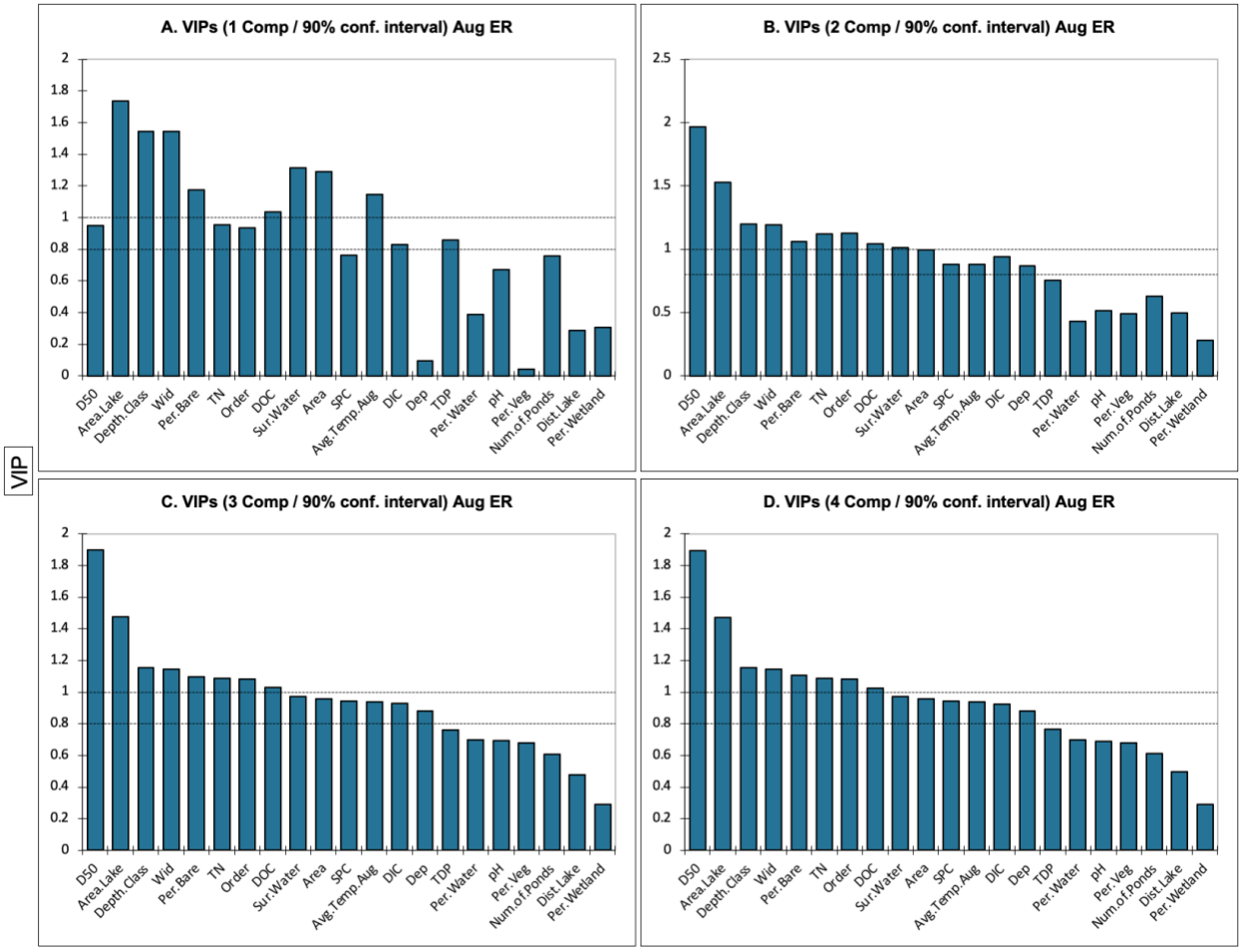

Figure 3.6: Environmental VIPs of August ER Barplot. VIPs (Variable Importance for the Projection) for each explanatory variable of the first to fourth component. All values above 1 are considered highly influential variables, and values above 0.8 are considered moderately influential. Only the fourth component was considered having a significant impact on the log of daily average ER.

3.7 CHAPTER 3 TABLES

Table 3.1: The Predictor Environmental Variables, their Units, and the Notations to Be Used for Analysis

Variable	**Unit of Measurement**	**Notation**
Water Quality and Channel Form		
Stream Width	m	Wid
Stream Depth	m	Dep
Nutrients (DIC, DOC, TN, TDP)	Concentration in mg L^{-1}	DIC, DOC, TN, TDP
pH	1-7	pH
D50	cm	D50
Conductivity		SPC
Subwatershed Characteristics and Waterbodies		
Order	Strahler, 1-7	Ord.
Distance from closest Upstream Lake	km	Dist.Lake
Depth Class of the closest Upstream Lake	1-4	Depth.Class
Total surface area of closest upstream lake	km^2	Area.Lake
Number of Ponds Upstream	0-3. * Depth of all ponds is estimated < 1 m	Num.of.Pond
Total area of the subcatchment	km^2	Area
Percentage of the subcatchment covered in surface water	Ha	Per.Water
Total amount of the subcatchment covered in surface water	Ha	Sur.water
Percentage of subcatchment covered in wetlands	Ha	Per.Wetland
Percentage of subcatchment without vegetation or surface water	Ha	Per.Veg
Percentage of catchment with bare land (no water or vegetation)	Ha	Per.Bare

Table 3.2: In Stream Environmental Variables for July 2019 Greiner Lake Watershed

Site	Average Temperature July	Width	Depth	Ratio	Width Class	DIC	DOC	TN	pH	TDP	SPC	D50
CB04	8.74	48.92	0.64	76.44	Very Wide	12	4.1	0.299	7.9	0.0054	199	8.5
CB05	8.63	18.28	0.31	58.16	Very Wide	13.8	3.4	0.323	7.94	0.0058	225	9
CB06	9.68	20.22	0.30	68.10	Very Wide	11.3	3	0.251	7.93	0.005	183	6.8
CB14	10.27	9.632	0.30	31.85	Wide	15.6	4.1	0.331	7.73	0.0043	234	8.2
CB15	9.08	5.48	0.23	23.48	Wide	6.9	2.5	0.279	7.71	0.0046	83.3	5.25
CB16	10.21	9.68	0.30	32.05	Wide	9.8	3.3	0.274	7.88	0.0051	134	15.5
CB20	10.40	8.97	0.34	26.40	Wide	9.8	2.9	0.252	7.86	0.0044	160	19
CB21	10.84	3.4	0.18	18.76	Narrow	23.5	7.5	0.545	8.32	0.0078	427	10.5
CB22	10.55	7.42	0.37	19.98	Narrow	12.4	4	0.345	8.01	0.0046	172	10
CB24	10.37	0.874	0.35	2.53	Narrow	17.35	5.75	0.436	7.92	0.0057	525	0.2
CB26	9.68	2.42	0.32	7.59	Narrow	12	2.2	0.213	7.94	0.0035	128	4.5
CB27	10.65	7.86	0.20	39.42	Wide	13.6	4.3	0.413	8.14	0.0067	224	9
CB29	7.93	1.01	0.13	7.79	Narrow	18.75	3.3	0.258	8.045	0.0051	269.5	6
ER03	11.73	1.554	0.15	10.61	Narrow	18.4	7.1	0.586	8.14	0.0056	413	1.4
ER04	10.07	1.11	0.43	2.58	Narrow	16.9	3.9	0.32	8.14	0.0041	268	2

Table 3.3: In Stream Environmental Variables for August 2019 Greiner Lake Watershed

Site	Average Temperature August	Width	Depth	Ratio	Width Class	DIC	DOC	TN	pH	TDP	SPC	D50
CB04	10.65	33.16	0.45	74.48	Very Wide	13.95	3.65	0.2765	8.155	0.00415	226	8.5
CB05	11.17	5.54	0.15	35.89	Wide	20.4	4.45	0.357	8.31	0.0058	235	5.25
CB06	10.73	14.16	0.21	66.29	Very Wide	17.7	3.55	0.283	8.18	0.0044	276	9
CB14	11.35	0.61	0.16	3.93	Narrow	28.5	9.1	0.681	8.32	0.0061	639	1.4
CB15	11.06	20.33	0.15	133.84	Very Wide	18.8	3.75	0.3105	8.29	0.00625	298	6.8
CB16	10.67	0.78	0.47	1.66	Narrow	25.8	4.1	0.309	8.26	0.0045	362	6
CB20	10.86	0.70	0.21	3.25	Narrow	32.3	6	0.408	8.35	0.0043	517	2
CB21	11.16	4.36	0.15	28.23	Wide	22.15	5.35	0.422	8.455	0.00555	348	9
CB22	11.26	7.77	0.26	29.69	Wide	17.1	4.1	0.297	8.3	0.0059	275	19
CB24	10.80	1.44	0.89	1.61	Narrow	30.4	6.1	0.372	8.33	0.0042	326	4.5
CB26	11.49	3.15	0.12	26.87	Wide	32.5	8.2	0.539	8.5	0.0064	499	10.5
CB27	10.78	0.50	0.19	2.71	Narrow	36.6	9.6	0.648	8.07	0.0059	893	0.2
CB29	11.07	8.12	0.26	31.19	Wide	22.3	5	0.385	8.34	0.0054	298	15.5
ER03	11.09	6.28	0.14	46.32	Wide	24.4	5.6	0.425	8.22	0.0058	320	10
ER04	10.67	0.49	0.42	1.17	Narrow	29.4	5.4	0.407	8.16	0.0057	429	8.2

Table 3.4: Subwatershed Environmental Variables of the Greiner Lake Watershed

Site	Dist.Lake	Area.Lake	Depth.Class	Num.of.Ponds	Area	Sur.Water	Per.Water	Per.Wetland	Per.Veg	Per.Bare
CB04	0.879	315	4	1	117884	26067	22	30	46	1
CB05	0.909	111	4	1	14235	3797	27	24	48	1
CB06	1.966	501	4	3	13715	3670	27	24	48	1
CB14	1.019	48	4	2	276	78	28	21	49	1
CB15	1.073	344	4	0	4348	895	21	31	47	1
CB16	0.521	74	2	0	6409	1380	22	28	49	1
CB20	1.368	47	3	2	13765	3248	24	31	44	1
CB21	0.186	18	2	0	2449	358	15	29	55	1
CB22	2.486	18	1	1	7557	1498	20	28	51	1
CB24	0.555	47	1	0	179	50	28	26	45	2
CB26	3.899	353	3	0	2009	496	25	30	44	1
CB27	0.957	21	1	0	6800	1516	22	28	45	1
CB29	0.212	44	4	0	472	59	12	26	61	1
ER03	0.137	30	1	0	752	87	23	30	45	1
ER04	1.566	74	4	2	337	171	26	31	41	1

Table 3.5: Environmental VIPs for August GPP. Highly influential variables extracted for the model of log average of daily GPP values. The most influential variables were extracted from the fourth component, which had the highest model quality.

Variable	VIPs
D50	1.369
Area	1.335
Sur.Water	1.335
Per.Veg	1.268
Width	1.156
Per.Wetland	1.152
Area.Lake	1.085
TDP	1.032

Table 3.6: Environmental VIPs for August ER. Highly influential variables extracted for the model of log average of daily ER values. The most influential variables were extracted from the third component, which had the highest model quality

Variable	VIPs
D50	1.898
Area.Lake	1.474
Depth.Class	1.155
Wid	1.147
Per.Bare	1.096
TN	1.090
Order	1.083
DOC	1.029

CHAPTER 4: SUMMARY AND SYNTHESIS

4.1 Introduction

Stream metabolism is an excellent biomonitoring tool for assessing stream ecological processes and can help measure the impact of changes in a stream's surrounding environment (Bernot et al., 2010; Mulholland et al., 2001). However, the remoteness of the Canadian Arctic, and the 24-hour light during Arctic summers complicate using standard measurements of stream metabolism. These traditional methods often require a period of complete darkness and a reaeration coefficient to measure ER, both of which are difficult-to-impossible to measure during an Arctic summer. Furthermore, very few studies have assessed how Arctic streams are influenced by their surrounding environment. Studies have examined how GPP rates are affected by nutrient availability, and the carbon cycling capabilities of Arctic streams (Rocher-Ros., 2019). However, most studies on metabolism have not tried to assess environmental drivers across many sites in a catchment (Myrstener et al., 2021; Rocher-Ros et al., 2019). The goal of this study was to 1) explore a viable method for measuring stream metabolism by comparing models that attempted to deal with these challenges, 2) determine if metabolism in tundra streams was significantly different from each other and how metabolism changes through time, and 3) establish the effects of stream characteristics on daily rates of GPP and ER. Chapter 2 addressed the first aim by critically comparing two methods of stream metabolism measurements: streamMetabolizer, and a combination of linear regression and ER interpolation. Chapter 3 addresses Objectives 2 and 3 by using streamMetabolizer estimates of stream metabolism to determine if average stream GPP and ER were significantly different from each other across a watershed and through time and investigated associations of environmental drivers

with GPP and ER. Here I synthesize the findings of Chapters 2 and 3, discuss the significance of this research, and suggest future research based on these findings.

4.2 Summary

4.2.1 Chapter 2

After modifying streamMetabolizer so that it could only produce values of GPP ≥0, and ER≤0, I found that streamMetabolizer was a viable model for producing daily average rates of GPP and ER that were representative of an Arctic tundra stream, without requiring direct K600 measurements, eliminating dates, or altering light values. The interpolation and regression methods produced sporadic daily rates, and values beyond a reasonable range for Arctic tundra streams and were therefore not considered moving forward. Model diagnostics of stream metabolism showed that 13 sites had process errors of ≥1.1, 9 sites had observation errors ≥1.1, and 5 sites with no significant correlation between ER and K600, and 8 sites with a correlation of ≤0.6 Compared to other methods in this study, this method was deemed satisfactory and was therefore used moving forward in Chapter 3.

4.2.2 Chapter 3

Chapter 3 demonstrated that GPP at most sites were significantly different from each other across the watershed, however, the actual values of GPP were biologically similar, as there was minimal variation in environmental variables im the watershed. In contrast, ER across all sites in the watershed were generally not significantly different, except for 2 sites that had much higher rates of ER. In terms of temporal variation, no consistent patterns were observed for GPP or ER, except for two sites (CB14, CB20) that showed a significant decrease in ER throughout the study period. The PLSR analysis showed that D_{50} was significantly, positively correlated with natural log of GPP, and stream width and area of upstream lakes were positively correlated with natural

log of ER. A Pearson correlation analysis further indicated these relationships to be statistically significant.

4.2.3 Research Significance

streamMetabolizer can produce values of daily GPP and ER that fall within a realm of possibility for streams across the Arctic tundra, more so than other currently developed empirical methods. This is likely because streamMetabolizer is algorithm based, which helps the model make informed decisions. This helps avoid "equifinality", which is the phenomena of many combinations of GPP, ER and K600 producing the same values, thus creating unreliable results (i.e., outliers). The algorithm in streamMetabolizer constrains the possible values of GPP, ER and K600 so that these fall within a logical range (this can be determined by values taken from previous studies in similar environments) while still allowing the model to be flexible enough to show variation caused by the environment and not poor model performance. This is often the case when oxygen curves are low, which is common in environments with low productivity such as Arctic streams that have low nutrient levels, cold temperatures, and intense seasonality and associated natural disturbance regimes. Equifinality was likely why the linear regression and ER interpolation methods produced sporadic and unreasonable for a low productivity Arctic stream. The ability for streamMetabolizer to produce reasonable results is an encouraging discovery for estimates the productivity of streams in the Arctic because metabolism estimates can be obtained without the logistical constraints (e.g., time and financial investments) of other methods. Moreover, long-term studies can be conducted in remote locations such as the Greiner Lake Watershed with minimal effort and will better be able to track changes in stream processes.

Due to the success of streamMetabolizer, I was able to explore the environmental variables that play a role in stream metabolism such as the significance of substrate size. The positive

relationship between D_{50} and GPP is most likely due to larger rocks creating a more stable environment for the growth of primary producers (algae, macrophytes, etc.), an affect that has been observed in temperate streams (Pastor et al., 2017), but to my knowledge, not in other Arctic tundra streams. Larger rocks require greater tractive force to be moved during flooding disturbances when increase scouring occurs. It is notable that scouring is well established as a factor that can reduce stream productivity (Kurz et al., 2017). In addition, large rocks provide microhabitats with reduced velocity on the downstream side of flow, a higher surface area for growth, and habitat closer to the surface which likely warms faster and experiences more sunlight (depending on rock dimensions). This relationship with D_{50} was more significant than any other in this study which suggests that disturbance patterns and velocity may be the most limiting factor for GPP for streams in the Greiner Lake Watershed.

Success in measuring stream metabolism also allowed me to discover that ER is positively related to area of upstream lakes and stream width. It is well known that lakes can greatly alter the type of environment by controlling flow patterns, temperature, and nutrients downstream in temperate streams (Baker et al., 2016; Fritz et al., 2018; Hauptman et al., 2016; Marcarelli & Wurtsbraugh, 2007), thus creating a habitat that is different than the same stream further downstream.

Lakes with wider areas have longer perimeters where they can be exposed to more bankside vegetation/organic inputs and wider lakes will have higher surface area to enable production. Therefore, I concluded that there is likely a connection between ER and the amount of organic matter, such as coarse particulate organic matter, being transported downstream as affected by the greater input of organic material from surrounding vegetation and from growth within the lake. A similar conclusion was drawn for stream width, as wider streams may be interacting with

surrounding vegetation and terrestrial environments more than narrow streams, and increased width may be providing more surface area for growth of biofilms relative to free-flowing water volume. This is significant as vegetation shifts are expected in the Canadian Arctic as the climate warms. Furthermore, if these vegetation shifts provide more organic matter in streams, there may be a spike in CO_2 outputs to the atmosphere. However, to my knowledge not there has been limited research on the importance of allochthonous inputs to streams in the Arctic to date. It is well understood that temperate streams have an integral connection to their surrounding environments, particularly streams with leaf litter inputs in the fall. Although my study points to a potential connection between terrestrial vegetation and organic matter inputs, it is unlikely that Arctic streams follow the same pattern as temperate streams, and more research needs to be conducted.

4.2.4 Future Research Directions

streamMetabolizer has proven to be the most viable method for calculating daily rates of metabolism across the Greiner Lake Watershed. Even so, there are still options that we did not use in the streamMetabolizer software that could be implemented including K600 estimates for pooling, and better priors. K600 pooling refers to the input of any measurements of stream width, depth, and discharge, whether it be once or twice in the study, to help estimate stream metabolism. K600 pooling can constrict the values of possible K600 and can control the level on constriction. With a minimal input of field effort (measurements of discharge at each site during the deployment of loggers), better estimates of reaeration values are possible. Furthermore, as more studies are being published about Arctic streams, we can update the priors that are used in the model, meaning that we can better inform the model as to what GPP and ER values are most

likely in these streams to help constrain values. This would likely decrease process error, observation error, and reduce equifinality that may still exist in my models.

Furthermore, to better understand the major controls of GPP, flood patterns should be observed. Although the purpose of this study was to create a snapshot of what stream metabolism is like during the summer in the Greiner Lake Watershed, it is likely that spring flooding affects summer rates of GPP, as disturbance regimes have proven to affect stream metabolism in previous studies (Prowse et al., 2006b; Nilsson, Polvi & Lind, 2015). The connection between GPP and D_{50} lead to the idea that stable habitat availability is a major control of productivity during the summer. This suggests that habitats that are more easily disturbed by spring floods take longer to recover. To better understand GPP, it is likely important to quantify the intensity of flooding by deploying depth loggers earlier in the season, to be used as a proxy for flood intensity. We would then expect streams with higher D_{50} relative to flood intensity to recover faster.

To better understand the major controls of ER, more research needs to be done on the relationship between proximal vegetation on streams and lakes. The positive relationship between ER and stream width and lake area may be due to an increase in interaction with the terrestrial environment, which may provide the streams with more organic matter. In this study, only the percent area of the vegetation of the subcatchment was considered, which did not have any significant effect on daily rates of ER. A shift to focusing on the vegetation density covering the site reach (within 50 – 100m of the loggers) may shed light on these relationships. Furthermore, we could correlate the density of vegetation with in-stream organic matter, with the expectation that increases in nutrient abundance are due to vegetation entering the stream. Lastly, more research needs to be conducted on the interaction between streams and large waterbodies.

If a lake is oligotrophic, it would be inaccurate to assume that organic matter is coming from the in-lake vegetation and other organisms being transported downstream. Instead, ER may be increasing because lakes do not process any organic matter, and any organic matter inputs are being transported downstream.

4.2.3 Integrative Nature of Research

Much ecological research exists in symbiosis with fields such as chemistry, physics, biology, statistics, and geography. Much of this thesis requires knowledge and techniques from all disciplines. Calculating metabolism requires a basic understanding of physics and biology. Reaeration rates are estimated using coefficients developed by observing hundreds of other streams, to be able to estimate how much O_2 will naturally exchange with the atmosphere based on the hydraulics of a stream, and one must understand the behaviour of different organisms in the stream such as autotrophs and heterotrophs. streamMetabolizer requires a basic understanding of Bayesian statistics to understand the quality of the models being produced, which leads to essential decision making. To integrate this knowledge, one must have a basic understanding of the geography of a landscape to determine what characteristics of the landscapes are controlling stream metabolism, whether it be from the nutrients being released through permafrost thaw, underlying bedrock chemistry, or knowing how to how to delineate a catchment using GIS. This thesis was based on all the different fields of science has to offer and would not have been possible otherwise. Furthermore, my research contributes to a growing understanding of the Greiner Lake Watershed in the Canadian High Arctic Research Centre which has been previously research by other Laurier students in the Culp laboratory. Specifically, research by Kuhrt (2022) related the feeding patterns of Ninespine Stickleback to the surrounding environmental variables of streams across the Greiner Lake Watershed.

4.3 CHAPTER 4 REFERENCES

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