**INTRODUCTION**

Streams receive large amounts of carbon (C) from terrestrial ecosystems (Drake, Raymond, & Spencer, 2017) and emit a large fraction of this as CO₂ to the atmosphere (Raymond et al., 2013). The magnitude of CO₂ evasion from running waters is similar to the net ocean CO₂ exchange, and therefore represents a critical component in the global C cycle (IPCC, 2013). While terrestrial organic carbon (OC) is a major source of stream CO₂, it can be...
mineralized in soils and subsequently transported to streams in gas form (Oquist et al., 2009), respired within the stream ecosystem (Fisher & Likens, 1973; Hedin, 1990), and/or photo-oxidized in the water column (Cory, Ward, Crump, & Kling, 2014). Resolving these different pathways is necessary to determine the fate of OC at regional scales, including the magnitude of CO₂ evasion and water-borne C export to recipient systems (Webb, Santos, Maher, & Finlay, 2018).

While processes delivering CO₂ to streams have been extensively researched, individual studies often reach different conclusions in terms of assigning relative contribution to any one mechanism. A potential reason for these differences is that each pathway operates within distinct compartments of fluvial ecosystems, and thus, studies on specific mechanisms often fail to capture others (but see Demars, 2018; Lupon et al., 2019; Rasilo, Hutchins, Ruiz-Gonzalez, & del Giorgio, 2016). For instance, studies of photo-oxidation suggest this as an important CO₂ source in streams (>70%; Cory et al., 2014), but these typically consider only processes that occur in the water column. Other studies indicate that the contribution from soil respiration to stream CO₂ evasion is more than 90% (Winterdahl et al., 2016), but these often neglect the potential role of benthic and hyporheic processes. Finally, while there has been decades of research on stream metabolism (Hoelllein, Bruesewitz, & Richardson, 2013), these rates have not been integrated with estimates of CO₂ evasion until recently (Hotchkiss et al., 2015). Overall, while the different conclusions drawn from these studies likely reveal real variation in contributing processes among systems, the large variability also reflects the challenge of partitioning these sources at meaningful spatial and temporal scales.

One way to partition the different pathways contributing to CO₂ evasion is to couple continuous measurements of stream CO₂ dynamics with independent and simultaneous estimates of aquatic ecosystem metabolism based on O₂ measurements. Ecosystem metabolism in streams has been measured and modelled for decades using diel measurements of O₂ concentrations in water (Hall & Hotchkiss, 2017; Odum, 1956). This approach assumes that the concentration of O₂ in water is affected by three processes: (a) gross primary production (GPP) that produces O₂, (b) ecosystem respiration (ER) that consumes O₂ and (c) stream water turbulence that affects the air–water exchange of O₂. Recent advances in O₂ sensor technology, together with new modelling tools, make it possible to estimate daily GPP, ER and net ecosystem production (NEP; NEP = GPP – ER) using continuous time series of O₂, light and hydrological parameters (Appling, Hall, Yackulic, & Arroita, 2018; Hall & Hotchkiss, 2017; Holtgrieve, Schindler, Branch, & A’mar, 2010). Importantly, GPP and ER also consume and produce CO₂, respectively, and thus provide estimates of aquatic C processing rates that can be compared to independent measures of CO₂. In this way, estimating metabolism modelled from O₂ data is a powerful tool to understand CO₂ sources to streams (Hotchkiss et al., 2015), yet few studies have coupled high frequency measurements of O₂ and CO₂ with the goal of resolving these different pathways (but see Gómez-Gener, von Schiller, et al., 2016; Stets et al., 2017).

The few existing studies that address how stream metabolism may contribute to CO₂ evasion are from boreal (Crawford, Striegl, Wickland, Dornblaser, & Stanley, 2013; Rasilo et al., 2016) or temperate ecosystems (Cole & Caraco, 2001; Crawford et al., 2014; Gómez-Gener, von Schiller, et al., 2016; Hotchkiss et al., 2015), while studies of these processes in the Arctic tundra are lacking. Tundra streams are characterized by cold temperatures, long days with high incident light during a short summer and winters that span for more than 6 months. Yet, these streams often drain soils with large C stocks (Schuur et al., 2015), and export vast quantities of OC to the Arctic ocean (Cooper et al., 2008). Furthermore, streams represent considerable sources of CO₂ evasion in the Arctic landscape (Lundin et al., 2016; Stackpoole et al., 2017) and emit more C than is exported to the ocean (Serikova et al., 2018). Given that climate change is drastically altering the hydrology and biogeochemistry of Arctic landscapes (Drake et al., 2018; Kendrick et al., 2018), understanding how C is mineralized and evaded within streams (e.g. Giesler et al., 2013) is necessary to understand and predict the effects of environmental change on C cycling in this region.

In this study, we ask: how do stream metabolic processes affect CO₂ dynamics and evasion in Arctic stream networks? To answer this, we measured CO₂ and O₂ concentrations continuously in six streams in an Arctic catchment during the summer of 2015 and 2016. Specifically, we (a) quantified the contribution of the stream NEP to CO₂ evasion and (b) explored whether GPP can explain diel changes in CO₂ evasion. To achieve this, we modelled metabolic rates using the O₂ data and estimated CO₂ evasion simultaneously.

2 | MATERIALS AND METHODS

2.1 | Site description

The Miellajokka catchment (52.5 km²) in north-western Sweden (Figure 1; 68°21′14″N, 18°56′16″E) is located near the Abisko Scientific Research Station. For the period 1990–2013, average annual air temperature was 0.3°C and the average annual precipitation was 337 mm (Abisko Station Meteorological Data: www.polar.se/abisko). Climate in the Miellajokka catchment is characterized by long winters with precipitation as snow from October to May and a short terrestrial growing season from June to September (Christensen et al., 2012). Hydrologic patterns reflect the seasonal climate regime, with a spring flood in May or June during snow melt (discharge at the outlet of 20–25 m³/s), and base flow of about 0.05–0.1 m³/s during the autumn and winter (Lyon et al., 2018). Dissolved organic carbon (DOC) in Miellajokka can reach 8–10 mg C/L during spring flood and decrease to about 2 mg C/L during summer base flow (Giesler et al., 2014). Dissolved inorganic carbon is around 4 mg C/L during summer base flow conditions, but is lower during spring flood (<2 mg C/L; Giesler et al., 2014). The pH in the catchment is circumneutral and with little seasonal variation (Giesler et al., 2013). The stream network ranges
from first to fourth Strahler order streams (Table 1), with a total length of 44.6 km and a total stream surface area of 0.151 km² (Rocher-Ros, Sponseller, Lidberg, Mörth, & Giesler, 2019). Streams are moderately steep with slopes ranging from 0.07 to 0.32 m/m (Lyon et al., 2018), and several medium-sized waterfalls. There are two lakes in the catchment, covering in total 0.69 km².

The Miellajokka catchment is north-facing and elevation ranges between 384 and 1,731 meters above sea level (m a.s.l.). In this

**TABLE 1** Physical and chemical properties of the streams monitored. Discharge, water temperature and pCO₂ show the average value and the 0.05–0.95 quantile in parenthesis

| Site | Elevation (m a.s.l.) | Catchment area (km²) | Strahler order | Discharge (L/s) | Water temperature (°C) | pCO₂ (ppm) |
|------|----------------------|----------------------|----------------|-----------------|------------------------|-------------|
| M1   | 381                  | 51.5                 | 4              | 1,513 (643–3,849) | 7.6 (5.2–10)            | 1,130 (910–1,320) |
| M6   | 747                  | 1.8                  | 2              | 101 (47–247)    | 6.1 (3.8–8.4)           | 840 (610–1,120)  |
| M9   | 800                  | 10.9                 | 2              | 654 (316–1,080) | 8.1 (4.1–11.9)          | 880 (650–1,100)  |
| M10  | 815                  | 8.6                  | 3              | 361 (287–482)   | 7.2 (4.6–10.2)          | 740 (460–1,080)  |
| M16  | 385                  | 0.7                  | 2              | 128 (71–208)    | 6.9 (5.1–8.3)           | 1,990 (1,700–2,230) |
| M17  | 706                  | 0.11                 | 1              | 14 (9–18)       | 5.4 (1.5–8.7)           | 2,460 (1,900–3,100) |

**FIGURE 1** Map of the Miellajokka catchment with the coloration indicating changes in elevation. The black dots represent the location of the measuring sites in this study. The inset shows the location of the Miellajokka catchment within Scandinavia, and the dashed line represents the Arctic circle.
region, sporadic permafrost occurs at low elevations and discontinuous to continuous permafrost at high elevation zones (Gisnás et al., 2017). At elevations above 1,200 m a.s.l., the land is mostly barren, with several permanent snowfields. Between 700 and 1,200 m, the landscape is characterized by tundra vegetation and cryoturbated soils (Becher, Olid, & Klaminder, 2013). The tree line is at approximately 700 m, and below this elevation, the landscape consists of sparse mountain birch forest (Betula pubescens spp. Czerepanovii) with mixed tundra heath vegetation. Below 400 m, there is a more productive birch forest with a denser canopy cover. The sites M1 and M16 are located here, and the riparian forest cover results in less incident light compared to streams draining tundra vegetation (Myrstener et al., 2018).

2.2 Continuous measurements

We recorded water temperature, water level and dissolved concentrations of CO₂ and O₂ at six stream locations from late June to early September in 2015 and 2016 (Figure 1). Water temperature and water level were recorded hourly using HOBO water level loggers (model U20-001-04; Onset Computer Corporation). Stream CO₂ concentrations were measured hourly using infrared gas analyser (IRGA) adapted for wet environments. In streams M1 and M16, we used a Vaisala GMT220 sensor (Vaisala) covered with a PTFE layer highly permeable to dissolved gasses but not to water, following (Johnson et al., 2010). At sites M6, M9, M10 and M17, we used eosGP CO₂ concentration probes (Eosense Inc.). The eosGP sensor uses the same technique as the Vaisala, but with a PTFE membrane included by design. The Vaisala and eosGP sensors were connected to CR1000 data loggers (Campbell Scientific Inc.), powered with 12 V lead-acid batteries. The sensors were calibrated with standard gases in the lab before and after deployment in the field, using gas concentrations of 400, 2,000 and 5,000 ppm of CO₂. Sensors were placed with protective casings to avoid damage due to floods and rock movements in the water and were inspected and gently cleaned every 3 weeks. Due to the fragile material of the membrane and the extreme conditions in some streams, several malfunctions and subsequent data loss occurred, particularly at M1. We monitored O₂ concentrations every 10 min using miniDOT oxygen loggers (Precision Measurement Engineering Inc.). The loggers were installed with a copper mesh to avoid biofouling, and the sensor was placed in the opposite direction of the flow to prevent accumulation of debris and impact of stones. Prior and post deployment, the sensors were intercalibrated using aerated water to achieve a 100% saturation of O₂, and then by adding dry yeast to decrease the O₂ saturation to 0%.

All loggers were attached in the stream using a perforated steel pipe attached to a heavy metal platform to prevent movement. The temperature/water level loggers were placed firmly inside the pipe, the CO₂ sensor outside but downstream of the pipe, to be exposed to flowing water, and the O₂ sensor parallel to the flow with the sensor facing downstream. We selected these sites taking into account three criteria: (a) a suitable location within the thalweg to install loggers so that they would not be exposed to air during base flow conditions, while also avoiding deep pools; (b) lack of upstream tributaries (in all streams except M16 the distance to the nearest tributary was >1 km); and (c) minimal groundwater inputs immediately upstream of deployment sites. On two to six occasions, we quantified local groundwater inputs by comparing discharge estimates made with salt slugs at the deployment site with those made upstream: 50–500 m, depending on stream size. For each site, we observed similar discharge values, differing less than 10%, for example, the precision of the slug discharge measurements (Moore, 2005). This indicates low rates of groundwater input within the likely footprint of the metabolism estimate.

Snow/ice cover and peak flow conditions during snow melt restricted the time period of our measurements to June–September. Due to these climatic constraints, in 2015, we installed the loggers between 5 and 7 July until 7 September, and in 2016, between 15 and 17 June until 8 September. Other climatic variables used in this study were atmospheric air pressure and light irradiance. We used data measured in the meteorological station in Stordalen (SITES Sweden monitoring station, circa 4 km from the catchment outlet). To obtain atmospheric pressure in each site, the atmospheric pressure was corrected by the elevation difference following the barometric formula (Hall & Hotchkiss, 2017).

2.3 Discharge and the gas exchange coefficient ($K_{600}$)

Discharge ($Q$) was measured at every site on several occasions with the salt slug method (Moore, 2005). At M1, M6 and M16, we obtained more than 10 measurements, while in sites M9, M10 and M17, we performed four discharge measurements. The discrete measures were then related to depth that was continuously monitored with a pressure logger to obtain continuous discharge estimates. The relationship between depth and discharge used was linear, with an $R^2 > .85$ in all streams. To relate the depth of the logger position to the average channel depth, we measured depth every 5–20 cm (depending on the stream size) along 8–10 cross sections upstream of the sensors at each site.

The gas exchange coefficient ($K_{600}$) was primarily obtained using the night-time regression method (Hornberger & Kelly, 1975; Odum, 1956). Briefly, at sunset when GPP approaches zero, O₂ in water decreases as there is no biological input. The rate of decrease in O₂ concentrations is therefore dependent on the rate in which O₂ can reach a new equilibrium with the atmosphere, and thus proportional to the $K_{600}$. During the period when this occurs, $K_{O2}$ is approximated by the slope of the relationship between the rate of change in O₂ concentration and the O₂ deficit in the water (Odum, 1956), that can be converted to $K_{600}$ (Aristegi, Izagirre, & Elosegi, 2009). Given that the length of the night shifts strongly through the summer at high latitudes, we used an algorithm to perform six linear regressions each day at different periods to capture the night-time drop of O₂ using an R script (https://github.com/rocher-ros/nighttime_regression_multiple). We selected days when night was at least 2 hr long (from 25 July onwards), and days when the night-time regression had an
\[ K_x = K_{600} / (600/SC_x)^{-0.5} , \] (1)

where \( K_x \) is the gas exchange coefficient for a given gas \( x \), and \( SC_x \) is the Schmidt number of that gas (in this study CO\(_2\) or O\(_2\)). The Schmidt numbers for each gas were calculated using the published Schmidt coefficients (Raymond et al., 2012), for O\(_2\) was calculated as:

\[ SCO_2 = 1800.6 - (120.1 \times T) + \left(3.78 \times T^2\right) - \left(0.0476 \times T^3\right). \] (2)

And for CO\(_2\) as:

\[ SCCO_2 = 1911.1 - (118.1 \times T) + \left(3.45 \times T^2\right) - \left(0.0413 \times T^3\right). \] (3)

where \( T \) is the water temperature in °C. With the gas specific Schmidt numbers (Equations 2 and 3), it was therefore possible to calculate the \( K_{O_2} \) and the \( K_{CO_2} \) (Equation 1).

### 2.4 | Stream metabolism modelling

Stream metabolism was modelled based on the open channel diel oxygen method (Odum, 1956). Mean NEP is the balance between GPP and ER, and these two processes affect the diel oxygen concentrations. These diel patterns can be used to estimate GPP and ER by analysing O\(_2\) time series. We used a Bayesian inverse model from Hall and Hotchkiss (2017), governed by the following equation:

\[
O_2_i - O_{2_{i-1}} = \frac{GPP \times \frac{\text{PAR}_{i-1}}{z} + \text{ER} \times \Delta t}{z} + K_{O_2} \times (\text{O}_{2_{sat}} - \text{O}_{2_{i-1}}) \times \Delta t, \]

where \( O_2_i \) is the oxygen concentration at time \( t \) (in g \( O_2 \)/m\(^3\)), \( z \) is the channel depth (in m), PAR is the photosynthetically active radiation (in mol m\(^{-2}\) s\(^{-1}\)), \( K_{O_2} \) is the gas exchange coefficient of \( O_2 \) (in day\(^{-1}\)), \( \Delta t \) is the time steps of the time series (10 min) and \( O_{2_{sat}} \) is the concentration of \( O_2 \) in the water if it would be 100% saturated. GPP and ER are obtained as areal rates (g \( O_2 \)/m\(^2\) day\(^{-1}\)) and were converted to C assuming that 1 mol of \( O_2 \) is produced/consumed for 1 mol of \( CO_2 \) (Demars et al., 2016). We acknowledge that the conversion between \( O_2 \) and \( CO_2 \) depends on the chosen respiratory or photosynthetic quotient and could thus bias results (Berggren, Lapierre, & Del Giorgio, 2012; Williams & Robertson, 1991).

We modelled the three parameters (GPP, ER and \( K_{CO_2} \)), but using priors for \( K \) that were strongly constrained to minimize the problem of equifinality (Appling et al., 2018). Models that predict the three parameters avoid errors associated with estimating \( K_{600} \) empirically (Aristegui et al., 2009; Holtgrieve, Schindler, & Jankowski, 2016), but can give multiple solutions where different combinations of GPP, ER and \( K_{600} \) reproduce the same \( O_2 \) data, so-called equifinality (Appling et al., 2018). A solution for this is to relate \( K_{600} \) to hydrological measures such as discharge, which should be a proxy for \( K_{600} \) within a site (Appling et al., 2018). We used the relationship between \( K_{600} \) and \( Q \) from each site obtained from the night-time regression method (see above), to obtain an approximate \( K_{600} \) for each day with its error associated. Then, for each day, the prior distribution of \( K_{CO_2} \) was defined by the mean and standard deviation (SD) obtained from the \( K_{600} - Q \) relationship (Figure S4). The priors for GPP and ER were largely uninformative, with a mean of 1 and -5 g \( O_2 \)/m\(^2\)/day, respectively, and an SD of 2. The priors of GPP and ER were chosen to be similar to the mean values measured in another Arctic stream in Alaska (Hruby, Bishaw, & Parker, 2014). To simulate the posterior distributions of the parameters, we used the \( \text{metrop()} \) function of the \( \text{mcmc} \) package in R (R Core Team, 2017; version 3.4). Each model was run 150,000 times for each day and used the last 100,000 simulations to assure the convergence of the posterior distributions, based on visual observations. All metabolism computations were performed following Hall and Hotchkiss (2017), using a modified version of the R script available in that publication.

We further filtered the modelled estimates of metabolism through the following quality tests: (a) we calculated the mean average error (MAE) between the observed and the modelled \( O_2 \) concentrations. If the MAE was larger than 0.2, we discarded that day. The threshold of 0.2 was determined after visually inspecting the plot of \( O_2 \) concentrations and was similar to the threshold used in another study (Lupon et al., 2019). (b) One of the model assumptions is that depth and \( K_{600} \) are constant throughout the day (Odum, 1956). We removed days when depth (which is also the proxy used for \( K_{600} \)) changed more than 10% within the day. (c) Finally, daily outputs were plotted to visually inspect that the model reproduced \( O_2 \) concentrations accurately. Here, we inspected each day manually and removed any days showing poor model fit. After this, 165 observations of daily metabolic metabolism were removed from a total of 875.

### 2.5 | Estimating \( CO_2 \) evasion

The \( CO_2 \) exchange with the atmosphere (\( E_{CO_2} \)) was calculated as (Raymond et al., 2012):

\[ E_{CO_2} = K_{CO_2} \times z \times (\text{[CO}_2]_{w} - \text{[CO}_2]_{a}). \] (5)
(in mol/m³). We used an atmospheric CO₂ concentration of 380 ppm, obtained from the mean of several air CO₂ measurements performed in the field. The concentrations of CO₂ in mol/m³ were calculated using the pCO₂ measurements and Henry’s law, using the temperature measured in the oxygen sensor. The units of ECO₂ were converted from mol C m⁻² day⁻¹ to g C m⁻² day⁻¹.

2.6 | Mass balance along a single stream reach

In a previous study in this catchment, we measured CO₂ evasion and discharge at a high spatial resolution (Rocher-Ros et al., 2019). Here, we used this data set to do mass balance calculations for CO₂ in order to generate estimates of net CO₂ production along a stream reach (2.1 km) that loses a major fraction of water into the nearby forest as it crosses an alluvial deposit (Figure S13). We used these independent estimates and compared them with estimates derived from metabolism modelling. Along this reach, CO₂ concentrations, discharge, K₆₀₀ and channel hydraulics (wetted width, depth and velocity) were measured every 300–480 m. Therefore, it is possible to use a mass balance calculation for CO₂ within each segment of this reach:

\[ C_{\text{out}} = C_{\text{in}} + C_{\text{GW}} + P - E. \]  
(6)

where \( C_{\text{out}} \) is the CO₂ leaving the segment, calculated as the product of discharge at the downstream end (\( Q_{\text{out}} \) in m³/day) and the CO₂ concentration (\( \text{CO}_2 \); in g C/m³); \( C_{\text{in}} \) is the CO₂ entering the segment, calculated as the product of discharge at the entrance (\( Q_{\text{in}} \); in m³/day) and the CO₂ concentration (\( \text{CO}_2 \); in g C/m³); \( C_{\text{GW}} \) is the CO₂ input from groundwater (GW), as the product of groundwater flow (\( Q_{\text{GW}} \)) and the groundwater CO₂ concentration (\( \text{CO}_2 \); in g C/m³); \( P \) is the production of CO₂ within the stream segment; and \( E \) is evasion of CO₂ in the stream segment. Thus, to estimate the unknown \( P \) (stream production of CO₂), Equation (6) can be rearranged as:

\[ P = C_{\text{out}} - C_{\text{in}} - C_{\text{GW}} + E. \]  
(7)

Equation (7) can be further decomposed in its components as:

\[ P = Q_{\text{out}} \times \text{CO}_2_{\text{out}} - Q_{\text{in}} \times \text{CO}_2_{\text{in}} - Q_{\text{GW}} \times \text{CO}_2_{\text{GW}} + E_{\text{CO}_2} \times A, \]  
(8)

where \( E_{\text{CO}_2} \) is the CO₂ evasion rate (in g C/m²) using the average CO₂ concentration and \( A \) is the stream segment area (in m²). \( Q_{\text{GW}} \) can be estimated as the difference between \( Q_{\text{in}} \) and \( Q_{\text{out}} \) for each stream segment. Importantly, because this is a losing reach, there is no net increase in groundwater contribution; therefore, all CO₂ produced originated within the stream channel, and the parameter \( \text{CO}_2_{\text{GW}} \) is the mean stream CO₂ concentration. All these parameters were measured in the field and therefore used to estimate the internal stream CO₂ production (\( P \)).

2.7 | Data analysis and statistics

All data were analysed using R (R Core Team, 2017; version 3.5.1), the data set with daily summary data and an R script to reproduce these figures can be found in the Supporting Information. Linear regressions were performed to test the prediction that GPP is related to diel changes in CO₂ evasion. The \( \Delta \text{CO}_2 \) to summarize the diel change in CO₂ concentration was calculated as the difference between the highest and lowest CO₂ concentration within each day. The diel change in CO₂ evasion was calculated as the cumulative CO₂ evasion occurring between sunrise and sunset, and subtracting the CO₂ evasion before sunrise. The coefficient of variation (CV) was calculated as SD/average × 100, where SD is the standard deviation. Significant differences refer to the \( p < .05 \) level unless otherwise stated.

3 | RESULTS

3.1 | Physical and chemical characteristics of streams

Overall, streams were clearly separated by \( K_{600} \) with the more turbulent sites (M6, M9 and M10) having the highest values, ranging between 21 and 57 day⁻¹ (Figure 2). By contrast, in less turbulent streams

![Figure 2](image-url)
(M1, M16 and M17), $K_{600}$ values were considerably lower, that is, ranging between 4 and 17 day$^{-1}$ (Figure 2). Henceforth, the streams are labelled so that those that have a low $K_{600}$ (M1$_{LK}$, M16$_{LK}$, M17$_{LK}$) are easily separated for those with high $K_{600}$ (M6$_{HK}$, M9$_{HK}$, M10$_{HK}$). All streams were supersaturated in CO$_2$, with average concentrations ranging from 740 to 2,460 ppm (Table 1). We observed the highest average CO$_2$ concentrations in the two smallest streams, M17$_{LK}$ and M16$_{LK}$, and the lowest concentration in M10$_{HK}$ (Table 1). The amplitude of diel change in CO$_2$ concentration ranged from 0 to 920 ppm; this varied throughout the measuring periods, but also differed markedly among streams (Figure S1). Specifically, the diel change in pCO$_2$ ($\Delta$CO$_2$) was more pronounced in M1$_{LK}$, M16$_{LK}$ and M17$_{LK}$ compared to M6$_{HK}$, M9$_{HK}$ and M10$_{HK}$ (Figures 3 and 4). The average diel change of pCO$_2$ in M1$_{LK}$, M16$_{LK}$ and M17$_{LK}$ was 290, 490 and 430, respectively (Figure 3a,c,e), with changes as large as 920 and 870 ppm in M1$_{LK}$ and M16$_{LK}$ respectively.

3.2 | Stream metabolic rates

Rates of ER were an order of magnitude higher than GPP (Figure S6). Average ER across all streams was $-1.8$ g C m$^{-2}$ day$^{-1}$, with individual site averages ranging from $-1.35$ (M17$_{LK}$) to $-2.63$ g C m$^{-2}$ day$^{-1}$ (M1$_{LK}$, Table 2). Temporal variation in ER, described by the % CV, was greatest at M10$_{HK}$ (59%) and lowest at M1$_{LK}$ (27%). Average GPP across all streams was $0.22$ g C m$^{-2}$ day$^{-1}$ with averages for individual sites ranging from 0.19 to 0.28 g C m$^{-2}$ day$^{-1}$ (Table 2). GPP also varied over time within sites with the highest % CV in M9$_{HK}$ (85%) and the lowest in M16$_{LK}$ (41%). GPP and ER were significantly and linearly related in four of the six sites, with a degree of explanation ($R^2$) ranging from .28 to .5 (Figure S9). In all sites, we found that ER was linearly related with discharge, with an $R^2$ ranging from .65 to .93 (Figure S10). GPP was also significantly related to discharge in four of the six sites, with an $R^2$ ranging from .22 to .64 (Figure S11). There was also a strong relationship between ER with $K_{600}$ in all sites, with an $R^2$ ranging from .62 to .87 (Figure S12).

3.3 | GPP and diel patterns of CO$_2$ concentration and evasion

All streams had higher CO$_2$ concentrations at night compared to day, displaying a clear diel change in pCO$_2$ ($\Delta$CO$_2$; Figures 3 and 4). The diel pattern in pCO$_2$ resulted in higher night-time CO$_2$ evasion rates compared to daytime rates (Table 2). Not surprisingly, this effect on CO$_2$ evasion was highest in the streams with a strong diel pattern.
in pCO$_2$ (Figure 3). Specifically, CO$_2$ evasion at midnight compared to noon was 45%, 37% and 34% higher in sites M1$_{LK}$, M16$_{LK}$ and M17$_{LK}$ respectively. The impact on CO$_2$ evasion for the streams with a weaker diel pCO$_2$ pattern was lower but still important, with midnight evasion rates 26% and 24% higher than noon in sites M9$_{HK}$ and M10$_{HK}$ respectively. In site M6$_{HK}$, the pCO$_2$ diel pattern was the weakest, and CO$_2$ evasion rates at midnight were just 1% higher than noon. The magnitude of diel change in evasion was positively related to GPP rates in all streams, with significant relationships in all cases except M6$_{HK}$ during the year 2015 (Figures 3 and 4). For the streams with large diel changes in pCO$_2$ (M1$_{LK}$, M16$_{LK}$ and M17$_{LK}$), GPP explained between 31% and 78% of the variability in the diel change in CO$_2$ evasion (Figure 3b,e,f). For the streams with low K$_{600}$, the degree of explanation of GPP was weaker, ranging from 4% to 58% (Figure 4b,e,f).

Furthermore, the effect of GPP was also visible directly on diel changes in pCO$_2$ in the three streams with low K$_{600}$. In M1$_{LK}$, GPP explained 74% and in M16$_{LK}$ 83% of the amplitude in ΔCO$_2$ with values close to the 1:1 line (Figure S8). For stream M17$_{LK}$, GPP also had a significant, linear relationship with the diel pattern in pCO$_2$ and explained 65% and 32% of the variability for the years 2015 and 2016 respectively (Figure S8). In the other three

### Table 2

| Site | N (days) | NEP (g C m$^{-2}$ day$^{-1}$) | GPP (g C m$^{-2}$ day$^{-1}$) | ER (g C m$^{-2}$ day$^{-1}$) | CO$_2$ evasion (g C m$^{-2}$ day$^{-1}$) | Noon/midnight CO$_2$ evasion (g C m$^{-2}$ day$^{-1}$) |
|------|---------|-------------------------------|-------------------------------|-------------------------------|----------------------------------|--------------------------------------|
| M1   | 39      | −2.4 (−1.8 to −3.7)           | 0.21 (0.09–0.38)              | −2.63 (−1.9 to −3.9)          | 1.3 (1.0–1.9)                    | 1.02/1.51                            |
| M6   | 132     | −1.9 (−0.8 to −3.6)           | 0.15 (0.04–0.33)              | −2.08 (−0.9 to −3.9)          | 1.5 (0.8–2.2)                    | 1.53/1.55                            |
| M9   | 135     | −1.4 (−0.5 to −3.5)           | 0.24 (0.07–0.69)              | −1.29 (−0.5 to −2.6)          | 1.3 (0.4–3.2)                    | 1.21/1.52                            |
| M10  | 88      | −1.3 (−0.4 to −2.7)           | 0.28 (0.05–0.62)              | −1.61 (−0.6 to −3.2)          | 0.8 (0.3–1.4)                    | 0.75/0.93                            |
| M16  | 46      | −2.1 (−1.3 to −3.7)           | 0.24 (0.11–0.43)              | −2.37 (−1.5 to −3.9)          | 2.7 (1.5–4.9)                    | 2.19/3.01                            |
| M17  | 53      | −1.2 (−0.5 to −1.9)           | 0.19 (0.06–0.36)              | −1.35 (−0.6 to −2.2)          | 1.4 (0.6–2.2)                    | 1.26/1.67                            |
streams, the diel change in pCO₂ was lower, with an average of 40 (M6_HK), 190 (M9_HK) and 140 ppm (M10_HK; Figure 4a,c,e). At these sites, where K₆₀₀ was higher than 20 day⁻¹, and hence, streams were more turbulent, GPP had no significant relationship with the diel change in CO₂ concentrations (Figure S8).

### 3.4 CO₂ evasion and the contribution of stream metabolism

Average daily CO₂ evasion rates of the sites ranged from 0.1 to 6.2 g C m⁻² day⁻¹ (Table 2), with an average of 1.4 g C m⁻² day⁻¹. The highest average evasion rate was at M16_LK and the lowest at M10_HK (Table 2). All streams were undersaturated with O₂ and supersaturated with CO₂ relative to the atmosphere (Figure 5a). Consequently, all streams had negative NEP (ER > GPP) and were therefore net sources of CO₂, with NEP rates comparable to CO₂ evasion rates (Figure 5b). Average NEP among streams ranged from −1.2 to −2.4 g C m⁻² day⁻¹ (Table 2). The median contribution of NEP to CO₂ evasion across sites varied from 80% in M17_LK to 182% in M1_LK (Figure 5c). The sites that had clear diel patterns in CO₂ (M1_LK, M16_LK and M17_LK) were the sites that also had strong, significant linear relationships between NEP and CO₂ evasion, with R² values of .74, .96 and .71 respectively (Table S1). This relationship was much weaker in the sites with a low diel pattern in CO₂ but still significant for sites M6_HK and M10_HK, with R² of .1 and .23, while for site M9_HK, the relationship was not significant.

A direct comparison of departures from equilibrium of O₂ and CO₂ concentrations also captured similar results but without the effect of K₆₀₀ and its potential uncertainties (Figure 5a). All streams were close to the 1:1 line and were significantly related, with the highest R² found in the streams M1_LK, M9_HK, M16_LK and M17_LK (.73, .5, .85 and .45, respectively), while for M6_HK and M10_HK, the R² was .06 and .07 respectively. Although the departure from O₂ and CO₂ equilibrium does not incorporate the effect of the K₆₀₀, its effect determines the potential for the departure. Here, the streams with high K₆₀₀ (M6_HK, M9_HK, M10_HK) are closer to saturation for both O₂ and CO₂ than the streams with low K₆₀₀ (M1_LK, M16_LK, M17_LK). Additionally, the spread along the 1:1 line was also larger for low compared to high K₆₀₀ streams (Figure 5a). The streams M16_LK and M17_LK showed an offset relative to the 1:1 line, indicating that there is an external source of CO₂ uncoupled from O₂ dynamics. This external source of CO₂ for these same streams is also detected by comparing NEP and CO₂ evasion rates (Figure 5c), where NEP accounts for <100% of CO₂ evasion rates.

### 3.5 CO₂ mass balance along a stream reach

Mass balance calculations along single segments of the stream reach provided evidence for net CO₂ production within the stream. The water lost along the entire reach (Figure S13) was more than 50% (Figure 6a), as discharge decreased from 1.33 to 0.68 m³/s. Along this same distance, pCO₂ increased more than twofold, from 400 to 1,000 ppm (Figure 6b). K₆₀₀ also decreased markedly along the reach, with K₆₀₀ values dropping...
from 54.3 to 7.8 day$^{-1}$. CO$_2$ produced within five individual segments (300–480 m) ranged from 0.86 to 5.46 g C m$^{-2}$ day$^{-1}$, with an average of 2.6 g C m$^{-2}$ day$^{-1}$ (Figure 5c). This average CO$_2$ production in the reach was similar to the average CO$_2$ evasion (2.7 g C m$^{-2}$ day$^{-1}$) and close to the NEP (~2.81 g C m$^{-2}$ day$^{-1}$) measured the same day at the site M1 (800 m downstream) was 2.8 g C m$^{-2}$ day$^{-1}$.

4 | DISCUSSION

In this study, we simultaneously assessed continuous O$_2$ and CO$_2$ data to show that aquatic biological processes play an important role in the C cycle of these Arctic streams. In the Swedish northern landscape, the signature of aquatic metabolism was imprinted upon stream CO$_2$ dynamics in two distinct ways: photosynthesis created a clear day–night difference in CO$_2$ evasion and in-stream respiration sustained CO$_2$ evasion from streams throughout the summer. Streams were consistently heterotrophic, indicating that respiration in these ecosystems relies on organic C exported from land. Thus, through both autotrophic and heterotrophic processes, aquatic metabolism has the potential to regulate the transformation and the fate of terrestrial organic matter exported from Arctic landscapes.

4.1 | Diel patterns in CO$_2$ evasion

We observed a consistent and sometimes dramatic day–night change in pCO$_2$ (Figure 3) with night-time evasion rates that were between 24% and 45% higher than during the day in five of the six streams, a similar magnitude as reported in other studies in lower latitude regions (Peter et al., 2014; Reiman & Jun Xu, 2018; Schelker, Singer, Ulseth, Hengsberger, & Battin, 2016). Our results further indicate that this diel change in CO$_2$ evasion was caused by photosynthetic activity during the day (Figures 3 and 4). The effect of GPP was also visible directly in diel changes in pCO$_2$, but only in streams with less turbulence and lower K$_{SO2}$ (Figure S8). This suggests that degassing in more turbulent streams conceals the effect of GPP on stream CO$_2$ concentrations, as observed for O$_2$ concentrations (Appling et al., 2018). Regardless, despite relatively low GPP rates (Figure S6), photosynthesis acts as important, short-term C sink in these streams. Furthermore, this day–night pattern implies that estimates of CO$_2$ evasion based on daytime observations may grossly underestimate the total daily efflux, in this study by as much as 27%. By showing how low and high K$_{SO2}$ environments differ in their capacity to support strong diel patterns, these results may help to correct regional and global estimates of CO$_2$ evasion.

Our results show that aquatic photosynthesis drives diel changes in CO$_2$ evasion and pCO$_2$ in these Arctic streams (Figures 3 and 4). However, in the Alaskan Arctic, it has been suggested that photooxidation can account for as much as 70%–95% of the CO$_2$ production in the water column of streams and rivers (Cory et al., 2014). If this light-dependent process was the main driver of CO$_2$ production in our streams, we would expect to see an increase in pCO$_2$ from night to day, that is, in contrary to our observations (Figure 3). The discrepancy of our results with Cory et al. (2014) could be due to the clear, low DOC water in Miellajokka streams (Giesler et al., 2018), as compared to the more coloured and DOC rich waters in Alaska. Still, photochemical measurements are performed in the water column, which represents a minor fraction (<5%) of C mineralization from benthic and hyporheic sediments (Demars, 2018).
Indeed, even considering the highest rate of photo-oxidation from Alaska (0.3 g C m$^{-2}$ day$^{-1}$; Cory et al., 2014), this process would only account for 20% of average CO$_2$ evasion in our streams, and an even lower fraction in other Arctic sites that have reported considerably higher evasion rates (Denfeld, Frey, Sobczak, Mann, & Holmes, 2013; Lundin, Giesler, Persson, Thompson, & Karlsson, 2013; Serikova et al., 2018). Thus, without a spatial assessment of CO$_2$ evasion that included other hotspots of C inputs and evasion (Rocher-Ros et al., 2019), the conclusion of this study would have overestimated the contribution of in-stream metabolism. This stresses the importance of combining different tools, approaches and scales that capture unique pathways for C processing and evasion in stream networks.

4.2 | Contribution of stream NEP to CO$_2$ evasion

While GPP can have a strong impact on stream CO$_2$ dynamics, rates of ER were an order of magnitude higher (Table 2), and therefore had a stronger overall effect on the stream C cycle. Indeed, NEP in our streams was strongly negative due to high ER rates, a common observation across riverine ecosystems (Hoellein et al., 2013), and was the major contributor to CO$_2$ evasion (Figure 5). This indicates that these streams mineralize substantial amounts of the organic C received from land that otherwise would have been exported downstream to lakes or marine systems. Our reported values of the contribution of aquatic NEP to CO$_2$ evasion are high compared to other studies of small streams in high latitudes (40%-75%; Lupon et al., 2019; Rasilo et al., 2016), and typically the largest contributions to date have been observed for considerably larger rivers (85%-97%; e.g. Cole & Caraco, 2001; Lynch, Beatty, Seidel, Jungst, & DeGrandpre, 2010). Therefore, our results seemingly contradict the expected minor contribution of stream NEP to CO$_2$ evasion in headwaters (Hotchkiss et al., 2015), although we did find an increase in the average contribution of NEP with stream size (Figure 5c).

The discrepancy of our results with other studies reporting smaller contribution of aquatic NEP to CO$_2$ evasion may reflect constraints imposed on site selection when estimating stream metabolism. Importantly, we avoided reaches for metabolism modelling that constraints imposed on site selection when estimating stream metabolism. Importantly, we avoided reaches for metabolism modelling that accounted for 20% of the organic C received from land that otherwise would have been exported downstream to lakes or marine systems. Our reported values of the contribution of aquatic NEP to CO$_2$ evasion are high compared to other studies of small streams in high latitudes (40%-75%; Lupon et al., 2019; Rasilo et al., 2016).

Despite this plausible mechanism, the close correspondence between ER and discharge needs to be taken with caution because it also reflects covariance between $K_{600}$ and ER (Figure S12). In this study, the observed relationship between ER and discharge (or $K_{600}$) emerges from a persistent deficit of O$_2$ across a large range of flow conditions (see Figures S2 and S3). The covariance between ER and another parameter such as $K_{600}$ can be problematic when studying within site variability of ER, and so we are conservative and focus on average rates of ER, as other studies have done (Blaszcak, Delesantrio, Urban, Doyle, & Bernhardt, 2018). Regardless, since $K_{600}$ is used both for metabolism modelling and for CO$_2$ evasion (Equations 4 and 5), potential biases arising from $K_{600}$ estimates would affect NEP and CO$_2$ evasion rates to a similar extent and direction. This is also reflected in the similar departure from equilibrium for both O$_2$ and CO$_2$ (Figure 5a), which indicates a strong coupling of both gases in these streams. Finally, mass balance estimates of CO$_2$ production provided an independent validation of NEP rates, which were remarkably similar to NEP measured via metabolism modelling in the same stream on the same day (2.6 g C m$^{-2}$ day$^{-1}$ vs. 2.8 g C m$^{-2}$ day$^{-1}$; Figure 6). Together, these multiple observations provide additional confidence in our conclusions regarding the important role of aquatic respiration to CO$_2$ evasion.

Strikingly, our results further suggest that rates of NEP can exceed evasion locally, leading to an accumulation and downstream export of CO$_2$ (Figure 5). While this condition (NEP > $E_{CO2}$) was evident from our continuous, modelled data, we also tested whether this is reasonable using a mass balance approach. In this case, along a 2 km stream reach, we observed a large increase of pCO$_2$ (Figure 6). Given that this is a hydrologically loosing reach, most of the CO$_2$ must be produced internally and thus originate from stream processes. Furthermore, continuous sensor data identified this reach as...
one of the sites where NEP > E_{CO2} (Site M1_{4k} in Figure 5). Together, these observations suggest that in-stream biological processes can actively generate CO2 in streams and override lateral transport. Overall, whether a stream reach can or cannot export CO2 downstream will ultimately be controlled by the turbulence of the water and the capacity to evade CO2, which is highly variable at fine spatial scales (Rocher-Ros et al., 2019). The interplay between stream reaches that are importers or exporters of CO2 creates a strong heterogeneity and dynamism within stream networks that has important implications for understanding how C is processed and evaded along the aquatic continuum.

4.3 | Understanding the effects of climate change for C cycling in high-latitude streams

The Arctic is currently confronted by a wide array of changes due to global warming, with increased temperatures that result in the mobilization of old OC in soils (Schuur et al., 2015) and increased discharge into the Arctic Ocean (Peterson et al., 2002). These changes are currently altering the functioning of stream ecosystems (e.g. Kendrick et al., 2018) and also appear to have strong effects on CO2 evasion from fluvial networks (Serikova et al., 2018). Our results suggest that Arctic streams and rivers not only play an important role in C export and CO2 evasion, but are active components in the biological mineralization of OC.

However, the Arctic is large and diverse, with variation in permafrost extent and soil C storage (Hugelius et al., 2014), as well as regional differences in vegetation structure and growth trends (Huang et al., 2017), which together underpin largely unknown variability in stream biogeochemistry and aquatic ecosystem dynamics. Thus, multiple Arctic regions may respond uniquely to global change, and this variability needs to be captured in future studies, given current focus on few Arctic areas (Metcalf et al., 2018). Regardless, owing to the importance of the Arctic C feedback on climate change (Schuur et al., 2015) and the dependence of stream respiration to discharge and C supply (Demars, 2018), we suggest to include stream metabolism and its response to environmental change (e.g. Song et al., 2018) in future scenarios for the prediction of the effects of climate change.

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CONFLICT OF INTEREST
The authors declare no competing interests.

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