

Appendix 2: Analysis for Partitioning inorganic carbon fluxes using paired  $O_2$ - $CO_2$  sensors in a headwater stream, Costa Rica,  
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## Contents

Publication information . . . . .	1
Load packages and explore the data . . . . .	2
Figure 2- Time Series . . . . .	2
Figure 3- Stream and Well CO <sub>2</sub> . . . . .	8
Figure 4- Departure . . . . .	9
Figure 5- Hydrograph Separation . . . . .	13
Figure 6- Areal Fluxes . . . . .	18
Figure 7- GW on pH . . . . .	27
Fig S2- Hydrograph Separation . . . . .	29
Fig S3- Diel Variation . . . . .	31
Fig S4- Sensitivity Analysis . . . . .	35
Figs S5-11- Groundwater input method evaluation — . . . . .	39
Session info . . . . .	48

## Publication information

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## Load packages and explore the data

```
# data manipulation
library(dplyr)
library(tidyr)
library(lubridate)
library(tidyquant)
# plotting
library(ggplot2)
library(cowplot)
library(ggrepel)
library(scales)
library(ggsci)
# stats
library(lmodel2)
library(ellipse)
library(purrr)
library(lsmeans)
library(emmeans)
library(ARTTool)
# hydrology
library(hydrostats)
# reproducibility
library(pander)

# Read in time-series data
Tac_all <- readRDS("Tac_all.rds")
```

This RDS file contains hourly data from April 1 - September 27, including: stream and well Vaisala pCO<sub>2</sub> sensors (CO<sub>2</sub>\_ppm, wellCO<sub>2</sub>), YSI sonde (temp.water, pH, DO.obs, DO.sat, cond), discharge (sumQ\_m3\_hr, meanQ\_m3\_s), and meteorological data (relative humidity (RH), Rainfall, barometric pressure (bp\_mmHg)) from the weather station located at La Selva Biological Station. Rainfall is collected at 15-minute intervals, and there data here are aggregated to hourly sums. Discharge is collected at 15-minute intervals, and is shown as both mean discharge for the hour (m<sup>3</sup>/s) and sum of the 4 contributing measurements (m<sup>3</sup>/hr). Groundwater discharge (GW\_Q) is described in the text. Mean depth is taken from the weir.

We will use this dataset build on with the following calculations at the hourly resolution and aggregate to daily scale at the end of the document.

## Figure 2- Time Series

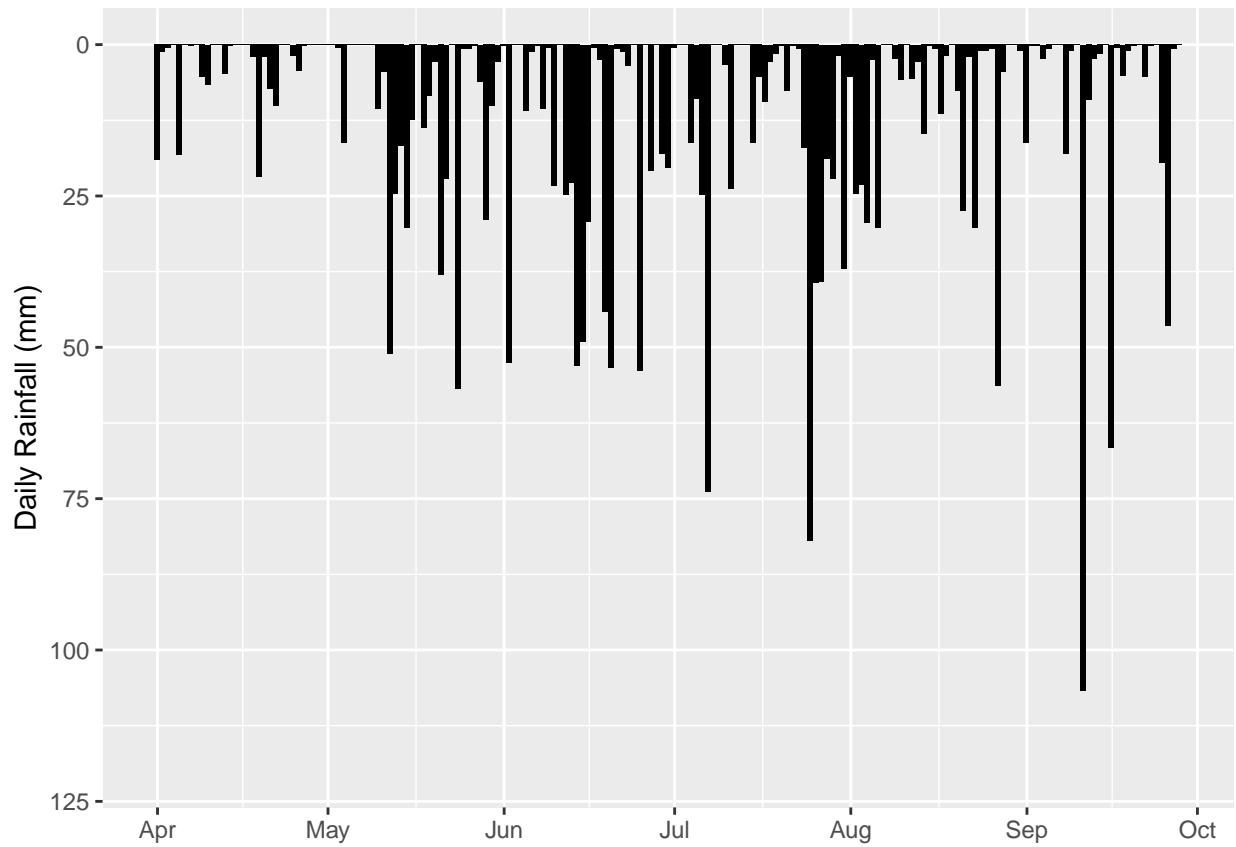
Figure 2 details the stream measurements. We plot rainfall, discharge, groundwater discharge, dissolved oxygen, CO<sub>2</sub> in the stream and in the riparian well.

```
plot_rain <- ggplot(Tac_all %>%
                      select(Timestamp, Rainfall) %>%
```

```

        group_by(Date = date(Timestamp)) %>%
        summarise(dayRain = sum(Rainfall, na.rm = TRUE)))+
geom_bar(aes(x = as.POSIXct(Date),
            y = dayRain),
         stat = 'identity', fill = 'black')+
ylim(120, 0)+
ylab('Daily Rainfall (mm)')+
scale_x_datetime(date_breaks = "1 month", date_labels = "%b")+
theme(axis.title.x = element_blank())
plot_rain

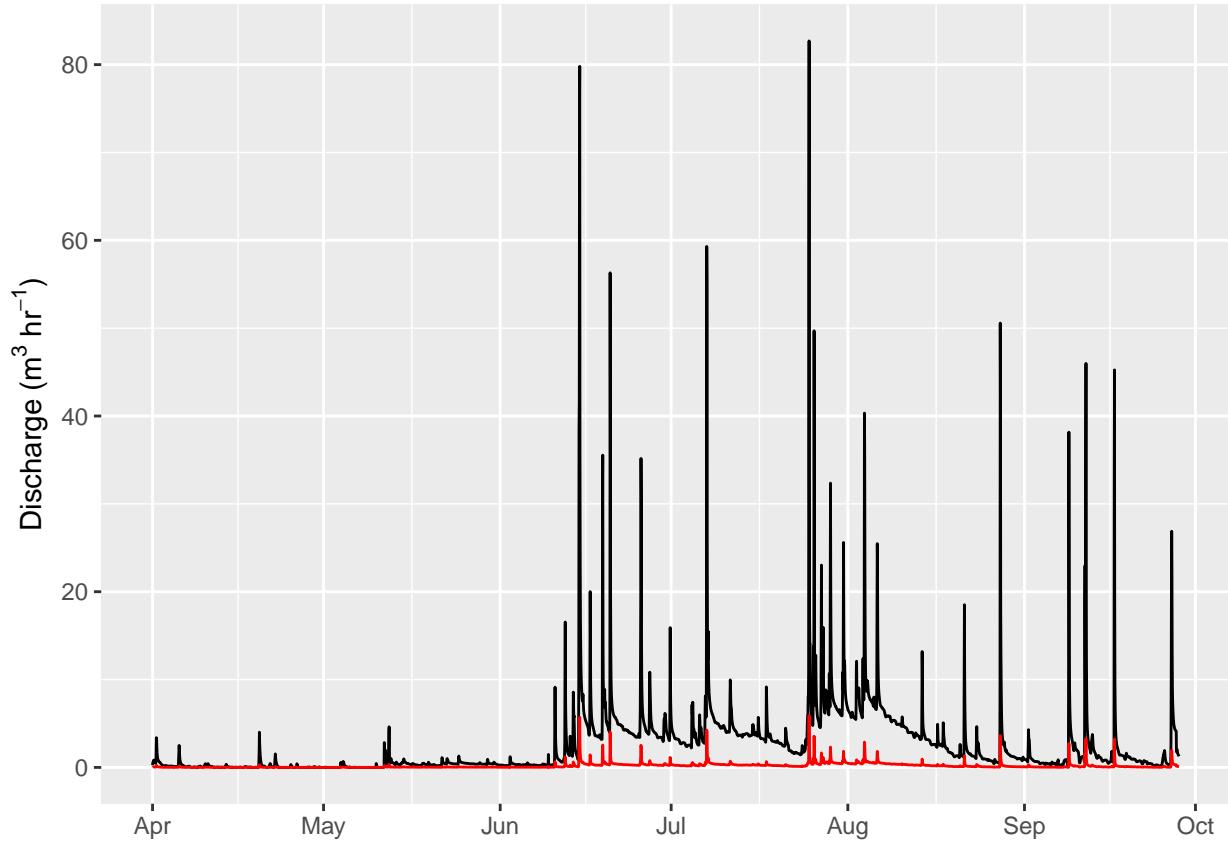
```



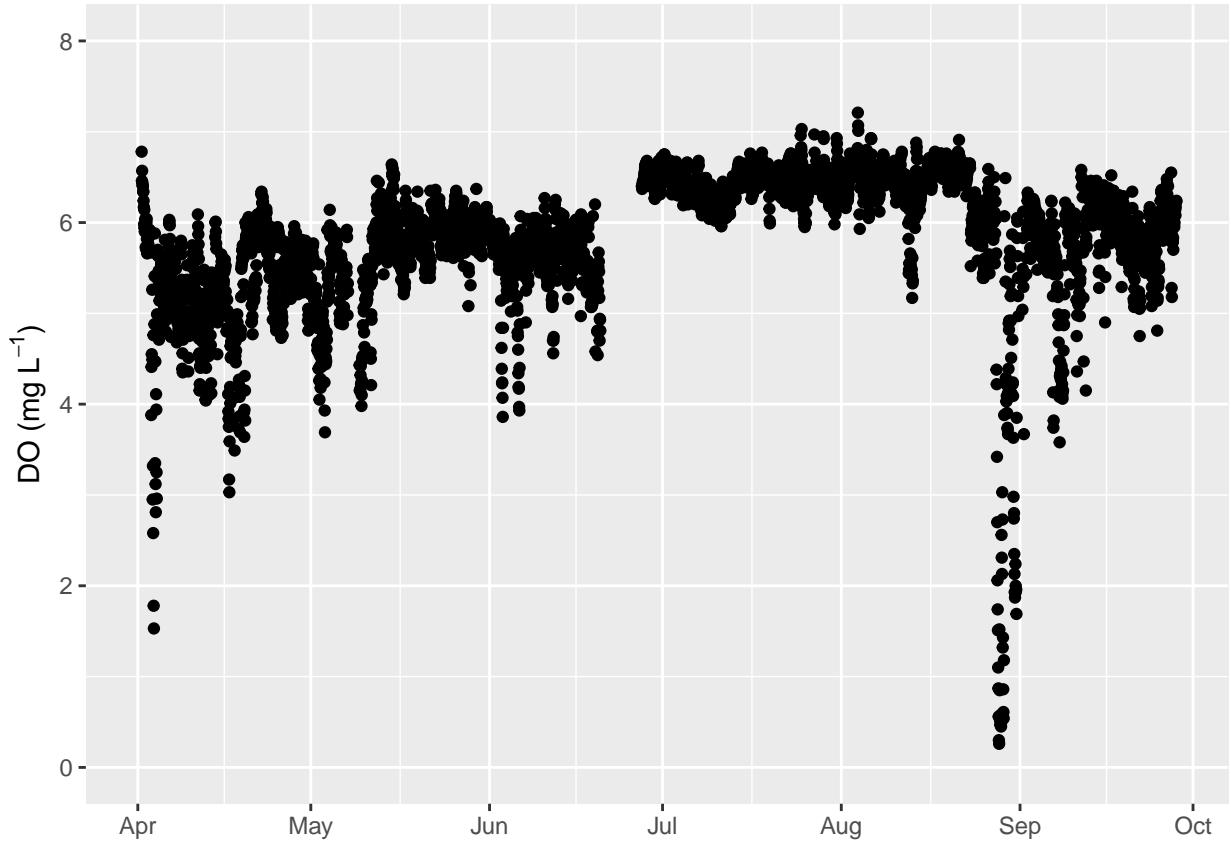
```

plot_Q <- ggplot(Tac_all,
                   aes(x = Timestamp))+
  geom_line(aes(y = sumQ_m3_hr),
            color = 'black')+
  geom_line(aes(y = GW_Q),
            color = 'red')+
  ylab(expression(paste("Discharge (", m^3, " ", hr^-1, ")")))
  scale_color_manual(values = c('black',
                                'red'))+
  scale_x_datetime(date_breaks = "1 month",
                  date_labels = "%b")+
  theme(axis.title.x = element_blank())
plot_Q

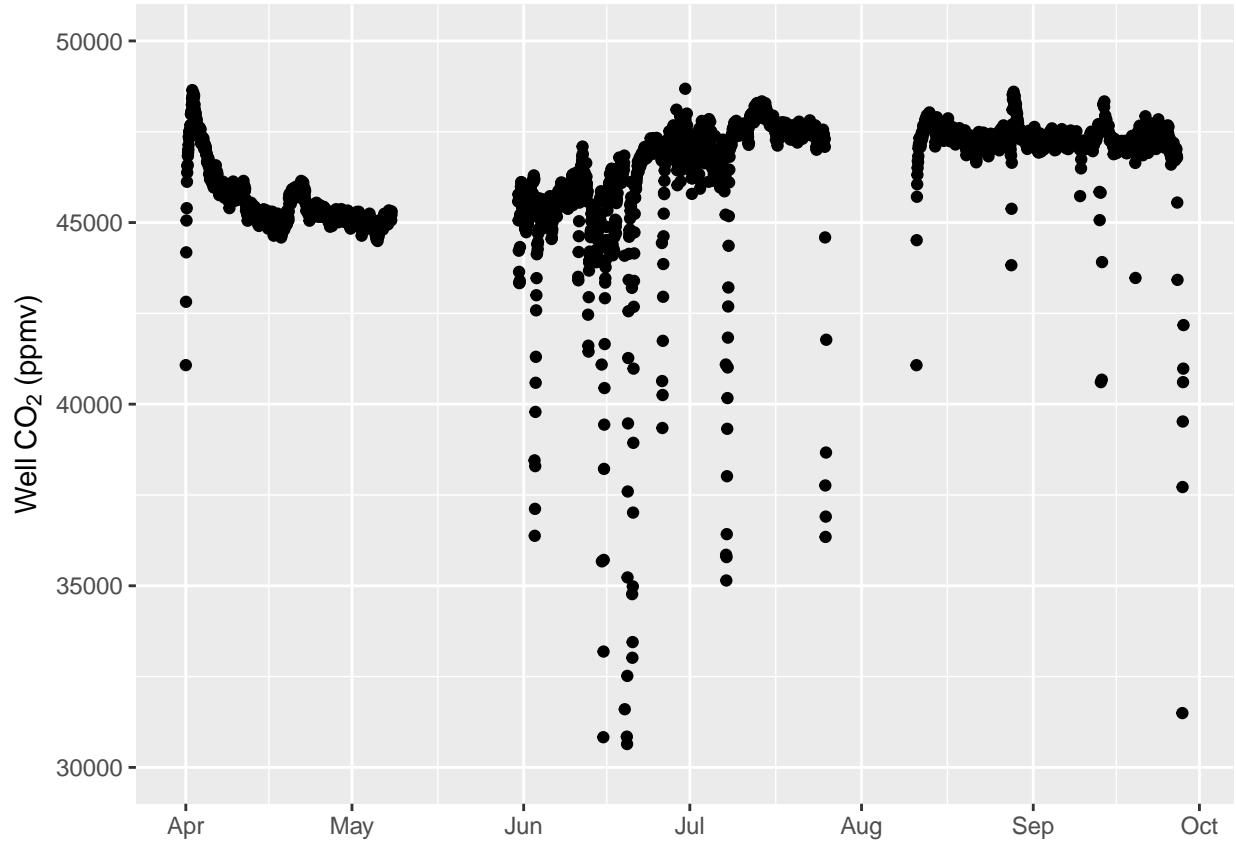
```



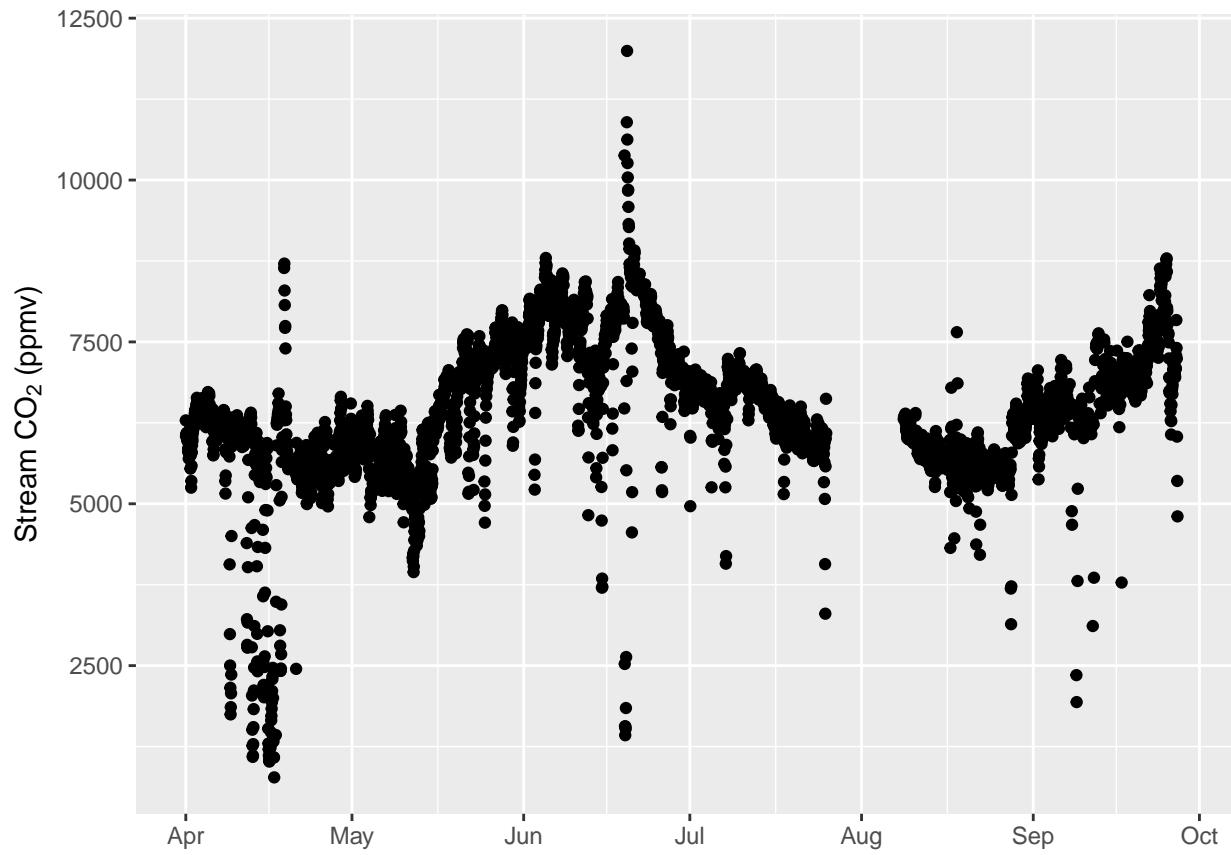
```
plot_do <- ggplot(data = Tac_all, aes(x = Timestamp))+  
  geom_point(aes(y = DO.obs))+  
  labs(x = "Time",  
       y = expression(paste("DO (mg ", L^{-1}, ")")))+  
  ylim(0,8)+  
  theme(axis.title.x = element_blank())+  
  scale_x_datetime(date_breaks = "1 month",  
                    labels = date_format("%b"))  
plot_do
```



```
plot_wellCO2 <- ggplot(Tac_all,
                        aes(x = Timestamp))+
  geom_point(aes(y = wellCO2),
             color = 'black')+
  ylab(expression(paste("Well ", CO[2], " ", "(ppmv)")))+
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b")+
  theme(axis.title.x = element_blank())+
  ylim(30000, 50000)
plot_wellCO2
```



```
plot_streamCO2 <- ggplot(Tac_all,
                           aes(x = Timestamp))+
  geom_point(aes(y = CO2_ppm),
             color = 'black')+
  ylab(expression(paste("Stream ", CO[2], " ", "(ppmv)")))+
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b")+
  theme(axis.title.x = element_blank())
plot_streamCO2
```



```
Fig2 <- plot_grid(plot_rain, plot_Q, plot_do, plot_streamCO2, plot_wellCO2,  
  nrow = 5,  
  align = 'hv',  
  labels = 'auto', label_fontface = 'plain',  
  hjust = c(-9, -10, -10.5, -10, -9), vjust = 2)
```

Fig2

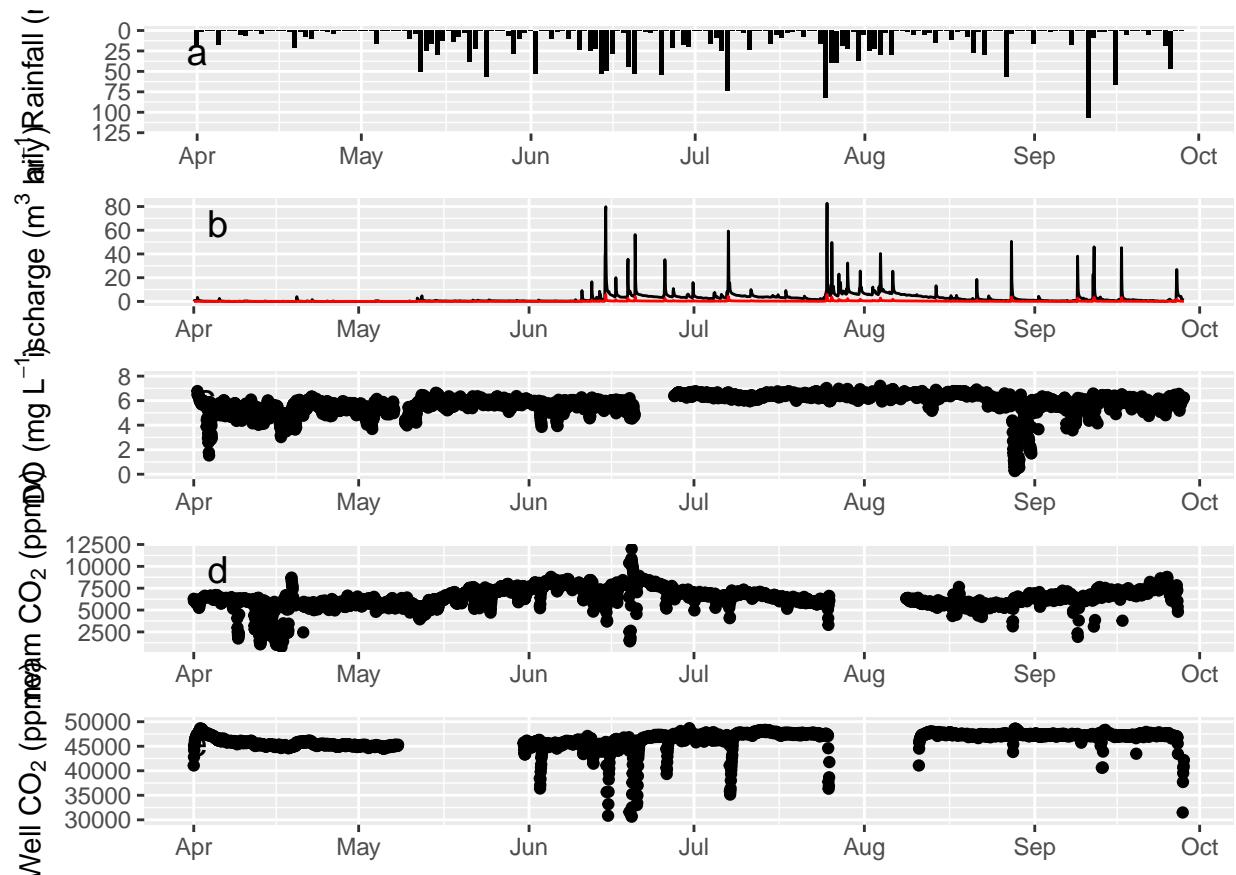


Figure 3- Stream and Well CO2

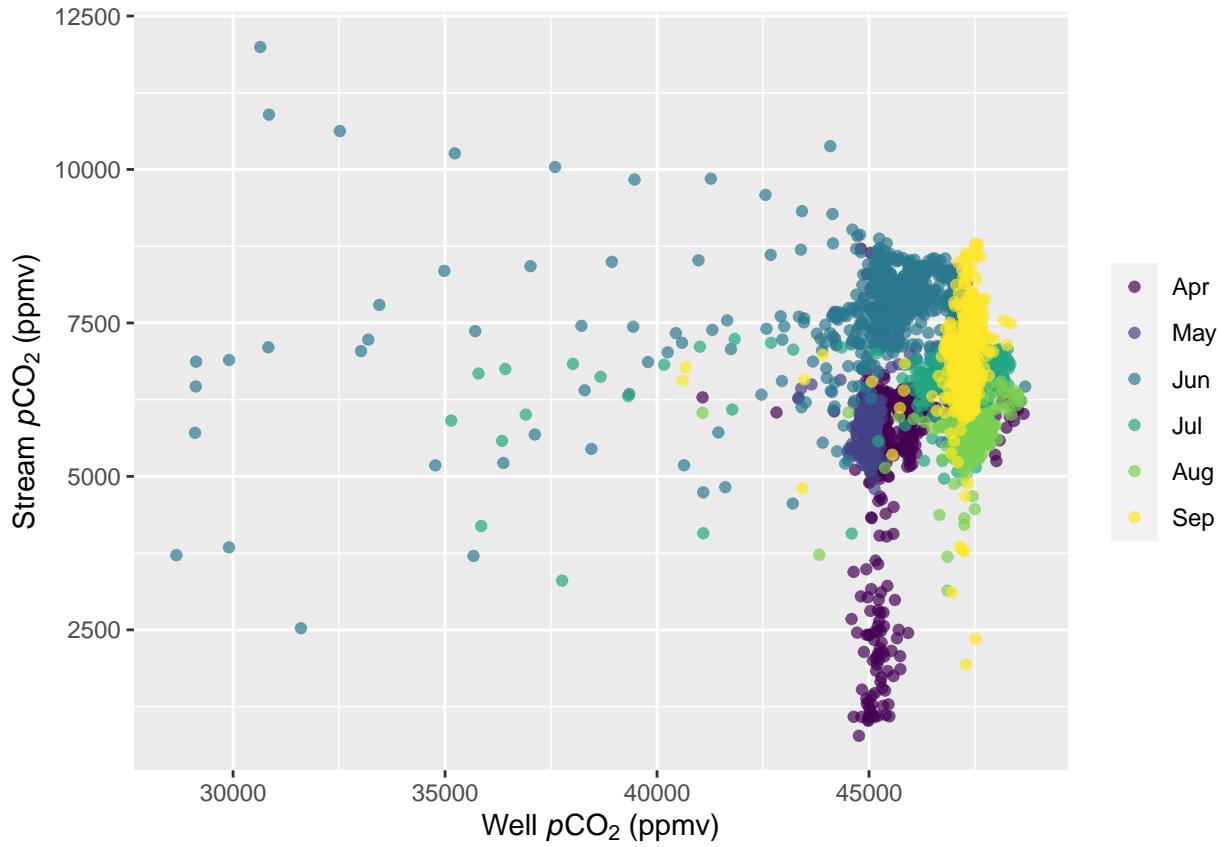
```

Fig3 <- ggplot(Tac_all,
  aes(x = wellCO2,
      y = CO2_ppm,
      color = month(Timestamp, abbr = TRUE, label = TRUE)))+
  geom_point(alpha = 0.7)+  

  scale_color_viridis_d(name = element_blank())+
  labs(y = expression(paste('Stream ', italic(p), CO[2], ' (ppmv)')),
       x = expression(paste('Well ', italic(p), CO[2], ' (ppmv)')))

Fig3

```



**Figure 4- Departure**

Here, we plot CO<sub>2</sub> and O<sub>2</sub> in respect to their atmospheric saturation concentrations. We calculate saturation concentrations for O<sub>2</sub> using a barometric pressure model (Hall and Hotchkiss 2017) and for CO<sub>2</sub> assuming atmospheric CO<sub>2</sub> of 400 ppm. We then explore the mean departure coordinates for the entire data collection period and for each month. The coordinates and slope inform processes that simultaneously control O<sub>2</sub>[2] and CO<sub>2</sub>[2] in the stream.

```
Tac_departure <- Tac_all %>%
  mutate(
    # temperature-corrected Henry's Law constant (Plummer and Busenberg 1982)
    kH = 29.41*exp(-2400*(1/(273 + temp.water) - (1/298))),

    # in-stream CO2-aq calculations
    CO2_aq = ((CO2_ppm/1e6)/kH)*1000,           # aqueous CO2: mol CO2 m-3
    CO2_sat = ((400/1e6)/kH)*1000,

    ts = log((298.15 - temp.water)/(298.15 + temp.water)),   # function as part of O2 saturation, Hall
    u = 10^(8.10765 - (1750.3/(235 + temp.water))),        # function as part of O2 saturation

    Osat = exp(2.00907 +
      (3.22014*ts) +
      (4.0501*ts^2) +
      (4.94457*ts^3) -
      (0.256847*ts^4) +
      (0.000118*ts^5) +
      (0.000001*ts^6))
  )
```

```

        (3.88767*ts^5)) *
((bp_mmHg - u)/(760 - u))*1.42905,
CO2_dep = (CO2_aq - CO2_sat)*1000,    # umol/L
O2_dep = ((DO.obs - Osat)/32)*1000    # umol/L

Tac_dep_clean <- na.omit(Tac_departure)

Tac_dep_clean$month = lubridate::month(Tac_dep_clean$Timestamp,
                                         abbr = TRUE, label = TRUE)

# calculate mean and sd
Tac_mu <- c(mean(Tac_dep_clean$CO2_dep, na.rm = TRUE),
            mean(Tac_dep_clean$O2_dep, na.rm = TRUE))
Tac_sd <- c(sd(Tac_dep_clean$CO2_dep, na.rm = TRUE),
            sd(Tac_dep_clean$O2_dep, na.rm = TRUE))
# correlation and covariance matrix
Tac_corMat <- cor(cbind(Tac_dep_clean$CO2_dep,
                         Tac_dep_clean$O2_dep))
Tac_covMat <- cov(cbind(Tac_dep_clean$CO2_dep,
                         Tac_dep_clean$O2_dep))
# eigen values
Tac_evals <- eigen(Tac_covMat)$values
Tac_ell_length <- 2*sqrt(5.991*Tac_evals)

# run linear model
Tac_reg <- lmodel2(data = Tac_dep_clean,
                     O2_dep ~ CO2_dep,
                     nperm = 99)

```

## RMA was not requested: it will not be computed.

```

# extract values from regression
Tac_inter = Tac_reg$regression.results[2,2]
Tac_slope = Tac_reg$regression.results[2,3]
Tac_correlation = Tac_reg$r

# create new data frame
Tac_metrics <- data.frame(meanCO2dep = Tac_mu[1],
                           meanO2dep = Tac_mu[2],
                           offset = Tac_mu[1] + Tac_mu[2],
                           EQ = 1/abs(Tac_slope),
                           width = Tac_ell_length[2],
                           stretch = Tac_ell_length[1])
Tac_metrics

```

```

##   meanCO2dep meanO2dep      offset      EQ      width  stretch
## 1   203.8241 -32.04432 171.7798 9.461728 128.9109 188.8561

```

```

# plot- all data points with 95% CI ellipsis
Fig4 <- ggplot(data = Tac_departure,

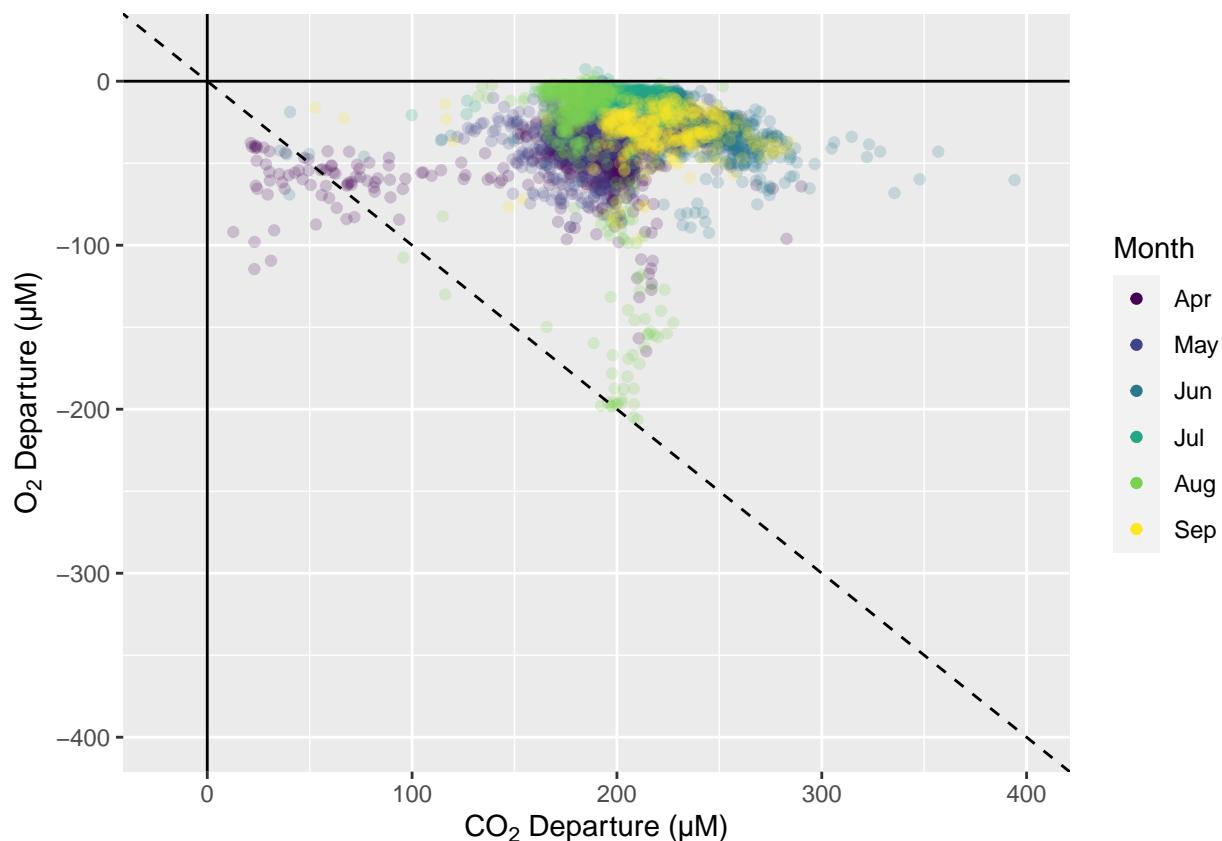
```

```

aes(x = CO2_dep,
    y = O2_dep,
    color = factor(month(Timestamp)))+
geom_point(alpha = 0.2)+
geom_hline(yintercept = 0)+
geom_vline(xintercept = 0)+
geom_abline(intercept = 0, slope = -1, linetype = 2)+
xlim(-20, 400)+
ylim(-400, 20)+
xlab(expression(paste(CO[2], " Departure (\u00b5M)")))+
ylab(expression(paste(O[2], " Departure (\u00b5M)")))+
guides(colour = guide_legend(override.aes = list(alpha = 1)))+
scale_color_viridis_d(name = "Month",
    labels = c("Apr", "May", "Jun", "Jul", "Aug", "Sep"))

```

Fig4



```

# summary for each month of the data
Tac_summary_mon <- Tac_dep_clean %>%
  group_by(month(Timestamp, label = TRUE, abbr = TRUE)) %>%
  dplyr::summarise(meanCO2_dep = mean(CO2_dep, na.rm = TRUE),
    meanO2_dep = mean(O2_dep, na.rm = TRUE),
    sdCO2_dep = sd(CO2_dep, na.rm = TRUE),
    sdO2_dep = sd(O2_dep, na.rm = TRUE),
    corMat = cor(cbind(CO2_dep, O2_dep)),
    covMat = cor(cbind(CO2_dep, O2_dep))) %>%

```

```

dplyr::mutate(offset = meanC02_dep + meanO2_dep,
              evals_1 = eigen(covMat)$values[1],
              evals_2 = eigen(covMat)$values[2],
              ell_length_1 = 2*sqrt(5.991*evals_1),
              ell_length_2 = 2*sqrt(5.991*evals_2)) %>%
dplyr::rename(month = `month(Timestamp, label = TRUE, abbr = TRUE)` %>%
group_by(month) %%%
filter(row_number() %% 2==0)

## 'summarise()' has grouped output by 'month(Timestamp, label = TRUE, abbr = ## TRUE)'. You can override using the '.groups' argument.

Tac_model_metrics <- Tac_dep_clean %>%
  select(Timestamp, C02_dep, O2_dep) %>%
  dplyr::mutate(month = factor(month(Timestamp, abbr= TRUE, label = TRUE))) %>%
  nest(-month) %>%
  mutate(model = map(data,
                     ~lmodel2(O2_dep ~ C02_dep, nperm = 99,
                               data = .)),
         tidy = map(model,
                    broom::tidy),
         glance = map(model,
                    broom::glance)) %>%
  unnest(tidy, glance) %>%
  select(month, method, term, estimate, r.squared) %>%
  mutate(r = -sqrt(r.squared)) %>%
  filter(method == 'OLS') %>%
  spread(term,
         estimate)

## RMA was not requested: it will not be computed.
##
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## RMA was not requested: it will not be computed.
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## RMA was not requested: it will not be computed.
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## RMA was not requested: it will not be computed.

```

```

Tac_metrics_mon <- data.frame(month = Tac_summary_mon$month,
                                meanC02_dep = Tac_summary_mon$meanC02_dep,
                                meanO2_dep = Tac_summary_mon$meanO2_dep,
                                sdC02_dep = Tac_summary_mon$sdC02_dep,
                                sdO2_dep = Tac_summary_mon$sdO2_dep,
                                cor = Tac_summary_mon$corMat[,1],
                                offset = Tac_summary_mon$offset,
                                slope = 1/abs(Tac_model_metrics$Slope),
                                width = Tac_summary_mon$ell_length_2,
                                stretch = Tac_summary_mon$ell_length_1)

```

## Figure 5- Hydrograph Separation

```

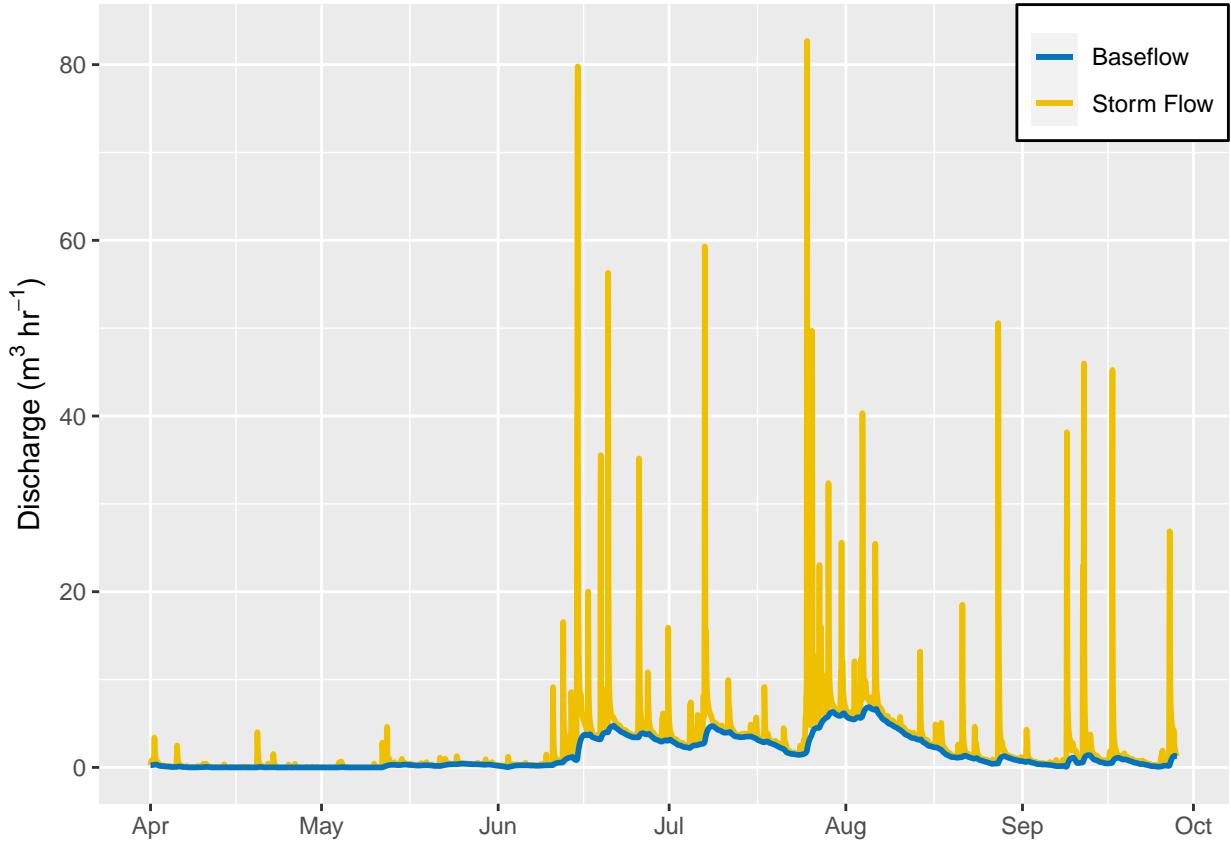
# baseflow separation approach
# see Fig S3 for the determination of alpha

# use alpha = 0.96
Tac_baseflow <- baseflows(Tac_all %>%
    select(Date = Timestamp,
           Q = sumQ_m3_hr),
    a = 0.96,
    n.reflected = 30,
    ts = 'daily') %>%
  mutate(bfi = bf/Q,
         stormflow = Q - bf,
         source = ifelse(bfi > 0.5,
                         'Baseflow',
                         'Storm Flow'),
         month = month(Date, label = TRUE, abbr = TRUE)) %>%
  rename(Timestamp = Date)
# bfi = fraction of baseflow calculated; bfi = 1 means all baseflow, 0 = all stormflow

# plot- baseflow on top of stream discharge
Fig5a <- ggplot(Tac_baseflow)+ 
  geom_line(aes(x = Timestamp,
                 y = Q,
                 color = 'Storm Flow'),
             size = 1)+ 
  geom_line(aes(x = Timestamp,
                 y = bf,
                 color = 'Baseflow'),
             size = 1)+ 
  scale_color_jco()+
  ylab(expression(paste('Discharge (', m^3, ' ', hr^-1, ')')))+
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b")+
  theme(axis.title.x = element_blank(),
        legend.position = c(1, 1),
        legend.justification = c(1, 1),
        legend.background = element_rect(color = 'black'),
        legend.title = element_blank())

```

Fig5a



```

# join hydrograph separation with pCO2 data
Tac_baseflow_hyst <- left_join(
  Tac_baseflow,
  Tac_all %>%
    select(Timestamp, CO2_ppm, sumQ_m3_hr, GW_Q))

## Joining, by = "Timestamp"

shapiro.test(Tac_baseflow_hyst$CO2_ppm)

##
## Shapiro-Wilk normality test
##
## data: Tac_baseflow_hyst$CO2_ppm
## W = 0.91907, p-value < 2.2e-16

pco2_source_art <- art(data = Tac_baseflow_hyst %>%
  dplyr::mutate(source_f = factor(source)) %>%
  dplyr::select(month, source_f, CO2_ppm) %>%
  tidyr::drop_na(),
  CO2_ppm ~ month * source_f)

anova(pco2_source_art)

```

```

## Analysis of Variance of Aligned Rank Transformed Data
##
## Table Type: Anova Table (Type III tests)
## Model: No Repeated Measures (lm)
## Response: art(CO2_ppm)
##
##          Df Df.res F value    Pr(>F)
## 1 month      5   3717 478.189 < 2.22e-16 ***
## 2 source_f     1   3717 660.905 < 2.22e-16 ***
## 3 month:source_f 5   3717  41.348 < 2.22e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

art.con(pco2_source_art,
        'source_f')

## NOTE: Results may be misleading due to involvement in interactions

## contrast           estimate    SE   df t.ratio p.value
## Baseflow - Storm Flow    1146 44.6 3717  25.708 <.0001
##
## Results are averaged over the levels of: month

art.con(pco2_source_art,
        'month',
        method = "pairwise")

## NOTE: Results may be misleading due to involvement in interactions

## contrast   estimate    SE   df t.ratio p.value
## Apr - May   -816.4 46.0 3717 -17.767 <.0001
## Apr - Jun   -2178.7 50.5 3717 -43.125 <.0001
## Apr - Jul   -1086.8 63.2 3717 -17.196 <.0001
## Apr - Aug     -71.4 68.1 3717 -1.048 0.9017
## Apr - Sep   -1536.3 53.8 3717 -28.567 <.0001
## May - Jun   -1362.3 44.3 3717 -30.774 <.0001
## May - Jul    -270.4 58.3 3717 -4.636 0.0001
## May - Aug     745.1 63.6 3717 11.709 <.0001
## May - Sep   -719.9 48.0 3717 -15.012 <.0001
## Jun - Jul   1091.9 62.0 3717 17.616 <.0001
## Jun - Aug   2107.4 67.0 3717 31.452 <.0001
## Jun - Sep   642.5 52.3 3717 12.273 <.0001
## Jul - Aug   1015.4 77.0 3717 13.185 <.0001
## Jul - Sep   -449.5 64.7 3717 -6.950 <.0001
## Aug - Sep  -1464.9 69.5 3717 -21.080 <.0001
##
## Results are averaged over the levels of: source_f
## P value adjustment: tukey method for comparing a family of 6 estimates

contrast(emmeans(arlml(pco2_source_art, 'month:source_f'),
                     ~ month:source_f),
         method = 'pairwise', interaction = TRUE)

```

```

## month_pairwise source_f_pairwise      estimate   SE   df t.ratio p.value
## Apr - May     Baseflow - Storm Flow    -784 119 3717  -6.611 <.0001
## Apr - Jun     Baseflow - Storm Flow     240 130 3717   1.838 0.0661
## Apr - Jul     Baseflow - Storm Flow     396 163 3717   2.430 0.0151
## Apr - Aug     Baseflow - Storm Flow     576 176 3717   3.277 0.0011
## Apr - Sep     Baseflow - Storm Flow     744 139 3717   5.361 <.0001
## May - Jun     Baseflow - Storm Flow    1024 114 3717   8.960 <.0001
## May - Jul     Baseflow - Storm Flow    1181 151 3717   7.842 <.0001
## May - Aug     Baseflow - Storm Flow    1360 164 3717   8.283 <.0001
## May - Sep     Baseflow - Storm Flow    1528 124 3717  12.348 <.0001
## Jun - Jul     Baseflow - Storm Flow     157 160 3717   0.980 0.3273
## Jun - Aug     Baseflow - Storm Flow     337 173 3717   1.946 0.0517
## Jun - Sep     Baseflow - Storm Flow     505 135 3717   3.734 0.0002
## Jul - Aug     Baseflow - Storm Flow     180 199 3717   0.904 0.3658
## Jul - Sep     Baseflow - Storm Flow     348 167 3717   2.083 0.0373
## Aug - Sep     Baseflow - Storm Flow     168 179 3717   0.936 0.3492

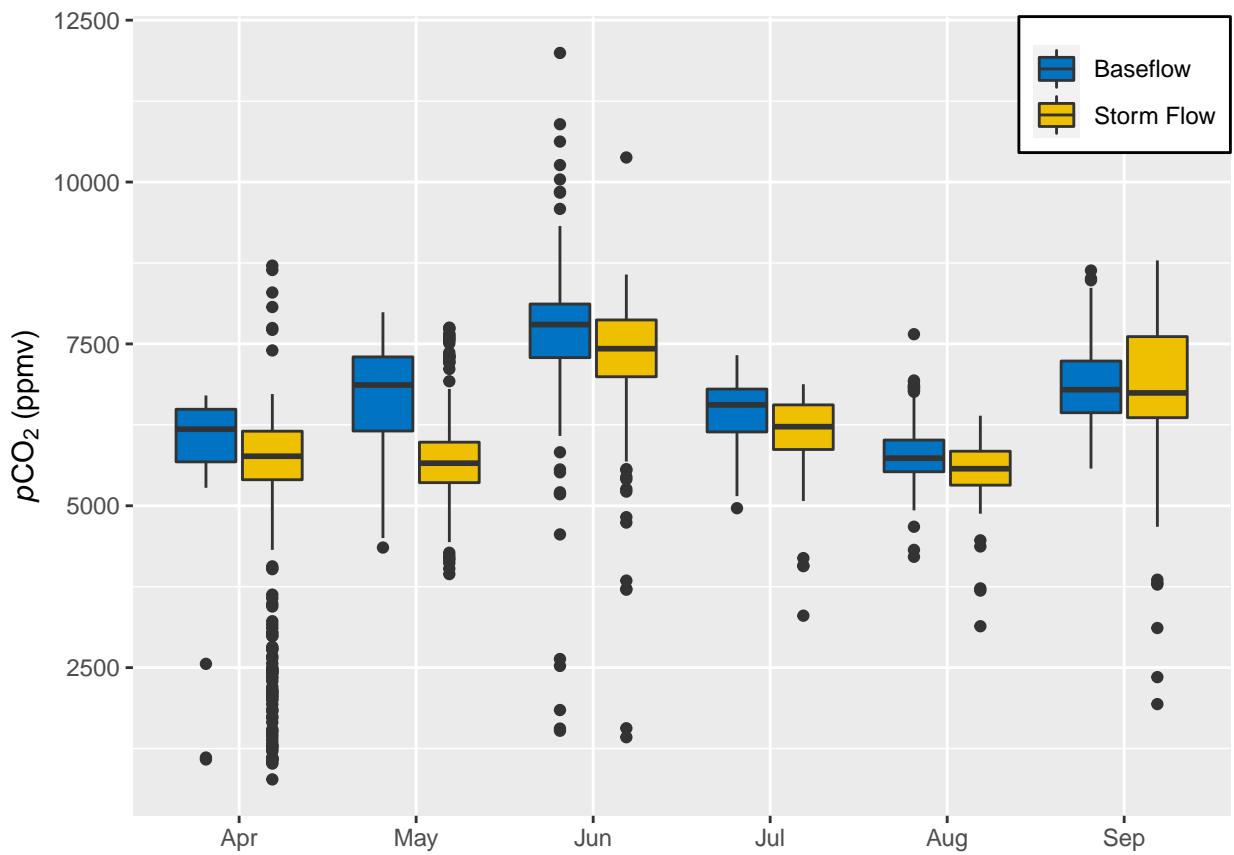
```

```

# plot CO2 vs stormflow
Fig5b <- ggplot(Tac_baseflow_hyst,
                 aes(x = month,
                     y = CO2_ppm,
                     fill = source)) +
  geom_boxplot() +
  ylab(expression(paste(italic(p), CO[2], ' (ppmv)'))) +
  scale_fill_jco() +
  theme(axis.title.x = element_blank(),
        legend.position = c(1, 1),
        legend.justification = c(1, 1),
        legend.background = element_rect(color = 'black'),
        legend.title = element_blank())

```

Fig5b



```
# combine plots
Fig5 <- plot_grid(Fig5a, Fig5b,
                    align = 'v', nrow = 2,
                    labels = 'auto', label_fontface = 'plain',
                    hjust = -10)
Fig5
```

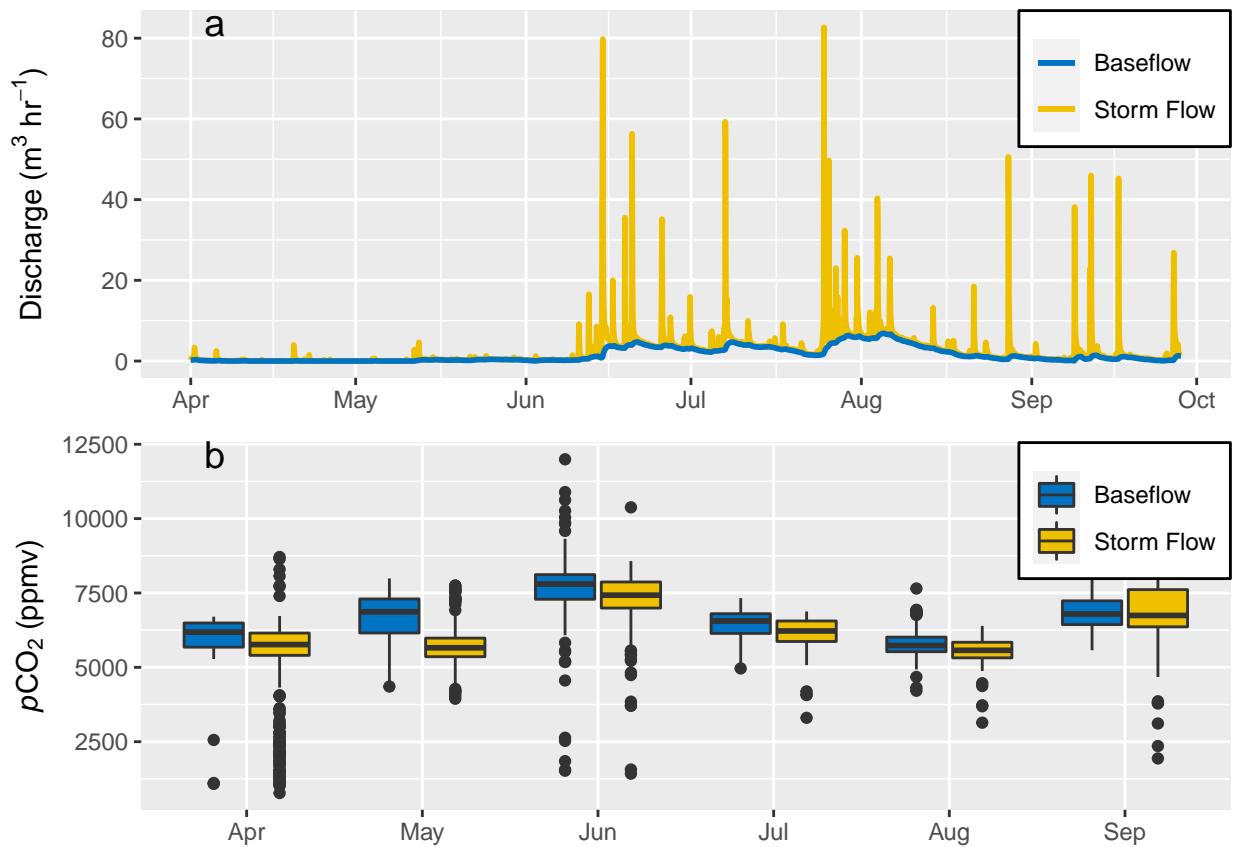


Figure 6- Areal Fluxes

```

Tac_length = 1587.4          # total length of the main-stem Taconazo
Tac_reach = 75               # m
Tac_width_upper_dry = 1.4    # m
Tac_width_upper_wet = 1.8    # m
Tac_width_lower_dry = 1.5    # m
Tac_width_lower_wet = 2.8    # m
Tac_slope = 0.0024           # m/m

# calculate mean temperature
temp_mean = mean(Tac_all$temp.water,
                  na.rm = TRUE)

# estimate Schmidt numbers
Sc_prop = 3545.60 - (203.41*temp_mean) + (4.78*(temp_mean^2)) - (0.0404*(temp_mean^3))
Sc_CO2 = 1686.08 - (89.66*temp_mean) + (2.07*(temp_mean^2)) - (0.018*(temp_mean^3))
Sc_O2 = 1568 - (86.04*temp_mean) + (2.142*(temp_mean^2)) - (0.0216*(temp_mean^3))

K_prop_wet = 10.2      # gas exchange coefficient for wet season propane (d^-1); 95% CI = 4.2
K_prop_dry = 27.2       # gas exchange coefficient for dry season propane (d^-1); 95% CI = 3.6

K_CO2_dry = K_prop_dry*(Sc_prop/Sc_CO2)^-0.5 # dry season gas exchange coefficient for CO2, d^-1
K_CO2_wet = K_prop_wet*(Sc_prop/Sc_CO2)^-0.5 # wet gas exchange coefficient for CO2, d^-1

```

```

# Convert to units for O2
K_O2_dry = K_prop_dry*(Sc_prop/Sc_O2)^-0.5 # gas exchange coefficient for O2, d^-1
K_O2_wet = K_prop_wet*(Sc_prop/Sc_O2)^-0.5 # gas exchange coefficient for O2, d^-1

Tac_gas_flux <- Tac_all %>%
  # get the necessary data
  select(Timestamp,
         temp.water,
         CO2_ppm,
         DO.obs, bp_mmHg,
         sumQ_m3_hr,
         mean_depth) %>%
  mutate(
    mean_depth = mean_depth*0.7,

    # Henry's Law constant based on temperature correction (Plummer and Busenberg 1982)
    kH = 29.41*exp(-2400*(1/(273 + temp.water) - (1/298))),
    # calculate aqueous CO2 and CO2-sat (mol CO2 m-3)
    CO2_aq = ((CO2_ppm/1e6)/kH)*1000,
    CO2_sat = ((400/1e6)/kH)*1000,
    # calculate CO2 efflux (mol CO2 m-2 h-1)
    CO2_efflux = ifelse(month(Timestamp) == '4',
                          (CO2_aq - CO2_sat)*(K_O2_dry/24)*mean_depth,
                          (CO2_aq - CO2_sat)*(K_O2_wet/24)*mean_depth
    ),
    # calculate NEP
    ts = log((298.15 - temp.water)/(298.15 + temp.water)),      # function as part of O2 saturation
    u = 10^(8.10765 - (1750.3/(235 + temp.water))),           # function as part of O2 saturation

    # calculate O2 saturation
    Osat = exp(2.00907 +
               (3.22014*ts) +
               (4.0501*ts^2) +
               (4.94457*ts^3) -
               (0.256847*ts^4) +
               (3.88767*ts^5)) *
               ((bp_mmHg - u)/(760 - u))*1.42905,
    # hourly NEP (mol C m-2 h-1)
    direct_met_mol = ifelse(month(Timestamp) == '4',
                           (diff(DO.obs) - ((K_O2_dry/24)*(Osat - DO.obs))*(1/32))*-1*mean_depth,
                           (diff(DO.obs) - ((K_O2_wet/24)*(Osat - DO.obs)) * (1/32))*-1*mean_depth
    )
  )

Tac_GWC02 <- Tac_all %>%
  select(Timestamp,
         pH,
         temp.water, wellCO2,
         sumQ_m3_hr) %>%
  left_join(Tac_baseflow_hyst) %>%

```

```

mutate(
  # temperature-corrected Henry's Law constant (Plummer and Busenberg 1982)
  kH = 29.41*exp(-2400*(1/(273 + temp.water) - (1/298))),

  # CO2-well
  wellCO2_aq = ((wellCO2/1e6)/kH)*1000, # well aqueous CO2: mol CO2 m-3

  # Groundwater discharge (m3 h-1)
  GW_Q = ifelse(month(Timestamp) == 'April',      # calculate total groundwater discharge (m3/h)
                (0.1779*sumQ_m3_hr),          # 17.79% of stream Q in dry season (April); m3/h
                (0.0715*sumQ_m3_hr)),         # 7.15% of stream Q in wet season; m3/h

  # groundwater velocity (m h-1); divide GW discharge by reach area (length * width)
  GW_v = ifelse(month(Timestamp) == 'April',
                GW_Q/(Tac_reach * Tac_width_lower_dry),
                GW_Q/(Tac_reach * Tac_width_lower_wet))
  ),

  # GWC02 flux (mol CO2 m-2 h-1)
  GWC02 = GW_v * wellCO2_aq
)

## Joining, by = c("Timestamp", "sumQ_m3_hr")

# aggregate to the daily time-step

Tac_fluxes <- left_join(Tac_gas_flux,
                         Tac_GWC02,
                         by = 'Timestamp') %>%
  select(Timestamp, GWC02, CO2_efflux, direct_met_mol) %>%
  group_by(day = date(Timestamp)) %>%
  summarise(dayGW = sum(GWC02, na.rm = TRUE),
            dayF = sum(CO2_efflux, na.rm = TRUE),
            dayNEP = sum(direct_met_mol, na.rm = TRUE)) %>%
  filter(dayNEP < 1.5,
         dayGW > 0,
         dayF > 0)

Tac_fluxes %>%
  group_by(month(day)) %>%
  summarise(F_med = median(dayF),
            F_sd = sd(dayF),
            GW_med = median(dayGW),
            GW_sd = sd(dayGW),
            NEP_med = median(dayNEP),
            NEP_sd = sd(dayNEP))

## # A tibble: 6 x 7
##   `month(day)`  F_med    F_sd    GW_med    GW_sd NEP_med NEP_sd
##   <dbl>     <dbl>    <dbl>     <dbl>    <dbl>    <dbl>    <dbl>
## 1           4  0.381  0.173  0.000876  0.00251  0.128  0.114
## 2           5  0.0931 0.0592  0.0000701 0.00189  0.0311 0.0329

```

```

## 3      6 0.155  0.0598 0.0214    0.0371  0.0281 0.277
## 4      7 0.220  0.0365 0.0493    0.0352  0.0150 0.0498
## 5      8 0.159  0.0330 0.0235    0.0199  0.0121 0.196
## 6      9 0.0672 0.0433 0.00736   0.00701 0.0241 0.0759

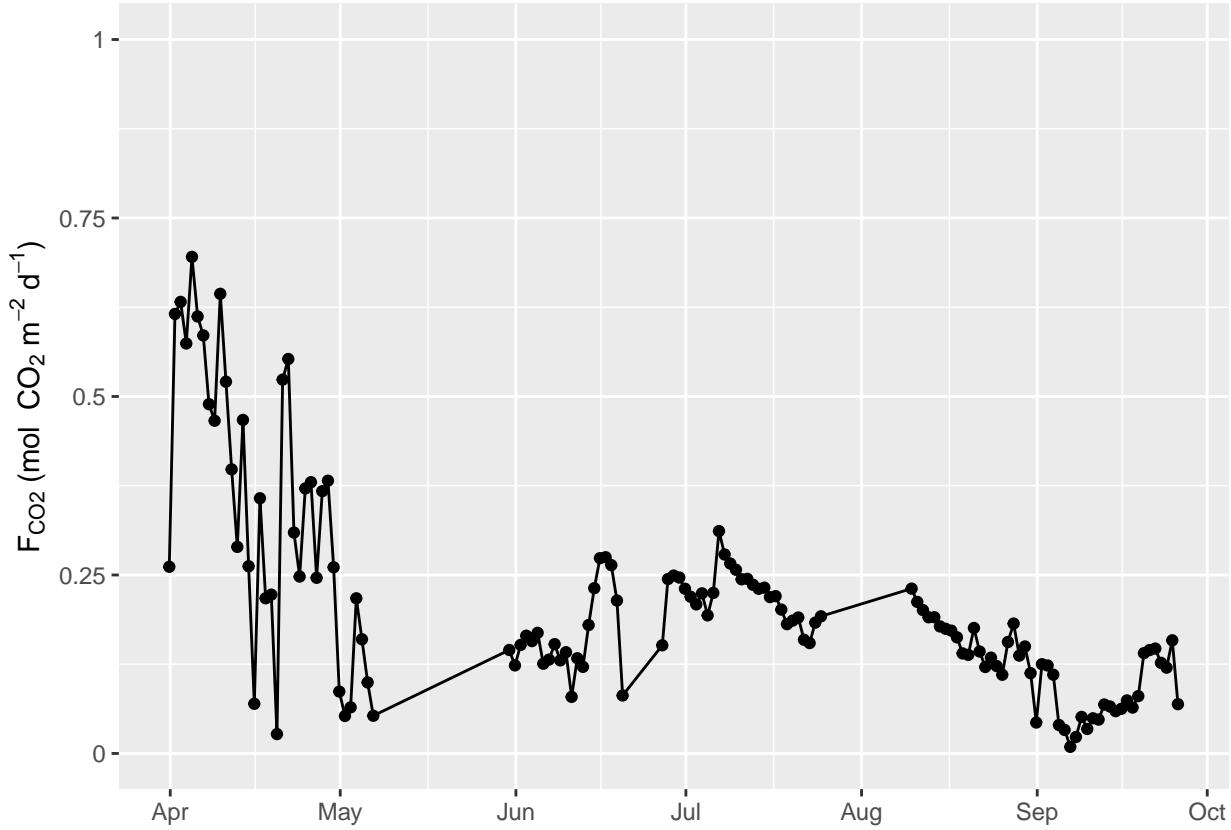
```

```

Fig6_F <- ggplot(Tac_fluxes %>%
                     filter(dayF > 0),
                     aes(x = as.POSIXct(day), y = dayF)) +
  geom_point() +
  geom_line() +
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b") +
  scale_y_continuous(breaks = c(0, 0.25, 0.5, 0.75, 1),
                     labels = c(0, 0.25, 0.5, 0.75, 1),
                     limits = c(0, 1)) +
  labs(x = element_blank(),
       y = expression(paste(F[CO2], ' (mol ', CO[2], ' ', m^-2, ' ', d^-1, ' )')))

Fig6_F

```



```

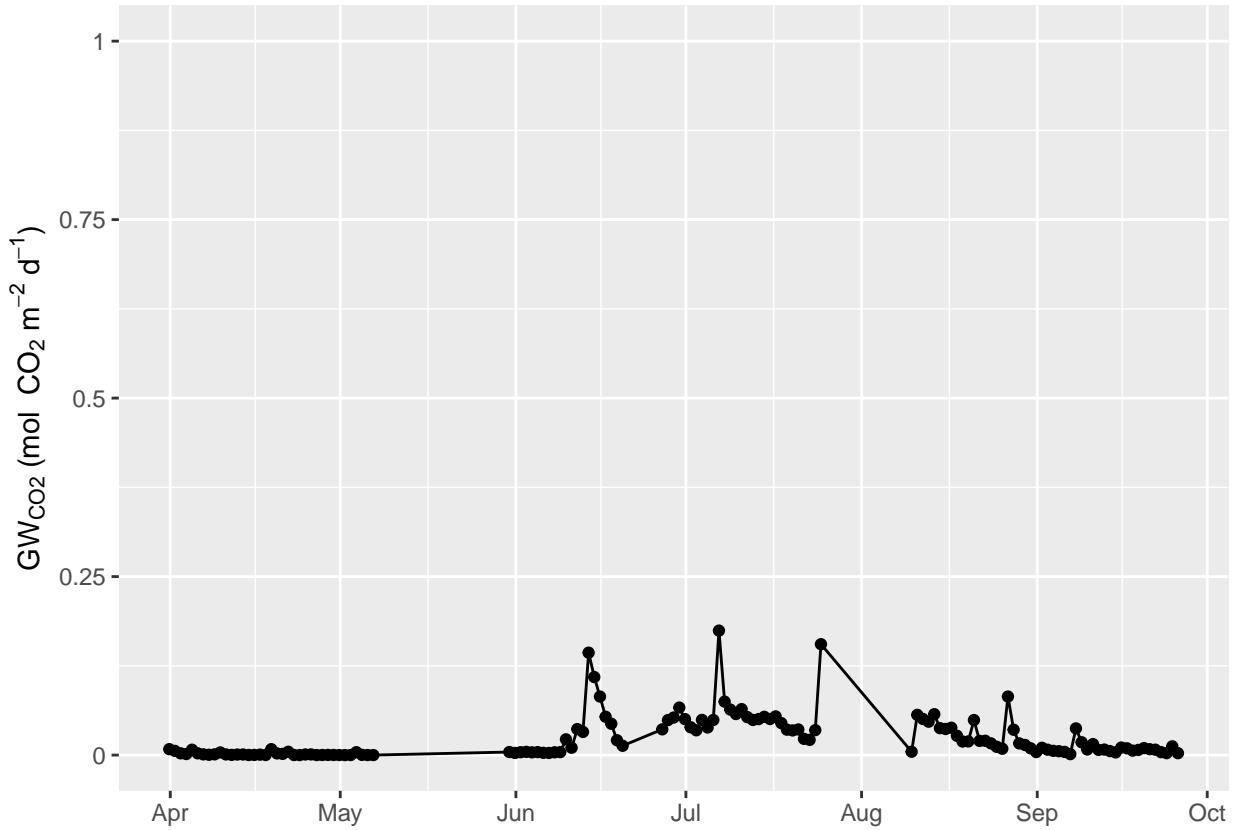
Fig6_GW <- ggplot(Tac_fluxes %>%
                     mutate(GWC02_mean = rowMeans(dplyr::select(., starts_with('dayGW')))),
                     aes(x = as.POSIXct(day))) +
  geom_point(aes(y = GWC02_mean)) +
  geom_line(aes(y = GWC02_mean))

```

```

))++
scale_x_datetime(date_breaks = "1 month",
                  date_labels = "%b")+
scale_y_continuous(breaks = c(0, 0.25, 0.5, 0.75, 1),
                  labels = c(0, 0.25, 0.5, 0.75, 1),
                  limits = c(0, 1))+
labs(x = element_blank(),
     y = expression(paste(GW[CO2], ' (mol ', CO[2], ' ', m^-2, ' ', d^-1, ' )'))))
Fig6_GW

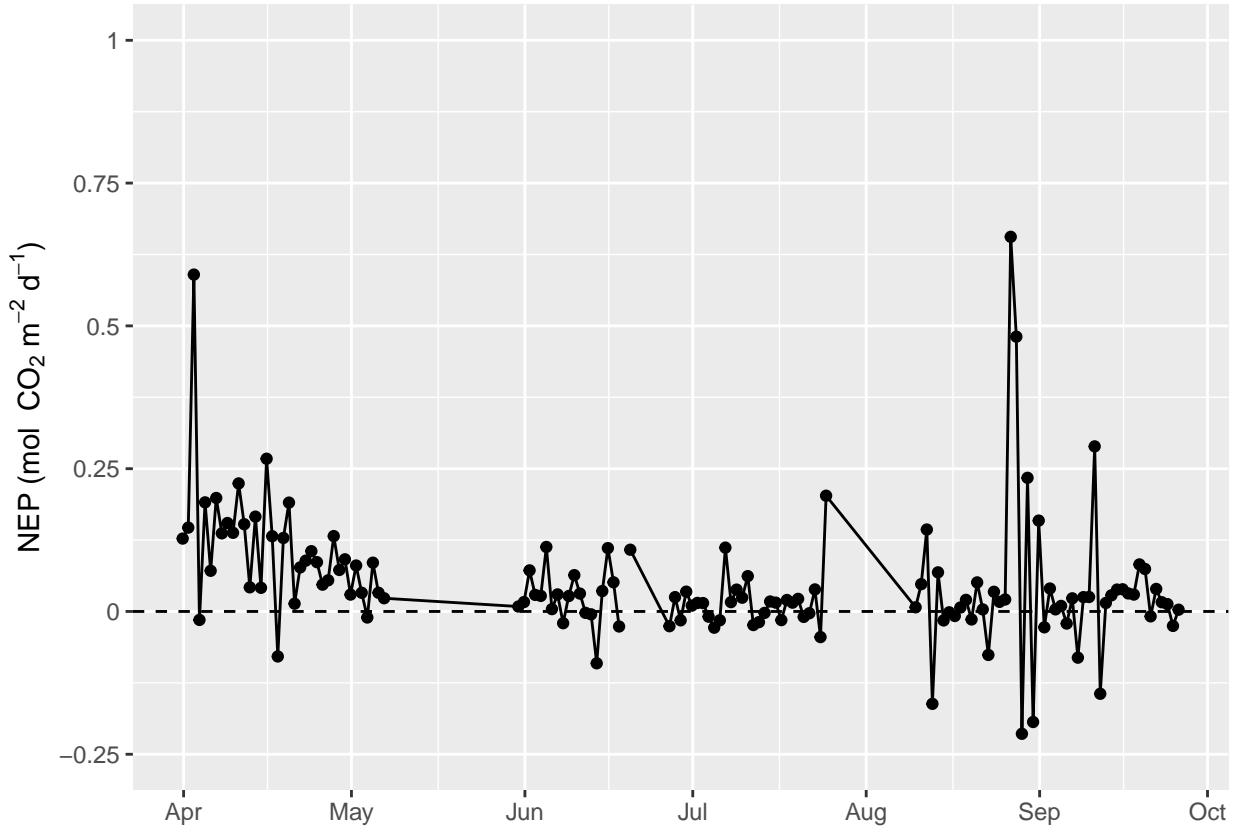
```



```

Fig6_NEP <- ggplot(Tac_fluxes %>%
                      filter(dayNEP < 1.5),
                      aes(x = as.POSIXct(day), y = dayNEP))+
  geom_point()+
  geom_line()+
  geom_hline(yintercept = 0, linetype = 'dashed')+
  scale_x_datetime(date_breaks = "1 month",
                  date_labels = "%b")+
  scale_y_continuous(breaks = c(-0.25, 0, 0.25, 0.5, 0.75, 1),
                  labels = c(-0.25, 0, 0.25, 0.5, 0.75, 1),
                  limits = c(-0.25, 1))+
  labs(x = element_blank(),
       y = expression(paste('NEP (mol ', CO[2], ' ', m^-2, ' ', d^-1, ' )'))))
Fig6_NEP

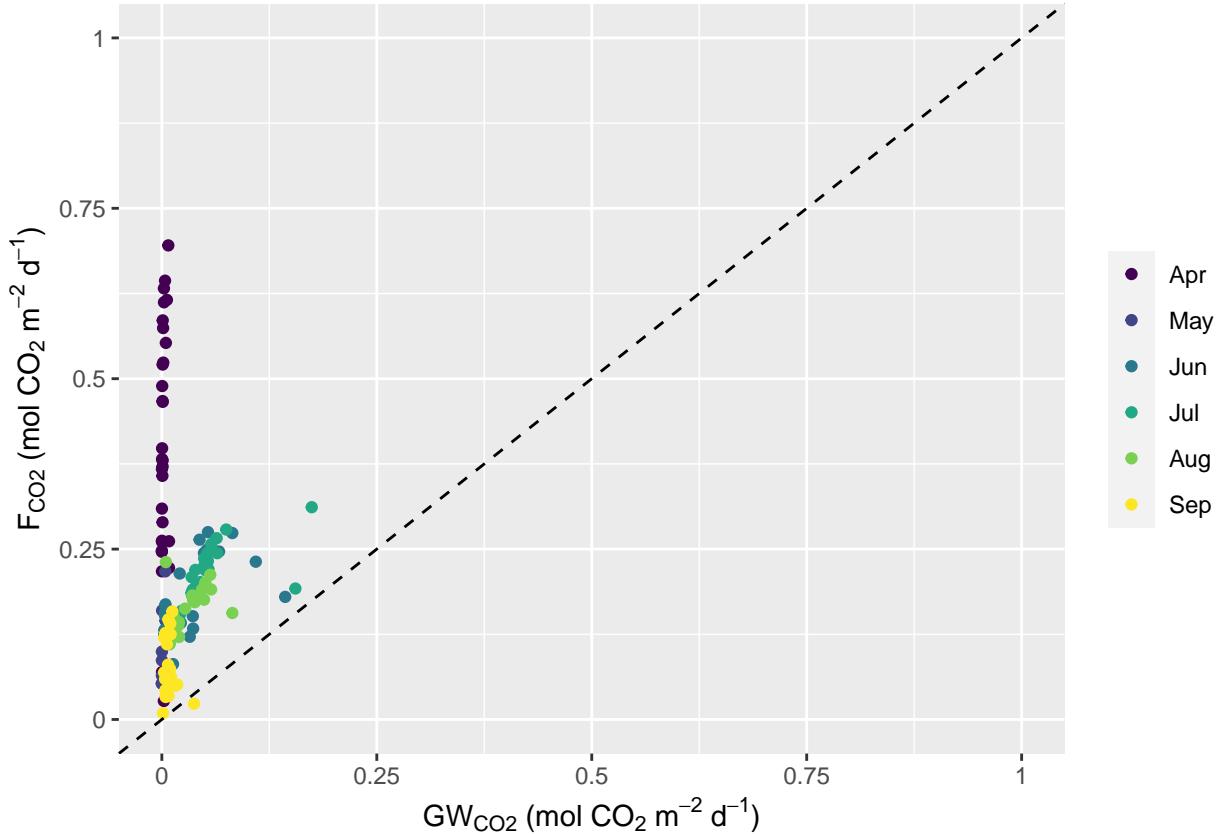
```



```
Fig6a <- plot_grid(Fig6_GW,
                     Fig6_NEP,
                     Fig6_F,
                     align = 'v', nrow = 3,
                     labels = 'auto', label_fontface = 'plain',
                     hjust = -9)
```

```
Fig6d <- ggplot(Tac_fluxes %>%
                    filter(dayGW > 0,
                          dayF > 0),
                    aes(x = dayGW,
                        y = dayF,
                        color = month(day, abbr = TRUE, label = TRUE)))+
  geom_point()+
  geom_abline(intercept = 0, slope = 1,
              linetype = 'dashed')+
  labs(x = expression(GW[CO2], ' (mol ', CO[2], ' ', m^-2, ' ', d^-1, ' )')),
       y = expression(F[CO2], ' (mol ', CO[2], ' ', m^-2, ' ', d^-1, ' )'))+
  scale_x_continuous(limits = c(0, 1),
                      breaks = c(0, 0.25, 0.5, 0.75, 1),
                      labels = c(0, 0.25, 0.5, 0.75, 1))+ 
  scale_y_continuous(limits = c(0, 1),
                      breaks = c(0, 0.25, 0.5, 0.75, 1),
                      labels = c(0, 0.25, 0.5, 0.75, 1))+ 
  scale_color_viridis_d(name = element_blank())
```

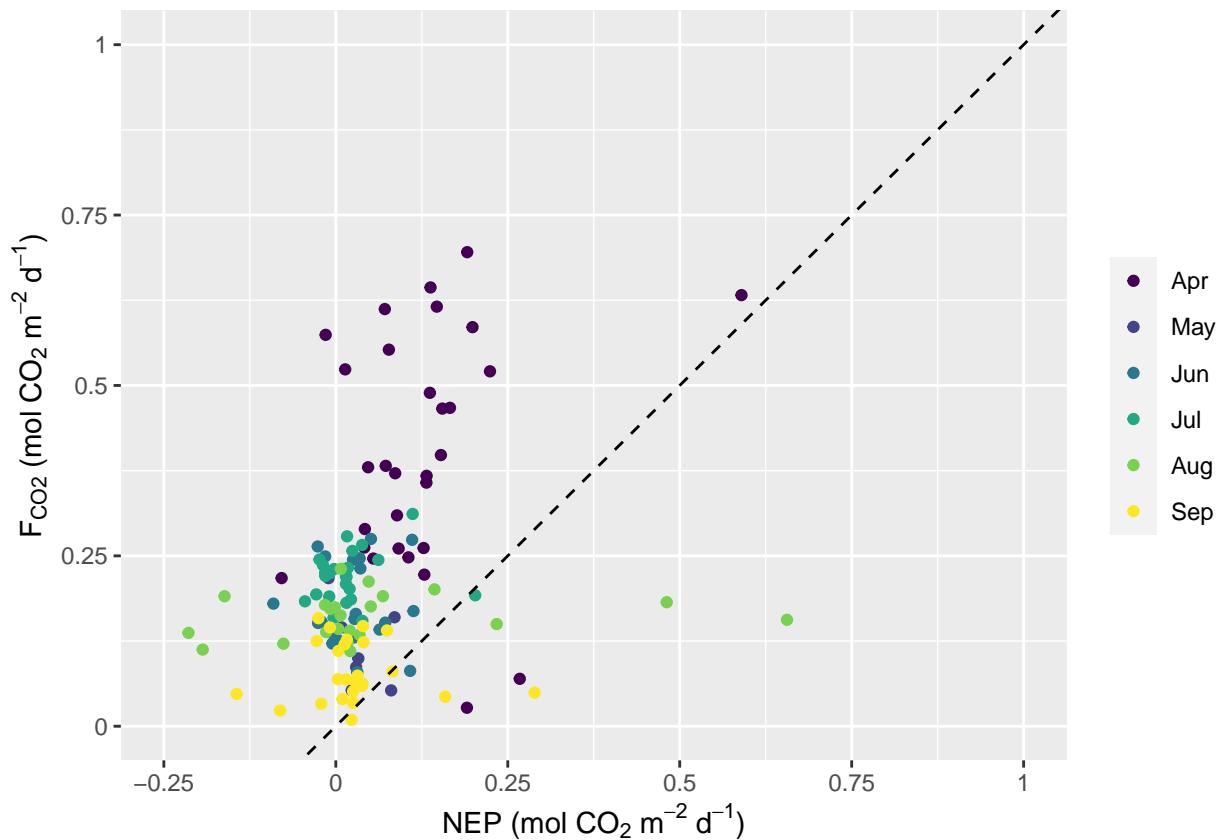
Fig6d



```
Fig6e <- ggplot(Tac_fluxes %>%
  filter(dayF > 0,
        dayNEP < 1.5),
  aes(x = dayNEP,
      y = dayF,
      color = month(day, abbr = TRUE, label = TRUE)))+
  geom_point()+
  geom_abline(intercept = 0, slope = 1,
              linetype = 'dashed')+
  labs(x = expression(paste('NEP (mol ', CO[2], ' ', m^-2, ' ', d^-1, ')')),
       y = expression(paste(F[CO2], ' (mol ', CO[2], ' ', m^-2, ' ', d^-1, ')'))+
  scale_color_viridis_d(name = element_blank())+
  scale_x_continuous(limits = c(-0.25, 1),
                     breaks = c(-0.25, 0, 0.25, 0.5, 0.75, 1),
                     labels = c(-0.25, 0, 0.25, 0.5, 0.75, 1))+
```

scale\_y\_continuous(limits = c(0, 1),
 breaks = c(0, 0.25, 0.5, 0.75, 1),
 labels = c(0, 0.25, 0.5, 0.75, 1))

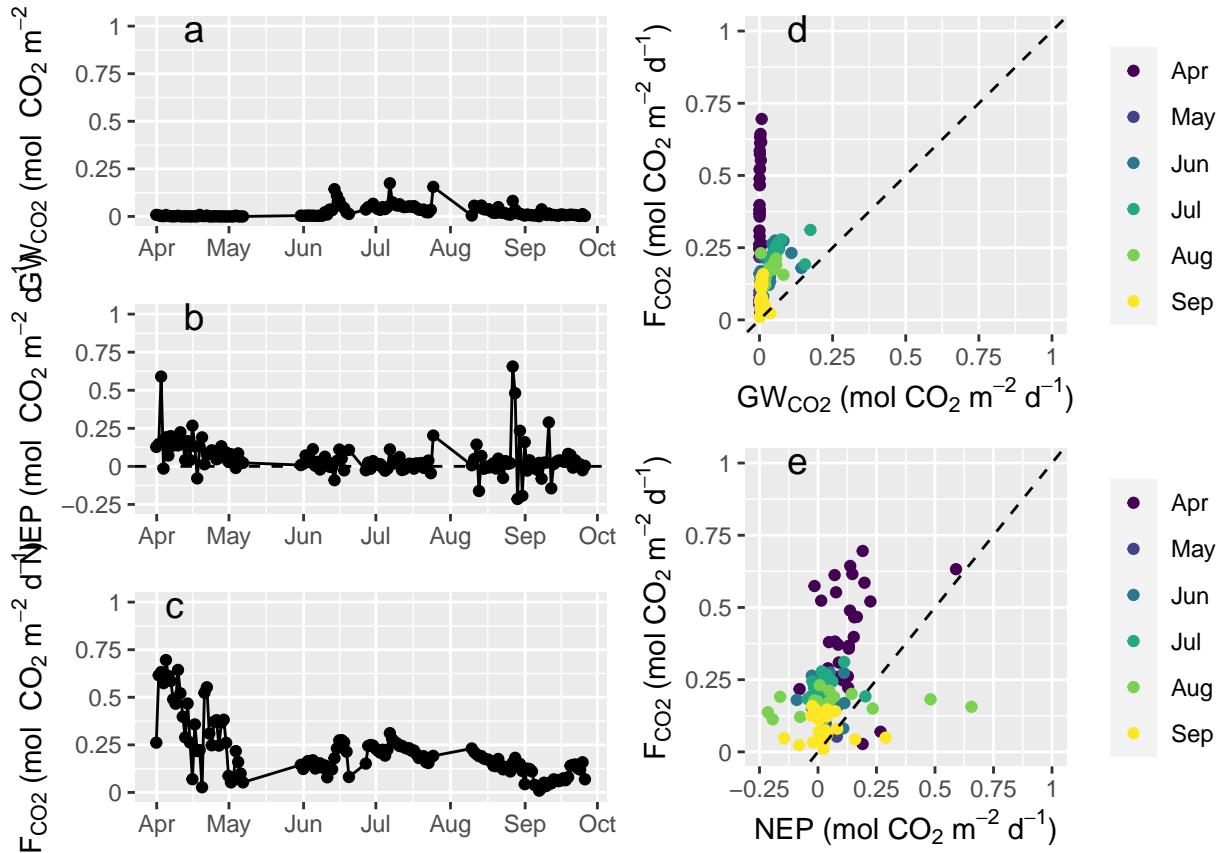
Fig6e



```
Fig6b <- plot_grid(Fig6d, Fig6e,
                     nrow = 2, align = 'v',
                     labels = c('d', 'e'), label_fontface = 'plain',
                     hjust = -8)
```

```
Fig6 <- plot_grid(Fig6a, Fig6b,
                   align = 'hv')
```

Fig6



```

summary(lm(
  data = Tac_fluxes,
  dayF ~ dayNEP
))

##
## Call:
## lm(formula = dayF ~ dayNEP, data = Tac_fluxes)
##
## Residuals:
##      Min       1Q   Median       3Q      Max 
## -0.26106 -0.07823 -0.02505  0.04274  0.45999 
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 0.19652    0.01301 15.103 < 2e-16 ***
## dayNEP      0.20449    0.07669  2.666  0.00862 ** 
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.141 on 133 degrees of freedom
## Multiple R-squared:  0.05074,    Adjusted R-squared:  0.04361 
## F-statistic:  7.11 on 1 and 133 DF,  p-value: 0.008619

```

```

summary(lm(
  data = Tac_fluxes,
  dayF ~ dayGW)
)

##
## Call:
## lm(formula = dayF ~ dayGW, data = Tac_fluxes)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -0.20111 -0.08685 -0.03017  0.03748  0.48557
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)  0.21048    0.01574 13.376 <2e-16 ***
## dayGW       -0.06226    0.41032 -0.152     0.88
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1447 on 133 degrees of freedom
## Multiple R-squared:  0.0001731, Adjusted R-squared:  -0.007344
## F-statistic: 0.02303 on 1 and 133 DF, p-value: 0.8796

Tac_fluxes %>%
  mutate(day_F_all = ifelse(month(day) == 'April',
                            dayF * 3008,                      # dry season mol CO2 per day
                            dayF * 5022)) %>%                  # wet season mol CO2 per day
  summarise(mean_F_all = mean(day_F_all),
            sd_F_all = sd(day_F_all))          # mean daily CO2 loss (mol CO2 per day)

## # A tibble: 1 x 2
##   mean_F_all sd_F_all
##       <dbl>    <dbl>
## 1      1050.     724.

Tac_gas_flux %>%
  mutate(C_export = sumQ_m3_hr * CO2_aq) %>%           # mol CO2 per hour
  group_by(day = date(Timestamp)) %>%                   # mol CO2 per day
  summarise(daily_export = sum(C_export)) %>%           # daily C export (mol C per day)
  summarise(mean_export = mean(daily_export, na.rm = TRUE),
            sd_export = sd(daily_export, na.rm = TRUE)) # mean daily export mol CO2 per day

## # A tibble: 1 x 2
##   mean_export sd_export
##       <dbl>    <dbl>
## 1        8.23     9.97

```

## Figure 7- GW on pH

Finally, we determine the effect of groundwater DIC inputs to the reach as drivers of pH decreases, both at seasonal and episodic scales.

```

Tac_GWC02_day <- Tac_GWC02 %>%
  group_by(day = date(Timestamp)) %>%
  summarise(meanpH = mean(pH, na.rm = TRUE),
            sd pH = sd(pH, na.rm = TRUE),
            dayGW = sum(GWC02, na.rm = TRUE))

# remove low pH outliers
outliers <- boxplot.stats(Tac_GWC02_day$meanpH)$out
# below 4.8 and above 5.91

Tac_GWC02_day <- Tac_GWC02_day[-which(Tac_GWC02_day$meanpH %in% outliers),]

summary(lm(data = Tac_GWC02_day %>%
  filter(dayGW > 0,
        meanpH > 4.75),
  meanpH ~ log10(dayGW)))
)

```

```

##
## Call:
## lm(formula = meanpH ~ log10(dayGW), data = Tac_GWC02_day %>%
##      filter(dayGW > 0, meanpH > 4.75))
##
## Residuals:
##    Min      1Q  Median      3Q     Max
## -0.55538 -0.07368  0.03558  0.08386  0.25283
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept) 5.18175   0.02831 183.044 < 2e-16 ***
## log10(dayGW) -0.07154   0.01231 -5.811 4.47e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.1242 on 131 degrees of freedom
## Multiple R-squared:  0.205, Adjusted R-squared:  0.1989
## F-statistic: 33.77 on 1 and 131 DF, p-value: 4.47e-08

```

```

Fig7 <- ggplot(Tac_GWC02_day %>%
  filter(dayGW > 0),
  aes(x = dayGW,
      y = meanpH))+
  geom_point(aes(color = month(day, label = TRUE, abbr = TRUE)))+
  geom_errorbar(aes(ymin = meanpH - sd pH,
                     ymax = meanpH + sd pH,
                     color = month(day, label = TRUE, abbr = TRUE)))+
  geom_abline(color = 'black',
              intercept = 5.20, slope = -0.06)+
  #ylim(3.8, 6)+
  scale_x_log10(breaks = trans_breaks("log10", function(x) 10^x),
                labels = trans_format("log10", math_format(10^.x)),
                #limits = c(1e-5, 10^(-0.5)))
)

```

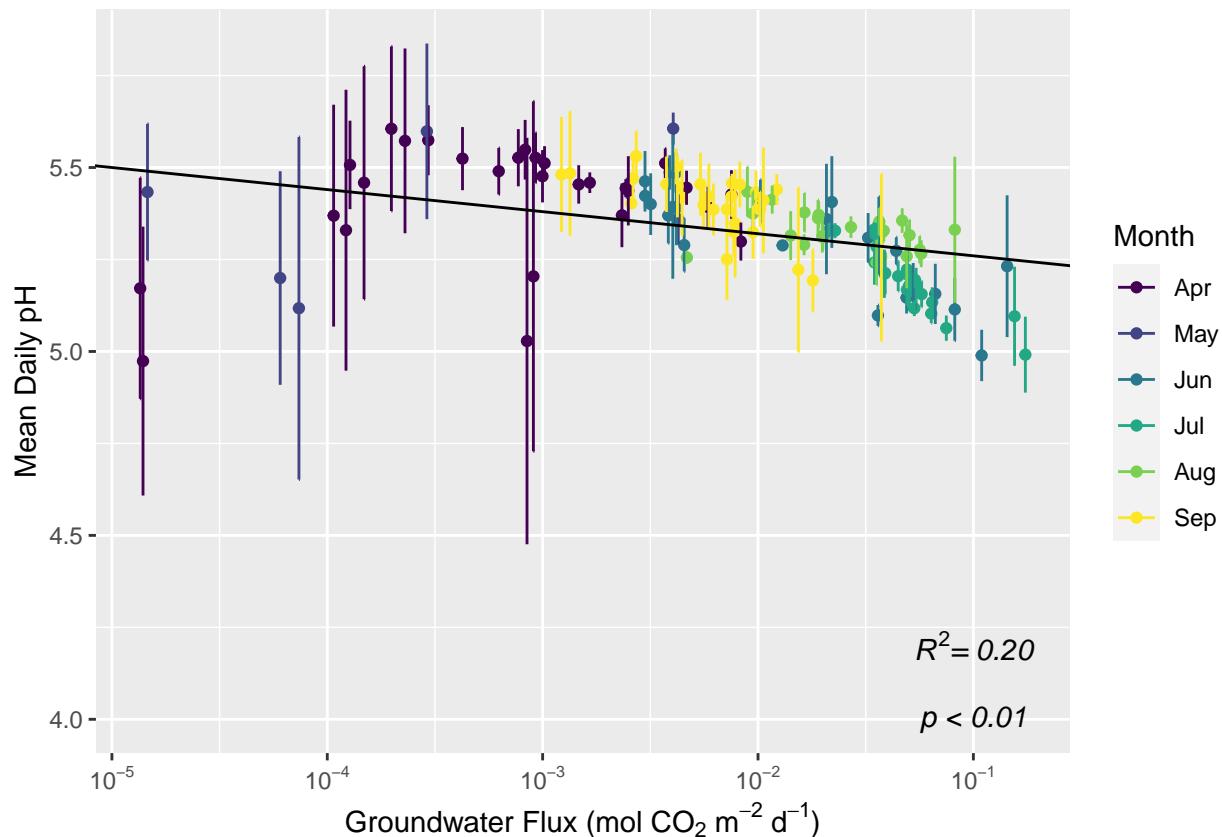
```

scale_color_viridis_d(name = 'Month')+
xlab(expression(paste('Groundwater Flux (mol ', CO[2], ', m^-2, ', d^-1, "))) +
ylab('Mean Daily pH')+
annotate(x = 0.1, y = 4, 'text', label = expression(italic("p < 0.01")))+  

  annotate(x = 0.1, y = 4.2, 'text', label = expression(italic(paste(R^2, "= 0.20"))))  

Fig7

```



**Fig S2- Hydrograph Separation**

Here, we explore the variation in pCO<sub>2</sub> during high and low flow events. We use a baseflow separation approach to distinguish flow and storm conditions by means of a filter parameter, alpha. To assess which alpha fits our reach, we vary alpha and visually evaluate the resulting separation time series.

```

# baseflow separation approach
# iterate alphas to determine the 'best' to use
alphas <- seq(0.9, 0.99, by = 0.01)

hydro_output_all <- tibble()

for(p in 1:length(alphas)) {
  hydro_output <- baseflows(flow.ts = Tac_all %>%
    select(Date = Timestamp,
           Q = sumQ_m3_hr),
    a = alphas[p],

```

```

    n.reflected = 30,
    ts = 'daily') %>%
mutate(bfi = bf/Q,
       alpha = !!alphas[p])

hydro_output_all <- rbind(hydro_output, hydro_output_all)
}

# plot Q and bf across the different alphas
FigS2 <- ggplot(hydro_output_all %>%
                  filter(alpha == 0.96),
                  aes(x = Date)) +
  geom_line(aes(y = Q, color = 'Storm Flow')) +
  geom_line(aes(y = bf, color = 'Baseflow')) +
  facet_wrap(. ~ alpha,
             ncol = 3) +
  ylab('Discharge (m3/h)') +
  theme(axis.title.x = element_blank(),
        legend.title = element_blank())

```

FigS2

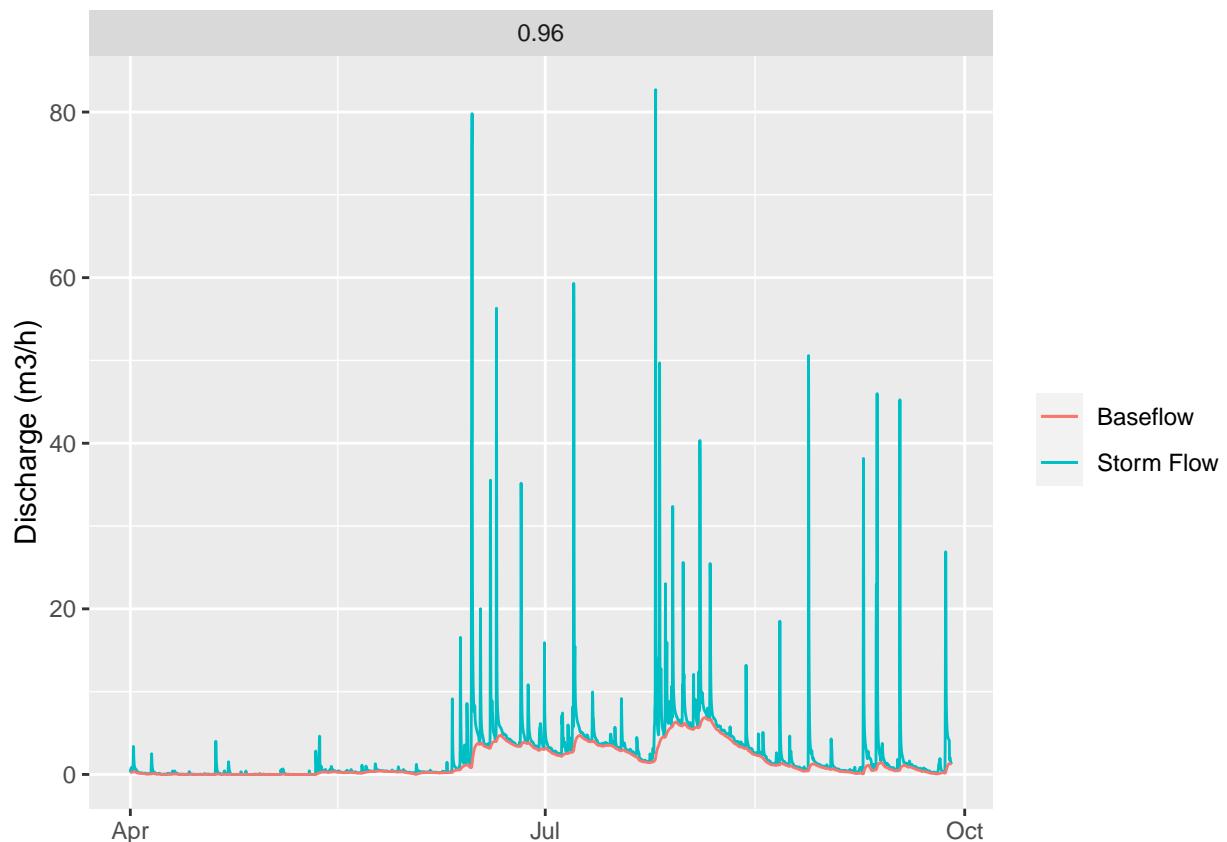


Fig S3- Diel Variation

```
tempHour <- ggplot(Tac_all,
                     aes(x = hour(Timestamp), y = temp.water))+  

  geom_line(alpha = 0.5,  

            aes(group = yday(Timestamp),  

                color = yday(Timestamp)))+  

  geom_point(alpha = 0.5,  

             aes(group = yday(Timestamp),  

                 color = yday(Timestamp)))+  

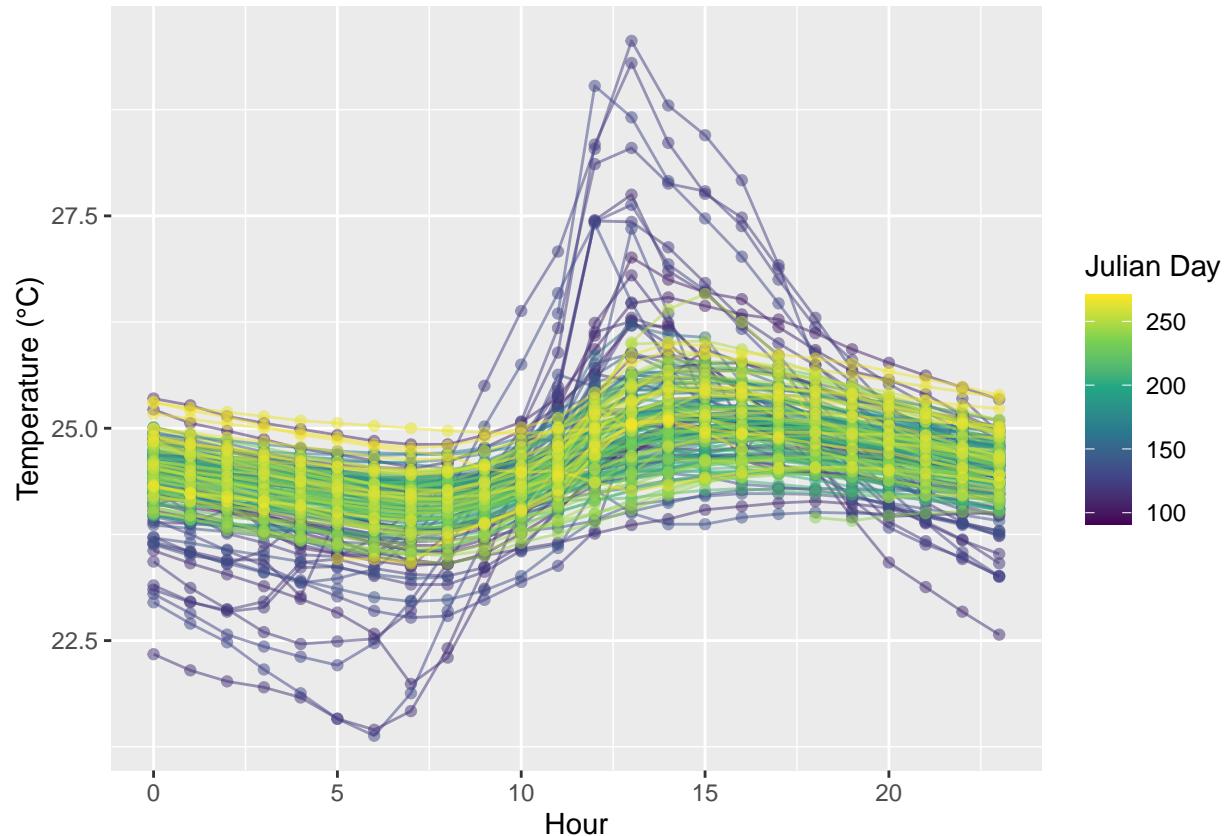
  xlab('Hour')+  

  scale_colour_viridis_c(name = "Julian Day") +  

  theme(legend.title = element_text(face = 'plain'))+  

  ylab("Temperature (°C)")  

tempHour
```



```
# pH  

pHHour <- ggplot(Tac_all,  

                  aes(x = hour(Timestamp), y = pH))+  

  geom_line(alpha = 0.5,  

            aes(group = yday(Timestamp),  

                color = yday(Timestamp)))+  

  geom_point(alpha = 0.5,  

             aes(group = yday(Timestamp),
```

```

            color = yday(Timestamp))+  

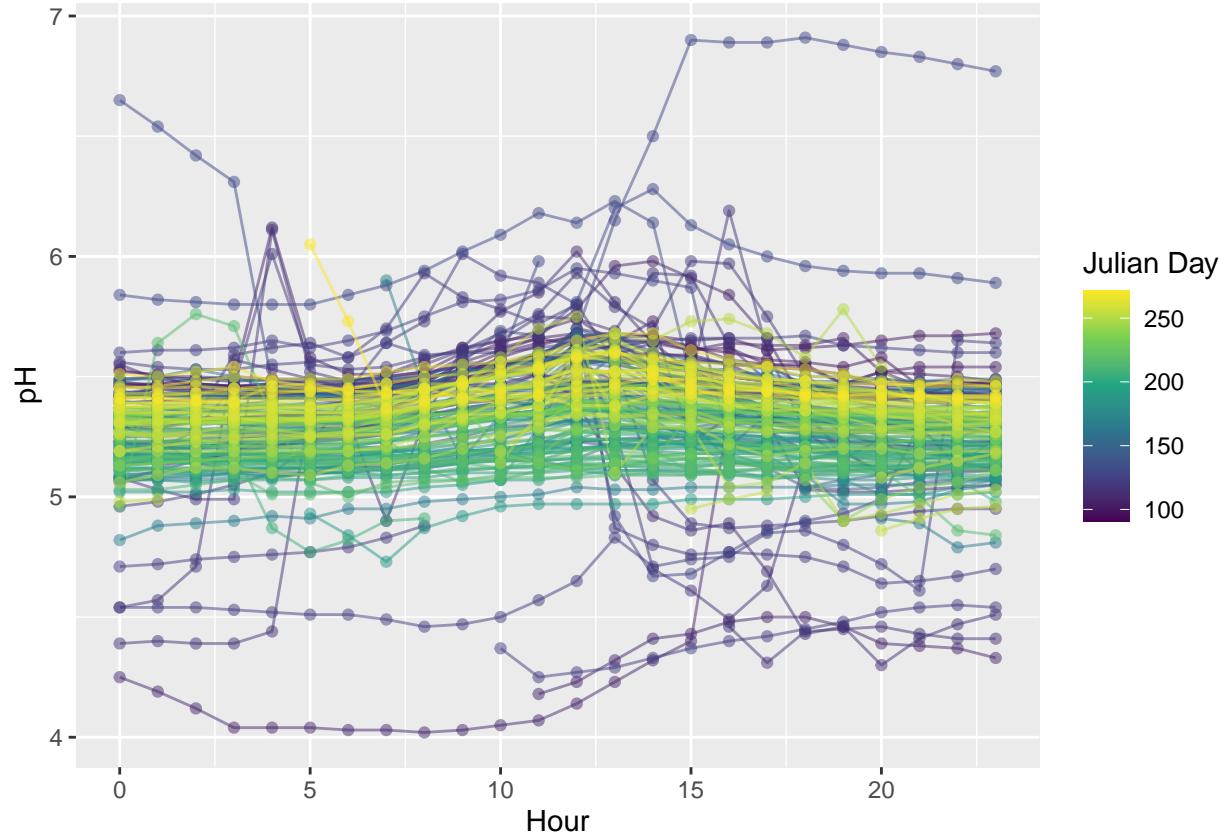
  labs(x = 'Hour', y = "pH") +  

  scale_colour_viridis_c(name = "Julian Day") +  

  theme(legend.title = element_text(face = 'plain'))  

pHHour

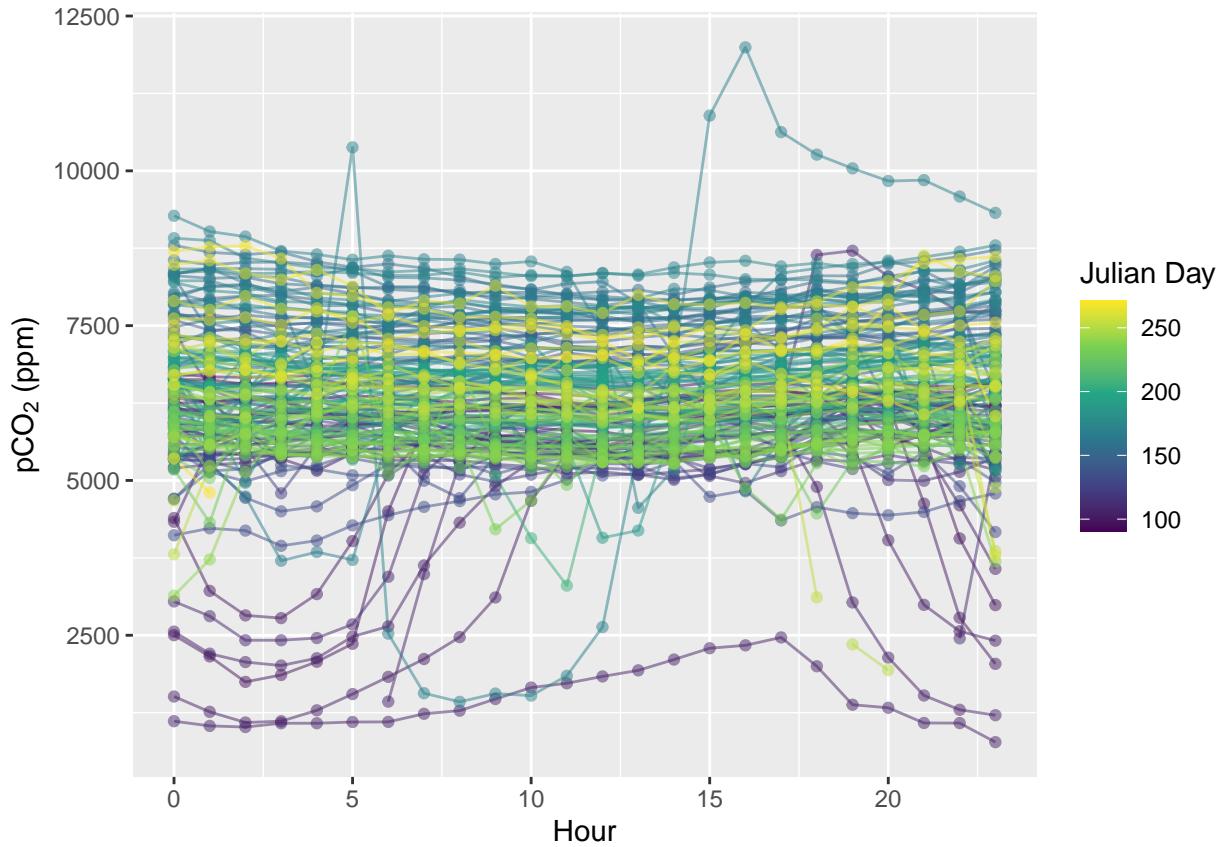
```



```

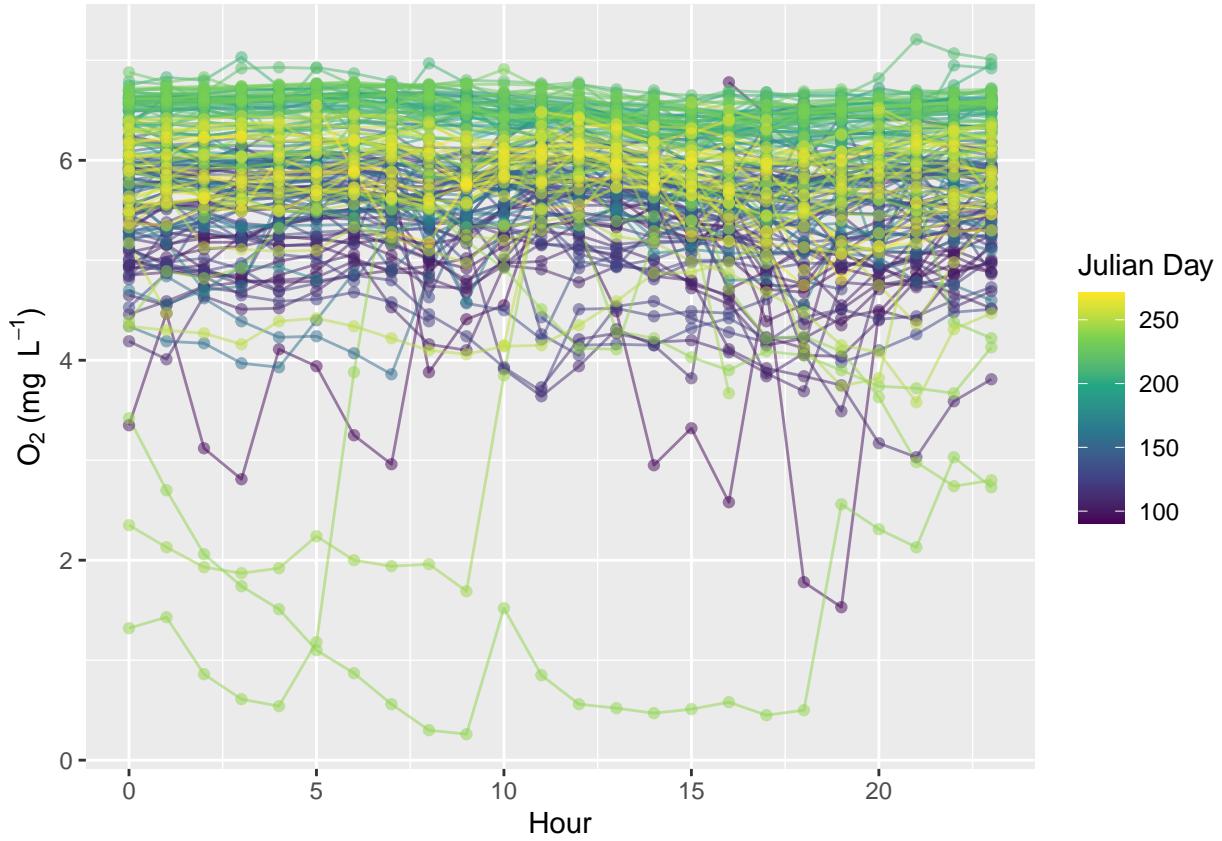
# stream CO2, ppm
CO2Hour = ggplot(Tac_all,
                  aes(x = hour(Timestamp), y = CO2_ppm)) +
  geom_line(alpha = 0.5,
            aes(group = yday(Timestamp), color = yday(Timestamp))) +
  geom_point(alpha = 0.5,
             aes(group = yday(Timestamp), color = yday(Timestamp))) +
  xlab('Hour') +
  ylab(expression(paste(pCO[2], ' (ppm)'))) +
  scale_colour_viridis_c(name = "Julian Day") +
  theme(legend.title = element_text(face = 'plain'))
CO2Hour

```



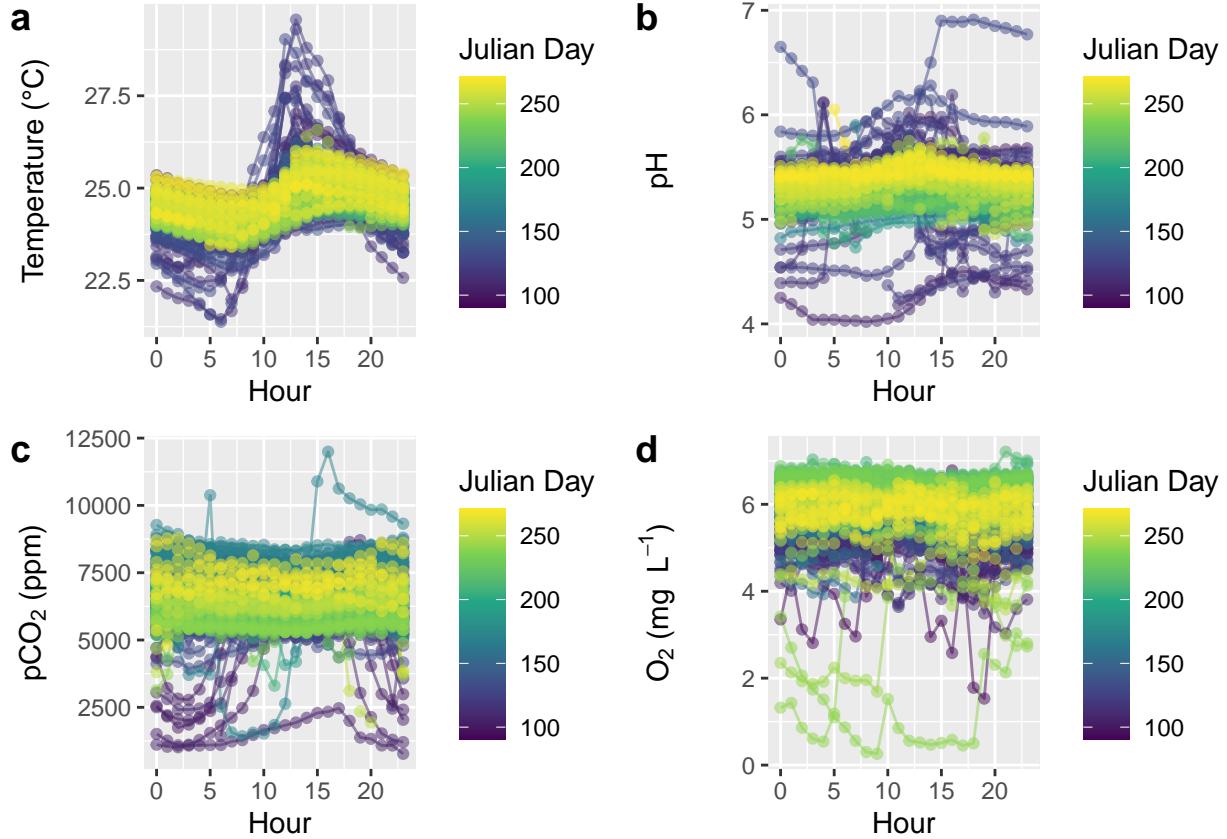
```
# dissolved oxygen
DOHour = ggplot(Tac_all,
                 aes(x = hour(Timestamp), y = DO.obs))+
  geom_line(alpha = 0.5,
            aes(group = yday(Timestamp), color = yday(Timestamp)))+
  geom_point(alpha = 0.5,
             aes(group = yday(Timestamp), color = yday(Timestamp)))+
  xlab('Hour')+
  ylab(expression(paste(0[2], " (mg ", ",L^{-1},")")))
  scale_colour_viridis_c(name = 'Julian Day')+
  theme(legend.title = element_text(face = 'plain'))
```

DOHour



```
FigS3 <- plot_grid(tempHour, pHHour, CO2Hour, DOHour,
                     ncol = 2, nrow = 2, align = 'hv',
                     labels = 'auto')
```

FigS3



**Fig S4- Sensitivity Analysis**

Here, we perform a sensitivity analysis on areal fluxes. We determine to what extent variation in 1) gas exchange influences changes in  $\text{F}[\text{CO}_2]$  and NEP and 2) groundwater discharge influences groundwater  $\text{CO}_2$  inputs. We explore variation at  $\pm 5\%$  and  $\pm 25\%$  of parameter values.

```
Tac_sens_K <- Tac_gas_flux %>%
  select(Timestamp, mean_depth,
         CO2_aq, CO2_sat, CO2_efflux,
         DO.obs, Osat, direct_met_mol) %>%
  mutate(
    FC02_high = ifelse(month(Timestamp) == '4',
                        (CO2_aq - CO2_sat)*((K_CO2_dry*1.25)/24)*mean_depth,
                        (CO2_aq - CO2_sat)*((K_CO2_wet*1.25)/24)*mean_depth),
    FC02_low = ifelse(month(Timestamp) == '4',
                      (CO2_aq - CO2_sat)*((K_CO2_dry*0.75)/24)*mean_depth,
                      (CO2_aq - CO2_sat)*((K_CO2_wet*0.75)/24)*mean_depth),
    NEP_high = ifelse(month(Timestamp) == '4',
                      (diff(DO.obs) - (((K_O2_dry*1.25)/24)*(Osat - DO.obs))*(1/32))*-1*mean_depth,
                      (diff(DO.obs) - (((K_O2_wet*1.25)/24)*(Osat - DO.obs))*(1/32))*-1*mean_depth),
    NEP_low = ifelse(month(Timestamp) == '4',
                      (diff(DO.obs) - (((K_O2_dry*0.75)/24)*(Osat - DO.obs))*(1/32))*-1*mean_depth,
                      (diff(DO.obs) - (((K_O2_wet*0.75)/24)*(Osat - DO.obs))*(1/32))*-1*mean_depth),
  ) %>%
  group_by(day = date(Timestamp)) %>%
```

```

summarise(sumF = sum(CO2_efflux, na.rm = TRUE),
          sumF_hi = sum(FCO2_high, na.rm = TRUE),
          sumF_low = sum(FCO2_low, na.rm = TRUE),
          sumNEP = sum(direct_met_mol, na.rm = TRUE),
          sumNEP_hi = sum(NEP_high, na.rm = TRUE),
          sumNEP_low = sum(NEP_low, na.rm = TRUE))

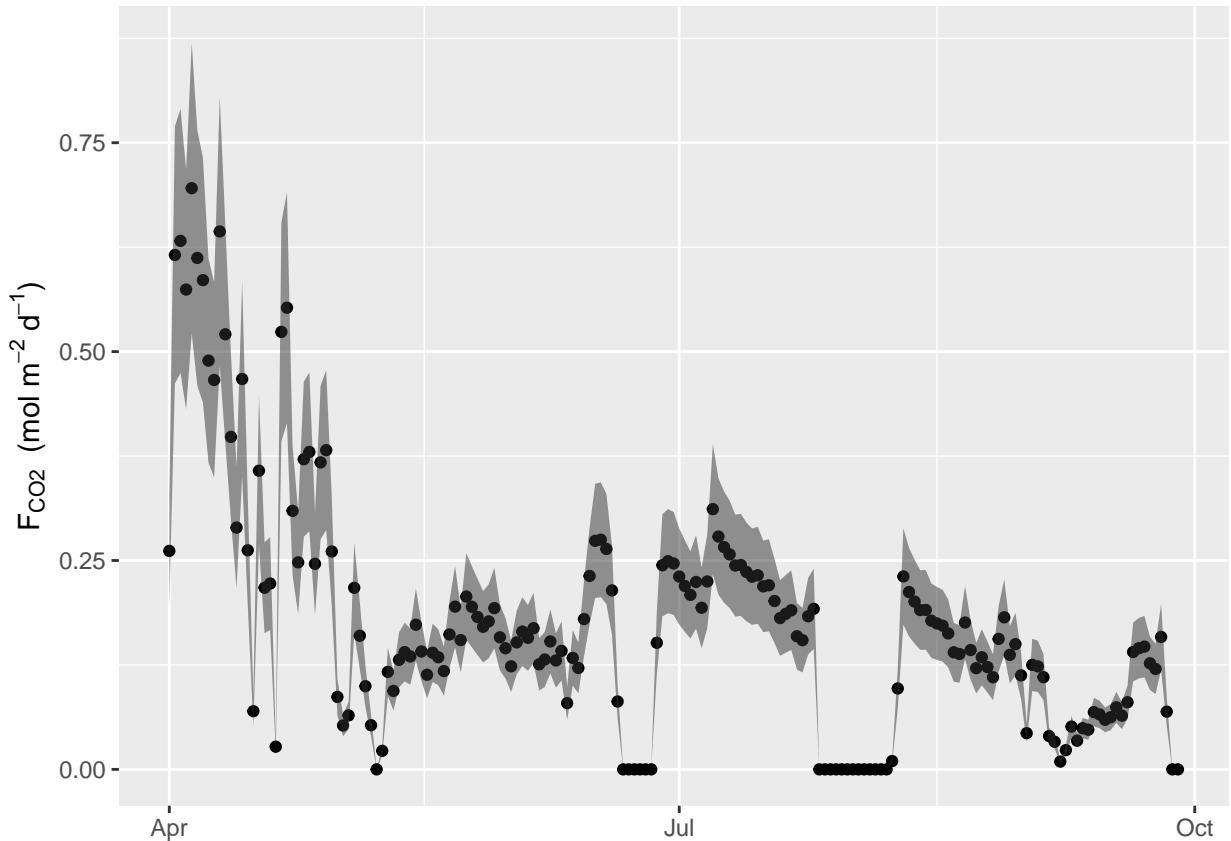
plot_sens_FCO2 <- ggplot(Tac_sens_K,
                           aes(x = day))+
  geom_point(aes(y = sumF))+  

  geom_ribbon(aes(ymin = sumF_low, ymax = sumF_hi),
              alpha = 0.5)+  

  ylab(expression(paste(F[CO2], ' (mol ', m^-2, ', d^-1, ')')))+  

  theme(axis.title.x = element_blank())
plot_sens_FCO2

```



```

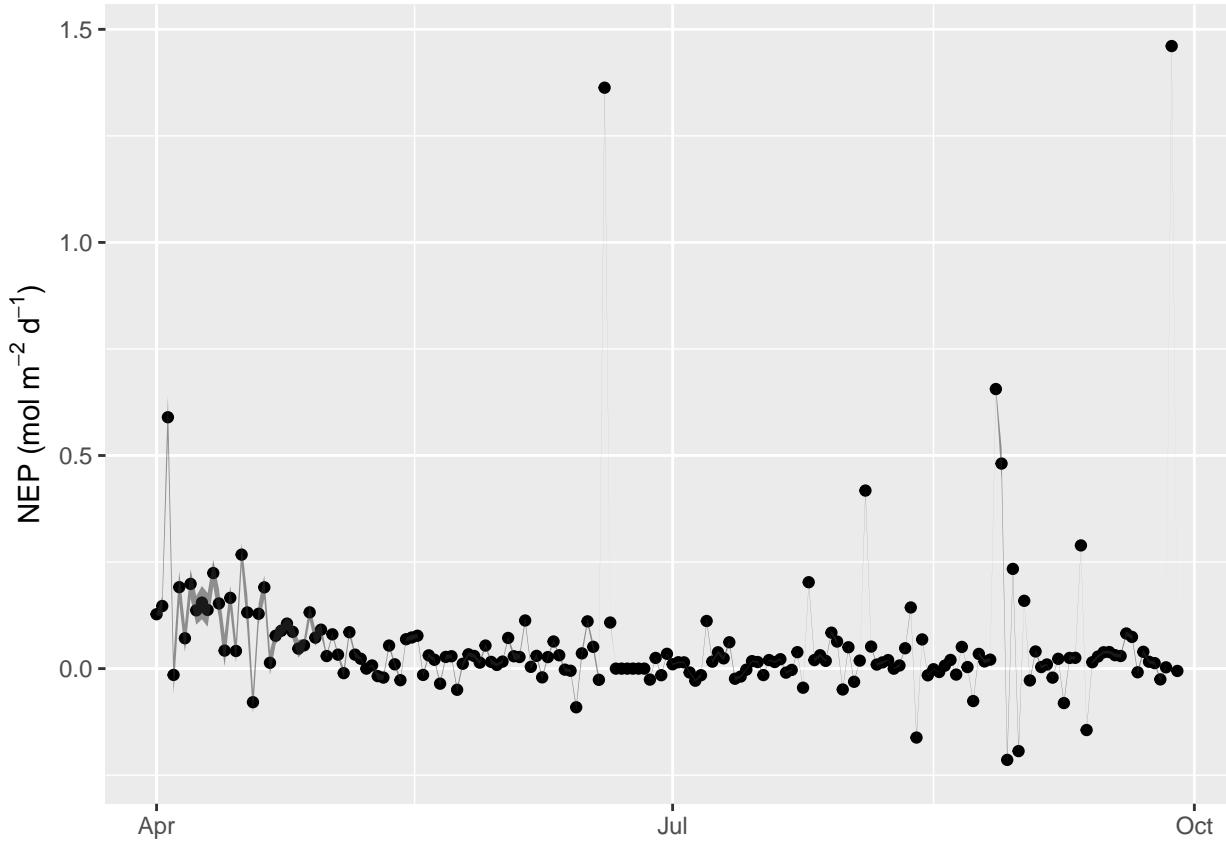
plot_sens_NEP <- ggplot(Tac_sens_K %>%
                           filter(sumNEP < 1.5),
                           aes(x = day))+
  geom_point(aes(y = sumNEP))+  

  geom_ribbon(aes(ymin = sumNEP_low, ymax = sumNEP_hi),
              alpha = 0.5)+  

  ylab(expression(paste('NEP (mol ', m^-2, ', d^-1, ')')))+  

  theme(axis.title.x = element_blank())
plot_sens_NEP

```



```

Tac_sens_gw <- Tac_GWC02 %>%
  select(Timestamp,
         wellCO2_aq,
         sumQ_m3_hr,
         GWC02) %>%
  mutate(
    GW_Q_hi = ifelse(month(Timestamp) == 'April',
                      ((0.1779*1.25)*sumQ_m3_hr),
                      ((0.0715*1.25)*sumQ_m3_hr)), # calculate total groundwater discharge (m3/h)
                                                # 17.79% of stream Q in dry season (April);
    GW_Q_low = ifelse(month(Timestamp) == 'April',
                      ((0.1779*0.75)*sumQ_m3_hr),
                      ((0.0715*0.75)*sumQ_m3_hr)), # calculate total groundwater discharge (m3/h)
                                                # 17.79% of stream Q in dry season (April)

    # groundwater velocity (m h-1); divide GW discharge by reach area (length * width)
    GW_v_hi = ifelse(month(Timestamp) == 'April',
                      GW_Q_hi/(Tac_reach * Tac_width_lower_dry),
                      GW_Q_hi/(Tac_reach * Tac_width_lower_wet)),
    GW_v_low = ifelse(month(Timestamp) == 'April',
                      GW_Q_low/(Tac_reach * Tac_width_lower_dry),
                      GW_Q_low/(Tac_reach * Tac_width_lower_wet)),

    # GWC02 flux (mol CO2 m-2 h-1)
    GWC02_hi = GW_v_hi * wellCO2_aq,
    GWC02_low = GW_v_low * wellCO2_aq
  ) %>%

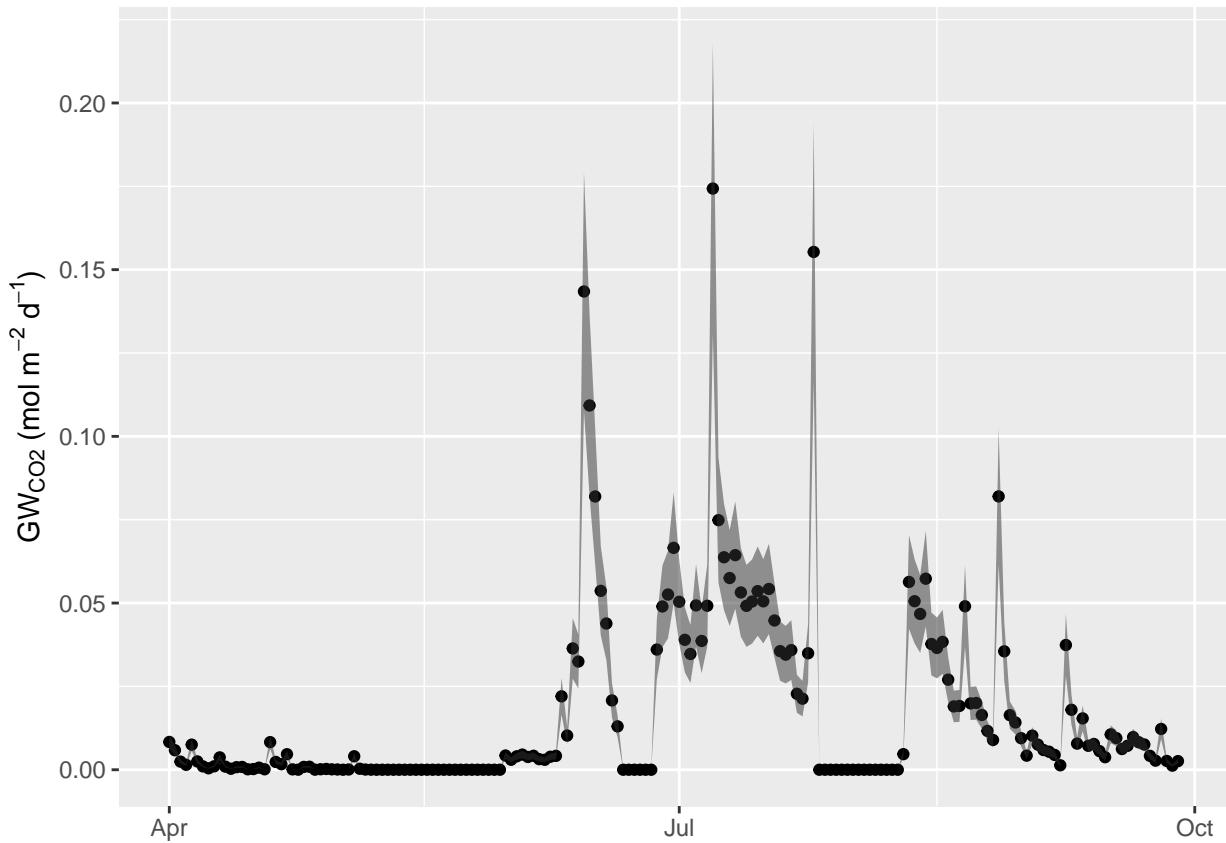
```

```

group_by(day = date(Timestamp)) %>%
  summarise(sumGW = sum(GWC02, na.rm = TRUE),
            sumGW_hi = sum(GWC02_hi, na.rm = TRUE),
            sumGW_low = sum(GWC02_low, na.rm = TRUE))

plot_sens_GW <- ggplot(Tac_sens_gw,
                        aes(x = day)) +
  geom_point(aes(y = sumGW)) +
  geom_ribbon(aes(ymax = sumGW_low, ymin = sumGW_hi),
              alpha = 0.5) +
  ylab(expression(paste(GW[CO2], ' (mol ', m^-2, ' ', d^-1, ')'))) +
  theme(axis.title.x = element_blank())
plot_sens_GW

```

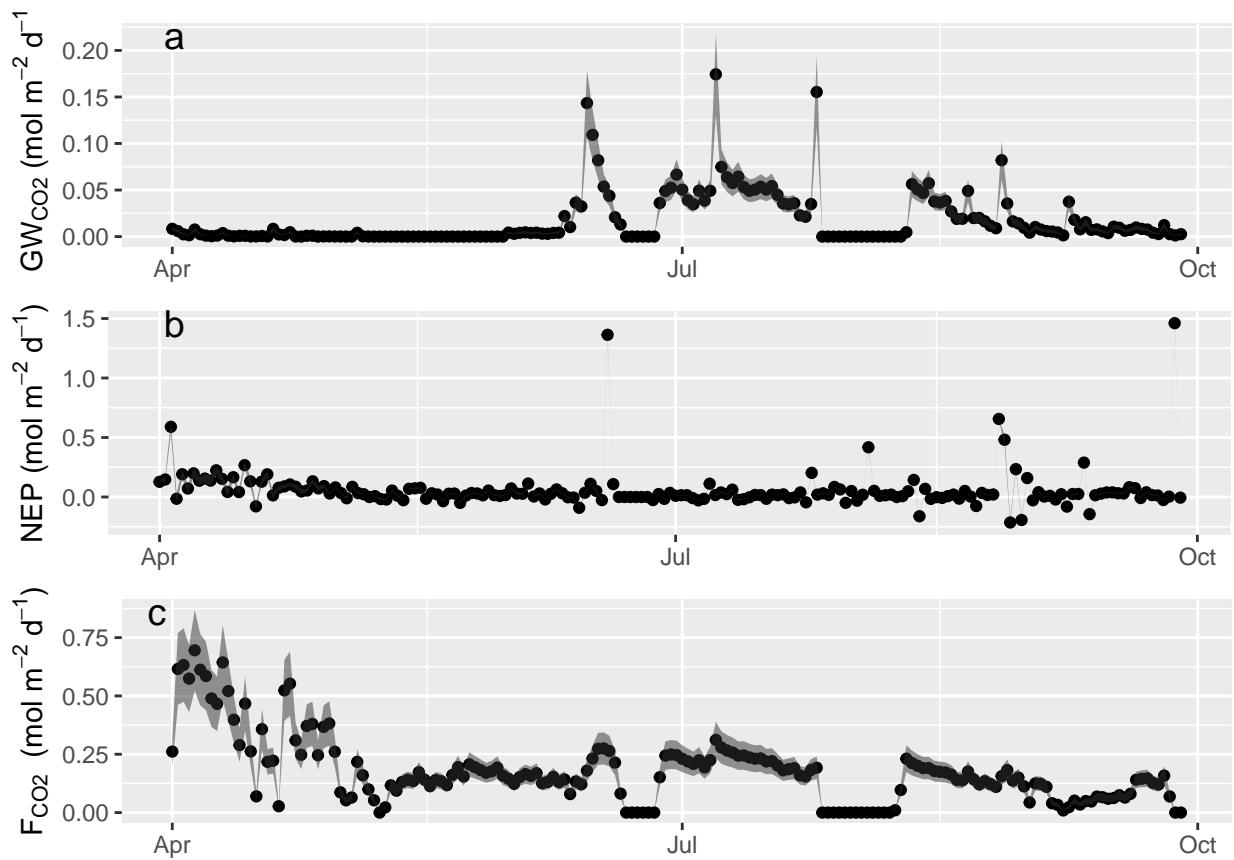


```

FigS4 <- plot_grid(plot_sens_GW,
                     plot_sens_NEP,
                     plot_sens_FC02,
                     nrow = 3,
                     labels = 'auto', label_fontface = 'plain',
                     hjust = -8)

```

FigS4



### Figs S5-11- Groundwater input method evaluation —

Here, we evaluate approaches to estimate groundwater inputs to our study reach. In addition to the approach used in the manuscript, which uses a fixed seasonal percentage based on empirical field data, we compare baseflow separation techniques and a linear interpolation of groundwater inputs.

```
# compare 4 methods
## 1: fixed percent- used in the ms
## 2: interpolation- develop a rating curve between discharge and the fraction of GW inputs using public
## 3: Baseflow separation
## 4: arealy corrected baseflow- using the baseflow calculated in #2, scale this estimate to our study

# For method 2, create a data frame with discharge and the measured fGW
rc <- data.frame(mon = c('Feb', 'Aug'),
                  discharge = c(14.16, 109.8),
                  fGW = c(17.8, 7.2))

# develop a rating curve between fGW and discharge
summary(lm(data = rc,
            fGW ~ discharge))

##
## Call:
## lm(formula = fGW ~ discharge, data = rc)
```

```

## 
## Residuals:
## ALL 2 residuals are 0: no residual degrees of freedom!
## 
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)    
## (Intercept) 19.3694      NaN      NaN      NaN    
## discharge   -0.1108      NaN      NaN      NaN    
## 
## Residual standard error: NaN on 0 degrees of freedom
## Multiple R-squared:      1, Adjusted R-squared:      NaN  
## F-statistic:    NaN on 1 and 0 DF,  p-value: NA

# fGW = 19.37 - discharge*0.11

# estimate fGW as a linear function of discharge for all discharges
Tac_baseflow_hyst_pred <- Tac_baseflow_hyst %>%
  mutate(fGW_pred = (19.37 - Q*0.11)/100,
        GW_Q_pred = Q*fGW_pred)

# merge all fGW estimates into one data frame
Tac_GWC02_eval <- Tac_all %>%
  select(Timestamp,
         pH,
         temp.water, wellCO2,
         sumQ_m3_hr) %>%
  left_join(Tac_baseflow_hyst_pred) %>%
  mutate(
    # temperature-corrected Henry's Law constant (Plummer and Busenberg 1982)
    kH = 29.41*exp(-2400*(1/(273 + temp.water) - (1/298))),

    # CO2-well
    wellCO2_aq = ((wellCO2/1e6)/kH)*1000, # well aqueous CO2: mol CO2 m-3

    # Method 1: Fixed percentage (m3 h-1)
    m1_GW_Q = ifelse(month(Timestamp) == 'April',      # calculate total groundwater discharge (m3/h)
                      (0.1779*sumQ_m3_hr),          # 17.79% of stream Q in dry season (April); m3/h
                      (0.0715*sumQ_m3_hr)),          # 7.15% of stream Q in wet season; m3/h

    # groundwater velocity (m h-1); divide GW discharge by reach area (length * width)
    m1_GW_v = ifelse(month(Timestamp) == 'April',
                      GW_Q/(Tac_reach * Tac_width_lower_dry),
                      GW_Q/(Tac_reach * Tac_width_lower_wet))
  ),

    # GWC02 flux (mol CO2 m-2 h-1)
    m1_GWC02 = m1_GW_v * wellCO2_aq,

    # Method 2: interpolation
    m2_GW_v = ifelse(month(Timestamp) == 'April',
                      GW_Q_pred/(Tac_reach * Tac_width_lower_dry),
                      GW_Q_pred/(Tac_reach * Tac_width_lower_wet))
  ),
    m2_inter_GWC02 = m2_GW_v * wellCO2_aq,

```

```

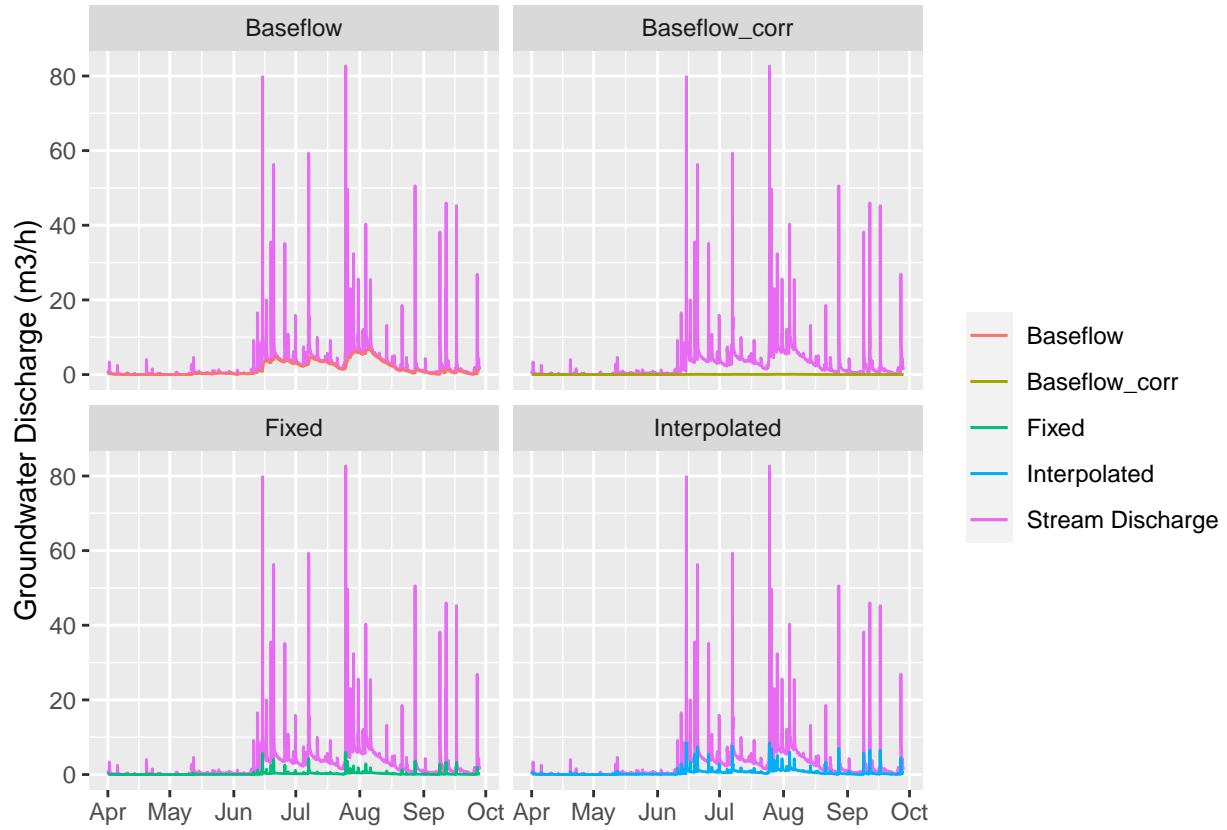
# Method 3: baseflow separation
m3_bf_v = ifelse(month(Timestamp) == 'April',
                  bf/(Tac_reach * Tac_width_lower_dry),
                  bf/(Tac_reach * Tac_width_lower_wet)),
m3_bf_GWC02 = m3_bf_v * wellCO2_aq,

# Method 4: area-corrected baseflow
m4_bf_corr = 0.011*bf,
m4_bf_corr_v = ifelse(month(Timestamp) == 'April',
                      m4_bf_corr/(Tac_reach * Tac_width_lower_dry),
                      m4_bf_corr/(Tac_reach * Tac_width_lower_wet)),
m4_bf_corr_GWC02 = m4_bf_corr_v * wellCO2_aq
)

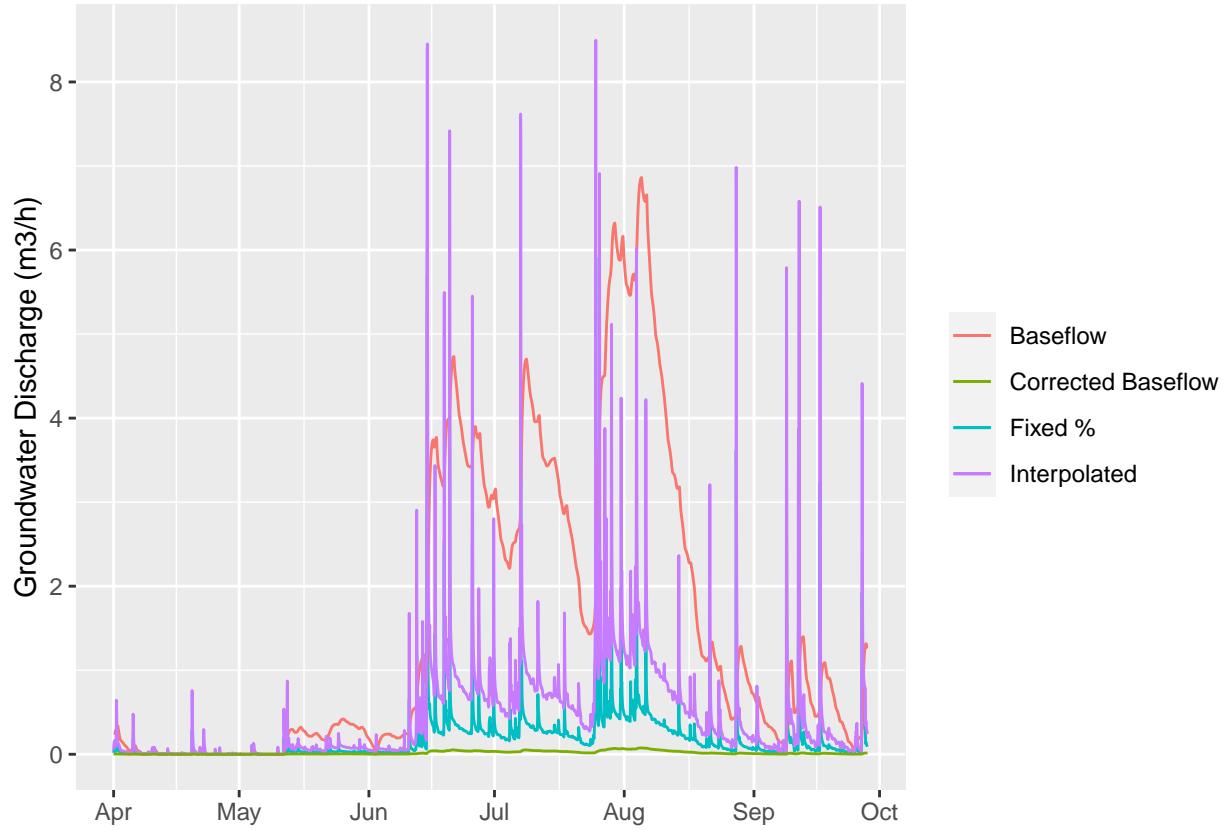
## Joining, by = c("Timestamp", "sumQ_m3_hr")

# plot: each estimate compared to stream discharge
Tac_GWC02_eval %>%
  select(Timestamp, sumQ_m3_hr,
         Fixed = m1_GW_Q,
         Baseflow = bf,
         Interpolated = GW_Q_pred,
         Baseflow_corr = m4_bf_corr) %>%
  pivot_longer(cols = 3:6,
               names_to = 'vars',
               values_to = 'vals') %>%
  ggplot(., aes(x = Timestamp))+
  geom_line(aes(y = sumQ_m3_hr, color = 'Stream Discharge'))+
  geom_line(aes(y = vals, color = vars))+
  facet_wrap(. ~ vars,
             nrow = 2, ncol = 2)+
  labs(x = element_blank(),
       y = 'Groundwater Discharge (m3/h)')+
  theme(legend.title = element_blank())+
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b")

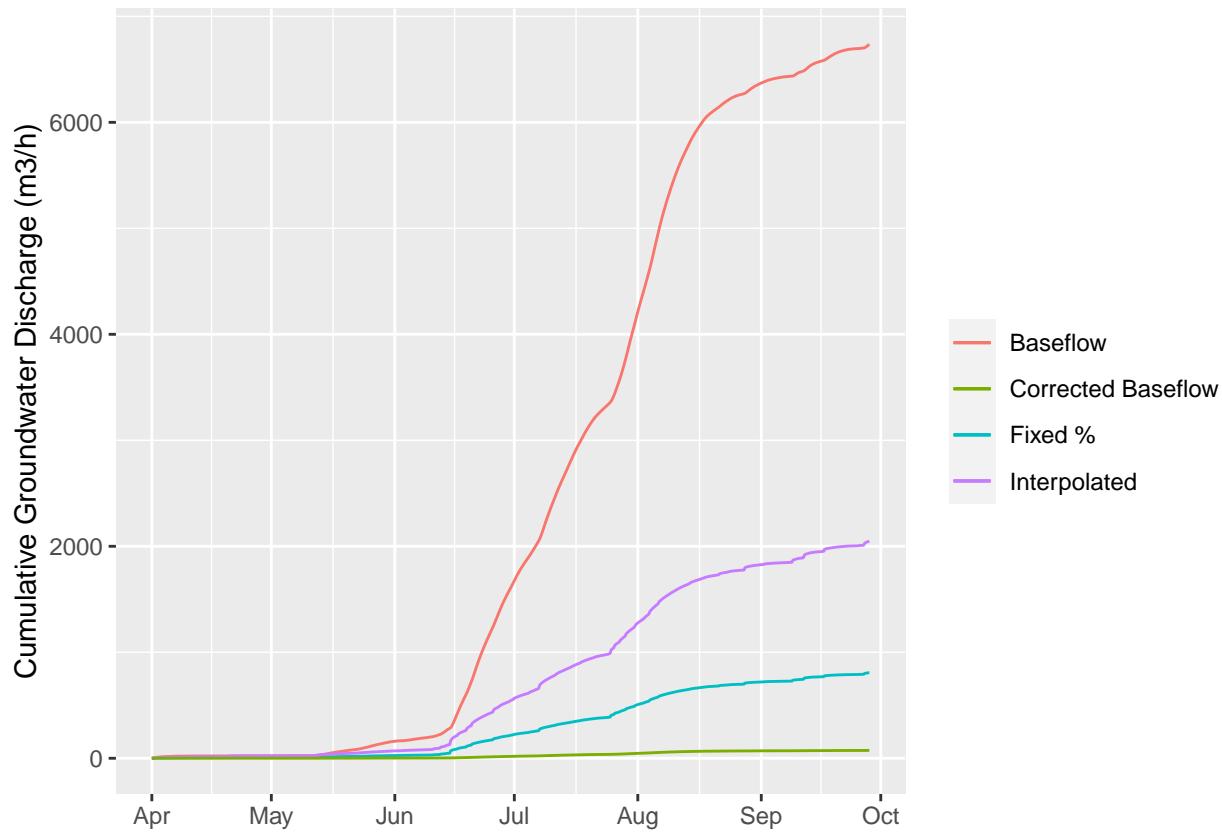
```



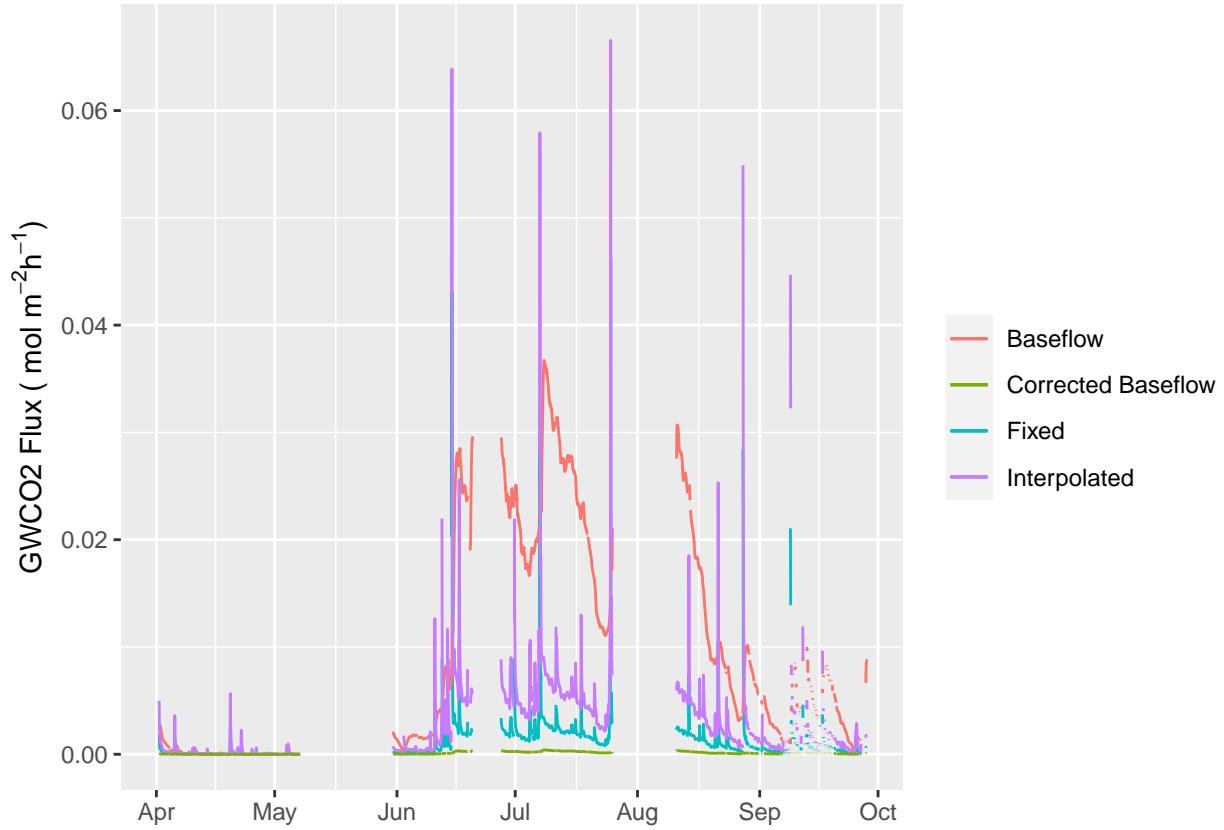
```
# plot: compare estimates of groundwater inputs
Tac_GWC02_eval %>%
  ggplot(., aes(x = Timestamp)) +
  geom_line(aes(y = m1_GW_Q, color = 'Fixed %')) +
  geom_line(aes(y = bf, color = 'Baseflow')) +
  geom_line(aes(y = GW_Q_pred, color = 'Interpolated')) +
  geom_line(aes(y = m4_bf_corr, color = 'Corrected Baseflow')) +
  labs(x = element_blank(),
       y = 'Groundwater Discharge (m³/h)') +
  theme(legend.title = element_blank()) +
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b")
```



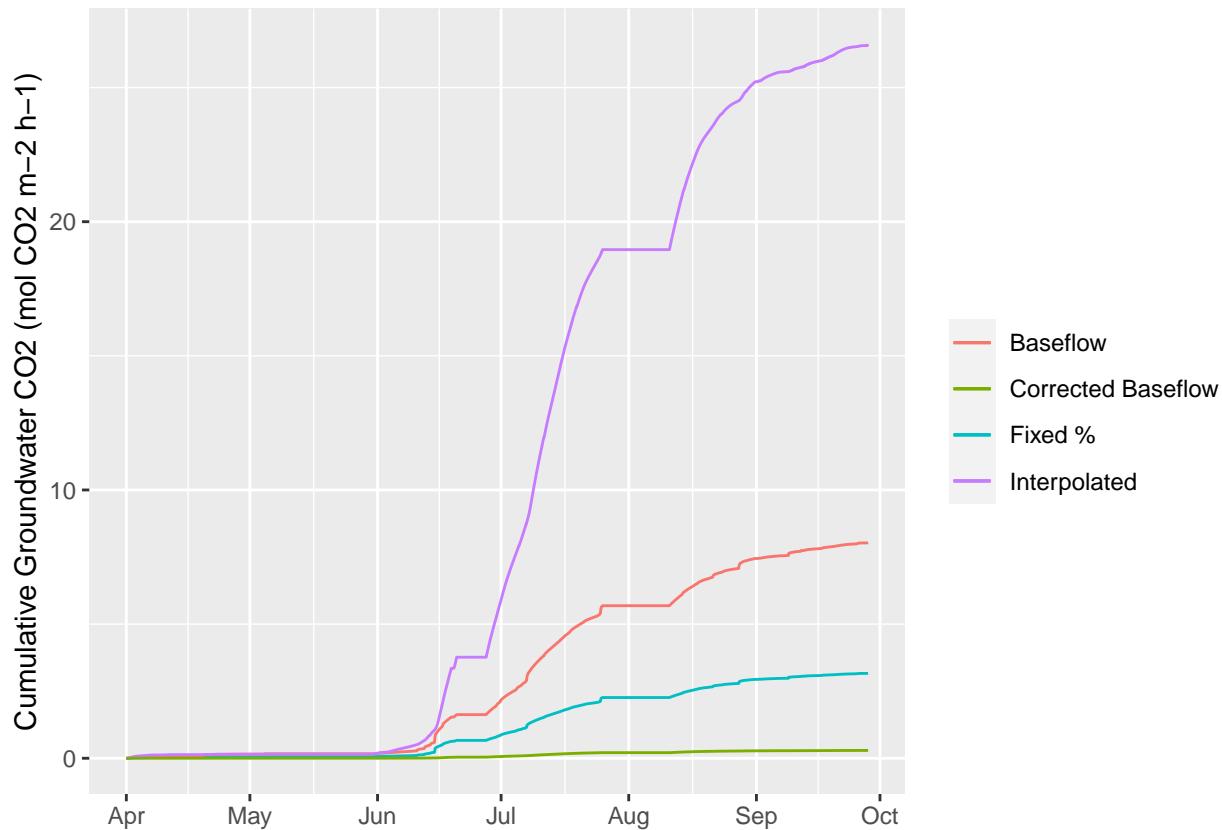
```
# plot: cumulative GW inputs
Tac_GWC02_eval %>%
  mutate(cum_m1 = cumsum(m1_GW_Q),
        cum_m2 = cumsum(bf),
        cum_m3 = cumsum(GW_Q_pred),
        cum_m4 = cumsum(m4_bf_corr)) %>%
  ggplot(., aes(x = Timestamp))+ 
  geom_line(aes(y = cum_m1, color = 'Fixed %'))+
  geom_line(aes(y = cum_m2, color = 'Baseflow'))+
  geom_line(aes(y = cum_m3, color = 'Interpolated'))+
  geom_line(aes(y = cum_m4, color = 'Corrected Baseflow'))+
  labs(x = element_blank(),
       y = 'Cumulative Groundwater Discharge (m³/h)')+
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b")+
  scale_color_discrete(name = element_blank())
```



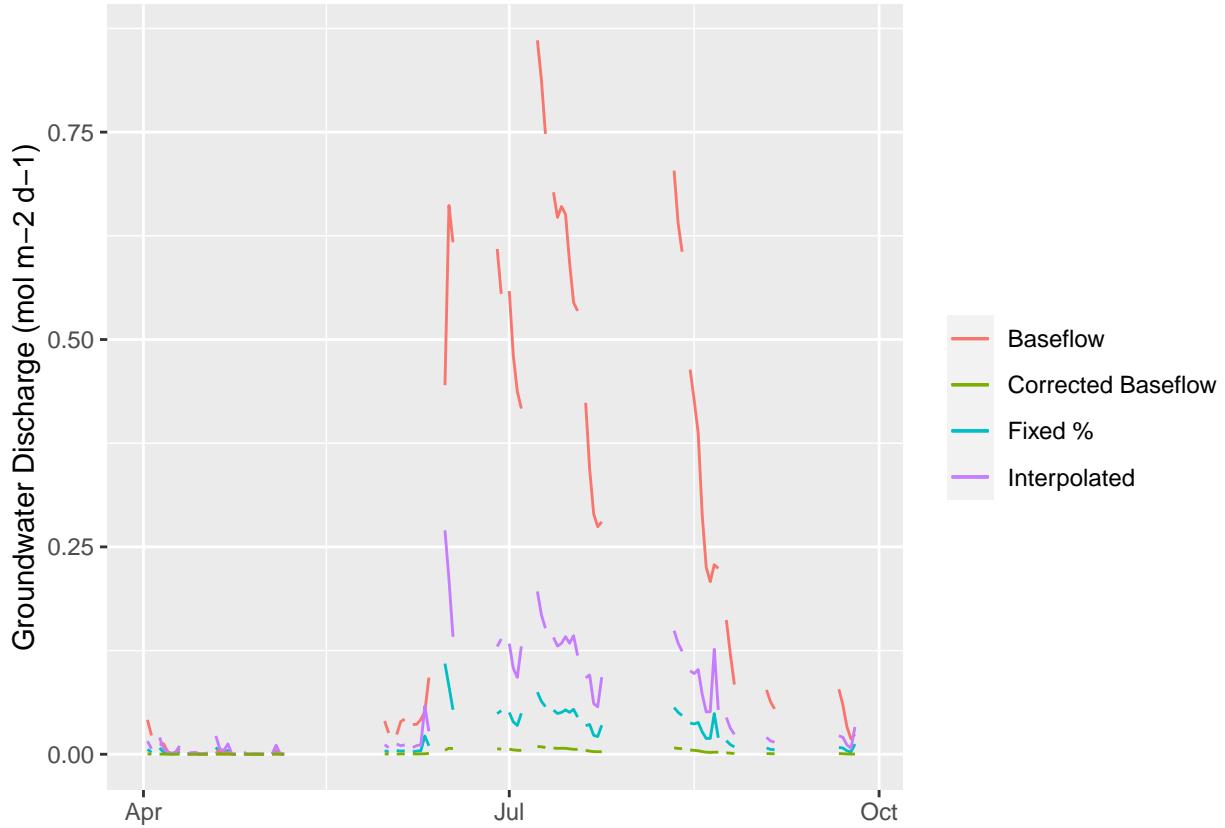
```
# plot: compare estimates of GWC02 flux
Tac_GWC02_eval %>%
  ggplot(., aes(x = Timestamp)) +
  geom_line(aes(y = m1_GWC02, color = 'Fixed')) +
  geom_line(aes(y = m3_bf_GWC02, color = 'Baseflow')) +
  geom_line(aes(y = m2_inter_GWC02, color = 'Interpolated')) +
  geom_line(aes(y = m4_bf_corr_GWC02, color = 'Corrected Baseflow')) +
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b") +
  scale_color_discrete(name = element_blank()) +
  labs(x = element_blank(),
       y = expression(paste('GWC02 Flux ( mol ', m^-2, h^-1, ')')))
```



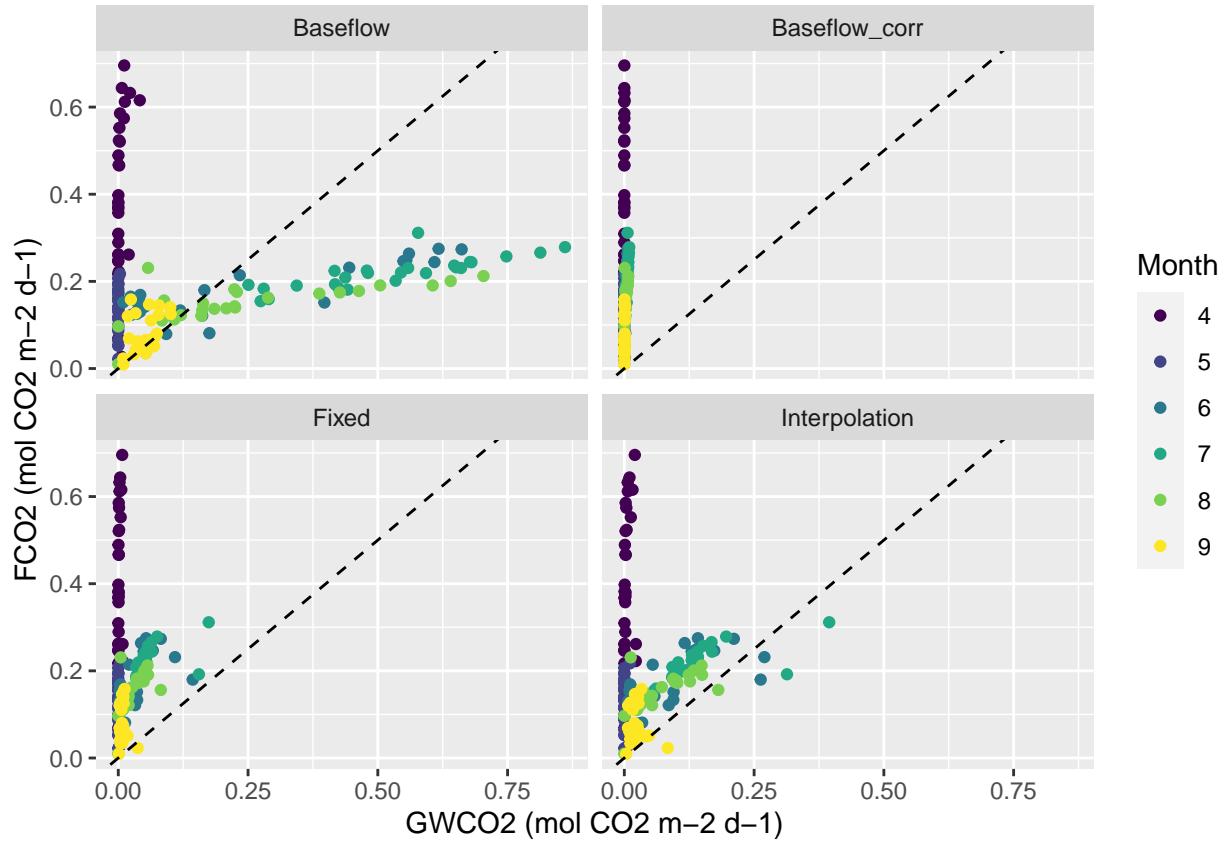
```
# plot: compare cumulative GWCO2 inputs
Tac_GWCO2_eval %>%
  mutate(cum_m1 = cumsum(replace_na(m1_GWCO2, 0)),
         cum_m3 = cumsum(replace_na(m3_bf_GWCO2, 0)),
         cum_m2 = cumsum(replace_na(m2_inter_GWCO2, 0)),
         cum_m4 = cumsum(replace_na(m4_bf_corr_GWCO2, 0))) %>%
  ggplot(., aes(x = Timestamp))+ 
  geom_line(aes(y = cum_m1, color = 'Fixed %'))+
  geom_line(aes(y = cum_m2, color = 'Baseflow'))+
  geom_line(aes(y = cum_m3, color = 'Interpolated'))+
  geom_line(aes(y = cum_m4, color = 'Corrected Baseflow'))+
  labs(x = element_blank(),
       y = 'Cumulative Groundwater CO2 (mol CO2 m-2 h-1)')+
  scale_x_datetime(date_breaks = "1 month",
                   date_labels = "%b")+
  scale_color_discrete(name = element_blank())
```



```
# plot: compare daily GWC02 inputs from the methods
Tac_GWC02_eval %>%
  group_by(day = date(Timestamp)) %>%
  summarise(m1_day = sum(m1_GWC02),
            m3_day = sum(m3_bf_GWC02),
            m2_day = sum(m2_inter_GWC02),
            m4_day = sum(m4_bf_corr_GWC02)) %>%
  ggplot(., aes(x = day)) +
  geom_line(aes(y = m1_day, color = 'Fixed %')) +
  geom_line(aes(y = m3_day, color = 'Baseflow')) +
  geom_line(aes(y = m2_day, color = 'Interpolated')) +
  geom_line(aes(y = m4_day, color = 'Corrected Baseflow')) +
  labs(x = element_blank(),
       y = 'Groundwater Discharge (mol m^-2 d^-1)') +
  # scale_x_datetime(date_breaks = "1 month",
  #                   date_labels = "%b") +
  scale_color_discrete(name = element_blank())
```



```
# plot: re-make Fig 6, using different estimates of GWC02 as drivers of FC02
left_join(Tac_gas_flux,
          Tac_GWC02_eval,
          by = 'Timestamp') %>%
  select(Timestamp, CO2_efflux, direct_met_mol,
         m1_GWC02, m3_bf_GWC02, m2_inter_GWC02, m4_bf_corr_GWC02) %>%
  group_by(day = date(Timestamp)) %>%
  summarise(dayF = sum(CO2_efflux, na.rm = TRUE),
            dayNEP = sum(direct_met_mol, na.rm = TRUE),
            Fixed = sum(m1_GWC02, na.rm = TRUE),
            Baseflow = sum(m3_bf_GWC02, na.rm = TRUE),
            Interpolation = sum(m2_inter_GWC02, na.rm = TRUE),
            Baseflow_corr = sum(m4_bf_corr_GWC02, na.rm = TRUE)) %>%
  filter(dayNEP < 1.5,
        dayF > 0) %>%
  pivot_longer(cols = 4:7,
               names_to = 'vars',
               values_to = 'vals') %>%
  ggplot(., aes(x = vals, y = dayF)) +
  geom_point(aes(color = factor(month(day, abbr = TRUE)))) +
  geom_abline(intercept = 0, slope = 1, linetype = 'dashed') +
  facet_wrap(. ~ vars, ncol = 2) +
  scale_color_viridis_d(name = 'Month') +
  labs(x = 'GWC02 (mol CO2 m^-2 d^-1)',
       y = 'FC02 (mol CO2 m^-2 d^-1)')
```



## Session info

```
pander(sessionInfo())
```

R version 4.1.3 (2022-03-10)

Platform: x86\_64-w64-mingw32/x64 (64-bit)

locale: LC\_COLLATE=English\_United States.1252, LC\_CTYPE=English\_United States.1252, LC\_MONETARY=English\_United States.1252, LC\_NUMERIC=C and LC\_TIME=English\_United States.1252

attached base packages: stats, graphics, grDevices, utils, datasets, methods and base

other attached packages: pander(v.0.6.5), hydrostats(v.0.2.9), ARTool(v.0.11.1), lsmeans(v.2.30-0), emmeans(v.1.7.5), purrr(v.0.3.4), ellipse(v.0.4.3), lmodel2(v.1.7-3), ggsci(v.2.9), scales(v.1.2.0), ggrepel(v.0.9.1), cowplot(v.1.1.1), ggplot2(v.3.3.6), tidyquant(v.1.0.4), quantmod(v.0.4.20), TTR(v.0.24.3), PerformanceAnalytics(v.2.0.4), xts(v.0.12.1), zoo(v.1.8-10), lubridate(v.1.8.0), tidyrr(v.1.2.0) and dplyr(v.1.0.8)

loaded via a namespace (and not attached): httr(v.1.4.3), viridisLite(v.0.4.0), jsonlite(v.1.8.0), splines(v.4.1.3), carData(v.3.0-5), assertthat(v.0.2.1), highr(v.0.9), yaml(v.2.3.5), backports(v.1.4.1), pillar(v.1.7.0), lattice(v.0.20-45), glue(v.1.6.2), quadprog(v.1.5-8), digest(v.0.6.29), minqa(v.1.2.4), colorspace(v.2.0-3), sandwich(v.3.0-2), htmltools(v.0.5.2), Matrix(v.1.4-1), plyr(v.1.8.7), pkgconfig(v.2.0.3), broom(v.0.8.0), xtable(v.1.8-4), mvtnorm(v.1.1-3), lme4(v.1.1-29), tibble(v.3.1.6), farver(v.2.1.0), generics(v.0.1.2), car(v.3.1-0), ellipsis(v.0.3.2), TH.data(v.1.1-1), withr(v.2.5.0), cli(v.3.2.0), survival(v.3.3-1), magrittr(v.2.0.2), crayon(v.1.5.1), estimability(v.1.3), evaluate(v.0.15), fansi(v.1.0.2), nlme(v.3.1-158),

*MASS(v.7.3-57), tools(v.4.1.3), lifecycle(v.1.0.1), multcomp(v.1.4-19), stringr(v.1.4.0), munsell(v.0.5.0), compiler(v.4.1.3), rlang(v.1.0.2), grid(v.4.1.3), nloptr(v.2.0.3), rstudioapi(v.0.13), labeling(v.0.4.2), rmarkdown(v.2.14), boot(v.1.3-28), gtable(v.0.3.0), codetools(v.0.2-18), abind(v.1.4-5), DBI(v.1.1.3), curl(v.4.3.2), R6(v.2.5.1), knitr(v.1.39), fastmap(v.1.1.0), utf8(v.1.2.2), Quandl(v.2.11.0), stringi(v.1.7.6), Rcpp(v.1.0.8.3), vctrs(v.0.3.8), tidyselect(v.1.1.2), xfun(v.0.30) and coda(v.0.19-4)*