Analyses and Rough Plots for Manuscript

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Upload jam Characteristics

Both jam characteristics and reach characteristics (below) were copied into a .csv from the Google Sheets data file in the West Creek Google Drive.

```
#upload jam data from .csv
jam_data <- read.csv('E:/WestCreek/data/WC_jam_orig.csv', header = TRUE) %>%
  tibble::add_row(reach = 32) %>%
  mutate_at('woodvolume_m3', ~replace(., is.na(.), 0))
```

Upload reach characteristics and join the two datasets by reach number

This creates one master file that we can use to calculate future reach characteristics.

```
#upload reach data from .csv
reach_data <- read.csv('E:/WestCreek/data/WC_reach_orig.csv',
                       header = TRUE)

#join reach and jam data by reach ID
master <- inner_join(jam_data, reach_data, by = 'reach')
```

Calculate more reach characteristics

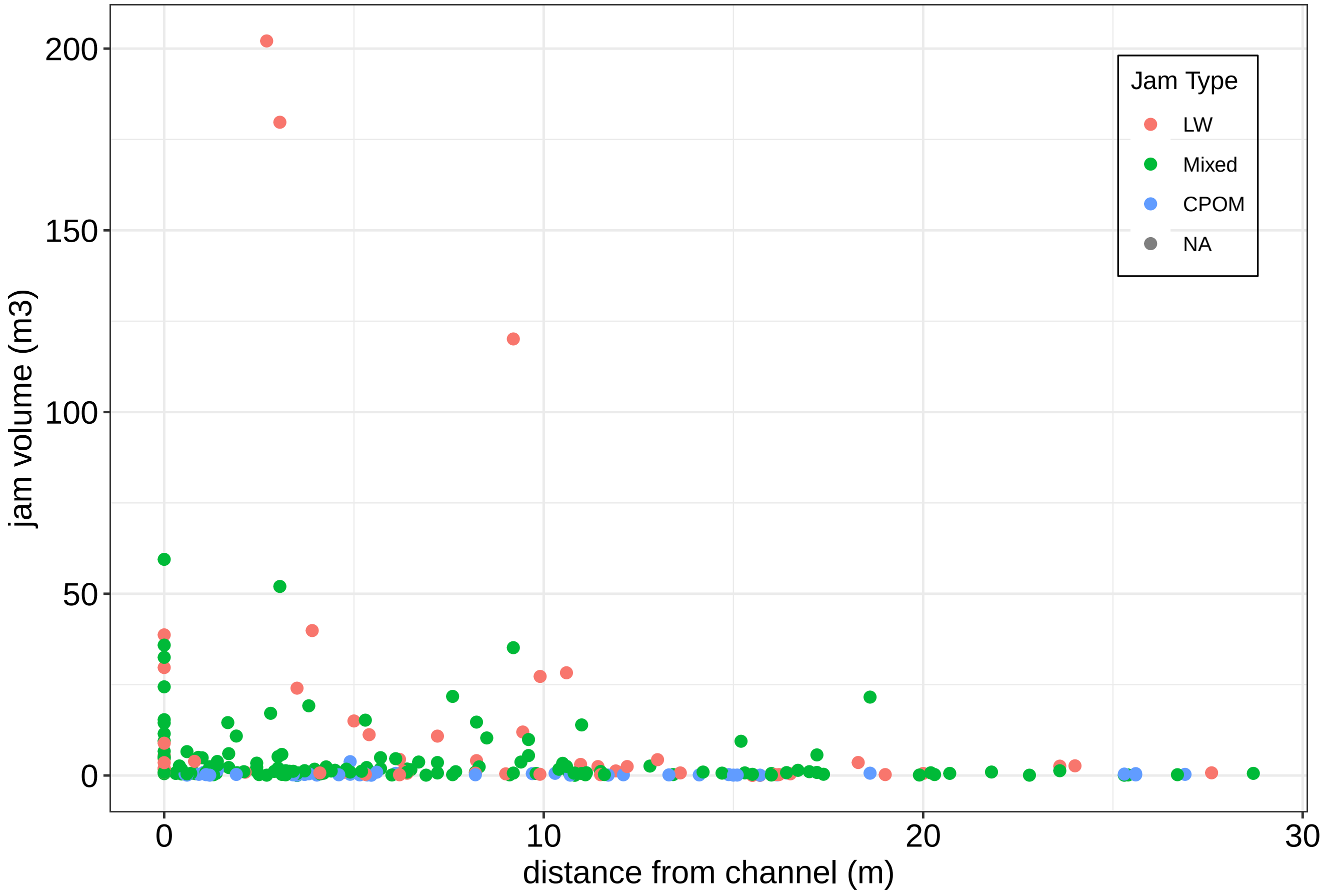
Calculated number of jams per type, total jam frequency, and jam frequency by type. Created two new dataframes: full_reach_ch which has all reach characteristics (summarized across all jam types) and full_freq (which includes separated frequencies by jam type).

H1a) inverse relationship between fp jam size and elevation above/distance from channel

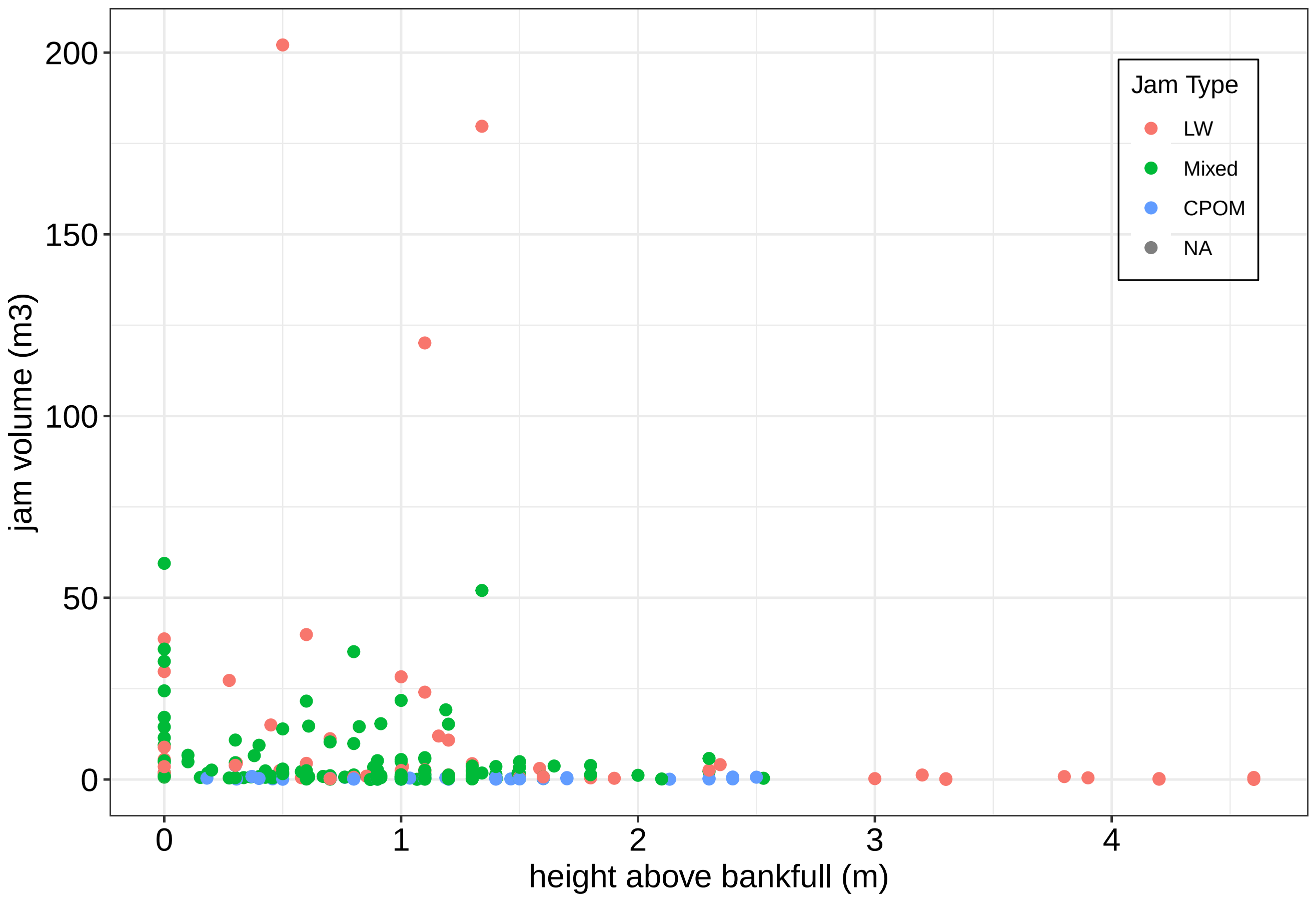
Method: Simple spearman correlation tests were used to assess the relationship between jam size and elevation above and distance from channel. A significant test result ($p < 0.05$) would mean that there is a statistical correlation between jam size and the predictor variable - either elevation above or distance from channel.

Result: Significant but weak inverse relationship between jam volume (m3) and height above bankfull (p« 0.05, r = -0.32) and distance from channel (p« 0.05, r = -0.32).

```
cor.test(master$woodvolume_m3, master$ht_above_bf_m, method = 'spearman')
cor.test(master$woodvolume_m3, master$dist_from_channel_m, method = 'spearman')
```



jam volume (m3)
200
150
100
50
0
0
10
20
30
distance from channel (m)
Jam Type
LW
Mixed
CPOM
NA

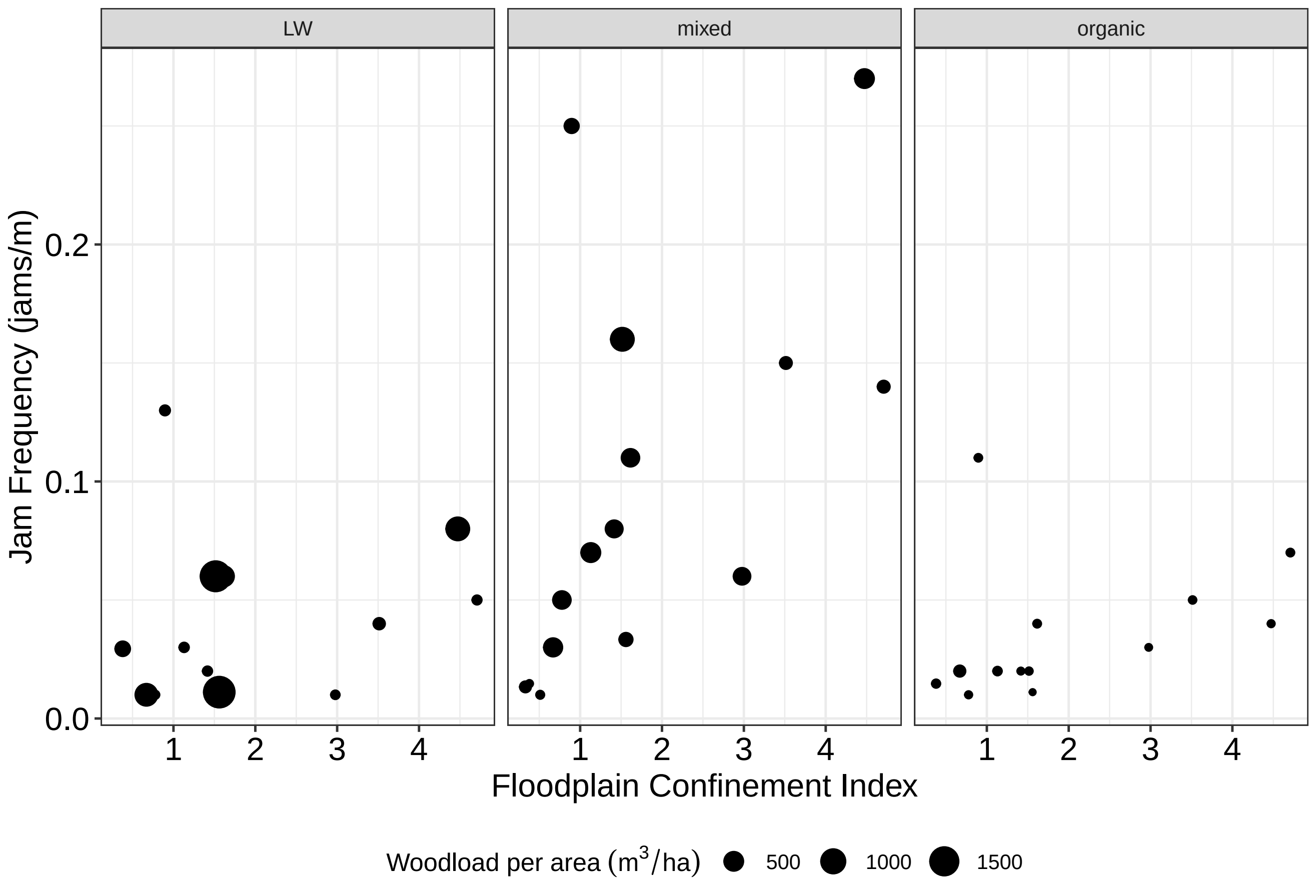


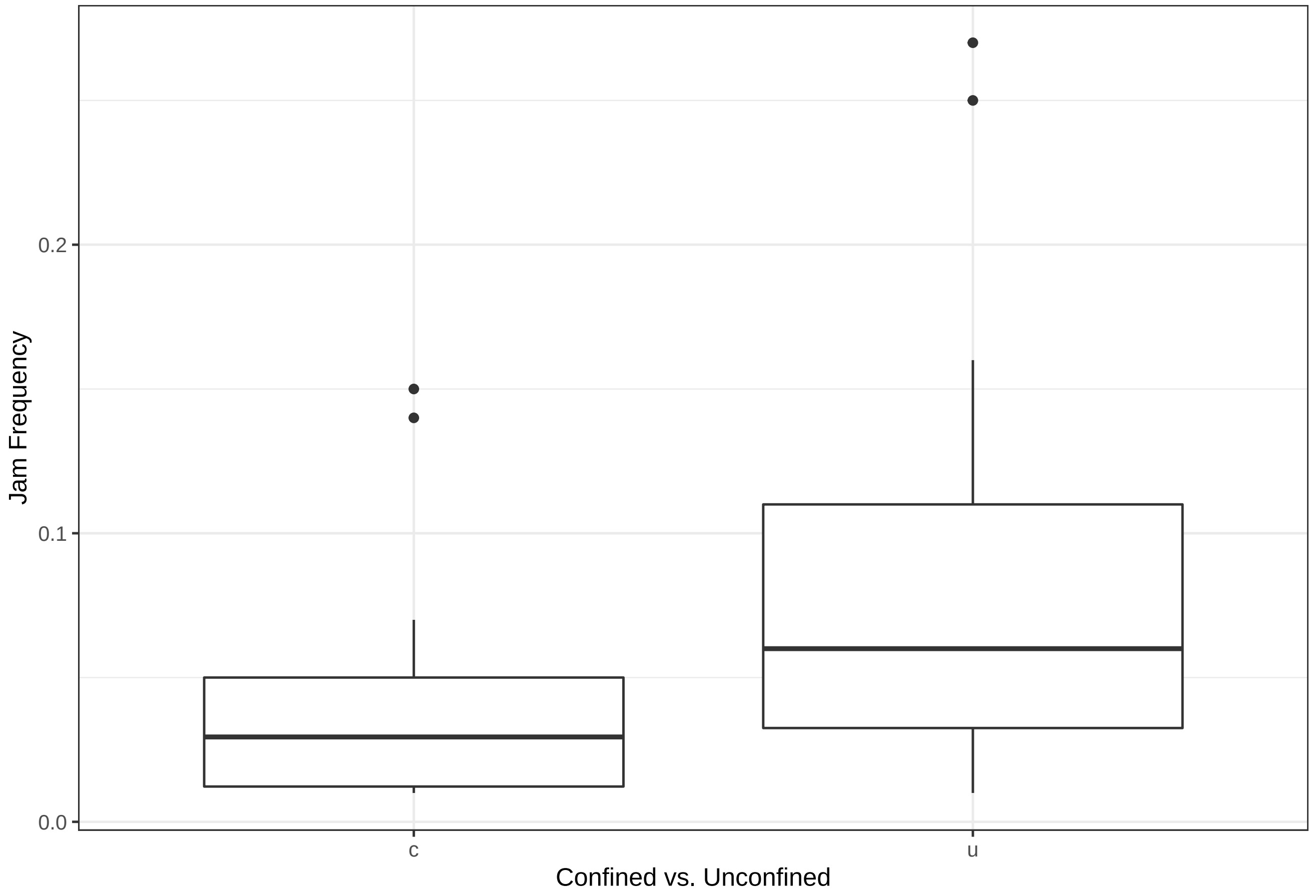
H1b) expect fp LW jam frequency and loads are higher in unconfined portions of the river

Method: Spearman correlation tests were also used to test the relationship between floodplain confinement index (RL_confinement) and jam frequency and load per area.

Results: There is a significant relationship between jam frequency and floodplain confinement index ($p = 0.003$, Spearman $r = 0.678$). The relationship between jam frequency and floodplain confinement appears to be strongest for mixed jams. Woodloads do not have a significant relationship with confinement ($p = 0.23$). Jam frequency is higher in unconfined reaches compared to confined reaches.

```
## correlation test
cor.test(full_reach_ch$jam_per_m, full_reach_ch$RL_confinement, method = 'spearman')
cor.test(full_reach_ch$woodload_m3perha, full_reach_ch$RL_confinement, method = 'spearman')
```


LW
mixed
organic
Jam Frequency (jams/m)
0.0
0.1
0.2
1
2
3
4
Floodplain Confinement Index
Woodload per area (m3/ha)
500
1000
1500



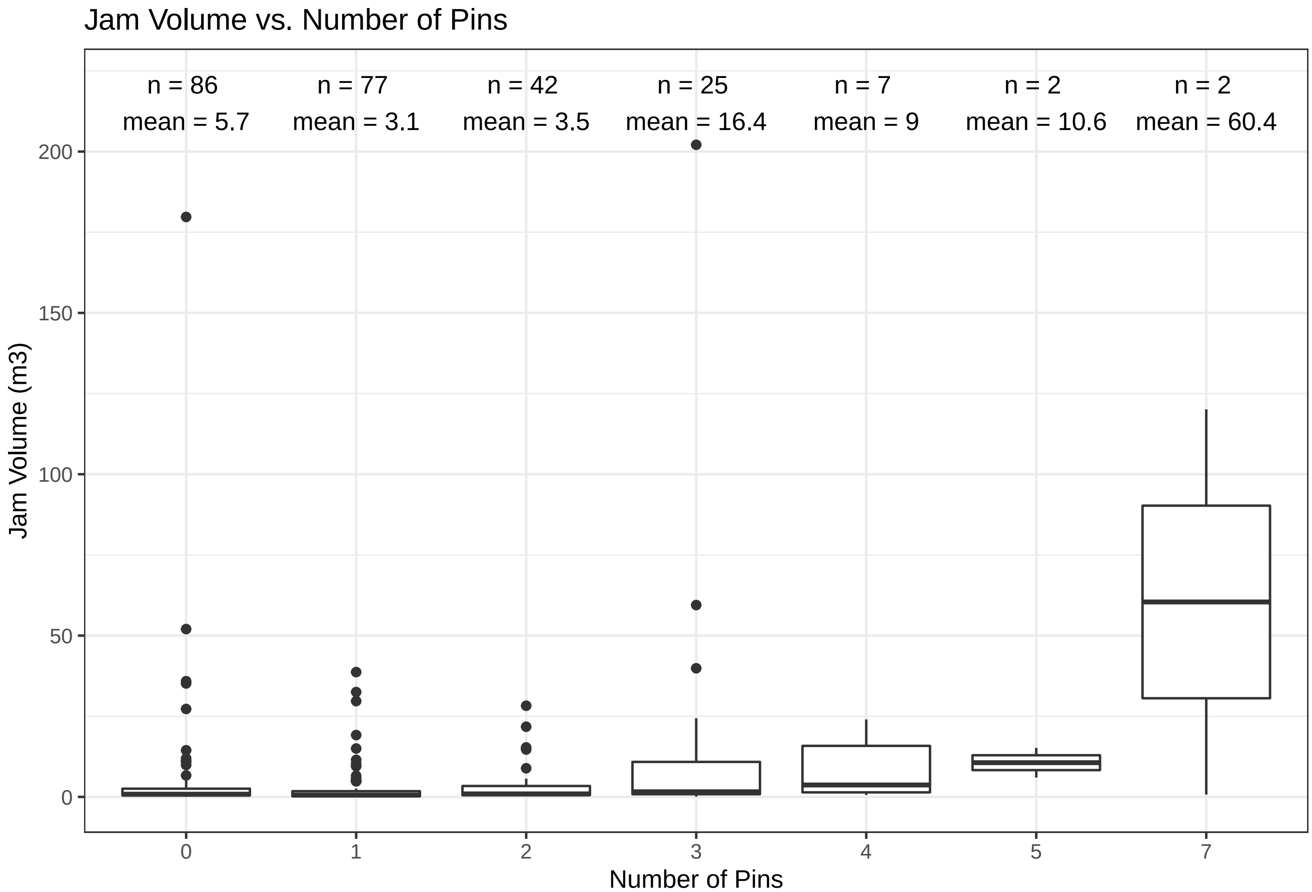
H2a) Primary trapping mechanism for floodplain jams is pinning

Method: Identified jams that were pinned on an object (typically a tree or rock) and then calculated percentage of jams that were pinned by one or multiple objects. Additionally, if pinning is the primary trapping mechanism for floodplain jams, then the volume of material trapped should increase with increasing pins. The relationship between pins and jam volume were investigated using a Type III ANOVA.

Results: 69.8% of jams were pinned on at least one tree (maximum number of pins was 7). Jam volume significantly increases with number of pins ($p = 0.0005$), but only a few jams were pinned more than 3 times.

```r
## ANOVA: woodvolume ~ pins
master$pins <- as.factor(master$pins)
pin_model <- lm(woodvolume_m3 ~ pins, data = master)
Anova(pin_model)
```

```
## Anova Table (Type II tests)
##
## Response: woodvolume_m3
##           Sum Sq  Df F value    Pr(>F)
## pins        9658   6  4.1711 0.0005273 ***
## Residuals  90305 234
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```



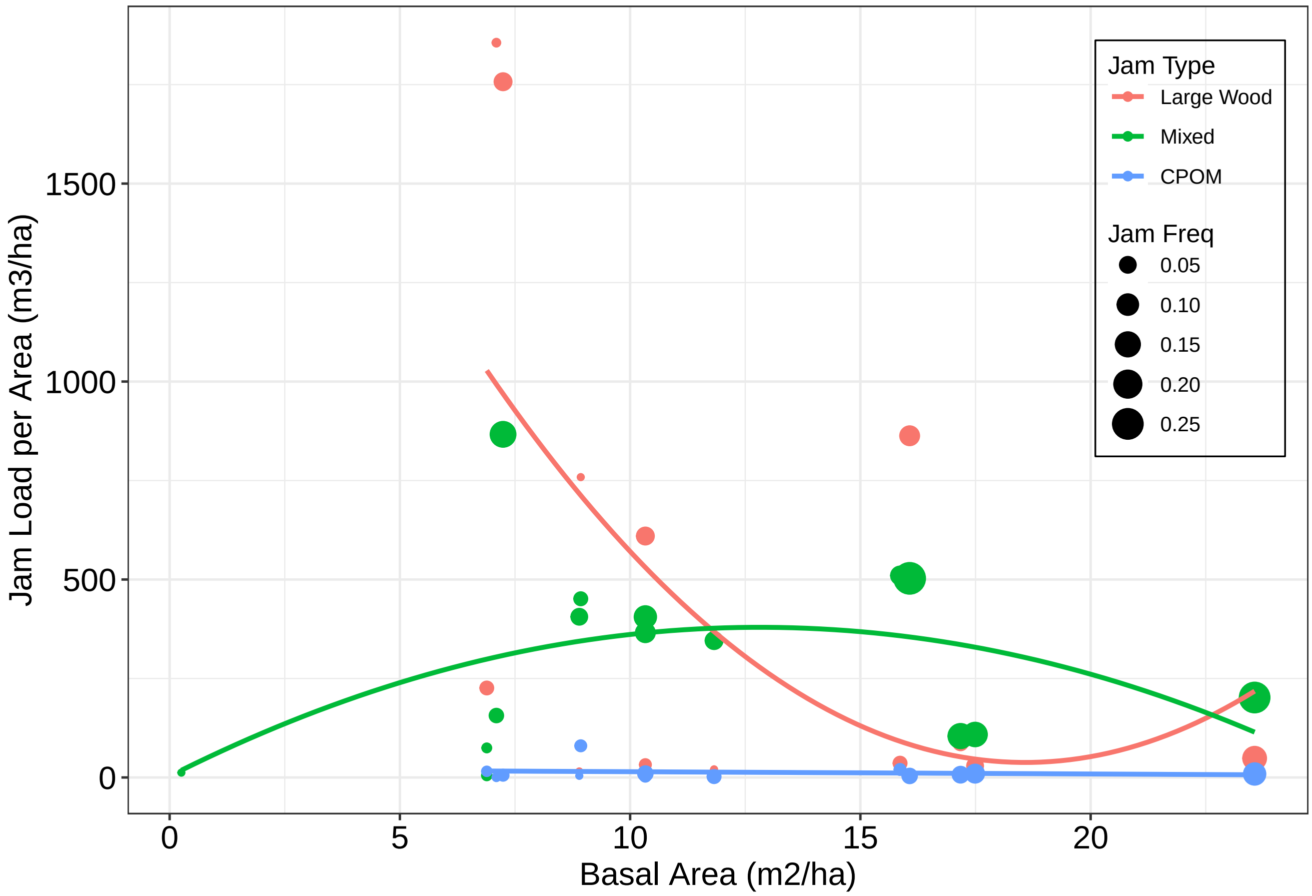
H2b) Intermediate floodplain forest stand density promotes the highest floodplain jam loads and frequency

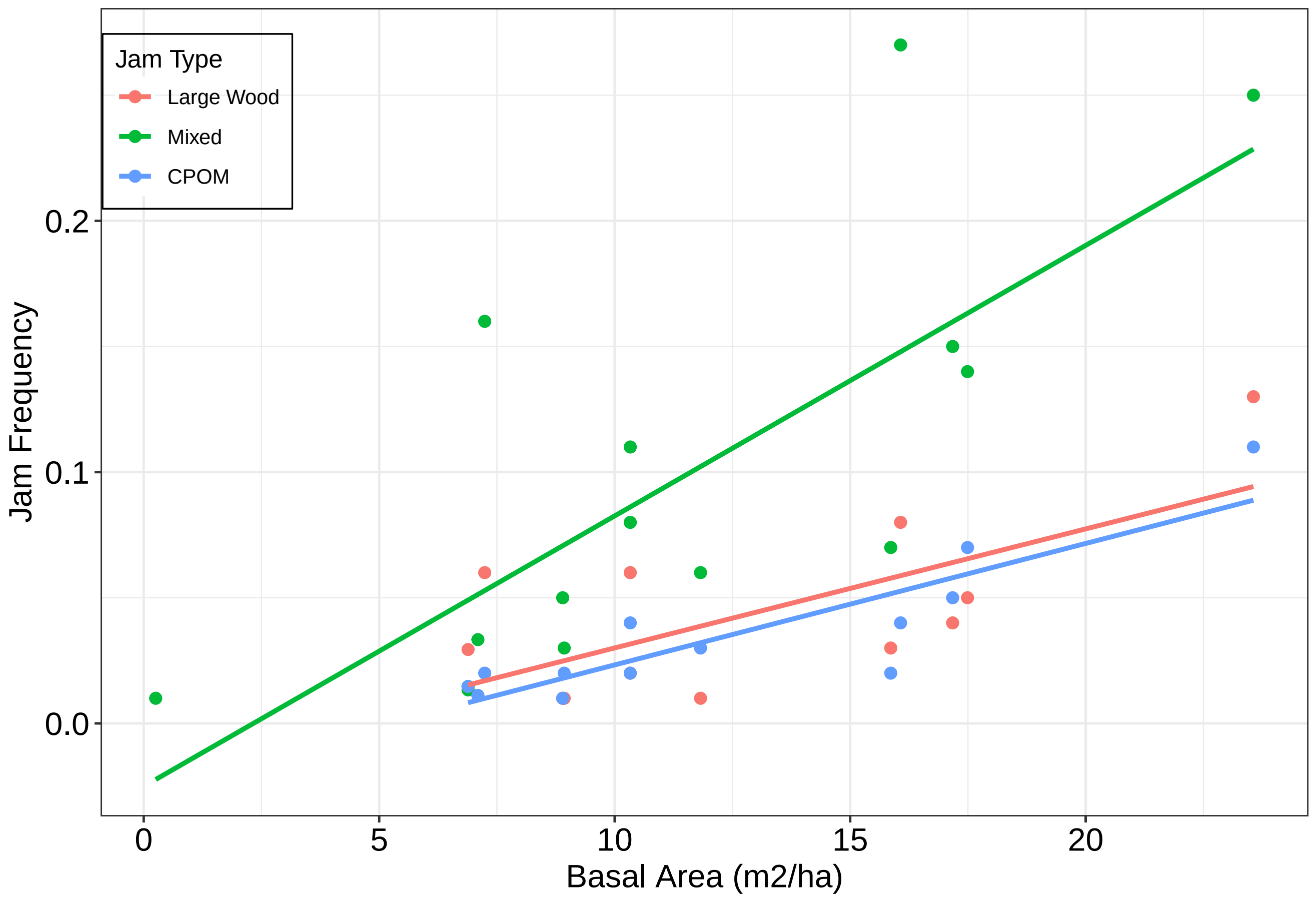
Method: Polynomial regressions were used to investigate non-linear relationships between floodplain forest stand density and jam loads as well as stand density and jam frequency.

Result: There appears to be a non-linear relationship between Jam Loads and Basal Area for LW and Mixed jams, but not for organic jams. However, according to the regressions, these relationships are not significant. Frequency linearly increases with increasing basal area - suggesting no tree stands were too dense to lower jam deposition.

```
##
## Call:
## lm(formula = woodload_perha_type ~ poly(basal_area_m2perha, 2),
##     data = filter(full_freq, jam_type == c("mixed", "LW")))
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -617.30 -236.78  -33.36  154.73 1154.34
##
## Coefficients:
##                              Estimate Std. Error t value Pr(>|t|)
## (Intercept)                     529.2      134.0   3.950  0.00273 **
## poly(basal_area_m2perha, 2)1   -249.4      483.1  -0.516  0.61683
## poly(basal_area_m2perha, 2)2   -567.8      483.1  -1.175  0.26708
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
##
## Residual standard error: 483.1 on 10 degrees of freedom
## Multiple R-squared:  0.1415, Adjusted R-squared:  -0.03021
## F-statistic: 0.824 on 2 and 10 DF,  p-value: 0.4664
```





H2c) Dense floodplain forest stands will correlate with smaller average jam sizes and a higher frequency of CPOM jams as opposed to LW jams.

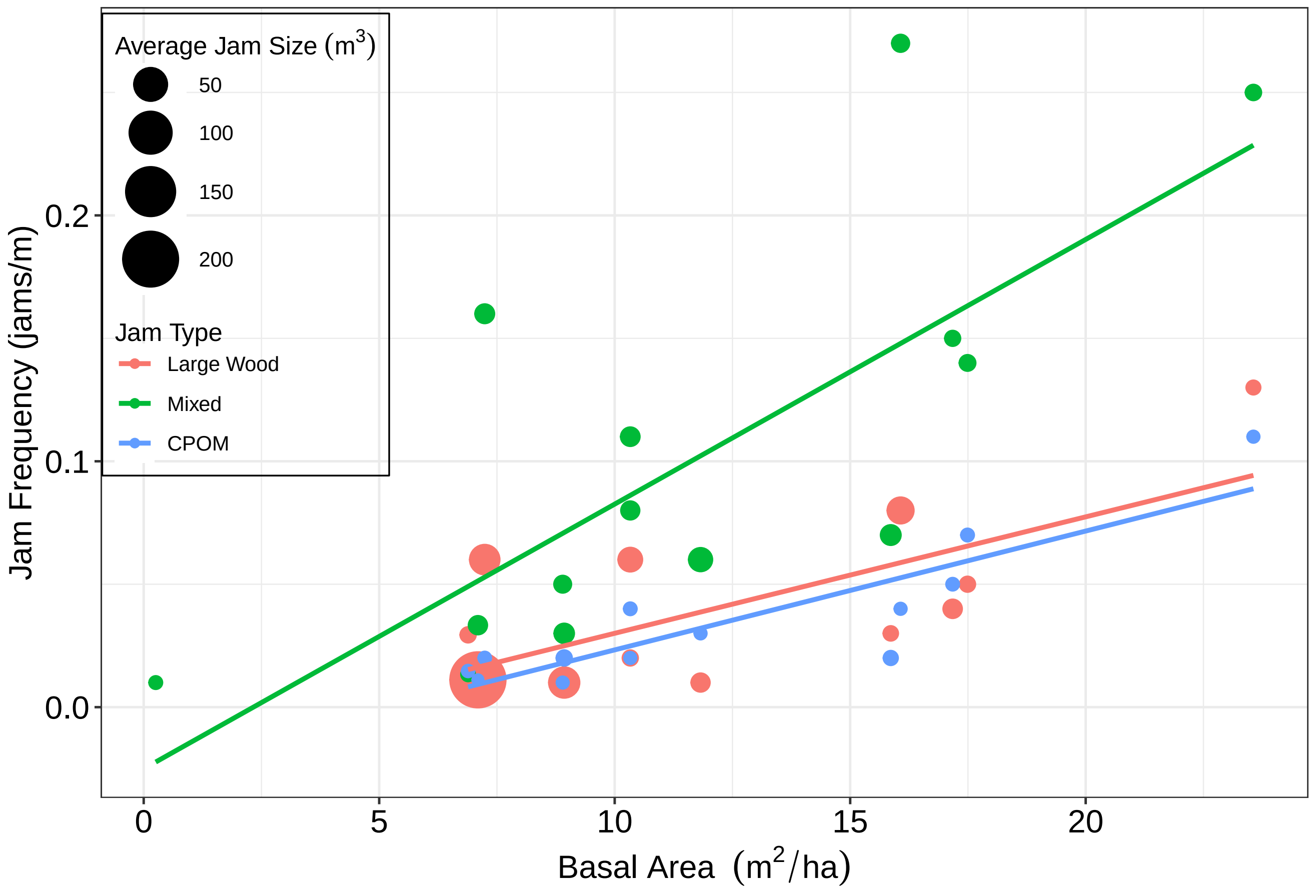
Method: A multiple linear regression was used to determine whether average jam size decreased with increasing floodplain forest stand and whether that relationship changed by jam type. A second multiple linear regression was used to determine the relationship between jam frequency and basal area by type. The emmeans() package is used to determine whether relationships change by jam type.

Result: Dense forests did correlate to smaller jam sizes ($p = 0.029$), but CPOM jams are not more frequent than LW jams in dense forests ($p = 0.9$). All jam types were more frequent in denser forest stands, though mixed jams were significantly more frequent than LW or CPOM jams (p « 0.05).

```r
jam_size_model <- lm(jam_size_avg_m3 ~ jam_type + basal_area_m2perha, data = full_freq)
#summary(jam_size_model)
#emmeans(jam_size_model, pairwise ~ jam_type)

jam_freq_model <- lm(frequency ~ jam_type + basal_area_m2perha, data = full_freq)
#summary(jam_freq_model)
emmeans(jam_freq_model, pairwise ~ jam_type)
```

```
## $emmeans
##  jam_type emmean     SE df lower.CL upper.CL
##  LW       0.0384 0.0113 37  0.01554   0.0613
##  mixed    0.1016 0.0105 37  0.08026   0.1229
##  organic  0.0319 0.0113 37  0.00903   0.0547
##
```

```
## Confidence level used: 0.95
##
## $contrasts
##  contrast         estimate     SE df t.ratio p.value
##  LW - mixed       -0.06320 0.0155 37 -4.086  0.0006
##  LW - organic      0.00652 0.0159 37  0.409  0.9122
##  mixed - organic   0.06971 0.0155 37  4.508  0.0002
##
## P value adjustment: tukey method for comparing a family of 3 estimates
```



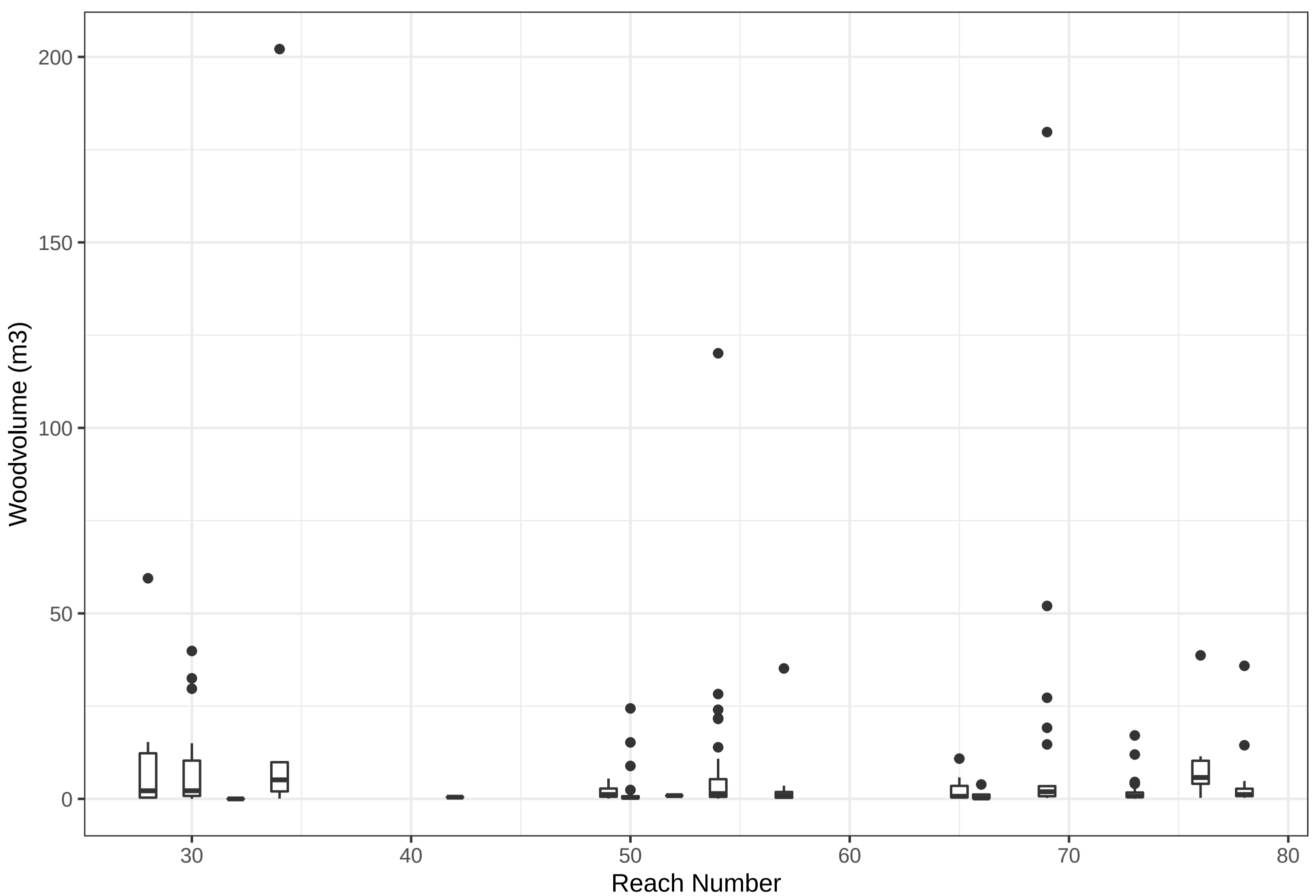
H1 versus H2: Multiple Linear Regression to see if morphology or stand characteristics best predict jams

Method

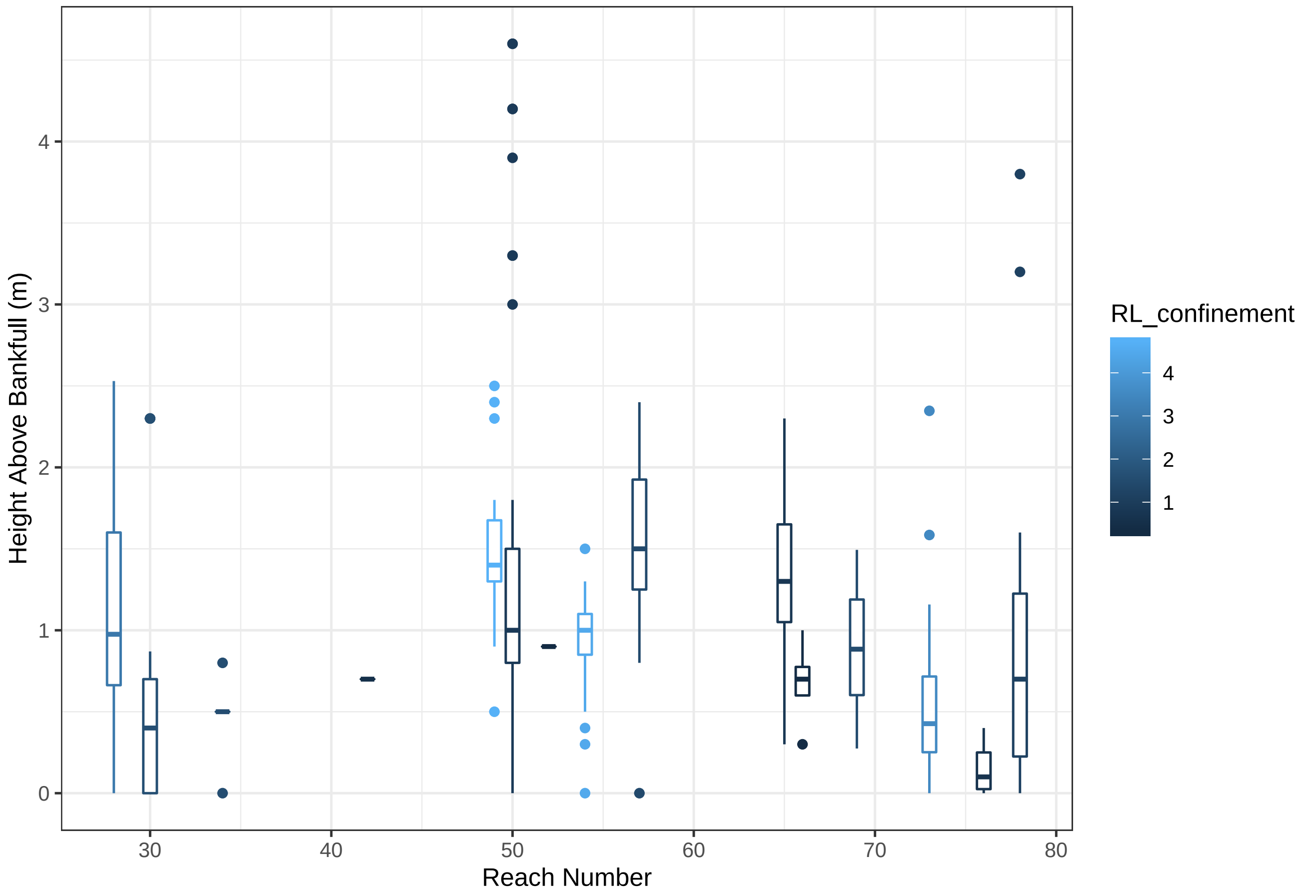
Multiple linear regressions will be used to determine which predictor variables have the strongest influence on jam frequency and loads. Predictor variables used in the regressions will include both morphology variables (bankfull width and floodplain confinement index) and forest stand variables (basal area). AICc will be used for selection of model variables; the model with the lowest AICc was chosen as the final model.

Do predictor variables change with increasing distance downstream?

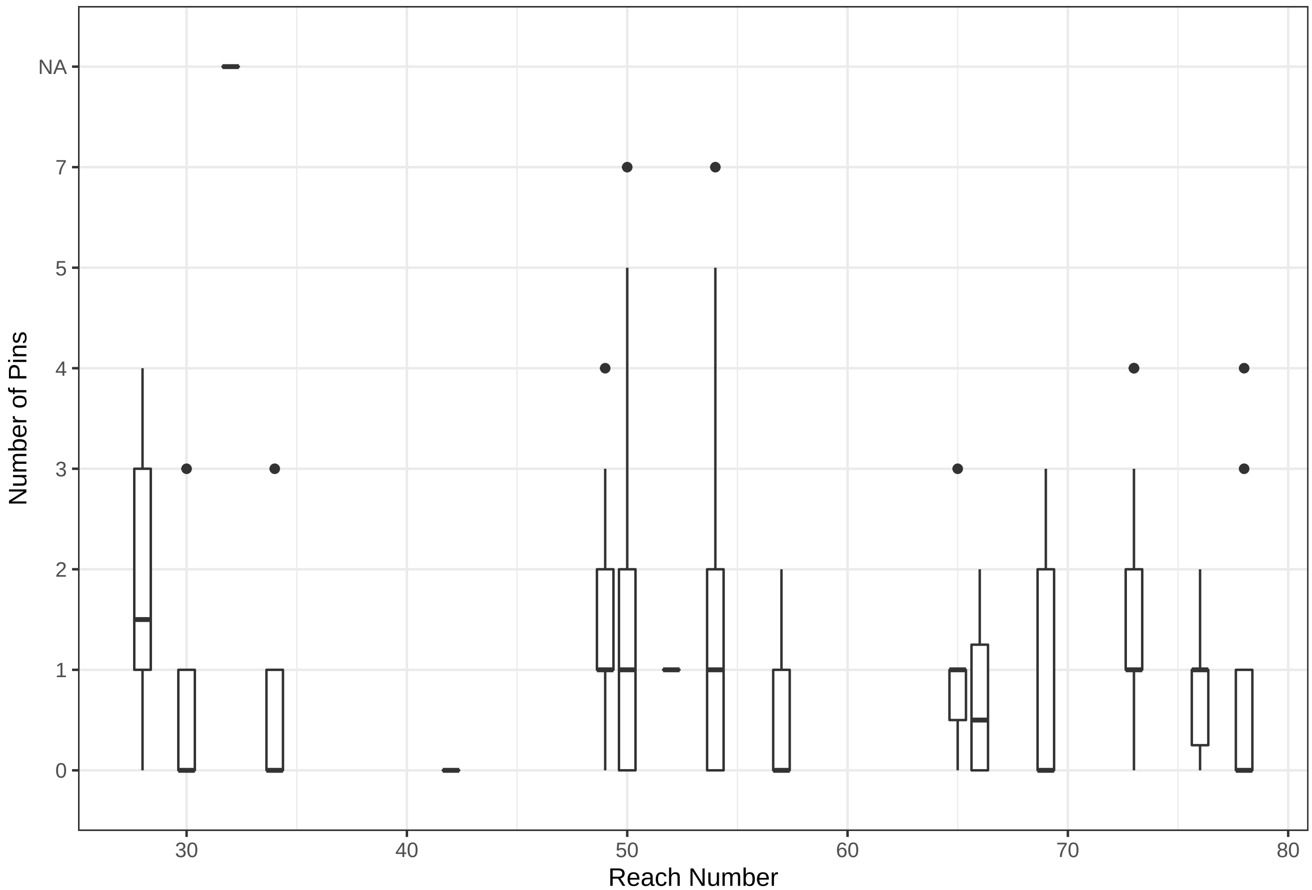
Does woodvolume (jam area) change with reach number?



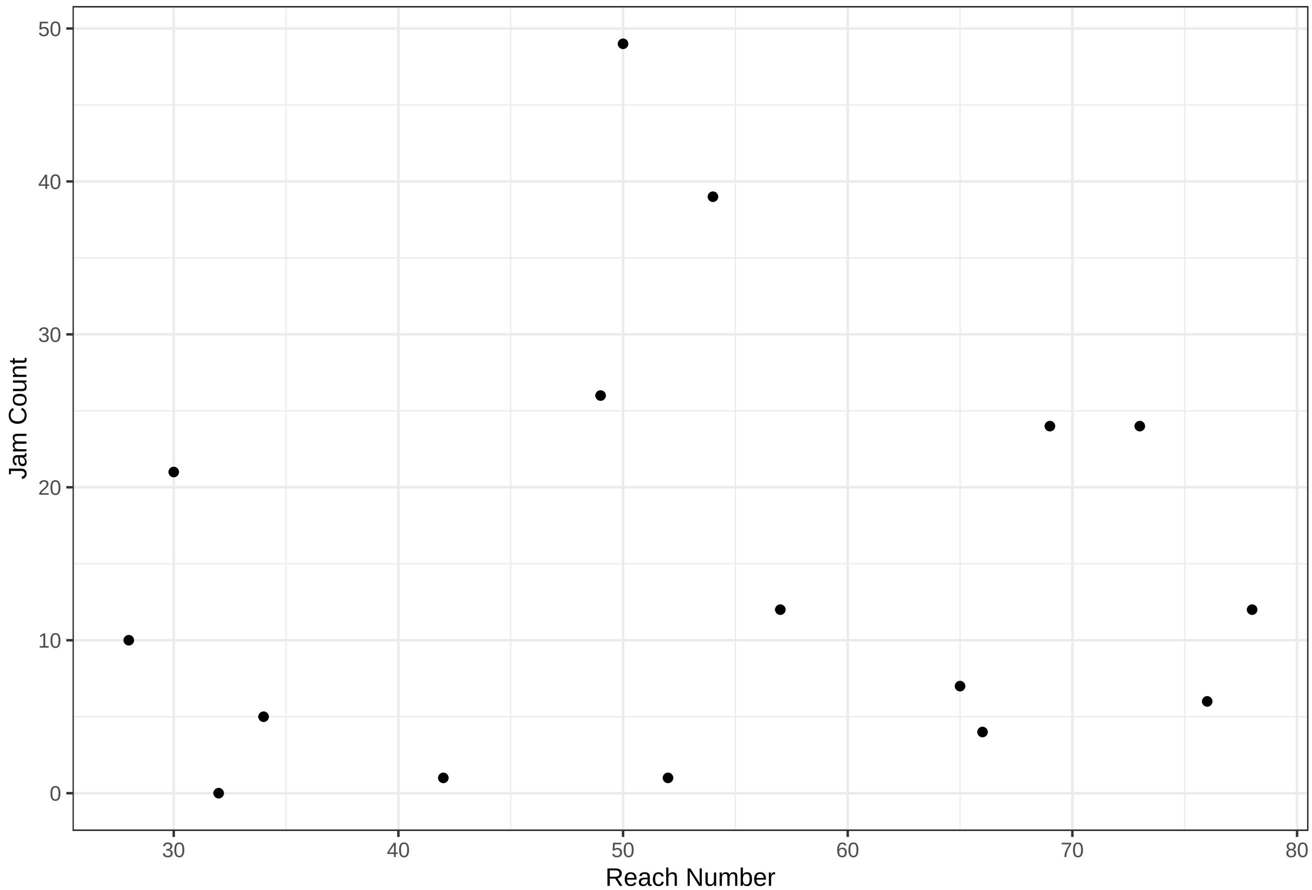
Does ht_above_bf change with reach number?



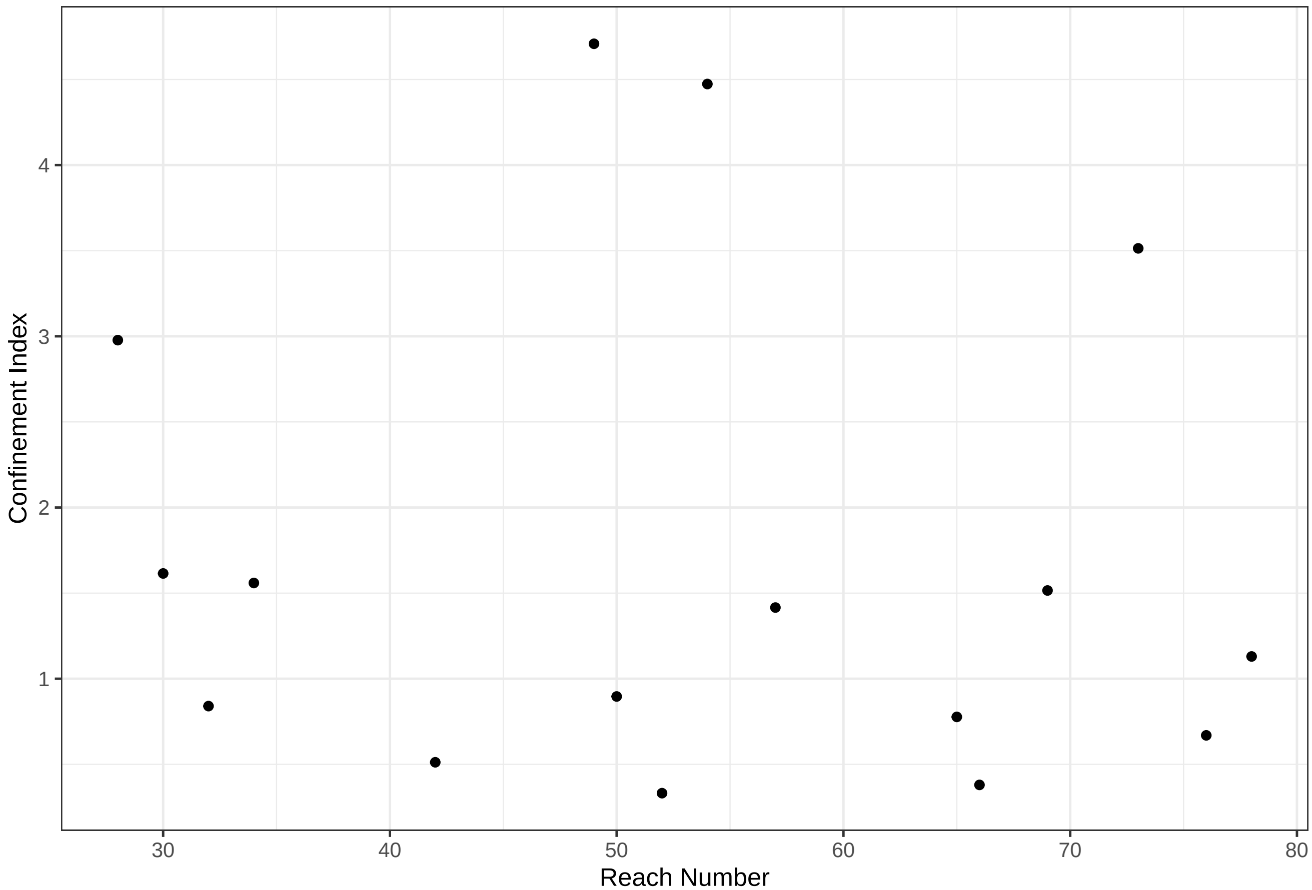
Does number of pins change with reach number?



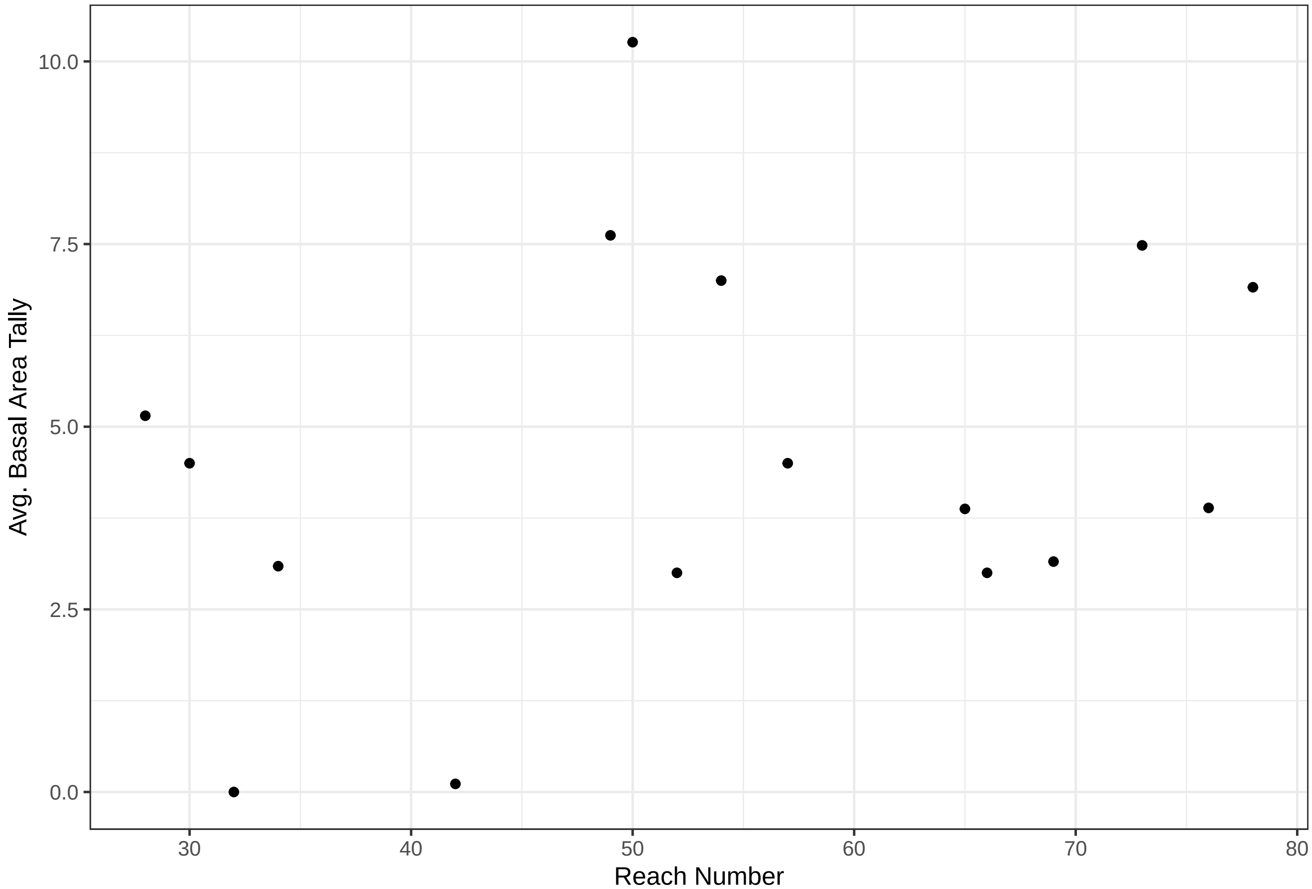
Does number of jams change with reach number?



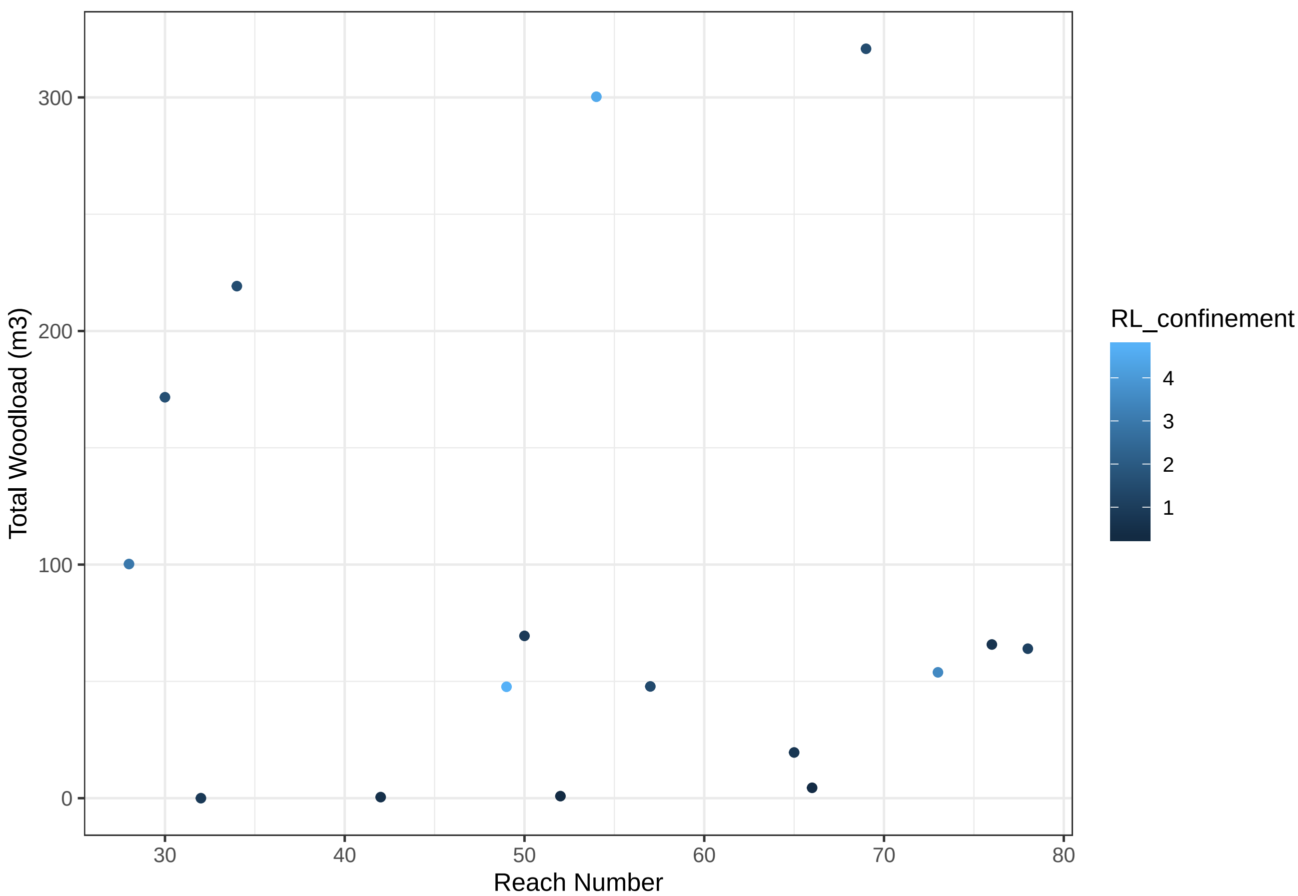
Does floodplain confinement change with reach?



Does Basal Area Tally change with reach? Note: checked correlation between reach number and basal area tally and it is not significant.



Does Total Woodload change with reach?



Multiple linear regressions

Model for woodload per area

Significant model at the 0.1 level - woodload per area correlates to polynomial of basal area.

```
## full model for woodload per area
woodload_mod_full <- lm(sqrt(woodload_m3perha) ~ bankfull_width_ave_m +
                          jam_total +
                          RL_confinement +
                          poly(basal_area_tally_ave, 2),
                          data = full_reach_ch,
                          na.action = "na.fail")
vif(woodload_mod_full)
```

```
##                                   GVIF Df GVIF^(1/(2*Df))
## bankfull_width_ave_m          7.035256  1        2.652406
## jam_total                     5.022477  1        2.241088
## RL_confinement                3.989267  1        1.997315
## poly(basal_area_tally_ave, 2) 9.642326  2        1.762160
```

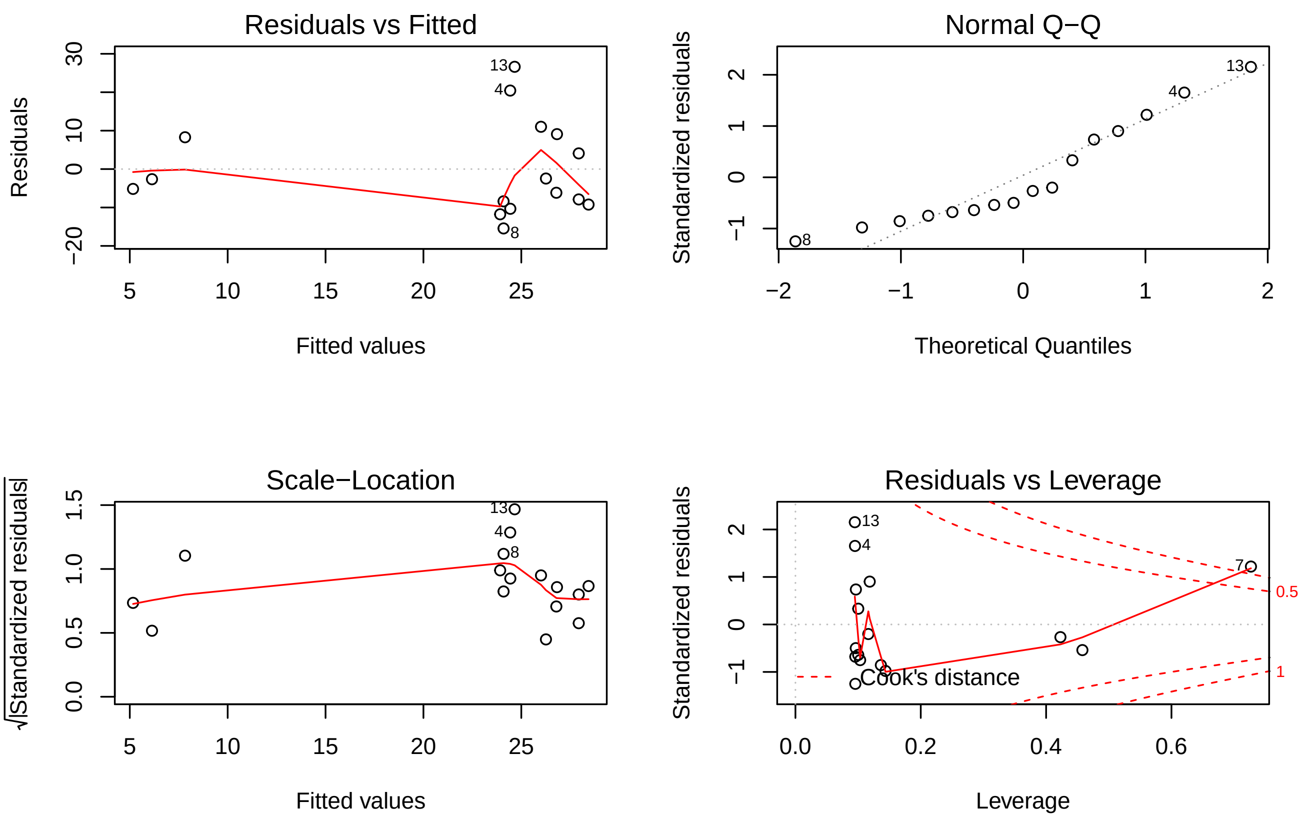
```
## dredge full model
woodload_dredge <- dredge(woodload_mod_full, rank = 'AICc', extra = "R^2")
importance(woodload_dredge)
```

```
##                      poly(basal_area_tally_ave, 2) jam_total
## Sum of weights:      0.78                          0.74
## N containing models:    8                             8
##                      bankfull_width_ave_m RL_confinement
## Sum of weights:      0.22                 0.14
## N containing models:    8                    8
```

```
## summary
head(woodload_dredge)
```

```
## Global model call: lm(formula = sqrt(woodload_m3perha) ~ bankfull_width_ave_m +
##     jam_total + RL_confinement + poly(basal_area_tally_ave, 2),
##     data = full_reach_ch, na.action = "na.fail")
## ---
## Model selection table
##     (Int) bnk_wdt_ave_m jam_ttl ply(bsl_are_tll_ave,2) RL_cnf     R^2 df
## 7   6.634               1.0320                      +        0.58250  5
## 8  -3.419         1.151  1.0090                      +        0.65520  6
## 1  22.180                                                    0.00000  2
## 15  9.364               1.1820                      + -2.923 0.63260  6
## 5  22.180                                           +        0.30410  4
## 3  18.170               0.2667                               0.06939  3
##     logLik  AICc delta weight
## 7  -57.987 132.0  0.00  0.503
## 8  -56.456 134.2  2.27  0.162
## 1  -64.975 134.9  2.90  0.118
## 15 -56.964 135.3  3.29  0.097
## 5  -62.075 135.8  3.81  0.075
## 3  -64.400 136.8  4.82  0.045
## Models ranked by AICc(x)
```

```r
## final model
woodload_final <- lm(sqrt(woodload_m3perha) ~ poly(basal_area_tally_ave, 2),
                     data = full_reach_ch)

## residual plots
par(mfrow = c(2,2))
plot(woodload_final)
```



Model for Jam Size (not averaged by reach)

Significant model with low R2. Final model includes distance from channel, bankfull width, and total blockage.

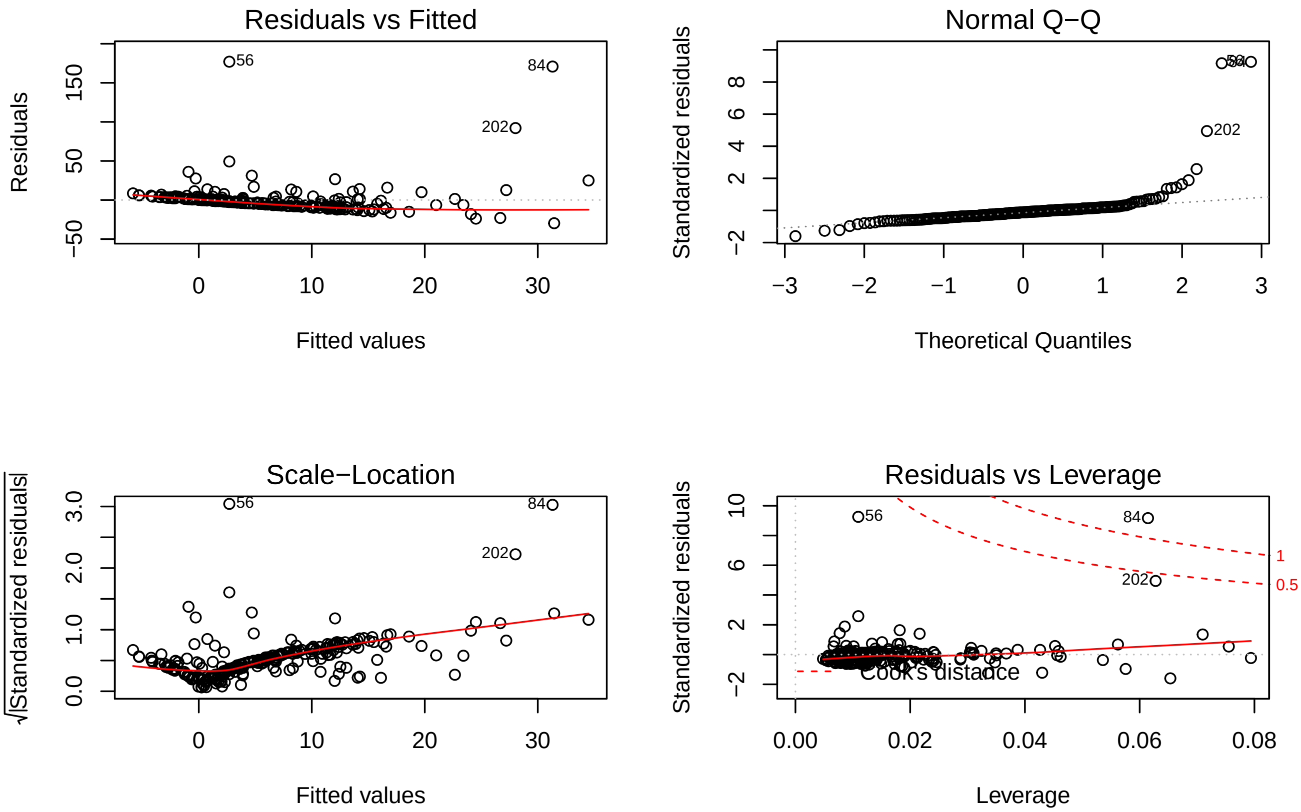
```
master$pins <- as.integer(master$pins)
master_jams <- master %>%
  filter(!(reach ==32))
jam_size_full <- lm(woodvolume_m3 ~ ht_above_bf_m + dist_from_channel_m + bf_width_m +
                      tot_blockage,
                    na.action = 'na.fail',
                    data = master_jams)

jam_size_dredge <- dredge(jam_size_full, rank = 'AICc', extra = 'R^2')
importance(jam_size_dredge)
```

```
##                        tot_blockage bf_width_m dist_from_channel_m ht_above_bf_m
## Sum of weights:      1.00         0.61       0.47                0.28
## N containing models:    8            8          8                   8
```

```
jam_size_final <- lm(woodvolume_m3 ~ dist_from_channel_m + bf_width_m + tot_blockage,
                     data = master_jams)

## summary and plots
summary(jam_size_final)
```

```
##
## Call:
## lm(formula = woodvolume_m3 ~ dist_from_channel_m + bf_width_m +
##     tot_blockage, data = master_jams)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -29.739  -6.661  -2.108   1.450 177.038
##
## Coefficients:
##                     Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -4.22168    5.08916  -0.830    0.408
## dist_from_channel_m -0.21951    0.18463  -1.189    0.236
## bf_width_m           0.87393    0.57298   1.525    0.129
## tot_blockage         0.19198    0.03732   5.144 5.65e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 19.24 on 237 degrees of freedom
## Multiple R-squared:  0.1227, Adjusted R-squared:  0.1116
## F-statistic: 11.05 on 3 and 237 DF,  p-value: 8.101e-07
```

```
par(mfrow = c(2,2))
plot(jam_size_final)
```


Residuals vs Fitted
Residuals
Fitted values
56
84
202
Normal Q−Q
Standardized residuals
Theoretical Quantiles
Scale−Location
√|Standardized residuals|
Residuals vs Leverage
Leverage
Cook's distance
1
0.5

Model for Average Jam Size

No significant model.

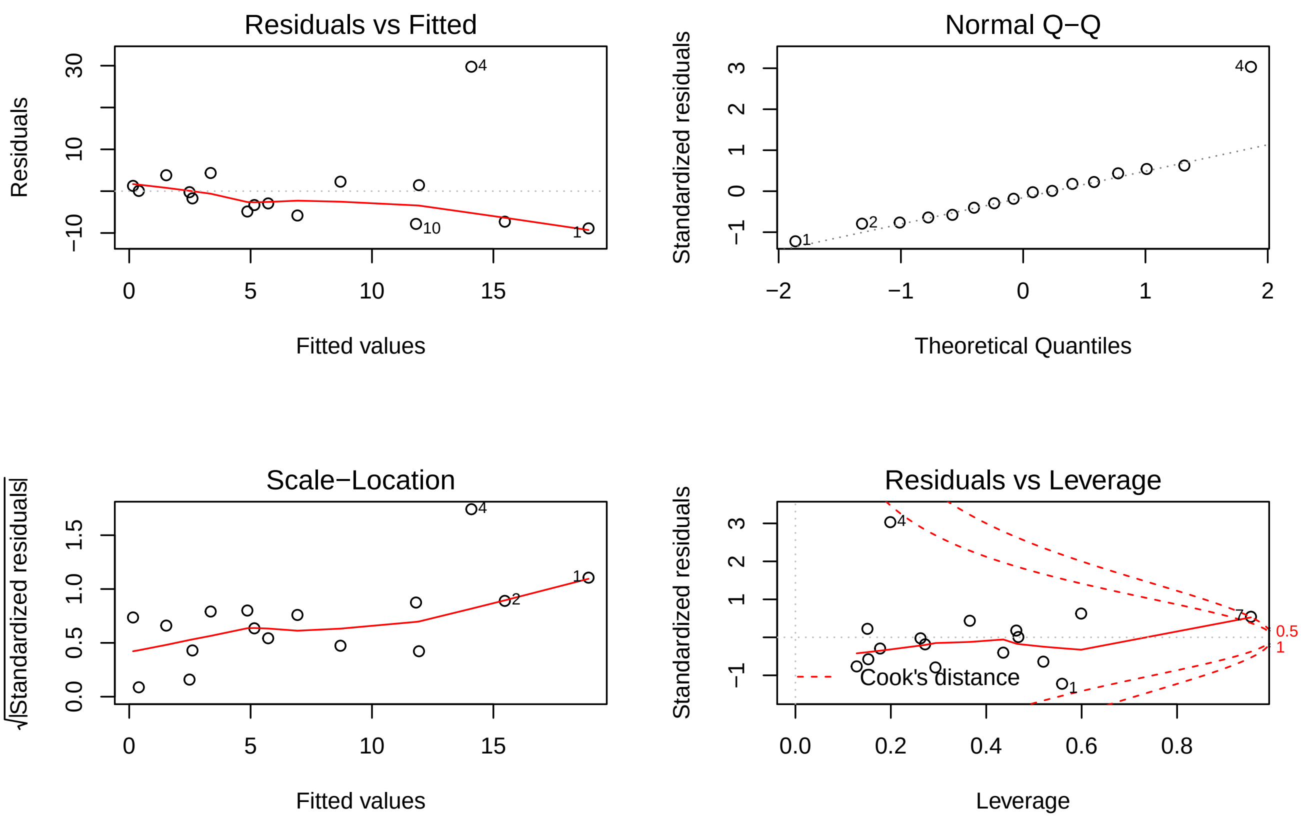
```r
## full model for jam size
size_full <- lm(jam_size_avg_m3 ~ bankfull_width_ave_m +
                           jam_total +
                           RL_confinement +
                           poly(basal_area_tally_ave, 2),
                           data = full_reach_ch,
                           na.action = 'na.fail')

## dredge full model
size_dredge <- dredge(size_full, rank = 'AICc', extra = "R^2")
importance(size_dredge)
```

```
##                      bankfull_width_ave_m jam_total RL_confinement
## Sum of weights:      0.174                0.171     0.164
## N containing models:     8                    8         8
##                      poly(basal_area_tally_ave, 2)
## Sum of weights:      0.071
## N containing models:     8
```

```r
## summary
head(size_dredge)
```

```
## Global model call: lm(formula = jam_size_avg_m3 ~ bankfull_width_ave_m + jam_total +
##     RL_confinement + poly(basal_area_tally_ave, 2), data = full_reach_ch,
##     na.action = "na.fail")
## ---
## Model selection table
##    (Int) bnk_wdt_ave_m  jam_ttl ply(bsl_are_tll_ave,2) RL_cnf      R^2 df
## 1  7.133                                                      0.000000  2
## 2  8.842       -0.1891                                        0.010570  3
## 3  8.273               -0.07567                               0.010370  3
## 9  6.505                                               0.3676 0.002424  3
## 5  7.133                                             +        0.113300  4
## 11 7.290               -0.13360                        1.0860 0.025470  4
##     logLik  AICc delta weight
## 1  -60.022 125.0  0.00  0.549
## 2  -59.936 127.9  2.91  0.128
## 3  -59.938 127.9  2.91  0.128
## 9  -60.002 128.0  3.04  0.120
## 5  -59.059 129.8  4.79  0.050
## 11 -59.815 131.3  6.30  0.024
## Models ranked by AICc(x)
```

```r
## residual plots
par(mfrow = c(2,2))
plot(size_full)
```


Residuals vs Fitted
Residuals
Fitted values
Normal Q−Q
Standardized residuals
Theoretical Quantiles
Scale−Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance
0.5
1

Model for Jam Frequency

Very significant model (p«0.05) with bankfull width and RL_confinement. R2 = 0.76.

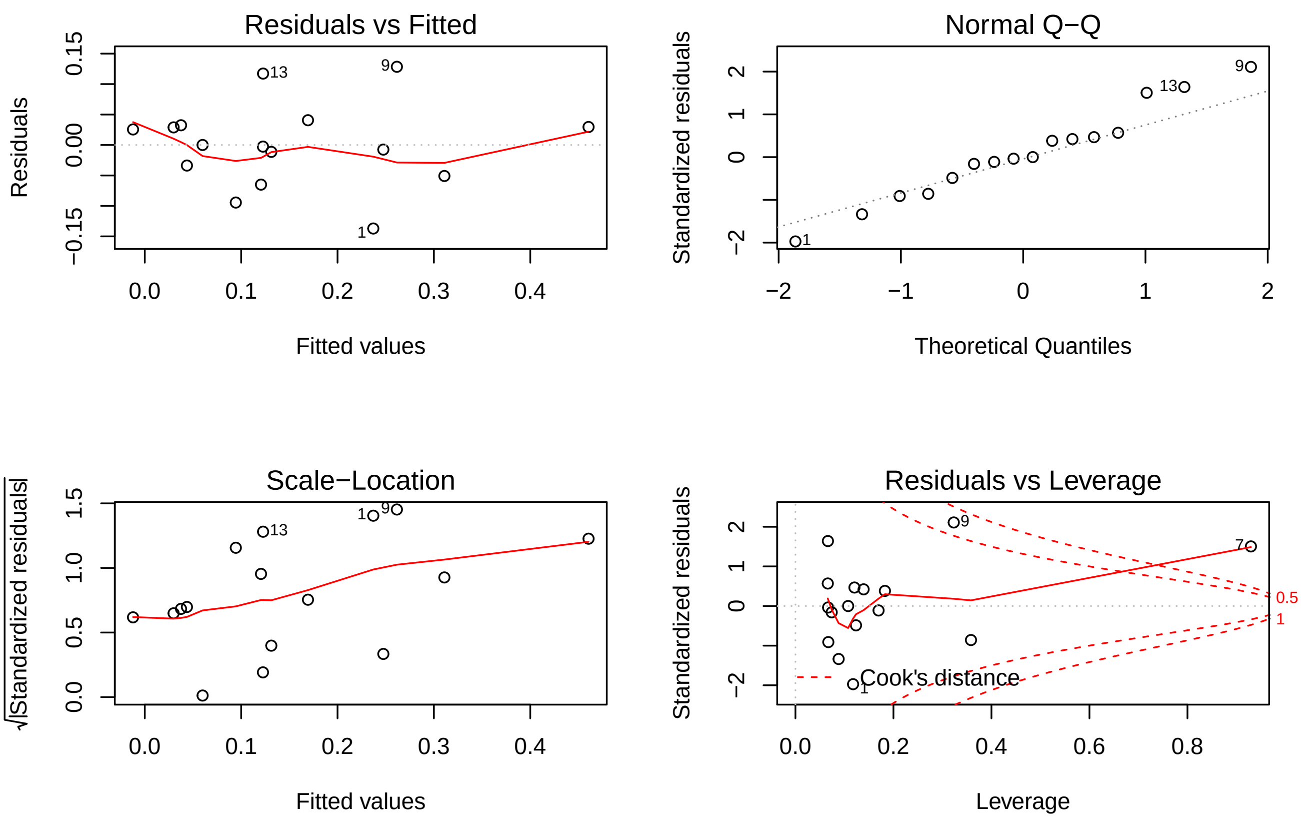
```
# full model for jam frequency
frequency_full <- lm(jam_per_m ~ bankfull_width_ave_m +
                       RL_confinement +
                       basal_area_tally_ave,
                     data = full_reach_ch,
                     na.action = 'na.fail')
frequency_dredge <- dredge(frequency_full, rank = 'AICc', extra = 'R^2')
importance(frequency_dredge)
```

```
##                      bankfull_width_ave_m RL_confinement basal_area_tally_ave
## Sum of weights:      0.71                 0.67           0.55
## N containing models:    4                    4              4
```

```
frequency_final <- lm(jam_per_m~bankfull_width_ave_m +
                        RL_confinement,
                      data = full_reach_ch)
summary(frequency_final)
```

```
##
## Call:
## lm(formula = jam_per_m ~ bankfull_width_ave_m + RL_confinement,
##     data = full_reach_ch)
##
## Residuals:
##       Min        1Q    Median        3Q       Max
## -0.137107 -0.038023 -0.001309  0.030252  0.128404
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          -0.115653   0.045326  -2.552 0.024121 *
## bankfull_width_ave_m  0.017308   0.003355   5.158 0.000184 ***
## RL_confinement        0.065372   0.013626   4.798 0.000348 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 0.07399 on 13 degrees of freedom
## Multiple R-squared:  0.7642, Adjusted R-squared:  0.7279
## F-statistic: 21.07 on 2 and 13 DF,  p-value: 8.346e-05
```

```
## residual plots
par(mfrow = c(2,2))
plot(frequency_final)
```


Residuals vs Fitted
Residuals
Fitted values
Normal Q−Q
Standardized residuals
Theoretical Quantiles
Scale−Location
√|Standardized residuals|
Fitted values
Residuals vs Leverage
Standardized residuals
Leverage
Cook's distance
0.5
1

Model for Jam Frequency by Type

All models are significant with bankfull width and RL_confinement. Basal area is not a significant predictor.

Large Wood Model

```
LW_freq <- filter(full_freq, jam_type == 'LW')
LW_frequency_full <- lm(frequency ~ bankfull_width_ave_m +
                         RL_confinement +
                         basal_area_tally_ave,
                        data = LW_freq,
                        na.action = 'na.fail')
LW_dredge <- dredge(LW_frequency_full, rank = 'AICc', extra = 'R^2')
importance(LW_dredge)
```

```
##                       bankfull_width_ave_m RL_confinement basal_area_tally_ave
## Sum of weights:      0.76                 0.40           0.38
## N containing models:    4                    4              4
```

```
head(LW_dredge)
```

```
## Global model call: lm(formula = frequency ~ bankfull_width_ave_m + RL_confinement +
##     basal_area_tally_ave, data = LW_freq, na.action = "na.fail")
## ---
## Model selection table
##       (Int) bnk_wdt_ave_m bsl_are_tll_ave    RL_cnf    R^2 df logLik  AICc
## 6 -0.021850      0.004604                 0.009964 0.6616  4 32.693 -52.4
## 2  0.004108      0.003940                          0.5040  3 30.207 -51.7
## 3 -0.017330                     0.0108700          0.4834  3 29.942 -51.2
## 4 -0.017480      0.002516       0.0064850          0.6101  4 31.771 -50.5
## 7 -0.015670                     0.0119200 -0.003709 0.5028  4 30.190 -47.4
## 8 -0.021960      0.004552       0.0001787  0.009781 0.6617  5 32.693 -46.8
##   delta weight
## 6  0.00  0.354
## 2  0.64  0.257
## 3  1.17  0.197
## 4  1.84  0.141
## 7  5.00  0.029
## 8  5.57  0.022
## Models ranked by AICc(x)
```

Mixed Jam Model

```
mix_freq <- unique(filter(full_freq, jam_type == 'mixed'))
mix_frequency_full <- lm(frequency ~ bankfull_width_ave_m +
                          RL_confinement +
                          basal_area_tally_ave,
                         data = mix_freq,
                         na.action = 'na.fail')
mix_dredge <- dredge(mix_frequency_full, rank = 'AICc', extra = 'R^2')
importance(mix_dredge)
```

```
##                        RL_confinement bankfull_width_ave_m basal_area_tally_ave
## Sum of weights:      0.64           0.56                 0.53
## N containing models:    4              4                    4
```

```
head(mix_dredge)
```

```
## Global model call: lm(formula = frequency ~ bankfull_width_ave_m + RL_confinement +
##     basal_area_tally_ave, data = mix_freq, na.action = "na.fail")
## ---
## Model selection table
##      (Int) bnk_wdt_ave_m bsl_are_tll_ave  RL_cnf    R^2 df logLik  AICc delta
## 6 -0.04812     0.0082260                 0.03957 0.6832  4 25.177 -38.4  0.00
## 3 -0.02506                       0.02471         0.5701  3 22.887 -37.6  0.76
## 7 -0.02947                       0.02022 0.01498 0.6202  4 23.815 -35.6  2.72
## 8 -0.04931     0.0064560         0.00593 0.03284 0.6913  5 25.372 -34.1  4.28
## 4 -0.02624     0.0005234         0.02399         0.5710  4 22.903 -33.8  4.55
## 5  0.03709                               0.03343 0.3430  3 19.706 -31.2  7.12
##   weight
## 6  0.457
## 3  0.312
## 7  0.117
## 8  0.054
## 4  0.047
## 5  0.013
## Models ranked by AICc(x)
```

CPOM Jam Model

```
org_freq <- filter(full_freq, jam_type == 'organic')
org_frequency_full <- lm(frequency ~ bankfull_width_ave_m +
                          RL_confinement +
                          basal_area_tally_ave,
                         data = org_freq,
                         na.action = 'na.fail')
org_dredge <- dredge(org_frequency_full, rank = 'AICc', extra = 'R^2')
importance(org_dredge)
```

```
##                        bankfull_width_ave_m RL_confinement basal_area_tally_ave
## Sum of weights:      0.98                 0.95           0.14
## N containing models:    4                    4              4
```

```
head(org_dredge)
```

```
## Global model call: lm(formula = frequency ~ bankfull_width_ave_m + RL_confinement +
##     basal_area_tally_ave, data = org_freq, na.action = "na.fail")
## ---
## Model selection table
##        (Int) bnk_wdt_ave_m bsl_are_tll_ave    RL_cnf    R^2 df logLik  AICc
## 6 -0.027840      0.004199                 0.011650 0.9078  4 43.884 -74.8
## 8 -0.029380      0.003523        0.002345  0.009250 0.9150  5 44.411 -70.2
## 4 -0.025140      0.001597        0.008309           0.8448  4 40.495 -68.0
## 3 -0.025050                      0.011100           0.7669  3 37.853 -67.0
## 7 -0.024520                      0.011430 -0.001191 0.7700  4 37.939 -62.9
## 2  0.002514      0.003423                           0.5794  3 34.016 -59.4
##   delta weight
## 6  0.00  0.860
## 8  4.52  0.090
## 4  6.78  0.029
## 3  7.73  0.018
## 7 11.89  0.002
## 2 15.40  0.000
## Models ranked by AICc(x)
```