Analysis of loadings

Wesley Brooks

1 Introduction

Minimizing the erosion of sediment into streams is a goal for water quality managers. In order to develop plans to limit the amount of sediment that gets into streams, those managers need to know how sediment gets into the water. A recent study [1] has shown that

The next block of code produces a set of bar charts that show the relative contributions of the snow-driven events, post-snow-pre-vegetation events, and the post-vegetation events.

2 Variable selection

In order to make a model of the load carried by the stream, we need to select the predictor variables that have explanatory power. We use stepwise regression with the Bayesian Information Criterion (BIC) to screen the potential predictor variables.

```
Call:
lm(formula = log_stot_tot ~ antecedent_qbase + theisen, data = eagle_nosnow)

Residuals:
     Min       1Q   Median       3Q      Max
-1.36985 -0.38539 -0.01636  0.36174  1.72769

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -1.35345    0.09295  -14.56   <2e-16 ***
antecedent_qbase  0.15791    0.00996   15.86   <2e-16 ***
theisen           0.86034    0.04071   21.13   <2e-16 ***
```

Solids:		
	Eagle	theisen, p15max, p60max, antecedent$_q base$
	Joos	theisen, p15max, ap$_2 day, antecedent_q base$
	Otter	theisen, julian, antecedent$_q base, antecedent_t mean$
	Brewery	theisen, p30max, tmean
Phosphorus:		
	Eagle	theisen, p15max, p30max, tmax, tmean, antecedent$_q base$
	Joos	theisen, p15max, ap$_2 day, antecedent_q base$
	Otter	theisen, tmean, julian, antecedent$_q base$
	Brewery	theisen, p30max, ap$_3 day, tmean$

```
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.5152 on 242 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared: 0.7554,       Adjusted R-squared: 0.7534
F-statistic: 373.8 on 2 and 242 DF,  p-value: < 2.2e-16

Call:
lm(formula = log_stot_tot ~ antecedent_qbase + theisen, data = joosvalley_nosnow)

Residuals:
     Min       1Q   Median       3Q      Max
-2.53840 -0.37911 -0.02301  0.32260  1.91902

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)      -1.34618    0.08411  -16.01   <2e-16 ***
antecedent_qbase  0.19763    0.01717   11.51   <2e-16 ***
theisen           0.85938    0.04357   19.72   <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.5812 on 251 degrees of freedom
  (3 observations deleted due to missingness)
```

```
Multiple R-squared: 0.6647,	Adjusted R-squared: 0.662
F-statistic: 248.8 on 2 and 251 DF,  p-value: < 2.2e-16

Call:
lm(formula = log_stot_tot ~ antecedent_qbase + theisen, data = otter_nosnow)

Residuals:
    Min      1Q  Median      3Q     Max
-1.3252 -0.2519 -0.0092  0.2702  1.3771

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -1.379094   0.054726  -25.20   <2e-16 ***
antecedent_qbase  0.121272   0.007881   15.39   <2e-16 ***
theisen           0.934789   0.046258   20.21   <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.4372 on 245 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared: 0.7385,	Adjusted R-squared: 0.7363
F-statistic: 345.9 on 2 and 245 DF,  p-value: < 2.2e-16

Call:
lm(formula = log_stot_tot ~ antecedent_qbase + theisen, data = brewery_nosnow)

Residuals:
    Min      1Q  Median      3Q     Max
-2.1064 -0.5225  0.1222  0.4687  1.7584

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.44937    0.19369  -2.320   0.0216 *
antecedent_qbase -0.07398    0.08070  -0.917   0.3606
theisen           0.69205    0.06874  10.068   <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.7512 on 161 degrees of freedom
```

```
  (128 observations deleted due to missingness)
Multiple R-squared: 0.3884,	Adjusted R-squared: 0.3808
F-statistic: 51.13 on 2 and 161 DF,  p-value: < 2.2e-16

Call:
lm(formula = log_ptot_tot ~ antecedent_qbase + theisen, data = eagle_nosnow)

Residuals:
     Min       1Q   Median       3Q      Max
-0.98156 -0.23430  0.00308  0.20073  1.46374

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.145134   0.067172  -2.161   0.0317 *
antecedent_qbase  0.108446   0.007198  15.067   <2e-16 ***
theisen           0.714547   0.029420  24.288   <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.3723 on 242 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared: 0.7826,	Adjusted R-squared: 0.7808
F-statistic: 435.6 on 2 and 242 DF,  p-value: < 2.2e-16

Call:
lm(formula = log_ptot_tot ~ antecedent_qbase + theisen, data = joosvalley_nosnow)

Residuals:
     Min       1Q   Median       3Q      Max
-1.82432 -0.22751 -0.04278  0.20511  1.72563

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.26036    0.06052  -4.302 2.43e-05 ***
antecedent_qbase  0.15271    0.01236  12.356  < 2e-16 ***
theisen           0.70562    0.03136  22.504  < 2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
```

```
Residual standard error: 0.4182 on 251 degrees of freedom
  (3 observations deleted due to missingness)
Multiple R-squared: 0.7151,	Adjusted R-squared: 0.7128
F-statistic:   315 on 2 and 251 DF,  p-value: < 2.2e-16

Call:
lm(formula = log_ptot_tot ~ antecedent_qbase + theisen, data = otter_nosnow)

Residuals:
     Min       1Q   Median       3Q      Max
-0.99166 -0.25833  0.01595  0.27079  1.03556

Coefficients:
                  Estimate Std. Error t value Pr(>|t|)
(Intercept)      -0.045816   0.046203  -0.992    0.322
antecedent_qbase  0.102279   0.006653  15.372   <2e-16 ***
theisen           0.783261   0.039054  20.056   <2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1

Residual standard error: 0.3691 on 245 degrees of freedom
  (2 observations deleted due to missingness)
Multiple R-squared: 0.7365,	Adjusted R-squared: 0.7344
F-statistic: 342.4 on 2 and 245 DF,  p-value: < 2.2e-16

Call:
lm(formula = log_ptot_tot ~ antecedent_qbase + theisen, data = brewery_nosnow)

Residuals:
     Min       1Q   Median       3Q      Max
-1.46780 -0.31817  0.02745  0.28340  1.34380

Coefficients:
                 Estimate Std. Error t value Pr(>|t|)
(Intercept)       0.55719    0.12465   4.470 1.47e-05 ***
antecedent_qbase -0.10602    0.05193  -2.041   0.0428 *
theisen           0.69750    0.04424  15.767  < 2e-16 ***
---
Signif. codes:  0 *** 0.001 ** 0.01 * 0.05 . 0.1   1
```

```
Residual standard error: 0.4834 on 161 degrees of freedom
  (128 observations deleted due to missingness)
Multiple R-squared: 0.6111,       Adjusted R-squared: 0.6062
F-statistic: 126.5 on 2 and 161 DF,  p-value: < 2.2e-16
```

The next block prints a table of the proportion of total phosphorus loading due to each class of event at each site

	snowmelt-driven	early post-snow	late post-snow
eagle	27.0%	29.1%	43.9%
joosvalley	26.9%	20.5%	52.6%
otter	35.4%	20.5%	44.1%
brewery	32.8%	4.5%	62.7%

Table 1: Proportion of total suspended solids loading contributed by each type of event

	snowmelt-driven	early post-snow	late post-snow
eagle	32.8%	22.9%	44.2%
joosvalley	36.4%	16.9%	46.7%
otter	46.5%	16.6%	36.9%
brewery	NA%	NA%	NA%

Table 2: Proportion of total phosphorus loading contributed by each type of event

Produce plots of the proportion of the suspended solids and phosphorus (both total loading and stormflow loading) that is contributed by each class of event at each stream site:

Figure out what proportion of total sediment loading is contributed by the top 10% of storms:

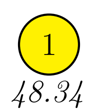
The top 10% of events contributed 89.1% of the sediment loading at Eagle Creek, 73.1% of the sediment loading at Otter Creek, and 93.4% of the sediment loading at

Joos Valley Creek.

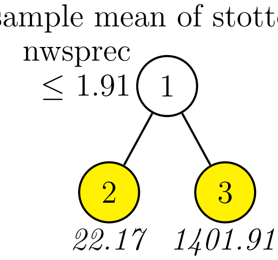
Now we want to know how these major events are distributed within the event classes; that is, whether snowmelt tends to produce major loading events, or whether it is the post-snow events. Note that the _tot column measures the total loading during an event. The snowmelt-driven events are different in kind than the rainfall-driven ones because they don't require continuous rain during the event. If the snowmelt-driven events are caused by warm weather, it seems reasonable that a single event might last for many days and cause more loading than a more-intense rainfall event that only lasts a day or two. To account for this, we will look both at total loading (_tot) and average daily loading during an event (_avg).

	Snowmelt		Early post-snow		Late post-snow	
Creek	All	Major	All	Major	All	Major
Eagle	42%	30%	13%	19%	45%	51%
Otter	41%	42%	11%	19%	48%	40%
Joos	46%	31%	11%	17%	43%	52%

The table shows that the major loading events that produce the majority of the loading can be occur during each of the three annual periods. However, the events caused by snowmelt produced a smaller proportion of major events than their proportion of all events, and their relative contribution to the total sediment load was smaller than their proportion of loading events. Taken together, these insights tell us that, while snowmelt can cause a major loading event, a snowmelt-driven event is less likely to be a major contributor to sediment load than is a rainfall-driven event.

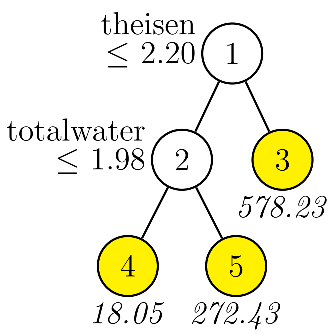


GUIDE piecewise constant least-squares regression tree model. At each intermediate node, a case goes to the left branch if and only if the condition is satisfied. Number in italics beneath leaf node is sample mean of stottot.



		Sediment		Phosphorus		
Creek	Period	All events	Major events	Loading	Major events	
	Snowmelt	48%	28%	40%	NA NA	Earl
10% Aggregated	23%	14%	NA NA	Late post-snow	43%	
46%	NA NA height	Snowmelt	42%	27%	30%	
37%	Eagle					
	Early post-snow	13%	29%	19%	23%	
	Late post-snow	45%	44%	51%	44%	
	Snowmelt	46%	27%	31%	36%	
Joos	Early post-snow	11%	20%	17%	17%	
	Late post-snow	43%	53%	52%	47%	
	Snowmelt	41%	35%	42%	47%	
Otter	Early post-snow	11%	20%	19%	17%	
	Late post-snow	48%	44%	40%	37%	

GUIDE piecewise constant least-squares regression tree model. At each intermediate node, a case goes to the left branch if and only if the condition is satisfied. Number in italics beneath leaf node is sample mean of stottot.



GUIDE piecewise constant least-squares regression tree model. At each intermediate node, a case goes to the left branch if and only if the condition is satisfied. Number in italics beneath leaf node is sample mean of stottot.

References

[1] M.E. Danz, S.R. Corsi, D.J. Graczyk, and R.T. Bannerman. Characterization of suspended solids and total phosphorus loadings from small watersheds in wiscon-

sin. Scientific Investigations Report 2010-5039, United States Geological Survey, 2010.

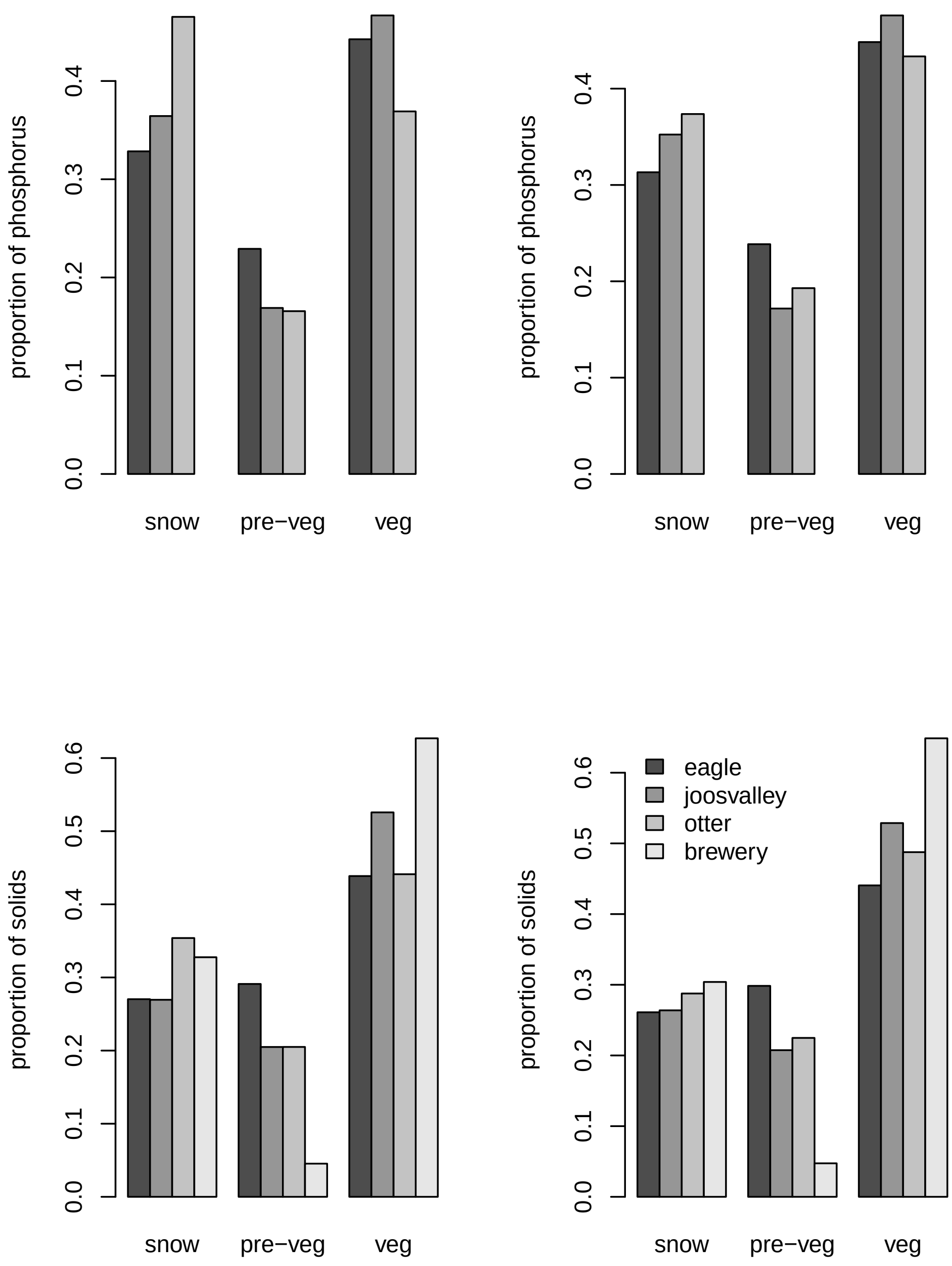
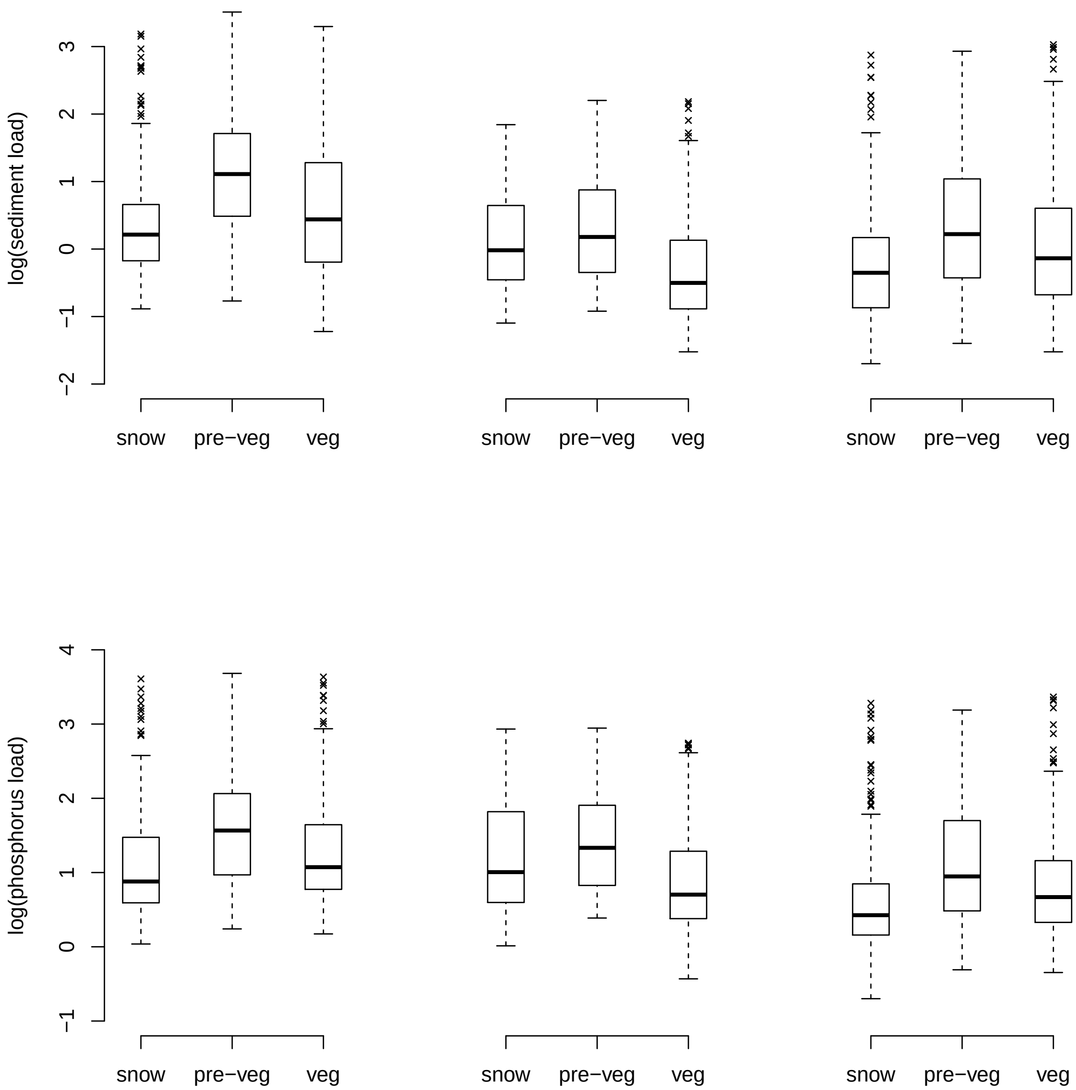


Figure 1: Cumulative storm loadings at the three creeks.


log(sediment load)
−2
−1
0
1
2
3
snow
pre−veg
veg
snow
pre−veg
veg
snow
pre−veg
veg
log(phosphorus load)
−1
0
1
2
3
4
snow
pre−veg
veg
snow
pre−veg
veg
snow
pre−veg
veg

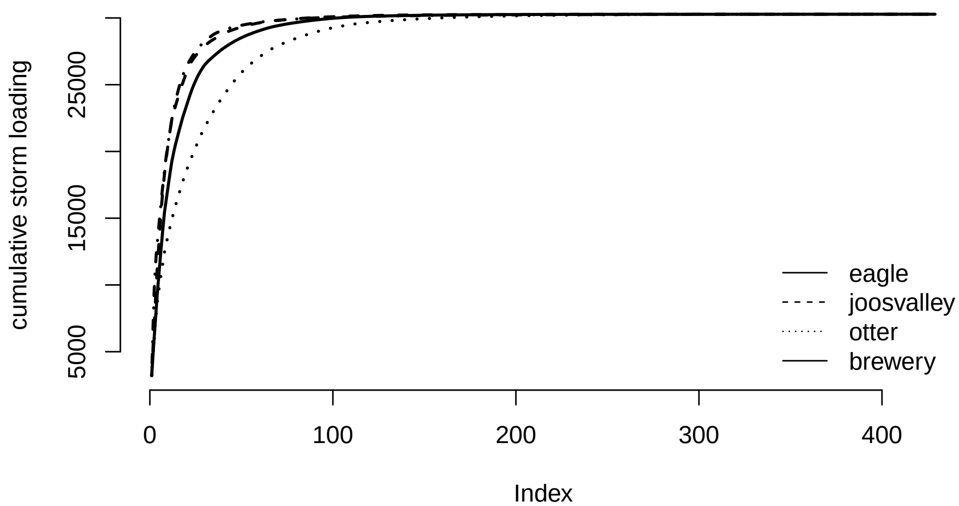


Figure 2: Cumulative storm loadings at the three creeks.

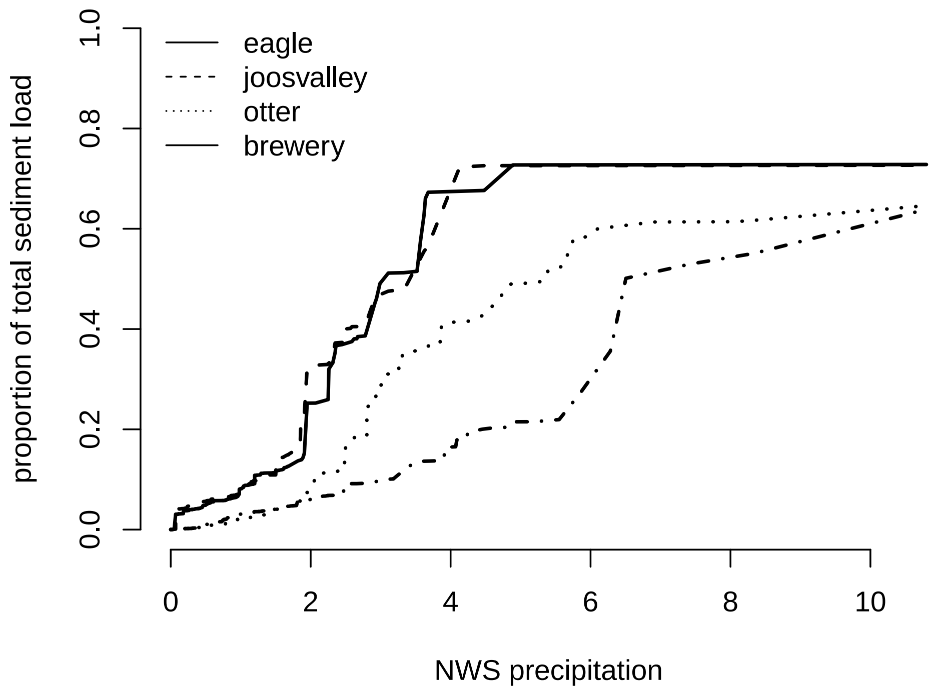


Figure 3: Proportion of the total sediment load contributed by rainfall events up to the size shown. Snowmelt-driven events are excluded.

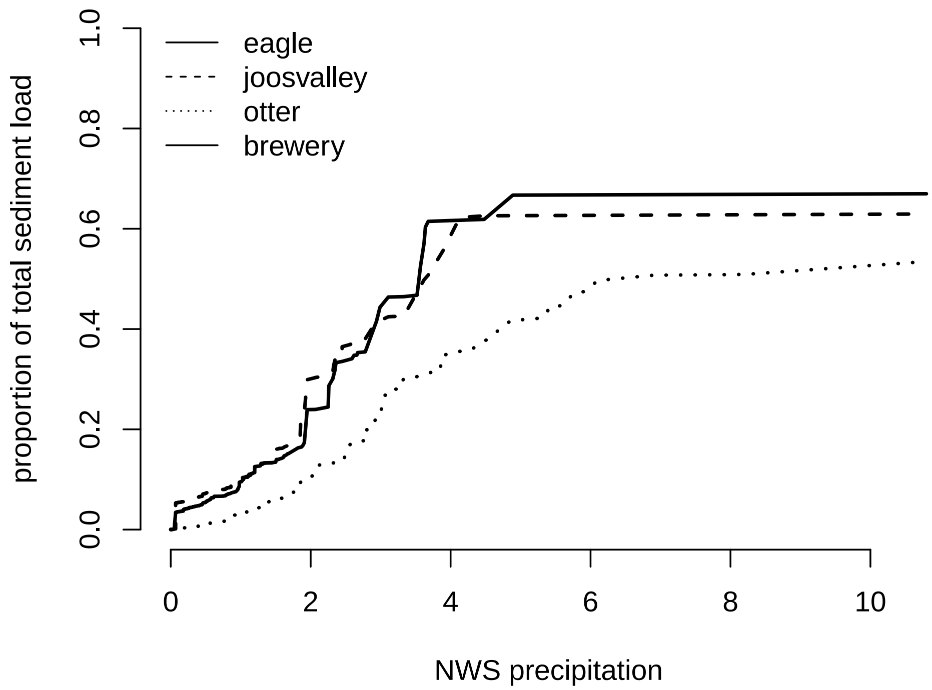


Figure 4: Proportion of the total phosphorus load contributed by rainfall events up to the size shown. Snowmelt-driven events are excluded.