Columbia River Project Water Use Plan

Arrow Reservoir Operations Management Plan

CLBMON-41: Arrow Reservoir Recreational Demand Study

Implementation Year 5 – Secondary Analysis of Overall Study Results

Reference: CLBMON-41

Secondary Analysis of CLBMON-41 Arrow Reservoir Recreational Demand Study.

Study Period: 2009 - 2013

Carl James Schwarz
StatMathComp Consulting

Feb 23, 2017

Supplemental analyses for
CLBMON 41 Arrow Reservoir Recreational Demand Study
Year 5 Report
Study Period : 2009-2013.

Carl James Schwarz
Department of Statistics and Actuarial Science
Simon Fraser University

cschwarz@stat.sfu.ca

2017-02-23

1. Introduction:

This reports on supplemental analyses to the final report by Lees and Associates (2015) (*CLBMON 41 Arrow Reservoir Recreational Demand Study*. *Year 5 Final Report Study Period : 2009-2013*) investigating, among other objectives, the impact of fluctuating water levels on usage and satisfaction of usage on the Arrow Lakes Reservoir, British Columbia. The supplemental analysis investigates three management questions about the relationship between the volume and type of usage to reservoir levels.

In this report, I have used the convention that tables and figures prefixed with an "A" refer to the appropriate table or figures in the authors' report, i.e., ATable A12 refers to Table 12 in the authors' report, while Table 12 refers to the table in this report.

The fully study protocol is present in the authors' report. Briefly, a five year study collected traffic count and interviews (on-site and on-line surveys) at 13 pre-selected, stratified monitoring sites comprised of 11 publicly accessible boat launches and two near-shore parks on the Arrow Lakes Reservoir. Weather information was obtained from Environment Canada measured at Nakusp.

The greatest challenge for this project is separating out the effects of confounding variables. For example, both the reservoir numbers and visitor numbers tend to be highest during the high season and lower during the shoulder and low seasons[1] along with other variables such as temperature (Figures 1, 2 and 3). Consequently, trying to disentangle the impact of reservoir elevation after adjusting for these other covariates will be challenging.

[1]The seasons are defined as: high season May 24 - Sept 30; shoulder season Apr 1 – May 23 & Oct 1 – Oct 30; and low season Nov 1 - Mar 31.

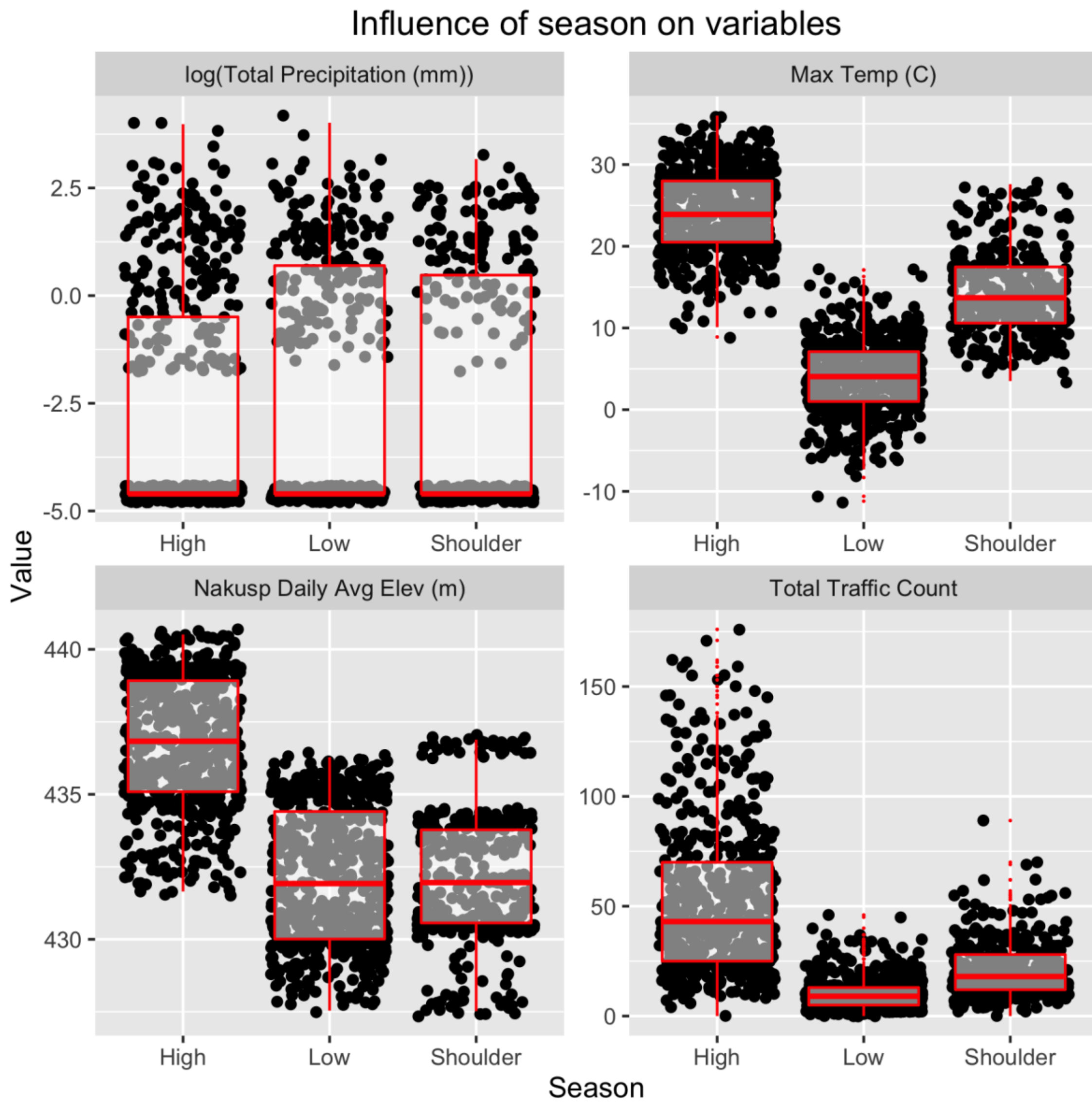

Figure 1. Plot of reservoir level, visitor numbers, mean daily temperatures by season.

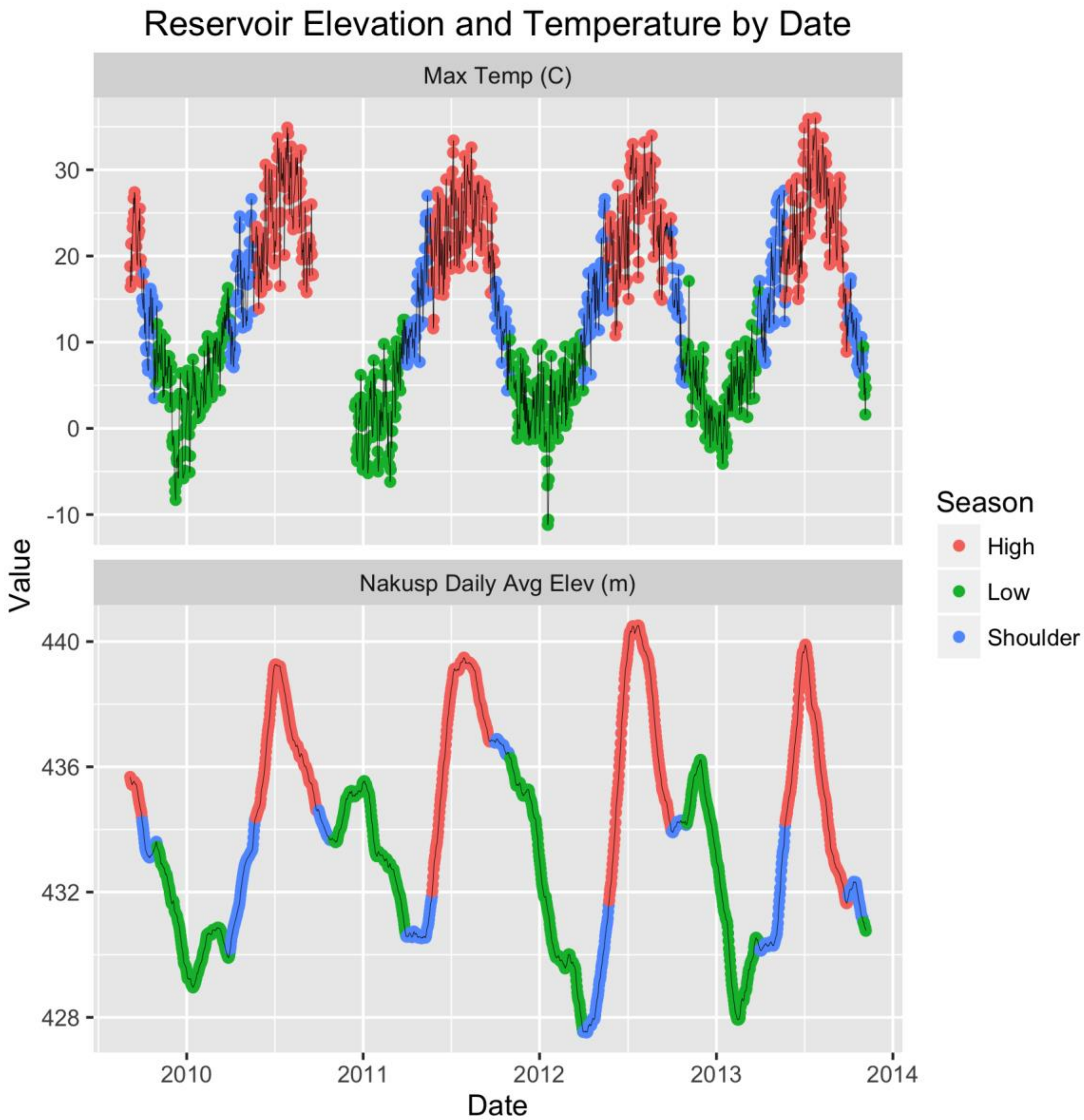

Figure 2. The relationship between maximum daily temperature and elevation vs. date. The color of the points indicates the season.

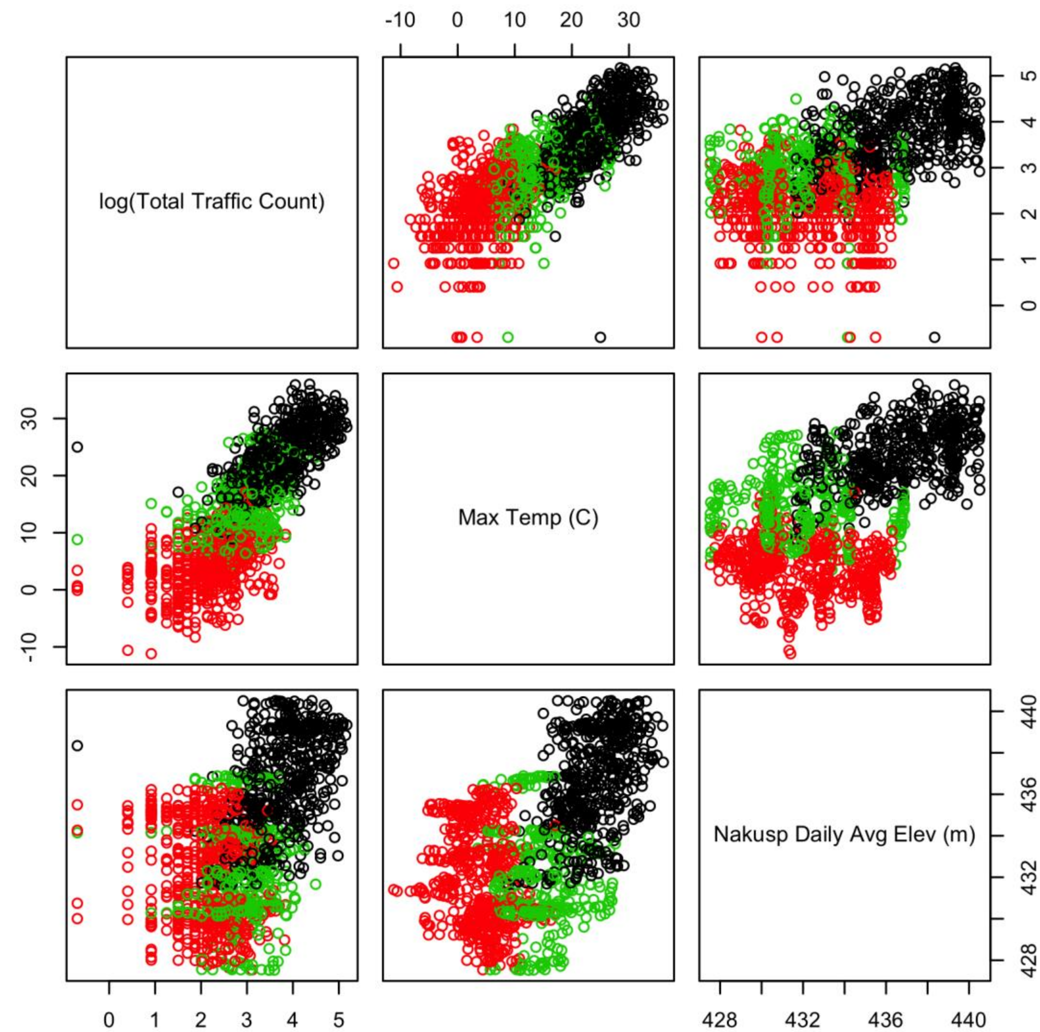

Figure 3. Pairwise plot showing the relationship between three important variables. The color of the points represents the season (red=low, green=shoulder, black=high).

A standard method to adjust for confounding variables is multiple regression. In this method, the marginal contribution of each variable (i.e., after accounting for the impact of the other variables in the regression model), is estimated using least-squares.

Regression methods are also available to deal with categorical data. For example, days can be classified as weekend or weekday and this classification (categorical predictor) can be included in models. Estimates of effects are now the difference in the mean response between a particular category and a baseline category.

If the response variable is categorical (e.g. will or will not return) a more advanced regression approach, logistic regression is used. In logistic regression, the **probability** that a respondent would return to the Arrow Lakes Reservoir can be modeled as a function of the actual elevation at the time of the survey using a more general method, maximum likelihood rather than least squares.

However, regression methods can only disentangle the effects of individual variables if there is contrast. For example, to disentangle the effects of elevation and temperature, periods are needed with high elevation and low temperatures, high elevations and high temperatures, low elevations and low temperatures and (ideally) also low elevations and high temperatures. If there is perfect correlation between elevation and temperature, it will be mathematically impossible to separate out the impacts of the two variables.

Predictors that have a high correlation are said to be nearly collinear. There are several impacts of colinearity:

- masking. The contribution of each variable may be masked by the other variable and so in the output from the regression model, neither variable looks important.
- bias in the estimates. Colinearity can lead to severe biases in the estimates.
- inflated standard errors. Colinearity will inflate the standard errors of the estimates. This is measured by the variance inflation factor (VIF) commonly available in most statistical packages.

Often there are several competing models for the same dataset. Rather than trying to select the single "best" model based on criteria such as R^2, a better method uses information theoretic methods (e.g. AICc as explained in Burnham and Anderson 2002). Briefly, for each model, the AICc statistic is computed. The AICc is a statistic that combines a measure of fit (the likelihood) and model complexity (number of terms in the model). In general, the model with the smallest AICc indicate the best model (in the model set) in terms of the tradeoff between fit and complexity. Other models with similar values of AICc indicate model that have similar fit and complexity. From the AICc values, the difference in the AICc from the best fitting model can be determined and from these difference, the model weight can be determined. The model weight can be thought of as a measure of "importance" of this model relative to the other models. These model weights provide a natural way to "weight" the different models in the model set. There is no need to select the best fitting model to make predictions or to estimate the marginal contribution of a variable to explain the variation in the response. Rather, predictions from each model, or the coefficients for a variable from each model are averaged using the model weights to compute a weighted mean. This is known as model averaging.

The key advantage of model averaging is that it automatically gives the appropriate weight to each model and so the final predicted curve is also a weighted average of the individual prediction curves. If the best fitting model is a simple linear (straight line) model with only small model weight to a quadratic fit, then the final model average predictions will essentially be linear. Conversely, if the linear and quadratic model both have substantial weights, then the final curve is a weighted average of the linear and quadratic fits.

The sum of the model weights for models that contain each variable is then a measure of the relative importance of each variable in explaining variation in the response.

The *R* software was used for all analyses in this report. Code is available on request. I have often just included directly raw output rather than reformatting the output.

2. Supplemental analyses

In this section, we report on supplemental analyses of the data that extend the analyses in more meaningful ways. It is arranged around consideration of each management question.

2.1 Management question

$H_{0A:}$ Frequency of public use of Arrow Lake is not influenced by fluctuating reservoir water levels

This management question is examined using (a) satisfaction as a proxy for the likelihood of visitors returning (b) and self-reported "will you return" under different future reservoir levels (lower, same, or higher compared to the reservoir level at the time of the survey). Note that the survey data is cross sectional with no linkage between multiple responses from the same subject, and there is no linkage between the responses to "will you return" to actual behavior of the subjects. As with all self-reported data, caution needs to be used in extrapolating from intentions (respondent indicates that she/he will return) to actions (respondent actually returns).

Question 5 of the survey asked respondent to rate their satisfaction with the water levels, as a whole, on the Arrow Lakes Reservoir. AFigure A10 shows the mean satisfaction level vs. the reservoir elevation.[2] Based on this plot, the authors' concluded that there was no substantial difference in satisfaction across different elevations, but the authors did not perform a regression fit.

A revised plot, along with a fitted regression line is found in Figure 4 and Table 1. There is evidence of a positive association between mean satisfaction and reservoir elevation with a slope of 0.06 (SE .007). This implies that a 1 m change in reservoir elevation increases mean satisfaction by .06. On a mean satisfaction of around 3, this is a 2% increase in satisfaction per meter change in elevation. Again, deciding if this is a substantial effect is not a statistical question, but it should be noted that over a 8 m change in elevation, this implies a change in the mean satisfaction by almost 0.5 which is a 16% change from the value of 3.

[2] It should be noted that in AFigure A10, the X-axis is treated as a category and NOT as a continuous variable so that the graph has not been properly scaled along the X-axis.

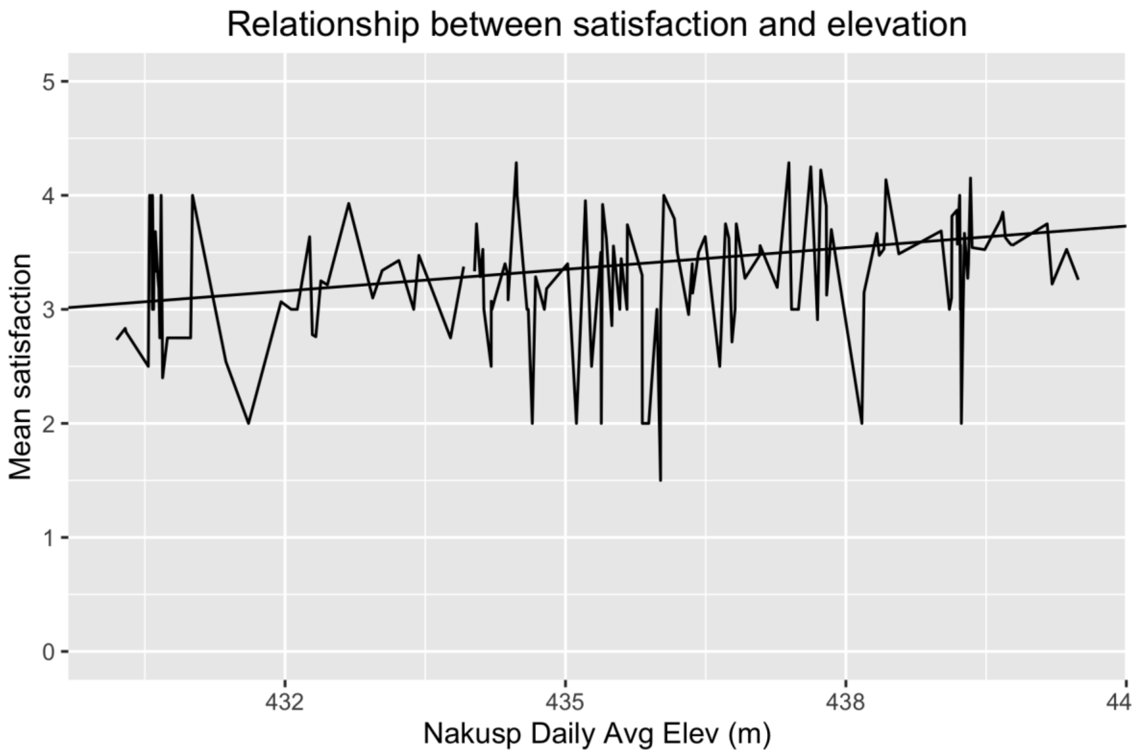

Figure 4. Mean satisfaction vs. the reservoir elevation at the time the survey as administered. The regression line from a regression of the individual satisfaction and reservoir elevation is also shown. The jagged line joins the mean daily responses, rather than the individual data points, because of the coarseness of the individual responses (0 to 5 on a Likert scale).

Table 1. Results from a regression analysis of mean satisfaction with the water levels on the whole by reservoir elevation. The estimated slope is in bold.

```
Analysis of Variance Table

                     Df  Sum Sq Mean Sq F value    Pr(>F)
Nakusp_Daily_Avg_m    1   80.31  80.311  77.403 < 2.2e-16 ***
Residuals          2172 2253.58   1.038


Coefficients:
                     Estimate Std. Error t value Pr(>|t|)
(Intercept)        -24.182629   3.137578  -7.707 1.94e-14 ***
Nakusp_Daily_Avg_m   0.063297   0.007195   8.798  < 2e-16 ***
 ---

Residual standard error: 1.019 on 2172 degrees of freedom
  (405 observations deleted due to missingness)
Multiple R-squared:  0.03441, Adjusted R-squared:  0.03397
F-statistic:  77.4 on 1 and 2172 DF,  p-value: < 2.2e-16
```

A multiple regression analysis was done using the reservoir elevation, temperature, day type, and precipitation for that day (Table 2) to disentangle the impact of reservoir elevation and other confounding covariates such as temperature. There was still evidence that satisfaction increases with reservoir elevation even after adjusting for temperature with an estimated slope of .056 (SE .010). This estimated slope is very similar to the previous estimate that was unadjusted for temperature and other covariates.

Table 2. Results from a multiple regression of mean visitor satisfaction with water levels on the whole as a function of reservoir elevation, maximum temperature, day type, and precipitation. The estimated slope for impacts of changes in reservoir elevation is in bold.

```
Anova Table (Type III tests)

                   Sum Sq   Df F value    Pr(>F)
(Intercept)          24.40    1 23.1518 1.626e-06 ***
Nakusp_Daily_Avg_m   31.33    1 29.7271 5.683e-08 ***
TotalPrecipmm         0.03    1  0.0332  0.855468
MaxTempC              7.84    1  7.4395  0.006445 **
DayType               4.92    1  4.6672  0.030880 *
Residuals          1842.04 1748


                     Estimate Std. Error t value Pr(>|t|)
(Intercept)        -21.239955   4.414296  -4.812 1.63e-06 ***
Nakusp_Daily_Avg_m   0.055868   0.010247   5.452 5.68e-08 ***
TotalPrecipmm       -0.001473   0.008088  -0.182  0.85547
MaxTempC             0.012428   0.004557   2.728  0.00644 **
DayType1            -0.053013   0.024539  -2.160  0.03088

Residual standard error: 1.027 on 1748 degrees of freedom
  (826 observations deleted due to missingness)
Multiple R-squared:  0.04542, Adjusted R-squared:  0.04323
F-statistic: 20.79 on 4 and 1748 DF,  p-value: < 2.2e-16
```

These results are somewhat unsatisfactory as the regression indicates that mean satisfaction increases with increasing reservoir elevation without any falloff effect at higher elevations.

There was evidence that the effect of elevation varied by temperature (Table 3) with largest impact of changes in reservoir elevation occurring at lower temperatures. Typically, lower temperatures are associated with the lowest reservoir elevation. Finally, weekday users were slightly less satisfied than weekend users (estimated difference in mean satisfaction is .10 (SE .05)).

Table 3. Results from a multiple regression of visitor satisfaction with water levels on the whole as a function of reservoir elevation, maximum temperature, day type, and precipitation. This model included an elevation-temperature interaction to investigate if the effect of elevation varied by temperature – there is evidence that it did and the table below shows how the slope declines with increasing temperature.

Anova Table (Type III tests)

	Sum Sq	Df	F value	Pr(>F)	
(Intercept)	15.84	1	15.0758	0.0001071	***
Nakusp_Daily_Avg_m	17.76	1	16.8999	4.123e-05	***
TotalPrecipmm	0.00	1	0.0002	0.9895073	
MaxTempC	6.22	1	5.9187	0.0150810	*
DayType	4.95	1	4.7120	0.0300864	*
Nakusp_Daily_Avg_m:MaxTempC	**6.10**	**1**	**5.8090**	**0.0160476**	*****
Residuals	1835.93	1747			

Estimated effect of changes in elevation as a function of temperature.

MaxTempC	Nakusp_Daily_Avg_m.trend	SE	lower.CL	upper.CL
0	0.125	0.030	0.065	0.184
5	0.110	0.025	0.061	0.158
10	0.094	0.019	0.057	0.132
15	0.079	0.014	0.052	0.107
20	0.064	0.011	0.043	0.085
25	0.049	0.011	0.028	0.070
30	0.034	0.014	0.007	0.061

The overall interpretation is that mean satisfaction with the water levels, on the whole, increases with reservoir elevation. However, there is evidence of an additional temperature effect so that the increase in satisfaction with increasing reservoir elevation actually declines with increasing temperature. Because higher temperatures are associated with higher elevations (see Figure 1), this can be interpreted as mean satisfaction with increases in reservoir elevation are smaller at higher reservoir elevations/higher temperatures than at lower reservoir elevations/lower temperatures, i.e., a leveling off in the effect.

The effect of reservoir elevation can be examined more directly using Questions 5 and 6. In Question 6, respondents indicated if they would return to Arrow Lake in the future and in Question 5, respondents indicated if they would return depending if future reservoir elevations were lower, higher or equal to the elevation at the time of the survey.

As noted in the authors' report, well over 99% of respondents indicated that they would return in the future (Question 6). There were no obvious associations with the respondents who indicated they would not return. As notes in the authors' report, there were so few respondents that indicated that they would not return, that no further analysis is possible on this item.

The responses to Question 6 did not consider the impact of current[3] and future reservoir elevations. AFigure A6 and Figure 5 (both graphs are the same but with axes reversed) show the proportion of respondents who would return to the Arrow Lakes Reservoir if the reservoir levels were higher, the same, or lower than the elevation experienced during their visit, but conditioned by the actual water level at the time of the visit. Both graphs show that respondents tend to prefer intermediate reservoir elevations, i.e., at lower actual elevations, a higher proportion of respondents want higher elevations; at higher elevations, a higher proportion of respondents want lower elevations; and at intermediate elevations, there is no apparent difference in preferences. These responses were further broken out by the actual elevation at the time of the survey in AFigures A7-A9. But the authors did not do a formal analysis of the results.

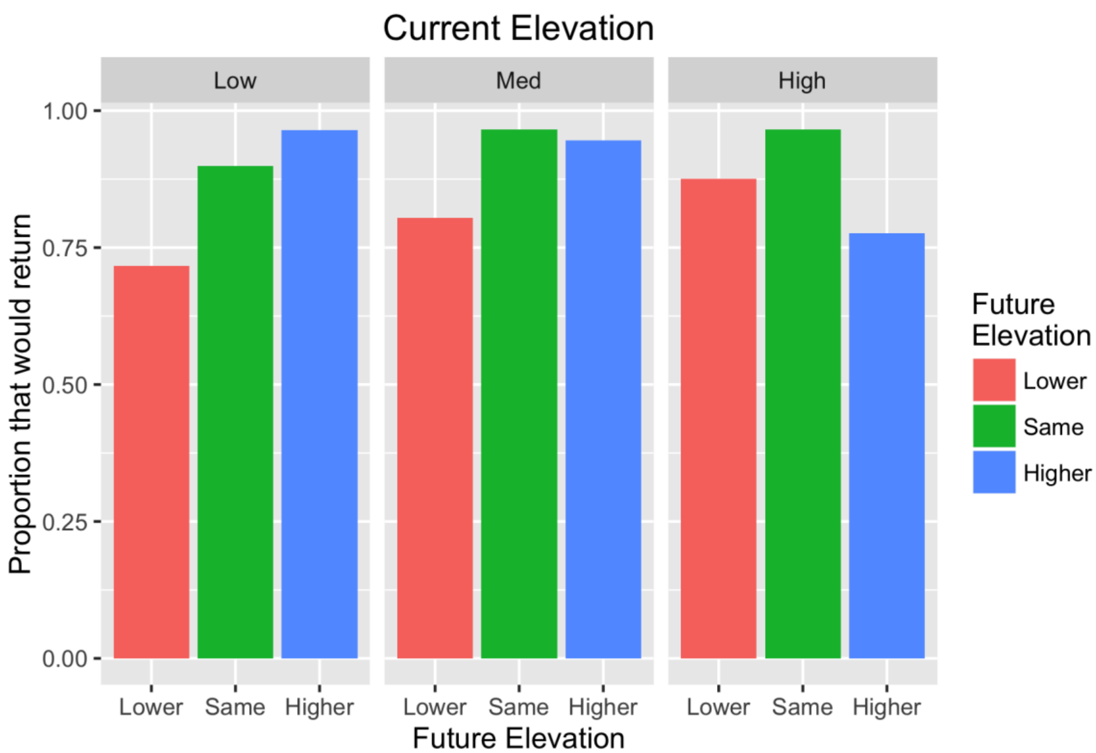

Figure 5. Proportion of respondents that would return to the Arrow Lakes Reservoir if the elevation were the same, lower, or higher as on the day of the survey. This plot is similar to Figure A6 except the axes have been reversed.

[3] Current elevation was segmented into three categories: low, medium and high. Low elevation is defined as less than 434.0 m ASL; medium elevation is between 434.0 m and 437.5 m ASL and high elevation is defined as greater than 437.5 m ASL.

Logistic regression can be used to investigate the impact of elevation (and other covariates) on stated decisions to return. A logistic regression where the probability of returning if the water level was the same as the day of the survey as a quadratic function of reservoir elevation as fit (Table 4; Figure 6). The quadratic fit had a much larger model weight vs. a linear fit, which is consistent with the previous observation that intermediate water levels are preferred.

Table 4. Results from a logistic regression where the probability of returning if the water level was the same as the day of the survey as a quadratic function of reservoir elevation. The analysis of deviance table is analogous to the ANOVA table in regular regression. There was evidence that the quadratic term was needed which indicates that the probability of returning is not constant over the current reservoir elevation, i.e., there is a quadratic trend.

```
Analysis of Deviance Table


                        Df Deviance Resid. Df Resid. Dev  Pr(>Chi)
NULL                                     2051     793.37
Nakusp_Daily_Avg_m       1   12.873      2050     780.50 0.0003334 ***
I(Nakusp_Daily_Avg_m^2)  1   14.896      2049     765.60 0.0001136 ***
```

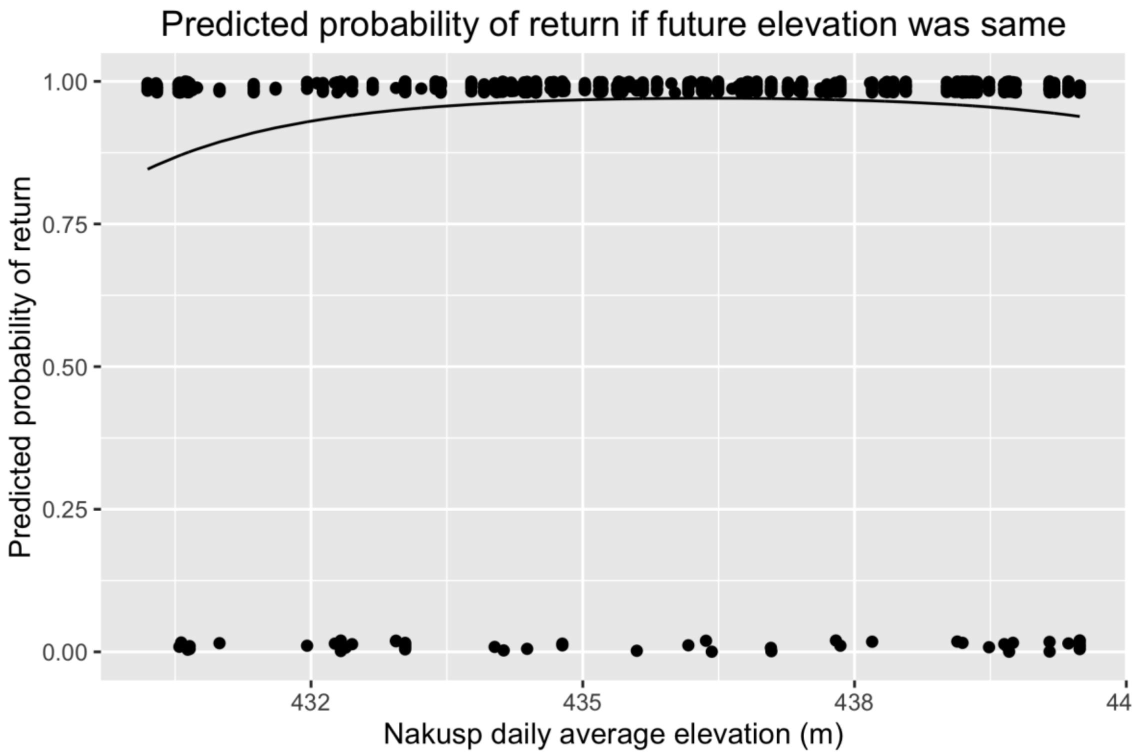

Figure 6. Fitted logistic regression to the probability that a respondent would return to the Arrow Lakes Reservoir if the elevation were the same as on the day of the survey. The actual responses (0=No, 1=Yes) are also shown (with some slight vertical jittering to prevent overplotting) showing the density of the responses.

Once again, elevation effects may be confounded with temperature effects. A multiple logistic regression can also be fit (not shown). There was no evidence of an effect of temperature on the probability of returning over and above the effect of the current reservoir elevation.

Similarly, logistic regressions can be fit on the probability of returning if the water level was lower or higher than on the day of the survey (not shown). All three predicted responses are shown in Figure 7. All three curves are consistent with the respondents favoring elevations that are intermediate between the lower and higher levels. Again, a logistic regression analysis including temperature as an additional covariate showed similar results (not shown).

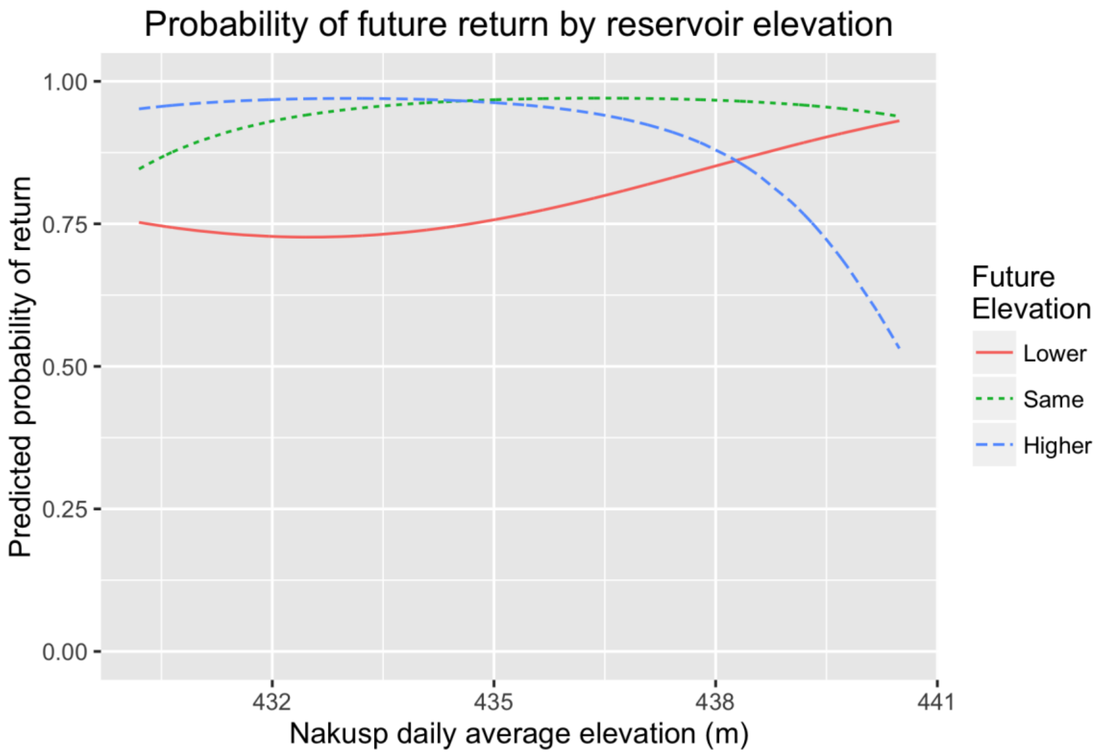

Figure 7. Predicted probability of returning to Arrow Lakes Reservoir as a function of actual elevation at the time of the survey and if the future elevation will be lower, same, or higher than actual elevation. Note that the line for "Same Elevation" (red) is the same as shown in Figure 6.

The overall conclusion is that at lower reservoir elevations, visitors are more likely to return if future elevations were higher that at the time of the survey vs. future elevations are lower. Similarly, at higher reservoir elevations, respondents are less likely to return if future elevations are higher than at the time of the survey.

2.2 Management question

$H_{0B:}$ Volume of public use of Arrow Lake is not influenced by fluctuating reservoir water levels.

This management question is investigated using the relationship between the traffic counts and elevation, controlling for weather.

We start with a reproduction of ATable A12 using the unstandardized coefficients. The results are reported in Table 5. I've ignored the effect of holidays because there are so few of them in the dataset. Now the coefficients have a direct interpretation. For example, the coefficient associated with Total Precipitation is -0.476 (SE .12) which implies that for every increase in precipitation of 1 mm, keeping all other variables fixed, the average number of boat counts declines by 0.47 boats. But according to this model, this is true both in summer when the boat counts tend to be higher and in winter when boat counts tend to be close to 0. This is not conceptually correct. Diagnostic plots of this model show lack of fit and increase in variation with the mean response (Figure 8) due to analyzing the data on the anti-logarithmic scale.

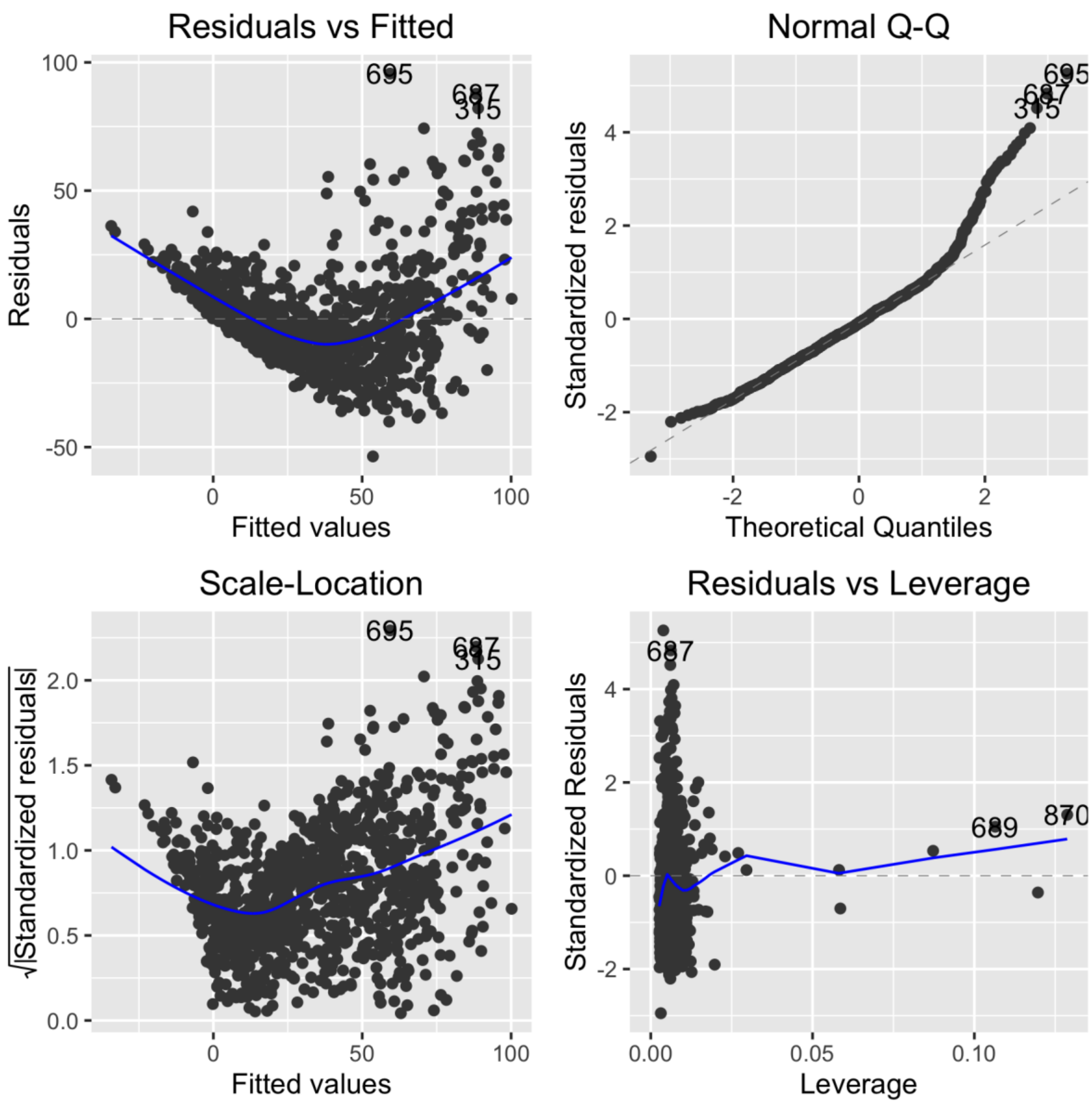

Figure 8. Diagnostic plots from the base model from Table A12. The residual plot (upper left) shows clear lack of fit; the normal probability plot (upper right) shows problematic fits at high values of boat counts; the scale-location plot (lower left) shows an increase in variation over time; the leverage plot (lower right) shows some potential leverage points. [Further investigation of the potential leverage points fails to show any problems so this plot is ok.]

As noted previously, an analysis on the log(count) scale will be more appropriate. The results from such a fit are shown in Table 6. Now the coefficients have a more sensible interpretation. Here every increase of 1 mm in total precipitation, keeping all other variables fixed, results in a 1.5% decline in the mean number of boat counts. This is true in both winter and summer, but a 1.5% decline in summer results in a much larger absolute decrease. The diagnostic plots (Figure 9) show a much improved fit.

Table 6. Relationship between log(daily traffic counts) and several weather variables

```
Anova Table (Type III tests)

                    Sum Sq   Df  F value    Pr(>F)
(Intercept)          2.413    1   8.6878 0.0032742 **
Nakusp_Daily_Avg_m   3.680    1  13.2482 0.0002861 ***
TotalPrecipmm        5.537    1  19.9332 8.885e-06 ***
MaxTempC           126.204    1 454.3489 < 2.2e-16 ***
DayType             93.718    1 337.3926 < 2.2e-16 ***
Season               0.517    2   0.9315 0.3942781
Residuals          292.214 1052

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        -8.695212   2.950022  -2.948 0.003274 **
Nakusp_Daily_Avg_m  0.024793   0.006812   3.640 0.000286 ***
TotalPrecipmm      -0.015503   0.003472  -4.465 8.88e-06 ***
MaxTempC            0.073014   0.003425  21.315  < 2e-16 ***
DayType1           -0.330665   0.018002 -18.368  < 2e-16 ***
Season1             0.049398   0.044458   1.111 0.266772
Season2            -0.056949   0.041724  -1.365 0.172576

Residual standard error: 0.527 on 1052 degrees of freedom
  (464 observations deleted due to missingness)
Multiple R-squared:  0.7333,  Adjusted R-squared:  0.7317
F-statistic:   482 on 6 and 1052 DF,  p-value: < 2.2e-16

> vif(tab12.fit.log) # Variance inflation factors
                       GVIF Df GVIF^(1/(2*Df))
Nakusp_Daily_Avg_m 1.987586  1        1.409818
TotalPrecipmm      1.036312  1        1.017994
MaxTempC           4.195348  1        2.048255
DayType            1.001394  1        1.000697
Season             5.340245  2        1.520163
```

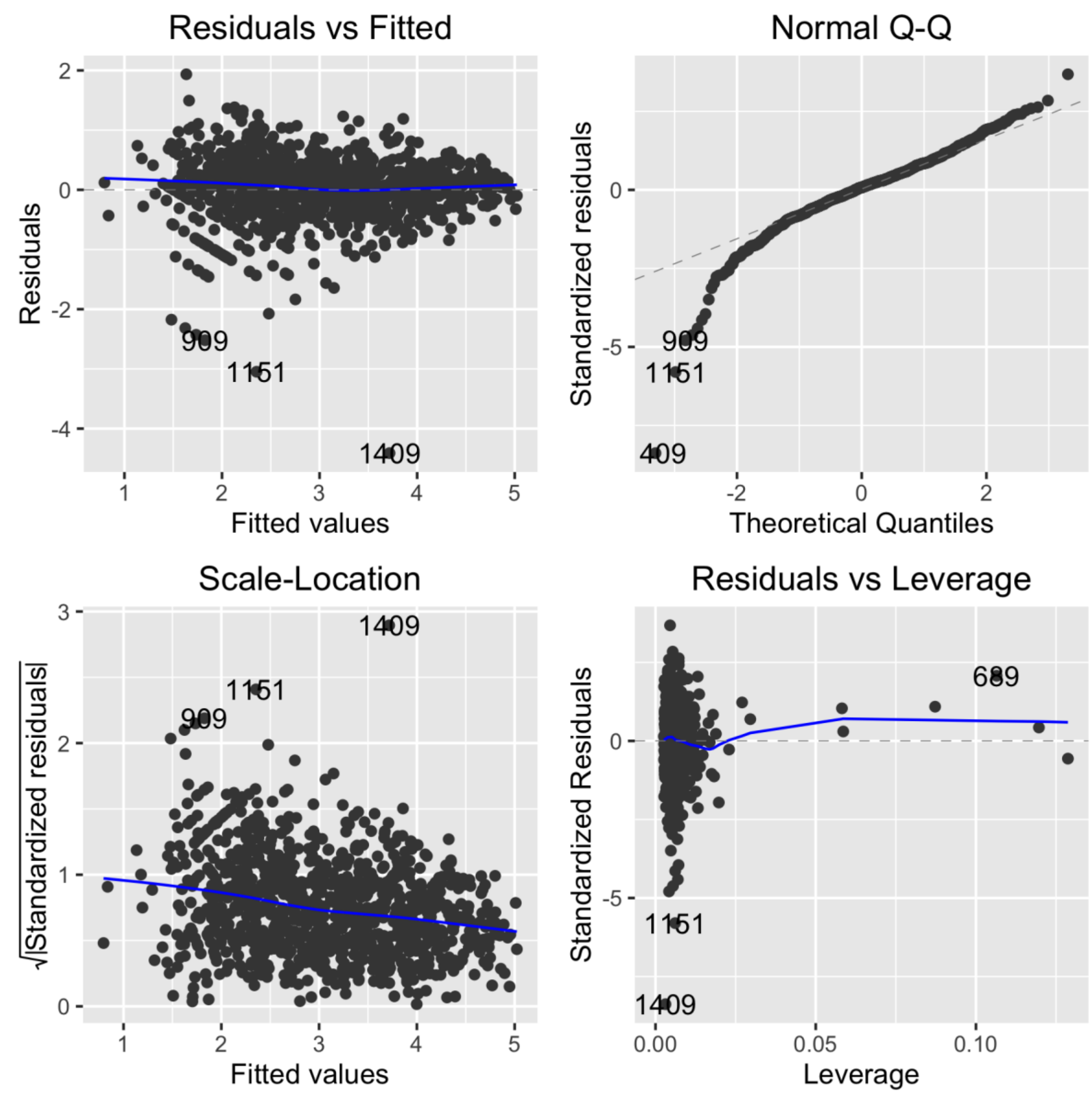

Figure 9. Diagnostic plots from the base model from Table A12 but conducted on the log(count). The residual plot (upper left) shows a good fit – the "diagonal" lines in the plot are artifacts of the discrete nature of count. ; the normal probability plot (upper right) shows some problematic fits at low values of boat counts; the scale-location plot (lower left) that variation is now relatively constant; the leverage plot (lower right) shows some potential leverage points. [Further investigation of the potential leverage points fails to show any problems so this plot is ok.]

From the results in Table 6, every increase in the elevation by 1 m, holding all other variable fixed, results in a 2.5% increase in the mean boat counts. At the same time, there is no evidence of a seasonal effect (p=.39).

Teasing out the contribution of predictor variables to the traffic count data will be challenging due to the high degree of association among several of the predictor variables. For example, Figures 2 and 3 show the relationship between the log(count), temperature, and elevation. There is strong relationship between the log(count) and the maximum daily temperature, but the maximum daily temperature and the elevation are also highly related. So an increase in reservoir elevation virtually always coincides with an increase in temperature. This explains why the regression analysis in Table 6 failed to detect an effect of season (p=0.39) – it has been subsumed by the effect of elevation/temperature.

Separating the impact of elevation and temperature will depend on time periods where the pattern between the two time series shown in Figure 2 is "broken". This would seem to indicate that the separation of the two effects occurs late 2010/early 2011 and late 2013 in the shoulder season where the elevation rose again while temperatures declines. Basing conclusions about the impact of elevation on these two short series of data in the low season could be misleading. This is perhaps the most serious deficiency in this observational study – the inability to disentangle two highly correlated predictor variables. Consequently to say that other variables are stronger predictors of traffic counts compared to reservoir elevation (ATable A1, 3rd row) overstates the conclusions possible from an analysis of these data.

The occurrence of high "correlation" among predictor variables is known as colinearity. A common diagnostic plot to measure the effect of colinearity is the *variance inflation factor* (VIF) whose values are reported at the bottom of Table 6. A value of 1 for the VIF indicates no impact of collinearity. Larger values, e.g. values of 4 reported or MaxTemp and 5 reported for Season indicate potential problems, and values of VIF >10 usually are taken as the cutoff for severe effects and coefficients should not be trusted. Here the VIF are reported in Table 6 are all reasonable except for the higher VIFs for the effect of temperature and season, which, as expected, are likely to be highly correlated.

We fit another model where we dropped the (redundant) effect of season (Table 7). Diagnostic plots (not shown) show no evidence of problems. The VIFs are all now all acceptable. **Now it is estimated that a 1 m increase in elevation, holding all other variables fixed, results in a 2.7% increase in mean traffic counts.** Note that in the high season, there can be as much as an 8 meter change in reservoir elevation implying that given all other variables remaining fixed, the mean traffic count is estimated to change by over 16% between these two elevation extremes.

Table 7. Relationship between log(daily traffic counts) and several weather variables after dropping the (redundant) effect of season.

```
Anova Table (Type III tests)

                   Sum Sq   Df  F value    Pr(>F)
(Intercept)          3.89    1   13.994 0.0001933 ***
Nakusp_Daily_Avg_m   5.60    1   20.148 7.955e-06 ***
TotalPrecipmm        5.20    1   18.733 1.647e-05 ***
MaxTempC           375.41    1 1351.675 < 2.2e-16 ***
DayType             93.75    1  337.552 < 2.2e-16 ***
Residuals          292.73 1054

Coefficients:
                    Estimate Std. Error t value Pr(>|t|)
(Intercept)        -9.634503   2.575471  -3.741 0.000193 ***
Nakusp_Daily_Avg_m  0.026836   0.005979   4.489 7.96e-06 ***
TotalPrecipmm      -0.014903   0.003443  -4.328 1.65e-05 ***
MaxTempC            0.076648   0.002085  36.765  < 2e-16 ***
DayType1           -0.330707   0.018000 -18.373  < 2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.527 on 1054 degrees of freedom
  (464 observations deleted due to missingness)
Multiple R-squared:  0.7328,  Adjusted R-squared:  0.7318
F-statistic: 722.6 on 4 and 1054 DF,  p-value: < 2.2e-16

> vif(tab12.fit.log.ns)
Nakusp_Daily_Avg_m  TotalPrecipmm    MaxTempC     DayType
          1.531357       1.019115    1.554312    1.001306
```

Models were also fit to assess if the effects are constant over the other variable or if there is an interaction between the effects and other variables. For example, a model was fit where the effect of elevation was allowed to vary by temperature (an elevation-temperature interaction). There was evidence that this interaction effect is needed (Table 8, p<.0001), and the estimated effect differs depending on the maximum temperature. For example, at 10 ºC, a change in elevation of 1 m is predicted to change the average boat counts by only 1%, but this increases to 4.7% at 25 ºC (refer to bottom of Table 8).

Table 8. Relationship between log(daily traffic counts) and several weather variables after dropping the (redundant) effect of season but including an interaction between the effects of elevation and temperature. Note that in models with interaction terms, tests for main effects cannot be interpreted.

```
Anova Table (Type III tests)

Response: log.Arrow.count
                             Sum Sq   Df  F value    Pr(>F)    
(Intercept)                   0.658    1   2.4030 0.1214020    
Nakusp_Daily_Avg_m            0.365    1   1.3344 0.2482843    
TotalPrecipmm                 5.030    1  18.3694 1.986e-05 ***
MaxTempC                      3.757    1  13.7192 0.0002233 ***
DayType                      92.827    1 338.9822 < 2.2e-16 ***
Nakusp_Daily_Avg_m:MaxTempC   4.376    1  15.9805 6.846e-05 ***
Residuals                   288.355 1053
```

Estimated effects of elevation changes at different temperatures

```
 MaxTempC Nakusp_Daily_Avg_m.trend    SE lower.CL upper.CL
        0                   -0.014 0.012   -0.037    0.009
        5                   -0.002 0.009   -0.020    0.017
       10                    0.010 0.007   -0.004    0.025
       15                    0.023 0.006    0.011    0.034
       20                    0.035 0.006    0.022    0.047
       25                    0.047 0.008    0.031    0.062
       30                    0.059 0.010    0.039    0.078
```

There was no evidence (not shown) that the effect of an elevation change differs among day types (weekends vs. weekdays).

There was no evidence (not shown) that an effect of wind gust/direction using a simple coding of “None”, “sw”, or “ne” to categorize both the effects of gust speed and the direction of the gusts on the log(count).

The data has been collected on a daily level and could suffer from autocorrelation. For example, a week of fine weather could cause all the traffic counts to be higher than predicted for all days in that weeks, while a week of poor weather could depress counts for all days in that week. Fortunately, estimates of the regression coefficients are still unbiased under moderate autocorrelation, but the reported standard errors are typically too small, leading to reported p-values that are also too small (too many false positives), and confidence intervals that are too narrow. As a rough rule of thumb, the corrected standard error is found by multiplying the reported standard error by a factor of $\sqrt{(1+r)/(1-r)}$ where r is the estimated temporal autocorrelation (Bence, 1995). For example, if the estimated autocorrelation is 0.3, the reported standard errors should be inflated by a factor of 1.36, i.e., 36% larger. The corrected standard errors can then be used to compute corrected p-values. The Durbin-Watson test is commonly used to test for the presence of autocorrelation and to provide an estimate of autocorrelation.

When the Durbin-Watson test is applied to the model using reservoir elevation, total precipitation, maximum daily temperature, day type, and the interaction between reservoir elevation and temperature, the estimated temporal autocorrelation is 0.35 which implies that a correction factor of approximately 1.4 needs to be applied. I fit a model that accounted for autocorrelation (Table 9). The revised ANOVA table still shows evidence of an interaction between reservoir elevation and maximum temperature, but the revised p-values are larger compared to the previous model. Similarly, the estimated effects of changes in reservoir elevation are similar, but the revised estimates have larger (corrected) standard errors and wider (corrected) confidence intervals compared to the model without adjustments for autocorrelation. This approximate correction factor of 1.4 for the standard should be kept in mind when interpreting the standard errors of all regression estimates, but the sample sizes are so large that this correction is somewhat moot – even after correcting for the autocorrelation, standard errors are still small relative to the estimates.

Table 9. Relationship between log(daily traffic counts) and several weather variables but now accounting for autocorrelation. Note that in models with interaction terms, tests for main effects cannot be interpreted.

```
Correlation Structure: AR(1)
Parameter estimate(s):
     Phi
0.359417
```

Analysis of Variation Table (corrected for autocorrelaton)

	numDF	F-value	p-value
(Intercept)	1	16797.944	<.0001
Nakusp_Daily_Avg_m	**1**	**505.833**	**<.0001**
TotalPrecipmm	1	56.502	<.0001
MaxTempC	1	725.638	<.0001
DayType	1	301.335	<.0001
Nakusp_Daily_Avg_m:MaxTempC	1	5.786	0.0163

Estimated effects of elevation changes at different temperatures

MaxTempC	Nakusp_Daily_Avg_m.trend	SE	lower.CL	upper.CL
0	-0.003	0.016	-0.035	0.028
5	0.007	0.013	-0.019	0.032
10	0.016	0.010	-0.004	0.036
15	0.026	0.009	0.009	0.043
20	0.036	0.009	0.018	0.053
25	0.046	0.011	0.024	0.067
30	0.055	0.014	0.029	0.082

Appendix A.I indicated that there could be substantial year effects over and above the other covariates, but no regression models were fit. I also fit models that included a *year* effect and a year-elevation interaction to see if the effect of elevation, after adjusting for other variables, differed across years (Table 10). **A 1 m change in elevation in 2011 was estimated to cause a 10% change in the mean traffic count after adjusting for the other variables (refer to bottom of Table 10). The change in 2011 was found to be different from the change in all other years – in other years the confidence intervals for the individual year effect either included 0 or just excluded the value of 0.** Note that in Appendix I (p. 205), the authors stated

> "There was no construction activity or high water that adversely affected boat launch use in 2011. Thus this is likely the most "normal year" for comparison than any other year"

Hence, it is worrisome that in the most "normal year", the effect of elevation changes is most pronounced.

Table 10. Regression analysis of the impact of elevation and other covariates on log(counts). There was evidence that the effect of elevation changes varied across the years.

```
Anova Table (Type III tests)

                         Sum Sq   Df   F value    Pr(>F)
(Intercept)               0.431    1    1.6033    0.2057
Nakusp_Daily_Avg_m        0.371    1    1.3824    0.2400
TotalPrecipmm             5.316    1   19.7866 9.585e-06 ***
Year                      6.743    4    6.2740 5.460e-05 ***
MaxTempC                292.457    1 1088.5106 < 2.2e-16 ***
DayType                  93.632    1  348.4931 < 2.2e-16 ***
Nakusp_Daily_Avg_m:Year   6.757    4    6.2873 5.330e-05 ***
Residuals               281.036 1046
```

Estimates of the effect of elevation by year. The grouping variable (last column) shows that the effect of elevation appears to be quite different in 2011, but could not be distinguished among all other years.

```
Year Nakusp_Daily_Avg_m.trend          SE   df      lower.CL   upper.CL .group
 2009             -0.06464314 0.054980286 1046 -0.1725273605 0.04324107  1
 2012              0.01406619 0.008560577 1046 -0.0027316655 0.03086405  1
 2013              0.02307377 0.011215745 1046  0.0010658518 0.04508170  1
 2010              0.02522457 0.013059644 1046 -0.0004015106 0.05085066  1
 2011              0.10514839 0.018653529 1046  0.0685457871 0.14175098   2
```

We used information theoretic methods (e.g. AIC, Burnham and Anderson, 2002) to fit all possible models to the log(count) using elevation, temperature, precipitation, year, season, daytime, and wind speed and direction[4] and to combine information over this model set that contains over 100 possible models.

A plot of the importance of each variable is shown in Figure 10. Not unexpectedly, total precipitation, maximum temperature, day type, year and elevation are important predictors of boat counts, but the season and wind direction and speed are not important.

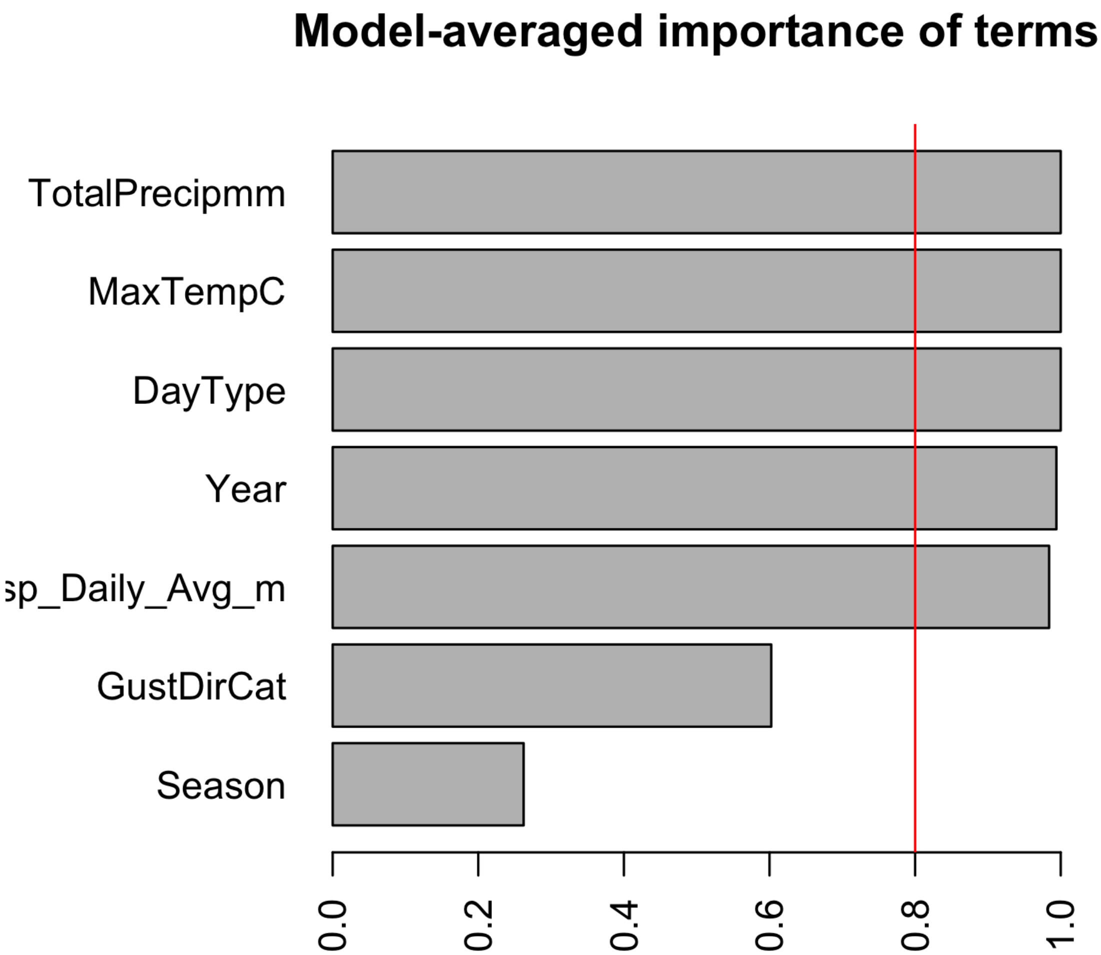

Figure 10. Variable importance in the regression of log(counts) against reservoir elevation and weather variables as ranked using AICc. Generally speaking, variables with a total weight of more than 0.80 are declared to be important in explaining variation in the response variable.

---

[4] Wind speed and direction were combined into a single variable with three categories as outlined earlier in the report.

The model averaged effect of elevation (i.e., the weighted average of the estimated slope over all possible models, not shown) was .023 (SE .007) which indicates that for each 1 m change in elevation, traffic counts are expected to increase by 2.3%.

The author concluded (Atable A2) that elevation changed do not significantly affect usage (as measured by boat counts). **However, we did detect effects of elevation (around 2-3% increase for every increase by 1 m in reservoir elevation), but I am unable to say if the percentage changes noted above are of real interest**. Note that the decision of which magnitude of effect represents a "substantial" effect is not a statistical question and CANNOT be determined by simply looking at the p-value, estimates or standard errors. This must be decided based on knowledge of the system and how observed changes affect behaviors.

2.3 Management question

$H_{0C:}$ The different types of public use are not affected by fluctuating water levels.

Similar analyses can be done as for Management Question H_{0A} except that now interest lies in how different classes of users rate satisfaction and future return as a function of water elevation. Note that if a user selects more than one type of activity in the survey, then they will be used multiple times. The same caveat about distinguishing between intentions and actions should be kept in mind.

Differences in the mean satisfaction with water levels as a whole were detected among beach users, campers, residents, and swimmers (Table 11 and ATable A13). There was no evidence of a difference in the mean satisfaction for anglers, boaters, and walkers. Beach walkers, campers, and swimmers were more satisfied, on average; residents were less satisfied on average compared to their complement. These conclusions mirror those made by the authors in their report (ATable A13). Again note the strong relationship between temperature and elevation, and the activities with higher mean satisfaction also tend to occur at higher temperatures and elevations.

Table 11. Overall mean satisfaction with the water levels on the Arrow Lakes Reservoir by different public uses. This is similar to Table A13.

Public Uses	Non-users	Users	Non-user mean	User mean	Diff in means	SE diff	P-value
Angling	1935	644	3.41	3.45	-0.04	0.061	0.5100
Beach Activities	2106	473	3.36	3.67	-0.31	0.054	0.0000
Boaters	2176	403	3.43	3.38	0.05	0.061	0.4165
Campers	2174	405	3.39	3.61	-0.22	0.055	0.0001
Residents	1728	849	3.52	3.24	0.28	0.047	0.0000
Swimmers	1972	607	3.35	3.66	-0.31	0.051	0.0000
Walkers	2001	578	3.42	3.41	0.01	0.060	0.8682

Respondents were classified by their activity on the day of the survey.

A quadratic regression (not shown) was used to model the mean satisfaction score for each user group as a function of the elevation at the time of the survey and the results are shown in Figure 11. In all cases, the mean satisfaction score increases with the reservoir elevation at the time the respondent completed the survey.

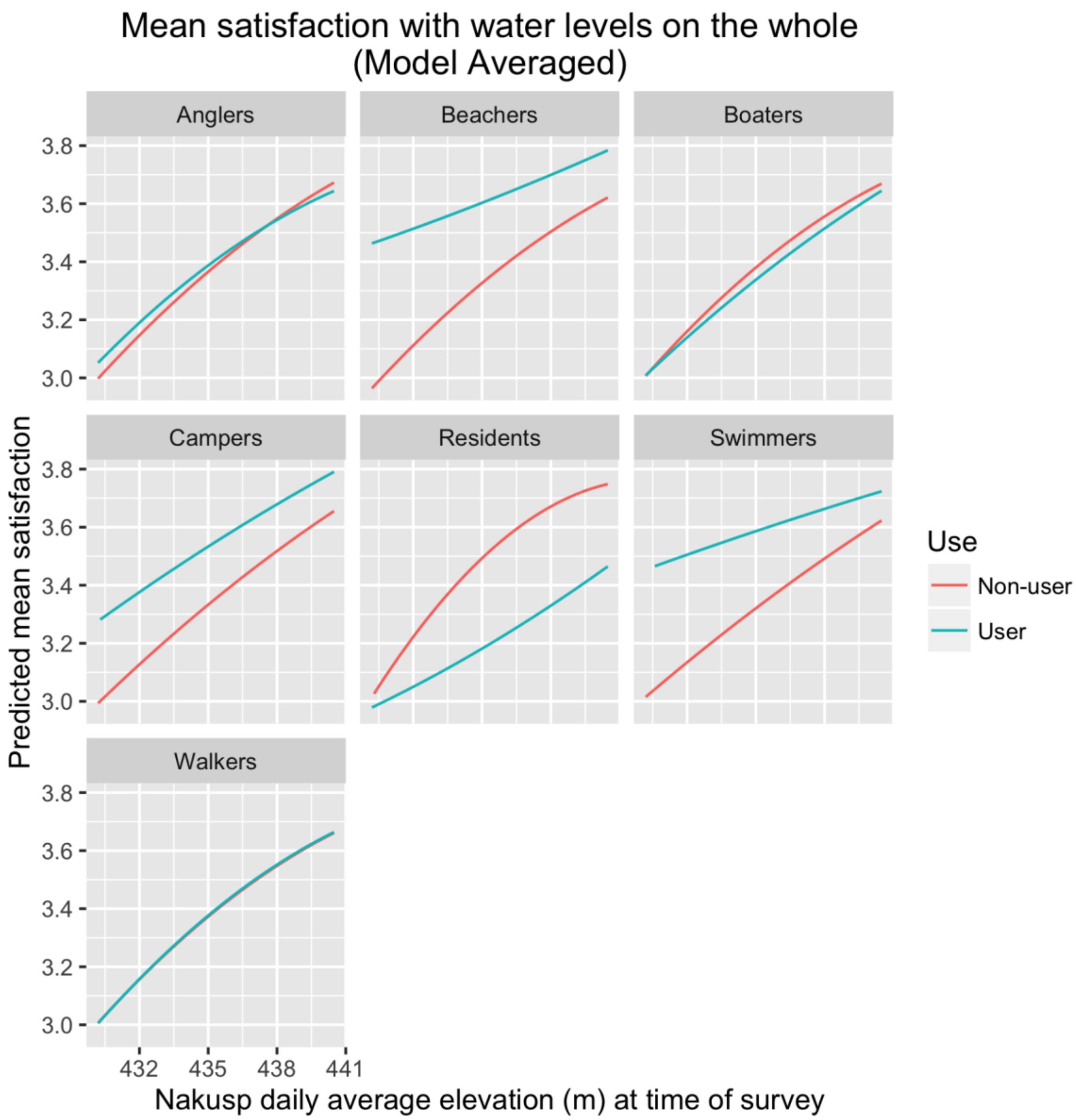

Figure 11. Mean satisfaction score with water levels on the whole by user group as a function of the Nakusp elevation at the time of the survey. A series of 4 models (separate quadratic, common quadratic, separate linear, common linear trends) were fit and ranked using AICc. The model averaged predictions are shown. In all cases, there was evidence of an increase in mean satisfaction score with the water levels as a whole with the elevation at the time of the survey. Note that there was no evidence of a difference in the curves for Walkers, Anglers and Boaters.

A logistic regression can also be used to investigate differences in satisfaction in more depth vs. the simple comparison shown in ATable A13, A14, A15, and A16. For example, the authors found that swimmers had a higher mean satisfaction rating that non-swimmers, but did not explore if these differences were related to current or future reservoir elevations.

A series of logistic regression models were fit that compared the probability that a user would return if future reservoir height was lower, the same, or higher than the height at the time of the survey and the (model averaged) results are plotting in Figure 12 (a), (b) and (c). The model set included quadratic and/or linear effect of elevation and if the curves were the same/different in the two classes of users within each category.

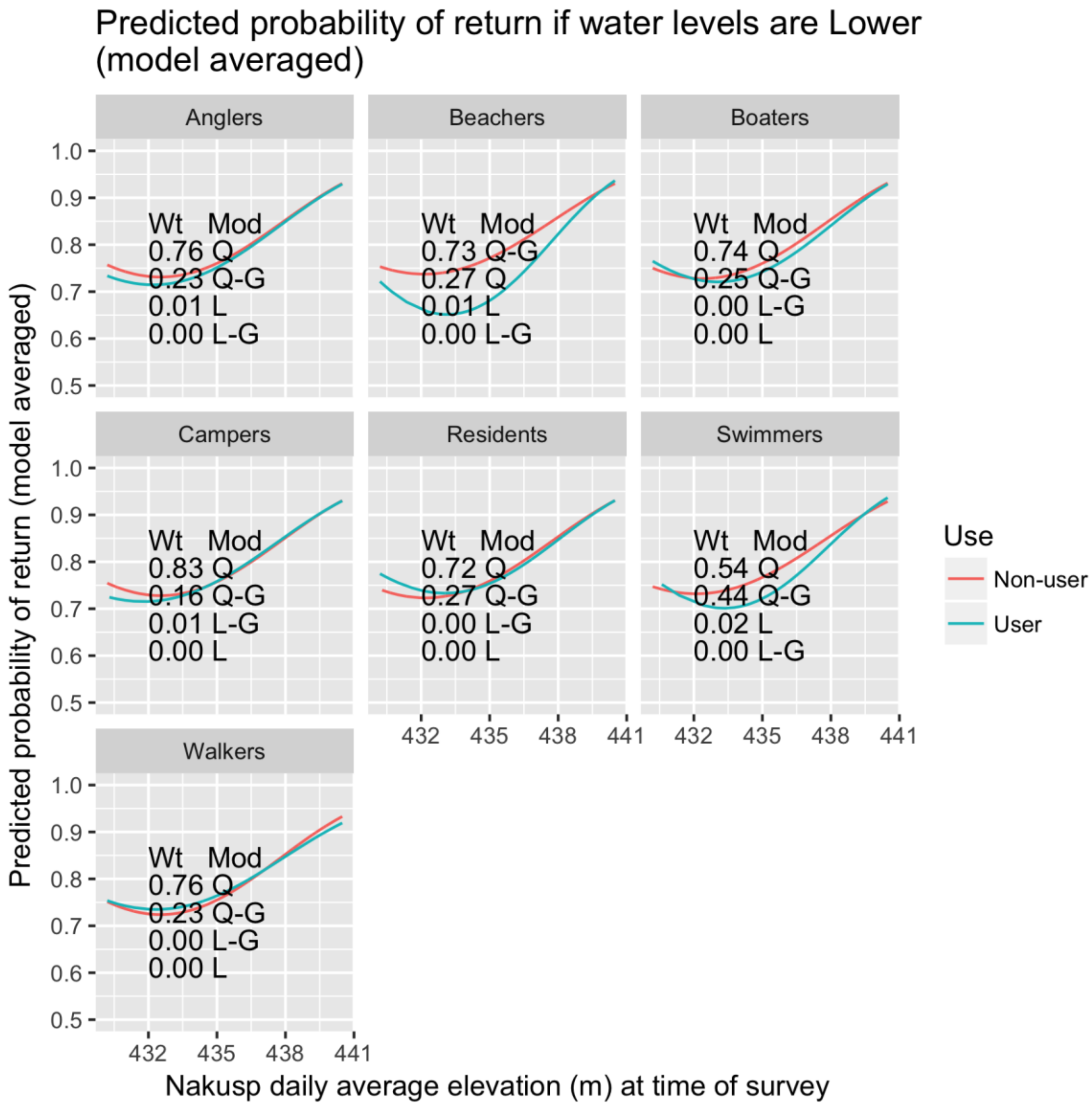

Figure 12 (a) Results of a logistic regression comparing the probability of return when future elevation is LOWER than the current elevation by user groups. Four different models were fit: Q-G with a separate quadratic curve for each user group; Q with a common quadratic curve over the two user groups; L-G with a separate linear curve for each user group; and L with a common linear curve for the two user groups. The model weights for each curve are shown on each panel and the model-averaged curve is plotted.

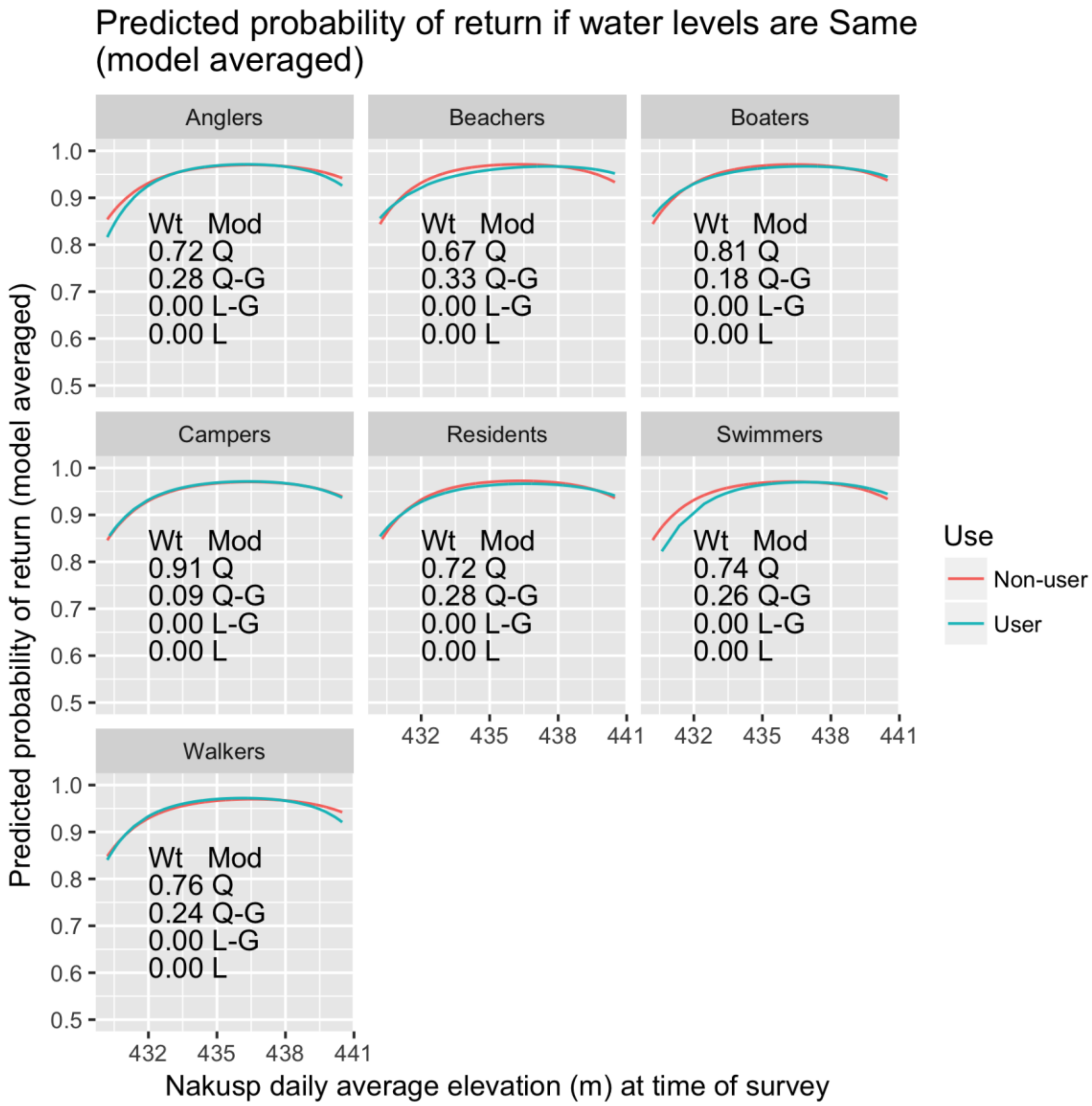

Figure 12 (b) Results of a logistic regression comparing the probability of return when future elevation is the SAME as current elevation by user groups. Four different models were fit: Q-G with a separate quadratic curve for each user group; Q with a common quadratic curve over the two user groups; L-G with a separate linear curve for each user group; and L with a common linear curve for the two user groups. The model weights for each curve are shown on each panel and the model-averaged curve is plotted.

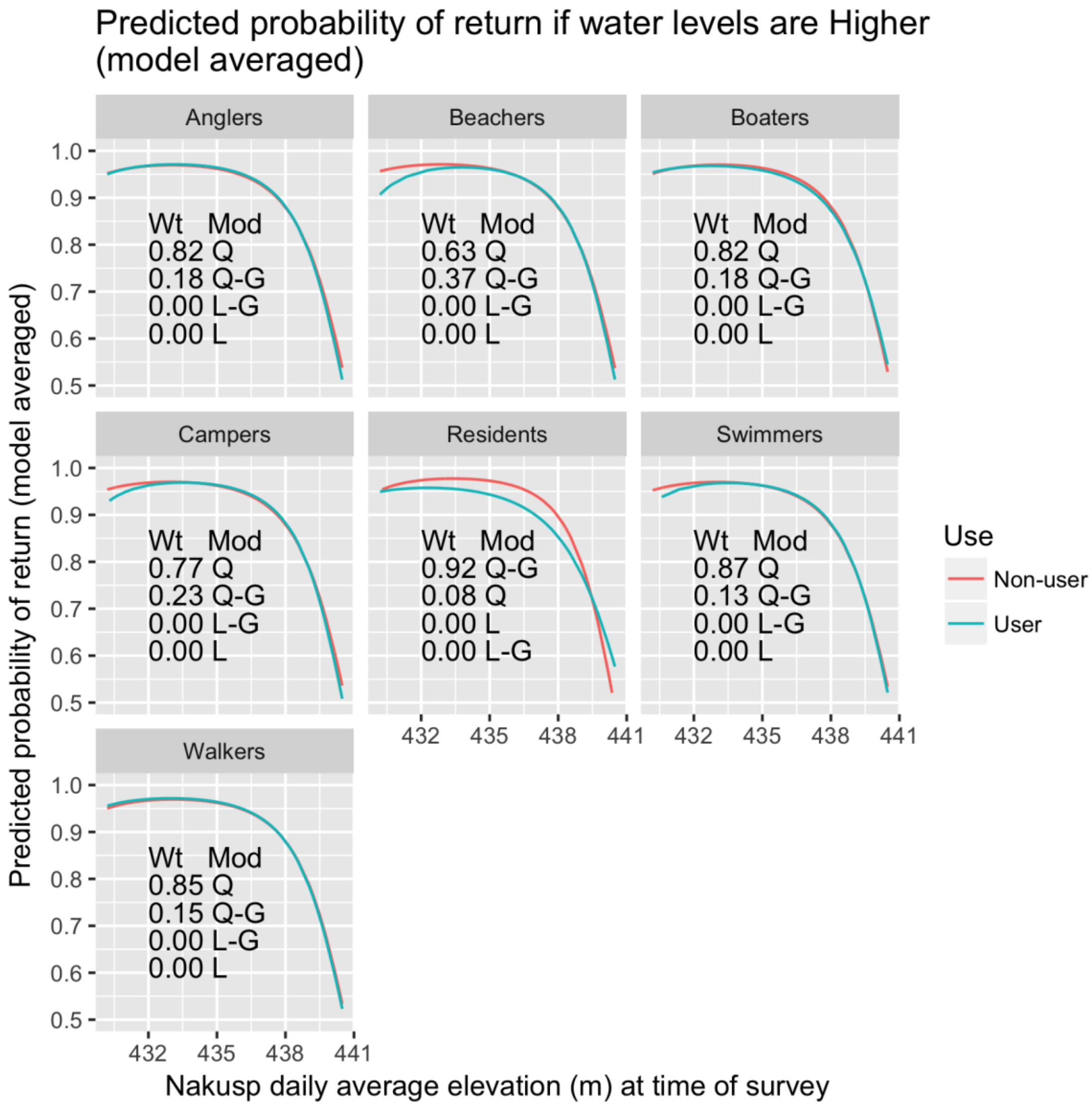

Figure 12(c) Results of a logistic regression comparing the probability of return when future elevation is HIGHER than the current elevation by user groups. Four different models were fit: Q-G with a separate quadratic curve for each user group; Q with a common quadratic curve over the two user groups; L-G with a separate linear curve for each user group; and L with a common linear curve for the two user groups. The model weights for each curve are shown on each panel and the model-averaged curve is plotted.

Generally speaking, a common quadratic curve was the most highly supported model (i.e., no evidence of a difference in the response profile among the two user groups in each category of user) except for Beach users when asked if they would return if future water levels were lower, and for Residental status when asked if they would return if future water levels were higher.

When the reservoir elevations are low, then users are typically less likely to return if the future elevations are even lower compared to if future elevations being higher. Similarly, user groups are more likely to return if the future elevation is similar to the elevation at the time of the survey and the current elevation is intermediate. Finally, user groups are less likely to return if the future elevations are higher and the current elevation is also higher. In other words, users tend to prefer the intermediate reservoir elevations – not surprisingly, the same conclusion as seen in Figure 8 which was pooled over all user groups.

3 Summary

In this supplemental analysis, there is clear evidence that an increase in reservoir elevation by 1 m results in a 2% to 3% increase in boat counts. It is unclear if this is a "important" change as statistical analyses don't answer that question. There is some evidence that this relationship may depend on the temperature or year of the survey, but these additional effects are difficult to disentangle because reservoir elevation and temperature are highly related.

Our analyses showed clear preferences for intermediate elevation levels (i.e., 434.0 m to 437.5 m ASL) even after adjusting for temperature and this was consistent over the different category of users.

References

Bence, J. R. (1995). Analysis of short time series: Correction for autocorrelation. Ecology 76, 628-639.

Burnham, K. P. and Anderson, D. R. (2002), Model Selection and Multimodel Inference: A Practical Information-Theoretic Approach (2nd ed.), Springer-Verlag,

Lees+Associates. (2015). CLBMON-41 Arrow Reservoir Recreational Demand Study. Year 5 Final Report Study Period – 2009-2013. Vancouver, BC. BC Hydro, Water License Requirements.