Site C Clean Energy Project

Peace River Water Level Fluctuation Monitoring Program (Mon-17)

Tasks 3a to 3e

Construction Year 4 (2018)

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Prepared for:

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EXECUTIVE SUMMARY

The Peace River Water Level Fluctuation Monitoring Program (Mon-17) represents one component of the Fisheries and Aquatic Habitat Monitoring and Follow-up Program (FAHMFP) that aims to investigate the effects of water level fluctuations on the catchability of fish and the biomass and production of periphyton in the Peace River downstream of the Site C Clean Energy Project (the Project). We examined the effect of flow fluctuations on the following:

- **Catchability and Fish Community** – Estimating the effects of environmental covariates on catch per unit effort (CPUE) for several fish species using data from the Peace River Large Fish Indexing Survey from 2004 to 2018.
- **Periphyton and Benthos** – Demonstrating the assessment method for understanding how lower trophic levels may change with changes in flow post-Project. This will use periphyton and benthos data collected during the Site C Environmental Impact Statement (EIS) and Mon-7 (Peace River Fish Food Organisms Monitoring Program).
- **Daily Growth** – Estimating the effects of flow on daily growth increments using otoliths collected from Mountain Whitefish and sucker species from 2014 to 2016, and 2018.
- **Recruitment** – Demonstrating the assessment method for understanding how variation in age class strength might change using historical age structure data.

We only conducted analyses for catchability and daily growth because there were data readily available. However, for periphyton and benthos and recruitment, the before-after comparison is necessary to make the analysis meaningful. Therefore, we only discuss the analysis method and completeness of data for these components of Mon-17.

Catchability and Fish Community

We examined the influence of discharge on catchability, as measured by CPUE (#/100 m) of several species in the Peace River Large Fish Indexing Survey and pre-Project surveys in the Peace River. This included Arctic Grayling, Bull Trout, Largescale Sucker, Longnose Sucker, Mountain Whitefish, Rainbow Trout, and White Sucker in Sections 1, 3, 5, 6, 7 and 9 of the Peace River.

The statistical analysis was conducted using a linear mixed-effects model using CPUE as the response variable, random effects of sample year and sample session, and the following fixed effects: discharge at 1 hour, mean discharge in the 6 hours prior to sampling, and mean discharge 30 days prior to sampling; an interaction term between flow at 1 hour and at 24 hours; the coefficient of variations for discharge over the previous 6 hours and 30 days; and an electroshocker setting term. CPUE was estimated at the level of sample-day-session because this aligned with the hourly discharge data from Water Survey Canada stations that were available. The different discharge variables included in the model reflected the different hypotheses presented in Mon-17, which may indicate different levels of behavioural responses from fish to changes in flow. Electroshocker settings were changed in 2014 from averaging 60 Hz and 4 amps to averaging 30 Hz and 2.5 amps. Lower power settings were adopted in 2014 to reduce potential fish mortality but this change may have also reduced catch rates; therefore, electroshocker settings needed to be accounted for in the model.

Overall the results of the analysis suggest that there was no clear trend in the CPUE data based on changes in the value and variability of discharge. We failed to reject the null hypotheses H_{1a} (species-specific catchability at a sampling site in the Peace River is independent of the water level at the time of sampling) and H_{1b-2} (species-specific catchability at a sampling site in the Peace River is independent of the pattern of variation in water level regime over the longer-term).

This finding suggests that future analyses of CPUE do not need to consider discharge values and variability. In the context of pre- and post-Project measurements of CPUE, this suggests that there is no need to correct CPUE measures for changes in discharge. Furthermore, because there was no consistent effect of discharge on CPUE, it is unlikely that we would detect a change in fish community composition due to changes in discharge.

Periphyton and Benthos

We demonstrated how to assess the effects of flow on periphyton and benthos. The purpose of the assessment was to determine whether available data are sufficient to document the effects of operations by comparing periphyton and benthos indicators pre- and post-Project. Periphyton and benthos are expected to respond to a variety of factors that are dependent (e.g. depth, velocity, exposure to air) and independent (e.g. turbidity, temperature, nutrients) of flow fluctuations. The effects of these factors, and their interactions (e.g. light availability), have been modeled using empirical data collected under Mon-7 (Schleppe et al. 2019).

For benthos that are submerged for 100% of the time, the factors that were significant depended on the analysis approach used. The EIS (App P3) used a regression analysis while Mon-7 used a random forest model to identify variables that explained variation in benthos indicators. For the EIS, the significant environmental variables were mean depth over a sampled substrate, median particle diameter, coefficient of variation of water velocity over a sampled substrate, and distance from W.A.C. Bennett Dam. The Mon-7 analysis reported depth, light and water velocity as significant variables (Schleppe et al. 2019). Generally, these results are similar and found that water velocity and depth were consistently important variables to consider for benthos that were continuously submerged.

However, in both analyses, the most significant factor was exposure, which led to a sharp decline in biomass (EIS, Vol. 2, App P3, Schleppe et al. 2019). This steep relationship is indicative of the drop in benthos productivity in the varial zone (i.e., the zone that is only sometimes wetted).

A coarse estimate of benthic biomass pre- and post-Project can be calculated using the ratio of the continuously wetted area because of the steep decline in benthic biomass with exposure. The continuously wetted area can be estimated from 2D model predictions generated by BC Hydro. A more detailed assessment of the effect of flow on benthic biomass would require depth and velocity data derived from hydrological models and a time series of discharge, temperature, and turbidity combined with models of benthos and periphyton response to environmental factors (EIS, App P2, Schleppe et al. 2019). Depth and velocity profiles for the Peace River in the Site C Local Assessment Area (LAA) can be included in this model to further refine the estimates of benthic biomass. The BC Hydro modelling team can produce the 2D hydrological model outputs if requested (Michael McArthur, pers. comm.). Four scenarios have been simulated to date using the 2D model inundation mapping:

- Without Site C, minimum flow from Peace Canyon Dam and 90th percentile flow from tributaries between Peace Canyon Dam and the Project;
- Without Site C, maximum turbine flow from Peace Canyon Dam combined with 10th percentile flow from tributaries between Peace Canyon Dam and the Project;
- With Site C, minimum flow from Peace Canyon Dam and 90th percentile flow from tributaries between Peace Canyon Dam and the Project; and
- With Site C, maximum turbine flow from Peace Canyon Dam combined with 10th percentile flow from tributaries between Peace Canyon Dam and the Project.

These model outputs could then be used to estimate the relative impact of changes in the benthic biomass post-Project. For now, we have demonstrated that the modelling and data collection are sufficient to understand the effects of flow fluctuations on future conditions.

The effect of flow on periphyton biomass was explored in the EIS at broad temporal and spatial scales. Using CE-QUAL models, sensitivity analyses were conducted on the change in periphyton biomass as a function of flow, nutrients, and TSS (EIS, Vol 2, Appendix P2). For flow, the different scenarios included in the sensitivity analyses included the average (i.e., expected scenario), dry (5th percentile of the 10-year moving average from the historical flow time series), and wet (the 95th percentile of the 10-year moving average from the historical flow time series). The outcomes of the sensitivity analysis demonstrated that the sensitivity of phytoplankton and periphyton biomasses to changes in flows was "small to negligible" and that they were most sensitive to changes in nutrient loadings.

More recent work (Mon-7) focused on processes that operate at much smaller spatial (meters) and temporal (hours) scales. Schleppe et al. (2019) quantified the effects of water velocity, light (turbidity, depth) and air exposure on periphyton productivity (PP) by measuring Chl a and biomass accumulation on Styrofoam substrates located on transects across the Peace River. At the transect scale, submergence patterns defined the upper bound of the varial zone, while light penetration determined the lower bound with the maximum PP occurring at, or slightly below, the continuously wetted elevation.

Estimating the change in PP in the downstream reach of the Peace River integrates reach scale and transect scale data into a single analysis. In general terms, reach scale data (nutrients, temperature, discharge regime) are used to model maximum PP at the optimum elevation through time. The combination of relative and maximum PP is expanded to the entire river area using an elevation map of the river bottom. Transect scale data (depth stratification, fluctuations in water elevation) are combined with turbidity to define the pattern of relative PP across a range of elevations and time scales. The actual analysis will occur when post-Project data become available and a before-after comparison can be made. This approach will use the same 2D models described for the benthic biomass estimates.

In the broader context, the predicted changes in periphyton and benthos pre- and post-Project are not expected to limit the fish community. In the EIS, the 27 different scenarios are based on different bookends of environmental conditions. The findings documented in the EIS suggest that benthic biomass will not be a limiting factor. Ecopath modelling conducted as part of the EIS (EIS, Vol. 2, App P3) demonstrated that the ecotrophic efficiency for benthos was well below 1.0 for all model runs, indicating that there was no shortage of benthos, despite forced reductions in benthic biomass as a function of periphyton biomass. Therefore, the evidence suggests that fish food will not be a limiting factor for higher tropic levels.

Daily Growth

We examined the influence of flow on daily growth, as measured by otolith growth increments in juvenile fish from fish sampled from 2014 to 2016, and 2018. The analysis was limited to age-0 and age-1 Mountain Whitefish, and sucker species. This summary focuses on age-0 Mountain Whitefish because they had the largest sample size and the results are representative of the other groups analyzed. Overall, there was weak evidence that flow variability had a weak effect on daily growth.

The statistical analysis was conducted using a linear mixed-effects model using daily growth as the response variable, random effects of fish, and the following fixed effects: flow range, mean flow, water temperature (and a second order polynomial of water temperature), and year (2016 or 2018). Interactions were also included. The effect sizes demonstrated that water temperature was an important predictor of otolith growth rates and explained at least half of the variability in Mountain Whitefish daily growth. Compared to discharge variables, the standardized effect size for the influence of water temperature was more than twice as large as all the discharge variables combined for age-0 Mountain Whitefish and age-0 suckers. The analysis suggests that the effect of flow fluctuation on daily growth is species-, age-, and year-specific. For age-0 Mountain Whitefish, daily growth increments changed significantly with changes in discharge range over a day, but the direction of the effect was dependent on year and mean discharge. Particularly, the effect was reversed depending on the year – in 2016, increases in mean discharge resulted in less growth, whereas in 2018, increases in mean discharge resulted in more growth. Conversely, no statistically significant effect of discharge was detected for the otolith growth of age-1 Mountain Whitefish or age-0 suckers. Overall, there is weak evidence to support the effect of discharge variability on otolith growth of juvenile fish; however, stronger evidence would be required to reject the null hypothesis that growth of age-0 and age-1 fishes in the LAA are independent of flow fluctuations.

Recruitment

We document the methods for how to assess the effect of flow variability on recruitment, which is defined as the process by which new individuals are added to a population by birth or immigration. With regards to sampling in the Peace River, recruitment into a population is the number of immature and mature fish that enter the population that is vulnerable to the Peace River Large Fish Indexing Survey each year.

The effect of flow fluctuations on recruitment cannot be fully evaluated at this time because the flow regime has not changed. Age structure provides information on recruitment and survival in three ways: (1) the slope of the descending limb of the catch curve represents adult survival; (2) gaps in age class structure are an indicator of periodic recruitment failure; and (3) an abrupt drop in year class abundance that tracks through successive years can be used to estimate the effect of abrupt recruitment failure potentially due to a change in habitat conditions (e.g., river diversion, reservoir filling). Current data provides baseline information for all three indicators. Data suggest that Mountain Whitefish fully recruit to the sampling gear at age-5 and that adult mortality rates are constant. This analysis compares the cohort strength across years. This method is demonstrated by comparing the 2002 and 2012 cohorts and shows significant natural variation in age-class strength.

Findings:

In general terms, Mon-17 has concluded:

- Catchability is not affected by changes in discharge over the short- (6 hours) and long-term (30 days).
- Current data collection under the FAHMFP can quantify the effects of changes in water level fluctuation on ecosystem productivity, which includes all of the important covariates for the analysis (depth, velocity, light levels, substrate).
- Differences among days in water level fluctuation has a weak effect on daily growth of small fish in the Peace River.
- Differences in year class strength among cohorts of Mountain Whitefish suggests that there is significant natural variation in survival among cohorts.

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1 INTRODUCTION

Fish[1] and fish habitat[2] are valued ecosystem components (VECs) of the Peace River because of their importance to Aboriginal groups, regulatory agencies, and stakeholders. For the Peace River downstream of the Site C Clean Energy Project (the Project), changes to the typical daily hydrograph could affect fish populations by altering the amount or quality of fish habitat, thereby influencing fish growth or survival (as summarized in the Environmental Impact Statement [EIS] Volume 2, Section 12). During Project operation, daily discharge fluctuations are expected to increase and the phase to shift to different times of the day. The daily range of water levels is predicted to increase from 0.5 m to 1.0 m at the Site C tailrace, increase from 0.4 m to 0.8 m near Taylor, BC, and increase from 0.5 to 0.9 m near the Alces River confluence[3].

The Peace River Water Level Fluctuation Monitoring Program (Mon-17) will focus on providing the information necessary to integrate these hydrological changes into the sampling design of the Fisheries and Aquatic Habitat Monitoring and Follow-up Program (FAHMFP). Specific issues include the sensitivity of electrofishing catchability to discharge under the Peace River Fish Community Monitoring Program (Mon-2) and the comparability of sampling sites for before-after comparisons under the Peace River Fish Food Organisms Monitoring Program (Mon-7). Secondly, Mon-17 will focus on a synthesis of information from the FAHMFP to develop cause and effect links between changes in hydrology and changes in fish and fish habitat. Most of the data used in this synthesis will be collected under other components of the FAHMFP, including the Peace River Physical Habitat Monitoring Program (Mon-3), the Peace River Water and Sediment Quality Monitoring Program (Mon-9), the Peace River Riparian Vegetation Monitoring Program (Mon-5), the Peace River Fish Food Organisms Monitoring Program (Mon-7) and the Peace River Fish Community Monitoring Program (Mon-2).

For example, the historical and predicted flows from the Peace River above Pine River[4] (07FA004) Water Survey of Canada (WSC) hydrometric station demonstrates a larger range of typical (i.e., 80% of the time) flows post-Project compared to pre-Project (Table 1). Post-Project estimates of median flow for the sampling time of day and time of year (defined in Table 1) are similar to historic (2000-2015) levels (1,240 vs. 1,231 $m^3 \cdot s^{-1}$), and the 90th and 10th percentile flows post-Project (390 and 1,780 $m^3 \cdot s^{-1}$) show a wider range of conditions than observed in the 2000-2015 sampling period (449 and 1,724 $m^3 \cdot s^{-1}$).

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[1] Fish includes fish abundance, biomass, composition, health, and survival.
[2] Fish habitat includes water quality, sediment quality, lower trophic levels (periphyton and benthic invertebrates), and physical habitat.
[3] EIS, Volume 2, Section 11.4.5.2.5
[4] Available at: https://wateroffice.ec.gc.ca/search/historical_e.html

Table 1: Historical and predicted flows for the August-September period at the Water Survey of Canada Peace River above Pine River (07FA004) hydrometric station. All hydrometric data provided in $m^3 \cdot s^{-1}$

Period	All Day Exceedances			Daylight Sampling Hours (08:00 - 17:00 local time) Exceedances			Non-Sampling Hours (0:00 - 7:00; 18:00 - 23:00, local time) Exceedances		
	10%	50%	90%	10%	50%	90%	10%	50%	90%
Historical Data (1979 - 1999)*	1651	1073	442	1574	977	436	1703	1152	450
Historical Data (2000 - 2009, 2010, 2014 - 2015)	1592	908	442	1724	1240	449	1467	855	441
Predicted Site C Flows* & **	1714	995	390	1780	1231	390	1540	746	390

* Based on the years 1979 through 1999 excluding 1980, 1981, 1983 and 1987 due to a lack of data in August and September (less than 50% data available)

** Predicted flows were completed using BC Hydro's GOM modeling, more information on this modeling is contained in the surface water section of the EIS.

This report is the final report for Mon-17 in the construction phase of the Project, with the next planned analysis in 2028 (Operations Year 5). It is important that this report documents how the data that have been collected to date are sufficient and the analysis methods are well understood to monitor how changes in the hydrograph may affect fish and fish habitat.

1.1 MANAGEMENT QUESTIONS AND HYPOTHESES:

Mon-17 poses a series of management questions and hypotheses[5]. The management questions from the FAHMFP are:

- How do changes in the hydrological regime affect estimates of catchability used in the Peace River Fish Community Monitoring Program (Mon-2)?
- How do changes in the hydrological regime affect fish and fish habitat of the Peace River?

During the construction phase of the Project, these two management questions cannot be evaluated directly. Therefore, an additional management question was developed for this report:

> Are the baseline data sufficient to determine how changes in the hydrograph may affect fish and fish habitat?

To support the management questions, the following management hypotheses, posed as a series of null hypotheses, were presented in Mon-17:

H_{1a}: Species-specific catchability at a sampling site in the Peace River is independent of the water level at the time of sampling.

H_{1b}: Species-specific catchability at a sampling site in the Peace River is independent of the pattern of variation in water level during the month prior to sampling, (The term “water level regime” is used to distinguish this effect from that of “water level at the time of sampling”).

H_2: Periphyton production among and within sites in the Peace River is independent of the magnitude and timing of flow fluctuations.

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[5] The management questions, hypotheses and task numbers referred to in this report include those recommended by the Site C Fisheries and Aquatic Habitat Mitigation and Monitoring Technical Committee. These are in addition to those listed in the FAHMFP (dated Dec 22, 2015).

H_3: Biomass of invertebrates (benthos) among and within sites in the Peace River is independent of the magnitude and timing of flow fluctuations.

H_4: Species-specific growth of age-0 and age-1 fish among sites in the Peace River is independent of the magnitude and timing of flow fluctuations.

H_5: Species-specific fish density among sites, as a measure of species composition, in the Peace River is independent of the magnitude and timing of flow fluctuations.

H_6: Species-specific recruitment is independent of the magnitude and timing of flow fluctuations.

2 METHODS AND RESULTS BY TASK

2.1 OVERVIEW

Mon-17 focuses on data analysis tasks using data from other monitoring programs in the FAHMFP (Table 2). This approach required careful integration among the different monitoring programs to ensure data were collected as necessary to meet the objectives of Mon-17. The only data collection task specific to Mon-17 was Task 2b in 2016 and 2018 – sampling of otoliths from three indicator species of small fish, which required dedicated field effort. The data analysis tasks that are conducted as part of Mon-17 are shown in Table 2, which also highlights the hypotheses each task addresses and the related data collection tasks.

Table 2: Peace River Water Level Fluctuation Monitoring Program (Mon-17) analysis tasks with hypotheses addressed and related data collection tasks

Analysis Task	Hypotheses addressed	Related Data Collection Tasks	Performance Measures	Survey Method	Expected Schedule	
					Construction Years 1 to 9	Operation Years 1 to 30
Task 3a – Catchability Examine the relationship between site-specific boat electroshocking catch rates to discharge at the time of sampling	H_{1a}, H_{1b}	**Mon-2, Task 2a –** Peace River Large Fish Indexing Survey	Catchability versus water level	Boat electroshocking under Mon-2	Data collected annually under Mon-2 and analyzed in Years 2 and 4	Data collected annually under Mon-2 and analyzed in Year 5
Task 3b – Benthos and Periphyton Examine the relationship between accrual of periphyton biomass and metrics of habitat attributes including flow variables. Examine the relationship between benthic biomass and metrics of habitat attributes including flow variables.	H_2, H_3	**Mon-7** periphyton and benthos data	Benthic invertebrate biomass and production	Benthic basket samplers and fish stomach contents	Data collected in Years 3 and 4 under Mon-7 and analyzed in Year 4	Data collected from Years 3 to 7 under Mon-7 and analyzed in Year 5
Task 3c – Daily Growth Examine the relationship between the width of daily growth rings on otoliths of indicator small fish species to daily flow variations	H_4	**Mon-2, Task 2b** – Peace River Fish Composition and Abundance Survey **Mon-17, Task 2b** – “Small Fish” (Construction Years 3 and 4 only)	Width of daily growth rings on otoliths collected from young target fish species	Beach seine, backpack electrofishing, or small fish boat electroshocking	Data collected in Years 3 and 4 (under Mon-17) and Years 6 and 7 (under Mon-2), and analyzed in Year 4	Data collected in Years 1 and 5, and analyzed in Year 5
Task 3d – Fish Community Composition Examine the relationship between fish community composition and flow fluctuations	H_5	**Mon-2, Task 2a** – Peace River Large Fish Indexing Survey **Mon-2, Task 2b** – Peace River Fish Composition and Abundance Survey	Fish community composition, species richness, species diversity	Beach seine, backpack electrofishing, and boat electroshocking under Mon-2	Data collected per the schedule for Tasks 2a and 2b of Mon-2, and analyzed in Year 4	Data collected annually under Mon-2 and analyzed in Year 5
Task 3e – Fish Recruitment Examine the relationship between population age-structure data to seasonal patterns in flow fluctuations	H_6	**Mon-2, Task 2a** – Peace River Large Fish Indexing Survey	Age cohort strength	Boat electroshocking under Mon-2	Data collected annually under Mon-2 and analyzed in Year 4	Data collected annually under Mon-2 and analyzed in Year 5

2.2 DISCHARGE DATA

Discharge data were collected for each of the six sections (1, 3, 5, 6, 7, and 9) using the closest Water Survey of Canada (WSC) station. Discharge in Section 5 of the Peace River was assessed using the Peace River above the Pine River hydrometric station, located between the Moberly River confluence to near the Canadian National Railway bridge, between river km 53.4 and 64.8, measured from the BC/AB border (Mainstream 2011). We derived discharge estimates from rating curves developed by WSC and reported in units of cubic metres per second ($m^3 \cdot s^{-1}$) on an hourly basis. Section 5 will experience fluctuating flows during operations, and there is a robust matching catch dataset in the Peace River Large Fish Indexing Survey. Furthermore, Section 5 has enough historical discharge data to cover a wide range of flow levels. Discharge estimates for Sections 1, 3, 6, 7, and 9 relied on other WSC stations. For Section 1, we used hourly releases from Peace Canyon Dam. For Section 3, we used the Peace Canyon Dam releases plus discharge out of the Halfway (07FA006). For Section 6, we used WSC station 07FD002 (Peace River near Taylor). For Section 7, the discharge estimate required subtracting flows from WSC station 07FD001 (Kiskatinaw) from the flow from WSC station 07FD010 (Peace River D/S of the Kiskatinaw). During the sampling period, there was no WSC station near Section 9.

Spatial and Temporal Variation in Water Elevation in the Peace River

Post-Project analyses for Tasks 3a and 3b will need to extrapolate water elevations across time and space by developing relationships between dam operations and the timing and magnitude of water elevation changes downstream. In particular the analysis will require:

- A 2D model that will be used to define the pattern of depths and velocities as a function of water elevation and discharge;
- Patterns in water elevation variation at the hourly, daily, seasonal and annual time scales;
- The relationship between the phase (diurnal timing) of discharge peaking and the phase of water elevation peaking at locations downstream; and
- The pattern of attenuation of water elevation fluctuations at points downstream.

There is no need to proceed with the full analysis prior to the first post-Project evaluation. The purpose of this section is to evaluate (1) the feasibility of the analysis and (2) evaluate some of the expectations concerning the hydrology of the system.

Inquiries with the BC Hydro hydrological modeling group have indicated that 2D depth-velocity modeling of steady discharge scenarios is clearly possible and has already been done for selected discharges, locations and reaches (e.g. Figure 1). Modeling of the entire river will be possible, but very data intensive and beyond the scope of the Mon-17 analysis at this point. Post-Project assessments could range from comparisons of selected sites to modeling of the entire river, depending on the interest of the assessment team. We anticipate that for future modeling under Mon-17, Tasks 3a and 3b will use data from both Mon-6/7 and WSC stations to model downstream water elevation versus time as a function of dam discharge versus time. These data would be combined with the steady state 2D model to define the depth and velocity landscape versus time for locations of interest downstream, but details of this process are not defined in this report.

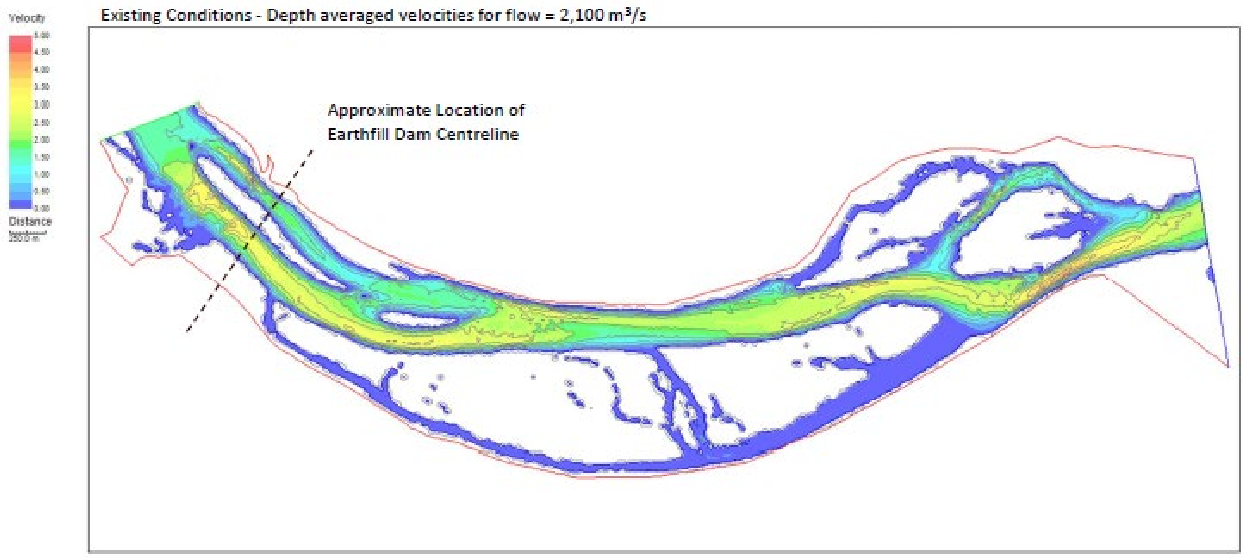

Figure 1. Example of the 2D model of velocities in the Peace River (reproduced from EIS Volume 2, Figure 11.4.11)

The pattern of water elevation variation can be illustrated using data collected in 2017 and 2018 as part of Mon-6/7 at a series of stations on the Peace River downstream of Peace Canyon Dam (Schleppe et al. 2019, Figure 2). The pattern of seasonal water elevations differed among the two years. In 2017, water elevation was low and steady from mid-June to mid-July before increasing by about 1.5 m and then remaining high from mid-August to late September (Figure 3a). In 2018, there was no clear trend in water elevation between mid-June and mid-September, but fluctuations in elevation were higher from mid-July on. Daily range in water elevation varied widely (Figure 3b). The timing of maximum water elevations occurred between 1200 and 2300 hrs with no sharp preference for a specific time (Figure 4a). At the weekly time scale, only Sunday had a noticeably lower incidence of water elevation that was within 20 cm of the weekly maximum (Figure 4b).

The phase and attenuation analysis is intended as a preliminary evaluation of existing perceptions. Maximum and minimum water elevation moved downstream at 8-9 km/hr and reached the Project 10 to 11 hrs after being observed at PR1 downstream of Peace Canyon Dam (Table 3, Table 4). The daily range in water elevation was highest at PR2 and diminished slowly with increasing distance downstream of Peace Canyon Dam (Figure 5).

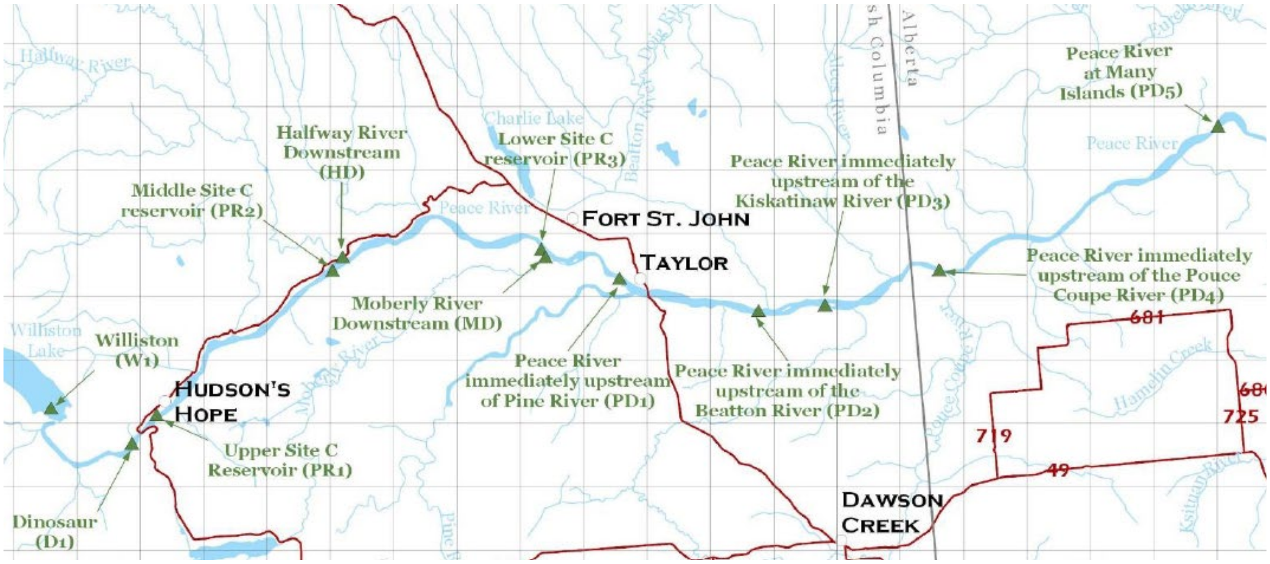

Figure 2. River elevation stations used by Schleppe et al. 2019.

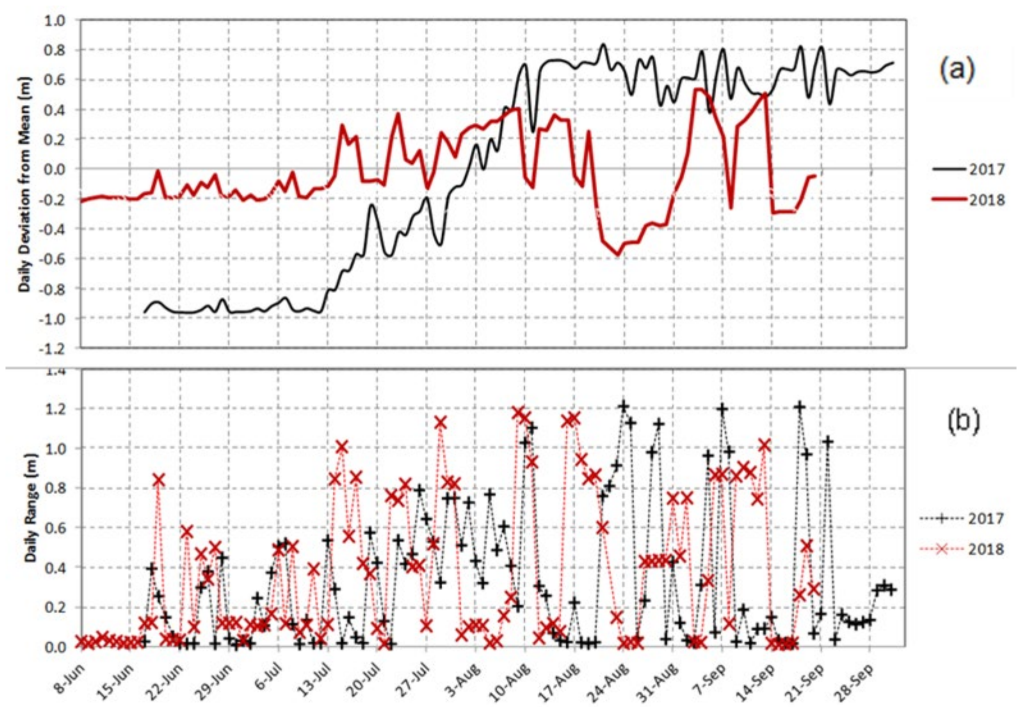

Figure 3. Variation in water elevation in the Peace River at Mon-6/7 site PR1 in the summer of 2017 and 2018. Deviation in the mean daily elevation is in comparison to the mean water elevation in the entire data set.

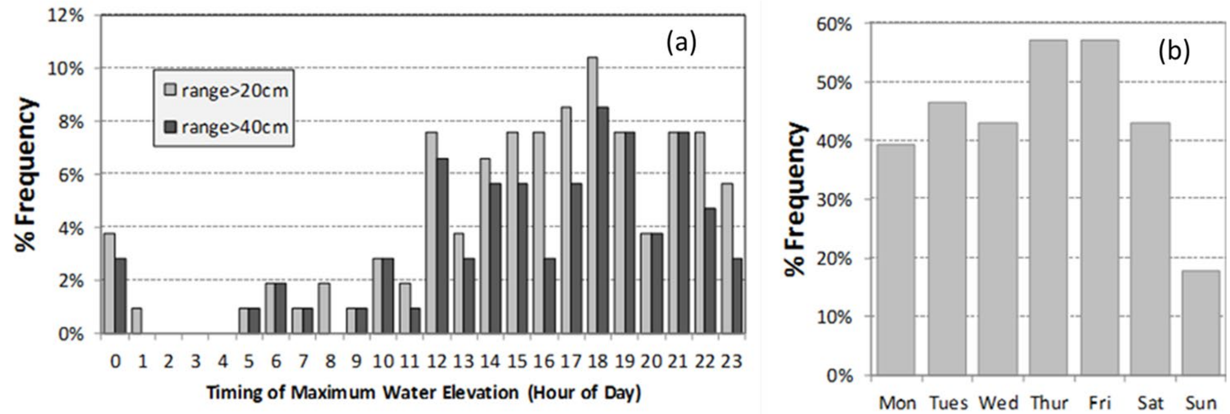

Figure 4. Daily and weekly times of peak water elevation. The distribution for daily timing only includes days where the daily range is >20cm (light gray) or >40 cm (dark gray). The distribution for weekly timing only includes weeks with >50 cm weekly range (n=26). Each day represents a tally of the number of times that the daily peak was within 20 cm of the weekly peak.

Table 3. Deviations in elevation for sites downstream of Peace Canyon Dam for a peaking event that started with the end of minimum flow on July 16, 2018 at 5 am. Distances downstream are the sum of straight line distances from the upstream stations. Water elevations were collected by Ecoscape Environmental Consultants (Schleppe et al. 2019).

	Water Elevation Deviations						
start of series =	7/16/18 5:00 AM		End Min Elevation	Peak Elevation			
Site =	PR1	PR2	PR3	PD1	PD2	PD4	PD5
km from PCN =	6	42	76	89	112	139	225
Hours	-0.33						
1							
2							
3							
4		-0.95					
5							
6							
7							
8			-0.62				
9							
10	0.671			-0.47			
11							
12							
13		1.			-0.29		
14		1.280					
15		1.2					
16		1					
17			1			-0.31	
18			1.				
19			1.141				
20			1				
21				0.996			
22							
23					0.758		
24					0.760		
25							-0.19
26							
27						0.857	
28						0.859	
29							
30							
31							
32							
33							
34							0.729
35							
36							

Table 4: Travel times for the peak and valley of a water elevation wave traveling downstream from PR1. Data are based on Table 3.

Station	Distance (km)	End of Minimum (hr)	Peak (hr)	End of Minimum (km/hr)	Peak (km/hr)
PR1	0	0.0	10.0	-	-
PR2	36	4.0	14.0	9	9
PR3	70	8.0	19.0	8	7
PD1	84	10.0	21.0	7	7
PD2	106	13.0	23.5	8	9
PD4	134	17.0	27.5	7	7
PD5	219	25.0	34.0	11	13
Average				8.2	8.6
Distance from Peace Canyon Dam to Site C				90	90
Phase Displacement (hr)				11	10

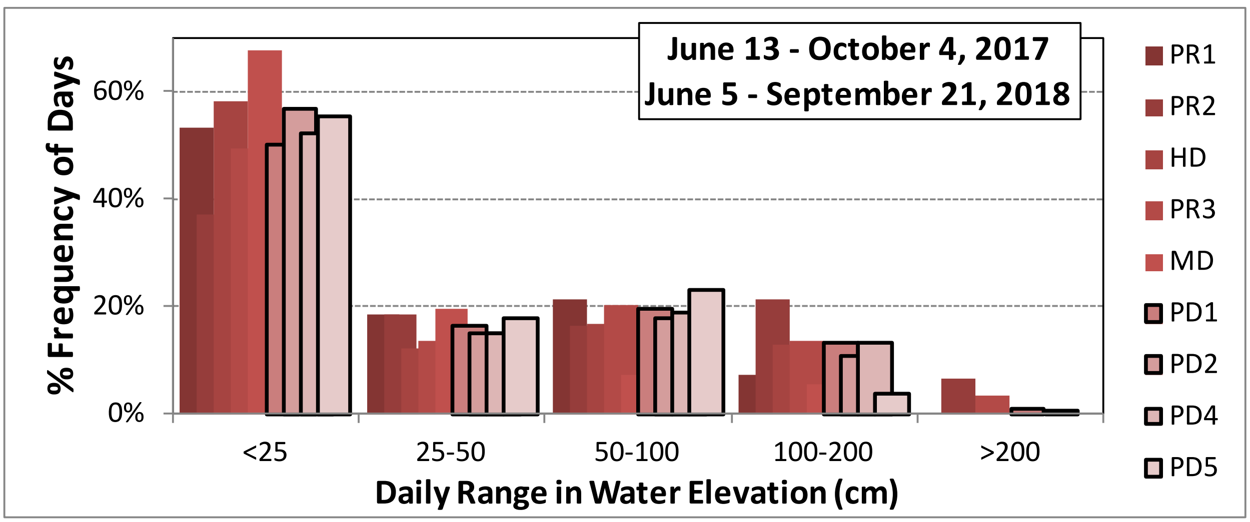

Figure 5. Range in water elevations in the Peace River during the summers of 2017 and 2018 arranged in sequence moving downstream from Peace Canyon Dam. PR stations are upstream of Site C, PD stations are downstream. HD and MD are just downstream of the Halfway and Moberly confluences, respectively.

These observations confirm our expectations concerning the potential for water elevation to affect catchability.

- Variation in seasonal patterns among years can be strong;
- If sampling in the Peace River occurs between 09:00 and 18:00, then PD1 (immediately downstream of the Project) will typically be sampled at lower elevations prior to the start of operations and at high water elevations post-Project. The reverse is true at PD5, which is about 135 km downstream of the Project;
- Daily variation in water elevation can be > 50 cm throughout the entire Site C Local Assessment Area (LAA); and
- More than 50% of days have minimal variation (< 25cm) in water elevation, which provides strong contrast to the remaining days where the daily range is often (30% of

days) greater than 50 cm.

These observations also confirm our expectations about analysis of depth, velocity and water elevation fluctuations as they relate to the Task 3b performance indicators for primary and secondary production.

- A 2D model is available to define the pattern of depths and velocities as a function of water elevation and discharge in the Peace River downstream of the Project;
- Differences of 0.5 to 1.5 m in water elevation are common at the hourly, daily, seasonal and annual time scales;
- Diurnal peaking in water elevation has a clear pattern but is not rigidly defined;
- Daily peaking in water elevation is lower on Sundays;
- Variation in seasonal patterns among years can be strong;
- A water elevation peaking wave is propagated downstream on a time scale of hours;
- Phase displacement at the Project is about 11 hours;
- The peak and trough of the wave move at similar speeds;
- Diurnal variation in water elevation varies widely among days and locations;
- Daily variation was < 25 cm on most days at all stations;
- Waves with amplitudes > 1 m are observed 100 to 150 km downstream of the point of control; and
- Other causes of daily water elevation variation (e.g. snow melt, precipitation events) need to be explored for stations downstream of the Pine River.

2.3 CATCHABILITY (TASK 3A) AND FISH COMMUNITY (TASK 3D)

2.3.1 Introduction

Catchability or capture efficiency is defined as the proportion of the population that is captured by a defined unit of effort (Ricker 1975). For many fish species, catch per unit effort (CPUE) will be used as a proxy for abundance of large fish species in the Peace River pre- and post-Project. CPUE is related to catchability following equation 1:

$$CPUE = qN \qquad \text{(equation 1)}$$

where the population (*N*) is defined as the abundance of fish of a given species within a reach, and *q* is defined as the proportion of the population captured by a unit of sampling effort (i.e., catchability). By measuring *CPUE*, we can understand how changes in habitat conditions, such as discharge, can affect catchability (*q*). Potential mechanisms can involve the capture process and/or fish behavior and can vary among locations and species. For example, *q* could be lower if fish move to higher depth/velocity habitat or if correlated factors affect the behavior or visibility of target fish (e.g., turbidity, temperature).

The objective of Task 3a is to determine if catchability is affected by changes in flow, and whether a correction factor is required. The catchability of boat electroshockers is known to vary with a variety of factors including species, fish size and habitat characteristics (e.g., Bayley and Austen 2002). Under the sampling protocols used in the Peace River Large Fish Indexing Survey, most of these biases can be assumed to be constant through time and therefore have predictable effects on CPUE as a relative index of changes in fish abundance by species through time. When biases are constant, a correction factor is not necessary to adjust CPUE. However, some habitat conditions like flow are not constant and may require a correction factor. Changes in the hydrograph, along with other changes to habitat conditions at the time of sampling, can lead to changes in electrofishing sampling efficiency or catchability (*q*) (Speas et al. 2004, Lyon et al. 2014). If a relationship exists between flow conditions and catchability for fish in the Peace River, this might affect the interpretation of the results such as species abundance comparisons pre- and post-Project.

We use the term sampling event to refer to an individual catch sample within a site within a section within a sampling session. A sampling session is a multi-day period where every site in every section is sampled. This language is consistent with Golder and Gazey (2018).

The ability to assess changes in the fish community may also be affected if changes in the relationship between flow and catchability are different among species. This is because as density or abundance become more important, differences in the species diversity curves (Leinster and Cobbold 2012) may be observed.

For Site C, there are two mechanisms where an evaluation of catchability as a function of flow is essential:

1. The point of riverine flow control will shift from Peace Canyon Dam to the Project, which means for the same position on the Peace River downstream of the Project, river flows would rise and fall 8 to 12 hours later than they would without the Project.
    a. Assuming a similar pattern of power generation, the timing of peak discharge will shift back in time 8 to 12 hrs.
    b. The pattern of power generation may change if water managers shift the magnitude, timing or frequency of discharge peaks in response to power demand or regulatory changes.

2. On an annual timescale, sequences of dry or wet years may cause systematic changes in flow that are unrelated to the start of operations at Site C.
   a. N years is small, so the before-after distribution of wet and dry years may be non-random.
   b. There may be long term trends in annual runoff.
   c. Water managers may reallocate water volumes among seasons, including the sampling season.

Ultimately these two mechanisms can be related to the following Mon-17 null hypotheses:

H_{1a}: Species-specific catchability at a sampling site in the Peace River is independent of the water level at the time of sampling.

H_{1b}: Species-specific catchability at a sampling site in the Peace River is independent of the pattern of variation in water level during the month prior to sampling. The term "water level regime" is used to distinguish this effect from that of "water level at the time of sampling".

Hypothesis H_{1a} is consistent with Mechanism 1, in that there may be an effect of daily flow fluctuations on catchability. Mon-17 explores several alternate metrics to assess the effect of daily changes in flow. Hypothesis H_{1b} is loosely consistent with Mechanism 2, that a given water year may be wet or dry, and this might change overall catchability of fish. However, Hypothesis H_{1b} infers a specific metric (flow over the last 30 days) to assess this pattern; therefore, we modified H_{1b} to be more open-ended, which allows us to explore a variety of metrics, including a year effect to assess the effect of water level regime. H_{1b} now becomes H_{1b-2}.

H_{1b-2}: Species-specific catchability at a sampling site in the Peace River is independent of the pattern of variation in water level regime over the longer-term.

There is strong support in the literature that fish in fluvial environments have clear depth and velocity preferences that vary with the size and species of fish (Lewis 1969, Moyle and Baltz 1985, Aadland 1993, Rosenfeld 2003, Gillenwater et al. 2006). When discharge is high and stable, fish are expected to be sorted by depth and velocity preferences that are driven by factors such as feeding opportunities, predation risk and energy expenditure (Figure 6a) and modified by hydraulic-independent factors, such as overhead cover. Under low and stable discharges, fish may tend to be concentrated because higher depth-velocity habitats are not available, and predation risk may force small fish to move to shallower water (Figure 6b). Unstable discharge regimes may force fish to remain in higher depth-velocity habitat if the costs of moving are higher than the benefits of a short-term move to preferred habitat (Figure 6c). Under high and unstable discharges, depths and velocities may change so rapidly that fish may find it difficult to locate their preferred habitat (Figure 6d).

These types of behavioral responses have the potential to affect catchability; however, controlling for the effects of discharge on catchability does not necessarily require an understanding of the behavioral responses to discharge if a more direct relationship between catchability and discharge can be quantified.

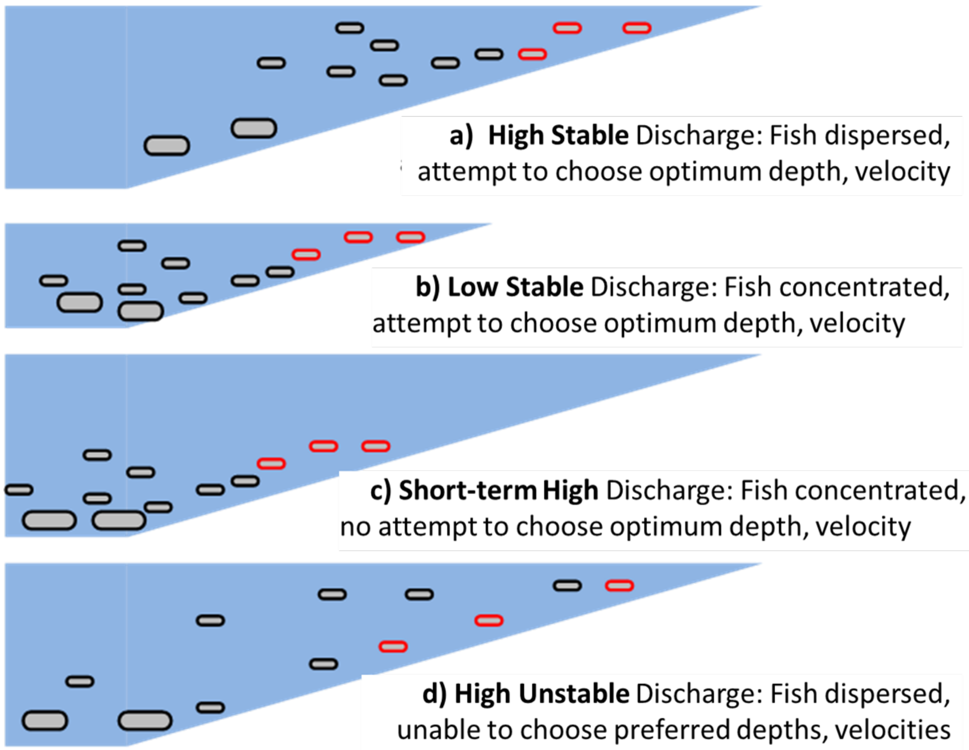

Figure 6. **Hypothetical distributions of a small fish species (red) that prefers lower velocity, shallow locations, and a species with a large maximum size (black) that prefers higher velocity, deeper locations.**

Previous efforts to examine the relationship between CPUE and discharge found no effect of discharge on the day of sampling compared to CPUE for Mountain Whitefish, Bull Trout and Arctic Grayling in Section 5 of the Peace River (ESSA and Golder 2018). However, the analysis in that report was based on a coarse-grain comparison of discharge during the entire sampling day against the CPUE for the full day. This led to a loss of resolution in the flows experienced at the time of sampling. Therefore, a recommendation of the report was to use a finer resolution of CPUE and flow data to re-evaluate the hypothesized relationships, and to expand the analysis to all species captured in the Peace River Large Fish Indexing Survey.

Additionally, the measure of fish community composition, which could be done using species diversity curves, can be estimated from year-to-year, as has been done in Golder and Gazey (2018) and Ma et al. (2015). This is captured in the Mon-17 hypothesis for fish community composition:

H_5: Species-specific fish density among sites, as a measure of species composition, in the Peace River is independent of the magnitude and timing of flow fluctuations.

Flow fluctuations could change estimates of fish community composition if the catchability of different species within the Peace River community differs with flow.

2.3.2 Data

Golder provided the catch data as a query to the Peace River Fish Indexing Database. The data query for this report was provided on December 4, 2019, and includes the following fields: sample session, sampling day, individual sample ID (i.e., sampling event), the start and end time of sampling, the number of fish caught per species, the effort per sampling event in both length sampled (in meters) and time sampled (in seconds), and a mean of ratios calculation for CPUE. The data range was from 2004 to 2018. The sections included in the dataset were Sections 1, 3, 5, 6, 7 and 9. The species included in the dataset were Arctic Grayling, Bull Trout, Largescale Sucker, Longnose Sucker, Mountain Whitefish, Rainbow Trout, and White Sucker.

Catch data were collected following the procedures outlined in Golder and Gazey (2018), which we briefly summarize here. Field crews captured fish during boat electroshocking surveys that were conducted as part of the Peace River Large Fish Indexing Survey. Surveys were conducted along the channel margins of the Peace River at previously established sites at water depths between 0.5 to 2.0 m. Field crews used Smith-Root high-output Generator Powered Pulsator (GPP 5.0) electroshockers (Smith-Root, Vancouver, WA, USA) operated from outboard jet-drive riverboats. The electroshocking procedure consisted of maneuvering the boat downstream along the shoreline of each sample site. Two crew members, positioned on a netting platform at the bow of the boat, netted stunned fish, while a third individual operated the boat and electroshocking unit. Captured fish were immediately placed into a 175 L onboard live-well equipped with a freshwater pump. Electroshocker settings were changed in 2014 from averaging 60 Hz and 4 amps to averaging around 30 Hz and 2.5 amps to reduce potential fish mortality.

The study area was divided into six different sections based on the delineations detailed in Mainstream (2010). Sampling within each section was limited to either previously established sites (e.g., P&E and Gazey 2002) or sites that were established for the purposes of this study. Between 16 and 21 individual sites were sampled within each section. Site length varied between 220 m and 1900 m (average = 999 m). Each site was sampled five or six times each year (i.e., five or six sessions).

For our analysis, the appropriate sampling unit for CPUE was at the sample day-sample session level because that is the unit of sampling that experiences the same discharge conditions. Therefore, data are rolled up to the sample day-session level and each is given a unique identifier (e.g., 2014-08-14-1 [Year-Month-Day-Session]). This meant that sampling at sites within a given sample day-session were combined to calculate CPUE by adding the number of fish caught across all sites and dividing that by the sum of the time or length sampled across all sites (depending on the CPUE measurement of #/s or #/100m respectively). Using the sum divided by the sum is often called the ratio of means method for calculating CPUE. This resulted in 628 unique sample-session-days.

We examined the proportion of zero-values in the CPUE data for each sample day-session across species and section. We applied a general guideline that if > 50% of data were zeroes, then we would exclude the species by section combination. This guideline was used as an estimate of whether the data followed a Poisson distribution. Based on these criteria, Table 5 demonstrates that Arctic Grayling should only be analyzed for Sections 3 and 5, Rainbow Trout analyses should not include Section 9, and White Sucker analyses should exclude Sections 1 and 3. Only Section 5 has enough data to do analyses across all seven species. Notably, Mountain Whitefish only have 2% zero values for CPUE in Section 6, with no other CPUE values of zero in the other sections. Before analyses were conducted, we normalized the CPUE data, using a natural-log-transformation of CPUE. We added a small constant to avoid taking the log of zero. In this case, we chose + ½ minimum non-zero CPUE value to each value.

Table 5: Percent of sample-day-sessions that have zero-values of CPUE (#/s) across species and sections. Red numbers denote values >50%, suggesting that the data do not follow a Poisson distribution and should be excluded from the analysis.

Section	AG	BT	CSU	LSU	MW	RB	WSU
1	72%	11%	42%	26%	0%	14%	66%
3	20%	2%	16%	11%	0%	9%	57%
5	14%	5%	13%	10%	0%	32%	38%
6	50%	19%	7%	2%	2%	43%	29%
7	54%	12%	4%	0%	0%	46%	8%
9	76%	26%	0%	0%	0%	74%	9%

Discharge data used for this analysis were collected as described in Section 2.2 and provided by Golder for this analysis. Depending on which section fish were caught in, different WSC survey stations were used to match up discharge data with the time and date of sampling (sample-day-session) from the catch data. Different measures of discharge were provided to align with hypotheses H_{1a} and H_{1b-2}. H_{1a} is addressed using the discharge at the time of sampling (D_{1h}) and mean discharge over the previous 6 hours (D_{6h}), as well as the estimate of variability as measured by the coefficient of variation (CV) for the previous 6 hours prior to sampling (CV.D_{6h}). H_{1b-2} is addressed using a longer-term discharge measure, which is the mean discharge over the last 30 days and the CV over the last 30 days.

Because of concerns of collinearity, each of the mean discharge metrics were standardized for each species and each section by subtracting the mean value and dividing the value by the standard deviation of the data. This standardization is called z-score normalization and was done using the scale() function in R. Variance estimates remained untouched, because the reduction in variance was by a constant factor meaning that changes in variance were consistent. Furthermore, when converting the discharge metrics into z-scores, the analyses can be interpreted in units of standard deviations; i.e., a value of +1 is 1 standard deviation greater than the mean. We found that a short-term time lag of 6 hours provided the best fit to the data. This preliminary analysis was conducted using only Mountain Whitefish in Section 5 because that species by section combination had the highest number of captures and the longest time series. We assumed that the other species and sections would follow the same pattern. We compared linear mixed effects models using short-term time lags of 24 hours, 12 hours, 6 hours and 3 hours (halving the lag each time) (Table 6). These were treated as separate models. We compared these models using model selection criteria (Akaike's Information Criterion [AIC]). A comparison of the models demonstrated that the 6h model was the best fit, but that it was considered the same as a 3h and 12h lag model. However, it was considered better than the 24h lag model (Burnham and Anderson 2004). We therefore used the 6h short-term lag in subsequent analyses.

Table 6: Model selection and weight using Akaike Information Criteria (AICc) values for models relating short-term lags in flow to CPUE (#/100m)

Model	Time-Lag	AICc	ΔAICc	Weight
D_{6h}	6 hours	108.95	-	0.396
D_{3h}	3 hours	109.25	-0.30	0.340
D_{12h}	12 hours	110.24	-1.29	0.207
D_{24h}	24 hours	112.83	-3.88	0.057

2.3.3 Methods

To test the revised hypotheses, we used a series of linear mixed effect models, treating the sampling year as a random factor, while examining the effects of discharge and electroshocking on estimates of CPUE. For each species *i* and section *j* that was analyzed (see Table 5), the full model followed the equation:

$$CPUE_{i,j} = D_{1h} + D_{6h} + CV.D_{6h} + D_{30d} + CV.D_{30d} + D_{1h} \times D_{6h} + E + (1|Y) + \varepsilon$$

where the dependent variable $CPUE_i$ is the CPUE in sample-day-session *i*. Discharge for each sampling event is represented as D_{1h}, D_{24h} and D_{30d}, representing either the discharge on the hour of sampling, the mean discharge over the 24 hours prior to sampling, and the mean discharge over the previous 30 days prior to sampling, respectively. Estimates of variation, using the coefficient of variation, were also provided for the discharge over the last 6 hours and 30 days ($CV.D_{6h}$ and $CV.D_{30d}$, respectively). The first two fixed effects correspond to Mon-17 hypothesis H_{1a}, while the third corresponds with hypothesis H_{1b-2}. Initially, for the short-term lag, we chose 6 hours prior to sampling because it allows for sufficient time for behavioural responses to changes in flow. We also included an interaction term between the 'instantaneous' flow D_{1h} and the short-term lag D_{6h}. If this term were to be significant, the direction of the term (positive or negative) would indicate whether flow was increasing or decreasing, and whether that impacted catchability. The final fixed effect is *E* which represents the electroshocker settings for a sampling event, which were changed in 2014 from averaging 60 Hz and 4 amps to averaging around 30 Hz and 2.5 amps. For Sections 6, 7, and 9, this term was excluded because sampling for these sections began in 2015. The random effects are the sampling year (*Y*) and random stochasticity (ε). We included the random year effect in the full model because we expect that the relationship between CPUE and discharge may differ depending on the sampling year, but we are not interested in the effects on variability for a given value.

We focused our analysis on CPUE as measured by the total number of fish caught per length of river sampled, measured as catch per 100 m (#/100 m). CPUE as a function of the time spent sampling was also recorded but was not used in this analysis. We expect that the results would be the same regardless of the metric. We used the lmer() function in the "lme4" package in R (Bates et al. 2015) to perform our analyses. The code, as well as the raw results, are presented in Appendix A in an R Markdown file. The results are presented in Appendix A, beginning with a table with the parameter estimates and P-values (Table 12), and then a series of figures by species and section. One key assumption in the analysis is that the total *N* for the entire river in the equation does not change during a sampling-day-session.

2.3.4 Results

Overall the results of the analysis suggest that there is no clear trend in the CPUE data based on changes in discharge. The entire analysis can be found in Appendix A and includes the analysis for each species (Arctic Grayling, Bull Trout, Largescale Sucker, Longnose Sucker, Mountain Whitefish, Rainbow Trout, and White Sucker) in each section (Sections 1, 3, 5, 6, 7 and 9).

For Mountain Whitefish in Section 5, the species and section with the most data, there was no statistically significant effect of discharge, but there was for electroshocker settings (Table 7; Figure 7).

Table 7: Parameter estimates for the fixed effects that explain variability in CPUE (# / 100 m) for Mountain Whitefish in Section 5. Yellow shaded cells are parameters that are P-values that are statistically significant at an alpha=0.05.

Parameter	Estimate	Std. Error	df	t value	Pr(>|t|)
(Intercept)	1.06	0.17	66.18	6.16	0.00
D_{1h}	-0.03	0.17	128.38	-0.18	0.86
D_{6h}	-0.11	0.16	128.90	-0.68	0.50
$CV.D_{6h}$	-1.33	0.93	128.59	-1.43	0.16
D_{30d}	0.05	0.06	53.29	0.78	0.44
$CV.D_{30d}$	0.88	0.49	99.26	1.80	0.07
E	-0.53	0.13	15.55	-4.05	0.00
$D_{1h} \times D_{6h}$	-0.02	0.03	135.50	-0.89	0.37

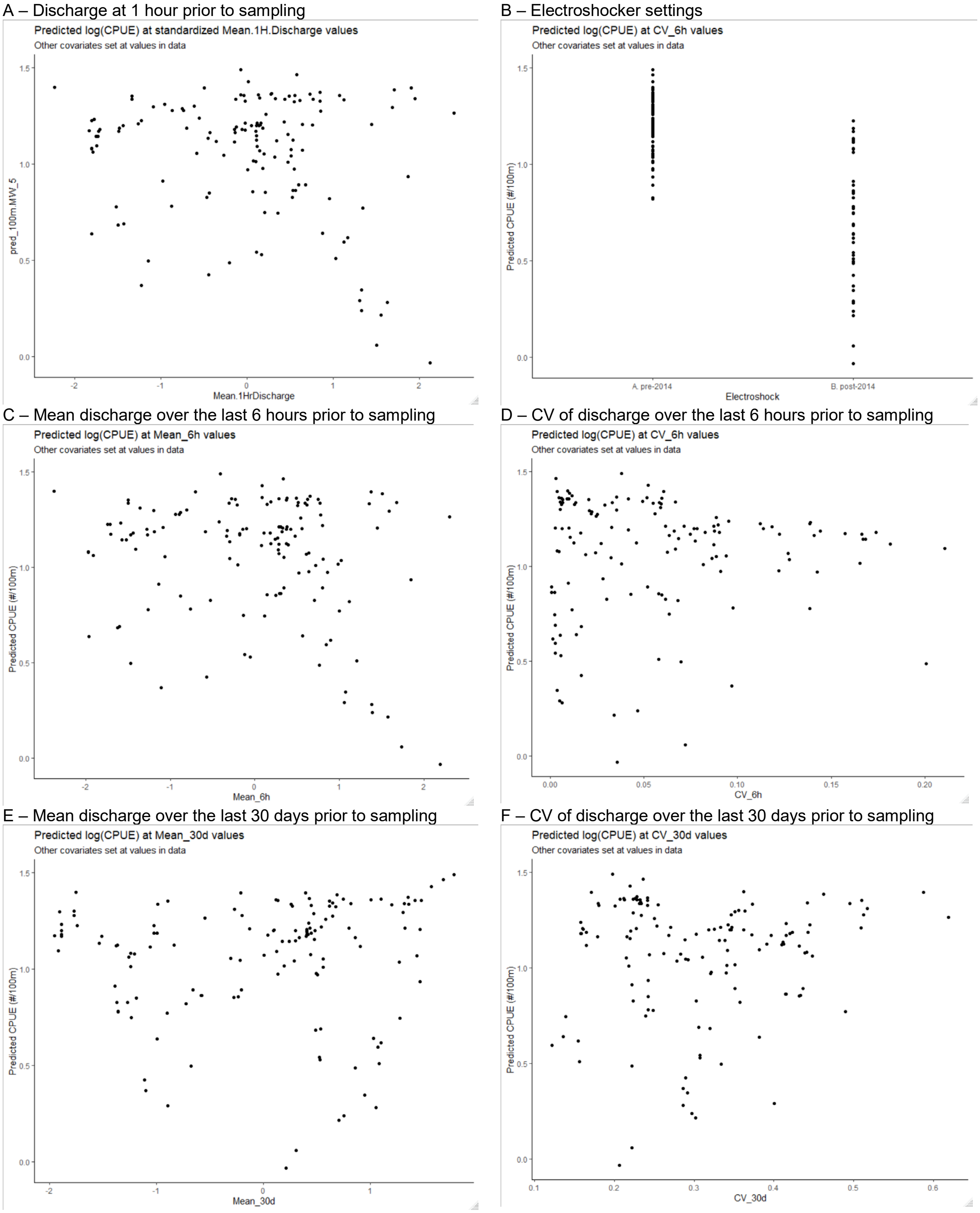

Figure 7: Predicted log(CPUE) of Mountain Whitefish in Section 5 at standardized values of each parameter of interest, keeping the other covariates in the data at the values in the data. The x-axis values are standardized measures of discharge in units of standard deviations.

When considering all species and sections, several of the linear mixed effect models showed statistically significant trends in the data (Table 12 in Appendix A). However, the inconsistent trends across sections and species suggests that the significant results are the linear mixed effects model fitting to noise. On closer inspection of the plots of each of the statistically significant discharge variables, the trends between CPUE and discharge are difficult to pick out, further reinforcing this notion. For example, Arctic Grayling in Section 3 had a statistically significant effect of coefficient of variation in the discharge over the previous 6 hours prior to sampling on the predicted CPUE (P=0.014, see Table 12 in Appendix A for full model results); however, a plot of the variable shows no clear trend (Figure 8).

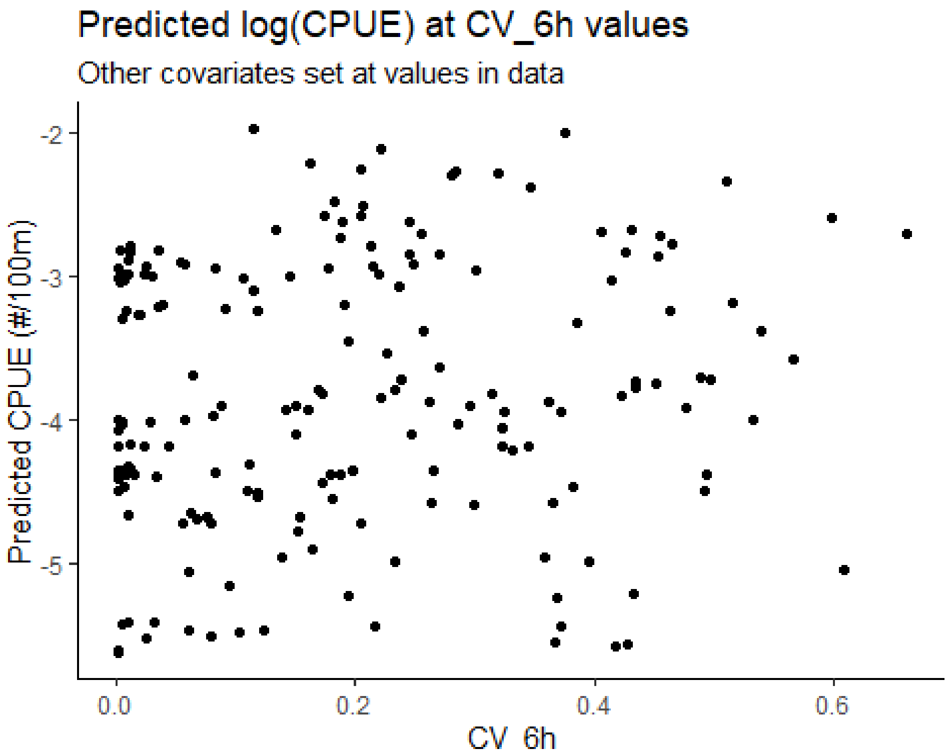

Figure 8: The effect of the coefficient of variation of discharge over the six hours prior to sample on predicted CPUE for Arctic Grayling in Section 3.

Another example is Bull Trout in Section 1, which showed a significant relationship between CPUE and the mean discharge over the past 30 days (P=0.038, see Table 12 in Appendix A for full model results). However, the plot demonstrates that there is no real trend in the CPUE based on changes in D_{30d} (Figure 9). Notably, because the discharge values are standardized, the x-axis is in units of standard deviations. This means that at 1 or 2 standard deviation units away from the mean value, the CPUE does not drastically change.

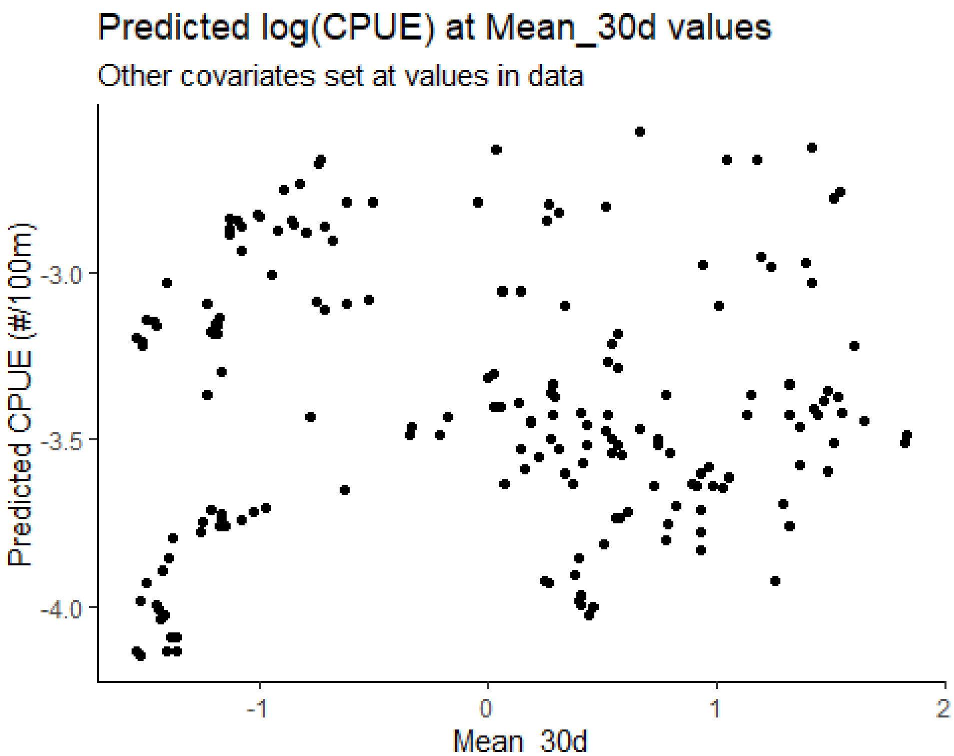

Figure 9: The effect of the standardized mean discharge over the last 30 days prior to sample on predicted CPUE for Bull Trout in Section 1.

Electroshocker settings were consistently significant for nearly all species and sections. The direction of the effect on catchability was consistent for each species but differed among species. CPUE for Mountain Whitefish, Arctic Grayling and Rainbow Trout declined from 2014 onward (under the new electroshocker settings), whereas CPUE for Longnose Sucker, Largescale Sucker and White Sucker increased from 2014 onward. Bull Trout CPUE varied with electroshocker settings based on the section.

The complete analysis is shown as an R markdown file in Appendix A, including all the tables and figures for statistically significant variables.

2.3.5 Discussion

The results suggest that there is no clear trend in CPUE based on discharge, either from the value of discharge, or the variability in discharge in the short-term (1 and 6 hours prior to sampling) or over the longer-term (30 d prior to sampling). In other words, we failed to reject the null hypotheses H_{1a} (species-specific catchability at a sampling site in the Peace River is independent of the water level at the time of sampling) and $H_{1b\text{-}2}$ (species-specific catchability at a sampling site in the Peace River is independent of the pattern of variation in water level regime over the longer-term). This result is based on the analysis of the effects of discharge on CPUE across multiple species and multiple sections. Although statistical significance is found in several of the terms, closer inspection of the results demonstrate that this is effectively fitting the model to noise in the data.

In the context of pre- and post-Project measurements of CPUE, this suggests that there is no need to correct CPUE measures for changes in discharge. This finding is based on the pre-Project values of discharge experienced in the Peace River. Furthermore, this analysis can be repeated post-Project, using the operations discharge. Changes in flow should have little bearing on the changes in CPUE experienced and therefore, future analyses of changes in CPUE could exclude discharge as a covariate.

Electroshocker settings affected CPUE and the results differed by species. CPUE declined for Mountain Whitefish, Arctic Grayling, Rainbow Trout, and sometimes Bull Trout, and this result was expected based on the lower power settings from 2014 onward. CPUE increased for the sucker species. However, this change was due to changes in capture methods rather than changes in electroshocker settings, as described in Golder and Gazey (2018). Prior to the FAHMFP, non-target fish (such as suckers) were not consistently targeted so capture was more variable and lower. Furthermore, sampling targeted fish <250 mm prior to 2014. These two factors are likely the cause of the change in CPUE of the sucker species, rather than changes in the electroshocker settings.

Furthermore, because the catchability of different species within the Peace River community did not discernably differ with changes in discharge, there does not appear to be an effect of flow on fish community composition or the ability to capture different species.

2.4 BENTHOS AND PERIPHYTON (TASK 3B)

2.4.1 Introduction

Task 3b examines the effects of flow fluctuations and the timing of peak flows on fish food in the Peace River. The management question of interest for the proposed analysis is:

> How do changes in the hydrological regime affect fish and fish habitat of the Peace River?

Differences in the hydrological regime in the Peace River before, during, and after construction of the Project have been anticipated in Volume 2, Section 11.4 of the EIS. Hypotheses 2 and 3 in Mon-17 are designed to quantify the effects of these changes:

H_2: Periphyton production among and within sites in the Peace River is independent of the magnitude and timing of flow fluctuations.

H_3: Biomass of invertebrates (benthos) among and within sites in the Peace River is independent of the magnitude and timing of flow fluctuations.

Periphyton and benthos are expected to respond to a variety of factors that are dependent (e.g. depth, velocity, exposure to air) and independent (e.g. turbidity, temperature, nutrients) of flow fluctuations. The effects of these factors, and their interactions (e.g. light availability), have been modeled using empirical data collected under Mon-7 (Schleppe et al 2019). In general terms, these analyses clearly reject both H_2 and H_3 and confirm that Peace River periphyton and benthos respond to environmental factors in predictable ways that are consistent with scientific studies elsewhere.

The purpose of the Mon-17 review is not to reiterate these findings but rather to assess whether the available data are sufficient to document the effects of operations by comparing periphyton and benthos indicators pre- and post-Project. Therefore, H_2 and H_3 are revised:

H_{2a}: Periphyton production in the Peace River is independent of changes in the magnitude and timing of flow fluctuations over time before, during, and after the construction of the Project.

H_{3a}: Biomass of invertebrates (benthos) in the Peace River is independent of changes in the magnitude and timing of flow fluctuations over time before, during, and after the construction of the Project.

The intent of the management question and these hypotheses is to determine if changes in flow fluctuations may limit fish food production and to the extent that food production becomes a limiting factor for the fish community.

There are two main issues in testing H_{2a} and H_{3a}:

- Expanding data from point sample measurements to the ecosystem level; and
- Accounting for changes in environmental factors that are correlated with the start of operations that are either a direct (phase change, minimum releases at Site C) or indirect effect of the Project (e.g. climate change).

Expansion to the ecosystem level is necessary because the direction and size of the response to changes in flow fluctuations will almost certainly differ among point samples. For example, if periphyton response to exposure depends on the time of day that the exposure occurs, then the shift in the point of control from Peace Canyon Dam to the Project will mean that some point samples will shift from day exposure to night exposure and vice versa. Expansion depends on having the relevant point site predictor variables available at the reach scale.

Accounting for correlated environmental factors depends on having an imperfect correlation between the effect of the Project and other environmental factors. For example, temperature varies enough from year to year to separate the effects of a temperature trend associated with climate change from the effects of the start of operations on periphyton and benthos. Similarly, the effects of flow fluctuation changes associated with the Project can be separated from existing flow fluctuation effects if flow fluctuations pre- and post-Project contain sufficient random variation. Discharge data from 2017 and 2018 vary substantially at hourly, daily, seasonal and annual time scales (Figure 3, Figure 4, Figure 5).

In the EIS[6], an Ecopath model was used to understand whether fish food biomass is likely to be an important factor in driving changes in fish biomass when considered in a community context (Section 6[7]). Predictions for benthic biomass are made using models derived from empirical data (Section 5). Predictions for periphyton biomass were made using 2D flow models and CE-QUAL-W2 (Section 3). The focus for this task is largely on benthic invertebrate biomass that is a direct measure of fish food. Periphyton biomass is examined more fully as part of the Ecopath modelling that is described in the EIS (Volume 2, Appendix P, Part 3).

The mass balance calculations in the Ecopath model indicate that fish biomass is not strongly limited by benthic and periphyton biomass. Ecotrophic efficiencies for both periphyton and benthos are low, which indicates that the proportion of biomass consumed by other species groups in the community is low for both groups.

2.4.2 Benthic Invertebrate Biomass

An assessment of the Mon-7 data suggests that even a minimal amount of air exposure plays a dominant role in driving benthos biomass. Measurement of benthic invertebrate biomass during sampler incubation periods of 44 and 66 d in the Peace River showed an “L-shaped” relationship between time exposed to air and benthic invertebrate biomass (EIS, Volume 2, Appendix P, Part 1) (Figure 10; Limnotek 2011). The Ephemeroptera, Plecoptera and

[6] Volume 2, Appendix P, Part 3, Future Aquatic Conditions in the Peace River
[7] Mass Balance Estimates of Changes in Peace River Fish Biomass and Food Webs Using Ecopath

Trichoptera (EPT) were particularly sensitive to periodic dewatering (Figure 10) and contributed most to the total biomass response to air exposure. This sensitivity is important because the EPT are important food organisms for fish in the Peace River (Golder 2011). Presence of the bottom part or leg of the “L” showed loss of animals in the samplers when they were out of the water for almost any period of time. The vertical part showed variation in biomass during continuous submergence.

Biomass data in Figure 10 are consistent with wide ranging published observations showing that dewatering of river substrata results in a loss of invertebrate biomass, taxon richness (Rosario and Resh 2000, Larned et al. 2007, Clarke et al. 2010) and biomass production (Chadwich and Hyrun 2007, Ledger et al. 2011). In an inundation experiment, Larned et al. (2007) found that invertebrate density decreased exponentially with the length of a preceding dry period (75% decrease in density after 5 days), while the relationship with richness was linear. The steep decline in biomass compared to richness is thought to result from the loss of a few large taxa that are sensitive to drying while maintaining a group of smaller bodied taxa that are resistant to drying (Larned et al. 2007). Similarly, Ledger et al. (2011) showed that smaller taxa with shorter life cycles are produced under intermittent drought conditions in place of large long-lived taxa, leading to an overall decline in biomass. These findings support observations from the Peace River (Figure 10) of the loss of invertebrate biomass among substrata exposed to air for various lengths of time. One conclusion is that production of fish food organisms will be much reduced or negligible along shorelines that are subject to frequent watering and dewatering in the Peace River. Hence, the varial zone in the Peace River is expected to support low or negligible production of benthic invertebrates that are food for fish due to frequent watering and dewatering.

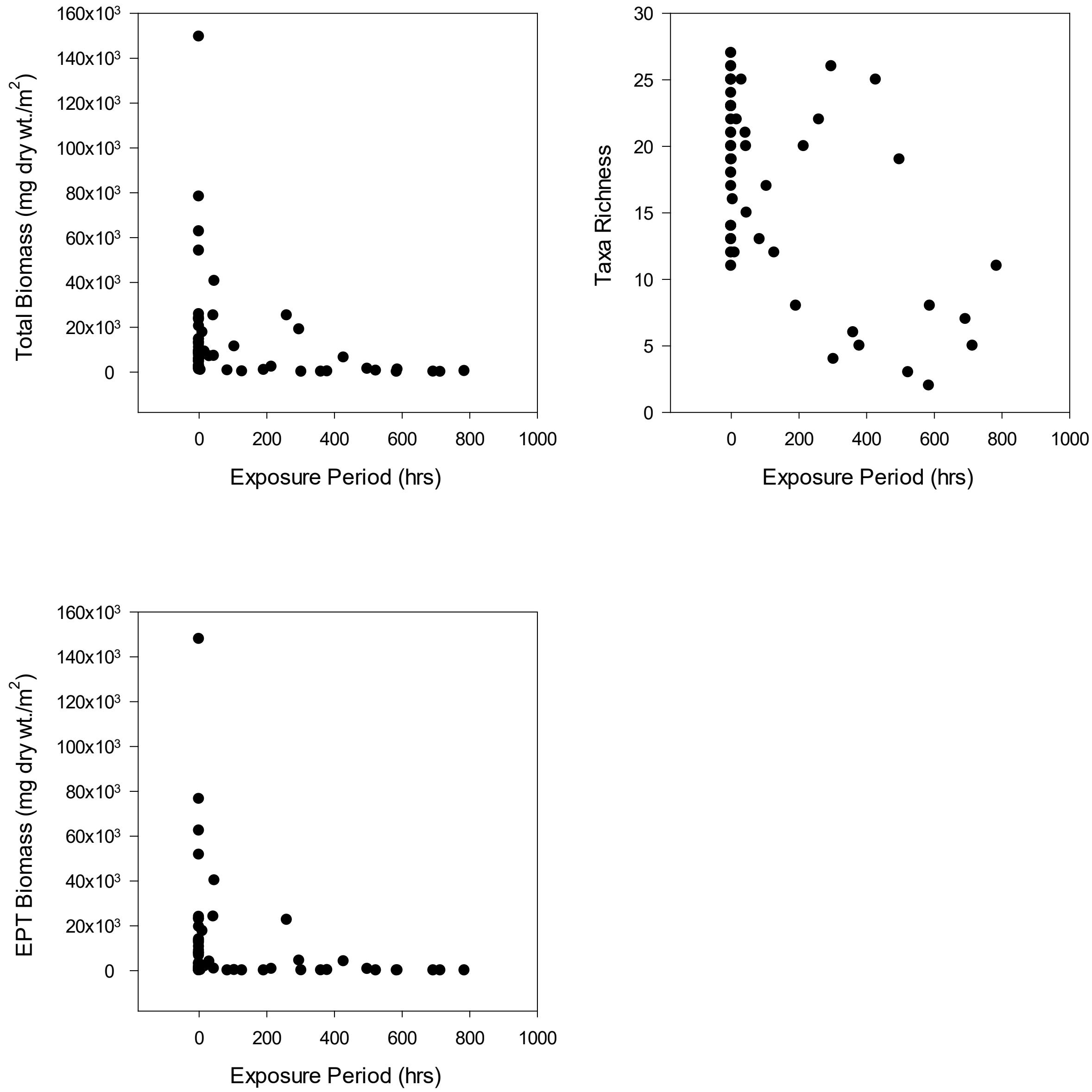

Figure 10: Total biomass, EPT biomass and taxa richness plotted against the basket exposure period (n=63) (reproduced from Limnotek 2011)

The EIS reported that variation in invertebrate biomass shown in the horizontal part of the "L-shaped" biomass curve (continuously submerged substrata) in Figure 10 was explained by several habitat attributes (EIS, Section 5, App P3). Those variables were median particle size (D50), mean water depth over a sampled substrate (i.e., basket depth) (BDEPTH), the coefficient of variation of water velocity over a sampled substrate (CV_BVEL), the distance from W.A.C. Bennett Dam (DFR), mean temperature (TEMP) and the coefficient of variation of site-specific flow (CVFLOW) during the time of sampler incubations. A predictive model showing change in invertebrate biomass as a function of these attributes was developed during the EIS (Section 5, App P3) and is shown in equation 3:

$$\text{EPTC biomass} = 10^{(-1.44 + 1.83 \log(D50+1) + 1.59 \log(BDEPTH+1) - CVBVEL + 1.45 \log(DFR+1))} - 1 \qquad \text{(eq. 3)}$$

The model had a high adjusted R^2 = 0.75, with the statistics for the regression analyses found in Table 8, showing the variables with a significant effect.

Table 8: Statistics of regression analyses to determine habitat attributes most strongly correlated with benthic invertebrate biomass in the Peace River. L10 indicates that the variable was log10(x+1) transformed. Taken from Table 5.3 in EIS, App P3.

Biological Metric	Independent Variables	Description of Predictor Variable	Standardized Coefficient	Tolerance	P_value
L10 EPTC Biomass (n=52)	Constant	Regression equation constant	0	N/A	0.008
	L10_D50	Median particle diameter	0.73	0.76	<0.001
	L10_BDEPTH	Mean water depth over a sampled substrate	0.22	0.98	0.004
	CV BVEL	Average coefficient of variation of water velocity over a sampled substrate	-0.44	0.72	<0.001
	L10_DFR	Distance from the Bennett Dam	0.57	0.89	<0.001
	Biomass fit statistics: Adjusted multiple R^2 = 0.75, Standard error of the estimate = 0.37				

As described in Section 6.3.5.2 (App P3), the authors adjusted estimates of benthic biomass for changes in periphyton proportional to benthic diet composition before using them in the Ecopath model.

Schleppe et al. (2019) also assessed the effects of environmental variables on benthos using the same methods (artificial substrates, rock basket) as Limnotek (2011) and reported similar findings. Instead of regression analysis, random forest models[8] were used to identify variables that explain variation in benthos indicators (Table 2-9 in Schleppe et al. 2019) among sampling locations and times. For benthos baskets submerged for 100% of their deployment, depth, light, and water velocity were the only 3 of 18 explanatory variables where the coefficient differed significantly from zero for at least one of the 3 response variables (Figure A188, Schleppe et al. 2019).

For baskets that were submerged for less than 100% of their deployment time, differences in the timing of exposure (i.e. air exposure at the start vs. end of the deployment period, multiple exposure periods) precluded a formal statistical analysis. However, data from 2017 and 2018 appeared to be similar to earlier data (Figure 10), in that benthos accumulation appeared to drop off quickly with increasing exposure. For example, in Figure 186 of Schleppe et al. (2019, reproduced as Figure 11 below), average biomass accumulation in baskets dropped off quickly as the proportion of time submerged declined (Figure 12). A more formal analysis is required to parameterize the curve in Figure 12, but conclusions concerning dewatering appear to be similar among the two datasets (2010-2011 and 2017-2018).

[8] For a simple, non-technical description see https://towardsdatascience.com/understanding-random-forest-58381e0602d2

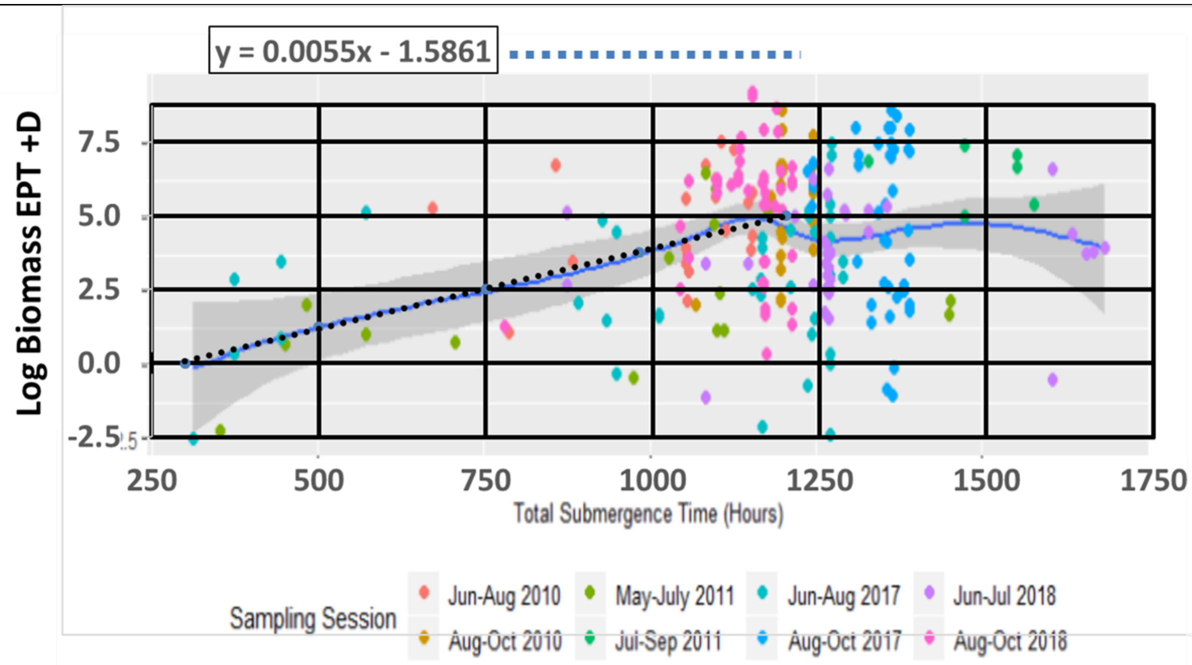

Figure 11. A reproduction of Figure A186 from Schleppe et al. 2019. EPT + D are families of invertebrates that are preferred fish food. The cloud of points between 1000-1500 hrs represent baskets that were submerged for their entire period of deployment which ranged from 41-60 days. The scattering of points between 300 and 1000 hrs represent baskets that were exposed to air during part of their deployment (i.e. Total Submergence Time < deployment duration). The solid blue line is the trend line in the original figure. The dotted black line that overlays the acending limb of the blue line is assumed to represent increasing biomass observed in baskets that are submerged for a higher proportion of their deployment period.

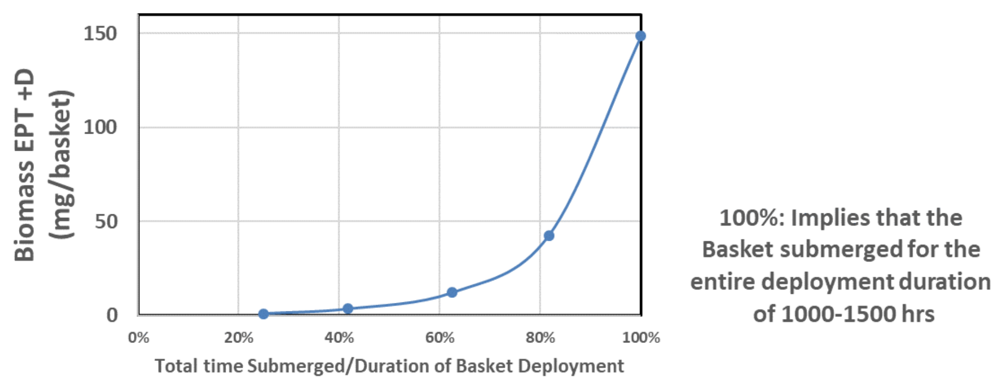

Figure 12. Replotting of the black dotted line in Figure 11 with an arithmetic scale on the vertical axis and Total Submergence Time expressed as a fraction of Deployment Time. For the purpose of this figure, Deployment Time is assumed to be fixed at 1200 hr (50 days).

Given this pattern of variation, we can expand point data measured before-after to the reach scale by dividing the downstream area of the river into continuously submerged and periodically submerged areas using a 2D velocity-depth model similar to the example in Figure 1 combined with time × discharge data pre- and post-Project. Continuously submerged areas are stratified at an appropriate spatial scale using depth, velocity, light conditions, substrate and temperature, which are the factors that influence benthos response (Limnotek 2011, Schleppe et al. 2019).

All of these variables will be available for the Peace River within the LAA. Depth and velocity are taken directly from the 2D modeling. Light conditions are defined using turbidity and depth. Substrate and channel morphology will be monitored under Mon-3 (Peace River Physical Habitat Monitoring Program). Temperature and turbidity are monitored under Mon-9 (Peace River Water and Sediment Quality Monitoring Program).

Benthos response in areas that are periodically exposed to air will be quantified relative to similar permanently wetted habitat. Preliminary estimates suggest that benthos declines quickly with increasing exposure and therefore the contribution of these areas to total benthos biomass is expected to be negligible. In addition to the proportion of time exposed, additional factors include time of day and substrate, which can be estimated for the entire varial zone using discharge patterns combined with 2D channel morphology data. Other relevant factors include air temperature and precipitation, which will also be monitored.

2.4.3 Periphyton Biomass

In the EIS, predictions for periphyton biomass were made using a CE-QUAL-W2 model, a 2D hydrodynamic and water quality model (Section 3, App P3). The details of the model are found in EIS, Volume 2, Appendix P, Part 2.

In the EIS, a sensitivity analysis was undertaken to evaluate how changes to key model inputs would affect CE-QUAL-W2 model predictions of periphyton and phytoplankton biomass (Appendix P, Part 2). The methods are described in Section 3.4 of Appendix P2. The key model inputs included TSS, nutrients, and flow. For flow, the different scenarios included in the sensitivity analyses included the average (i.e., expected scenario), dry (5^{th} percentile of the 10-year moving average from the historical flow time series), and wet (the 95^{th} percentile of the 10-year moving average from the historical flow time series). The flows included in the CE-QUAL-W2 model sensitivity analyses are shown in Table 9.

Table 9: Flow time series for water sources used in the sensitivity analysis (adapted from EIS, App P2 Table 3.9).

Water Source	Average Flows	Dry Flows	Wet Flows
For Site C Reservoir			
Peace River (Peace Canyon Dam)	Same as expected scenario	95% of expected scenario	105% of expected scenario
Halfway River	Same as expected scenario	84% of expected scenario	122% of expected scenario
For Peace River Between Site C Dam and Alces River			
Pine River	Same as expected scenario	92% of expected scenario	113% of expected scenario
Beatton River	Same as expected scenario	87% of expected scenario	122% of expected scenario

The outcomes of the sensitivity analysis demonstrated that the sensitivity of phytoplankton and periphyton biomasses to changes in flows was "small to negligible" and were most sensitive to changes in nutrient loadings. In combination with extreme values of TSS and nutrients, phytoplankton was less sensitive (+/- 5% of expected scenario values), while modelled periphyton biomass was responsive to variation to model inputs (5.8 to 9.0-fold change in biomass). This was attributable to periphyton remaining fixed in place within the model and being exposed to changes in nutrient loadings with small changes from TSS and small to negligible changes from flow. These extreme values of flow, TSS, and nutrient loadings formed the basis of the bookends for the Ecopath models (App P3), as shown in Table 10. The sensitivity analysis results are described in greater detail in Section 4.8 of the EIS Appendix P2.

Table 10: Combinations of fish community and phytoplankton / periphyton scenarios for the Ecopath models for the Site C LAA of the Peace River (Table 6.6 in EIS App P3).

Ecopath Fish Community Scenarios	CE-QUAL-W2 Scenarios of Phytoplankton / Periphyton Production					
	Highest Bookend		Most Likely		Lowest Bookend	
	Early	Longer Term	Early	Longer Term	Early	Longer Term
A. High Estimate						
B. Most Likely						
C. Low Estimate						

The EIS models operated at broad temporal and spatial scales and demonstrate the importance of temperature, nutrients, and average discharge in driving periphyton biomass at the reach scale. More recent work focused on processes that operate at much smaller spatial (meters) and temporal (hours) scales. Schleppe et al. (2019) quantified the effects of water velocity, light (turbidity, depth) and air exposure on periphyton productivity (PP) by measuring Chl a and biomass accumulation on Styrofoam substrates located on transects across the Peace River. In general terms, submergence patterns define the upper bound of the varial zone, while light penetration determines the lower bound. Factors such as nutrients and temperature clearly affect PP but are not sensitive to daily changes in discharge. Statistical models of the transect data (Schleppe et al. 2019) assign a significant fraction of the variation in PP to time (annual, seasonal) and space (site) strata, but these differences are presumably the result of differences in proximal variables such as temperature, turbidity etc.

The dynamic limitation of PP by exposure at higher elevations and light penetration at lower elevations produces a band of PP at intermediate elevations. Factors that affect the width of the band, and variation in PP across the band, can be quantified for the entire LAA downstream of the Project. These factors include site characteristics such as shoreline slope and substrate and time varying characteristics such as turbidity and water elevation.

Both reach scale (nutrients, temperature, discharge regime, turbidity) and transect scale (depth stratification, fluctuations in water elevation) data will be used to quantify the effects of the Project by integrating the effects of both types of environmental change on overall PP. Some processes are relatively simple to model; changes in discharge regimes will result in changes in the area of the PP productivity band. Others are more complex; an increase in turbidity can both inhibit PP by limiting light penetration) or enhance PP (by increasing the availability of inorganic nutrients).

Changes to the flow fluctuation regime clearly have the potential to affect PP at the transect scale. Increases in flow fluctuation can inhibit PP, by exposing a higher proportion of the PP band to desiccation, or enhance PP, by extending the photic zone to lower elevations. The interplay between these, and other factors, means that we cannot expect the PP response to operations to be uniform among transects. For example, if a transect shifts from low water at night to low water during the day, a positive response results if increasing light penetration more than compensates for the effects of switching from night to day desiccation and vice versa. If light penetration is an important limiting factor, higher minimum flows can have a positive effect if the photic zone moves to a lower shoreline slope and vice versa.

The net result is that before-after comparisons will involve both site specific comparisons and comparisons of PP totals at the reach scale. The site-specific response cannot be expected to be uniformly positive or negative. Instead, site responses will provide additional information on the factors that drive PP at the site scale. The important comparison will be at the reach scale but this comparison is expected to be more comprehensive than the “laterally averaged” response modelled in the EIS (App P2).

2.4.4 Summary of results from fish community modelling

Periphyton and benthos responses to the Project can be expected to attenuate in higher trophic levels. This includes that periphyton-benthos link where depth severely limits PP but does not strongly inhibit benthos biomass accumulation (Schleppe et al. 2019).

Mass balancing in Ecopath led to similar conclusions. In the Ecopath model runs for the Peace River, the ecotrophic efficiency for benthos was well below 1.0 for the High and Most Likely CE-QUAL-W2 scenarios (~0.1). For the low CE-QUAL-W2 scenarios, the ecotrophic efficiency was higher (~0.4) but still well below 1.0. This was indicative of no shortage of benthos, despite forced reductions in benthic biomass as a function of periphyton biomass. Therefore, fish food was not a limiting factor for higher trophic levels, even when considering the conservative assumptions made in the model.

2.4.5 Assessment of data availability

Data collected to date to test the effect of flow on benthos and periphyton are sufficient and high quality. Current data include 2010 to 2012 (Limnotek, App P3) and 2017 to 2018 (Schleppe et al. 2019). We have reviewed the data collected as part of Mon-6 and Mon-7 (Schleppe et al. 2019), and we found that it followed the same general sampling protocol as was used to assess baseline conditions (EIS, Volume 2, Appendix P1). The Mon-6 and Mon-7 sampling design extended the downstream sampling to two additional sites in Alberta: on the Peace River immediately upstream of the Pouce Coupe River, and at Many Islands, Alberta. Inorganic nutrient additions to streams demonstrate that large changes in primary productivity and benthos are reflected in production at higher trophic levels (Perrin et al. 1987, Peterson et a. 1993, Mulholland and Webster 2010) but expected changes in the Peace River biota are much smaller than those observed in these experiments.

2.4.6 What is the influence of flow fluctuations on fish food?

Changes in continuously wetted area will likely account for most of the effect of flow fluctuations on fish food although nutrients, temperature, turbidity, depth, and velocity will also influence biomass. This is because exposure results in a steep decline in invertebrate biomass as demonstrated by the empirical data from the Peace River (Figure 10, Figure 11, Figure 12) and elsewhere. Therefore, the proportional difference in the continuously wetted area pre- and post-Project, derived from data such as that in Figure 1, will provide a coarse estimate of the influence of flow fluctuations on benthic biomass.

A more detailed assessment of H_{2a} and H_{3a} (Section 2.4.1) requires depth and velocity data derived from hydrological models (see Figure 1) and time series of discharge, temperature and turbidity combined with models of benthos and periphyton response to environmental factors (EIS App P2, Schleppe et al. 2019) as discussed in Sections 2.4.2 and 2.4.3. We have reviewed the capabilities of the BC Hydro modelling team, and hydrological model outputs can be requested if necessary (Michael McArthur, pers. comm.). Four scenarios have been simulated to date:

- Without Site C, minimum flow from Peace Canyon Dam and 90th percentile flow from tributaries between Peace Canyon Dam and the Project;

- Without Site C, maximum turbine flow from Peace Canyon Dam combined with 10th percentile flow from tributaries between Peace Canyon Dam and the Project;
- With Site C, minimum flow from Peace Canyon Dam and 90th percentile flow from tributaries between Peace Canyon Dam and the Project; and
- With Site C, maximum turbine flow from Peace Canyon Dam combined with 10th percentile flow from tributaries between Peace Canyon Dam and the Project.

These model outputs could be used to estimate the relative impact of changes in the benthic biomass post-Project. For now, we have demonstrated that the modelling and data collection are sufficient to understand the effects of flow fluctuations on future conditions.

One key analysis will be to run the river 2D model to show change in area downstream of the Project that is exposed to air for any period of time between selected durations pre-Project and selected durations post-Project. Total continuously wetted area after the Project divided by total continuously wetted area pre-Project can provide an index of relative change in habitat available to benthic invertebrates. An increase in the ratio would indicate an increase in potentially available habitat and it would indicate a relative increase in benthic invertebrate biomass based on empirical evidence that is supported in the literature. A decrease in the ratio would show an opposite change, a decrease in potentially available habitat and an indication of a relative decrease in benthic invertebrate biomass based on empirical evidence that is supported in the literature.

Secondary analyses may include updating Figure 10 (the “L-shaped” biomass curve) in this document with new data that has been collected since the EIS was completed and updating the EIS model to show change in benthic invertebrate biomass as a function of habitat attributes among continuously submerged substrata. Updating Figure 10 would increase the precision with a greater sample size and thereby increase confidence in present conclusions about the effect of frequent dewatering on biomass of benthic invertebrates. The updated EIS model could be used to update estimates of change in benthic invertebrate biomass as a function of updated change among predictor variables pre- and post-Project among continuously submerged substrata in a defined area of river. All of these analyses can be done with existing data that has been collected as part of ongoing monitoring.

2.5 DAILY GROWTH (TASK 3C)

2.5.1 Introduction

The objective of Task 3c is to examine the influence of flow on daily growth, as measured by otolith growth increments in juvenile fish from fish sampled in 2014, 2016, and 2018. We limited the analysis to age-0 and age-1 Mountain Whitefish and suckers because there were the most samples for these species and age-classes. The Mon-17 null hypothesis is as follows:

H_4: Species-specific fish growth of age-0 and age-1 fish among sites in the Peace River is independent of the magnitude and timing of flow fluctuations.

This section provides an overall summary of the findings from the otolith study; Appendix B contains the full analysis.

2.5.2 Methods

To test hypothesis H_4, otoliths were collected from juvenile (age-0 and age-1) indicator fishes – Mountain Whitefish and suckers – and the width of daily growth rings (circuli) was linked to changes in flow. Samples were collected in 2014, 2015, 2016 and 2018.

The number of daily otolith growth rings varied among fish from 23 to 69 of the outermost rings (i.e., closest to the perimeter). The variability in the number was because the rings needed to be clearly identifiable. The distribution of fish collected across years is shown in Table 11. However, only data from Mountain Whitefish and suckers (combined) were analyzed, and of those species, only a subset of the otoliths were used in the analysis.

Table 11: Number of fish collected for use in assessing the effect of flow fluctuations on daily growth as part of Mon-17, collected under Task 2. 2014 and 2015 fish were collected as fish mortalities from the Large Fish Indexing Program. Numbers in brackets are the samples that were used in the statistical analysis.

Year	Mountain Whitefish	Suckers (Longnose, White, and Largescale)	Arctic Grayling	Northern Pike	Rainbow Trout
2014	4 (3 age-1)				
2015	1				
2016	77 (34 age-0)	4 (1 age-0)	6	1	1
2018	100 (67 age-0; 12 age-1)	20 (16 age-0)			

We conducted the statistical analysis using a repeated measures linear mixed-effects model using daily growth as the response variable, random effects of fish, and the following fixed effects: flow range, mean flow, water temperature (and a second order polynomial of water temperature), fork length, and year (2016 or 2018). Interactions were also included. By considering fixed effects other than discharge, we can potentially account for other sources of variation in daily fish growth. For age-1 Mountain Whitefish and age-0 suckers, fewer interaction terms were included because the available degrees of freedom were limited. The model also considered the random effects for individual fish as either a random intercept or random intercept and slope with interaction terms as they related to each of the fixed effects.

For discharge data (mean discharge and discharge range), we compared several time offsets to determine if the daily otolith growth increments lagged behind changes in flow conditions. The time offsets considered were no offset (0 h), 12 h, 24 h, and 48 h. We compared full models using these discharge data using model selection criteria (marginal AIC corrected for small sample size [mAICc]) for selection of variance structure and fixed effects, and likelihood ratio tests for the random effects. The full model considered for the three different groups differed based on the sample size. If fewer samples were available (i.e., age-1 Mountain Whitefish and age-0 suckers), then the full model was reduced with fewer interaction terms.

As with the catchability analysis (Section 2.3), we took discharge data from the Peace River above Pine River hydrometric station (Section 2.2).

For all otolith samples, the contrast in mean daily flows (Figure 13) and the daily discharge range experienced over the last ~50 days by each fish was relatively high.

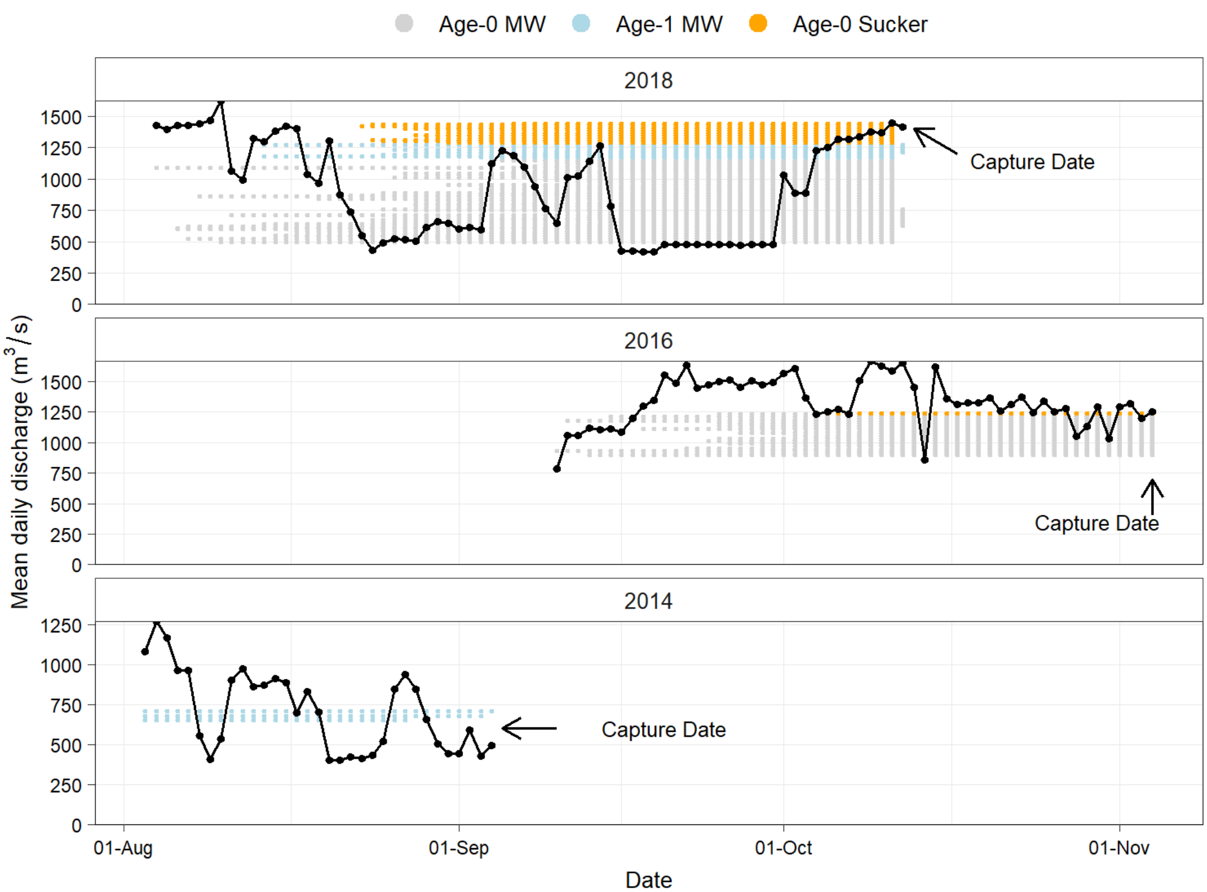

Figure 13: Mean daily discharge for the Peace River above the Pine River confluence during the 2014, 2016, and 2018 study periods. Each row of points (grey, blue, or orange) represents a fish whose otolith was measured, and each point represents a daily growth increment starting at the capture date on the right and extending as far back (left) as circuli were clearly distinguishable. (Appendix B)

2.5.3 Results and Discussion

Overall, there was weak evidence that flow variability had a weak effect on the growth increment on juvenile fish; stronger evidence would be required to reject the null hypothesis that growth of age-0 and age-1 fishes in the study area are independent of flow fluctuations. The effect sizes for each factor are summarized in Figure 14. The results demonstrated that water temperature was an important predictor of otolith growth rates and explained at least half of the variability in Mountain Whitefish daily growth (ESSA and Golder 2019). Compared to discharge variables, the standardized effect size for the influence of water temperature was more than twice as large as all the discharge variables combined for age-0 Mountain Whitefish and age-0 suckers. The analysis also suggests that the effect of flow fluctuation on daily growth is species-, age-, and year-specific. For age-0 Mountain Whitefish, daily growth increments changed significantly with changes in discharge range over a day, but the direction of the effect was dependent on year and mean discharge (Figure 14). Particularly, the effect was reversed depending on the year – in 2016, increases in mean discharge resulted in less growth, whereas in 2018, increases in mean discharge resulted in more growth. Conversely, we did not detect any statistically significant effect of discharge for the otolith growth of age-1 Mountain Whitefish (Figure 15) or age-0 suckers (Figure 16).

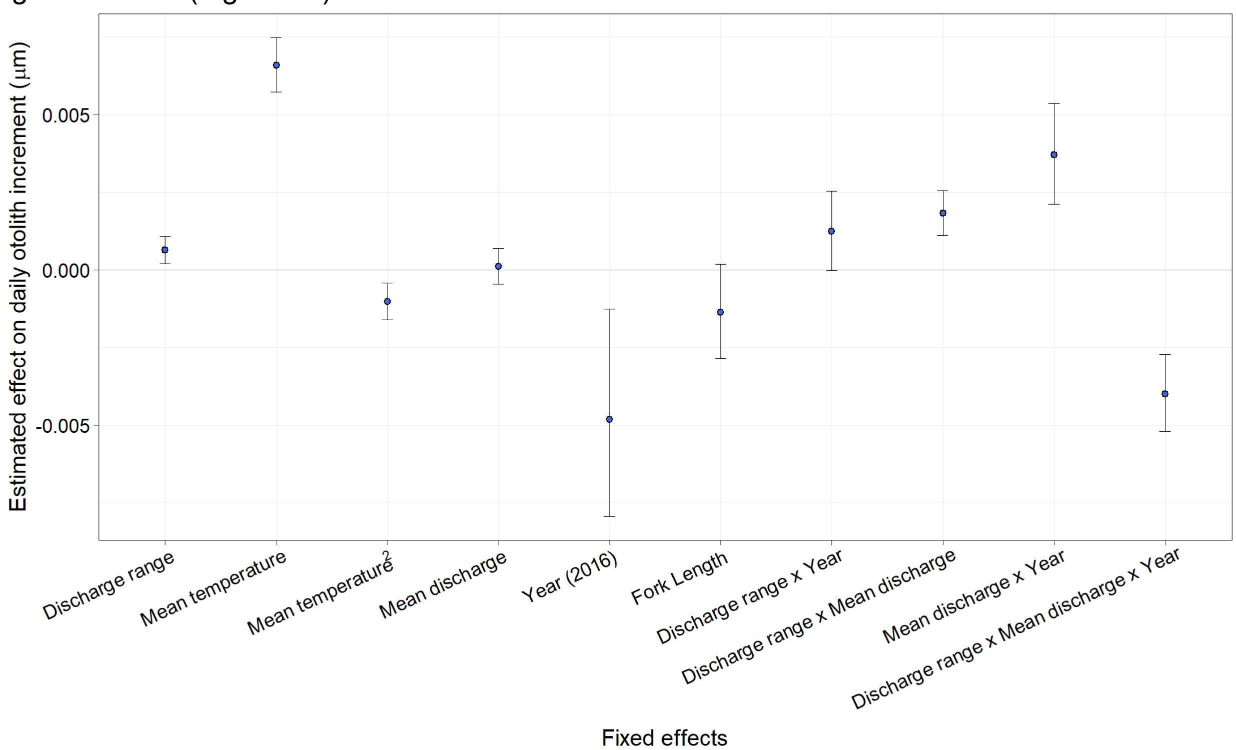

Figure 14: Estimated effect of fixed effect predictor variables on otolith growth increment of age-0 Mountain Whitefish. Values are means with 95% confidence intervals calculated from the estimated coefficients from the linear mixed effect model. As predictor variables were standardized, effect sizes for continuous variables (all variables except year) describe the change in otolith growth with an increase of 1 SD in the value of the respective environmental variable.

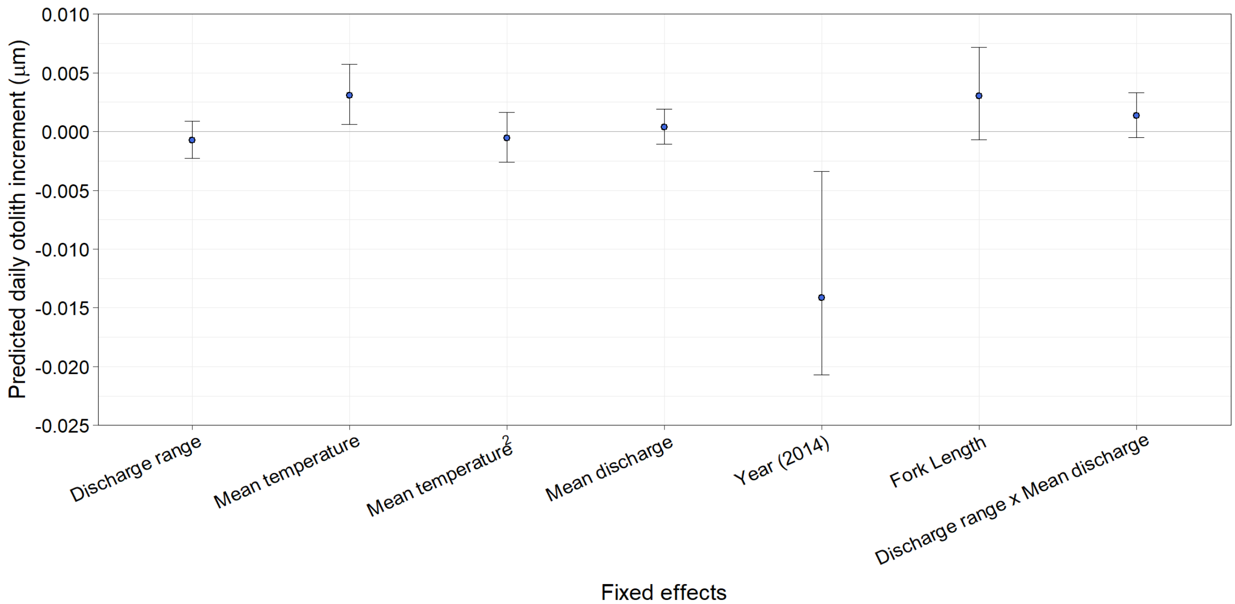

Figure 15: Estimated effect of fixed effect predictor variables on otolith growth increment of age-1 Mountain Whitefish. Values are means with 95% confidence intervals calculated from the estimated coefficients from the linear mixed effect model. As predictor variables were standardized, effect sizes for continuous variables (all variables except year) describe the change in otolith growth with an increase of 1 SD in the value of the respective environmental variable.

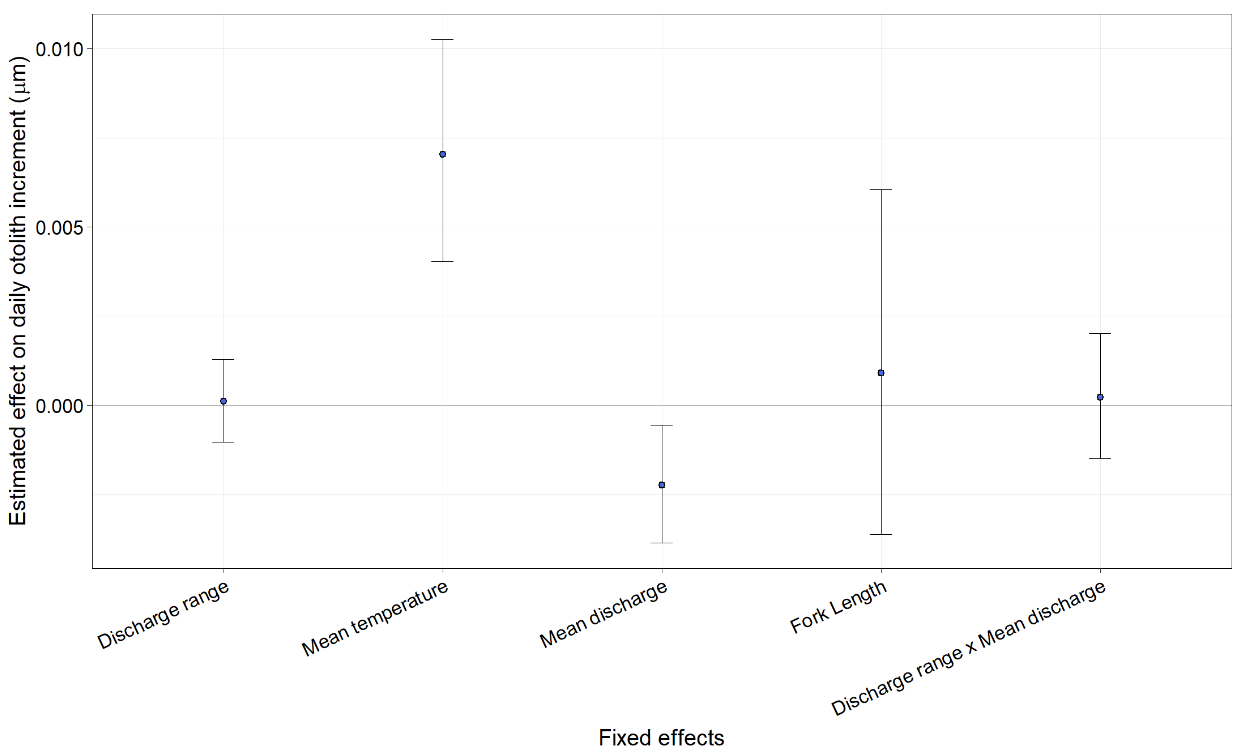

Figure 16: Estimated effect of fixed effect predictor variables on otolith growth increment of sucker species. Values are means with 95% confidence intervals calculated from the estimated coefficients from the linear mixed effect model. As predictor variables were standardized, effect sizes for continuous variables (all variables except year) describe the change in otolith growth with an increase of 1 SD in the value of the respective environmental variable.

2.6 RECRUITMENT (TASK 3E)

2.6.1 Introduction

Task 3e aims to determine the effect of flow variability on recruitment. Recruitment is defined as the process by which new individuals are added to a population by birth or immigration. For fish species in the Peace River, the population can be defined as fish that are vulnerable to the Peace River Large Fish Indexing Survey, which means that the population includes adults and variable fraction of immature fish. Recruitment is the number of fish that enter the vulnerable population each year. Cohort strength can be derived from catch-at-age data and the relative strength of each cohort can be assessed using the relative abundance of cohorts in the catch over several years.

The Mon-17 null hypothesis is as follows:

H_6: Species-specific recruitment is independent of the magnitude and timing of flow fluctuations.

Plausible mechanisms linking discharge fluctuations to recruitment can be formulated for almost any life history stage, including egg incubation, over-summer growth and over-winter survival. The statistical approach would include adding one or more time-lag parameters, but with a limited number of observations, these parameters are likely to be poorly defined by the data unless there are large, abrupt changes in the discharge regime.

This section provides an overview of the methodology that would be used to test this hypothesis, which would involve a comparison of variance among cohorts with any difference in cohort strength that is associated with the start of operations.

2.6.2 Methods

The effects of flow variation on the survival of young fish can be inferred from cohort analysis of selected indicator species, as stated in the monitoring plan. The analysis will use information from Mon-2, Task 2a to compare the between-year variation in water level fluctuation to the relative fish year class strength from cohort analysis to generate an indicator of recruitment as a function of water level fluctuation.

2.6.3 Results and Discussion

A preliminary examination of patterns in Mountain Whitefish age-frequency data from 2002 to 2016 suggests that there is natural variation in cohort strength (Figure 17). In a sequence of age-frequency data, strong cohorts can be recognized as higher than average abundance values that persist across years in a diagonal pattern (Figure 17, top panel). The percent contribution relative to adjacent cohorts for four age classes (ages 4 to 7) of 11 cohorts varies from 53 to 81% (Figure 17, bottom panel).

Currently, we cannot test this hypothesis because the nature of the analysis means that degrees of freedom are limited due to each measurement involving the demography of a cohort over several years. The most powerful statistical test will be a before-after comparison that can only be done after 10 or more years of operation of the Project. Although the data suggest that variation in year class strength is significant, an association between cohort strength and discharge fluctuation may be difficult to tease out because of uncertainties in the timing of the effects tracked across multiple years.

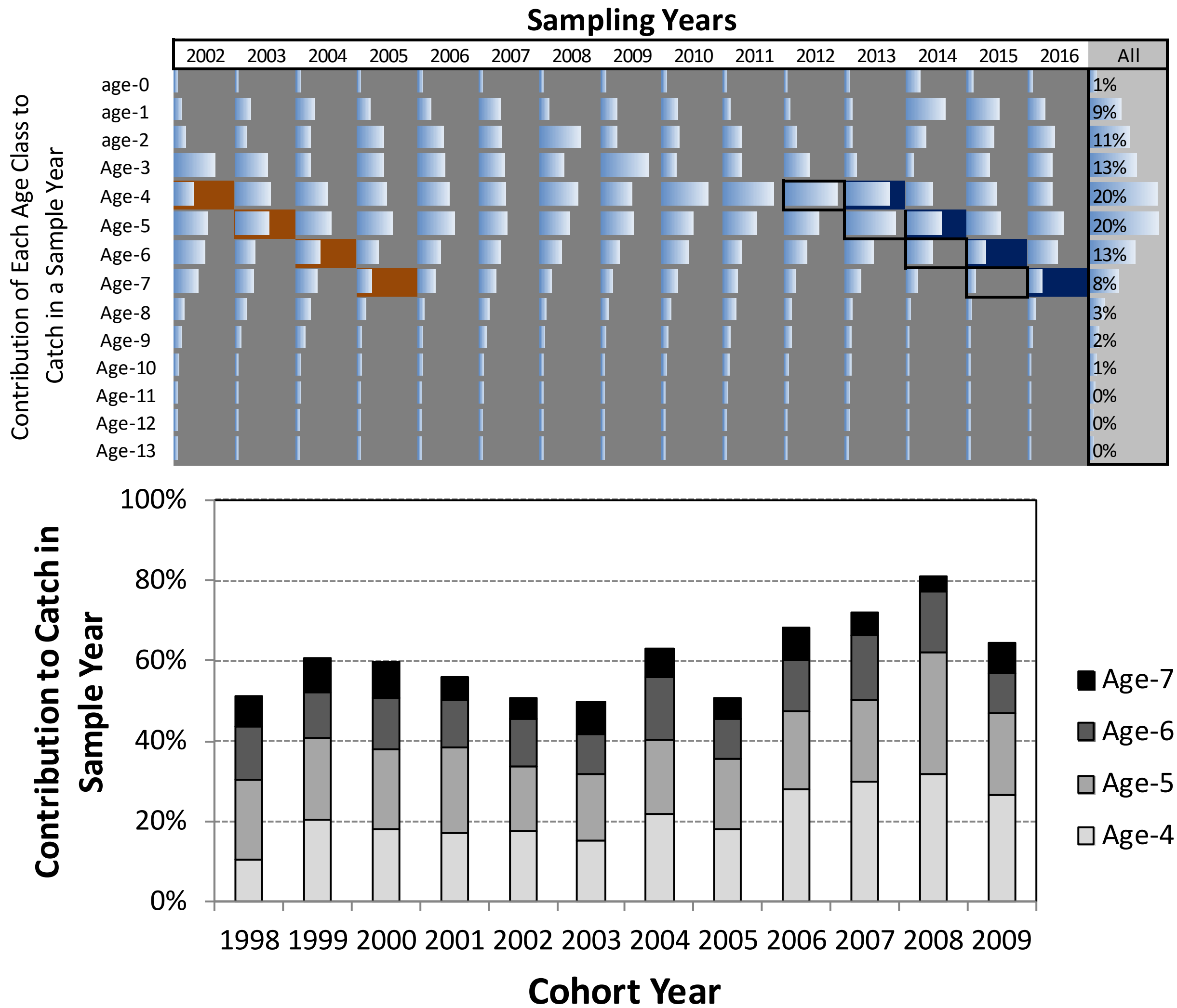

Figure 17: Patterns in the age structure of Mountain Whitefish in large fish index surveys by sample year (top panel) and cohort year (bottom panel). In the top panel, cohort years are highlighted in red (1998), blue (2009) and by boxes (the strong 2008 cohort). The stacked values of diagonals in the top panel represent the contribution of a cohort to the catch, relative to adjacent cohorts (bottom panel). Sample sizes for each year range from 401 in 2002 to 1090 in 2015.

The potential for future analyses can be illustrated using current data. Age structure provides information on recruitment and survival in three ways: (1) the slope of the descending limb of the catch curve represents adult survival; (2) the presence of gaps in age class structure is an indicator of periodic recruitment failure; and (3) an abrupt drop in year class abundance that tracks through successive years can be used to estimate the effect of abrupt recruitment failure potentially due to change in habitat conditions (i.e., river diversion, reservoir filling). Current data (Figure 18) provides baseline information for all three indicators. The data suggests that Mountain Whitefish fully recruit to the sampling gear at age-5 and that adult mortality rates are constant. Figure 18A illustrates the derivation of adult mortality rates and Figure 18B illustrates the expected patterns under the two types of recruitment failure. The between year variation in cohort strength as demonstrated by the data below (Figure 18) suggests that understanding the effects of flow variation on recruitment will be difficult due to high process error.

Errors in ageing and sampling bias are the key issues with this type of analysis. The analysis shown in Figure 18A assumes that catchability is constant on the descending limb, but relative changes can still be inferred as long as the bias is constant through time. Ageing errors blur the results of the Figure 18B analysis and may make periodic failures undetectable.

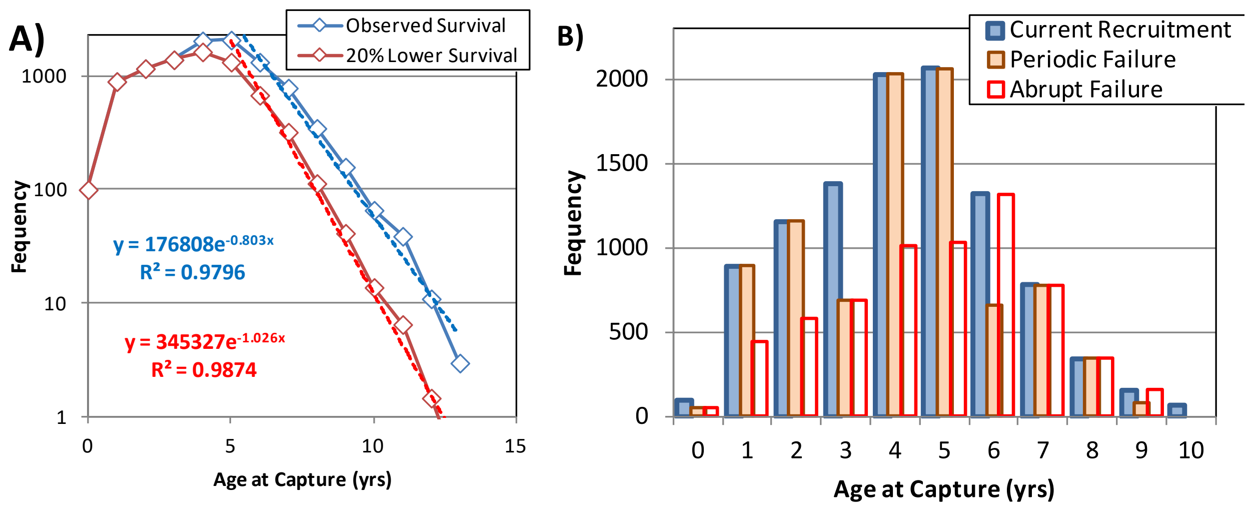

Figure 18: Current age-frequency distribution for Mountain Whitefish sampled between 2003 and 2013 in large fish index surveys *versus* hypothetical distributions representing three alternative mortality changes. A) The slope of the log plot is the instantaneous annual mortality rate (i.e., exp(-(1.026-0.803)) = 1 - 20%= 80%). B) The age-frequency distribution becomes more jagged under periodic recruitment failure. Under an abrupt recruitment failure, the age-frequency distribution becomes steeper in Years 1-4, flatter in Years 5-8 (as in B) before reverting to an approximation of the original shape.

3 SUMMARY

The Peace River Water Level Fluctuation Monitoring Program (Mon-17) of the FAHMFP examines the effects of flow fluctuations on five performance metrics: fish catchability, benthos and periphyton production, daily growth rate of fish, fish community composition, and fish recruitment. Unlike other monitoring programs, Mon-17 is largely focused on the analysis of data collected as part of other monitoring programs except for the otolith data which are collected as part of Task 2b.

Examination of discharge and water elevation data confirm that changes in discharge at the current point of control propagate downstream in a predictable manner. Changing the point of control from Peace Canyon Dam to the Project will advance the pattern of water level fluctuations in downstream reaches by 8 to 12 hrs.

Some of the variation in discharge is predictable because it is driven by daily and seasonal patterns of power demand. However, much of the variation in discharge is unpredictable because it is driven by factors such as water availability, maintenance and unplanned plant shutdowns and the need to balance supply and demand across the power grid. In addition, longer-term trends in factors such as battery technology and wind and solar generation may result in systematic differences in discharge patterns pre- and post-Project.

Management agencies raised four concerns that are linked to changes in the discharge regime;

1. Changes in catchability would make CPUE an unreliable index of abundance;
2. Changes in the patterns of water level fluctuation would lead to lower ecosystem productivity downstream of Site C;
3. Higher flow fluctuations would be associated with lower growth of small fish; and
4. Higher flow fluctuations would be associated with lower survival of small fish.

This report provides some preliminary findings on how the changes to fish and fish habitat post-Project might be associated with changes in flow. In general terms, analyses associated with Mon-17 concluded:

- Catchability is not affected by changes in discharge over the short- (6 hours) and long-term (30 days).
- Current data collection under the FAHMFP can quantify the effects of changes in water level fluctuation on ecosystem productivity, which includes all of the important covariates for the analysis (depth, velocity, light levels, substrate).
- Differences among days in water level fluctuation has a weak effect on daily growth of small fish in the Peace River.
- Differences in year class strength among cohorts of Mountain Whitefish suggests that there is significant natural variation in survival among cohorts. Identifying the causes of among year differences in survival will be challenging because:
  - There is limited potential to increase sample size beyond N=1 per year;
  - There are a large set of potential covariate candidates that may differ among cohorts and species; and
  - Many potential covariates are difficult to measure (e.g. abundance of predators, availability of predation refugia).

3.1 SUMMARY OF FINDINGS

Question	Answer
What is the context?	Mon-17 evaluates how changes in the Peace River flow regime might affect fish and fish habitat and how it is monitored. Unlike other monitoring programs, Mon-17 is analysis-focused, and relies on data collected from other monitoring programs.
What was implemented?	We estimated the effect of flow regime on: ▪ **Catchability** – Estimating the effects of environmental covariates on CPUE for several fish species using data from the Peace River Large Fish Indexing Survey from 2004 to 2018. ▪ **Periphyton and Benthos** – Examined the role of environmental factors in determining the rate of accumulation of benthos and periphyton. Assessed the availability of data required to expand site scale estimates to reach scale estimates of the status of benthos and periphyton. Reviewed the EIS methods and how these methods can be applied post-Project. ▪ **Daily Growth** – Examined daily growth increments using Mountain Whitefish and sucker otoliths collected from 2014 to 2016, and 2018. ▪ **Recruitment** – Examined the analysis of age class strength using historical age structure data.
What was the result?	▪ **Catchability,** as measured by catch per unit effort (CPUE) (#/100 m), was not affected by discharge over the short- (6 hours) and long-term (30 days). There was, however, a clear effect of electroshocker settings. ▪ **Periphyton and Benthos** – Benthos and periphyton accumulation are statistically correlated with environmental factors that are linked to flow fluctuation including water depth, water velocity, light availability and air exposure. Both benthos and periphyton accumulation can be expanded to the reach scale using monitoring data on discharge, turbidity, temperature, and incident light combined with hydrometric models of flow dynamics and bathymetric mapping of downstream reaches. Reach scale estimates were not performed as these are only meaningful when expressed as before-after values that can be compared with the values generated in the EIS. ▪ **Daily growth –** Overall, there was weak evidence that flow variability had a weak effect on the growth increment on juvenile fish; stronger evidence would be required to reject the null hypothesis that growth of age-0 and age-1 fishes in the LAA are independent of flow fluctuations. ▪ **Recruitment** – There was significant variation in age class strength but this cannot be attributed to changes in flow regime. Methods for comparing the cohorts pre- and post-Project are discussed.
What was learned?	▪ **Catchability** – In the context of pre- and post-Project measurements of CPUE, the results suggest that there is no need to correct CPUE measures for changes in discharge. ▪ **Periphyton and Benthos** – Flow fluctuations affect both benthos and

Question	Answer
	periphyton in predictable ways. Data collected to date are sufficient and can be used to assess changes. Hydrometric models, driven by discharge patterns and river geometry, can be used to generate the data needed to model the effect of changes in flow fluctuations on fish food availability downstream of the Project. ▪ **Daily Growth** – Otolith increment data can be used to quantify the effects of flow fluctuation, temperature and perhaps other factors affected by the Project. We suggest continuing to monitor as per the schedule outlined in Mon-17. ▪ **Recruitment** – Mountain Whitefish age class has varied (i.e., high process error) which will make it difficult to quantify the before-after effect of the Project.

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APPENDIX A: STATISTICAL MODEL OUTPUTS

Table 12: Model coefficients for the linear mixed effects models for each species and section comparing CPUE (#/100m) to different measures of discharge. Mean.1HrDischarge = D1h; Mean.Prev6hDischarge = D6h, Mean.30DayDischarge = D30d, and CV variants of these terms. The yellow cells are where P-values are less than an alpha of 0.05.

Species	Section	Parameter	Estimate	Std. Error	df	t value	Pr(>|t|)
AG	3	(Intercept)	-3.75	0.73	111.29	-5.12	0.00
AG	3	Mean.1HrDischarge	-0.66	0.31	178.96	-2.10	0.04
AG	3	Mean.Prev6hDischarge	0.44	0.29	182.26	1.54	0.12
AG	3	CV.Prev6hDischarge	2.39	0.97	175.72	2.46	0.01
AG	3	Mean.30DayDischarge	0.01	0.24	61.46	0.02	0.98
AG	3	CV.30DayDischarge	-0.51	1.87	139.94	-0.27	0.78
AG	3	ElectroshockB. post-2014	-1.16	0.47	16.66	-2.48	0.02
AG	3	Mean.1HrDischarge:Mean.Prev6hDischarge	0.02	0.11	190.00	0.18	0.86
AG	5	(Intercept)	-3.47	0.61	69.87	-5.73	0.00
AG	5	Mean.1HrDischarge	0.14	0.57	128.45	0.24	0.81
AG	5	Mean.Prev6hDischarge	0.06	0.55	129.04	0.11	0.91
AG	5	CV.Prev6hDischarge	2.40	3.18	128.83	0.75	0.45
AG	5	Mean.30DayDischarge	0.36	0.22	59.08	1.66	0.10
AG	5	CV.30DayDischarge	1.44	1.70	108.81	0.84	0.40
AG	5	ElectroshockB. post-2014	-1.18	0.48	16.73	-2.45	0.03
AG	5	Mean.1HrDischarge:Mean.Prev6hDischarge	0.02	0.10	134.97	0.25	0.80
BT	1	(Intercept)	-4.50	0.49	73.47	-9.16	0.00
BT	1	Mean.1HrDischarge	-0.03	0.38	180.43	-0.07	0.95
BT	1	Mean.Prev6hDischarge	-0.06	0.34	181.97	-0.17	0.87
BT	1	CV.Prev6hDischarge	0.06	1.07	177.71	0.05	0.96
BT	1	Mean.30DayDischarge	0.31	0.15	65.68	2.07	0.04
BT	1	CV.30DayDischarge	2.24	1.04	53.22	2.15	0.04
BT	1	ElectroshockB. post-2014	0.84	0.22	19.32	3.85	0.00
BT	1	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.06	0.11	169.15	-0.55	0.59
BT	3	(Intercept)	-2.44	0.32	192.00	-7.66	0.00
BT	3	Mean.1HrDischarge	0.06	0.20	192.00	0.33	0.74
BT	3	Mean.Prev6hDischarge	-0.09	0.18	192.00	-0.49	0.63
BT	3	CV.Prev6hDischarge	0.24	0.61	192.00	0.38	0.70
BT	3	Mean.30DayDischarge	0.08	0.09	192.00	0.91	0.36
BT	3	CV.30DayDischarge	-0.87	0.80	192.00	-1.09	0.28
BT	3	ElectroshockB. post-2014	-0.33	0.12	192.00	-2.75	0.01
BT	3	Mean.1HrDischarge:Mean.Prev6hDischarge	0.01	0.06	192.00	0.12	0.91
BT	5	(Intercept)	-3.18	0.33	137.00	-9.59	0.00
BT	5	Mean.1HrDischarge	0.12	0.46	137.00	0.27	0.79
BT	5	Mean.Prev6hDischarge	-0.10	0.44	137.00	-0.22	0.82
BT	5	CV.Prev6hDischarge	-2.85	2.57	137.00	-1.11	0.27
BT	5	Mean.30DayDischarge	0.29	0.12	137.00	2.52	0.01
BT	5	CV.30DayDischarge	0.34	0.95	137.00	0.36	0.72
BT	5	ElectroshockB. post-2014	0.33	0.17	137.00	1.89	0.06
BT	5	Mean.1HrDischarge:Mean.Prev6hDischarge	0.00	0.07	137.00	0.05	0.96
BT	6	(Intercept)	-4.34	0.85	8.65	-5.13	0.00
BT	6	Mean.1HrDischarge	2.00	0.82	40.70	2.43	0.02

Species	Section	Parameter	Estimate	Std. Error	df	t value	Pr(>|t|)
BT	6	Mean.Prev6hDischarge	-1.78	0.84	37.51	-2.12	0.04
BT	6	CV.Prev6hDischarge	-3.68	3.29	35.29	-1.12	0.27
BT	6	Mean.30DayDischarge	-0.05	0.29	7.73	-0.16	0.88
BT	6	CV.30DayDischarge	2.33	2.72	8.74	0.86	0.41
BT	6	Mean.1HrDischarge:Mean.Prev6hDischarge	0.03	0.16	39.38	0.17	0.87
BT	7	(Intercept)	-3.97	0.76	26.00	-5.23	0.00
BT	7	Mean.1HrDischarge	2.52	2.33	26.00	1.09	0.29
BT	7	Mean.Prev6hDischarge	-2.50	2.40	26.00	-1.04	0.31
BT	7	CV.Prev6hDischarge	1.09	6.62	26.00	0.17	0.87
BT	7	Mean.30DayDischarge	0.32	0.30	26.00	1.05	0.30
BT	7	CV.30DayDischarge	-1.68	1.90	26.00	-0.88	0.38
BT	7	Mean.1HrDischarge:Mean.Prev6hDischarge	0.74	0.26	26.00	2.87	0.01
BT	9	(Intercept)	-3.60	0.78	34.00	-4.62	0.00
BT	9	Mean.1HrDischarge	-0.54	1.78	34.00	-0.30	0.77
BT	9	Mean.Prev6hDischarge	0.96	1.67	34.00	0.57	0.57
BT	9	CV.Prev6hDischarge	-2.41	10.07	34.00	-0.24	0.81
BT	9	Mean.30DayDischarge	-0.22	0.28	34.00	-0.78	0.44
BT	9	CV.30DayDischarge	-4.04	3.34	34.00	-1.21	0.23
BT	9	Mean.1HrDischarge:Mean.Prev6hDischarge	0.23	0.32	34.00	0.71	0.48
CSU	1	(Intercept)	-6.32	0.78	106.29	-8.07	0.00
CSU	1	Mean.1HrDischarge	0.23	0.50	171.83	0.47	0.64
CSU	1	Mean.Prev6hDischarge	-0.09	0.45	175.39	-0.20	0.84
CSU	1	CV.Prev6hDischarge	-0.33	1.42	169.58	-0.23	0.82
CSU	1	Mean.30DayDischarge	0.00	0.25	73.91	0.00	1.00
CSU	1	CV.30DayDischarge	4.09	1.69	118.91	2.42	0.02
CSU	1	ElectroshockB. post-2014	2.38	0.47	17.65	5.08	0.00
CSU	1	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.21	0.16	181.19	-1.33	0.19
CSU	3	(Intercept)	-4.68	0.67	50.35	-7.02	0.00
CSU	3	Mean.1HrDischarge	0.17	0.37	186.39	0.45	0.65
CSU	3	Mean.Prev6hDischarge	-0.38	0.33	191.39	-1.15	0.25
CSU	3	CV.Prev6hDischarge	-0.01	1.15	180.51	-0.01	0.99
CSU	3	Mean.30DayDischarge	0.54	0.19	32.56	2.82	0.01
CSU	3	CV.30DayDischarge	3.05	1.71	42.40	1.78	0.08
CSU	3	ElectroshockB. post-2014	1.89	0.29	11.94	6.59	0.00
CSU	3	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.06	0.12	177.95	-0.55	0.58
CSU	5	(Intercept)	-4.37	0.53	30.86	-8.30	0.00
CSU	5	Mean.1HrDischarge	-1.34	0.71	136.86	-1.89	0.06
CSU	5	Mean.Prev6hDischarge	1.27	0.68	136.42	1.85	0.07
CSU	5	CV.Prev6hDischarge	-3.32	4.00	135.92	-0.83	0.41
CSU	5	Mean.30DayDischarge	0.45	0.18	41.15	2.44	0.02
CSU	5	CV.30DayDischarge	3.55	1.52	24.13	2.34	0.03
CSU	5	ElectroshockB. post-2014	1.76	0.28	11.34	6.32	0.00
CSU	5	Mean.1HrDischarge:Mean.Prev6hDischarge	0.05	0.11	95.29	0.42	0.67
CSU	6	(Intercept)	-2.43	0.72	42.00	-3.39	0.00
CSU	6	Mean.1HrDischarge	1.15	0.85	42.00	1.35	0.19
CSU	6	Mean.Prev6hDischarge	-1.33	0.89	42.00	-1.50	0.14
CSU	6	CV.Prev6hDischarge	-6.41	3.50	42.00	-1.83	0.07

Species	Section	Parameter	Estimate	Std. Error	df	t value	Pr(>|t|)
CSU	6	Mean.30DayDischarge	0.19	0.24	42.00	0.80	0.43
CSU	6	CV.30DayDischarge	3.26	2.30	42.00	1.42	0.16
CSU	6	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.28	0.16	42.00	-1.72	0.09
CSU	7	(Intercept)	-1.10	0.77	26.00	-1.44	0.16
CSU	7	Mean.1HrDischarge	1.57	2.35	26.00	0.67	0.51
CSU	7	Mean.Prev6hDischarge	-2.40	2.42	26.00	-0.99	0.33
CSU	7	CV.Prev6hDischarge	4.46	6.68	26.00	0.67	0.51
CSU	7	Mean.30DayDischarge	1.28	0.30	26.00	4.23	0.00
CSU	7	CV.30DayDischarge	-3.27	1.92	26.00	-1.71	0.10
CSU	7	Mean.1HrDischarge:Mean.Prev6hDischarge	0.21	0.26	26.00	0.80	0.43
CSU	9	(Intercept)	-2.93	0.54	7.03	-5.47	0.00
CSU	9	Mean.1HrDischarge	1.50	1.02	27.83	1.48	0.15
CSU	9	Mean.Prev6hDischarge	-1.42	0.94	26.53	-1.50	0.14
CSU	9	CV.Prev6hDischarge	15.90	5.85	32.21	2.72	0.01
CSU	9	Mean.30DayDischarge	-0.15	0.18	22.77	-0.85	0.40
CSU	9	CV.30DayDischarge	-3.64	2.09	19.23	-1.75	0.10
CSU	9	Mean.1HrDischarge:Mean.Prev6hDischarge	0.65	0.19	31.47	3.52	0.00
LSU	1	(Intercept)	-6.03	0.86	95.21	-7.03	0.00
LSU	1	Mean.1HrDischarge	0.12	0.55	169.33	0.22	0.83
LSU	1	Mean.Prev6hDischarge	0.04	0.50	173.74	0.08	0.94
LSU	1	CV.Prev6hDischarge	0.27	1.56	166.54	0.17	0.86
LSU	1	Mean.30DayDischarge	0.14	0.27	63.45	0.53	0.60
LSU	1	CV.30DayDischarge	5.02	1.85	107.95	2.71	0.01
LSU	1	ElectroshockB. post-2014	2.66	0.51	14.16	5.20	0.00
LSU	1	Mean.1HrDischarge:Mean.Prev6hDischarge	0.00	0.17	181.03	0.01	0.99
LSU	3	(Intercept)	-3.93	0.77	32.01	-5.07	0.00
LSU	3	Mean.1HrDischarge	-0.14	0.43	182.36	-0.34	0.74
LSU	3	Mean.Prev6hDischarge	-0.13	0.39	190.96	-0.33	0.74
LSU	3	CV.Prev6hDischarge	0.91	1.33	172.63	0.68	0.50
LSU	3	Mean.30DayDischarge	0.57	0.22	19.83	2.54	0.02
LSU	3	CV.30DayDischarge	4.06	1.98	26.39	2.05	0.05
LSU	3	ElectroshockB. post-2014	2.00	0.33	6.92	6.01	0.00
LSU	3	Mean.1HrDischarge:Mean.Prev6hDischarge	0.06	0.14	168.14	0.43	0.67
LSU	5	(Intercept)	-2.66	0.64	137.00	-4.17	0.00
LSU	5	Mean.1HrDischarge	-2.56	0.88	137.00	-2.92	0.00
LSU	5	Mean.Prev6hDischarge	2.54	0.84	137.00	3.01	0.00
LSU	5	CV.Prev6hDischarge	-2.19	4.94	137.00	-0.44	0.66
LSU	5	Mean.30DayDischarge	0.46	0.22	137.00	2.05	0.04
LSU	5	CV.30DayDischarge	3.23	1.83	137.00	1.76	0.08
LSU	5	ElectroshockB. post-2014	1.45	0.33	137.00	4.35	0.00
LSU	5	Mean.1HrDischarge:Mean.Prev6hDischarge	0.15	0.14	137.00	1.10	0.27
LSU	6	(Intercept)	-0.60	0.65	42.00	-0.92	0.36
LSU	6	Mean.1HrDischarge	0.45	0.78	42.00	0.58	0.57
LSU	6	Mean.Prev6hDischarge	-0.37	0.81	42.00	-0.46	0.65
LSU	6	CV.Prev6hDischarge	-2.24	3.19	42.00	-0.70	0.49
LSU	6	Mean.30DayDischarge	-0.11	0.22	42.00	-0.51	0.61
LSU	6	CV.30DayDischarge	1.43	2.10	42.00	0.68	0.50

Species	Section	Parameter	Estimate	Std. Error	df	t value	Pr(>|t|)
LSU	6	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.22	0.15	42.00	-1.46	0.15
LSU	7	(Intercept)	-0.13	0.44	26.00	-0.31	0.76
LSU	7	Mean.1HrDischarge	-0.78	1.34	26.00	-0.58	0.56
LSU	7	Mean.Prev6hDischarge	0.75	1.38	26.00	0.54	0.59
LSU	7	CV.Prev6hDischarge	8.61	3.81	26.00	2.26	0.03
LSU	7	Mean.30DayDischarge	0.29	0.17	26.00	1.68	0.11
LSU	7	CV.30DayDischarge	-1.45	1.09	26.00	-1.32	0.20
LSU	7	Mean.1HrDischarge:Mean.Prev6hDischarge	0.12	0.15	26.00	0.81	0.42
LSU	9	(Intercept)	-0.09	0.33	34.00	-0.28	0.78
LSU	9	Mean.1HrDischarge	0.17	0.76	34.00	0.22	0.82
LSU	9	Mean.Prev6hDischarge	-0.26	0.72	34.00	-0.37	0.72
LSU	9	CV.Prev6hDischarge	4.14	4.32	34.00	0.96	0.34
LSU	9	Mean.30DayDischarge	0.20	0.12	34.00	1.69	0.10
LSU	9	CV.30DayDischarge	-2.69	1.43	34.00	-1.88	0.07
LSU	9	Mean.1HrDischarge:Mean.Prev6hDischarge	0.08	0.14	34.00	0.57	0.57
MW	1	(Intercept)	1.04	0.19	113.25	5.62	0.00
MW	1	Mean.1HrDischarge	-0.11	0.12	171.25	-0.91	0.36
MW	1	Mean.Prev6hDischarge	-0.04	0.10	174.63	-0.41	0.68
MW	1	CV.Prev6hDischarge	-0.19	0.33	169.40	-0.57	0.57
MW	1	Mean.30DayDischarge	0.13	0.06	80.11	2.19	0.03
MW	1	CV.30DayDischarge	1.43	0.40	133.86	3.57	0.00
MW	1	ElectroshockB. post-2014	-0.54	0.12	18.43	-4.60	0.00
MW	1	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.03	0.04	180.27	-0.82	0.41
MW	3	(Intercept)	0.71	0.20	90.43	3.57	0.00
MW	3	Mean.1HrDischarge	0.00	0.09	177.38	-0.03	0.98
MW	3	Mean.Prev6hDischarge	-0.05	0.08	181.94	-0.62	0.54
MW	3	CV.Prev6hDischarge	0.33	0.28	172.82	1.18	0.24
MW	3	Mean.30DayDischarge	0.04	0.06	46.14	0.64	0.53
MW	3	CV.30DayDischarge	1.39	0.51	106.22	2.70	0.01
MW	3	ElectroshockB. post-2014	-0.47	0.12	13.17	-3.99	0.00
MW	3	Mean.1HrDischarge:Mean.Prev6hDischarge	0.01	0.03	191.30	0.18	0.86
MW	5	(Intercept)	1.06	0.17	66.18	6.16	0.00
MW	5	Mean.1HrDischarge	-0.03	0.17	128.38	-0.18	0.86
MW	5	Mean.Prev6hDischarge	-0.11	0.16	128.90	-0.68	0.50
MW	5	CV.Prev6hDischarge	-1.33	0.93	128.59	-1.43	0.16
MW	5	Mean.30DayDischarge	0.05	0.06	53.29	0.78	0.44
MW	5	CV.30DayDischarge	0.88	0.49	99.26	1.80	0.07
MW	5	ElectroshockB. post-2014	-0.53	0.13	15.55	-4.05	0.00
MW	5	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.02	0.03	135.50	-0.89	0.37
MW	6	(Intercept)	-1.10	0.68	42.00	-1.61	0.12
MW	6	Mean.1HrDischarge	0.26	0.81	42.00	0.32	0.75
MW	6	Mean.Prev6hDischarge	-0.18	0.84	42.00	-0.21	0.84
MW	6	CV.Prev6hDischarge	1.62	3.33	42.00	0.49	0.63
MW	6	Mean.30DayDischarge	-0.09	0.23	42.00	-0.37	0.71
MW	6	CV.30DayDischarge	4.31	2.19	42.00	1.97	0.06
MW	6	Mean.1HrDischarge:Mean.Prev6hDischarge	0.02	0.16	42.00	0.13	0.90
MW	7	(Intercept)	-0.60	0.41	26.00	-1.46	0.16

Species	Section	Parameter	Estimate	Std. Error	df	t value	Pr(>|t|)
MW	7	Mean.1HrDischarge	1.11	1.25	26.00	0.88	0.38
MW	7	Mean.Prev6hDischarge	-1.10	1.29	26.00	-0.85	0.40
MW	7	CV.Prev6hDischarge	-0.69	3.57	26.00	-0.19	0.85
MW	7	Mean.30DayDischarge	0.03	0.16	26.00	0.16	0.87
MW	7	CV.30DayDischarge	1.18	1.02	26.00	1.16	0.26
MW	7	Mean.1HrDischarge:Mean.Prev6hDischarge	0.37	0.14	26.00	2.66	0.01
MW	9	(Intercept)	-0.60	0.52	34.00	-1.15	0.26
MW	9	Mean.1HrDischarge	-0.13	1.20	34.00	-0.11	0.92
MW	9	Mean.Prev6hDischarge	-0.15	1.12	34.00	-0.14	0.89
MW	9	CV.Prev6hDischarge	2.22	6.74	34.00	0.33	0.74
MW	9	Mean.30DayDischarge	-0.05	0.19	34.00	-0.28	0.78
MW	9	CV.30DayDischarge	-1.96	2.24	34.00	-0.88	0.39
MW	9	Mean.1HrDischarge:Mean.Prev6hDischarge	0.15	0.21	34.00	0.69	0.49
RB	1	(Intercept)	-4.02	0.63	89.46	-6.35	0.00
RB	1	Mean.1HrDischarge	-0.58	0.44	175.95	-1.32	0.19
RB	1	Mean.Prev6hDischarge	0.42	0.39	179.19	1.07	0.29
RB	1	CV.Prev6hDischarge	2.35	1.24	172.96	1.89	0.06
RB	1	Mean.30DayDischarge	0.22	0.20	66.92	1.12	0.27
RB	1	CV.30DayDischarge	0.58	1.37	81.44	0.42	0.67
RB	1	ElectroshockB. post-2014	-0.32	0.33	18.25	-0.96	0.35
RB	1	Mean.1HrDischarge:Mean.Prev6hDischarge	0.13	0.14	181.19	0.93	0.35
RB	3	(Intercept)	-3.22	0.59	87.30	-5.42	0.00
RB	3	Mean.1HrDischarge	-0.40	0.28	182.27	-1.43	0.15
RB	3	Mean.Prev6hDischarge	0.45	0.26	186.45	1.76	0.08
RB	3	CV.Prev6hDischarge	0.64	0.87	177.95	0.73	0.46
RB	3	Mean.30DayDischarge	-0.16	0.18	48.54	-0.90	0.37
RB	3	CV.30DayDischarge	-0.97	1.53	90.32	-0.63	0.53
RB	3	ElectroshockB. post-2014	-0.07	0.32	16.02	-0.23	0.82
RB	3	Mean.1HrDischarge:Mean.Prev6hDischarge	0.01	0.09	191.91	0.11	0.91
RB	5	(Intercept)	-4.99	0.49	45.83	-10.23	0.00
RB	5	Mean.1HrDischarge	0.85	0.65	136.82	1.31	0.19
RB	5	Mean.Prev6hDischarge	-0.76	0.63	136.51	-1.22	0.22
RB	5	CV.Prev6hDischarge	5.63	3.66	136.14	1.54	0.13
RB	5	Mean.30DayDischarge	0.15	0.17	56.54	0.89	0.38
RB	5	CV.30DayDischarge	-0.53	1.41	37.47	-0.38	0.71
RB	5	ElectroshockB. post-2014	0.21	0.26	18.01	0.82	0.42
RB	5	Mean.1HrDischarge:Mean.Prev6hDischarge	0.24	0.10	112.00	2.34	0.02
RB	6	(Intercept)	-5.27	0.93	9.66	-5.65	0.00
RB	6	Mean.1HrDischarge	0.38	0.87	40.69	0.44	0.66
RB	6	Mean.Prev6hDischarge	-0.55	0.89	37.90	-0.61	0.54
RB	6	CV.Prev6hDischarge	3.48	3.48	35.90	1.00	0.32
RB	6	Mean.30DayDischarge	0.41	0.32	8.78	1.29	0.23
RB	6	CV.30DayDischarge	0.04	3.00	9.92	0.01	0.99
RB	6	Mean.1HrDischarge:Mean.Prev6hDischarge	0.25	0.17	39.64	1.48	0.15
RB	7	(Intercept)	-6.02	1.11	26.00	-5.44	0.00
RB	7	Mean.1HrDischarge	-2.88	3.39	26.00	-0.85	0.40
RB	7	Mean.Prev6hDischarge	2.85	3.50	26.00	0.81	0.42

Species	Section	Parameter	Estimate	Std. Error	df	t value	Pr(>|t|)
RB	7	CV.Prev6hDischarge	11.45	9.66	26.00	1.19	0.25
RB	7	Mean.30DayDischarge	0.41	0.44	26.00	0.94	0.36
RB	7	CV.30DayDischarge	0.23	2.77	26.00	0.08	0.94
RB	7	Mean.1HrDischarge:Mean.Prev6hDischarge	0.65	0.37	26.00	1.75	0.09
WSU	5	(Intercept)	-4.92	0.67	46.89	-7.30	0.00
WSU	5	Mean.1HrDischarge	-1.11	0.73	129.45	-1.53	0.13
WSU	5	Mean.Prev6hDischarge	0.99	0.70	129.38	1.42	0.16
WSU	5	CV.Prev6hDischarge	1.83	4.08	128.36	0.45	0.65
WSU	5	Mean.30DayDischarge	-0.29	0.24	36.41	-1.22	0.23
WSU	5	CV.30DayDischarge	-0.42	1.96	55.36	-0.21	0.83
WSU	5	ElectroshockB. post-2014	1.09	0.44	11.39	2.46	0.03
WSU	5	Mean.1HrDischarge:Mean.Prev6hDischarge	0.29	0.12	136.82	2.42	0.02
WSU	6	(Intercept)	-4.82	0.90	9.56	-5.33	0.00
WSU	6	Mean.1HrDischarge	1.07	0.96	41.14	1.11	0.27
WSU	6	Mean.Prev6hDischarge	-0.88	0.99	38.16	-0.89	0.38
WSU	6	CV.Prev6hDischarge	-3.30	3.89	36.12	-0.85	0.40
WSU	6	Mean.30DayDischarge	-0.02	0.31	8.26	-0.06	0.96
WSU	6	CV.30DayDischarge	4.04	2.91	9.31	1.39	0.20
WSU	6	Mean.1HrDischarge:Mean.Prev6hDischarge	-0.33	0.18	39.69	-1.82	0.08
WSU	7	(Intercept)	-5.29	0.67	26.00	-7.94	0.00
WSU	7	Mean.1HrDischarge	-6.88	2.04	26.00	-3.37	0.00
WSU	7	Mean.Prev6hDischarge	6.49	2.11	26.00	3.08	0.00
WSU	7	CV.Prev6hDischarge	18.81	5.82	26.00	3.23	0.00
WSU	7	Mean.30DayDischarge	0.37	0.26	26.00	1.42	0.17
WSU	7	CV.30DayDischarge	3.28	1.67	26.00	1.97	0.06
WSU	7	Mean.1HrDischarge:Mean.Prev6hDischarge	0.01	0.23	26.00	0.04	0.97
WSU	9	(Intercept)	-3.87	0.68	34.00	-5.64	0.00
WSU	9	Mean.1HrDischarge	-0.01	1.57	34.00	-0.01	1.00
WSU	9	Mean.Prev6hDischarge	0.22	1.47	34.00	0.15	0.88
WSU	9	CV.Prev6hDischarge	-4.51	8.86	34.00	-0.51	0.61
WSU	9	Mean.30DayDischarge	-0.36	0.25	34.00	-1.45	0.16
WSU	9	CV.30DayDischarge	0.58	2.94	34.00	0.20	0.84
WSU	9	Mean.1HrDischarge:Mean.Prev6hDischarge	0.49	0.28	34.00	1.74	0.09

CATCHABILITY 2020 ANALYSIS

Brian Ma

01/09/2020

```
# Load Libraries and Other Set Up -------------------------------------

#install.packages("lme4")
#install.packages("lmerTest")
#install.packages("rmarkdown")
#install.packages("ggplot2")
#install.packages("rmarkdown")
library(lme4)
```

```
## Loading required package: Matrix

library(lmerTest)

##
## Attaching package: 'lmerTest'

## The following object is masked from 'package:lme4':
##
##     lmer

## The following object is masked from 'package:stats':
##
##     step

library(rmarkdown)
library(ggplot2)

## Warning: package 'ggplot2' was built under R version 3.6.3

library(rmarkdown)
library(sjPlot)

## Warning: package 'sjPlot' was built under R version 3.6.3

## #refugeeswelcome

library(MuMIn)

## Registered S3 method overwritten by 'MuMIn':
##   method         from
##   predict.merMod lme4

library(dplyr)

##
## Attaching package: 'dplyr'

## The following objects are masked from 'package:stats':
##
##     filter, lag

## The following objects are masked from 'package:base':
##
##     intersect, setdiff, setequal, union

# Set and update the plotting themes for ggplot2
theme_set(theme_classic())
theme_update(legend.position="bottom")

#https://www.r-bloggers.com/format-and-interpret-linear-mixed-models/
#https://cran.r-project.org/web/packages/sjPlot/vignettes/plot_model_estimates.html
#https://www.quora.com/In-laymans-terms-why-is-dropping-insignificant-predictors-from-a-regres
sion-model-a-bad-idea
#https://sites.google.com/site/rforfishandwildlifegrads/home/mumin_usage_examples

# Load Processed Data
data2 <- read.csv("Processed Data noNA.csv",header=T)
listSpecies <- unique(data2$Species)
listSections <- unique(data2$Section)
listYear <- unique(data2$SampleYear)
listSampleSession2 <- unique(data2$SampleSession2)
```

```
# Data Analysis -------------------------------------------------------------------------------
----------

# CPUE_100m -----------------------------------------------------------------------------------
----------
listSpecies

## [1] AG  BT  CSU LSU MW  RB  WSU
## Levels: AG BT CSU LSU MW RB WSU

listSections

## [1] 1 3 5 6 7 9

#CS: you will need to scale variables for EACH section separately -- if if you scale all secti
ons together, you can then get stranger results because the mean is no longer 0 for each varia
ble in each section.
#CS: It makes no sense to standardize/scale a cv as the cv has standardized/scaled top and bot
tom variables already.
dataAG <- subset(data2, Species=="AG")
dataBT <- subset(data2, Species=="BT")
dataCSU <- subset(data2, Species=="CSU")
dataLSU <- subset(data2, Species=="LSU")
dataMW <- subset(data2, Species=="MW")
dataRB <- subset(data2, Species=="RB")
dataWSU <- subset(data2, Species=="WSU")

# Arctic Grayling (AG); Exclude Sections 1, 6, 7, and 9 based on the % of zero values
#fit100m.AG_1 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
#                     data=subset(dataAG,Section==1),REML = FALSE, control = lmerControl(optim
izer ="Nelder_Mead"))
dataAG3 <- subset(dataAG,Section==3)
dataAG3$Mean.1HrDischarge <- scale(dataAG3$Mean.1HrDischarge)
dataAG3$Mean.Prev6hDischarge <- scale(dataAG3$Mean.Prev6hDischarge)
dataAG3$Mean.30DayDischarge <- scale(dataAG3$Mean.30DayDischarge)
dataAG5 <- subset(dataAG,Section==5)
dataAG5$Mean.1HrDischarge <- scale(dataAG5$Mean.1HrDischarge)
dataAG5$Mean.Prev6hDischarge <- scale(dataAG5$Mean.Prev6hDischarge)
dataAG5$Mean.30DayDischarge <- scale(dataAG5$Mean.30DayDischarge)
dataAG6 <- subset(dataAG,Section==6)
dataAG6$Mean.1HrDischarge <- scale(dataAG6$Mean.1HrDischarge)
dataAG6$Mean.Prev6hDischarge <- scale(dataAG6$Mean.Prev6hDischarge)
dataAG6$Mean.30DayDischarge <- scale(dataAG6$Mean.30DayDischarge)
dataAG7 <- subset(dataAG,Section==7)
dataAG7$Mean.1HrDischarge <- scale(dataAG7$Mean.1HrDischarge)
dataAG7$Mean.Prev6hDischarge <- scale(dataAG7$Mean.Prev6hDischarge)
dataAG7$Mean.30DayDischarge <- scale(dataAG7$Mean.30DayDischarge)
dataAG9 <- subset(dataAG,Section==9)
dataAG9$Mean.1HrDischarge <- scale(dataAG9$Mean.1HrDischarge)
dataAG9$Mean.Prev6hDischarge <- scale(dataAG9$Mean.Prev6hDischarge)
dataAG9$Mean.30DayDischarge <- scale(dataAG9$Mean.30DayDischarge)

fit100m.AG_3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataAG3,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.AG_5 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
```

```
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataAG5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.AG_6 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataAG6,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.AG_7 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataAG7,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

fit100m.AG_9 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataAG9,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

# Bull Trout (BT)
dataBT1 <- subset(dataBT,Section==1)
dataBT1$Mean.1HrDischarge <- scale(dataBT1$Mean.1HrDischarge)
dataBT1$Mean.Prev6hDischarge <- scale(dataBT1$Mean.Prev6hDischarge)
dataBT1$Mean.30DayDischarge <- scale(dataBT1$Mean.30DayDischarge)
dataBT3 <- subset(dataBT,Section==3)
dataBT3$Mean.1HrDischarge <- scale(dataBT3$Mean.1HrDischarge)
dataBT3$Mean.Prev6hDischarge <- scale(dataBT3$Mean.Prev6hDischarge)
dataBT3$Mean.30DayDischarge <- scale(dataBT3$Mean.30DayDischarge)
dataBT5 <- subset(dataBT,Section==5)
dataBT5$Mean.1HrDischarge <- scale(dataBT5$Mean.1HrDischarge)
dataBT5$Mean.Prev6hDischarge <- scale(dataBT5$Mean.Prev6hDischarge)
dataBT5$Mean.30DayDischarge <- scale(dataBT5$Mean.30DayDischarge)
dataBT6 <- subset(dataBT,Section==6)
dataBT6$Mean.1HrDischarge <- scale(dataBT6$Mean.1HrDischarge)
dataBT6$Mean.Prev6hDischarge <- scale(dataBT6$Mean.Prev6hDischarge)
dataBT6$Mean.30DayDischarge <- scale(dataBT6$Mean.30DayDischarge)
dataBT7 <- subset(dataBT,Section==7)
dataBT7$Mean.1HrDischarge <- scale(dataBT7$Mean.1HrDischarge)
dataBT7$Mean.Prev6hDischarge <- scale(dataBT7$Mean.Prev6hDischarge)
dataBT7$Mean.30DayDischarge <- scale(dataBT7$Mean.30DayDischarge)
dataBT9 <- subset(dataBT,Section==9)
dataBT9$Mean.1HrDischarge <- scale(dataBT9$Mean.1HrDischarge)
dataBT9$Mean.Prev6hDischarge <- scale(dataBT9$Mean.Prev6hDischarge)
dataBT9$Mean.30DayDischarge <- scale(dataBT9$Mean.30DayDischarge)


fit100m.BT_1 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataBT1,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.BT_3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
```

```
                     data=dataBT3,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

fit100m.BT_5 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataBT5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

fit100m.BT_6 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataBT6,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.BT_7 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataBT7,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

fit100m.BT_9 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataBT9,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

# Largescale Suckers (CSU)
dataCSU1 <- subset(dataCSU,Section==1)
dataCSU1$Mean.1HrDischarge <- scale(dataCSU1$Mean.1HrDischarge)
dataCSU1$Mean.Prev6hDischarge <- scale(dataCSU1$Mean.Prev6hDischarge)
dataCSU1$Mean.30DayDischarge <- scale(dataCSU1$Mean.30DayDischarge)
dataCSU3 <- subset(dataCSU,Section==3)
dataCSU3$Mean.1HrDischarge <- scale(dataCSU3$Mean.1HrDischarge)
dataCSU3$Mean.Prev6hDischarge <- scale(dataCSU3$Mean.Prev6hDischarge)
dataCSU3$Mean.30DayDischarge <- scale(dataCSU3$Mean.30DayDischarge)
dataCSU5 <- subset(dataCSU,Section==5)
dataCSU5$Mean.1HrDischarge <- scale(dataCSU5$Mean.1HrDischarge)
dataCSU5$Mean.Prev6hDischarge <- scale(dataCSU5$Mean.Prev6hDischarge)
dataCSU5$Mean.30DayDischarge <- scale(dataCSU5$Mean.30DayDischarge)
dataCSU6 <- subset(dataCSU,Section==6)
dataCSU6$Mean.1HrDischarge <- scale(dataCSU6$Mean.1HrDischarge)
dataCSU6$Mean.Prev6hDischarge <- scale(dataCSU6$Mean.Prev6hDischarge)
dataCSU6$Mean.30DayDischarge <- scale(dataCSU6$Mean.30DayDischarge)
dataCSU7 <- subset(dataCSU,Section==7)
dataCSU7$Mean.1HrDischarge <- scale(dataCSU7$Mean.1HrDischarge)
dataCSU7$Mean.Prev6hDischarge <- scale(dataCSU7$Mean.Prev6hDischarge)
dataCSU7$Mean.30DayDischarge <- scale(dataCSU7$Mean.30DayDischarge)
dataCSU9 <- subset(dataCSU,Section==9)
dataCSU9$Mean.1HrDischarge <- scale(dataCSU9$Mean.1HrDischarge)
dataCSU9$Mean.Prev6hDischarge <- scale(dataCSU9$Mean.Prev6hDischarge)
dataCSU9$Mean.30DayDischarge <- scale(dataCSU9$Mean.30DayDischarge)

fit100m.CSU_1 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
```

```
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
                      data=dataCSU1,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.CSU_3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
                      data=dataCSU3,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.CSU_5 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
                      data=dataCSU5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.CSU_6 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataCSU6,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

fit100m.CSU_7 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataCSU7,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

fit100m.CSU_9 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataCSU9,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

# Longnose Suckers (LSU)
dataLSU1 <- subset(dataLSU,Section==1)
dataLSU1$Mean.1HrDischarge <- scale(dataLSU1$Mean.1HrDischarge)
dataLSU1$Mean.Prev6hDischarge <- scale(dataLSU1$Mean.Prev6hDischarge)
dataLSU1$Mean.30DayDischarge <- scale(dataLSU1$Mean.30DayDischarge)
dataLSU3 <- subset(dataLSU,Section==3)
dataLSU3$Mean.1HrDischarge <- scale(dataLSU3$Mean.1HrDischarge)
dataLSU3$Mean.Prev6hDischarge <- scale(dataLSU3$Mean.Prev6hDischarge)
dataLSU3$Mean.30DayDischarge <- scale(dataLSU3$Mean.30DayDischarge)
dataLSU5 <- subset(dataLSU,Section==5)
dataLSU5$Mean.1HrDischarge <- scale(dataLSU5$Mean.1HrDischarge)
dataLSU5$Mean.Prev6hDischarge <- scale(dataLSU5$Mean.Prev6hDischarge)
dataLSU5$Mean.30DayDischarge <- scale(dataLSU5$Mean.30DayDischarge)
dataLSU6 <- subset(dataLSU,Section==6)
dataLSU6$Mean.1HrDischarge <- scale(dataLSU6$Mean.1HrDischarge)
dataLSU6$Mean.Prev6hDischarge <- scale(dataLSU6$Mean.Prev6hDischarge)
dataLSU6$Mean.30DayDischarge <- scale(dataLSU6$Mean.30DayDischarge)
dataLSU7 <- subset(dataLSU,Section==7)
dataLSU7$Mean.1HrDischarge <- scale(dataLSU7$Mean.1HrDischarge)
dataLSU7$Mean.Prev6hDischarge <- scale(dataLSU7$Mean.Prev6hDischarge)
dataLSU7$Mean.30DayDischarge <- scale(dataLSU7$Mean.30DayDischarge)
dataLSU9 <- subset(dataLSU,Section==9)
dataLSU9$Mean.1HrDischarge <- scale(dataLSU9$Mean.1HrDischarge)
dataLSU9$Mean.Prev6hDischarge <- scale(dataLSU9$Mean.Prev6hDischarge)
dataLSU9$Mean.30DayDischarge <- scale(dataLSU9$Mean.30DayDischarge)
```

```
fit100m.LSU_1 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
                      data=dataLSU1,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.LSU_3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
                      data=dataLSU3,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.LSU_5 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
                      data=dataLSU5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

fit100m.LSU_6 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataLSU6,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

fit100m.LSU_7 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataLSU7,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

fit100m.LSU_9 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataLSU9,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

# Mountain Whitefish (MW)
dataMW1 <- subset(dataMW,Section==1)
dataMW1$Mean.1HrDischarge <- scale(dataMW1$Mean.1HrDischarge)
dataMW1$Mean.Prev6hDischarge <- scale(dataMW1$Mean.Prev6hDischarge)
dataMW1$Mean.30DayDischarge <- scale(dataMW1$Mean.30DayDischarge)
dataMW3 <- subset(dataMW,Section==3)
dataMW3$Mean.1HrDischarge <- scale(dataMW3$Mean.1HrDischarge)
dataMW3$Mean.Prev6hDischarge <- scale(dataMW3$Mean.Prev6hDischarge)
dataMW3$Mean.30DayDischarge <- scale(dataMW3$Mean.30DayDischarge)
dataMW5 <- subset(dataMW,Section==5)
dataMW5$Mean.1HrDischarge <- scale(dataMW5$Mean.1HrDischarge)
dataMW5$Mean.Prev6hDischarge <- scale(dataMW5$Mean.Prev6hDischarge)
dataMW5$Mean.30DayDischarge <- scale(dataMW5$Mean.30DayDischarge)
# extra values for MW5
dataMW5$Mean.Prev12hDischarge <- scale(dataMW5$Mean.Prev12hDischarge)
dataMW5$Mean.Prev6hDischarge <- scale(dataMW5$Mean.Prev6hDischarge)
dataMW5$Mean.Prev3hDischarge <- scale(dataMW5$Mean.Prev3hDischarge)
```

```
dataMW6 <- subset(dataMW,Section==6)
dataMW6$Mean.1HrDischarge <- scale(dataMW6$Mean.1HrDischarge)
dataMW6$Mean.Prev6hDischarge <- scale(dataMW6$Mean.Prev6hDischarge)
dataMW6$Mean.30DayDischarge <- scale(dataMW6$Mean.30DayDischarge)
dataMW7 <- subset(dataMW,Section==7)
dataMW7$Mean.1HrDischarge <- scale(dataMW7$Mean.1HrDischarge)
dataMW7$Mean.Prev6hDischarge <- scale(dataMW7$Mean.Prev6hDischarge)
dataMW7$Mean.30DayDischarge <- scale(dataMW7$Mean.30DayDischarge)
dataMW9 <- subset(dataMW,Section==9)
dataMW9$Mean.1HrDischarge <- scale(dataMW9$Mean.1HrDischarge)
dataMW9$Mean.Prev6hDischarge <- scale(dataMW9$Mean.Prev6hDischarge)
dataMW9$Mean.30DayDischarge <- scale(dataMW9$Mean.30DayDischarge)

fit100m.MW_1 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataMW1,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.MW_3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataMW3,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.MW_5 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataMW5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.MW_6 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataMW6,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

fit100m.MW_7 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataMW7,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

fit100m.MW_9 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataMW9,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

fit100m.MW_5.24 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev24hDischarge + Mean.1HrDisch
arge:Mean.Prev24hDischarge + CV.Prev24hDischarge + Mean.30DayDischarge + CV.30DayDischarge + E
lectroshock + (1|SampleYear),
                        data=dataMW5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Me
ad"))

## Warning: Some predictor variables are on very different scales: consider
## rescaling
```

```
## Warning: Some predictor variables are on very different scales: consider
## rescaling

fit100m.MW_5.12 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev12hDischarge + Mean.1HrDisch
arge:Mean.Prev12hDischarge + CV.Prev12hDischarge + Mean.30DayDischarge + CV.30DayDischarge + E
lectroshock + (1|SampleYear),
                        data=dataMW5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Me
ad"))

fit100m.MW_5.3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev3hDischarge + Mean.1HrDischar
ge:Mean.Prev3hDischarge + CV.Prev3hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Elect
roshock + (1|SampleYear),
                       data=dataMW5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

# Rainbow Trout (RB); Exclude Section 9.
dataRB1 <- subset(dataRB,Section==1)
dataRB1$Mean.1HrDischarge <- scale(dataRB1$Mean.1HrDischarge)
dataRB1$Mean.Prev6hDischarge <- scale(dataRB1$Mean.Prev6hDischarge)
dataRB1$Mean.30DayDischarge <- scale(dataRB1$Mean.30DayDischarge)
dataRB3 <- subset(dataRB,Section==3)
dataRB3$Mean.1HrDischarge <- scale(dataRB3$Mean.1HrDischarge)
dataRB3$Mean.Prev6hDischarge <- scale(dataRB3$Mean.Prev6hDischarge)
dataRB3$Mean.30DayDischarge <- scale(dataRB3$Mean.30DayDischarge)
dataRB5 <- subset(dataRB,Section==5)
dataRB5$Mean.1HrDischarge <- scale(dataRB5$Mean.1HrDischarge)
dataRB5$Mean.Prev6hDischarge <- scale(dataRB5$Mean.Prev6hDischarge)
dataRB5$Mean.30DayDischarge <- scale(dataRB5$Mean.30DayDischarge)
dataRB6 <- subset(dataRB,Section==6)
dataRB6$Mean.1HrDischarge <- scale(dataRB6$Mean.1HrDischarge)
dataRB6$Mean.Prev6hDischarge <- scale(dataRB6$Mean.Prev6hDischarge)
dataRB6$Mean.30DayDischarge <- scale(dataRB6$Mean.30DayDischarge)
dataRB7 <- subset(dataRB,Section==7)
dataRB7$Mean.1HrDischarge <- scale(dataRB7$Mean.1HrDischarge)
dataRB7$Mean.Prev6hDischarge <- scale(dataRB7$Mean.Prev6hDischarge)
dataRB7$Mean.30DayDischarge <- scale(dataRB7$Mean.30DayDischarge)

fit100m.RB_1 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataRB1,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.RB_3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataRB3,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.RB_5 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electro
shock + (1|SampleYear),
                     data=dataRB5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.RB_6 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
                     data=dataRB6,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))
fit100m.RB_7 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge
:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Samp
leYear),
```

```
                     data=dataRB7,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead"
))

## boundary (singular) fit: see ?isSingular

#fit100m.RB_9 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
#                     data=dataRB9,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mead
"))

# White Sucker (WSU); Exclude sections 1 and 3
dataWSU1 <- subset(dataWSU,Section==1)
dataWSU1$Mean.1HrDischarge <- scale(dataWSU1$Mean.1HrDischarge)
dataWSU1$Mean.Prev6hDischarge <- scale(dataWSU1$Mean.Prev6hDischarge)
dataWSU1$Mean.30DayDischarge <- scale(dataWSU1$Mean.30DayDischarge)
dataWSU3 <- subset(dataWSU,Section==3)
dataWSU3$Mean.1HrDischarge <- scale(dataWSU3$Mean.1HrDischarge)
dataWSU3$Mean.Prev6hDischarge <- scale(dataWSU3$Mean.Prev6hDischarge)
dataWSU3$Mean.30DayDischarge <- scale(dataWSU3$Mean.30DayDischarge)
dataWSU5 <- subset(dataWSU,Section==5)
dataWSU5$Mean.1HrDischarge <- scale(dataWSU5$Mean.1HrDischarge)
dataWSU5$Mean.Prev6hDischarge <- scale(dataWSU5$Mean.Prev6hDischarge)
dataWSU5$Mean.30DayDischarge <- scale(dataWSU5$Mean.30DayDischarge)
dataWSU6 <- subset(dataWSU,Section==6)
dataWSU6$Mean.1HrDischarge <- scale(dataWSU6$Mean.1HrDischarge)
dataWSU6$Mean.Prev6hDischarge <- scale(dataWSU6$Mean.Prev6hDischarge)
dataWSU6$Mean.30DayDischarge <- scale(dataWSU6$Mean.30DayDischarge)
dataWSU7 <- subset(dataWSU,Section==7)
dataWSU7$Mean.1HrDischarge <- scale(dataWSU7$Mean.1HrDischarge)
dataWSU7$Mean.Prev6hDischarge <- scale(dataWSU7$Mean.Prev6hDischarge)
dataWSU7$Mean.30DayDischarge <- scale(dataWSU7$Mean.30DayDischarge)
dataWSU9 <- subset(dataWSU,Section==9)
dataWSU9$Mean.1HrDischarge <- scale(dataWSU9$Mean.1HrDischarge)
dataWSU9$Mean.Prev6hDischarge <- scale(dataWSU9$Mean.Prev6hDischarge)
dataWSU9$Mean.30DayDischarge <- scale(dataWSU9$Mean.30DayDischarge)

#fit100m.WSU_1 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischar
ge:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Elect
roshock + (1|SampleYear),
#                     data=dataWSU1,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
#fit100m.WSU_3 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischar
ge:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Elect
roshock + (1|SampleYear),
#                     data=dataWSU3,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.WSU_5 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + Electr
oshock + (1|SampleYear),
                      data=dataWSU5,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.WSU_6 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataWSU6,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))
fit100m.WSU_7 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
```

```
                      data=dataWSU7,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

fit100m.WSU_9 <- lmer(CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarg
e:Mean.Prev6hDischarge + CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge + (1|Sam
pleYear),
                      data=dataWSU9,REML = FALSE, control = lmerControl(optimizer ="Nelder_Mea
d"))

## boundary (singular) fit: see ?isSingular

# REVIEW OF LAG ------------------------------------------------------------------------------
----------------
# Look at different lags in MW 5 only.
summary(fit100m.MW_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataMW5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    107.2    136.4    -43.6     87.2      127
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.07794 -0.55423  0.09466  0.53502  2.70396
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.04603  0.2145
##  Residual               0.09184  0.3031
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                        Estimate Std. Error        df
## (Intercept)                             1.06102    0.17222  66.17840
## Mean.1HrDischarge                      -0.02930    0.16620 128.38249
## Mean.Prev6hDischarge                   -0.10820    0.15942 128.90091
## CV.Prev6hDischarge                     -1.32555    0.92938 128.58848
## Mean.30DayDischarge                     0.04801    0.06191  53.29379
## CV.30DayDischarge                       0.87977    0.48892  99.25917
## ElectroshockB. post-2014               -0.53278    0.13158  15.55055
## Mean.1HrDischarge:Mean.Prev6hDischarge  -0.02471    0.02770 135.50281
##                                       t value Pr(>|t|)
## (Intercept)                             6.161 4.83e-08 ***
## Mean.1HrDischarge                      -0.176 0.860364
## Mean.Prev6hDischarge                   -0.679 0.498528
## CV.Prev6hDischarge                     -1.426 0.156210
## Mean.30DayDischarge                     0.775 0.441483
## CV.30DayDischarge                       1.799 0.074993 .
## ElectroshockB. post-2014               -4.049 0.000981 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  -0.892 0.373955
## ---
```

```
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.181
## Mn.Prv6hDsc  0.183 -0.976
## CV.Prv6hDsc -0.263  0.770 -0.740
## Mn.30DyDsch -0.460  0.005 -0.054  0.005
## CV.30DyDsch -0.818 -0.061  0.044 -0.061  0.444
## ElcB.p-2014 -0.376  0.009 -0.007  0.064  0.248  0.082
## M.1HD:M.P6D  0.126 -0.028  0.054 -0.052  0.065 -0.295 -0.037
```

```r
summary(fit100m.MW_5.12)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev12hDischarge + Mean.1HrDischarge:Mean.Prev12hDisc
harge +
##     CV.Prev12hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataMW5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    108.5    137.7    -44.2     88.5      127
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0411 -0.5347  0.1216  0.5590  2.7407
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.04544  0.2132
##  Residual               0.09292  0.3048
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                          Estimate Std. Error         df
## (Intercept)                              1.084678   0.177425  63.845695
## Mean.1HrDischarge                       -0.003589   0.082502 128.423830
## Mean.Prev12hDischarge                   -0.130462   0.081561 125.588065
## CV.Prev12hDischarge                     -0.944590   0.641815 126.737969
## Mean.30DayDischarge                      0.043004   0.063867  55.089451
## CV.30DayDischarge                        0.761311   0.489583  99.750854
## ElectroshockB. post-2014                -0.537720   0.132590  16.099310
## Mean.1HrDischarge:Mean.Prev12hDischarge -0.022028   0.028300 135.130757
##                                         t value Pr(>|t|)
## (Intercept)                              6.113 6.52e-08 ***
## Mean.1HrDischarge                       -0.044 0.965367
## Mean.Prev12hDischarge                   -1.600 0.112208
## CV.Prev12hDischarge                     -1.472 0.143568
## Mean.30DayDischarge                      0.673 0.503549
## CV.30DayDischarge                        1.555 0.123108
## ElectroshockB. post-2014                -4.055 0.000908 ***
## Mean.1HrDischarge:Mean.Prev12hDischarge -0.778 0.437717
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD M.P12D CV.P12 M.30DD CV.30D EB.p-2
```

```
## Mn.1HrDschr -0.128
## Mn.Prv12hDs  0.132 -0.903
## CV.Prv12hDs -0.347  0.438 -0.385
## Mn.30DyDsch -0.507  0.125 -0.223  0.203
## CV.30DyDsch -0.833 -0.008 -0.024  0.054  0.449
## ElcB.p-2014 -0.403  0.053 -0.054  0.171  0.275  0.097
## M.1HD:M.P12  0.087  0.088 -0.022  0.076  0.061 -0.291 -0.033

summary(fit100m.MW_5.24)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev24hDischarge + Mean.1HrDischarge:Mean.Prev24hDisc
harge +
##     CV.Prev24hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataMW5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    111.1    140.3    -45.5     91.1      127
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8730 -0.5067  0.1339  0.5497  2.6541
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0488   0.2209
##  Residual               0.0942   0.3069
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                          Estimate Std. Error         df
## (Intercept)                             1.647e+00  3.338e-01  1.367e+02
## Mean.1HrDischarge                       6.792e-02  1.241e-01  1.346e+02
## Mean.Prev24hDischarge                  -5.242e-04  2.672e-04  1.277e+02
## CV.Prev24hDischarge                    -5.943e-01  3.736e-01  1.363e+02
## Mean.30DayDischarge                     5.363e-02  6.590e-02  5.679e+01
## CV.30DayDischarge                       7.192e-01  5.181e-01  9.269e+01
## ElectroshockB. post-2014               -5.224e-01  1.379e-01  1.661e+01
## Mean.1HrDischarge:Mean.Prev24hDischarge -3.548e-05  1.032e-04  1.368e+02
##                                        t value Pr(>|t|)
## (Intercept)                              4.935  2.3e-06 ***
## Mean.1HrDischarge                        0.547  0.58496
## Mean.Prev24hDischarge                   -1.962  0.05198 .
## CV.Prev24hDischarge                     -1.591  0.11404
## Mean.30DayDischarge                      0.814  0.41910
## CV.30DayDischarge                        1.388  0.16842
## ElectroshockB. post-2014                -3.788  0.00152 **
## Mean.1HrDischarge:Mean.Prev24hDischarge  -0.344  0.73162
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD M.P24D CV.P24 M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.364
## Mn.Prv24hDs -0.806 -0.483
## CV.Prv24hDs -0.447 -0.239  0.194
## Mn.30DyDsch -0.099 -0.021 -0.231  0.139
```

```
## CV.30DyDsch -0.429  0.293 -0.073  0.157  0.456
## ElcB.p-2014 -0.201  0.033 -0.060  0.195  0.289  0.130
## M.1HD:M.P24  0.101 -0.791 -0.077  0.153  0.105 -0.317 -0.008
## fit warnings:
## Some predictor variables are on very different scales: consider rescaling
```

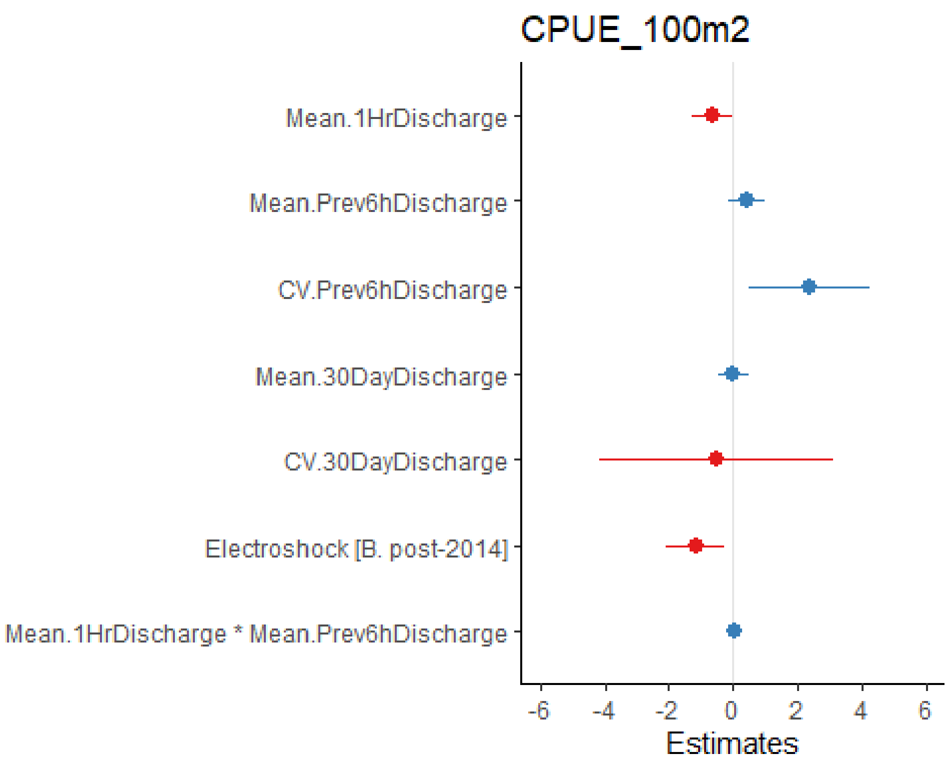
```
summary(fit100m.MW_5.3)
```

```
## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev3hDischarge + Mean.1HrDischarge:Mean.Prev3hDischa
rge +
##     CV.Prev3hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataMW5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    107.5    136.7    -43.8     87.5      127
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.9877 -0.5622  0.1352  0.5651  2.7887
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.04803  0.2192
##  Residual               0.09168  0.3028
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                        Estimate Std. Error        df
## (Intercept)                             1.04757    0.17432  65.41378
## Mean.1HrDischarge                       0.32411    0.35386 127.41404
## Mean.Prev3hDischarge                   -0.44842    0.35119 128.01262
## CV.Prev3hDischarge                     -0.95884    1.35293 127.08334
## Mean.30DayDischarge                     0.04443    0.06231  52.68662
## CV.30DayDischarge                       0.81778    0.49516  99.81210
## ElectroshockB. post-2014               -0.53206    0.13378  15.36449
## Mean.1HrDischarge:Mean.Prev3hDischarge  -0.02817    0.02731 135.54373
##                                       t value Pr(>|t|)
## (Intercept)                             6.009 9.16e-08 ***
## Mean.1HrDischarge                       0.916  0.36143
## Mean.Prev3hDischarge                   -1.277  0.20396
## CV.Prev3hDischarge                     -0.709  0.47980
## Mean.30DayDischarge                     0.713  0.47898
## CV.30DayDischarge                       1.652  0.10177
## ElectroshockB. post-2014               -3.977  0.00116 **
## Mean.1HrDischarge:Mean.Prev3hDischarge  -1.031  0.30416
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P3D CV.P3D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.162
## Mn.Prv3hDsc  0.162 -0.995
## CV.Prv3hDsc -0.266  0.771 -0.760
## Mn.30DyDsch -0.444 -0.027  0.005 -0.039
## CV.30DyDsch -0.811 -0.095  0.088 -0.077  0.441
```

```
## ElcB.p-2014 -0.378 -0.001  0.001  0.058  0.247  0.083
## M.1HD:M.P3D  0.122  0.003  0.008  0.008  0.065 -0.315 -0.029

# Calculate AIC values and weights
AIC(fit100m.MW_5, fit100m.MW_5.3, fit100m.MW_5.12, fit100m.MW_5.24)

##                 df      AIC
## fit100m.MW_5    10 107.2052
## fit100m.MW_5.3  10 107.5078
## fit100m.MW_5.12 10 108.4961
## fit100m.MW_5.24 10 111.0831

round(Weights(AIC(fit100m.MW_5, fit100m.MW_5.3, fit100m.MW_5.12, fit100m.MW_5.24)), 3)

##  model weights
## [1] 0.396 0.340 0.207 0.057

# OUTPUTS ------------------------------------------------------------------------------
----------------

# Batch Print summaries to file
woof <- NULL
woof <- rbind(woof,summary(fit100m.AG_3)$coefficients)
woof <- rbind(woof,summary(fit100m.AG_5)$coefficients)
woof <- rbind(woof,summary(fit100m.BT_1)$coefficients)
woof <- rbind(woof,summary(fit100m.BT_3)$coefficients)
woof <- rbind(woof,summary(fit100m.BT_5)$coefficients)
woof <- rbind(woof,summary(fit100m.BT_6)$coefficients)
woof <- rbind(woof,summary(fit100m.BT_7)$coefficients)
woof <- rbind(woof,summary(fit100m.BT_9)$coefficients)
woof <- rbind(woof,summary(fit100m.CSU_1)$coefficients)
woof <- rbind(woof,summary(fit100m.CSU_3)$coefficients)
woof <- rbind(woof,summary(fit100m.CSU_5)$coefficients)
woof <- rbind(woof,summary(fit100m.CSU_6)$coefficients)
woof <- rbind(woof,summary(fit100m.CSU_7)$coefficients)
woof <- rbind(woof,summary(fit100m.CSU_9)$coefficients)
woof <- rbind(woof,summary(fit100m.LSU_1)$coefficients)
woof <- rbind(woof,summary(fit100m.LSU_3)$coefficients)
woof <- rbind(woof,summary(fit100m.LSU_5)$coefficients)
woof <- rbind(woof,summary(fit100m.LSU_6)$coefficients)
woof <- rbind(woof,summary(fit100m.LSU_7)$coefficients)
woof <- rbind(woof,summary(fit100m.LSU_9)$coefficients)
woof <- rbind(woof,summary(fit100m.MW_1)$coefficients)
woof <- rbind(woof,summary(fit100m.MW_3)$coefficients)
woof <- rbind(woof,summary(fit100m.MW_5)$coefficients)
woof <- rbind(woof,summary(fit100m.MW_6)$coefficients)
woof <- rbind(woof,summary(fit100m.MW_7)$coefficients)
woof <- rbind(woof,summary(fit100m.MW_9)$coefficients)
woof <- rbind(woof,summary(fit100m.RB_1)$coefficients)
woof <- rbind(woof,summary(fit100m.RB_3)$coefficients)
woof <- rbind(woof,summary(fit100m.RB_5)$coefficients)
woof <- rbind(woof,summary(fit100m.RB_6)$coefficients)
woof <- rbind(woof,summary(fit100m.RB_7)$coefficients)
woof <- rbind(woof,summary(fit100m.WSU_5)$coefficients)
woof <- rbind(woof,summary(fit100m.WSU_6)$coefficients)
woof <- rbind(woof,summary(fit100m.WSU_7)$coefficients)
woof <- rbind(woof,summary(fit100m.WSU_9)$coefficients)

write.csv(woof,"coefficients.csv",row.names=T)

# Function to plot the effect size (using the sjPlot package)
```

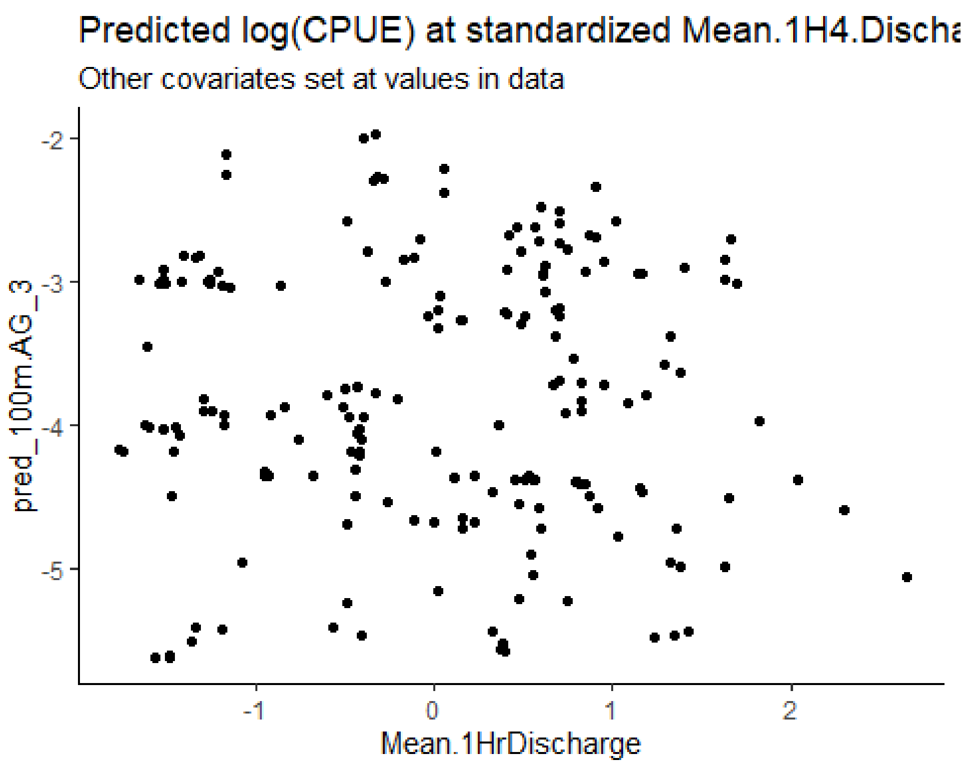
```
PlotAndSave <- function(dataObject, fileName) {
    plotObject <- plot_model(dataObject)
    ggsave(plotObject,file=fileName,w=7.5,h=7.5, units="in", dpi=300)
    plotObject
}

# Review of results for each section and species --------------------------------

# AG 3 ---------------------------------------------------------------------------
summary(fit100m.AG_3)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataAG3
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    662.8    695.4   -321.4    642.8      182
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0284 -0.5887  0.1925  0.6706  2.1622
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.6939   0.833
##  Residual               1.4077   1.186
## Number of obs: 192, groups:  SampleYear, 18
##
## Fixed effects:
##                                         Estimate Std. Error         df
## (Intercept)                            -3.746003   0.732351 111.292799
## Mean.1HrDischarge                      -0.656284   0.313210 178.964065
## Mean.Prev6hDischarge                    0.442024   0.286731 182.263083
## CV.Prev6hDischarge                      2.386173   0.970633 175.722401
## Mean.30DayDischarge                     0.005737   0.236525  61.463767
## CV.30DayDischarge                      -0.513577   1.869103 139.939623
## ElectroshockB. post-2014               -1.164958   0.469931  16.660356
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.019083   0.105647 190.003440
##                                        t value Pr(>|t|)
## (Intercept)                             -5.115 1.32e-06 ***
## Mean.1HrDischarge                       -2.095   0.0375 *
## Mean.Prev6hDischarge                     1.542   0.1249
## CV.Prev6hDischarge                       2.458   0.0149 *
## Mean.30DayDischarge                      0.024   0.9807
## CV.30DayDischarge                       -0.275   0.7839
## ElectroshockB. post-2014                -2.479   0.0242 *
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.181   0.8569
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.218
## Mn.Prv6hDsc -0.257 -0.877
## CV.Prv6hDsc -0.288 -0.751  0.630
```

```
## Mn.30DyDsch -0.429 -0.153  0.018  0.075
## CV.30DyDsch -0.877 -0.032  0.129 -0.004  0.413
## ElcB.p-2014 -0.274  0.046 -0.063 -0.017  0.210  0.074
## M.1HD:M.P6D -0.019 -0.128 -0.017  0.397 -0.079 -0.215 -0.048

PlotAndSave(fit100m.AG_3,"EffectSize_100m_AG_3.tiff")
```

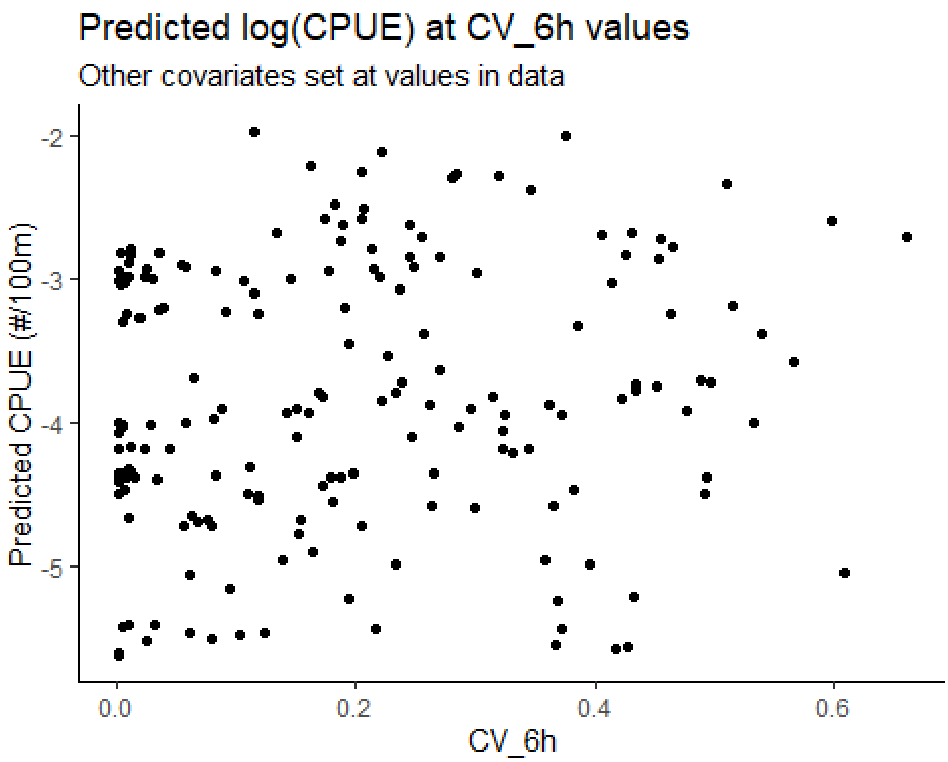



```
# Careful of looking at main effects in the presence of interactions.
# Type 2 tests more appropriate in cases with interactions
# The Type 2 test look at this variable + any other higher order interactions and is a combine
d test.
# So the Type 2 test fo Mean.1h4Discharge is a combined test of the Mean.1hr.Discharge+ mean.1
h.Discharge:Mean.Prev6h4.discharge.
car::Anova(fit100m.AG_3, type=2)

## Registered S3 methods overwritten by 'car':
##   method                          from
##   influence.merMod                lme4
##   cooks.distance.influence.merMod lme4
##   dfbeta.influence.merMod         lme4
##   dfbetas.influence.merMod        lme4

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       4.3657  1    0.03667 *
## Mean.Prev6hDischarge                    2.3868  1    0.12237
## CV.Prev6hDischarge                      6.0436  1    0.01396 *
## Mean.30DayDischarge                     0.0006  1    0.98065
## CV.30DayDischarge                       0.0755  1    0.78349
## Electroshock                            6.1454  1    0.01318 *
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.0326  1    0.85666
```

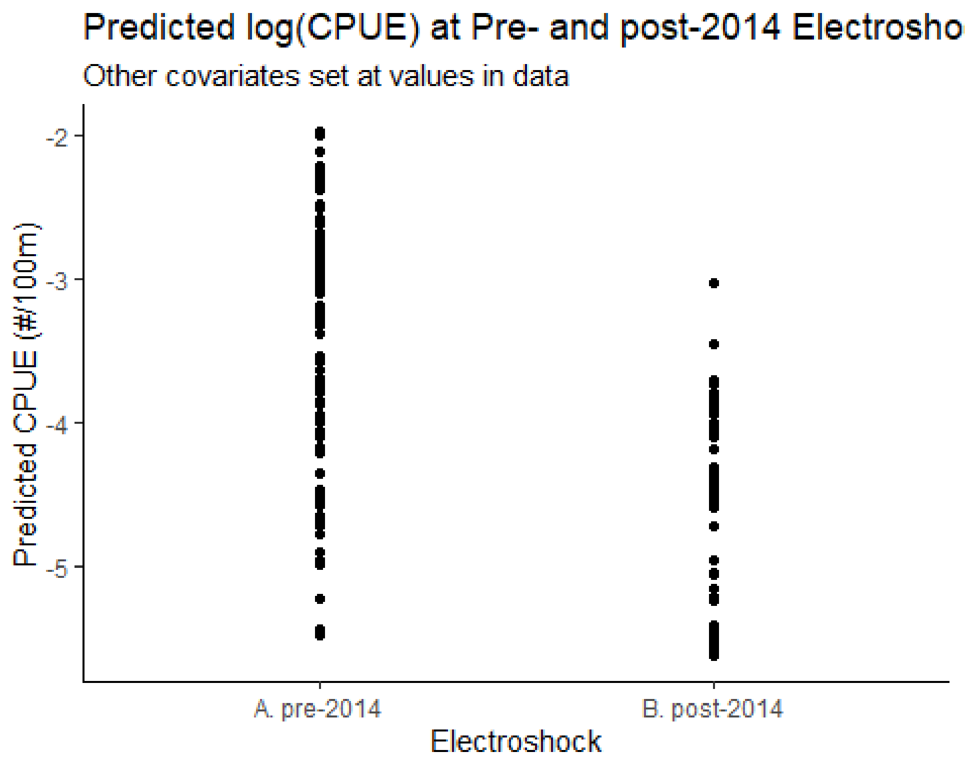
```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Use predict to get estimated CPUE for each row in the data

dataAG3.p <- cbind(dataAG3, pred_100m.AG_3=predict(fit100m.AG_3, newdata=dataAG3))


# 1h discharge
ggplot(data=dataAG3.p, aes(x=Mean.1HrDischarge, y=pred_100m.AG_3))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```




```
# CV 6h
ggplot(data=dataAG3.p, aes(x=CV.Prev6hDischarge, y=pred_100m.AG_3))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_6h") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```

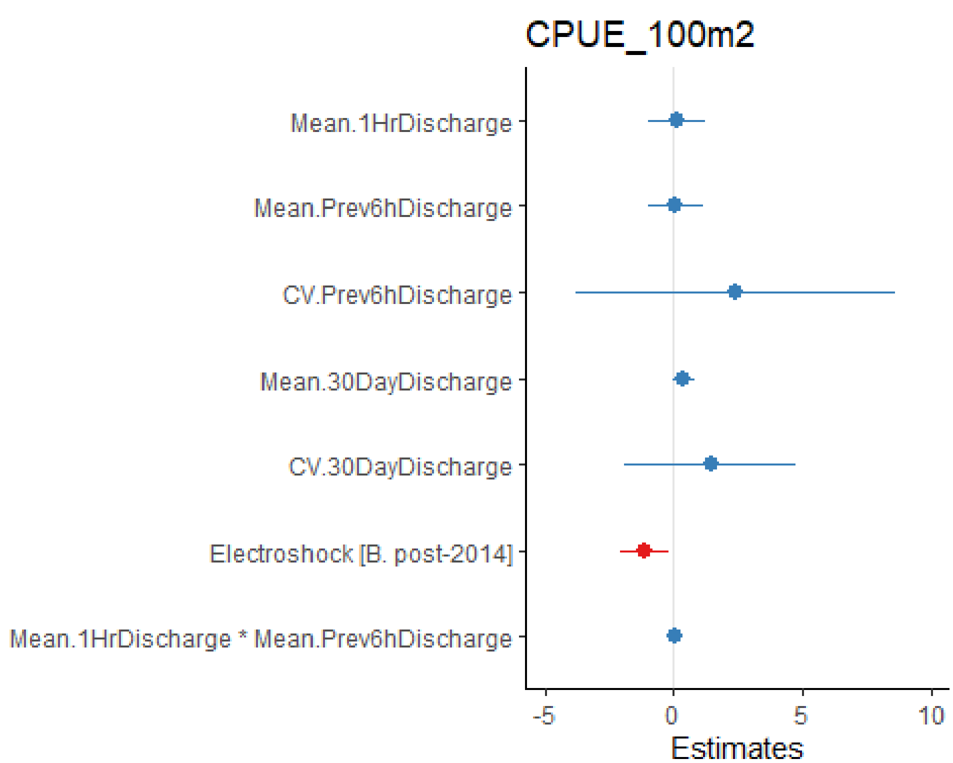



```
# Electroshock
ggplot(data=dataAG3.p, aes(x=Electroshock, y=pred_100m.AG_3))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```



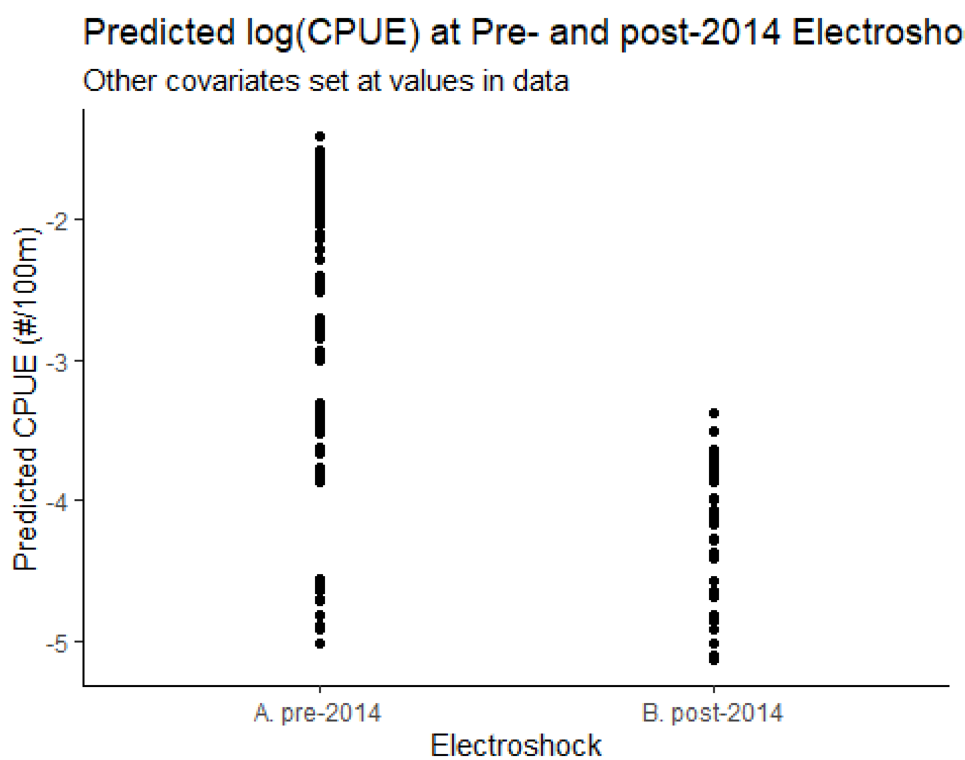

```
# AG 5 -------------------------------------------------------------------------------------
-----------------
summary(fit100m.AG_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataAG5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    446.1    475.3   -213.0    426.1      127
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.73093 -0.43696  0.07514  0.57470  1.93393
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.6356   0.7972
##  Residual               1.0734   1.0361
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                           Estimate Std. Error        df
## (Intercept)                               -3.47053    0.60599  69.86994
## Mean.1HrDischarge                          0.13787    0.56937 128.44655
## Mean.Prev6hDischarge                       0.05846    0.54624 129.03527
## CV.Prev6hDischarge                         2.39736    3.18413 128.83133
```

```
## Mean.30DayDischarge                         0.36390    0.21875  59.08093
## CV.30DayDischarge                           1.43767    1.70428 108.80643
## ElectroshockB. post-2014                   -1.17593    0.48031  16.72694
## Mean.1HrDischarge:Mean.Prev6hDischarge      0.02386    0.09520 134.96626
##                                           t value Pr(>|t|)
## (Intercept)                                -5.727 2.37e-07 ***
## Mean.1HrDischarge                           0.242   0.8091
## Mean.Prev6hDischarge                        0.107   0.9149
## CV.Prev6hDischarge                          0.753   0.4529
## Mean.30DayDischarge                         1.664   0.1015
## CV.30DayDischarge                           0.844   0.4008
## ElectroshockB. post-2014                   -2.448   0.0257 *
## Mean.1HrDischarge:Mean.Prev6hDischarge      0.251   0.8024
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.172
## Mn.Prv6hDsc  0.173 -0.976
## CV.Prv6hDsc -0.250  0.770 -0.740
## Mn.30DyDsch -0.454 -0.001 -0.043 -0.005
## CV.30DyDsch -0.811 -0.065  0.048 -0.066  0.442
## ElcB.p-2014 -0.384  0.006 -0.004  0.057  0.243  0.080
## M.1HD:M.P6D  0.122 -0.026  0.053 -0.052  0.073 -0.291 -0.032

PlotAndSave(fit100m.AG_5,"EffectSize_100m_AG_5.tiff")
```



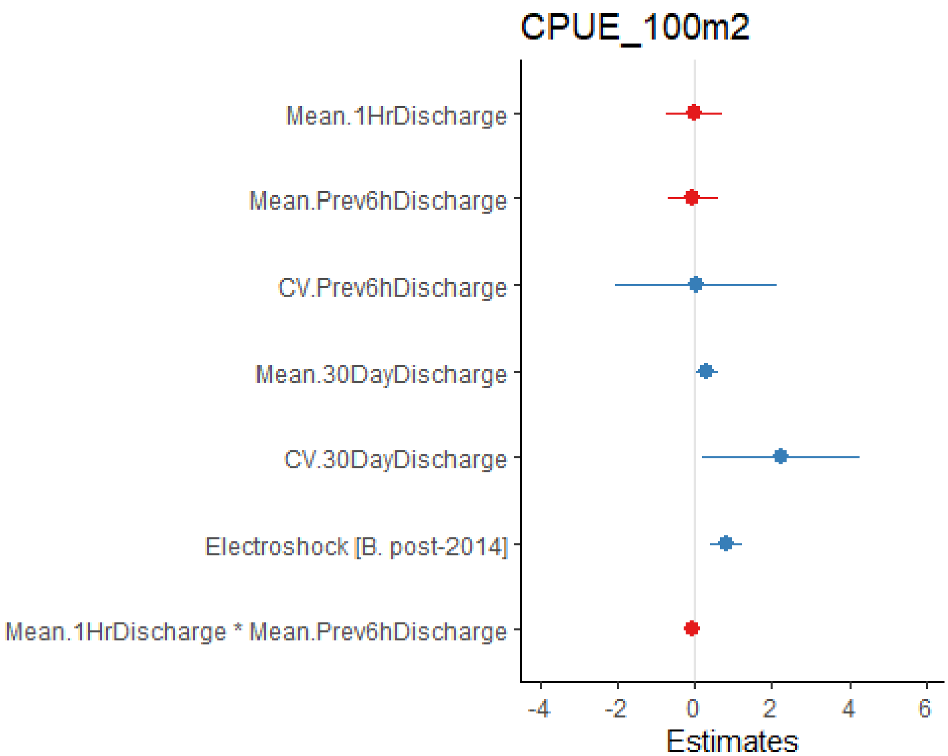

```
car::Anova(fit100m.AG_5, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
```

```
##                                           Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                        0.0619  1    0.80353
## Mean.Prev6hDischarge                     0.0088  1    0.92517
## CV.Prev6hDischarge                       0.5669  1    0.45150
## Mean.30DayDischarge                      2.7675  1    0.09620 .
## CV.30DayDischarge                        0.7116  1    0.39891
## Electroshock                             5.9940  1    0.01435 *
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.0628  1    0.80206
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataAG5.p <- cbind(dataAG5, pred_100m.AG_5=predict(fit100m.AG_5, newdata=dataAG5))

# Electroshock
ggplot(data=dataAG5.p, aes(x=Electroshock, y=pred_100m.AG_5))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other
covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```

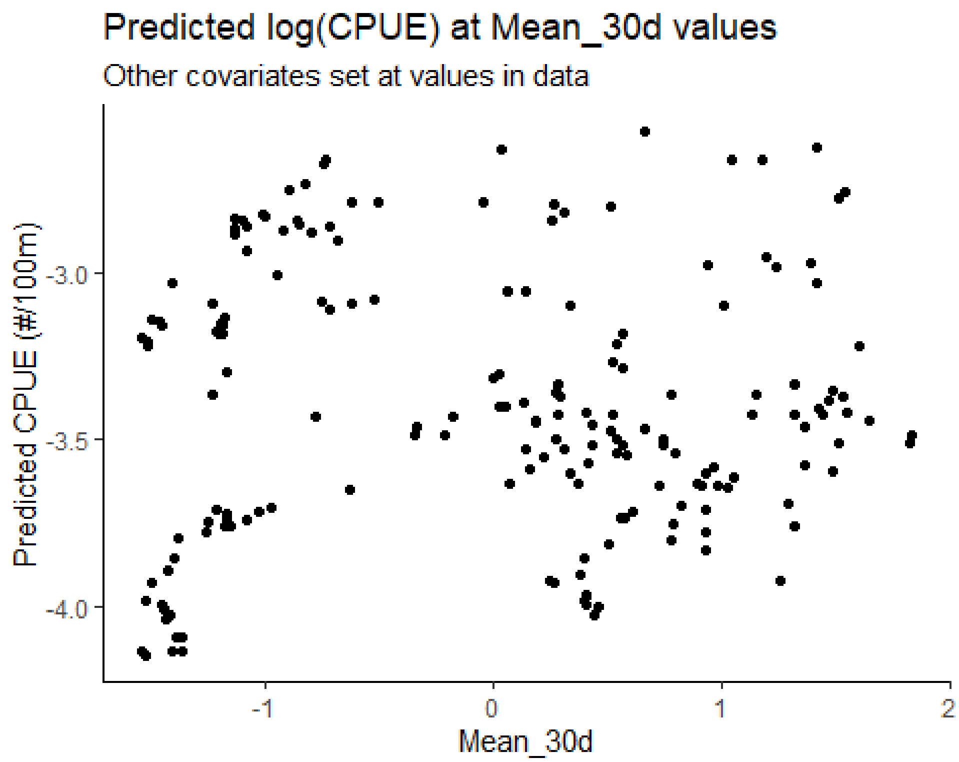



```
# BT 1 ---------------------------------------------------------------------------------------
-------------------
summary(fit100m.BT_1)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
```

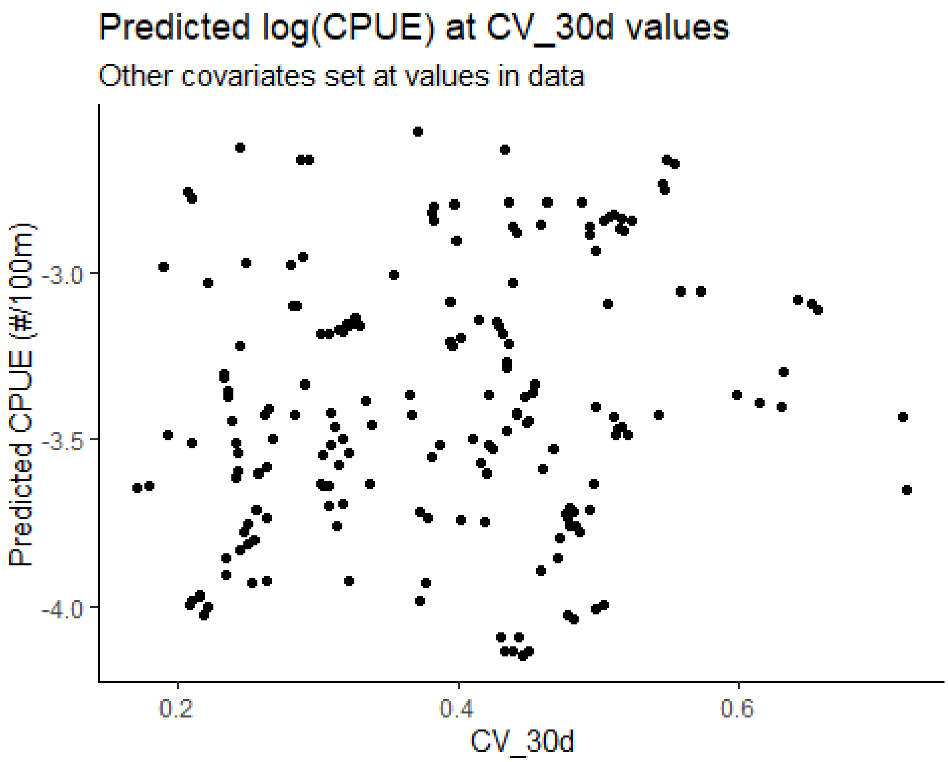
```
##     Electroshock + (1 | SampleYear)
##    Data: dataBT1
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    579.0    611.0   -279.5    559.0      172
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.2722 -0.2799  0.2398  0.6280  1.4287
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.03744  0.1935
##  Residual               1.23005  1.1091
## Number of obs: 182, groups:  SampleYear, 18
##
## Fixed effects:
##                                         Estimate Std. Error        df
## (Intercept)                             -4.49720    0.49088  73.46607
## Mean.1HrDischarge                       -0.02583    0.37630 180.42912
## Mean.Prev6hDischarge                    -0.05585    0.33606 181.96621
## CV.Prev6hDischarge                       0.05737    1.07262 177.70868
## Mean.30DayDischarge                      0.30971    0.14958  65.68372
## CV.30DayDischarge                        2.23944    1.04191  53.21994
## ElectroshockB. post-2014                 0.84201    0.21886  19.32216
## Mean.1HrDischarge:Mean.Prev6hDischarge  -0.06229    0.11394 169.14771
##                                        t value Pr(>|t|)
## (Intercept)                             -9.161 8.78e-14 ***
## Mean.1HrDischarge                       -0.069  0.94535
## Mean.Prev6hDischarge                    -0.166  0.86820
## CV.Prev6hDischarge                       0.053  0.95740
## Mean.30DayDischarge                      2.071  0.04234 *
## CV.30DayDischarge                        2.149  0.03617 *
## ElectroshockB. post-2014                 3.847  0.00106 **
## Mean.1HrDischarge:Mean.Prev6hDischarge  -0.547  0.58534
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.463
## Mn.Prv6hDsc -0.416 -0.940
## CV.Prv6hDsc -0.528 -0.875  0.833
## Mn.30DyDsch -0.565 -0.217  0.038  0.130
## CV.30DyDsch -0.809 -0.057  0.053  0.024  0.551
## ElcB.p-2014 -0.255  0.146 -0.160 -0.116  0.290  0.222
## M.1HD:M.P6D -0.128 -0.237  0.121  0.405  0.055 -0.284 -0.107

PlotAndSave(fit100m.BT_1,"EffectSize_100m_BT_1.tiff")
```



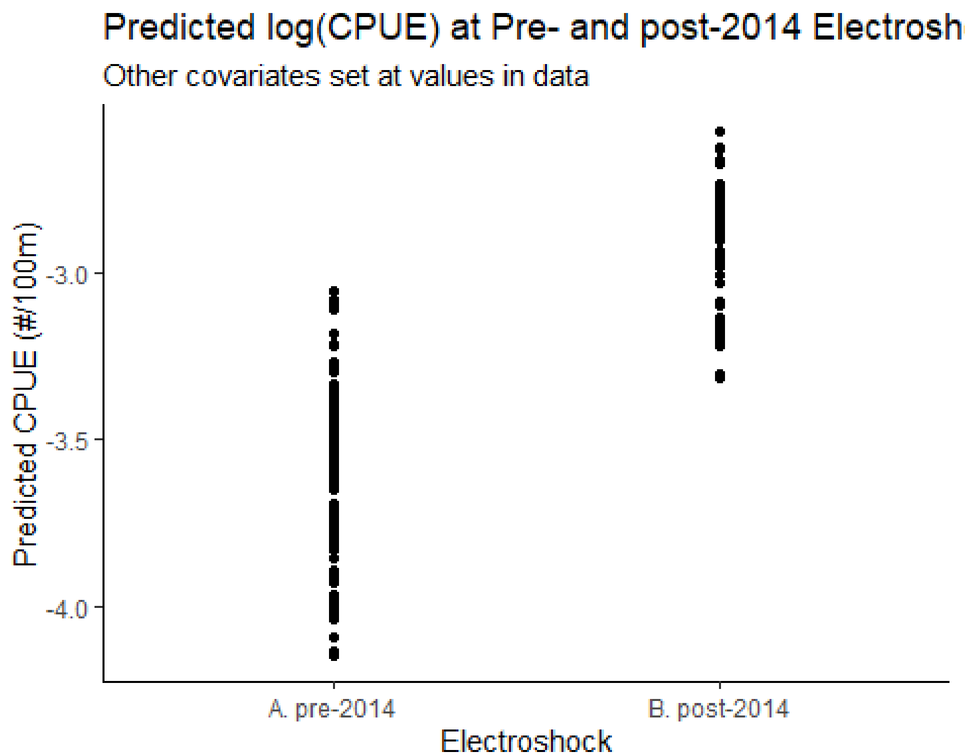

```
car::Anova(fit100m.BT_1, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                           Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                        0.0415  1  0.8385814
## Mean.Prev6hDischarge                     0.0102  1  0.9195299
## CV.Prev6hDischarge                       0.0029  1  0.9573421
## Mean.30DayDischarge                      4.2871  1  0.0384033 *
## CV.30DayDischarge                        4.6197  1  0.0316065 *
## Electroshock                            14.8011  1  0.0001195 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.2988  1  0.5846188
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataBT1.p <- cbind(dataBT1, pred_100m.BT_1=predict(fit100m.BT_1, newdata=dataBT1))

# Mean 30 Days
ggplot(data=dataBT1.p, aes(x=Mean.30DayDischarge, y=pred_100m.BT_1))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()
```




```r
# CV Prev 30 Days
ggplot(data=dataBT1.p, aes(x=CV.30DayDischarge, y=pred_100m.BT_1))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()
```

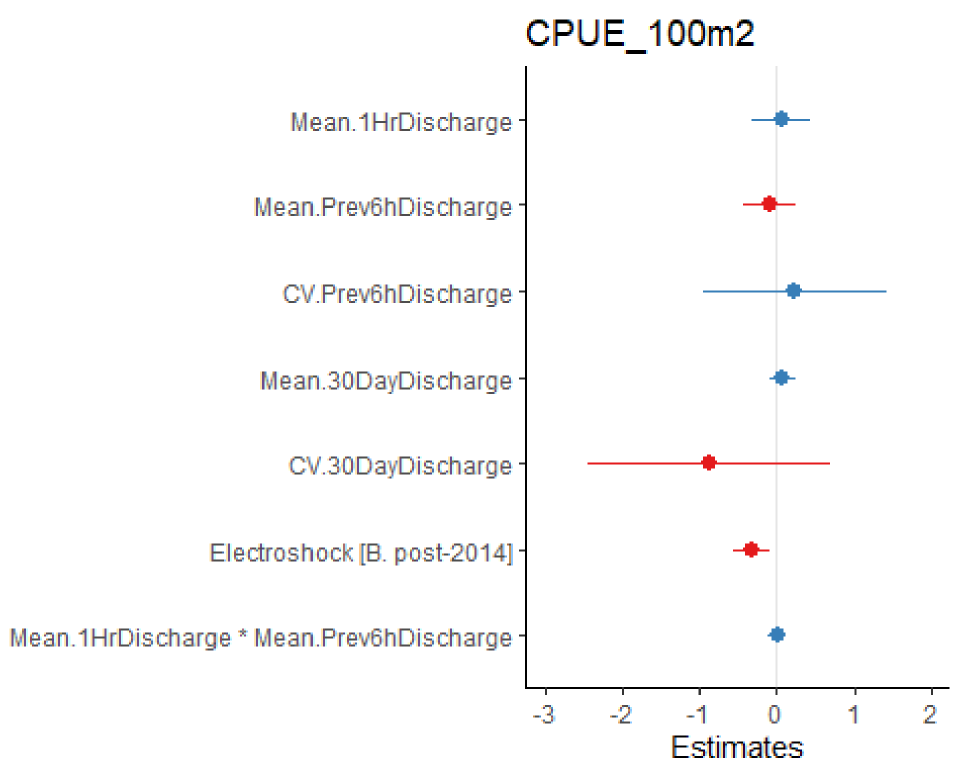



```
#Electroshocking
ggplot(data=dataBT1.p, aes(x=Electroshock, y=pred_100m.BT_1))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()
```



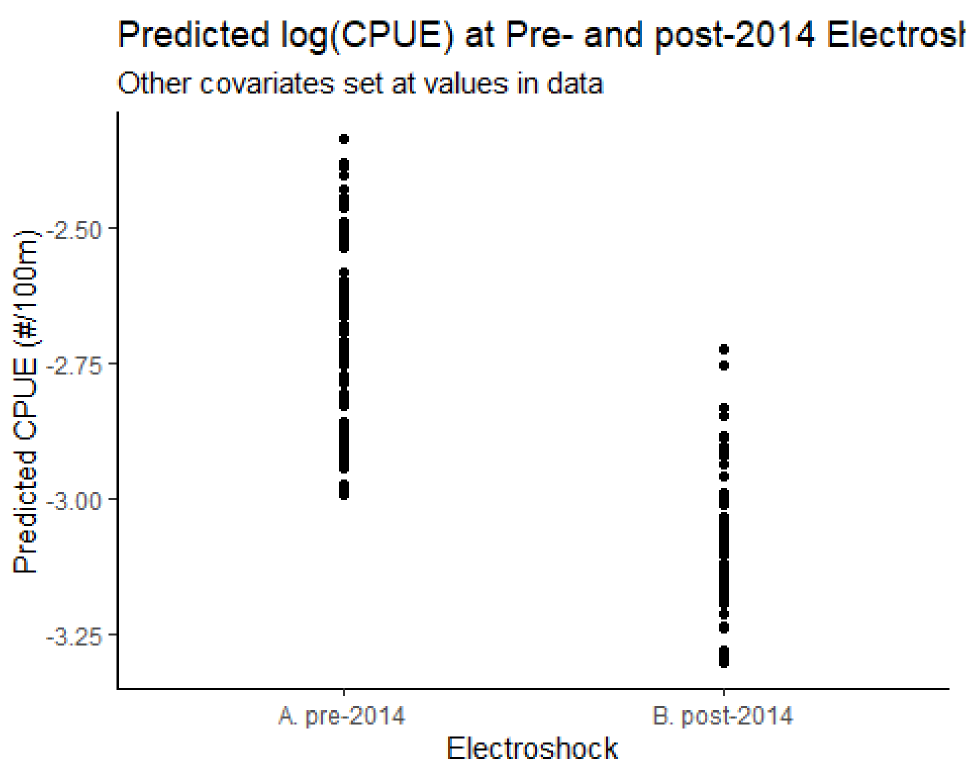

```
# BT 3 -------------------------------------------------------------------------------------
-------------------
summary(fit100m.BT_3)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataBT3
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    462.5    495.1   -221.3    442.5      182
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5889 -0.4459  0.2116  0.5852  2.0930
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.000
##  Residual               0.5868   0.766
## Number of obs: 192, groups:  SampleYear, 18
##
## Fixed effects:
##                                        Estimate Std. Error        df
## (Intercept)                            -2.44370    0.31905 192.00000
## Mean.1HrDischarge                       0.06420    0.19510 192.00000
## Mean.Prev6hDischarge                   -0.08558    0.17511 192.00000
## CV.Prev6hDischarge                      0.23591    0.61328 192.00000
```

```
## Mean.30DayDischarge                          0.08185    0.08999 192.00000
## CV.30DayDischarge                           -0.87395    0.80475 192.00000
## ElectroshockB. post-2014                    -0.33380    0.12136 192.00000
## Mean.1HrDischarge:Mean.Prev6hDischarge       0.00707    0.06082 192.00000
##                                             t value Pr(>|t|)
## (Intercept)                                  -7.659 8.96e-13 ***
## Mean.1HrDischarge                             0.329  0.74248
## Mean.Prev6hDischarge                         -0.489  0.62561
## CV.Prev6hDischarge                            0.385  0.70090
## Mean.30DayDischarge                           0.910  0.36418
## CV.30DayDischarge                            -1.086  0.27884
## ElectroshockB. post-2014                     -2.751  0.00652 **
## Mean.1HrDischarge:Mean.Prev6hDischarge        0.116  0.90758
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.367
## Mn.Prv6hDsc -0.403 -0.889
## CV.Prv6hDsc -0.407 -0.803  0.692
## Mn.30DyDsch -0.482 -0.205 -0.032  0.134
## CV.30DyDsch -0.871 -0.068  0.180 -0.010  0.450
## ElcB.p-2014 -0.274  0.089 -0.113 -0.044  0.258  0.187
## M.1HD:M.P6D -0.097 -0.199  0.064  0.404  0.044 -0.226 -0.075
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.BT_3,"EffectSize_100m_BT_3.tiff")
```



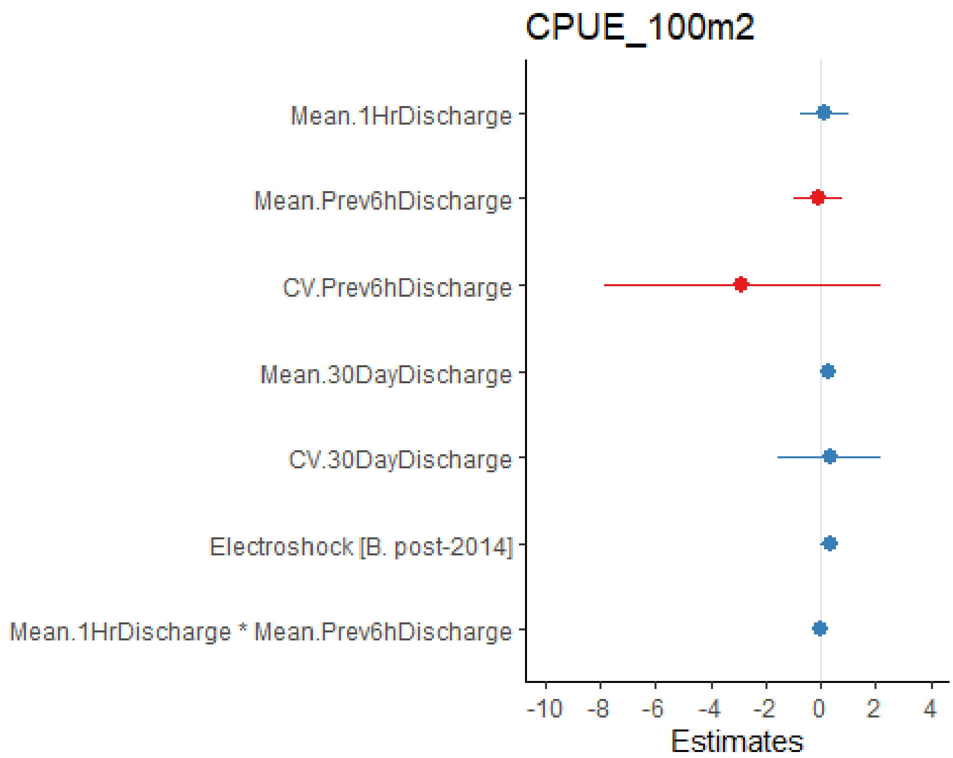

```
car::Anova(fit100m.BT_3, type=2)
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                        Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                     0.1292  1    0.71927
## Mean.Prev6hDischarge                  0.2472  1    0.61909
## CV.Prev6hDischarge                    0.1480  1    0.70048
## Mean.30DayDischarge                   0.8273  1    0.36304
## CV.30DayDischarge                     1.1794  1    0.27748
## Electroshock                          7.5654  1    0.00595 **
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.0135  1    0.90746
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataBT3.p <- cbind(dataBT3, pred_100m.BT_3=predict(fit100m.BT_3, newdata=dataBT3))

#Electroshocking
ggplot(data=dataBT3.p, aes(x=Electroshock, y=pred_100m.BT_3))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```

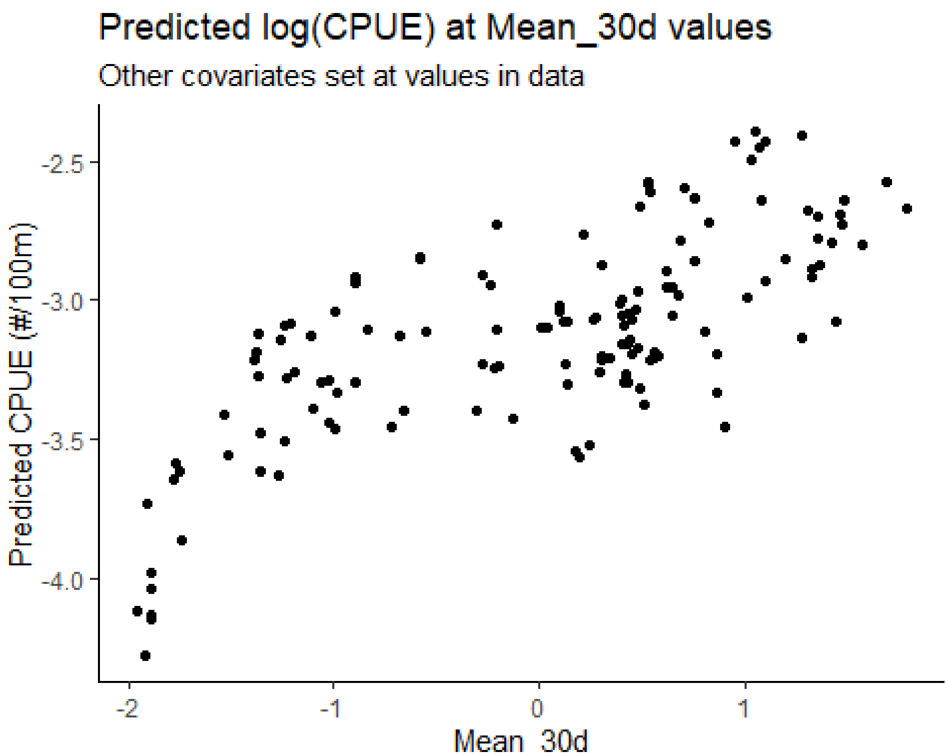



```
# BT 5 ---------------------------------------------------------------------------------------------------
summary(fit100m.BT_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
```

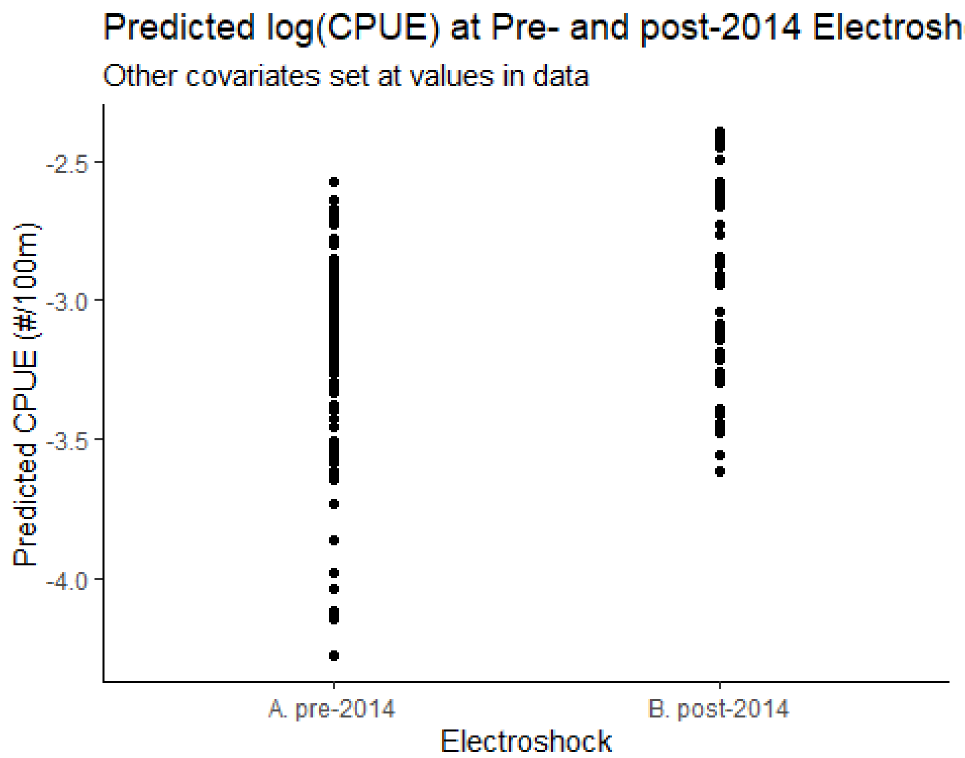
```
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataBT5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    373.6    402.8   -176.8    353.6      127
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.8159 -0.4215  0.1343  0.5926  1.7886
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.7734   0.8794
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                         Estimate Std. Error         df
## (Intercept)                            -3.181444   0.331759 137.000000
## Mean.1HrDischarge                       0.121611   0.457003 137.000000
## Mean.Prev6hDischarge                   -0.098392   0.439222 137.000000
## CV.Prev6hDischarge                     -2.851387   2.571035 137.000000
## Mean.30DayDischarge                     0.294356   0.116713 137.000000
## CV.30DayDischarge                       0.341441   0.953053 137.000000
## ElectroshockB. post-2014                0.327445   0.173439 137.000000
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.003656   0.070317 137.000000
##                                       t value Pr(>|t|)
## (Intercept)                            -9.590   <2e-16 ***
## Mean.1HrDischarge                       0.266   0.7906
## Mean.Prev6hDischarge                   -0.224   0.8231
## CV.Prev6hDischarge                     -1.109   0.2694
## Mean.30DayDischarge                     2.522   0.0128 *
## CV.30DayDischarge                       0.358   0.7207
## ElectroshockB. post-2014                1.888   0.0611 .
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.052   0.9586
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.344
## Mn.Prv6hDsc  0.361 -0.975
## CV.Prv6hDsc -0.472  0.790 -0.759
## Mn.30DyDsch -0.532  0.105 -0.229  0.165
## CV.30DyDsch -0.825  0.004 -0.039  0.017  0.470
## ElcB.p-2014 -0.303  0.085 -0.102  0.205  0.281  0.073
## M.1HD:M.P6D  0.168 -0.104  0.120 -0.081 -0.011 -0.360 -0.115
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.BT_5,"EffectSize_100m_BT_5.tiff")
```




```
car::Anova(fit100m.BT_5, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       0.0745  1    0.78488
## Mean.Prev6hDischarge                    0.0538  1    0.81661
## CV.Prev6hDischarge                      1.2300  1    0.26741
## Mean.30DayDischarge                     6.3607  1    0.01167 *
## CV.30DayDischarge                       0.1284  1    0.72015
## Electroshock                            3.5644  1    0.05903 .
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.0027  1    0.95854
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataBT5.p <- cbind(dataBT5, pred_100m.BT_5=predict(fit100m.BT_5, newdata=dataBT5))

# Mean 30 Days
ggplot(data=dataBT5.p, aes(x=Mean.30DayDischarge, y=pred_100m.BT_5))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```



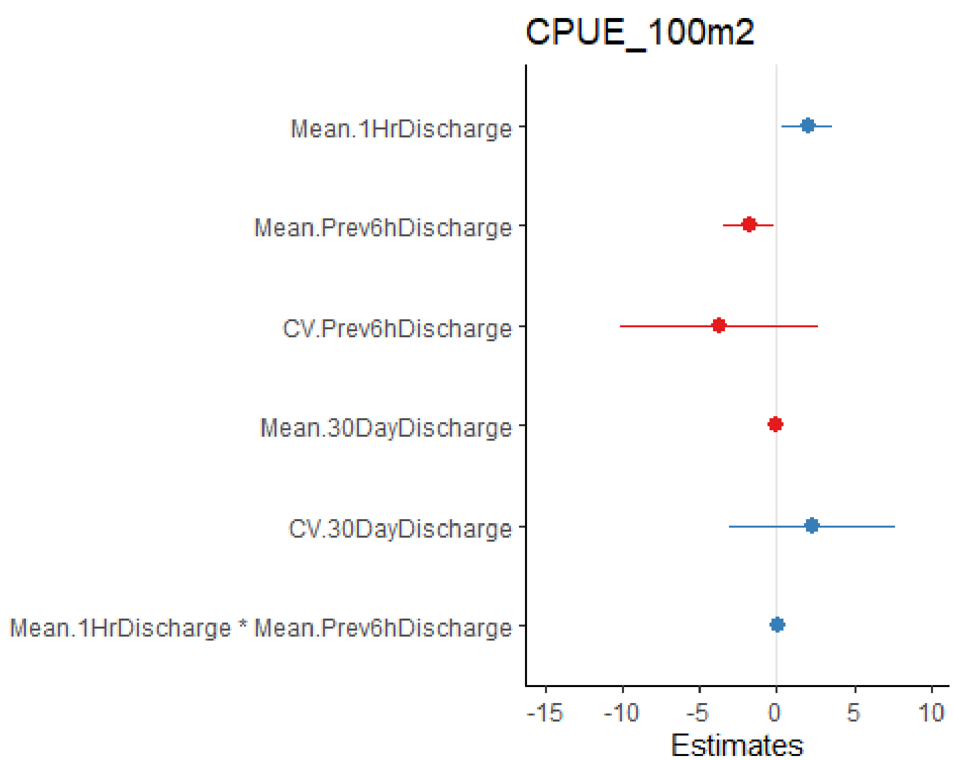

```
#Electroshocking
ggplot(data=dataBT5.p, aes(x=Electroshock, y=pred_100m.BT_5))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```




```
# BT 6 ---------------------------------------------------------------------------------------
-------------------
summary(fit100m.BT_6)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataBT6
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    157.2    172.8    -69.6    139.2       33
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1300 -0.4551  0.2437  0.6026  1.7858
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.1831   0.4279
##  Residual               1.4806   1.2168
## Number of obs: 42, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error       df
## (Intercept)                              -4.33658    0.84556  8.65283
## Mean.1HrDischarge                         2.00155    0.82246 40.69986
## Mean.Prev6hDischarge                     -1.78356    0.83949 37.50686
## CV.Prev6hDischarge                       -3.67920    3.28788 35.28984
```

```
## Mean.30DayDischarge                         -0.04510    0.28815  7.72834
## CV.30DayDischarge                            2.32839    2.72084  8.73815
## Mean.1HrDischarge:Mean.Prev6hDischarge       0.02592    0.15614 39.37921
##                                             t value Pr(>|t|)
## (Intercept)                                  -5.129 0.000702 ***
## Mean.1HrDischarge                             2.434 0.019429 *
## Mean.Prev6hDischarge                         -2.125 0.040273 *
## CV.Prev6hDischarge                           -1.119 0.270691
## Mean.30DayDischarge                          -0.157 0.879630
## CV.30DayDischarge                             0.856 0.414979
## Mean.1HrDischarge:Mean.Prev6hDischarge        0.166 0.868995
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.150
## Mn.Prv6hDsc -0.194 -0.956
## CV.Prv6hDsc -0.164 -0.034  0.086
## Mn.30DyDsch -0.064  0.091 -0.192  0.064
## CV.30DyDsch -0.907 -0.171  0.209 -0.065  0.033
## M.1HD:M.P6D -0.054  0.107 -0.126  0.226  0.205 -0.157
```

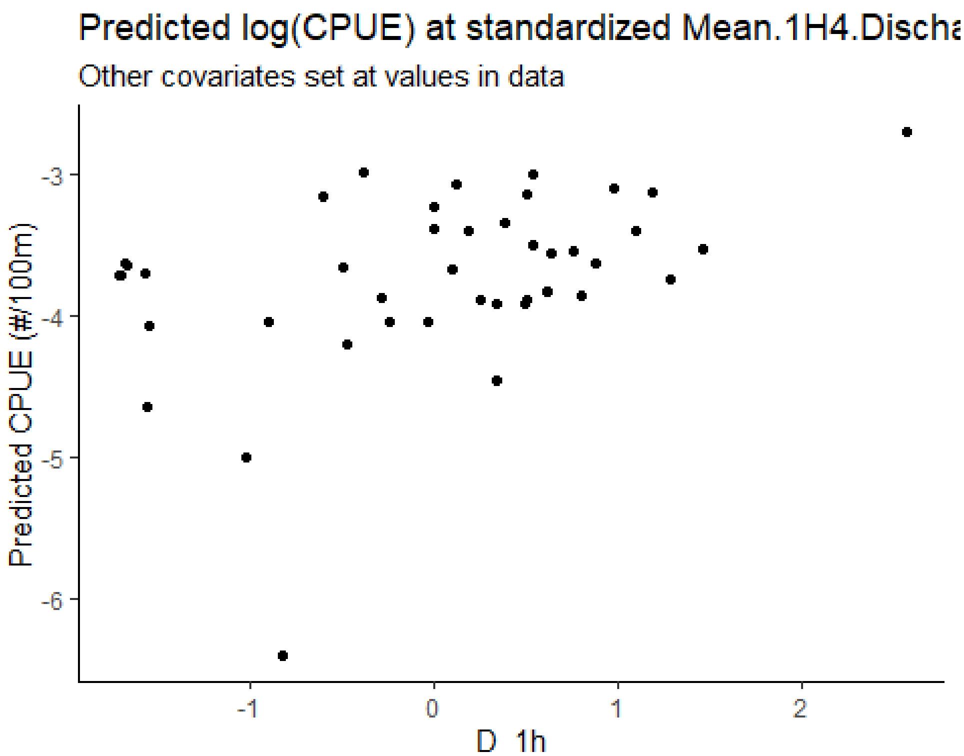
```
PlotAndSave(fit100m.BT_6,"EffectSize_100m_BT_6.tiff")
```



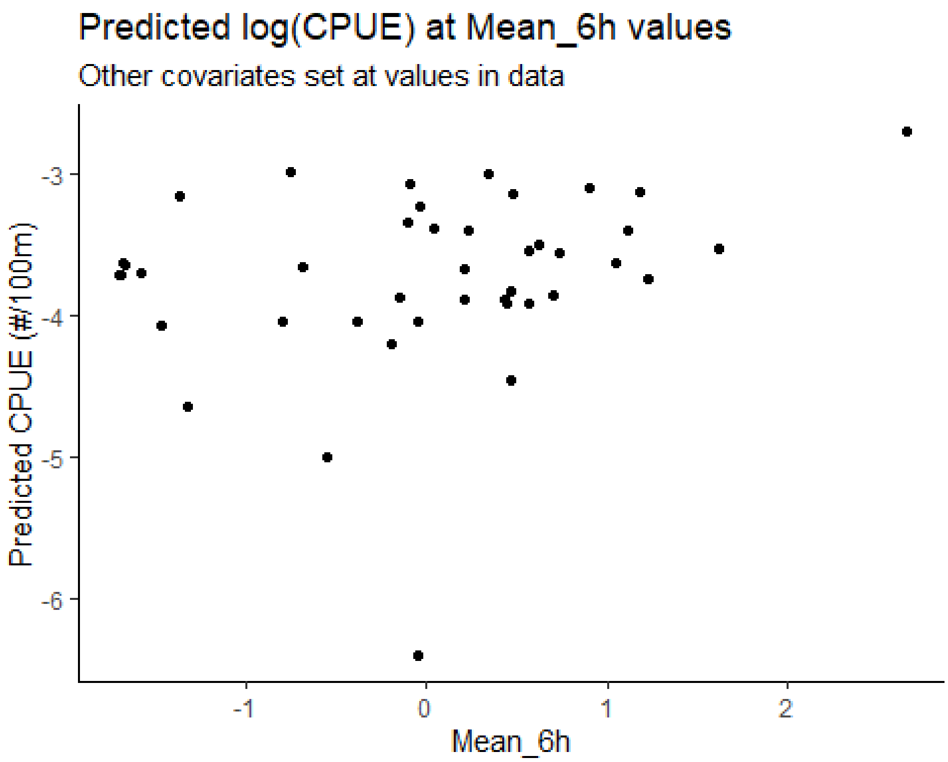

```
car::Anova(fit100m.BT_6, type=2)
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                           Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                        5.9040  1    0.01511 *
## Mean.Prev6hDischarge                     4.4969  1    0.03396 *
```

```
## CV.Prev6hDischarge                        1.2522  1     0.26313
## Mean.30DayDischarge                       0.0245  1     0.87562
## CV.30DayDischarge                         0.7323  1     0.39213
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.0276  1     0.86815
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataBT6.p <- cbind(dataBT6, pred_100m.BT_6=predict(fit100m.BT_6, newdata=dataBT6))

# Mean 1h
ggplot(data=dataBT6.p, aes(x=Mean.1HrDischarge, y=pred_100m.BT_6))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    ylab("Predicted CPUE (#/100m)") +
    xlab("D_1h") +
    geom_point()
```

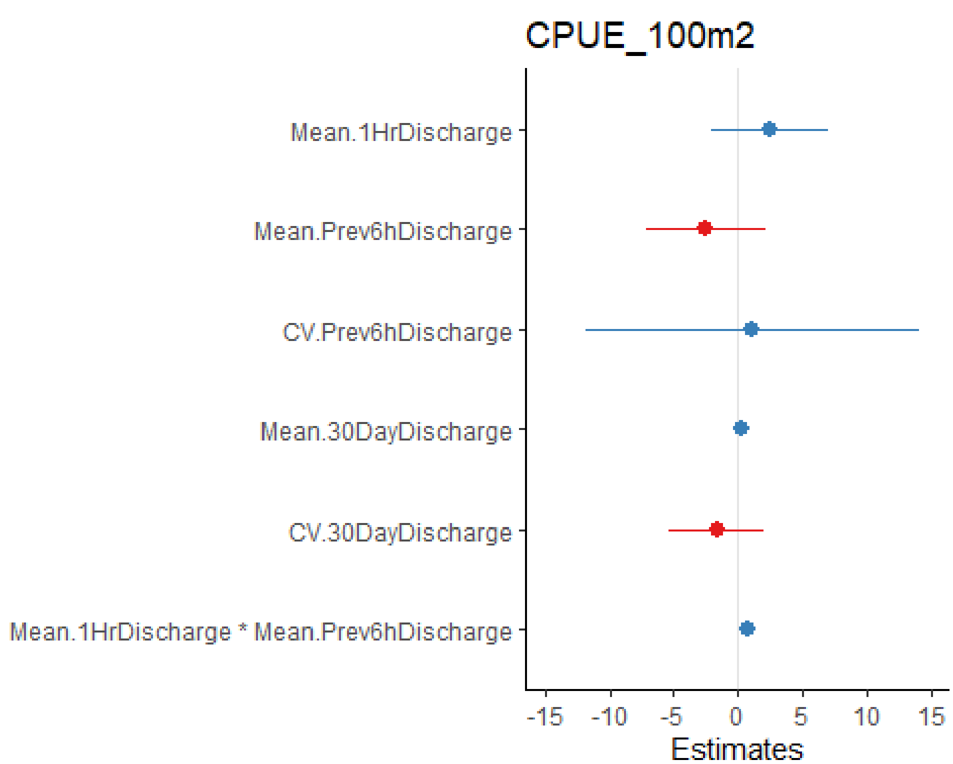



```
# Mean Prev 6
ggplot(data=dataBT6.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.BT_6))+
    ggtitle("Predicted log(CPUE) at Mean_6h values",subtitle="Other covariates set at values i
n data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()
```



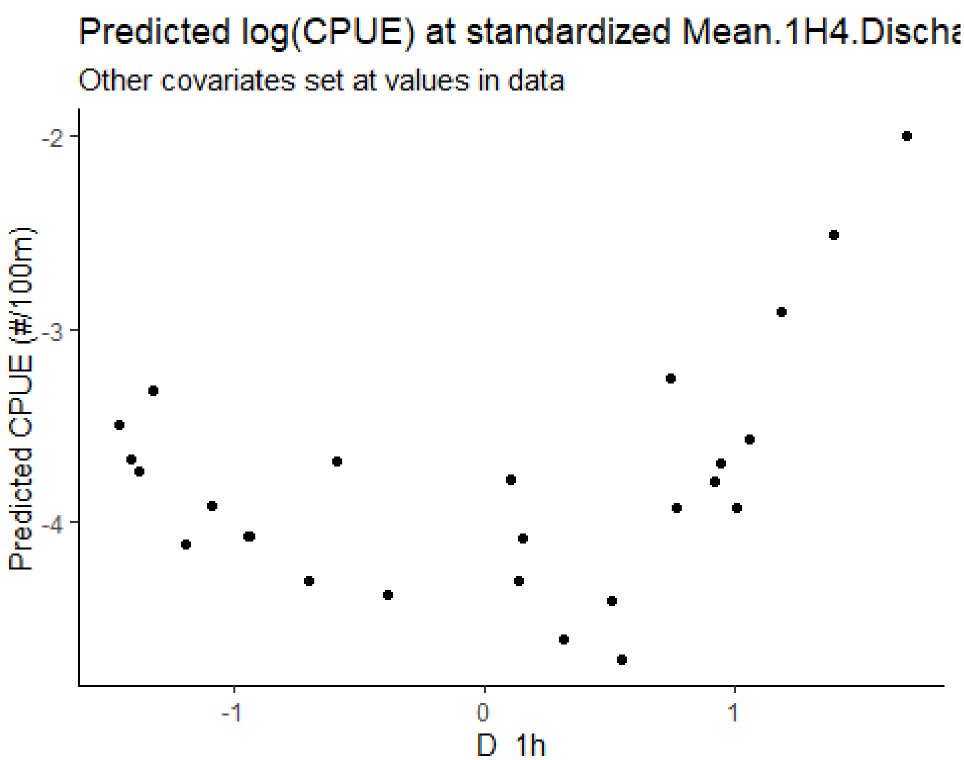

```
# BT 7 -----------------------------------------------------------------------------------------
-------------------
summary(fit100m.BT_7)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataBT7
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     82.4     93.7    -32.2     64.4       17
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.4017 -0.3177  0.1060  0.6350  1.6812
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.6975   0.8351
## Number of obs: 26, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error      df t value
## (Intercept)                               -3.9655     0.7586 26.0000  -5.227
## Mean.1HrDischarge                          2.5235     2.3257 26.0000   1.085
## Mean.Prev6hDischarge                      -2.4972     2.3981 26.0000  -1.041
## CV.Prev6hDischarge                         1.0935     6.6185 26.0000   0.165
```

```
## Mean.30DayDischarge                         0.3150     0.2993 26.0000   1.052
## CV.30DayDischarge                          -1.6774     1.8975 26.0000  -0.884
## Mean.1HrDischarge:Mean.Prev6hDischarge      0.7362     0.2565 26.0000   2.871
##                                           Pr(>|t|)
## (Intercept)                               1.85e-05 ***
## Mean.1HrDischarge                          0.28787
## Mean.Prev6hDischarge                       0.30731
## CV.Prev6hDischarge                         0.87005
## Mean.30DayDischarge                        0.30226
## CV.30DayDischarge                          0.38479
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.00803 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.216
## Mn.Prv6hDsc -0.232 -0.993
## CV.Prv6hDsc -0.343 -0.737  0.733
## Mn.30DyDsch  0.251  0.084 -0.173  0.073
## CV.30DyDsch -0.863 -0.072  0.082  0.018 -0.256
## M.1HD:M.P6D -0.454  0.178 -0.150  0.116 -0.196  0.119
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.BT_7,"EffectSize_100m_BT_7.tiff")
```

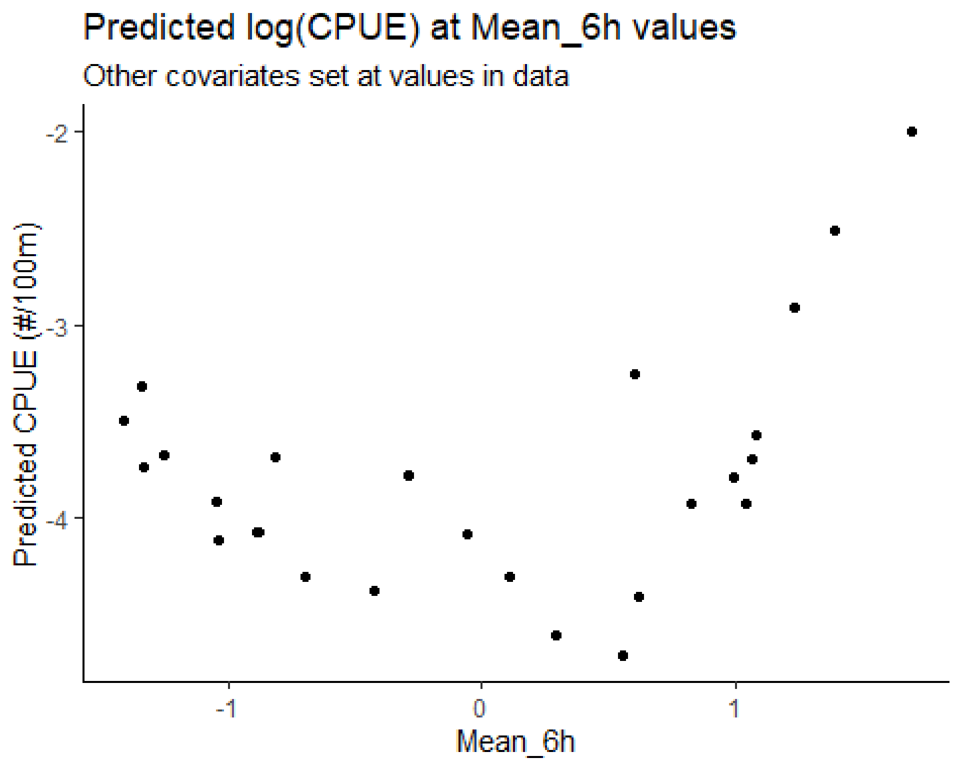



```
car::Anova(fit100m.BT_7, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
```

```
## Mean.1HrDischarge                          0.3417  1   0.558874
## Mean.Prev6hDischarge                       0.3826  1   0.536191
## CV.Prev6hDischarge                         0.0273  1   0.868771
## Mean.30DayDischarge                        1.1077  1   0.292572
## CV.30DayDischarge                          0.7815  1   0.376690
## Mean.1HrDischarge:Mean.Prev6hDischarge 8.2420  1   0.004093 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataBT7.p <- cbind(dataBT7, pred_100m.BT_7=predict(fit100m.BT_7, newdata=dataBT7))

# Mean 1h
ggplot(data=dataBT7.p, aes(x=Mean.1HrDischarge, y=pred_100m.BT_7))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    ylab("Predicted CPUE (#/100m)") +
    xlab("D_1h") +
    geom_point()
```

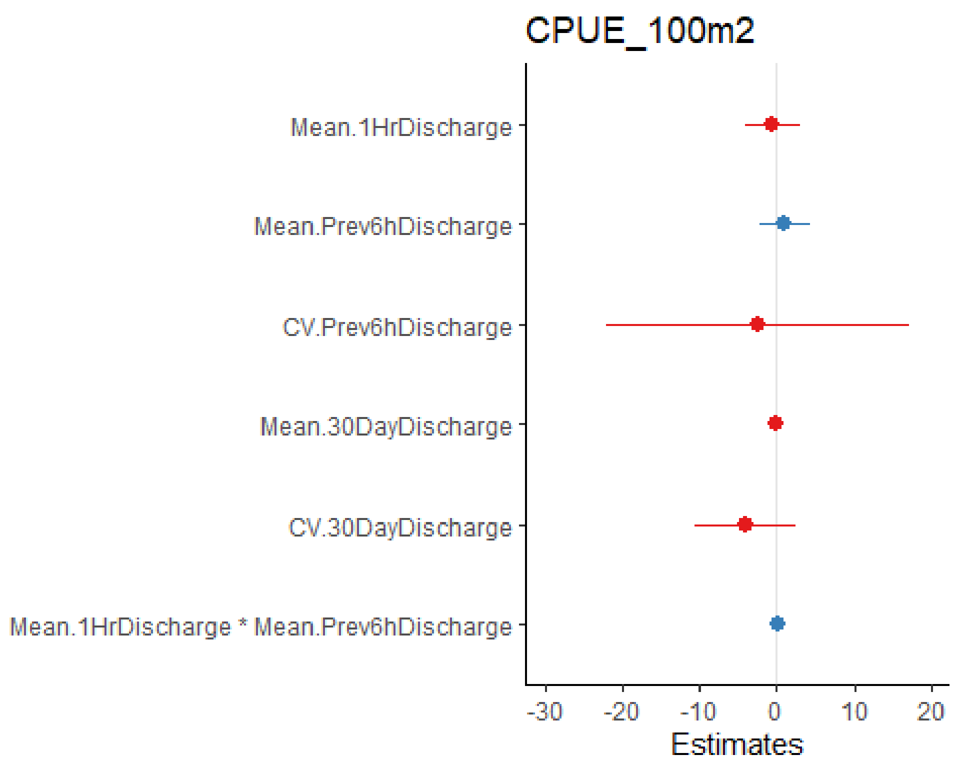



```
# Mean Prev 6
ggplot(data=dataBT7.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.BT_7))+
    ggtitle("Predicted log(CPUE) at Mean_6h values",subtitle="Other covariates set at values i
n data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()
```




```
# BT 9 -----------------------------------------------------------------------------------
-------------------
summary(fit100m.BT_9)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataBT9
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    119.6    133.3    -50.8    101.6       25
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9846 -0.6879  0.2394  0.7366  1.4343
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.000    0.000
##  Residual               1.162    1.078
## Number of obs: 34, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error      df t value
## (Intercept)                               -3.5954     0.7784 34.0000  -4.619
## Mean.1HrDischarge                         -0.5369     1.7842 34.0000  -0.301
## Mean.Prev6hDischarge                       0.9558     1.6709 34.0000   0.572
## CV.Prev6hDischarge                        -2.4058    10.0667 34.0000  -0.239
```

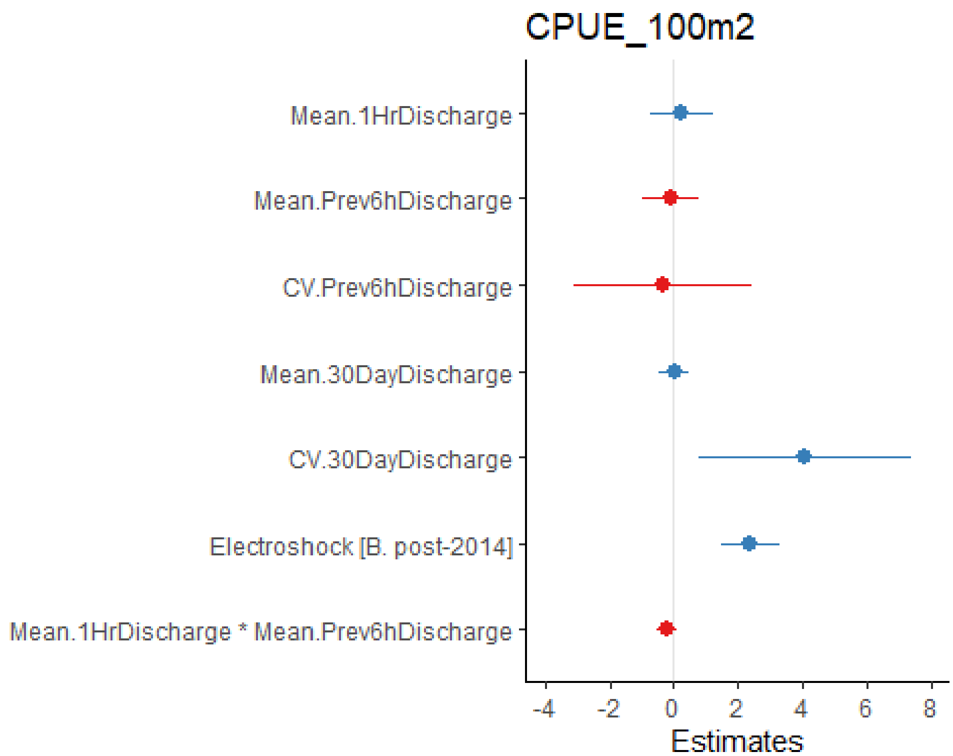
```
## Mean.30DayDischarge                          -0.2186     0.2809 34.0000  -0.778
## CV.30DayDischarge                            -4.0446     3.3377 34.0000  -1.212
## Mean.1HrDischarge:Mean.Prev6hDischarge        0.2285     0.3198 34.0000   0.715
##                                             Pr(>|t|)
## (Intercept)                                 5.33e-05 ***
## Mean.1HrDischarge                              0.765
## Mean.Prev6hDischarge                           0.571
## CV.Prev6hDischarge                             0.813
## Mean.30DayDischarge                            0.442
## CV.30DayDischarge                              0.234
## Mean.1HrDischarge:Mean.Prev6hDischarge         0.480
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr -0.218
## Mn.Prv6hDsc  0.180 -0.984
## CV.Prv6hDsc -0.264  0.820 -0.786
## Mn.30DyDsch -0.215 -0.280  0.180 -0.327
## CV.30DyDsch -0.772 -0.256  0.244 -0.299  0.508
## M.1HD:M.P6D  0.088  0.458 -0.362  0.516 -0.582 -0.607
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.BT_9,"EffectSize_100m_BT_9.tiff")
```




```
car::Anova(fit100m.BT_9, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                           Chisq Df Pr(>Chisq)
```

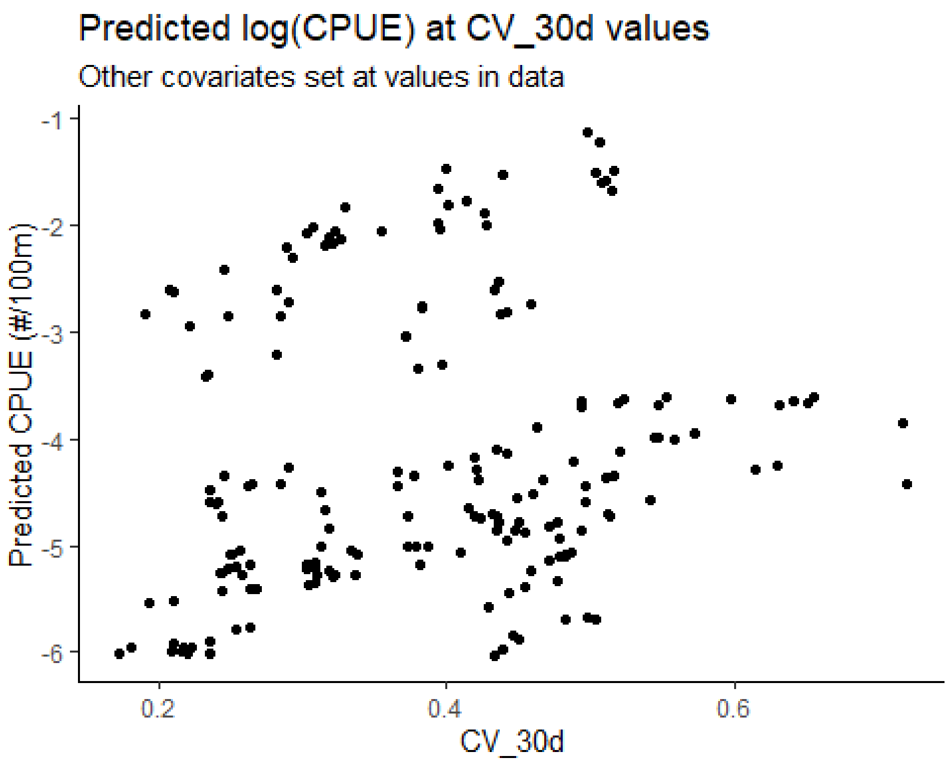
```
## Mean.1HrDischarge                      0.5000  1     0.4795
## Mean.Prev6hDischarge                   0.7942  1     0.3728
## CV.Prev6hDischarge                     0.0571  1     0.8111
## Mean.30DayDischarge                    0.6055  1     0.4365
## CV.30DayDischarge                      1.4685  1     0.2256
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.5107  1     0.4749

dataBT9.p <- cbind(dataBT9, pred_100m.BT_9=predict(fit100m.BT_9, newdata=dataBT9))

#NONE

# CSU 1 -----------------------------------------------------------------------------------------------
summary(fit100m.CSU_1)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischarge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataCSU1
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    692.7    724.8   -336.4    672.7      172
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.56920 -0.75734  0.06763  0.70898  2.32047
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.5788   0.7608
##  Residual               2.0675   1.4379
## Number of obs: 182, groups:  SampleYear, 18
##
## Fixed effects:
##                                         Estimate Std. Error         df
## (Intercept)                           -6.318e+00  7.833e-01  1.063e+02
## Mean.1HrDischarge                      2.333e-01  5.010e-01  1.718e+02
## Mean.Prev6hDischarge                  -9.060e-02  4.516e-01  1.754e+02
## CV.Prev6hDischarge                    -3.286e-01  1.419e+00  1.696e+02
## Mean.30DayDischarge                    9.251e-04  2.485e-01  7.391e+01
## CV.30DayDischarge                      4.088e+00  1.691e+00  1.189e+02
## ElectroshockB. post-2014               2.375e+00  4.678e-01  1.765e+01
## Mean.1HrDischarge:Mean.Prev6hDischarge -2.100e-01  1.579e-01  1.812e+02
##                                        t value Pr(>|t|)
## (Intercept)                             -8.066 1.18e-12 ***
## Mean.1HrDischarge                        0.466   0.6421
## Mean.Prev6hDischarge                    -0.201   0.8412
## CV.Prev6hDischarge                      -0.232   0.8171
## Mean.30DayDischarge                      0.004   0.9970
## CV.30DayDischarge                        2.417   0.0172 *
## ElectroshockB. post-2014                 5.077 8.33e-05 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  -1.330   0.1851
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
```

```
##               (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.370
## Mn.Prv6hDsc -0.338 -0.937
## CV.Prv6hDsc -0.442 -0.866  0.827
## Mn.30DyDsch -0.553 -0.161  0.049  0.116
## CV.30DyDsch -0.829 -0.030  0.028  0.018  0.538
## ElcB.p-2014 -0.299  0.099 -0.096 -0.061  0.249  0.162
## M.1HD:M.P6D -0.074 -0.258  0.155  0.413  0.035 -0.280 -0.062

PlotAndSave(fit100m.CSU_1,"EffectSize_100m_CSU_1.tiff")
```

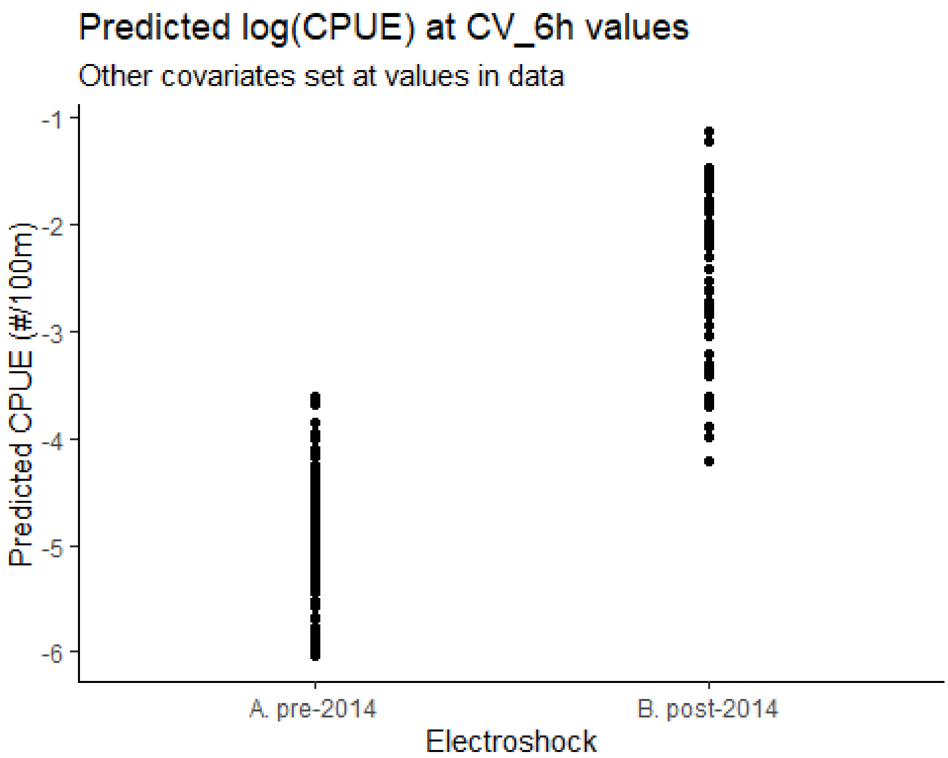



```
car::Anova(fit100m.CSU_1, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       0.0160  1    0.89929
## Mean.Prev6hDischarge                    0.0000  1    0.99585
## CV.Prev6hDischarge                      0.0536  1    0.81684
## Mean.30DayDischarge                     0.0000  1    0.99703
## CV.30DayDischarge                       5.8408  1    0.01566 *
## Electroshock                           25.7796  1  3.827e-07 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  1.7695  1    0.18344
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataCSU1.p <- cbind(dataCSU1, pred_100m.CSU_1=predict(fit100m.CSU_1, newdata=dataCSU1))

# CV Prev 30 Days
ggplot(data=dataCSU1.p, aes(x=CV.30DayDischarge, y=pred_100m.CSU_1))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
```

```
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()
```

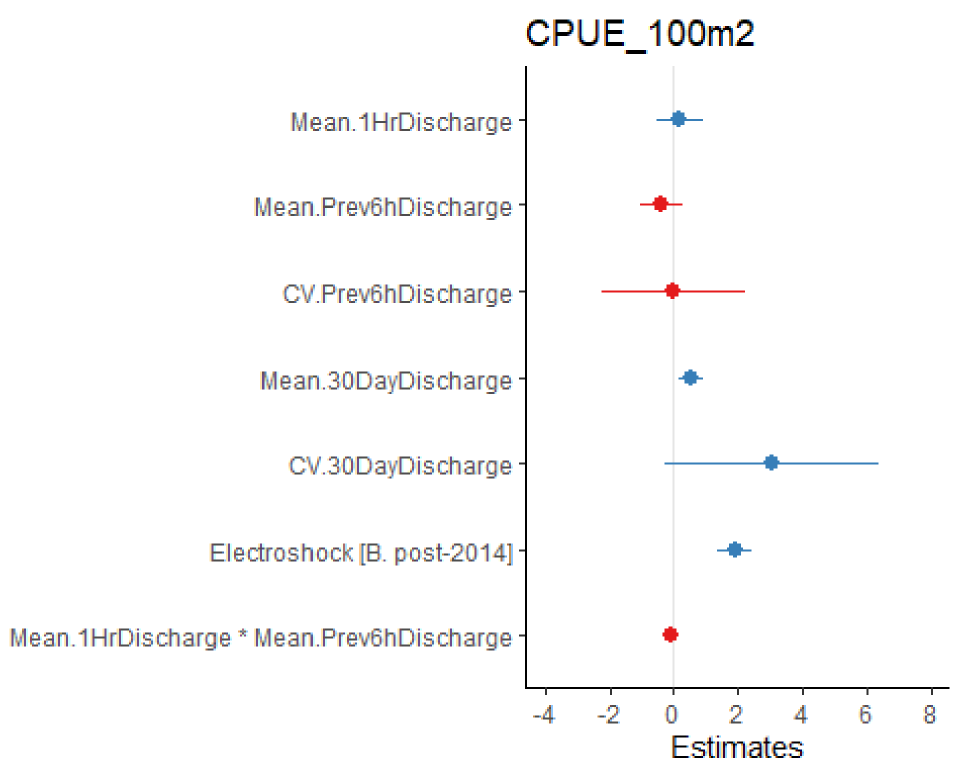



```
    # NOISE?

#Electroshocking
ggplot(data=dataCSU1.p, aes(x=Electroshock, y=pred_100m.CSU_1))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()
```



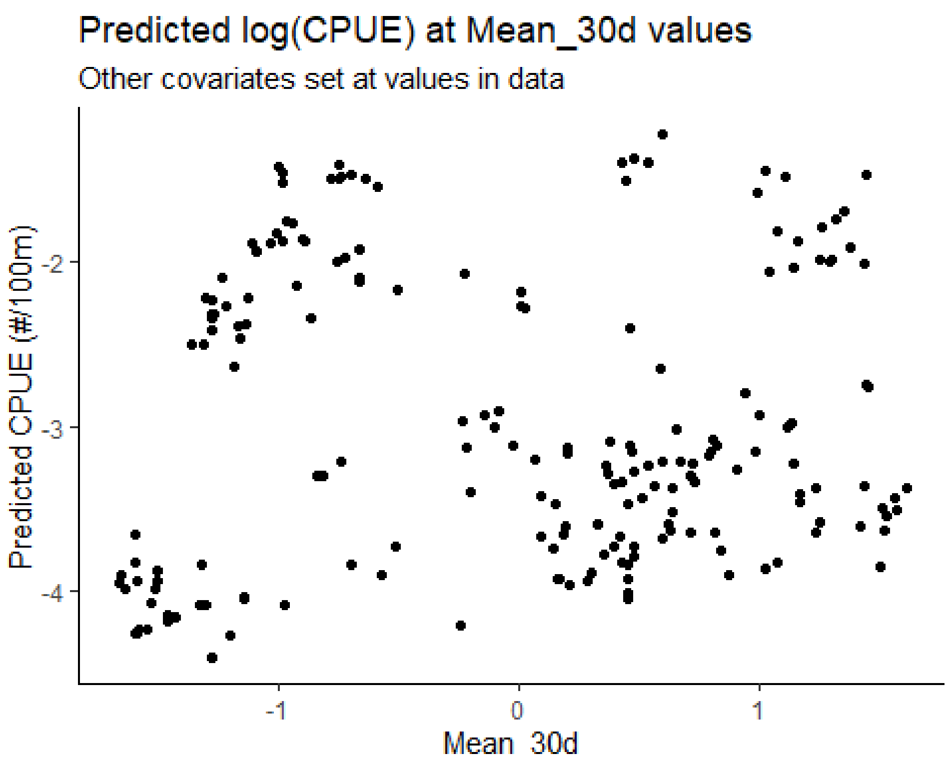

```
    # Pretty clear trend

# CSU 3 ----------------------------------------------------------------------------------------------
summary(fit100m.CSU_3)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataCSU3
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    707.9    740.5   -343.9    687.9      182
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8724 -0.3735  0.2552  0.7242  1.6288
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.1096   0.331
##  Residual               2.0190   1.421
## Number of obs: 192, groups:  SampleYear, 18
##
## Fixed effects:
##                                          Estimate Std. Error        df
## (Intercept)                              -4.68317    0.66724  50.35191
## Mean.1HrDischarge                         0.16624    0.36673 186.39051
```

```
## Mean.Prev6hDischarge                       -0.38111    0.33175 191.38512
## CV.Prev6hDischarge                         -0.01042    1.14742 180.50863
## Mean.30DayDischarge                         0.54483    0.19339  32.56328
## CV.30DayDischarge                           3.04830    1.70870  42.40120
## ElectroshockB. post-2014                    1.88790    0.28670  11.93840
## Mean.1HrDischarge:Mean.Prev6hDischarge     -0.06473    0.11768 177.95113
##                                           t value Pr(>|t|)
## (Intercept)                                -7.019 5.42e-09 ***
## Mean.1HrDischarge                           0.453  0.65085
## Mean.Prev6hDischarge                       -1.149  0.25207
## CV.Prev6hDischarge                         -0.009  0.99276
## Mean.30DayDischarge                         2.817  0.00817 **
## CV.30DayDischarge                           1.784  0.08158 .
## ElectroshockB. post-2014                    6.585 2.66e-05 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge     -0.550  0.58296
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.313
## Mn.Prv6hDsc -0.351 -0.884
## CV.Prv6hDsc -0.368 -0.784  0.669
## Mn.30DyDsch -0.490 -0.186 -0.025  0.118
## CV.30DyDsch -0.885 -0.054  0.163 -0.007  0.464
## ElcB.p-2014 -0.263  0.080 -0.106 -0.034  0.252  0.149
## M.1HD:M.P6D -0.073 -0.175  0.032  0.400  0.014 -0.219 -0.062

PlotAndSave(fit100m.CSU_3,"EffectSize_100m_CSU_3.tiff")
```



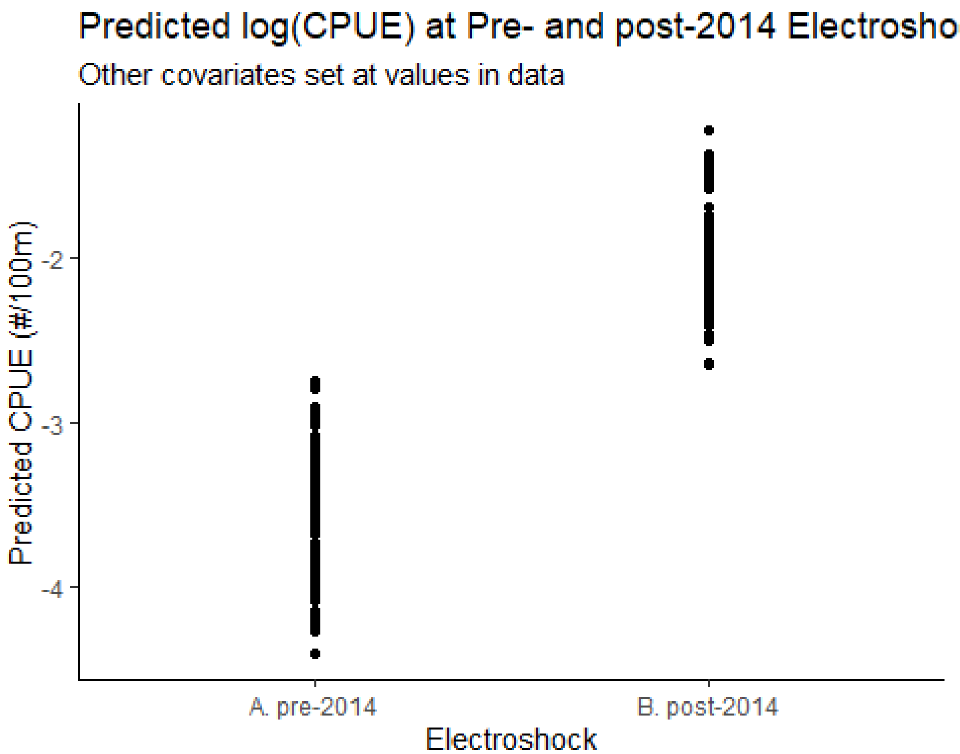

```
car::Anova(fit100m.CSU_3, type=2)
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       0.1316  1   0.716828
## Mean.Prev6hDischarge                    1.2803  1   0.257835
## CV.Prev6hDischarge                      0.0001  1   0.992752
## Mean.30DayDischarge                     7.9368  1   0.004844 **
## CV.30DayDischarge                       3.1826  1   0.074425 .
## Electroshock                           43.3626  1  4.548e-11 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.3026  1   0.582268
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataCSU3.p <- cbind(dataCSU3, pred_100m.CSU_3=predict(fit100m.CSU_3, newdata=dataCSU3))

# Mean 30 Days
ggplot(data=dataCSU3.p, aes(x=Mean.30DayDischarge, y=pred_100m.CSU_3))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```



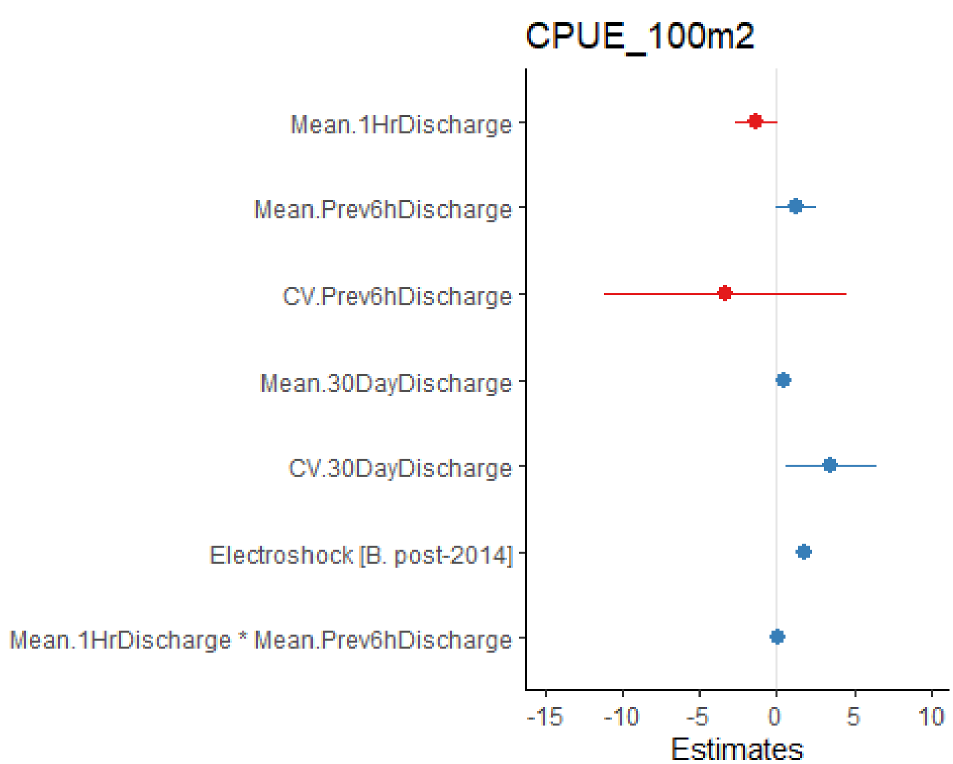

```
    #Noise

#Electroshocking
ggplot(data=dataCSU3.p, aes(x=Electroshock, y=pred_100m.CSU_3))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other
covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
```

```
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```

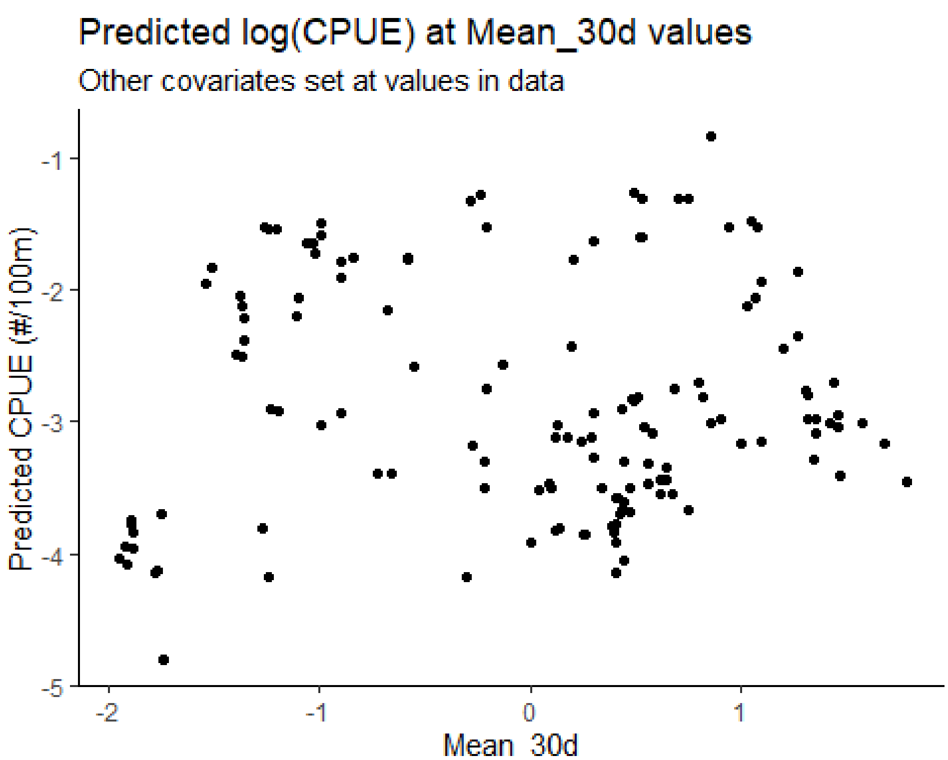



```
# CSU 5 ---------------------------------------------------------------------------------
--------------------
summary(fit100m.CSU_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataCSU5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    494.6    523.8   -237.3    474.6      127
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.4261 -0.4223  0.2780  0.6908  1.8609
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.01817  0.1348
##  Residual               1.85339  1.3614
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
```

```
##                                        Estimate Std. Error       df
## (Intercept)                             -4.36556    0.52582  30.86179
## Mean.1HrDischarge                       -1.33986    0.71063 136.85633
## Mean.Prev6hDischarge                     1.26517    0.68274 136.42056
## CV.Prev6hDischarge                      -3.32064    3.99561 135.92347
## Mean.30DayDischarge                      0.44888    0.18431  41.15252
## CV.30DayDischarge                        3.55018    1.51553  24.13001
## ElectroshockB. post-2014                 1.76157    0.27894  11.34232
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.04645    0.11014  95.28983
##                                        t value Pr(>|t|)
## (Intercept)                             -8.302 2.31e-09 ***
## Mean.1HrDischarge                       -1.885   0.0615 .
## Mean.Prev6hDischarge                     1.853   0.0660 .
## CV.Prev6hDischarge                      -0.831   0.4074
## Mean.30DayDischarge                      2.436   0.0193 *
## CV.30DayDischarge                        2.343   0.0277 *
## ElectroshockB. post-2014                 6.315 4.98e-05 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.422   0.6741
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.334
## Mn.Prv6hDsc  0.350 -0.975
## CV.Prv6hDsc -0.460  0.789 -0.757
## Mn.30DyDsch -0.528  0.099 -0.219  0.157
## CV.30DyDsch -0.827  0.001 -0.034  0.013  0.469
## ElcB.p-2014 -0.305  0.078 -0.094  0.196  0.280  0.075
## M.1HD:M.P6D  0.166 -0.097  0.114 -0.077 -0.010 -0.357 -0.111

PlotAndSave(fit100m.CSU_5,"EffectSize_100m_CSU_5.tiff")
```

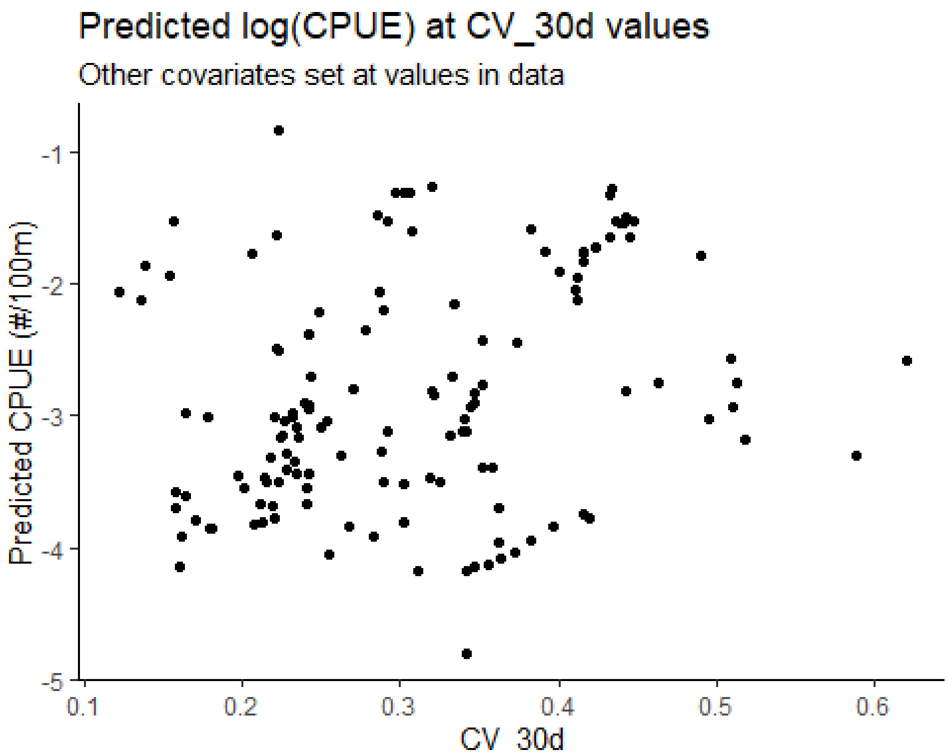


```
car::Anova(fit100m.CSU_5, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                        Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                     3.4347  1    0.06384 .
## Mean.Prev6hDischarge                  3.3011  1    0.06923 .
## CV.Prev6hDischarge                    0.6907  1    0.40593
## Mean.30DayDischarge                   5.9319  1    0.01487 *
## CV.30DayDischarge                     5.4875  1    0.01915 *
## Electroshock                         39.8831  1  2.696e-10 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.1779  1    0.67319
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataCSU5.p <- cbind(dataCSU5, pred_100m.CSU_5=predict(fit100m.CSU_5, newdata=dataCSU5))

# Mean 30 Days
ggplot(data=dataCSU5.p, aes(x=Mean.30DayDischarge, y=pred_100m.CSU_5))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```

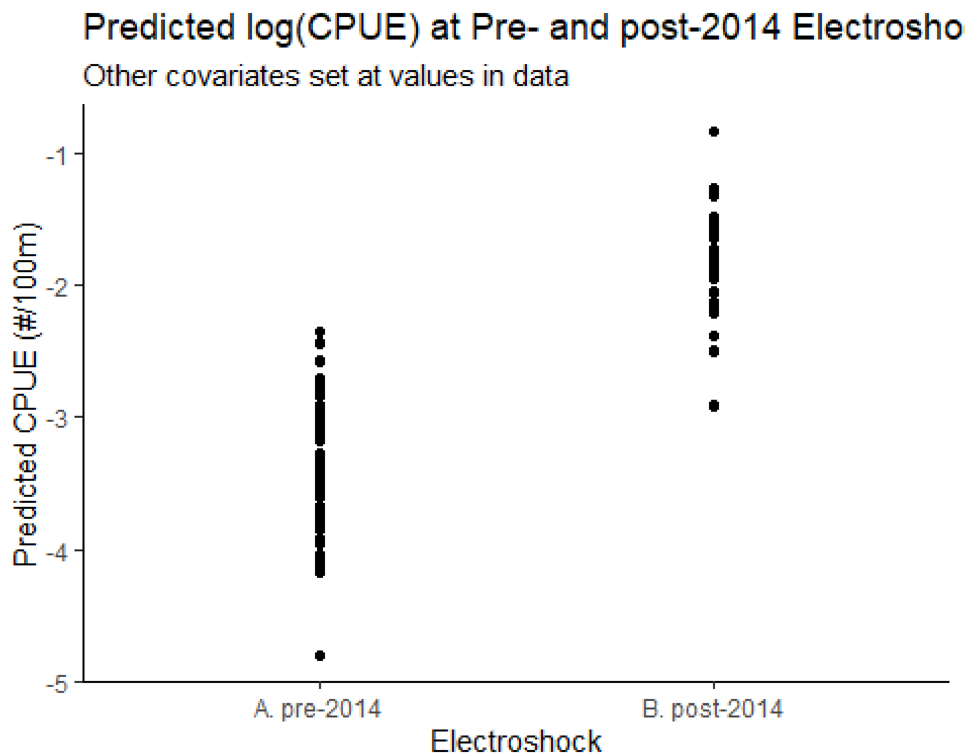



```
# CV Prev 30 Days
ggplot(data=dataCSU5.p, aes(x=CV.30DayDischarge, y=pred_100m.CSU_5))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
```

```
    xlab("CV_30d") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```

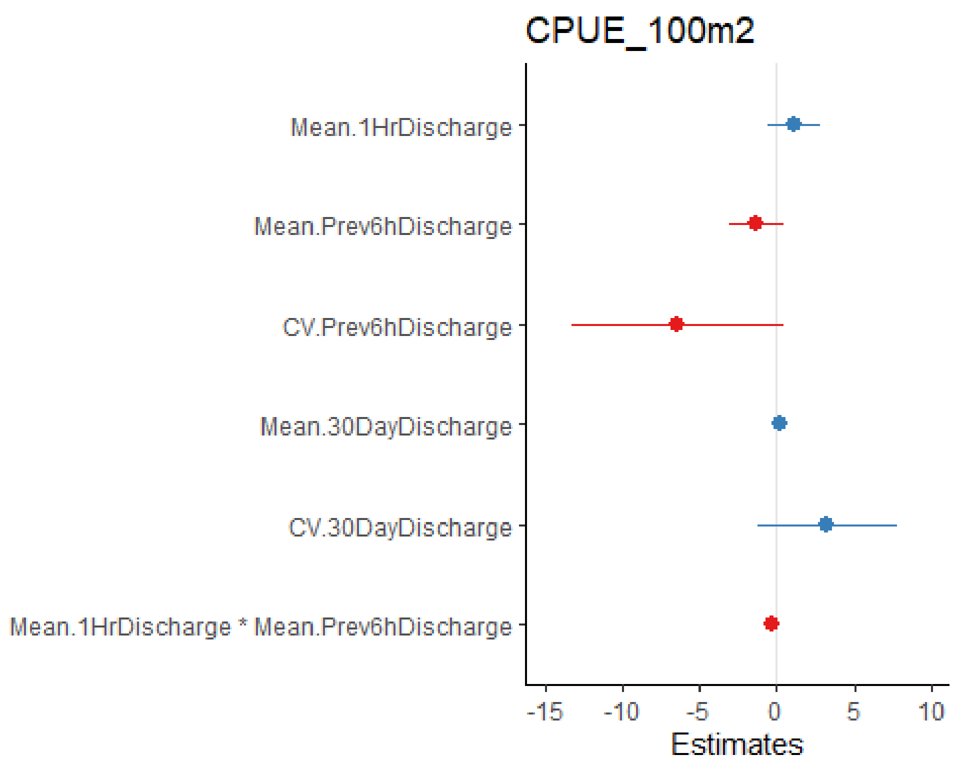



```
#Electroshocking
ggplot(data=dataCSU5.p, aes(x=Electroshock, y=pred_100m.CSU_5))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other
covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```



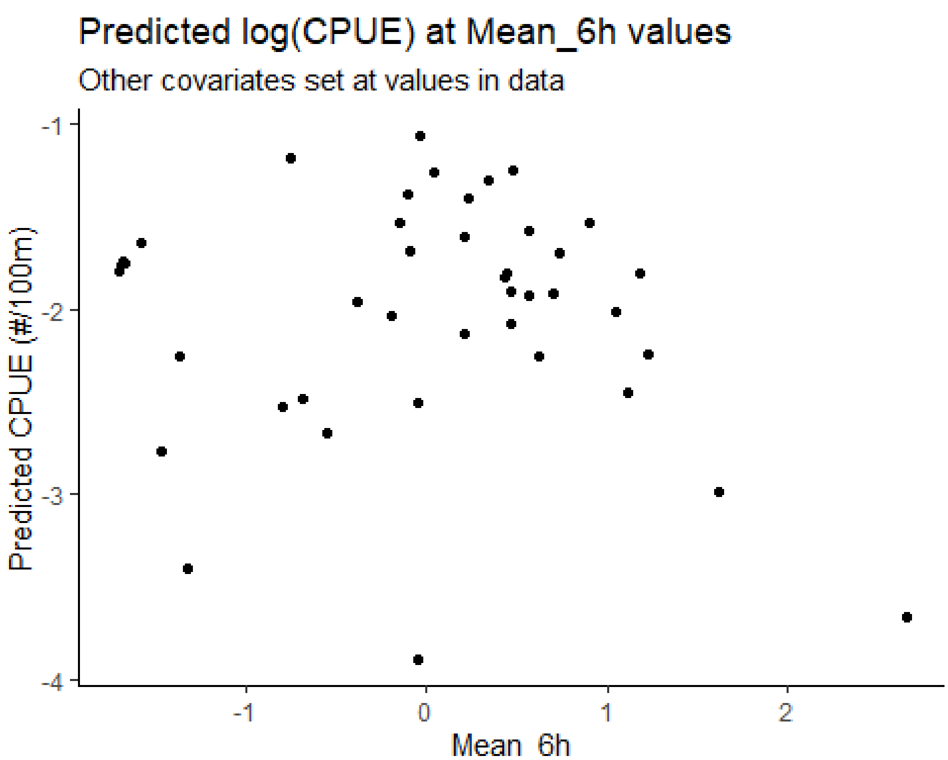

```
# CSU 6 ---------------------------------------------------------------------------------------------------
summary(fit100m.CSU_6)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataCSU6
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    159.0    174.6    -70.5    141.0       33
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.6209 -0.2073  0.1716  0.6158  1.4688
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.00     0.000
##  Residual               1.68     1.296
## Number of obs: 42, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error      df t value
## (Intercept)                               -2.4304     0.7179 42.0000  -3.386
## Mean.1HrDischarge                          1.1474     0.8530 42.0000   1.345
## Mean.Prev6hDischarge                      -1.3250     0.8861 42.0000  -1.495
## CV.Prev6hDischarge                        -6.4147     3.5007 42.0000  -1.832
```

```
## Mean.30DayDischarge                         0.1927     0.2401 42.0000   0.803
## CV.30DayDischarge                           3.2621     2.3023 42.0000   1.417
## Mean.1HrDischarge:Mean.Prev6hDischarge     -0.2806     0.1636 42.0000  -1.716
##                                           Pr(>|t|)
## (Intercept)                                0.00155 **
## Mean.1HrDischarge                          0.18580
## Mean.Prev6hDischarge                       0.14229
## CV.Prev6hDischarge                         0.07399 .
## Mean.30DayDischarge                        0.42665
## CV.30DayDischarge                          0.16389
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.09358 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.159
## Mn.Prv6hDsc -0.218 -0.960
## CV.Prv6hDsc -0.216 -0.037  0.089
## Mn.30DyDsch -0.012  0.092 -0.223  0.063
## CV.30DyDsch -0.896 -0.184  0.235 -0.069 -0.038
## M.1HD:M.P6D -0.008  0.130 -0.141  0.229  0.157 -0.269
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.CSU_6,"EffectSize_100m_CSU_6.tiff")
```




```
car::Anova(fit100m.CSU_6, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                            Chisq Df Pr(>Chisq)
```

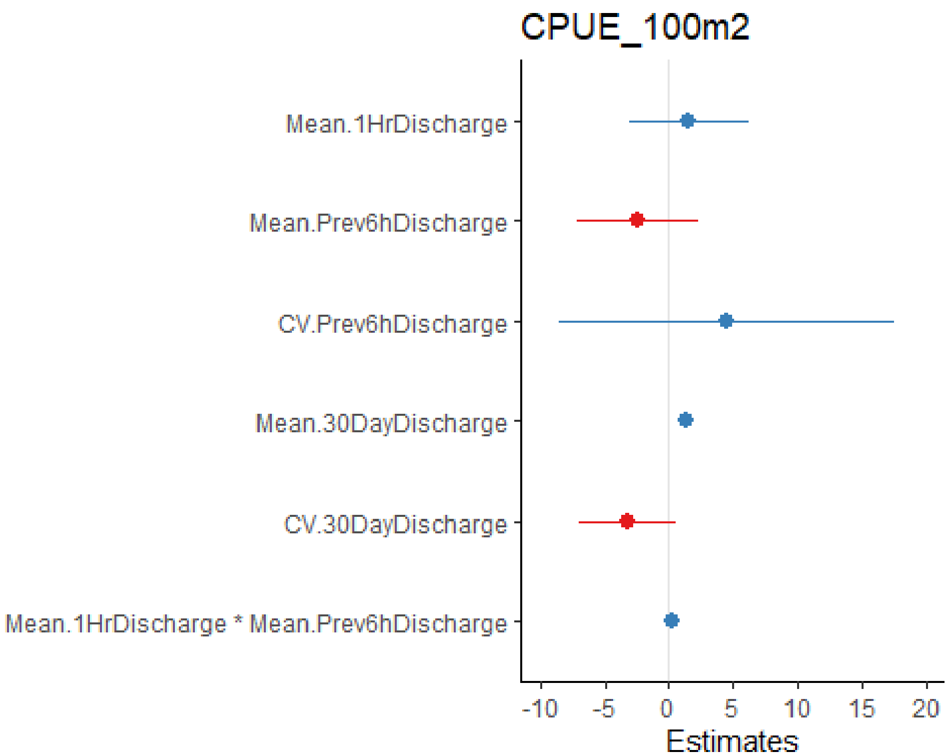
```
## Mean.1HrDischarge                       2.5019  1    0.11371
## Mean.Prev6hDischarge                    3.0787  1    0.07932 .
## CV.Prev6hDischarge                      3.3577  1    0.06689 .
## Mean.30DayDischarge                     0.6444  1    0.42214
## CV.30DayDischarge                       2.0076  1    0.15651
## Mean.1HrDischarge:Mean.Prev6hDischarge 2.9438  1    0.08621 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataCSU6.p <- cbind(dataCSU6, pred_100m.CSU_6=predict(fit100m.CSU_6, newdata=dataCSU6))

# Mean Prev 24
ggplot(data=dataCSU6.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.CSU_6))+
    ggtitle("Predicted log(CPUE) at Mean_6h values",subtitle="Other covariates set at values i
n data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()
```



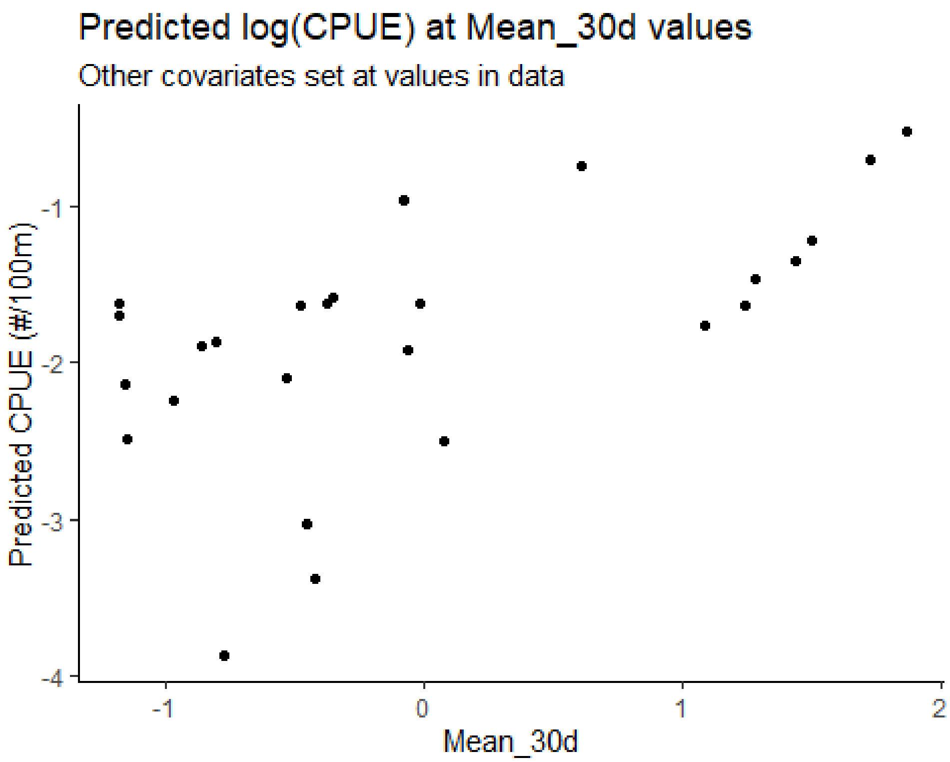

```
    # Noise

# CSU 7 ----------------------------------------------------------------------------------
-------------------
summary(fit100m.CSU_7)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataCSU7
```

```
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     82.9     94.3    -32.5     64.9       17
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.88604 -0.58572  0.04602  0.73901  1.57090
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.7113   0.8434
## Number of obs: 26, groups:  SampleYear, 5
##
## Fixed effects:
##                                       Estimate Std. Error      df t value
## (Intercept)                            -1.1003     0.7661 26.0000  -1.436
## Mean.1HrDischarge                       1.5691     2.3487 26.0000   0.668
## Mean.Prev6hDischarge                   -2.4041     2.4218 26.0000  -0.993
## CV.Prev6hDischarge                      4.4562     6.6840 26.0000   0.667
## Mean.30DayDischarge                     1.2781     0.3023 26.0000   4.228
## CV.30DayDischarge                      -3.2739     1.9162 26.0000  -1.708
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.2061     0.2590 26.0000   0.796
##                                       Pr(>|t|)
## (Intercept)                           0.162842
## Mean.1HrDischarge                     0.509968
## Mean.Prev6hDischarge                  0.330009
## CV.Prev6hDischarge                    0.510836
## Mean.30DayDischarge                   0.000257 ***
## CV.30DayDischarge                     0.099459 .
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.433470
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.216
## Mn.Prv6hDsc -0.232 -0.993
## CV.Prv6hDsc -0.343 -0.737  0.733
## Mn.30DyDsch  0.251  0.084 -0.173  0.073
## CV.30DyDsch -0.863 -0.072  0.082  0.018 -0.256
## M.1HD:M.P6D -0.454  0.178 -0.150  0.116 -0.196  0.119
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

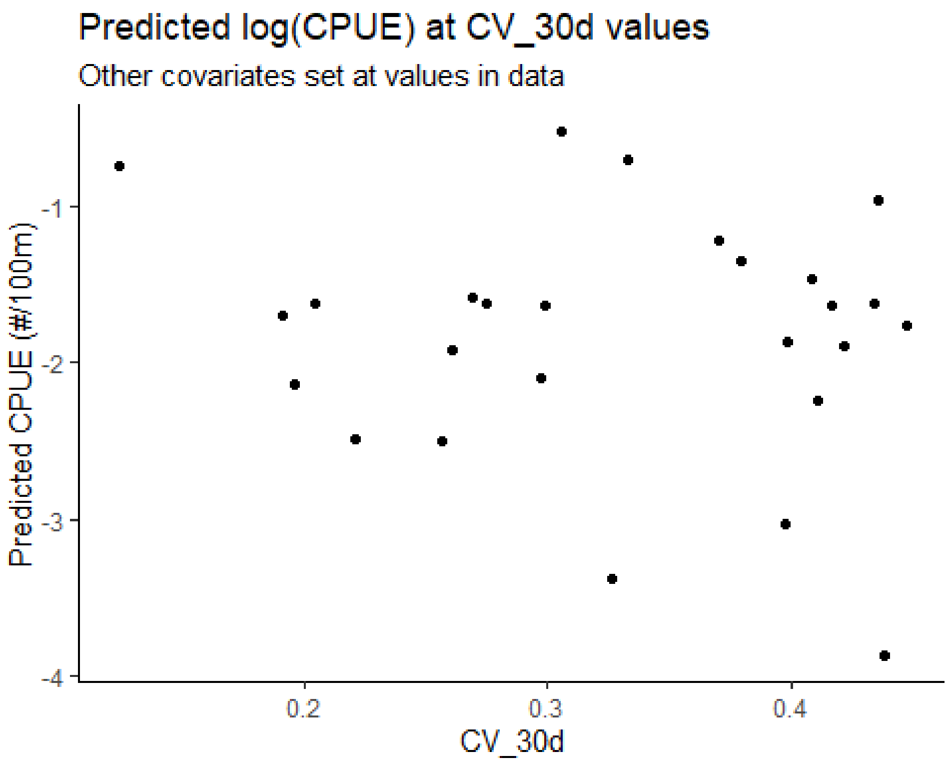
```
PlotAndSave(fit100m.CSU_7,"EffectSize_100m_CSU_7.tiff")
```




```
car::Anova(fit100m.CSU_7, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                              Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                           0.2866  1    0.59244
## Mean.Prev6hDischarge                        0.7807  1    0.37693
## CV.Prev6hDischarge                          0.4445  1    0.50496
## Mean.30DayDischarge                        17.8755  1  2.358e-05 ***
## CV.30DayDischarge                           2.9189  1    0.08754 .
## Mean.1HrDischarge:Mean.Prev6hDischarge      0.6330  1    0.42627
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataCSU7.p <- cbind(dataCSU7, pred_100m.CSU_7=predict(fit100m.CSU_7, newdata=dataCSU7))

# Mean 30 Days
ggplot(data=dataCSU7.p, aes(x=Mean.30DayDischarge, y=pred_100m.CSU_7))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()
```

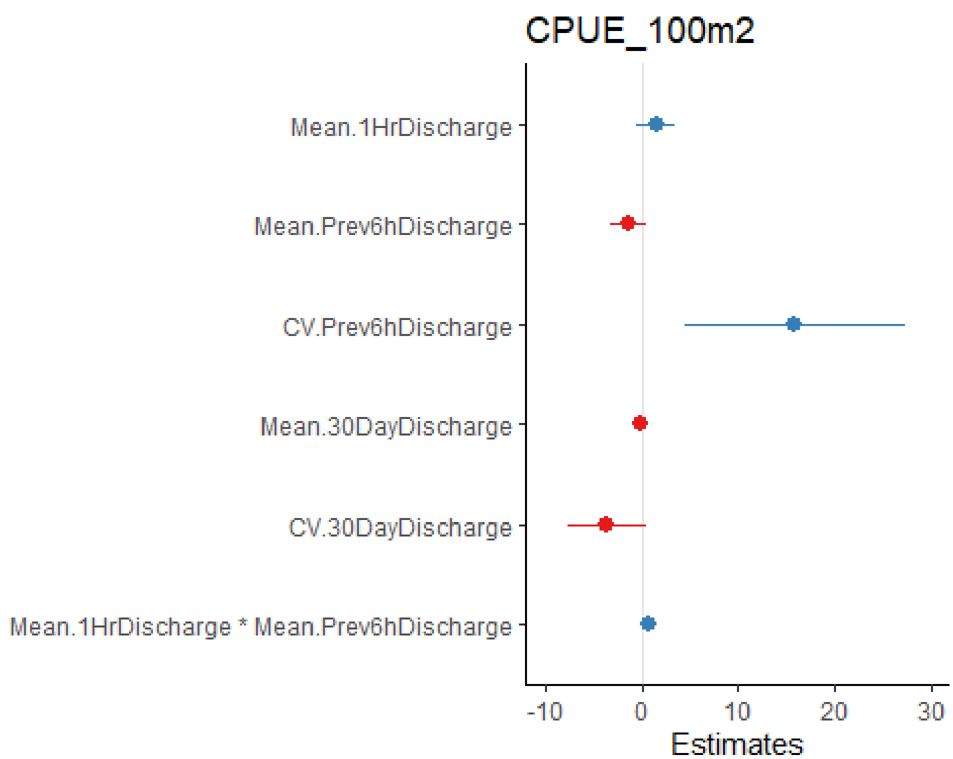



```
# CV Prev 30 Days
ggplot(data=dataCSU7.p, aes(x=CV.30DayDischarge, y=pred_100m.CSU_7))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()
```



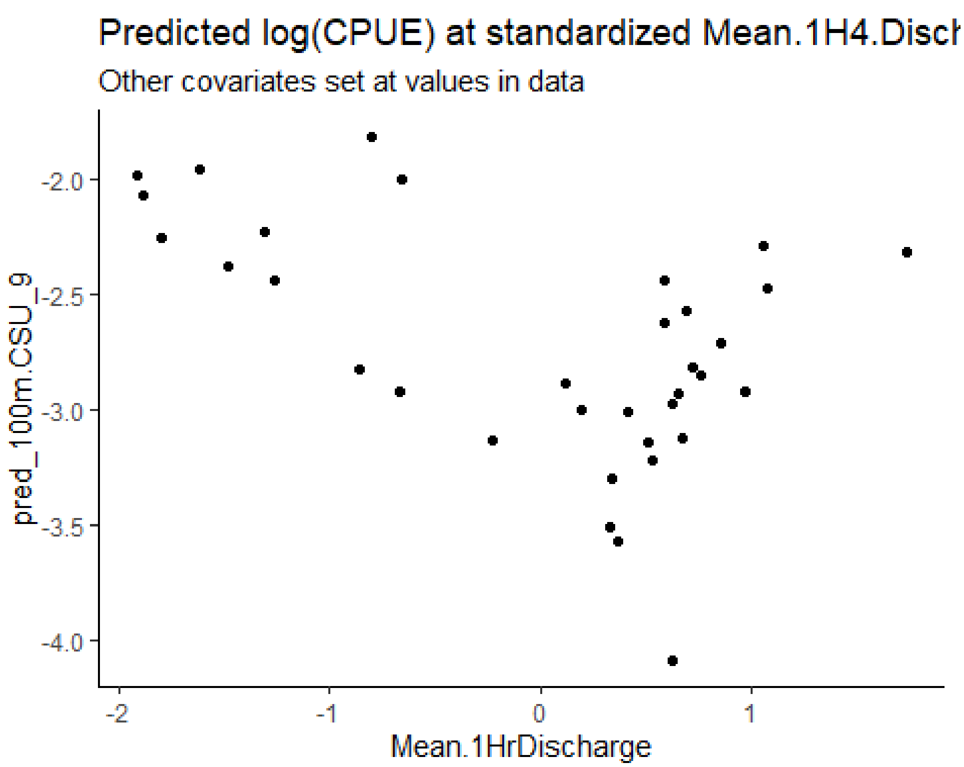

```
    # All noise

# CSU 9 -----------------------------------------------------------------------------------------------
summary(fit100m.CSU_9)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischarge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataCSU9
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     83.8     97.6    -32.9     65.8       25
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.0445 -0.7179  0.1347  0.8244  1.7833
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.06313  0.2512
##  Residual               0.36341  0.6028
## Number of obs: 34, groups:  SampleYear, 5
##
## Fixed effects:
##                                         Estimate Std. Error      df t value
## (Intercept)                              -2.9277     0.5356  7.0324  -5.466
## Mean.1HrDischarge                         1.5048     1.0157 27.8320   1.482
```

```
## Mean.Prev6hDischarge                         -1.4216     0.9449 26.5350  -1.505
## CV.Prev6hDischarge                           15.9041     5.8451 32.2074   2.721
## Mean.30DayDischarge                          -0.1522     0.1792 22.7720  -0.850
## CV.30DayDischarge                            -3.6439     2.0874 19.2263  -1.746
## Mean.1HrDischarge:Mean.Prev6hDischarge        0.6509     0.1851 31.4691   3.516
##                                              Pr(>|t|)
## (Intercept)                                  0.000925 ***
## Mean.1HrDischarge                            0.149670
## Mean.Prev6hDischarge                         0.144249
## CV.Prev6hDischarge                           0.010411 *
## Mean.30DayDischarge                          0.404324
## CV.30DayDischarge                            0.096832 .
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.001353 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr -0.171
## Mn.Prv6hDsc  0.139 -0.983
## CV.Prv6hDsc -0.278  0.817 -0.778
## Mn.30DyDsch -0.075 -0.277  0.169 -0.340
## CV.30DyDsch -0.781 -0.261  0.248 -0.247  0.349
## M.1HD:M.P6D -0.003  0.470 -0.376  0.538 -0.507 -0.511

PlotAndSave(fit100m.CSU_9,"EffectSize_100m_CSU_9.tiff")
```

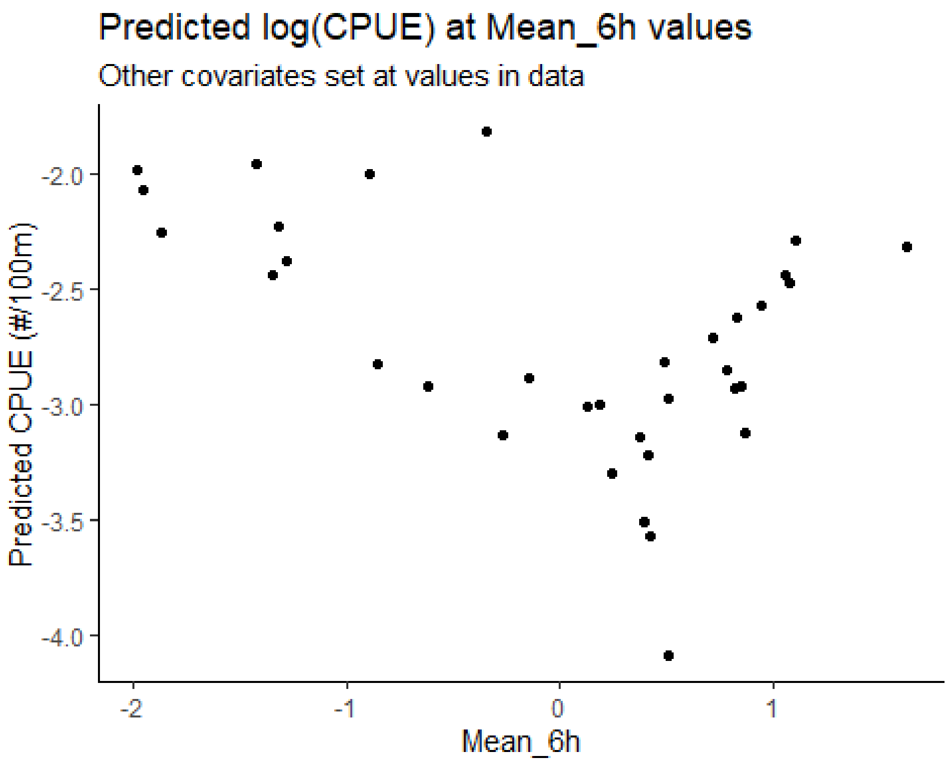



```
car::Anova(fit100m.CSU_9, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
```

```
## Mean.1HrDischarge                        0.0377  1  0.8461313
## Mean.Prev6hDischarge                     0.0391  1  0.8432832
## CV.Prev6hDischarge                       7.4035  1  0.0065097 **
## Mean.30DayDischarge                      0.7220  1  0.3954784
## CV.30DayDischarge                        3.0473  1  0.0808705 .
## Mean.1HrDischarge:Mean.Prev6hDischarge 12.3650  1  0.0004375 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataCSU9.p <- cbind(dataCSU9, pred_100m.CSU_9=predict(fit100m.CSU_9, newdata=dataCSU9))

# 1h discharge
ggplot(data=dataCSU9.p, aes(x=Mean.1HrDischarge, y=pred_100m.CSU_9))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    geom_point()
```

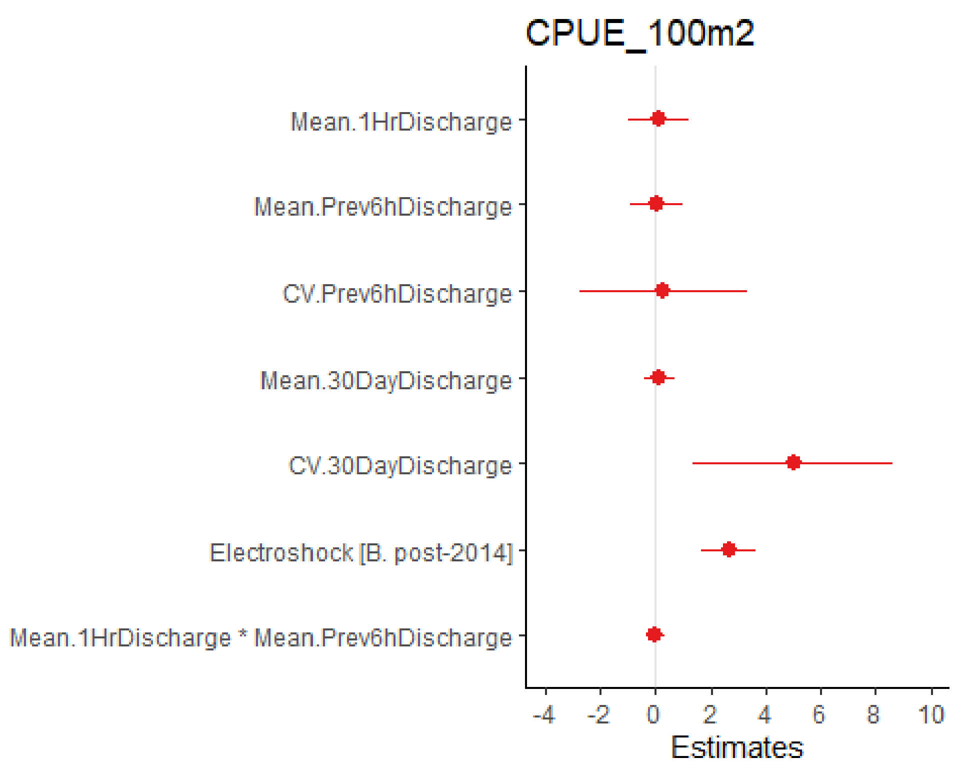



```
# Mean Prev 6
ggplot(data=dataCSU9.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.CSU_9))+
    ggtitle("Predicted log(CPUE) at Mean_6h values",subtitle="Other covariates set at values i
n data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()
```



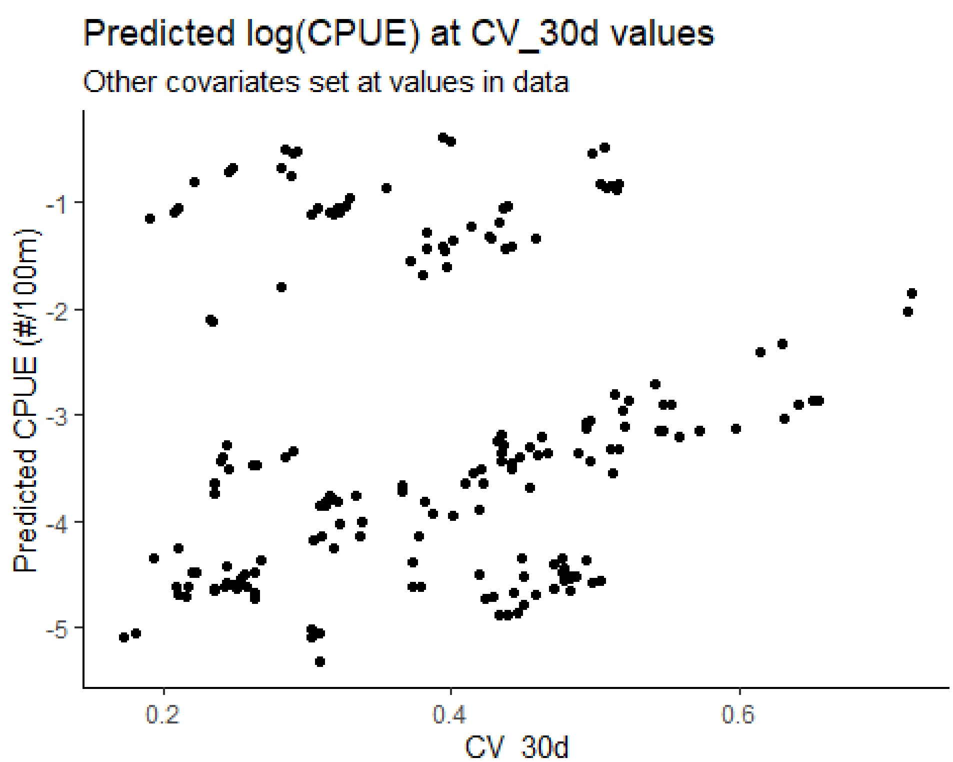

```
    # Chasing noise?


# LSU 1 ---------------------------------------------------------------------------------------------
summary(fit100m.LSU_1)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataLSU1
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    726.2    758.2   -353.1    706.2      172
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.1578 -0.9154  0.2314  0.7317  2.2452
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.689    0.8301
##  Residual               2.487    1.5770
## Number of obs: 182, groups:  SampleYear, 18
##
## Fixed effects:
##                                            Estimate Std. Error         df
## (Intercept)                               -6.032962   0.857991  95.206339
```

```
## Mean.1HrDischarge                          0.119636   0.549406 169.326208
## Mean.Prev6hDischarge                       0.038043   0.495231 173.740695
## CV.Prev6hDischarge                         0.266138   1.555593 166.539426
## Mean.30DayDischarge                        0.143560   0.272035  63.449837
## CV.30DayDischarge                          5.015354   1.852765 107.953150
## ElectroshockB. post-2014                   2.658966   0.511173  14.163835
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.001746   0.173066 181.029550
##                                          t value Pr(>|t|)
## (Intercept)                               -7.031 3.09e-10 ***
## Mean.1HrDischarge                          0.218 0.827882
## Mean.Prev6hDischarge                       0.077 0.938856
## CV.Prev6hDischarge                         0.171 0.864365
## Mean.30DayDischarge                        0.528 0.599530
## CV.30DayDischarge                          2.707 0.007895 **
## ElectroshockB. post-2014                   5.202 0.000129 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.010 0.991960
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.371
## Mn.Prv6hDsc -0.338 -0.937
## CV.Prv6hDsc -0.443 -0.866  0.827
## Mn.30DyDsch -0.553 -0.161  0.049  0.116
## CV.30DyDsch -0.829 -0.030  0.028  0.018  0.538
## ElcB.p-2014 -0.299  0.099 -0.096 -0.062  0.249  0.163
## M.1HD:M.P6D -0.075 -0.258  0.154  0.413  0.035 -0.280 -0.063

PlotAndSave(fit100m.LSU_1,"EffectSize_100m_LSU_1.tiff")
```

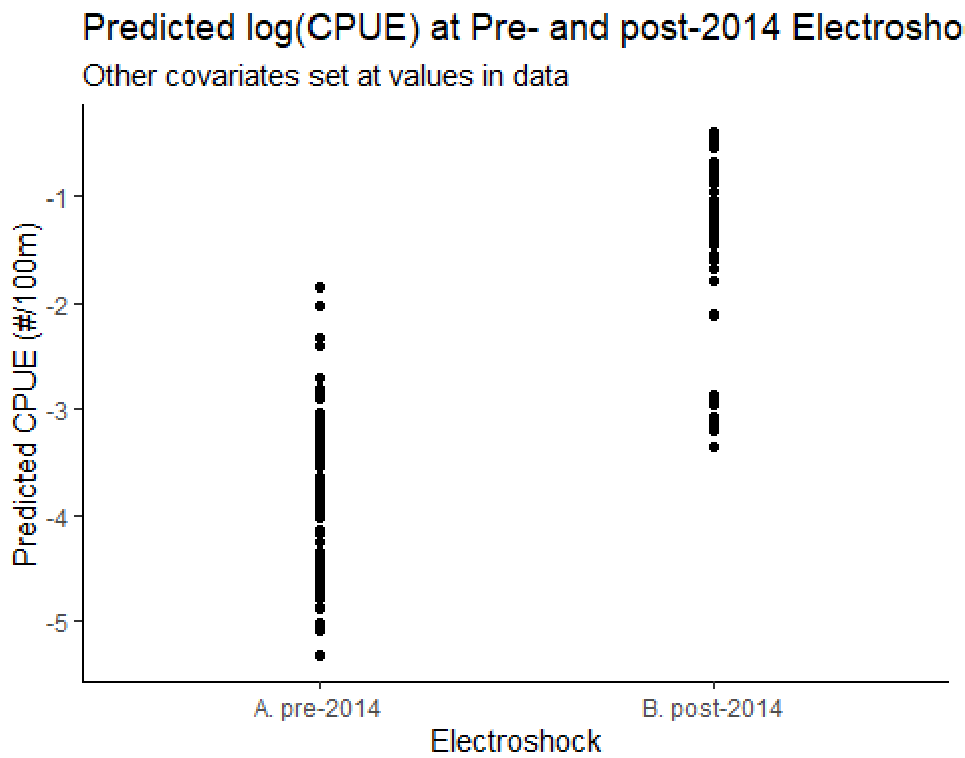



```
car::Anova(fit100m.LSU_1, type=2)
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                        Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                     0.0520  1    0.81958
## Mean.Prev6hDischarge                  0.0058  1    0.93928
## CV.Prev6hDischarge                    0.0293  1    0.86416
## Mean.30DayDischarge                   0.2785  1    0.59769
## CV.30DayDischarge                     7.3276  1    0.00679 **
## Electroshock                         27.0576  1  1.975e-07 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.0001  1    0.99195
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataLSU1.p <- cbind(dataLSU1, pred_100m.LSU_1=predict(fit100m.LSU_1, newdata=dataLSU1))

# CV Prev 30 Days
ggplot(data=dataLSU1.p, aes(x=CV.30DayDischarge, y=pred_100m.LSU_1))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()
```

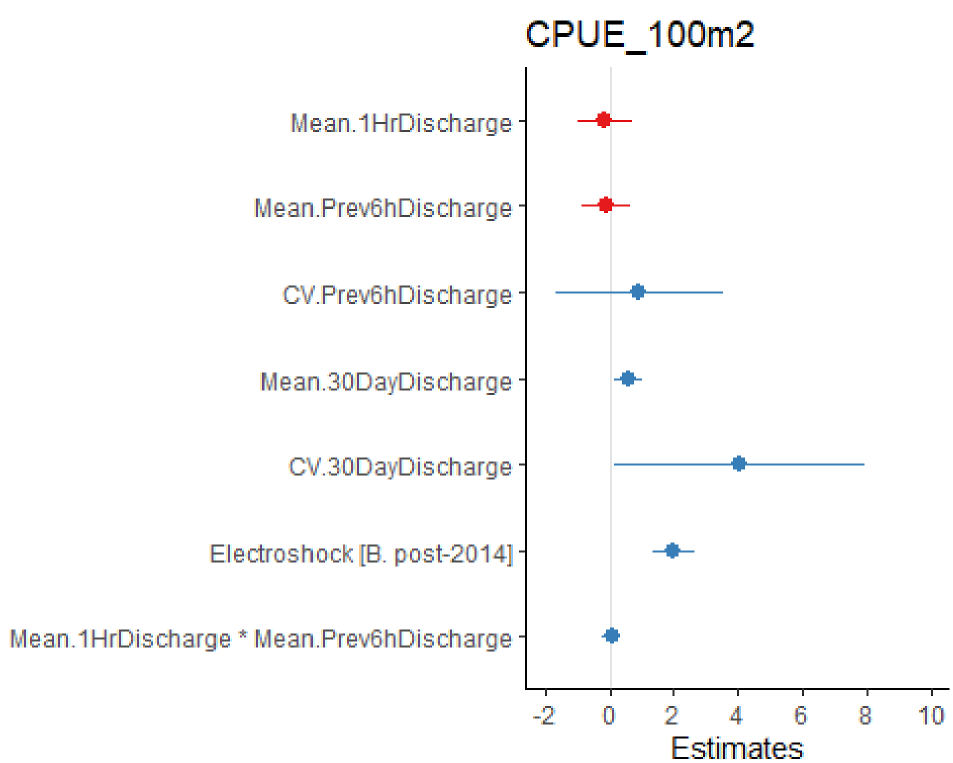



```
#Electroshocking
ggplot(data=dataLSU1.p, aes(x=Electroshock, y=pred_100m.LSU_1))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other
covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()
```



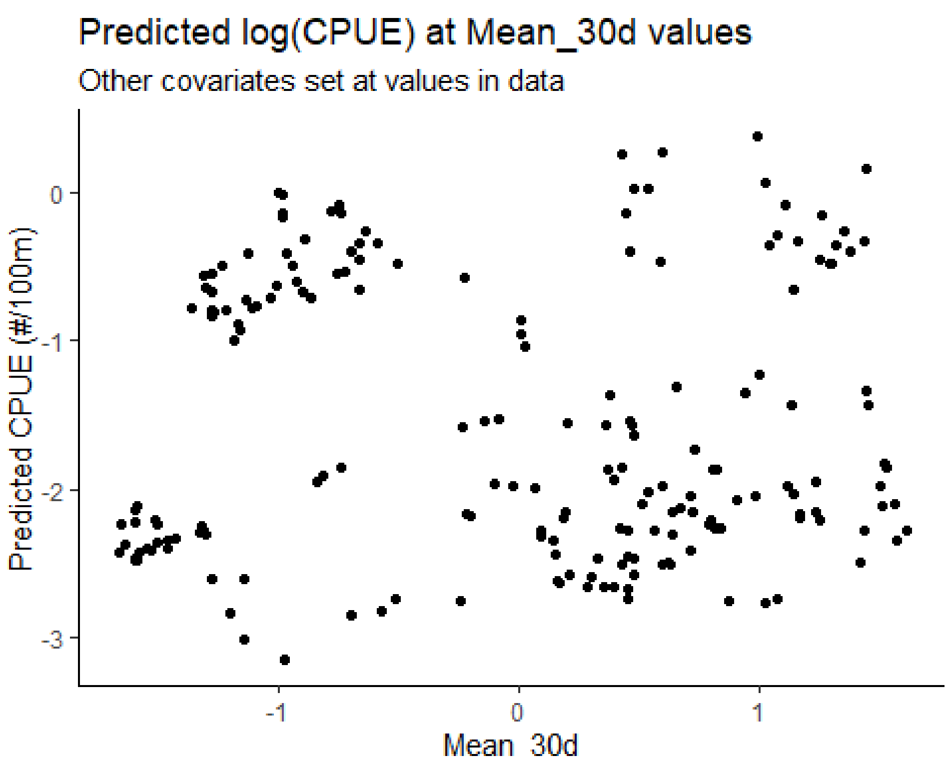

```
# LSU 3 ------------------------------------------------------------------------------------
--------------------
summary(fit100m.LSU_3)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataLSU3
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    765.3    797.9   -372.6    745.3      182
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.5818 -0.2377  0.2687  0.6338  1.3144
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.1457   0.3818
##  Residual               2.7239   1.6504
## Number of obs: 192, groups:  SampleYear, 18
##
## Fixed effects:
##                                           Estimate Std. Error        df
## (Intercept)                               -3.92774    0.77402  32.01398
## Mean.1HrDischarge                         -0.14283    0.42591 182.36058
## Mean.Prev6hDischarge                      -0.12903    0.38526 190.95857
## CV.Prev6hDischarge                         0.90654    1.33264 172.62934
```

```
## Mean.30DayDischarge                       0.57004    0.22426  19.83224
## CV.30DayDischarge                         4.05985    1.98189  26.38809
## ElectroshockB. post-2014                  1.99761    0.33212   6.92437
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.05899    0.13663 168.14454
##                                         t value Pr(>|t|)
## (Intercept)                              -5.074  1.6e-05 ***
## Mean.1HrDischarge                        -0.335 0.737735
## Mean.Prev6hDischarge                     -0.335 0.738049
## CV.Prev6hDischarge                        0.680 0.497253
## Mean.30DayDischarge                       2.542 0.019493 *
## CV.30DayDischarge                         2.048 0.050582 .
## ElectroshockB. post-2014                  6.015 0.000557 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.432 0.666472
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.313
## Mn.Prv6hDsc -0.352 -0.884
## CV.Prv6hDsc -0.369 -0.784  0.669
## Mn.30DyDsch -0.490 -0.186 -0.025  0.118
## CV.30DyDsch -0.884 -0.055  0.163 -0.007  0.464
## ElcB.p-2014 -0.263  0.080 -0.106 -0.034  0.252  0.150
## M.1HD:M.P6D -0.073 -0.175  0.033  0.400  0.014 -0.219 -0.062

PlotAndSave(fit100m.LSU_3,"EffectSize_100m_LSU_3.tiff")
```

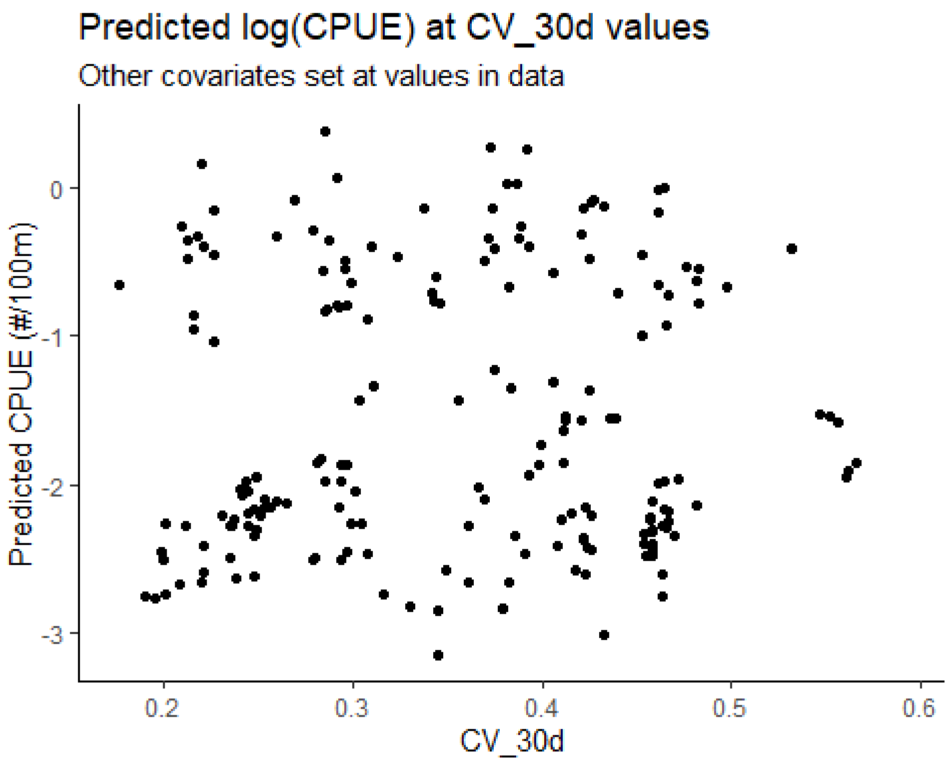



```
car::Anova(fit100m.LSU_3, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
```

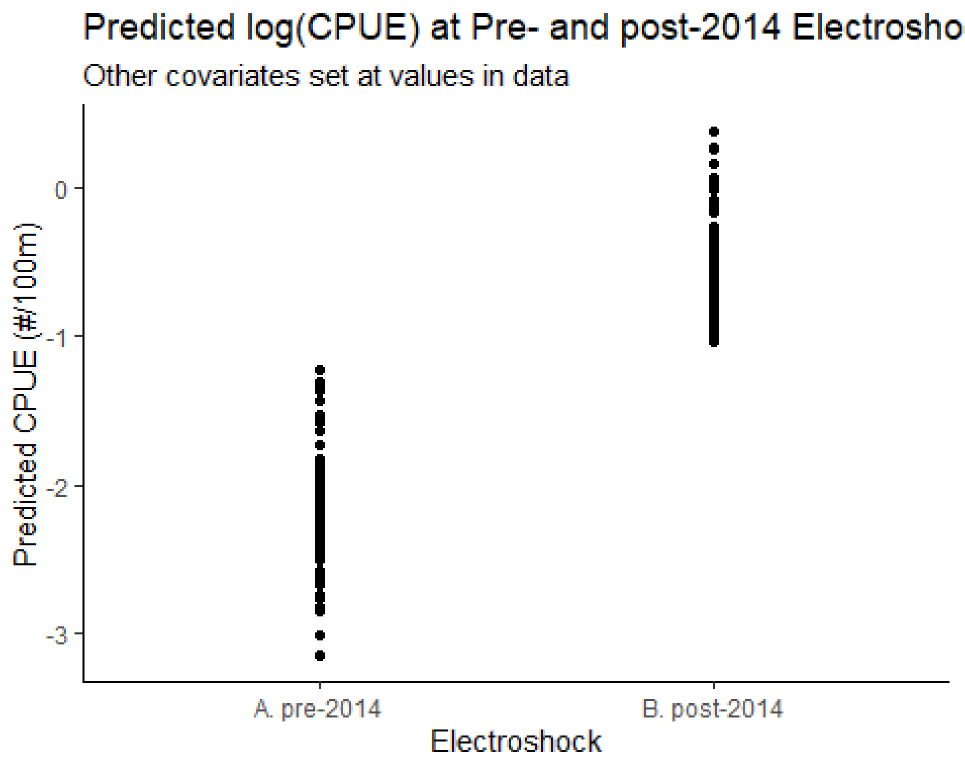
```
##                                            Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                         0.0696  1    0.79191
## Mean.Prev6hDischarge                      0.1220  1    0.72689
## CV.Prev6hDischarge                        0.4628  1    0.49634
## Mean.30DayDischarge                       6.4608  1    0.01103 *
## CV.30DayDischarge                         4.1962  1    0.04051 *
## Electroshock                             36.1775  1  1.801e-09 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.1864  1    0.66592
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataLSU3.p <- cbind(dataLSU3, pred_100m.LSU_3=predict(fit100m.LSU_3, newdata=dataLSU3))

# Mean 30 Days
ggplot(data=dataLSU3.p, aes(x=Mean.30DayDischarge, y=pred_100m.LSU_3))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```




```
# CV Prev 30 Days
ggplot(data=dataLSU3.p, aes(x=CV.30DayDischarge, y=pred_100m.LSU_3))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```

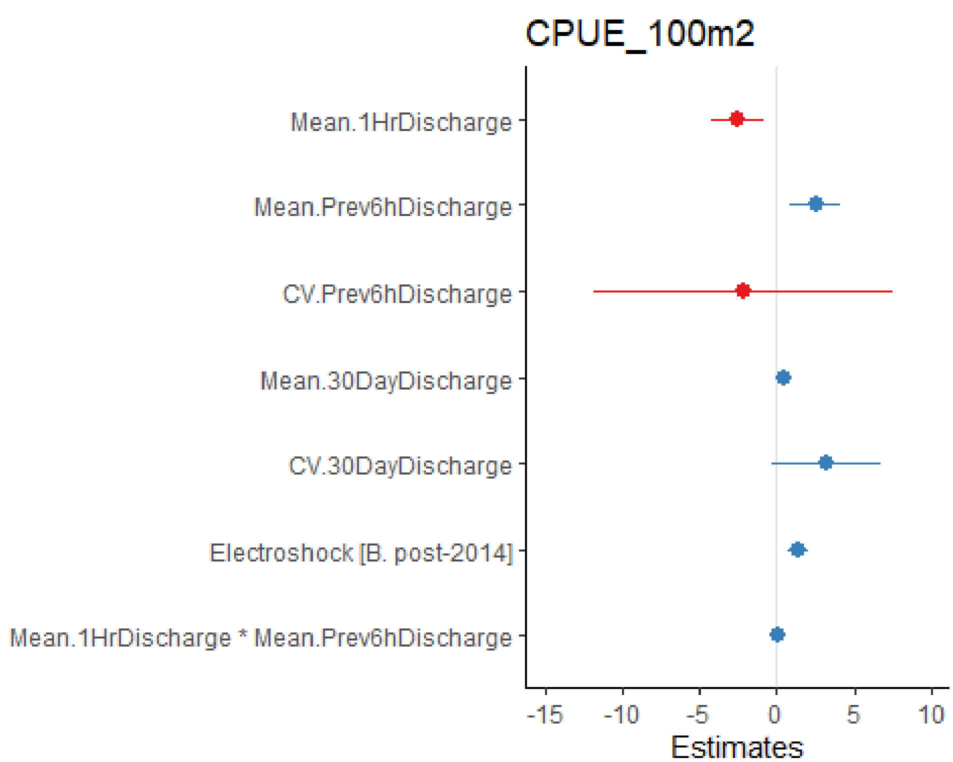



```
#Electroshocking
ggplot(data=dataLSU3.p, aes(x=Electroshock, y=pred_100m.LSU_3))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other
covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```




```
# LSU 5 -------------------------------------------------------------------------------------
-------------------
summary(fit100m.LSU_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataLSU5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    552.7    581.9   -266.3    532.7      127
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.0457 -0.2580  0.2597  0.6304  1.5089
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.000    0.000
##  Residual               2.859    1.691
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                          Estimate Std. Error       df
## (Intercept)                               -2.6602     0.6378 137.0000
## Mean.1HrDischarge                         -2.5648     0.8786 137.0000
## Mean.Prev6hDischarge                       2.5381     0.8444 137.0000
## CV.Prev6hDischarge                        -2.1934     4.9429 137.0000
```

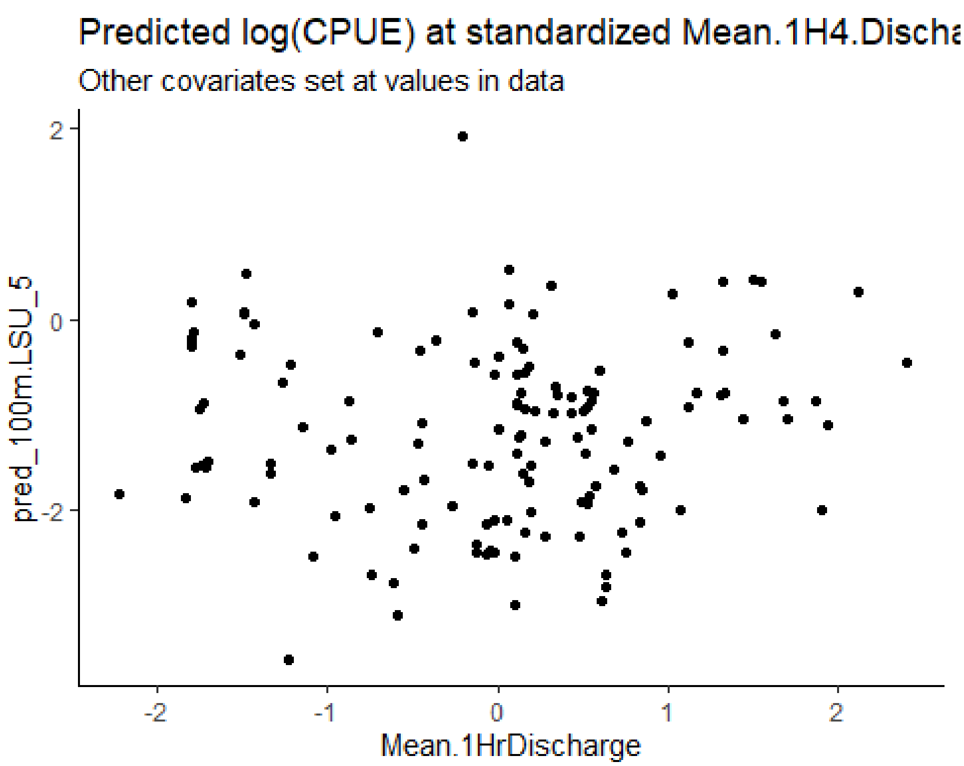
```
## Mean.30DayDischarge                          0.4610     0.2244 137.0000
## CV.30DayDischarge                            3.2273     1.8323 137.0000
## ElectroshockB. post-2014                     1.4514     0.3334 137.0000
## Mean.1HrDischarge:Mean.Prev6hDischarge       0.1488     0.1352 137.0000
##                                            t value Pr(>|t|)
## (Intercept)                                 -4.171 5.36e-05 ***
## Mean.1HrDischarge                           -2.919  0.00410 **
## Mean.Prev6hDischarge                         3.006  0.00315 **
## CV.Prev6hDischarge                          -0.444  0.65792
## Mean.30DayDischarge                          2.055  0.04183 *
## CV.30DayDischarge                            1.761  0.08041 .
## ElectroshockB. post-2014                     4.353 2.61e-05 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge       1.101  0.27295
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.344
## Mn.Prv6hDsc  0.361 -0.975
## CV.Prv6hDsc -0.472  0.790 -0.759
## Mn.30DyDsch -0.532  0.105 -0.229  0.165
## CV.30DyDsch -0.825  0.004 -0.039  0.017  0.470
## ElcB.p-2014 -0.303  0.085 -0.102  0.205  0.281  0.073
## M.1HD:M.P6D  0.168 -0.104  0.120 -0.081 -0.011 -0.360 -0.115
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.LSU_5,"EffectSize_100m_LSU_5.tiff")
```



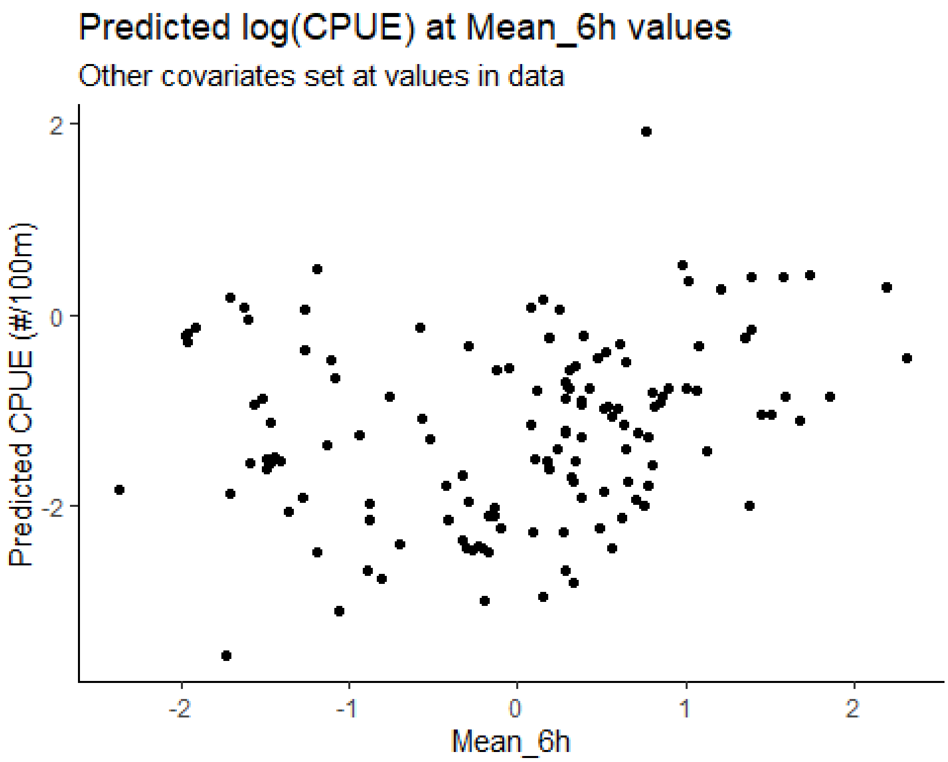

```
car::Anova(fit100m.LSU_5, type=2)
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                        Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                     7.9540  1   0.004798 **
## Mean.Prev6hDischarge                  8.3796  1   0.003794 **
## CV.Prev6hDischarge                    0.1969  1   0.657225
## Mean.30DayDischarge                   4.2210  1   0.039926 *
## CV.30DayDischarge                     3.1023  1   0.078183 .
## Electroshock                         18.9461  1  1.345e-05 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  1.2116  1   0.271025
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

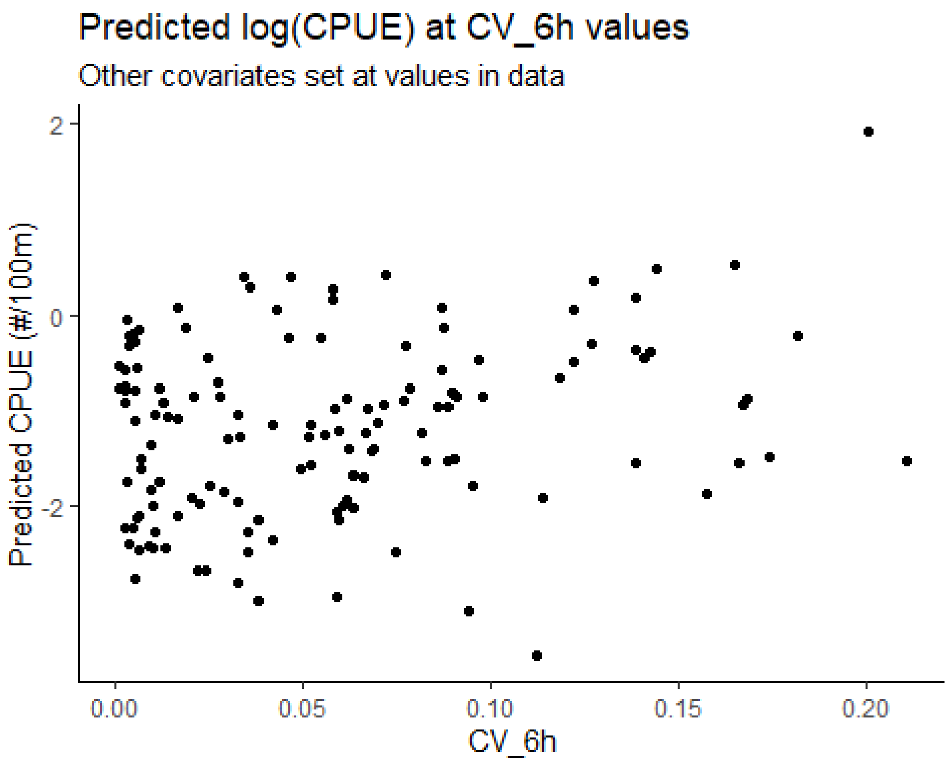
```
dataLSU5.p <- cbind(dataLSU5, pred_100m.LSU_5=predict(fit100m.LSU_5, newdata=dataLSU5))

ggplot(data=dataLSU5.p, aes(x=Mean.1HrDischarge, y=pred_100m.LSU_5))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```



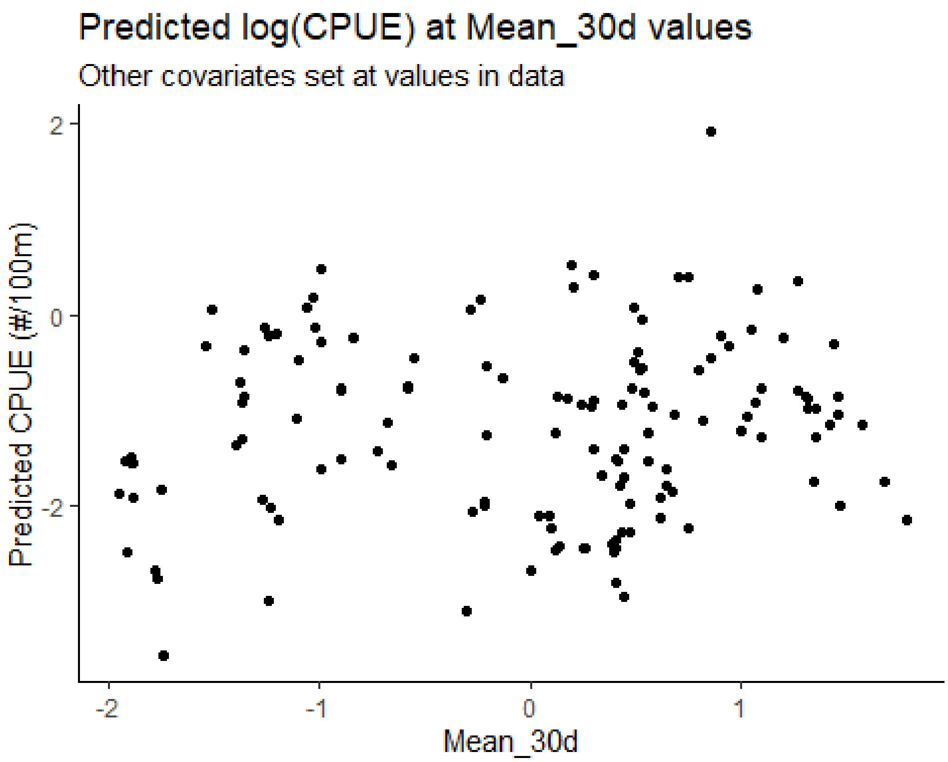

```
# Mean Prev 6
ggplot(data=dataLSU5.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.LSU_5))+
    ggtitle("Predicted log(CPUE) at Mean_6h values",subtitle="Other covariates set at values i
n data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```



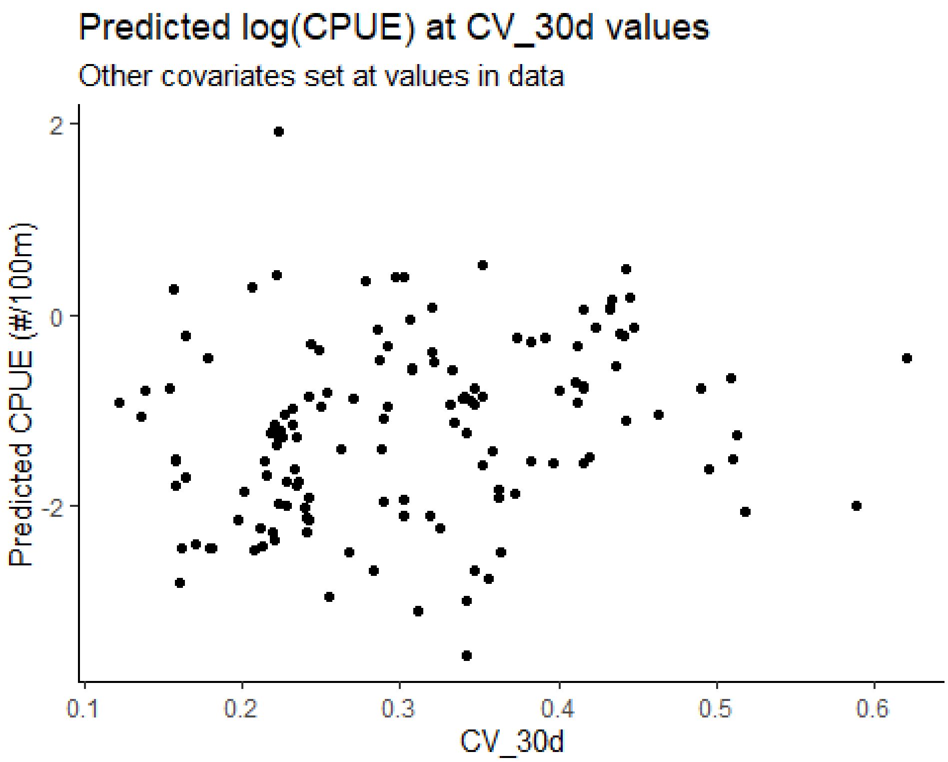

```r
# CV Prev 24 h
ggplot(data=dataLSU5.p, aes(x=CV.Prev6hDischarge, y=pred_100m.LSU_5))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_6h") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```



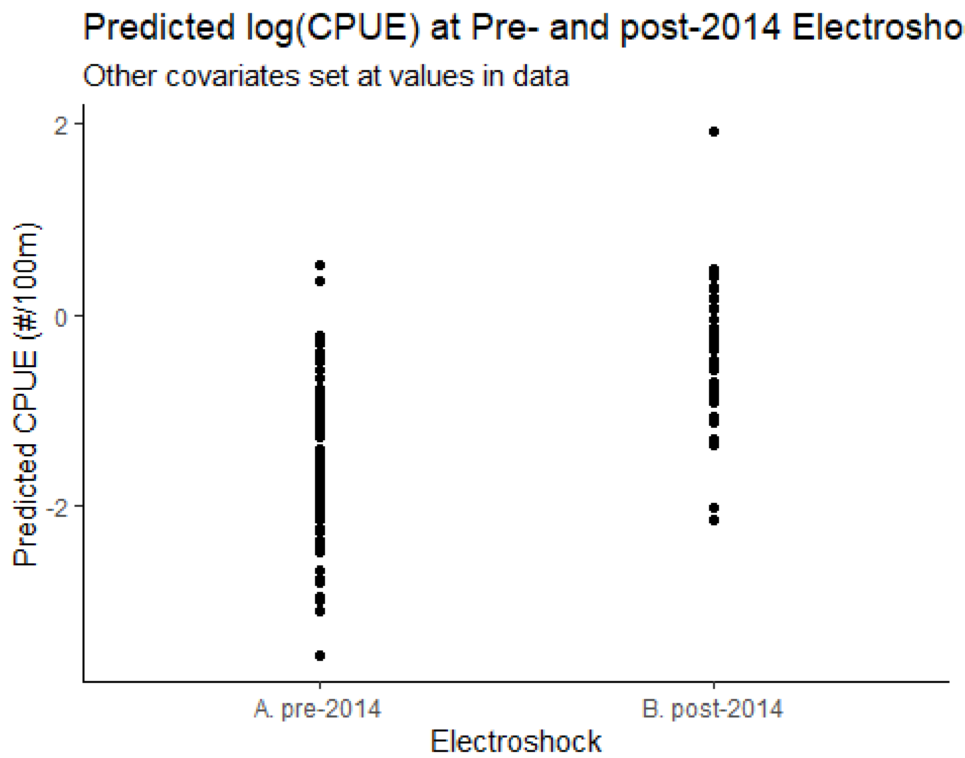

```
# Mean 30 Days
ggplot(data=dataLSU5.p, aes(x=Mean.30DayDischarge, y=pred_100m.LSU_5))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```




```
# CV Prev 30 Days
ggplot(data=dataLSU5.p, aes(x=CV.30DayDischarge, y=pred_100m.LSU_5))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```



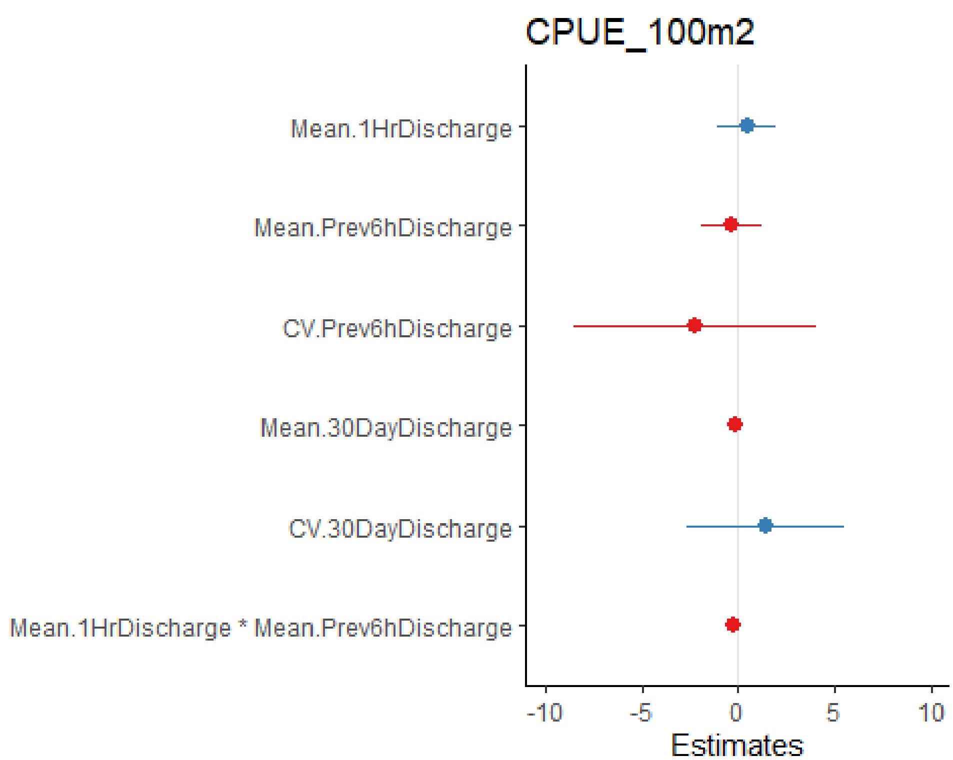

```
#Electroshocking
ggplot(data=dataLSU5.p, aes(x=Electroshock, y=pred_100m.LSU_5))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other
covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```




```
# LSU 6 ---------------------------------------------------------------------------------------
-------------------
summary(fit100m.LSU_6)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataLSU6
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    151.3    166.9    -66.6    133.3       33
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.5484 -0.2200  0.1379  0.5710  1.0981
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.000    0.000
##  Residual               1.399    1.183
## Number of obs: 42, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error      df t value
## (Intercept)                               -0.6013     0.6550 42.0000  -0.918
## Mean.1HrDischarge                          0.4487     0.7783 42.0000   0.577
## Mean.Prev6hDischarge                      -0.3696     0.8084 42.0000  -0.457
## CV.Prev6hDischarge                        -2.2447     3.1940 42.0000  -0.703
```

```
## Mean.30DayDischarge                         -0.1111     0.2191 42.0000  -0.507
## CV.30DayDischarge                            1.4287     2.1006 42.0000   0.680
## Mean.1HrDischarge:Mean.Prev6hDischarge      -0.2176     0.1492 42.0000  -1.458
##                                            Pr(>|t|)
## (Intercept)                                   0.364
## Mean.1HrDischarge                             0.567
## Mean.Prev6hDischarge                          0.650
## CV.Prev6hDischarge                            0.486
## Mean.30DayDischarge                           0.615
## CV.30DayDischarge                             0.500
## Mean.1HrDischarge:Mean.Prev6hDischarge        0.152
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.159
## Mn.Prv6hDsc -0.218 -0.960
## CV.Prv6hDsc -0.216 -0.037  0.089
## Mn.30DyDsch -0.012  0.092 -0.223  0.063
## CV.30DyDsch -0.896 -0.184  0.235 -0.069 -0.038
## M.1HD:M.P6D -0.008  0.130 -0.141  0.229  0.157 -0.269
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

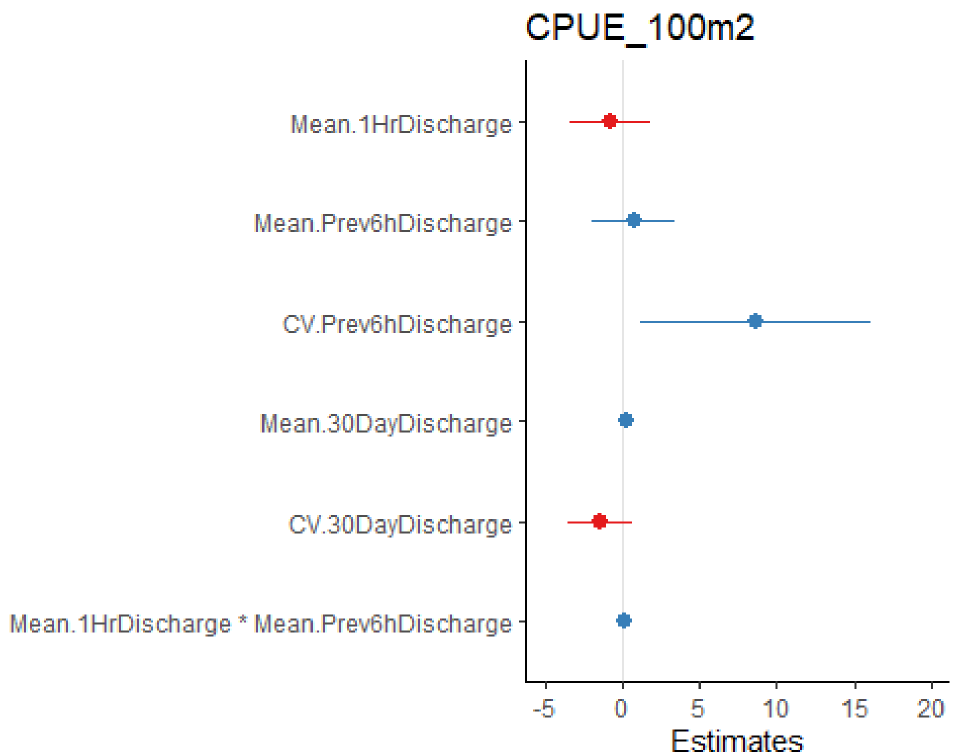
```
PlotAndSave(fit100m.LSU_6,"EffectSize_100m_LSU_6.tiff")
```




```
car::Anova(fit100m.CSU_6, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       2.5019  1    0.11371
## Mean.Prev6hDischarge                    3.0787  1    0.07932 .
```

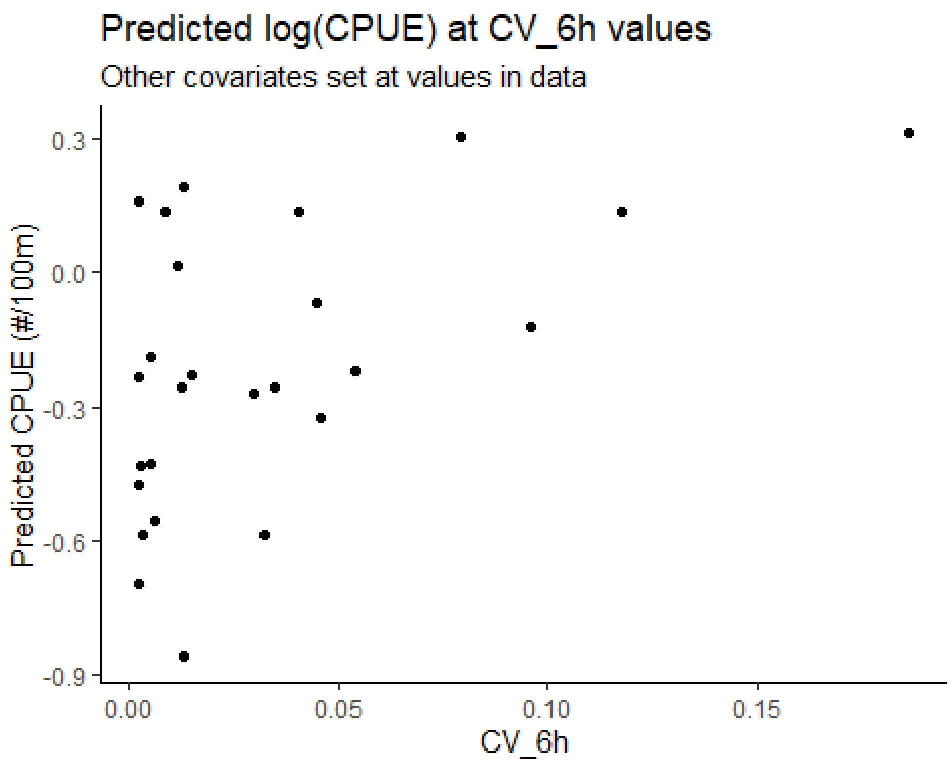
```
## CV.Prev6hDischarge                         3.3577  1    0.06689 .
## Mean.30DayDischarge                        0.6444  1    0.42214
## CV.30DayDischarge                          2.0076  1    0.15651
## Mean.1HrDischarge:Mean.Prev6hDischarge 2.9438  1    0.08621 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataCSU6.p <- cbind(dataCSU6, pred_100m.CSU_6=predict(fit100m.CSU_6, newdata=dataCSU6))

# NONE

# LSU 7 ---------------------------------------------------------------------------------
-------------------
summary(fit100m.LSU_7)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataLSU7
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     53.7     65.0    -17.9     35.7       17
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.23654 -0.66742  0.06118  0.55714  1.68745
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.2313   0.4809
## Number of obs: 26, groups:  SampleYear, 5
##
## Fixed effects:
##                                        Estimate Std. Error      df t value
## (Intercept)                             -0.1337     0.4368 26.0000  -0.306
## Mean.1HrDischarge                       -0.7810     1.3392 26.0000  -0.583
## Mean.Prev6hDischarge                     0.7482     1.3809 26.0000   0.542
## CV.Prev6hDischarge                       8.6053     3.8112 26.0000   2.258
## Mean.30DayDischarge                      0.2891     0.1724 26.0000   1.677
## CV.30DayDischarge                       -1.4475     1.0926 26.0000  -1.325
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.1199     0.1477 26.0000   0.812
##                                        Pr(>|t|)
## (Intercept)                              0.7620
## Mean.1HrDischarge                        0.5648
## Mean.Prev6hDischarge                     0.5925
## CV.Prev6hDischarge                       0.0326 *
## Mean.30DayDischarge                      0.1055
## CV.30DayDischarge                        0.1968
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.4241
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.216
```

```
## Mn.Prv6hDsc -0.232 -0.993
## CV.Prv6hDsc -0.343 -0.737  0.733
## Mn.30DyDsch  0.251  0.084 -0.173  0.073
## CV.30DyDsch -0.863 -0.072  0.082  0.018 -0.256
## M.1HD:M.P6D -0.454  0.178 -0.150  0.116 -0.196  0.119
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.LSU_7,"EffectSize_100m_LSU_7.tiff")
```




```
car::Anova(fit100m.LSU_7, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                       Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                    0.5463  1    0.45982
## Mean.Prev6hDischarge                 0.4502  1    0.50225
## CV.Prev6hDischarge                   5.0981  1    0.02395 *
## Mean.30DayDischarge                  2.8131  1    0.09350 .
## CV.30DayDischarge                    1.7551  1    0.18524
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.6595  1    0.41675
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataLSU7.p <- cbind(dataLSU7, pred_100m.LSU_7=predict(fit100m.LSU_7, newdata=dataLSU7))

# CV Prev 6 h
ggplot(data=dataLSU7.p, aes(x=CV.Prev6hDischarge, y=pred_100m.LSU_7))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
```

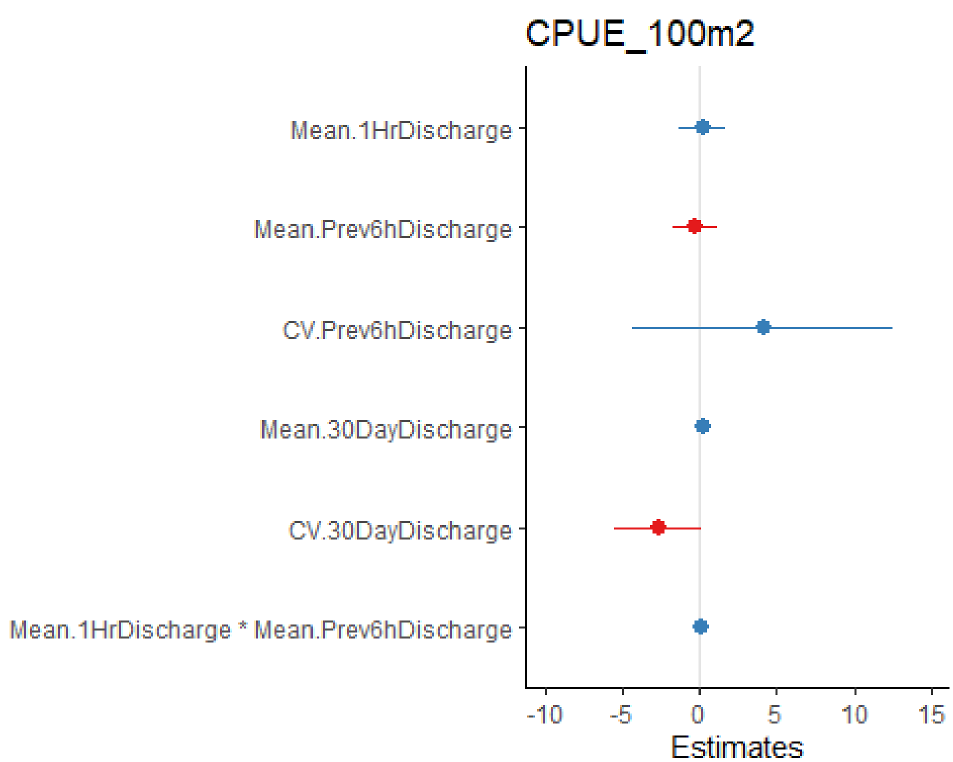
```
    xlab("CV_6h") +
    geom_point()
```




```
# LSU 9 ------------------------------------------------------------------------------
-------------------
summary(fit100m.LSU_9)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataLSU9
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     62.0     75.7    -22.0     44.0       25
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.49678 -0.71208  0.07245  0.69803  2.09663
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.000
##  Residual               0.2134   0.462
## Number of obs: 34, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error       df
## (Intercept)                              -0.09383    0.33365 34.00000
```

```
## Mean.1HrDischarge                          0.17122    0.76480 34.00000
## Mean.Prev6hDischarge                      -0.26300    0.71621 34.00000
## CV.Prev6hDischarge                         4.13770    4.31511 34.00000
## Mean.30DayDischarge                        0.20391    0.12039 34.00000
## CV.30DayDischarge                         -2.69257    1.43070 34.00000
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.07801    0.13707 34.00000
##                                          t value Pr(>|t|)
## (Intercept)                               -0.281   0.7802
## Mean.1HrDischarge                          0.224   0.8242
## Mean.Prev6hDischarge                      -0.367   0.7157
## CV.Prev6hDischarge                         0.959   0.3444
## Mean.30DayDischarge                        1.694   0.0995 .
## CV.30DayDischarge                         -1.882   0.0684 .
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.569   0.5730
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr -0.218
## Mn.Prv6hDsc  0.180 -0.984
## CV.Prv6hDsc -0.264  0.820 -0.786
## Mn.30DyDsch -0.215 -0.280  0.180 -0.327
## CV.30DyDsch -0.772 -0.256  0.244 -0.299  0.508
## M.1HD:M.P6D  0.088  0.458 -0.362  0.516 -0.582 -0.607
## convergence code: 0
## boundary (singular) fit: see ?isSingular
```

```
PlotAndSave(fit100m.LSU_9,"EffectSize_100m_LSU_9.tiff")
```

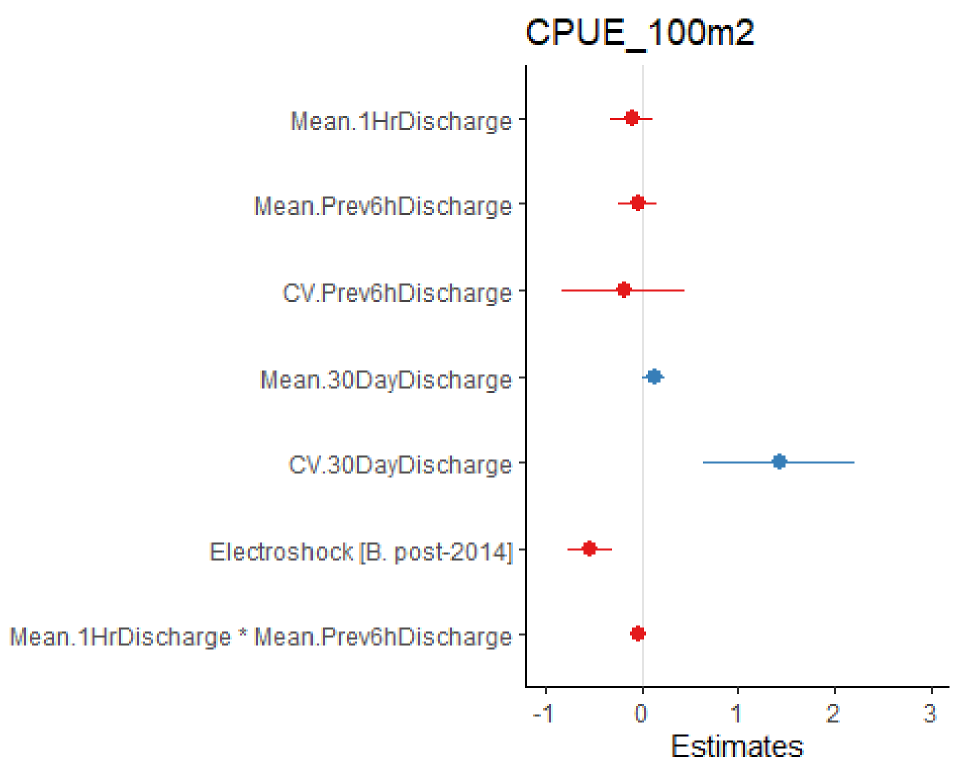



```
car::Anova(fit100m.LSU_9, type=2)
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                         Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                      0.0017  1    0.96680
## Mean.Prev6hDischarge                   0.0299  1    0.86272
## CV.Prev6hDischarge                     0.9195  1    0.33762
## Mean.30DayDischarge                    2.8685  1    0.09033 .
## CV.30DayDischarge                      3.5419  1    0.05984 .
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.3239  1    0.56928
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataLSU9.p <- cbind(dataLSU9, pred_100m.LSU_9=predict(fit100m.LSU_9, newdata=dataLSU9))

# NONE

# MW 1 -----------------------------------------------------------------------------------------------
summary(fit100m.MW_1)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischarge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataMW1
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    162.8    194.8    -71.4    142.8      172
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -3.7882 -0.4606  0.0287  0.5322  2.7535
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.03806  0.1951
##  Residual               0.11073  0.3328
## Number of obs: 182, groups:  SampleYear, 18
##
## Fixed effects:
##                                         Estimate Std. Error        df
## (Intercept)                              1.04448    0.18592 113.24504
## Mean.1HrDischarge                       -0.10573    0.11621 171.25325
## Mean.Prev6hDischarge                    -0.04290    0.10487 174.63436
## CV.Prev6hDischarge                      -0.18786    0.32886 169.39573
## Mean.30DayDischarge                      0.12991    0.05943  80.10680
## CV.30DayDischarge                        1.42678    0.40014 133.85565
## ElectroshockB. post-2014                -0.53582    0.11647  18.42883
## Mean.1HrDischarge:Mean.Prev6hDischarge  -0.03017    0.03675 180.27423
##                                        t value Pr(>|t|)
## (Intercept)                              5.618  1.4e-07 ***
## Mean.1HrDischarge                       -0.910 0.364218
## Mean.Prev6hDischarge                    -0.409 0.682956
## CV.Prev6hDischarge                      -0.571 0.568597
## Mean.30DayDischarge                      2.186 0.031736 *
## CV.30DayDischarge                        3.566 0.000504 ***
```

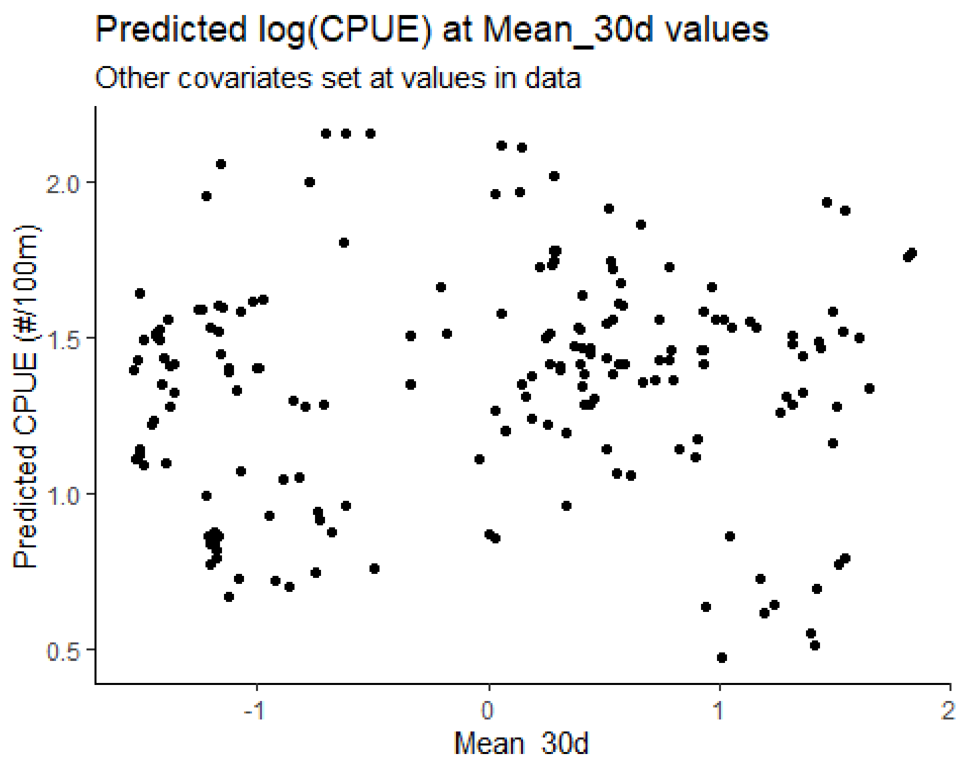
```
## ElectroshockB. post-2014                -4.601 0.000210 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  -0.821 0.412675
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.361
## Mn.Prv6hDsc -0.330 -0.937
## CV.Prv6hDsc -0.433 -0.865  0.826
## Mn.30DyDsch -0.548 -0.155  0.053  0.116
## CV.30DyDsch -0.827 -0.027  0.026  0.018  0.533
## ElcB.p-2014 -0.306  0.093 -0.088 -0.055  0.242  0.154
## M.1HD:M.P6D -0.069 -0.260  0.158  0.414  0.035 -0.279 -0.057
```

```
PlotAndSave(fit100m.MW_1,"EffectSize_100m_MW_1.tiff")
```

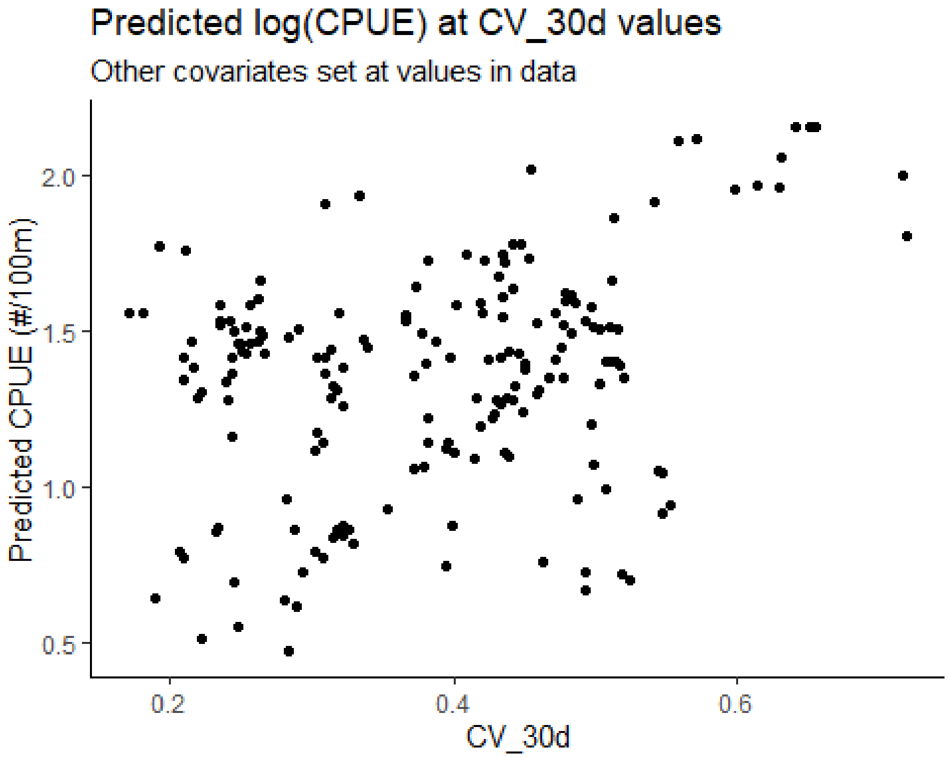



```
car::Anova(fit100m.MW_1, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       1.3536  1  0.2446531
## Mean.Prev6hDischarge                    0.0800  1  0.7773210
## CV.Prev6hDischarge                      0.3263  1  0.5678396
## Mean.30DayDischarge                     4.7786  1  0.0288162 *
## CV.30DayDischarge                      12.7145  1  0.0003628 ***
## Electroshock                           21.1652  1  4.213e-06 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.6742  1  0.4115908
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

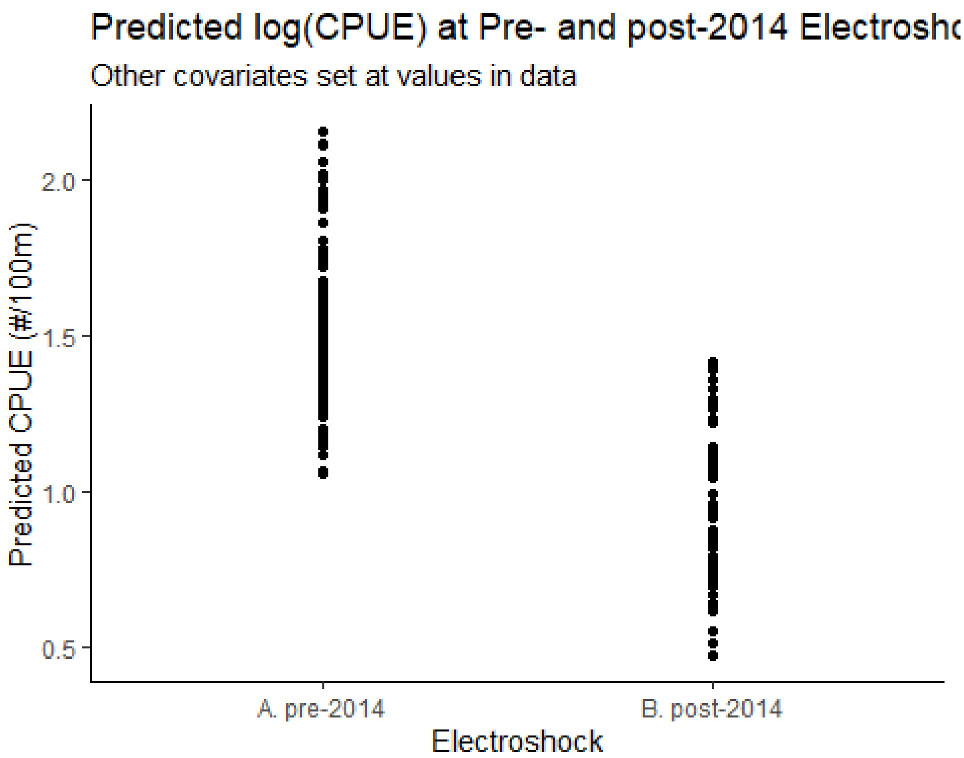
```
dataMW1.p <- cbind(dataMW1, pred_100m.MW_1=predict(fit100m.MW_1, newdata=dataMW1))

# Mean 30 Days
ggplot(data=dataMW1.p, aes(x=Mean.30DayDischarge, y=pred_100m.MW_1))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_30d") +
    geom_point()
```




```
# CV Prev 30 Days
ggplot(data=dataMW1.p, aes(x=CV.30DayDischarge, y=pred_100m.MW_1))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()
```

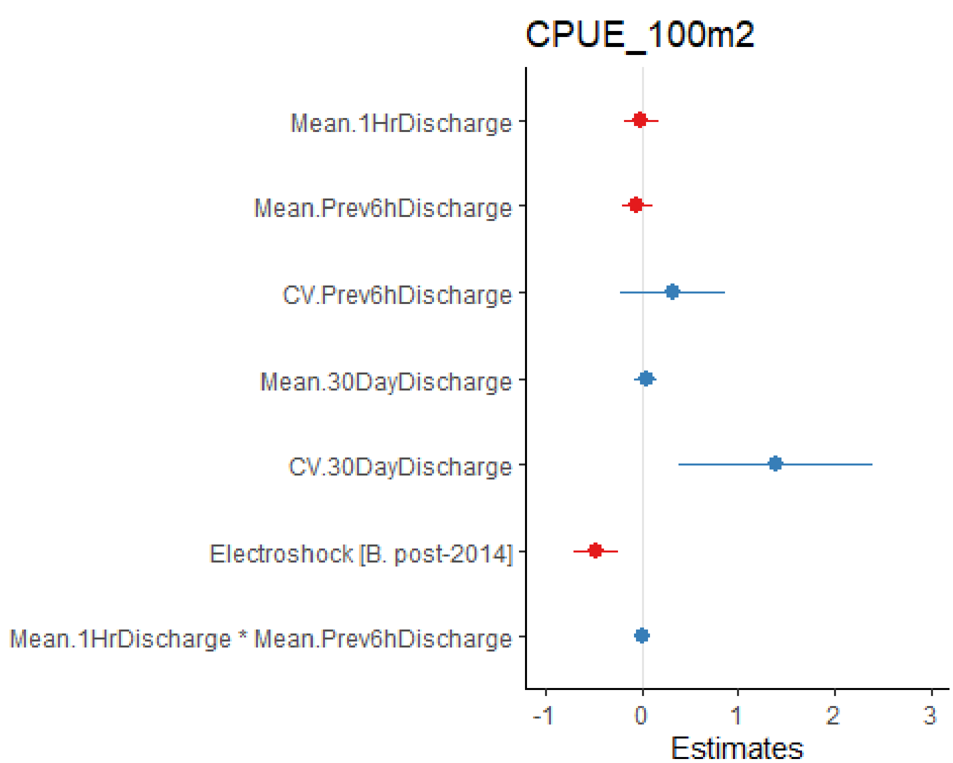



```
#Electroshocking
ggplot(data=dataMW1.p, aes(x=Electroshock, y=pred_100m.MW_1))+
    ggtitle("Predicted log(CPUE) at Pre- and post-2014 Electroshock Settings",subtitle="Other covariates set at values in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()
```




```
# MW 3 -------------------------------------------------------------------------------------
------------------
summary(fit100m.MW_3)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataMW3
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    176.9    209.4    -78.4    156.9      182
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.04829 -0.57281  0.07938  0.55454  3.07246
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.04063  0.2016
##  Residual               0.11483  0.3389
## Number of obs: 192, groups:  SampleYear, 18
##
## Fixed effects:
##                                            Estimate Std. Error         df
## (Intercept)                                0.713475   0.199966  90.426623
## Mean.1HrDischarge                         -0.002241   0.089198 177.375384
## Mean.Prev6hDischarge                      -0.050253   0.081531 181.937868
## CV.Prev6hDischarge                         0.326367   0.276800 172.819926
```

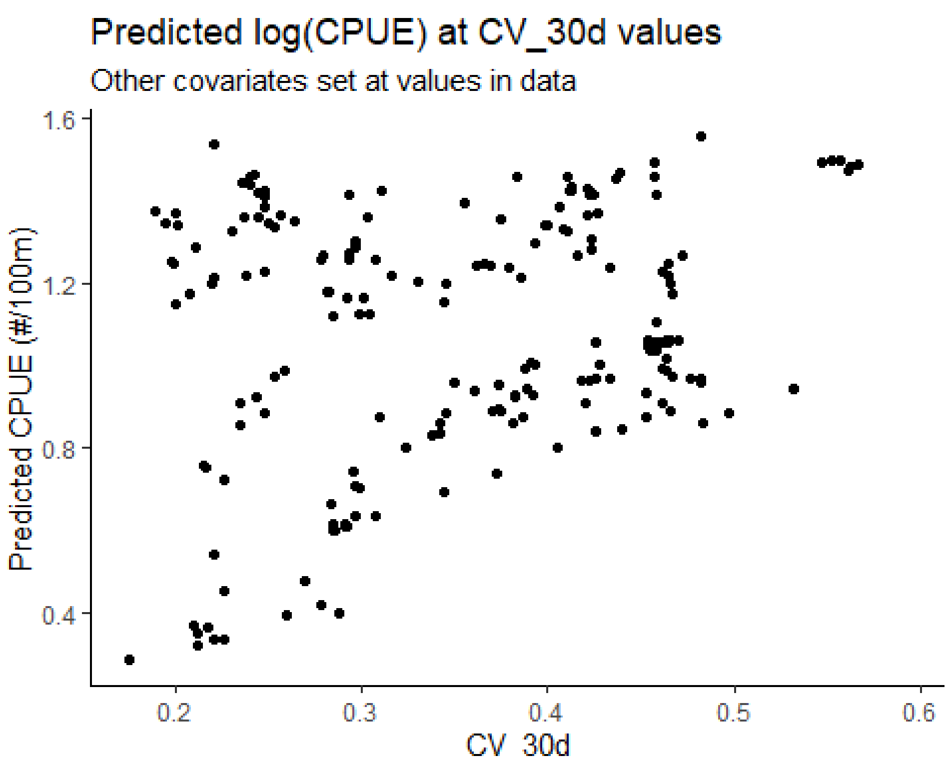
```
## Mean.30DayDischarge                          0.040229   0.063129  46.142660
## CV.30DayDischarge                            1.389030   0.513922 106.224166
## ElectroshockB. post-2014                    -0.469799   0.117732  13.173430
## Mean.1HrDischarge:Mean.Prev6hDischarge       0.005391   0.029886 191.300719
##                                             t value Pr(>|t|)
## (Intercept)                                   3.568 0.000578 ***
## Mean.1HrDischarge                            -0.025 0.979984
## Mean.Prev6hDischarge                         -0.616 0.538420
## CV.Prev6hDischarge                            1.179 0.239991
## Mean.30DayDischarge                           0.637 0.527109
## CV.30DayDischarge                             2.703 0.008007 **
## ElectroshockB. post-2014                     -3.990 0.001502 **
## Mean.1HrDischarge:Mean.Prev6hDischarge        0.180 0.857039
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.231
## Mn.Prv6hDsc -0.270 -0.878
## CV.Prv6hDsc -0.301 -0.755  0.635
## Mn.30DyDsch -0.450 -0.157  0.008  0.082
## CV.30DyDsch -0.885 -0.035  0.134 -0.004  0.433
## ElcB.p-2014 -0.267  0.053 -0.072 -0.019  0.220  0.087
## M.1HD:M.P6D -0.027 -0.135 -0.011  0.397 -0.063 -0.215 -0.050

PlotAndSave(fit100m.MW_3,"EffectSize_100m_MW_3.tiff")
```



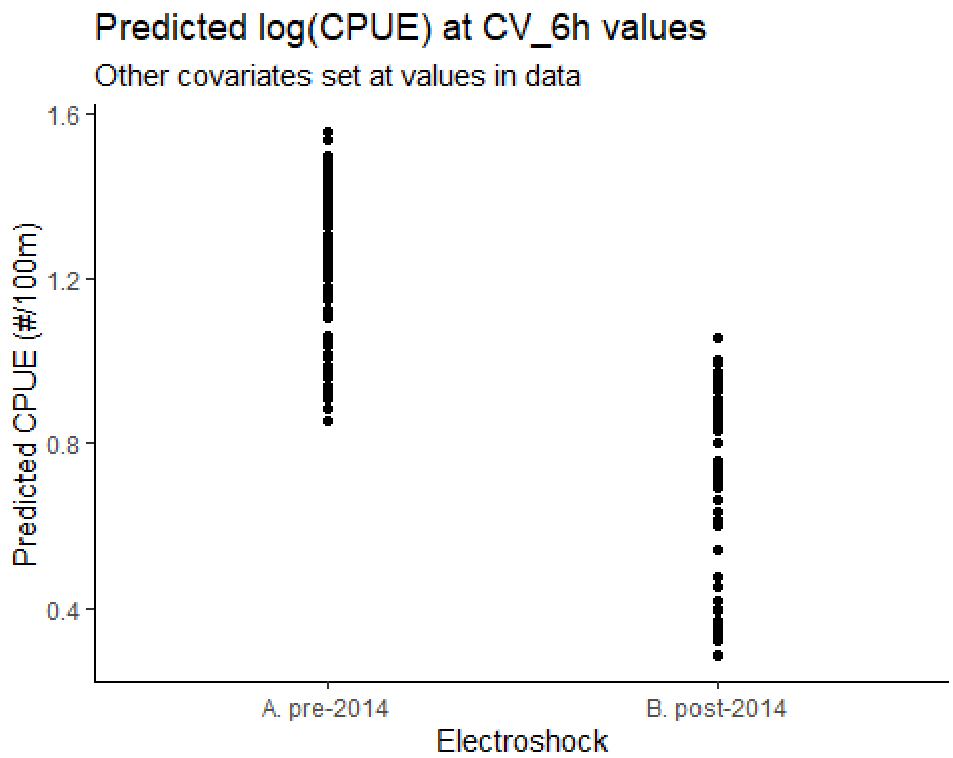

```
car::Anova(fit100m.MW_3, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
```

```
##                                            Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                         0.0000  1   0.999315
## Mean.Prev6hDischarge                      0.3776  1   0.538889
## CV.Prev6hDischarge                        1.3902  1   0.238370
## Mean.30DayDischarge                       0.4061  1   0.523960
## CV.30DayDischarge                         7.3051  1   0.006876 **
## Electroshock                             15.9233  1  6.596e-05 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.0325  1   0.856848
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
dataMW3.p <- cbind(dataMW3, pred_100m.MW_3=predict(fit100m.MW_3, newdata=dataMW3))

# CV Prev 30 Days
ggplot(data=dataMW3.p, aes(x=CV.30DayDischarge, y=pred_100m.MW_3))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```

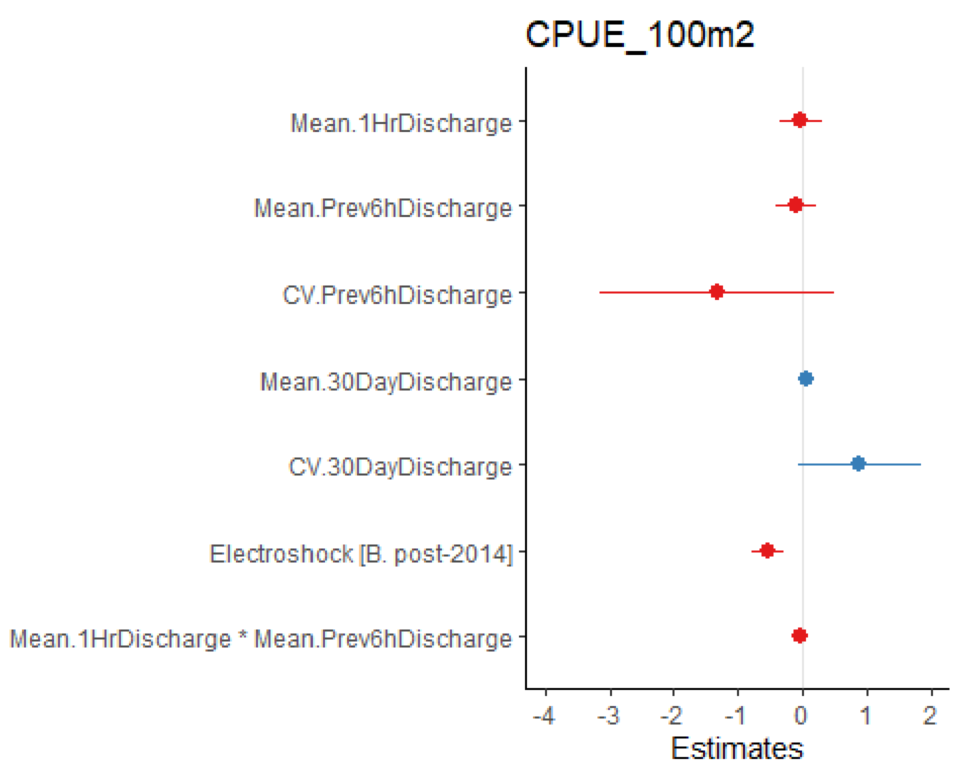



```
#Electroshocking
ggplot(data=dataMW3.p, aes(x=Electroshock, y=pred_100m.MW_3))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 14 rows containing missing values (geom_point).
```



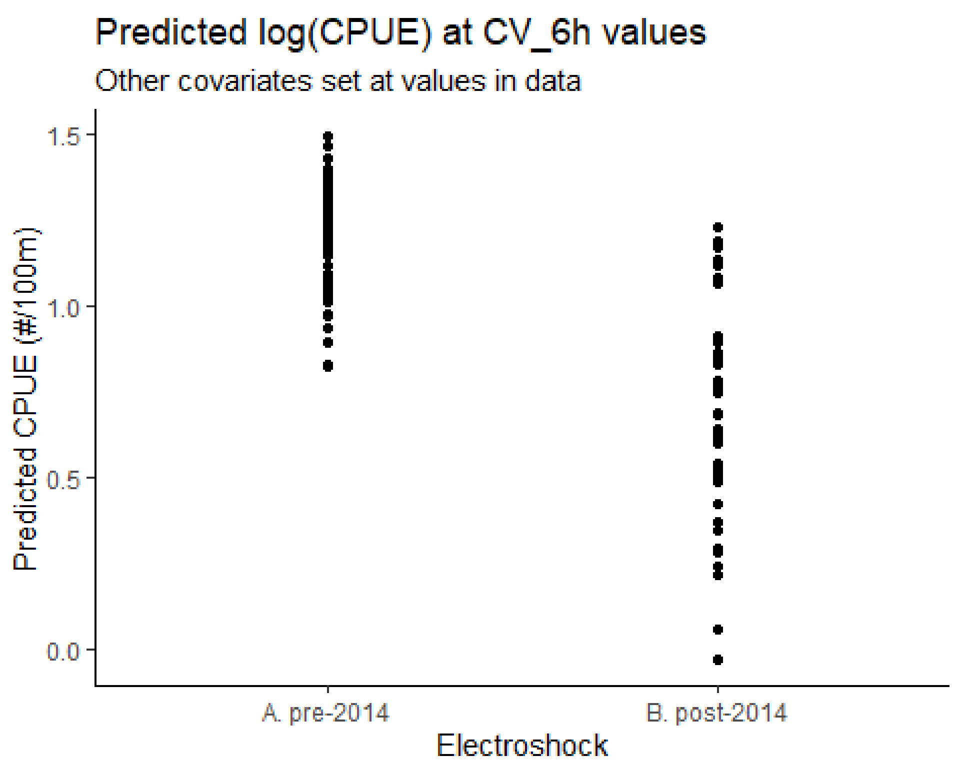

```
# MW 5 ------------------------------------------------------------------------------------------
------------------
summary(fit100m.MW_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataMW5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    107.2    136.4    -43.6     87.2      127
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -3.07794 -0.55423  0.09466  0.53502  2.70396
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.04603  0.2145
##  Residual               0.09184  0.3031
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                           Estimate Std. Error        df
## (Intercept)                                1.06102    0.17222  66.17840
## Mean.1HrDischarge                         -0.02930    0.16620 128.38249
## Mean.Prev6hDischarge                      -0.10820    0.15942 128.90091
## CV.Prev6hDischarge                        -1.32555    0.92938 128.58848
```

```
## Mean.30DayDischarge                       0.04801    0.06191  53.29379
## CV.30DayDischarge                         0.87977    0.48892  99.25917
## ElectroshockB. post-2014                 -0.53278    0.13158  15.55055
## Mean.1HrDischarge:Mean.Prev6hDischarge   -0.02471    0.02770 135.50281
##                                         t value Pr(>|t|)
## (Intercept)                               6.161 4.83e-08 ***
## Mean.1HrDischarge                        -0.176 0.860364
## Mean.Prev6hDischarge                     -0.679 0.498528
## CV.Prev6hDischarge                       -1.426 0.156210
## Mean.30DayDischarge                       0.775 0.441483
## CV.30DayDischarge                         1.799 0.074993 .
## ElectroshockB. post-2014                 -4.049 0.000981 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge   -0.892 0.373955
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.181
## Mn.Prv6hDsc  0.183 -0.976
## CV.Prv6hDsc -0.263  0.770 -0.740
## Mn.30DyDsch -0.460  0.005 -0.054  0.005
## CV.30DyDsch -0.818 -0.061  0.044 -0.061  0.444
## ElcB.p-2014 -0.376  0.009 -0.007  0.064  0.248  0.082
## M.1HD:M.P6D  0.126 -0.028  0.054 -0.052  0.065 -0.295 -0.037

PlotAndSave(fit100m.MW_5,"EffectSize_100m_MW_5.tiff")
```



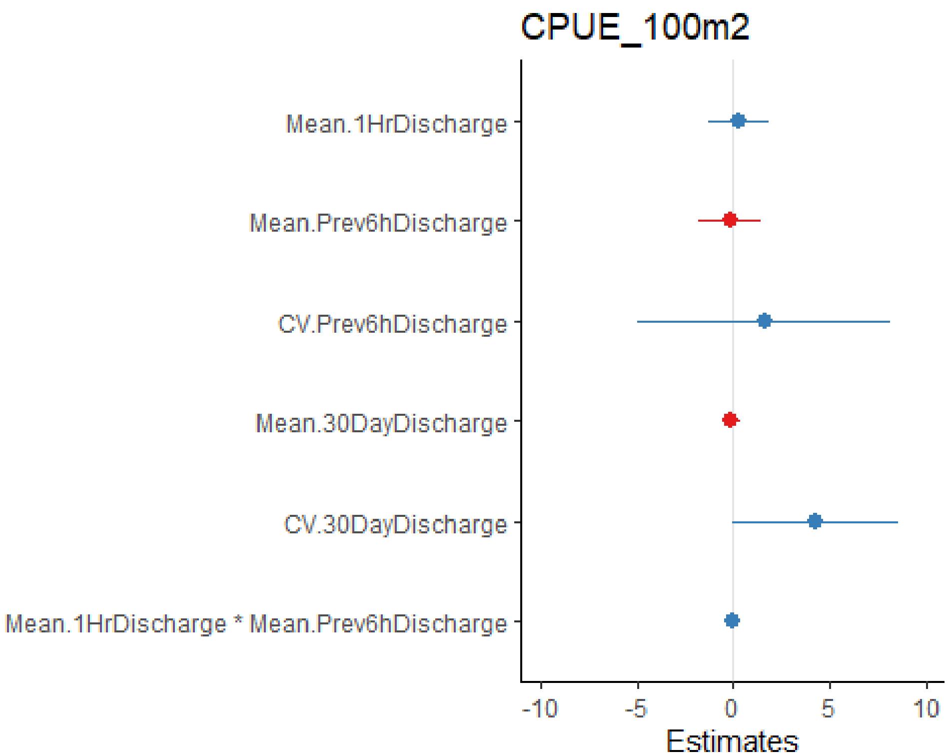

```
car::Anova(fit100m.MW_5, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
```

```
##                                            Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                         0.0406  1    0.84027
## Mean.Prev6hDischarge                      0.3986  1    0.52781
## CV.Prev6hDischarge                        2.0343  1    0.15379
## Mean.30DayDischarge                       0.6014  1    0.43805
## CV.30DayDischarge                         3.2379  1    0.07195 .
## Electroshock                             16.3948  1  5.142e-05 ***
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.7957  1    0.37237
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataMW5.p <- cbind(dataMW5, pred_100m.MW_5=predict(fit100m.MW_5, newdata=dataMW5))

#Electroshocking
ggplot(data=dataMW5.p, aes(x=Electroshock, y=pred_100m.MW_5))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```

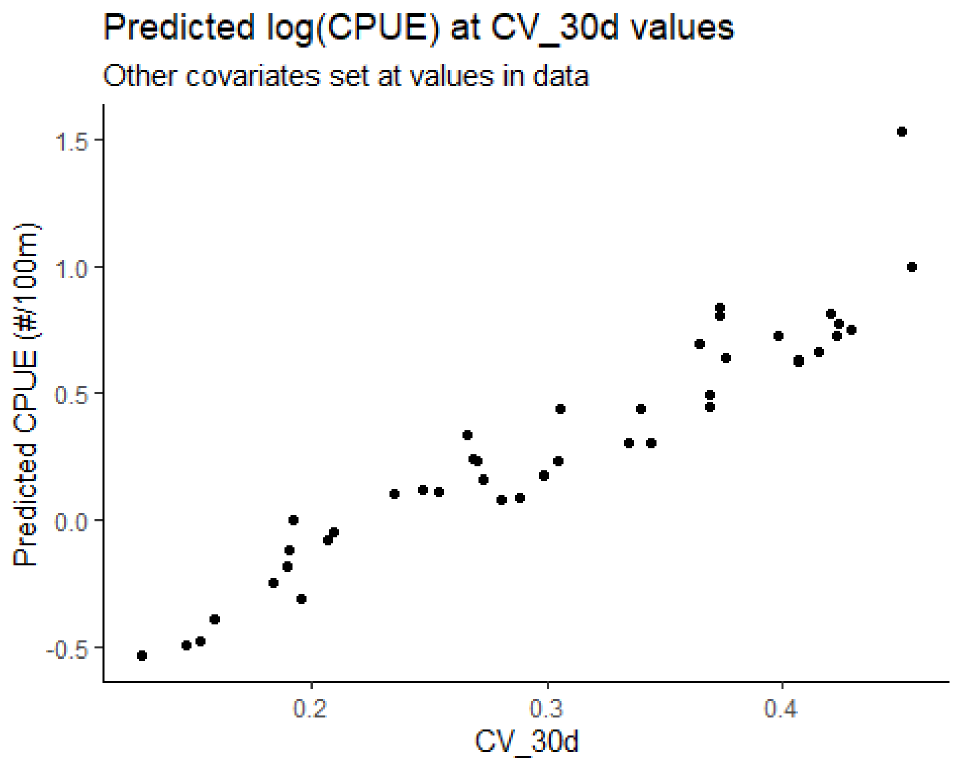



```
# MW 6 ---------------------------------------------------------------------------------
------------------
summary(fit100m.MW_6)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
```

```
##     (1 | SampleYear)
##    Data: dataMW6
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    154.8    170.5    -68.4    136.8       33
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.8547 -0.3229  0.1373  0.6456  1.1646
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.000    0.000
##  Residual               1.522    1.234
## Number of obs: 42, groups:  SampleYear, 5
##
## Fixed effects:
##                                      Estimate Std. Error       df
## (Intercept)                          -1.09918    0.68330 42.00000
## Mean.1HrDischarge                     0.26111    0.81190 42.00000
## Mean.Prev6hDischarge                 -0.17505    0.84338 42.00000
## CV.Prev6hDischarge                    1.62201    3.33204 42.00000
## Mean.30DayDischarge                  -0.08564    0.22854 42.00000
## CV.30DayDischarge                     4.30913    2.19138 42.00000
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.01958    0.15567 42.00000
##                                      t value Pr(>|t|)
## (Intercept)                           -1.609   0.1152
## Mean.1HrDischarge                      0.322   0.7494
## Mean.Prev6hDischarge                  -0.208   0.8366
## CV.Prev6hDischarge                     0.487   0.6289
## Mean.30DayDischarge                   -0.375   0.7097
## CV.30DayDischarge                      1.966   0.0559 .
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.126   0.9005
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.159
## Mn.Prv6hDsc -0.218 -0.960
## CV.Prv6hDsc -0.216 -0.037  0.089
## Mn.30DyDsch -0.012  0.092 -0.223  0.063
## CV.30DyDsch -0.896 -0.184  0.235 -0.069 -0.038
## M.1HD:M.P6D -0.008  0.130 -0.141  0.229  0.157 -0.269
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.MW_6,"EffectSize_100m_MW_6.tiff")
```

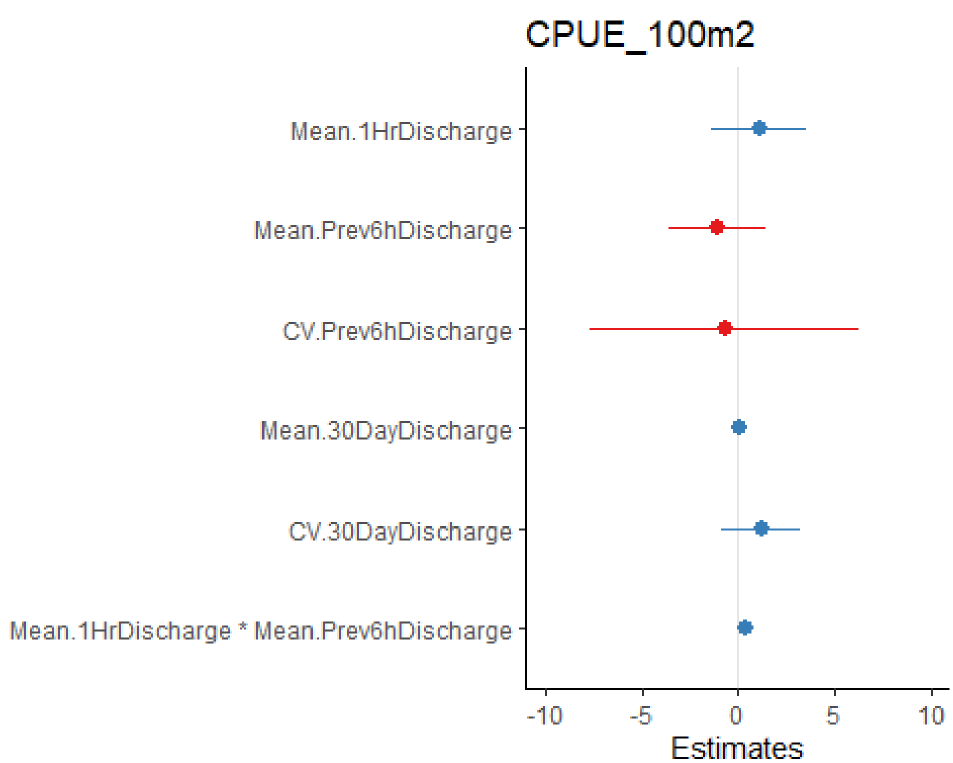



```
car::Anova(fit100m.MW_6, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       0.0948  1    0.75819
## Mean.Prev6hDischarge                    0.0368  1    0.84794
## CV.Prev6hDischarge                      0.2370  1    0.62641
## Mean.30DayDischarge                     0.1404  1    0.70785
## CV.30DayDischarge                       3.8668  1    0.04925 *
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.0158  1    0.89991
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataMW6.p <- cbind(dataMW6, pred_100m.MW_6=predict(fit100m.MW_6, newdata=dataMW6))

# CV Prev 30 Days
ggplot(data=dataMW6.p, aes(x=CV.30DayDischarge, y=pred_100m.MW_6))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()
```




```
    # INTERESTING TREND, BUT RANGE OF CV VALUES IS TOO SMALL TO BE MEANINGFUL CHANGES IN CPUE

# MW 7 -----------------------------------------------------------------------------------------------
summary(fit100m.MW_7)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataMW7
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     50.3     61.6    -16.2     32.3       17
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.61240 -0.52487  0.04903  0.33242  2.27957
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.2028   0.4503
## Number of obs: 26, groups:  SampleYear, 5
##
## Fixed effects:
##                                        Estimate Std. Error       df
## (Intercept)                            -0.59638    0.40906 26.00000
## Mean.1HrDischarge                       1.10905    1.25411 26.00000
```

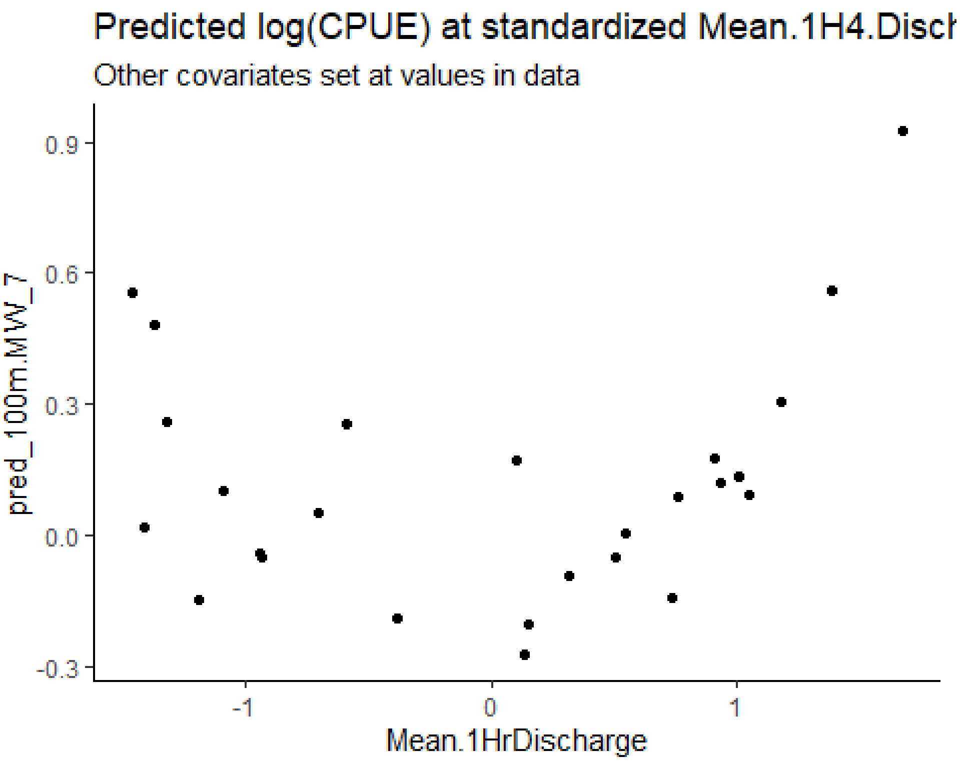
```
## Mean.Prev6hDischarge                      -1.09805    1.29315 26.00000
## CV.Prev6hDischarge                        -0.69399    3.56893 26.00000
## Mean.30DayDischarge                        0.02614    0.16141 26.00000
## CV.30DayDischarge                          1.18217    1.02319 26.00000
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.36812    0.13829 26.00000
##                                          t value Pr(>|t|)
## (Intercept)                               -1.458   0.1568
## Mean.1HrDischarge                          0.884   0.3846
## Mean.Prev6hDischarge                      -0.849   0.4036
## CV.Prev6hDischarge                        -0.194   0.8473
## Mean.30DayDischarge                        0.162   0.8726
## CV.30DayDischarge                          1.155   0.2584
## Mean.1HrDischarge:Mean.Prev6hDischarge     2.662   0.0131 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.216
## Mn.Prv6hDsc -0.232 -0.993
## CV.Prv6hDsc -0.343 -0.737  0.733
## Mn.30DyDsch  0.251  0.084 -0.173  0.073
## CV.30DyDsch -0.863 -0.072  0.082  0.018 -0.256
## M.1HD:M.P6D -0.454  0.178 -0.150  0.116 -0.196  0.119
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.MW_7,"EffectSize_100m_MW_7.tiff")
```



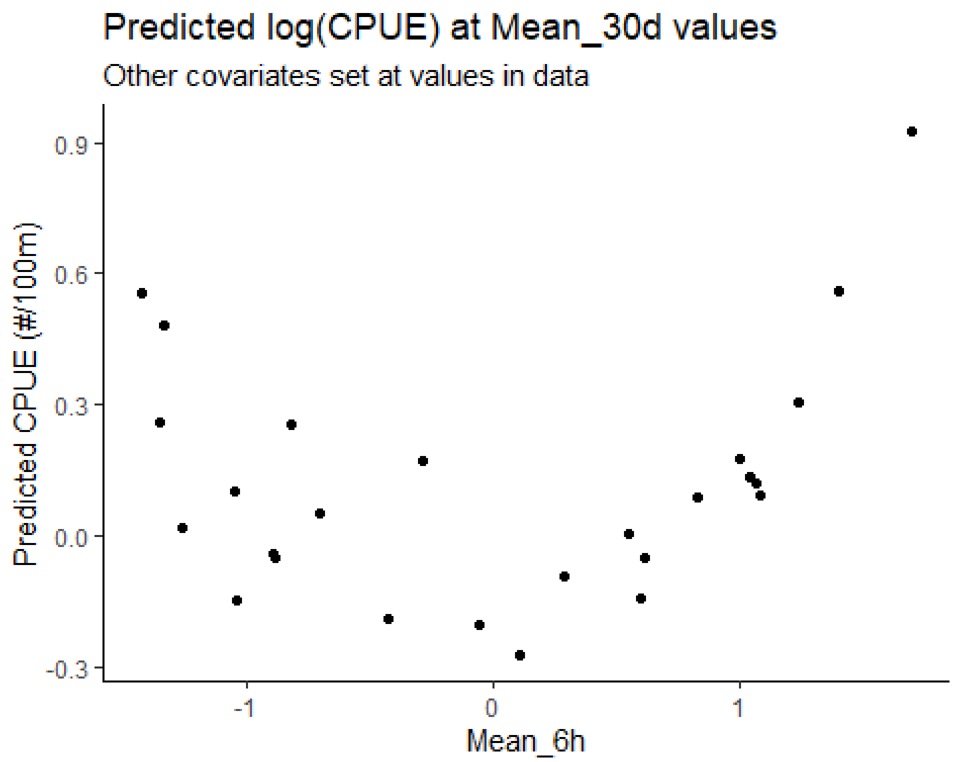

```
car::Anova(fit100m.MW_7, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
```

```
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       0.1749  1   0.675751
## Mean.Prev6hDischarge                    0.2078  1   0.648527
## CV.Prev6hDischarge                      0.0378  1   0.845821
## Mean.30DayDischarge                     0.0262  1   0.871321
## CV.30DayDischarge                       1.3349  1   0.247934
## Mean.1HrDischarge:Mean.Prev6hDischarge 7.0863  1   0.007768 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
dataMW7.p <- cbind(dataMW7, pred_100m.MW_7=predict(fit100m.MW_7, newdata=dataMW7))

# Prev 1 h
ggplot(data=dataMW7.p, aes(x=Mean.1HrDischarge, y=pred_100m.MW_7))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    geom_point()
```

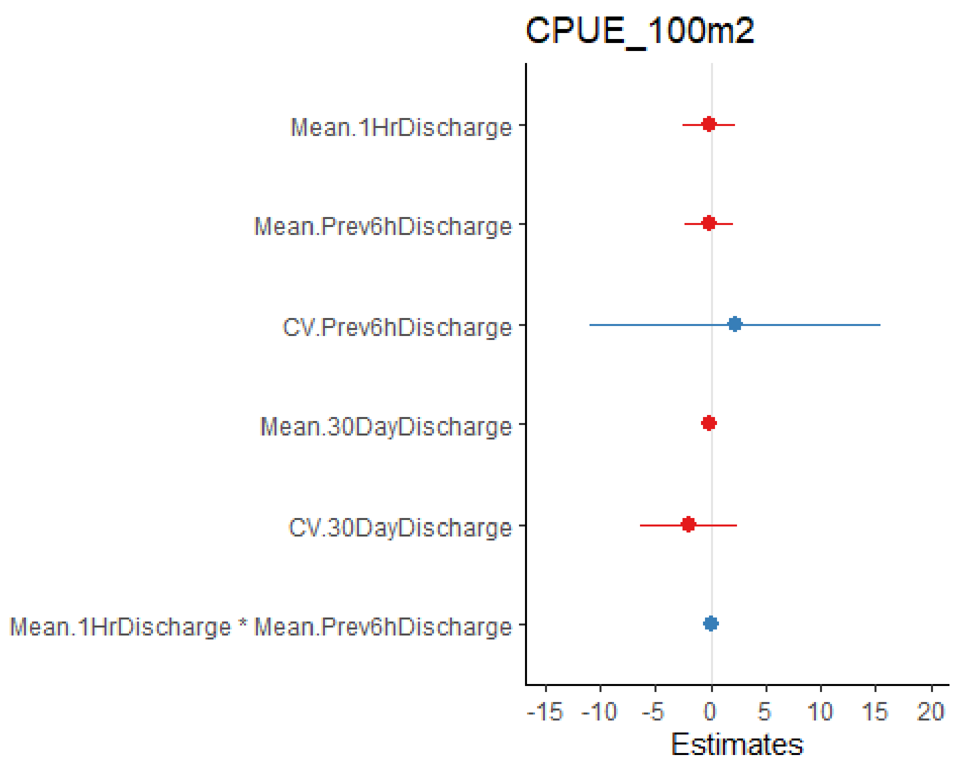



```
# Mean 6h
ggplot(data=dataMW7.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.MW_7))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()
```




```
# Collinearity seems likely with this.

# MW 9 -------------------------------------------------------------------------------------------
------------------
summary(fit100m.MW_9)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataMW9
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     92.3    106.1    -37.2     74.3       25
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.8670 -0.6252  0.1714  0.8861  1.3910
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.5214   0.7221
## Number of obs: 34, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error       df
## (Intercept)                              -0.60096    0.52149 34.00000
## Mean.1HrDischarge                        -0.12649    1.19537 34.00000
```

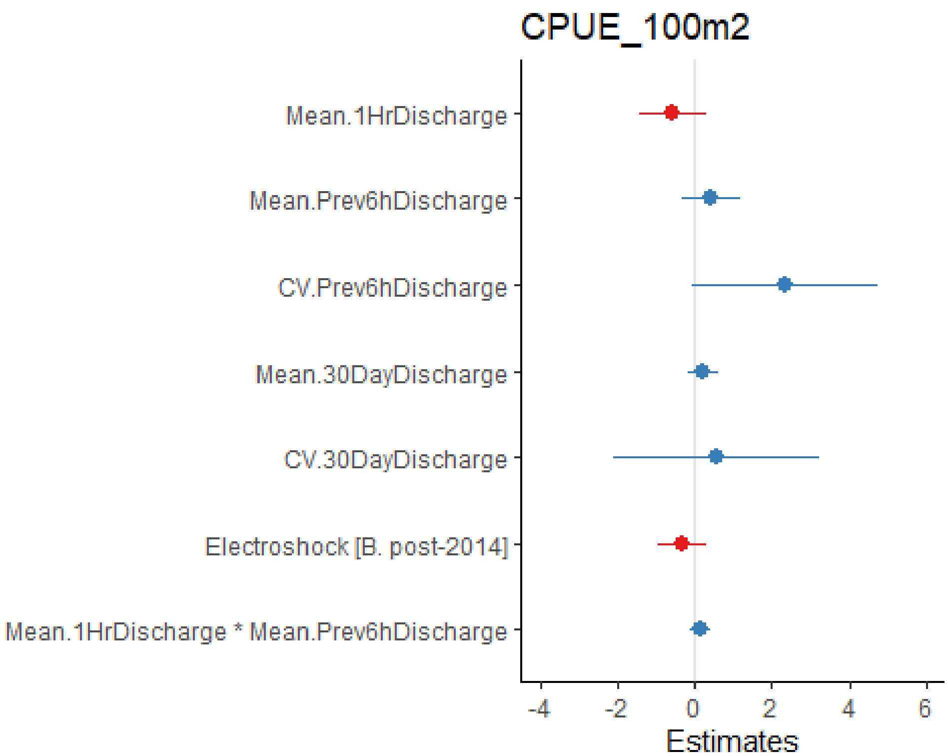
```
## Mean.Prev6hDischarge                      -0.15269    1.11943 34.00000
## CV.Prev6hDischarge                         2.21713    6.74445 34.00000
## Mean.30DayDischarge                       -0.05194    0.18817 34.00000
## CV.30DayDischarge                         -1.96287    2.23616 34.00000
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.14785    0.21423 34.00000
##                                           t value Pr(>|t|)
## (Intercept)                                -1.152    0.257
## Mean.1HrDischarge                          -0.106    0.916
## Mean.Prev6hDischarge                       -0.136    0.892
## CV.Prev6hDischarge                          0.329    0.744
## Mean.30DayDischarge                        -0.276    0.784
## CV.30DayDischarge                          -0.878    0.386
## Mean.1HrDischarge:Mean.Prev6hDischarge      0.690    0.495
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr -0.218
## Mn.Prv6hDsc  0.180 -0.984
## CV.Prv6hDsc -0.264  0.820 -0.786
## Mn.30DyDsch -0.215 -0.280  0.180 -0.327
## CV.30DyDsch -0.772 -0.256  0.244 -0.299  0.508
## M.1HD:M.P6D  0.088  0.458 -0.362  0.516 -0.582 -0.607
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.MW_9,"EffectSize_100m_MW_9.tiff")
```




```
car::Anova(fit100m.MW_9, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                           Chisq Df Pr(>Chisq)
```

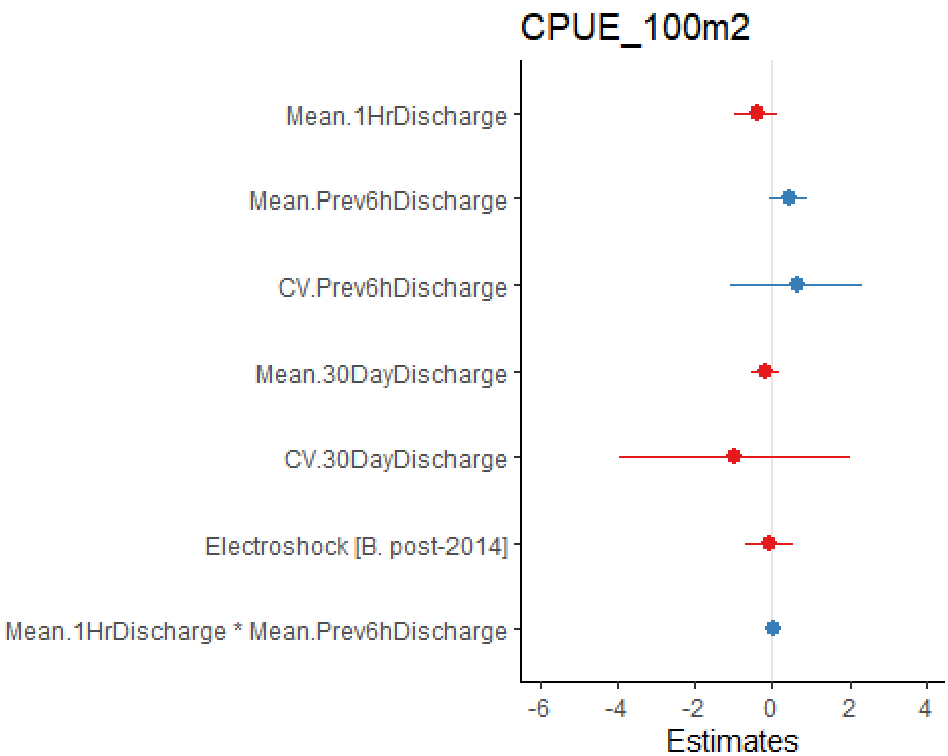
```
## Mean.1HrDischarge                        0.2256  1     0.6348
## Mean.Prev6hDischarge                     0.0148  1     0.9032
## CV.Prev6hDischarge                       0.1081  1     0.7424
## Mean.30DayDischarge                      0.0762  1     0.7825
## CV.30DayDischarge                        0.7705  1     0.3801
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.4763  1     0.4901

dataMW9.p <- cbind(dataMW9, pred_100m.MW_9=predict(fit100m.MW_9, newdata=dataMW9))

# NONE

# RB 1 -----------------------------------------------------------------------------------
-------------------
summary(fit100m.RB_1)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataRB1
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    638.2    670.2   -309.1    618.2      172
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.5531 -0.3369  0.1569  0.6466  1.7759
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.2133   0.4618
##  Residual               1.6078   1.2680
## Number of obs: 182, groups:  SampleYear, 18
##
## Fixed effects:
##                                          Estimate Std. Error       df
## (Intercept)                               -4.0218     0.6330  89.4635
## Mean.1HrDischarge                         -0.5780     0.4376 175.9517
## Mean.Prev6hDischarge                       0.4210     0.3930 179.1855
## CV.Prev6hDischarge                         2.3491     1.2420 172.9638
## Mean.30DayDischarge                        0.2194     0.1962  66.9177
## CV.30DayDischarge                          0.5756     1.3678  81.4399
## ElectroshockB. post-2014                  -0.3157     0.3278  18.2531
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.1265     0.1359 181.1880
##                                          t value Pr(>|t|)
## (Intercept)                               -6.353 8.61e-09 ***
## Mean.1HrDischarge                         -1.321   0.1883
## Mean.Prev6hDischarge                       1.071   0.2856
## CV.Prev6hDischarge                         1.891   0.0603 .
## Mean.30DayDischarge                        1.118   0.2675
## CV.30DayDischarge                          0.421   0.6750
## ElectroshockB. post-2014                  -0.963   0.3481
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.931   0.3530
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
```

```
##               (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.407
## Mn.Prv6hDsc -0.368 -0.938
## CV.Prv6hDsc -0.477 -0.869  0.829
## Mn.30DyDsch -0.564 -0.183  0.040  0.119
## CV.30DyDsch -0.827 -0.039  0.037  0.019  0.550
## ElcB.p-2014 -0.280  0.120 -0.124 -0.083  0.269  0.189
## M.1HD:M.P6D -0.095 -0.250  0.141  0.410  0.039 -0.280 -0.081

PlotAndSave(fit100m.RB_1,"EffectSize_100m_RB_1.tiff")
```



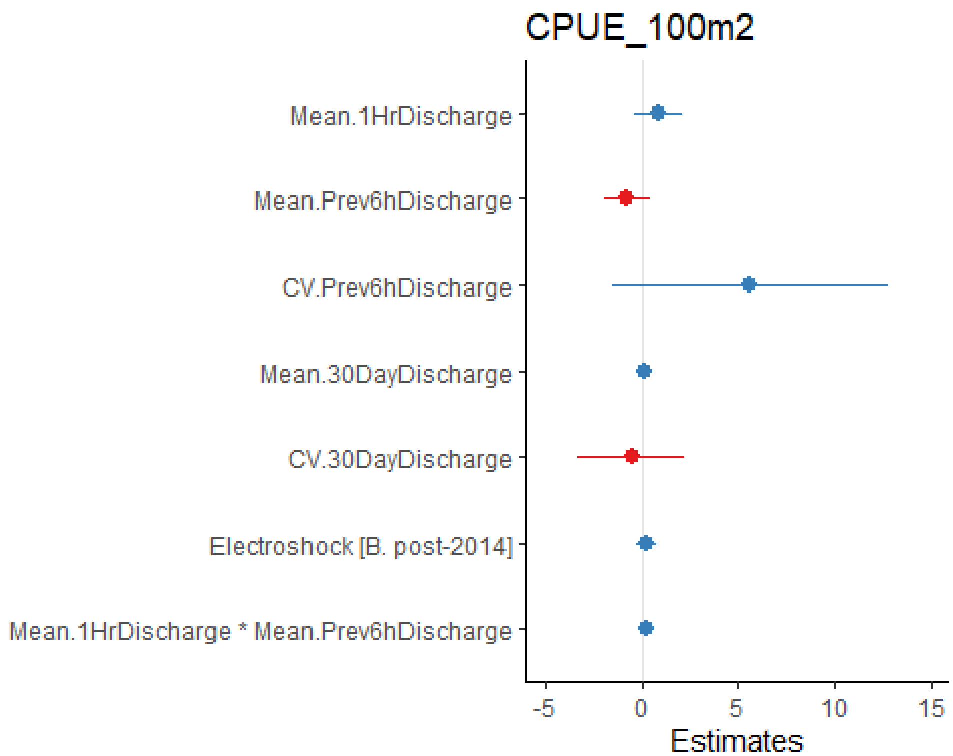

```
car::Anova(fit100m.RB_1, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                        Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                     1.2625  1    0.26118
## Mean.Prev6hDischarge                  0.9008  1    0.34256
## CV.Prev6hDischarge                    3.5771  1    0.05858 .
## Mean.30DayDischarge                   1.2505  1    0.26346
## CV.30DayDischarge                     0.1771  1    0.67389
## Electroshock                          0.9275  1    0.33550
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.8670  1    0.35180
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataRB1.p <- cbind(dataRB1, pred_100m.RB_1=predict(fit100m.RB_1, newdata=dataRB1))

# NONE

# RB 3 -------------------------------------------------------------------------------------
```

```
------------------
summary(fit100m.RB_3)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataRB3
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    612.4    645.0   -296.2    592.4      182
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.7817 -0.4013  0.2064  0.6714  2.6082
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.2569   0.5069
##  Residual               1.1450   1.0701
## Number of obs: 192, groups:  SampleYear, 18
##
## Fixed effects:
##                                         Estimate Std. Error         df
## (Intercept)                            -3.218157   0.593581  87.304926
## Mean.1HrDischarge                      -0.402267   0.280381 182.271744
## Mean.Prev6hDischarge                    0.449673   0.255677 186.447599
## CV.Prev6hDischarge                      0.639143   0.871882 177.947616
## Mean.30DayDischarge                    -0.164213   0.182053  48.538239
## CV.30DayDischarge                      -0.967521   1.531619  90.322158
## ElectroshockB. post-2014               -0.073483   0.315071  16.022147
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.009943   0.092982 191.911180
##                                        t value Pr(>|t|)
## (Intercept)                             -5.422 5.19e-07 ***
## Mean.1HrDischarge                       -1.435   0.1531
## Mean.Prev6hDischarge                     1.759   0.0803 .
## CV.Prev6hDischarge                       0.733   0.4645
## Mean.30DayDischarge                     -0.902   0.3715
## CV.30DayDischarge                       -0.632   0.5292
## ElectroshockB. post-2014                -0.233   0.8185
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.107   0.9150
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr  0.250
## Mn.Prv6hDsc -0.290 -0.879
## CV.Prv6hDsc -0.319 -0.762  0.643
## Mn.30DyDsch -0.471 -0.164 -0.004  0.092
## CV.30DyDsch -0.890 -0.039  0.141 -0.005  0.452
## ElcB.p-2014 -0.262  0.061 -0.083 -0.023  0.231  0.104
## M.1HD:M.P6D -0.039 -0.144 -0.001  0.398 -0.041 -0.215 -0.053

PlotAndSave(fit100m.RB_3,"EffectSize_100m_RB_3.tiff")
```

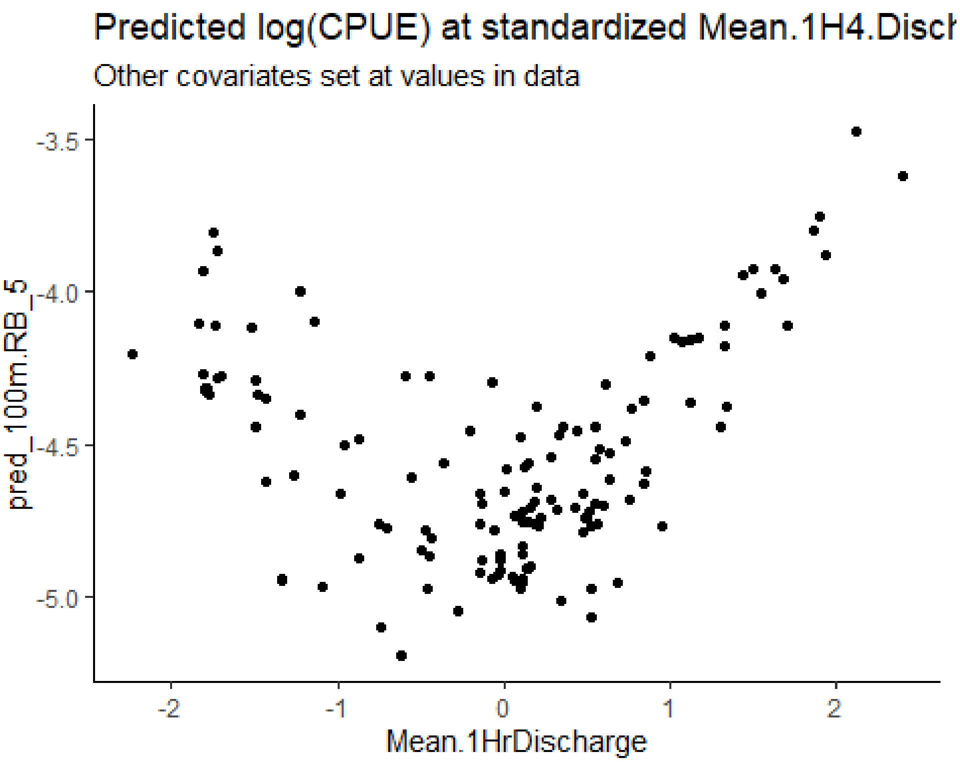



```
car::Anova(fit100m.RB_3, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       2.0573  1    0.15148
## Mean.Prev6hDischarge                    3.0935  1    0.07861 .
## CV.Prev6hDischarge                      0.5374  1    0.46352
## Mean.30DayDischarge                     0.8136  1    0.36705
## CV.30DayDischarge                       0.3990  1    0.52758
## Electroshock                            0.0544  1    0.81559
## Mean.1HrDischarge:Mean.Prev6hDischarge 0.0114  1    0.91484
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataRB3.p <- cbind(dataRB3, pred_100m.RB_3=predict(fit100m.RB_3, newdata=dataRB3))

#NONE

# RB 5 --------------------------------------------------------------------------------
------------------
summary(fit100m.RB_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##      CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##      Electroshock + (1 | SampleYear)
##     Data: dataRB5
## Control: lmerControl(optimizer = "Nelder_Mead")
```

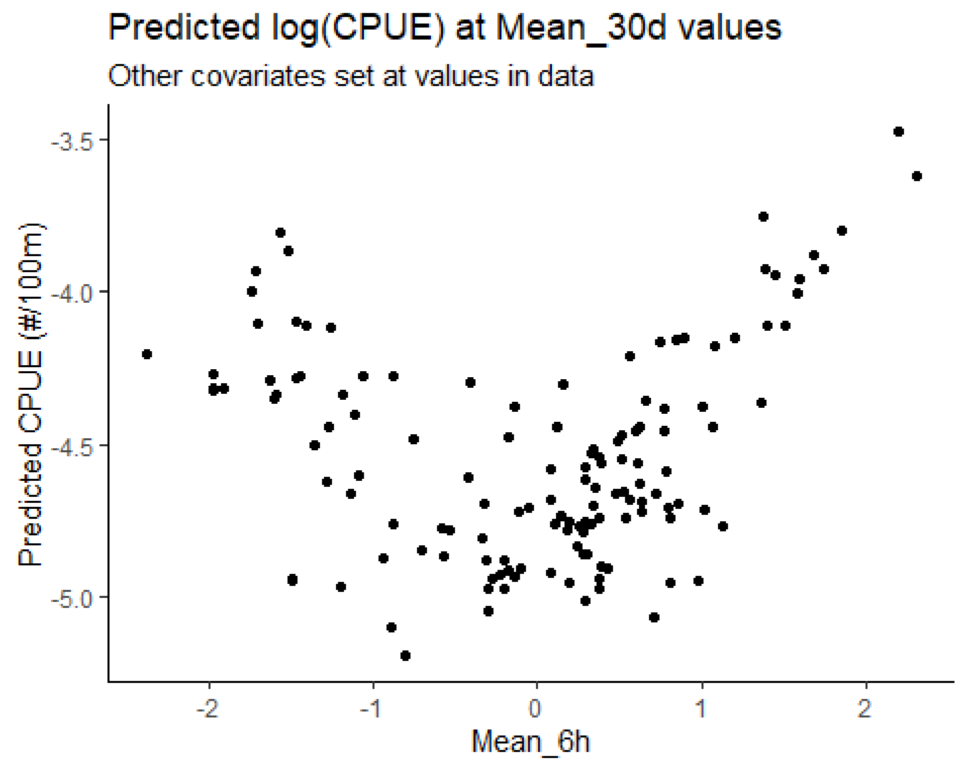
```
##
##      AIC      BIC   logLik deviance df.resid
##    470.5    499.7   -225.3    450.5      127
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9113 -1.1007  0.3069  0.7450  2.0827
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.02562  0.1601
##  Residual               1.54533  1.2431
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                       Estimate Std. Error       df
## (Intercept)                            -4.9872     0.4874  45.8257
## Mean.1HrDischarge                       0.8506     0.6507 136.8214
## Mean.Prev6hDischarge                   -0.7640     0.6250 136.5100
## CV.Prev6hDischarge                      5.6258     3.6572 136.1407
## Mean.30DayDischarge                     0.1520     0.1705  56.5405
## CV.30DayDischarge                      -0.5285     1.4075  37.4699
## ElectroshockB. post-2014                0.2136     0.2611  18.0059
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.2375     0.1013 111.9951
##                                       t value Pr(>|t|)
## (Intercept)                           -10.232 2.04e-13 ***
## Mean.1HrDischarge                       1.307   0.1933
## Mean.Prev6hDischarge                   -1.222   0.2236
## CV.Prev6hDischarge                      1.538   0.1263
## Mean.30DayDischarge                     0.892   0.3763
## CV.30DayDischarge                      -0.375   0.7094
## ElectroshockB. post-2014                0.818   0.4240
## Mean.1HrDischarge:Mean.Prev6hDischarge  2.344   0.0208 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.327
## Mn.Prv6hDsc  0.342 -0.975
## CV.Prv6hDsc -0.453  0.787 -0.756
## Mn.30DyDsch -0.526  0.096 -0.213  0.151
## CV.30DyDsch -0.829 -0.002 -0.031  0.010  0.469
## ElcB.p-2014 -0.306  0.074 -0.089  0.190  0.280  0.076
## M.1HD:M.P6D  0.165 -0.093  0.110 -0.075 -0.009 -0.354 -0.109

PlotAndSave(fit100m.RB_5,"EffectSize_100m_RB_5.tiff")
```




```
car::Anova(fit100m.RB_5, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       2.3463  1    0.12558
## Mean.Prev6hDischarge                    2.2187  1    0.13635
## CV.Prev6hDischarge                      2.3664  1    0.12398
## Mean.30DayDischarge                     0.7952  1    0.37253
## CV.30DayDischarge                       0.1410  1    0.70730
## Electroshock                            0.6694  1    0.41326
## Mean.1HrDischarge:Mean.Prev6hDischarge 5.4961  1    0.01906 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataRB5.p <- cbind(dataRB5, pred_100m.RB_5=predict(fit100m.RB_5, newdata=dataRB5))

# Prev 1 h
ggplot(data=dataRB5.p, aes(x=Mean.1HrDischarge, y=pred_100m.RB_5))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```



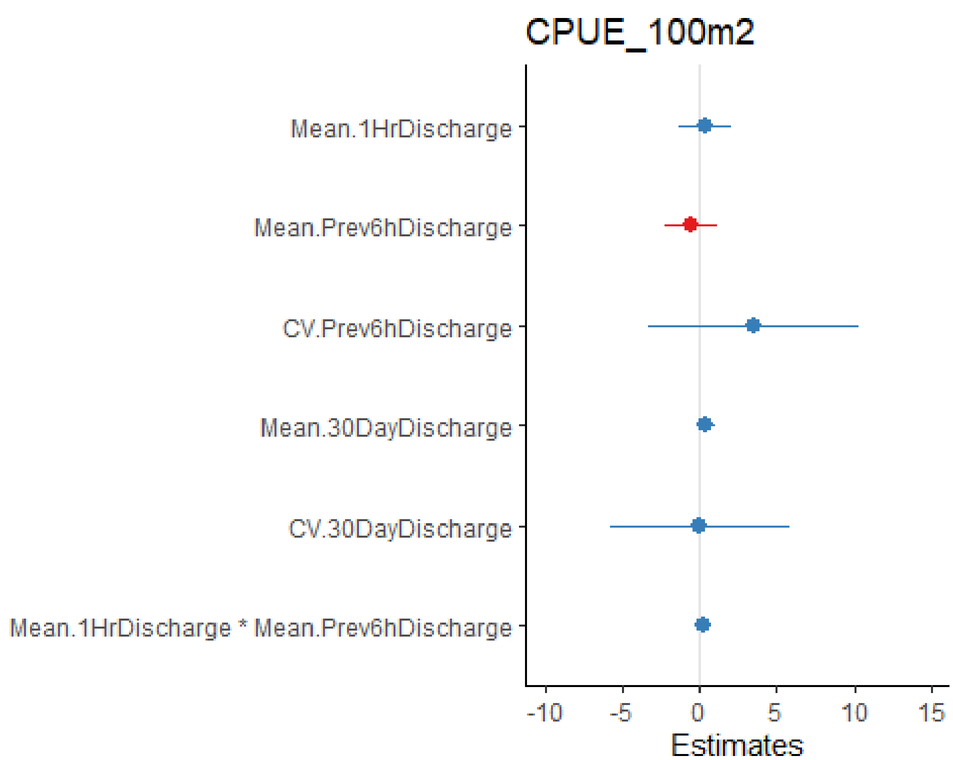

```
# Mean 6h
ggplot(data=dataRB5.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.RB_5))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```




```
# RB 6 -------------------------------------------------------------------------------------
------------------
summary(fit100m.RB_6)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataRB6
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    162.6    178.2    -72.3    144.6       33
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -1.57262 -0.83952  0.00867  0.78119  1.79253
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.2596   0.5096
##  Residual               1.6594   1.2882
## Number of obs: 42, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error       df
## (Intercept)                              -5.26563    0.93127  9.65862
## Mean.1HrDischarge                         0.38372    0.87446 40.69319
## Mean.Prev6hDischarge                     -0.54736    0.89016 37.89987
## CV.Prev6hDischarge                        3.48049    3.48121 35.89826
```

```
## Mean.30DayDischarge                      0.40981    0.31806  8.78124
## CV.30DayDischarge                        0.03706    2.99553  9.92153
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.24580    0.16580 39.64166
##                                        t value Pr(>|t|)
## (Intercept)                             -5.654  0.00024 ***
## Mean.1HrDischarge                        0.439  0.66312
## Mean.Prev6hDischarge                    -0.615  0.54229
## CV.Prev6hDischarge                       1.000  0.32410
## Mean.30DayDischarge                      1.288  0.23048
## CV.30DayDischarge                        0.012  0.99038
## Mean.1HrDischarge:Mean.Prev6hDischarge   1.482  0.14612
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.150
## Mn.Prv6hDsc -0.191 -0.955
## CV.Prv6hDsc -0.155 -0.034  0.085
## Mn.30DyDsch -0.067  0.093 -0.189  0.065
## CV.30DyDsch -0.908 -0.170  0.206 -0.064  0.039
## M.1HD:M.P6D -0.062  0.104 -0.124  0.226  0.212 -0.140
```

```
PlotAndSave(fit100m.RB_6,"EffectSize_100m_RB_6.tiff")
```

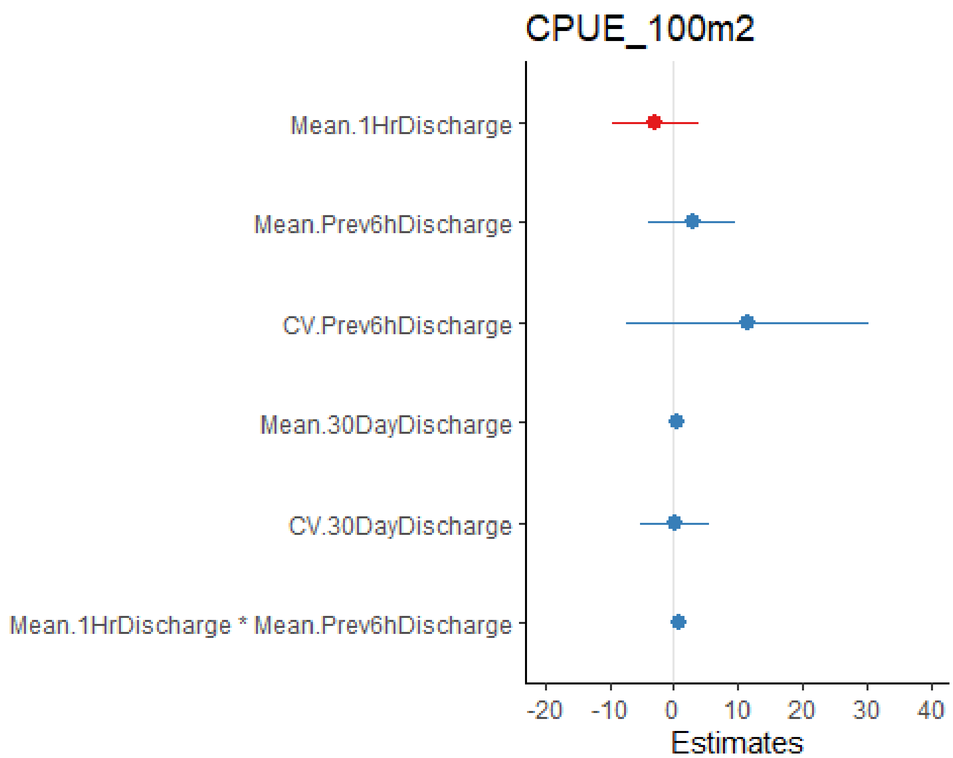



```
car::Anova(fit100m.RB_6, type=2)
```

```
## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                         Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                      0.0819  1     0.7747
## Mean.Prev6hDischarge                   0.1884  1     0.6642
```

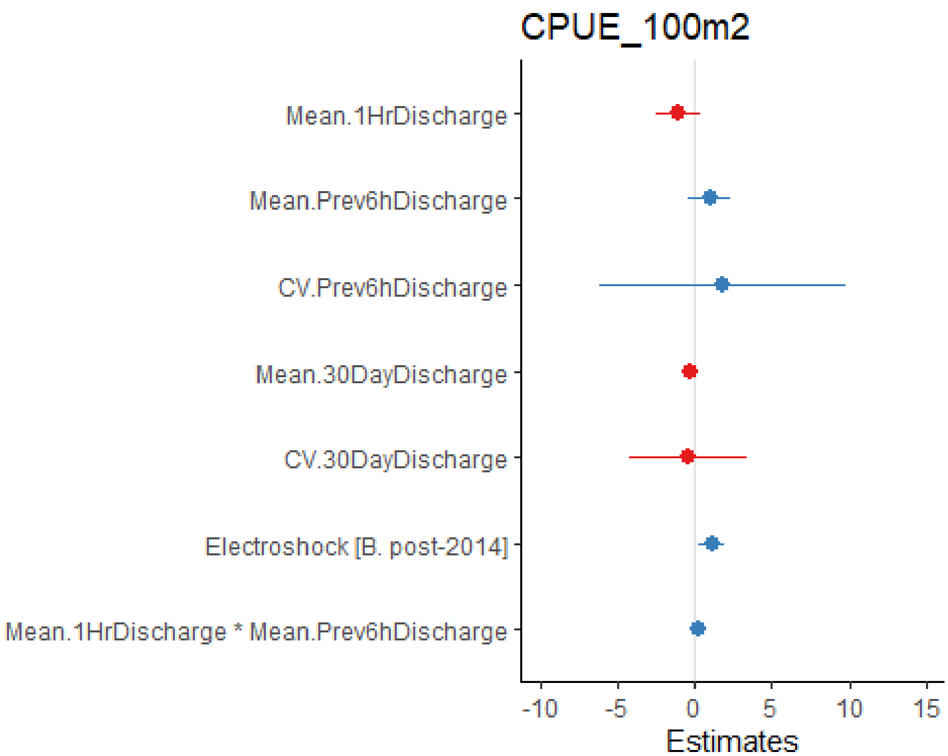
```
## CV.Prev6hDischarge                        0.9996  1     0.3174
## Mean.30DayDischarge                       1.6602  1     0.1976
## CV.30DayDischarge                         0.0002  1     0.9901
## Mean.1HrDischarge:Mean.Prev6hDischarge 2.1977  1     0.1382

dataRB6.p <- cbind(dataRB6, pred_100m.RB_6=predict(fit100m.RB_6, newdata=dataRB6))

# NONE

# RB 7 ---------------------------------------------------------------------------------------
------------------
summary(fit100m.RB_7)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataRB7
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    102.1    113.4    -42.0     84.1       17
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.4486 -0.8180 -0.1087  0.5937  2.6442
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.000    0.000
##  Residual               1.486    1.219
## Number of obs: 26, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error      df t value
## (Intercept)                              -6.0244     1.1073 26.0000  -5.441
## Mean.1HrDischarge                        -2.8763     3.3948 26.0000  -0.847
## Mean.Prev6hDischarge                      2.8528     3.5005 26.0000   0.815
## CV.Prev6hDischarge                       11.4543     9.6608 26.0000   1.186
## Mean.30DayDischarge                       0.4106     0.4369 26.0000   0.940
## CV.30DayDischarge                         0.2278     2.7697 26.0000   0.082
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.6536     0.3743 26.0000   1.746
##                                          Pr(>|t|)
## (Intercept)                              1.05e-05 ***
## Mean.1HrDischarge                          0.4046
## Mean.Prev6hDischarge                       0.4225
## CV.Prev6hDischarge                         0.2465
## Mean.30DayDischarge                        0.3560
## CV.30DayDischarge                          0.9351
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.0926 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.216
## Mn.Prv6hDsc -0.232 -0.993
## CV.Prv6hDsc -0.343 -0.737  0.733
```

```
## Mn.30DyDsch  0.251  0.084 -0.173  0.073
## CV.30DyDsch -0.863 -0.072  0.082  0.018 -0.256
## M.1HD:M.P6D -0.454  0.178 -0.150  0.116 -0.196  0.119
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.RB_7,"EffectSize_100m_RB_7.tiff")
```

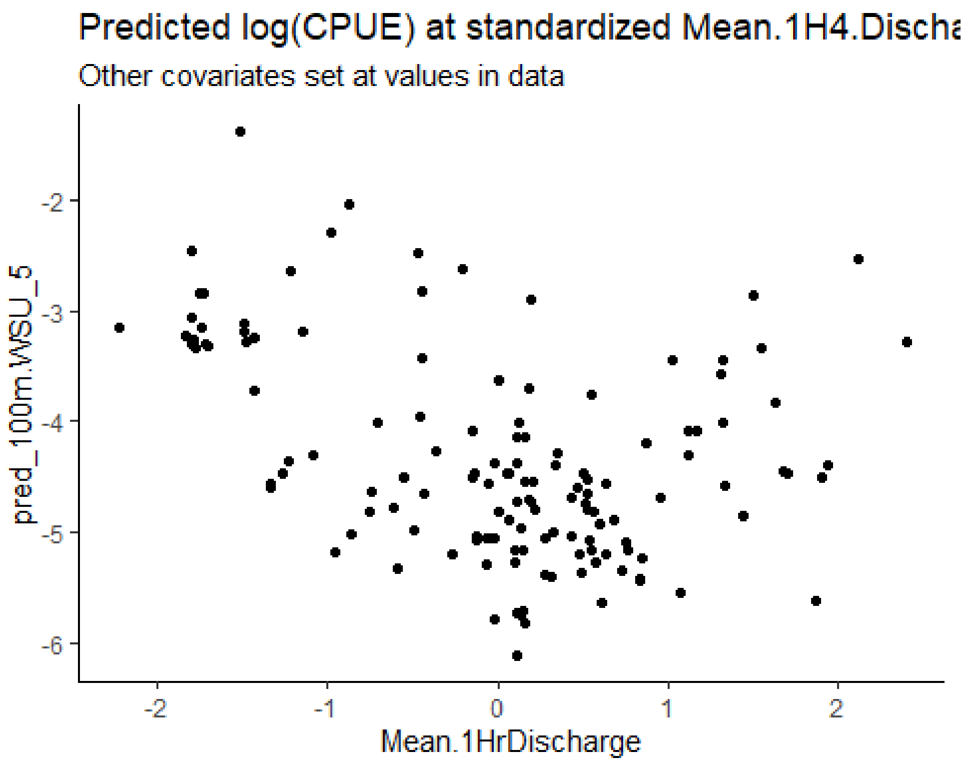



```
car::Anova(fit100m.RB_7, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       1.3830  1    0.23959
## Mean.Prev6hDischarge                    1.1850  1    0.27634
## CV.Prev6hDischarge                      1.4057  1    0.23576
## Mean.30DayDischarge                     0.8831  1    0.34735
## CV.30DayDischarge                       0.0068  1    0.93446
## Mean.1HrDischarge:Mean.Prev6hDischarge 3.0485  1    0.08081 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataRB7.p <- cbind(dataRB7, pred_100m.RB_7=predict(fit100m.RB_7, newdata=dataRB7))

# None

# WSU 5 -----------------------------------------------------------------------------
-------------------
summary(fit100m.WSU_5)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
```

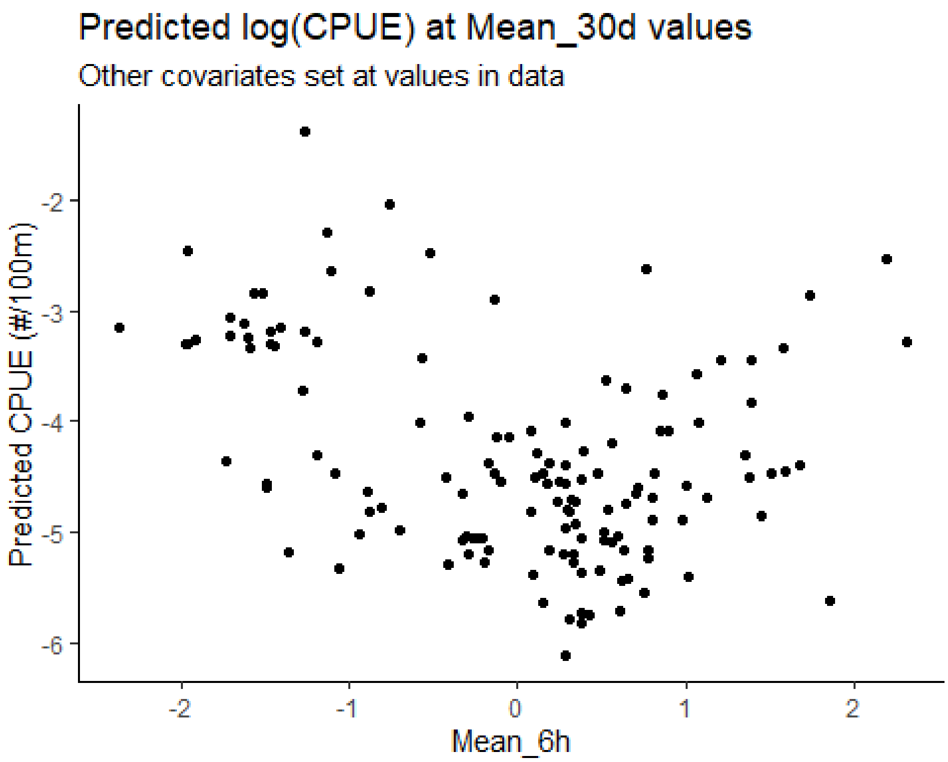
```
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     Electroshock + (1 | SampleYear)
##    Data: dataWSU5
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    506.7    535.9   -243.4    486.7      127
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.42117 -0.82144  0.05293  0.82392  1.79921
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.4155   0.6446
##  Residual               1.8081   1.3447
## Number of obs: 137, groups:  SampleYear, 15
##
## Fixed effects:
##                                        Estimate Std. Error       df
## (Intercept)                             -4.9159     0.6731  46.8874
## Mean.1HrDischarge                       -1.1127     0.7290 129.4507
## Mean.Prev6hDischarge                     0.9947     0.6990 129.3763
## CV.Prev6hDischarge                       1.8270     4.0781 128.3636
## Mean.30DayDischarge                     -0.2890     0.2368  36.4066
## CV.30DayDischarge                       -0.4188     1.9576  55.3565
## ElectroshockB. post-2014                 1.0929     0.4434  11.3896
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.2897     0.1195 136.8205
##                                        t value Pr(>|t|)
## (Intercept)                             -7.303 2.88e-09 ***
## Mean.1HrDischarge                       -1.526   0.1294
## Mean.Prev6hDischarge                     1.423   0.1571
## CV.Prev6hDischarge                       0.448   0.6549
## Mean.30DayDischarge                     -1.220   0.2302
## CV.30DayDischarge                       -0.214   0.8314
## ElectroshockB. post-2014                 2.465   0.0308 *
## Mean.1HrDischarge:Mean.Prev6hDischarge   2.423   0.0167 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D EB.p-2
## Mn.1HrDschr -0.227
## Mn.Prv6hDsc  0.232 -0.976
## CV.Prv6hDsc -0.325  0.774 -0.743
## Mn.30DyDsch -0.486  0.035 -0.108  0.056
## CV.30DyDsch -0.837 -0.043  0.021 -0.037  0.454
## ElcB.p-2014 -0.343  0.024 -0.028  0.101  0.266  0.085
## M.1HD:M.P6D  0.142 -0.042  0.065 -0.054  0.031 -0.315 -0.062

PlotAndSave(fit100m.WSU_5,"EffectSize_100m_WSU_5.tiff")
```



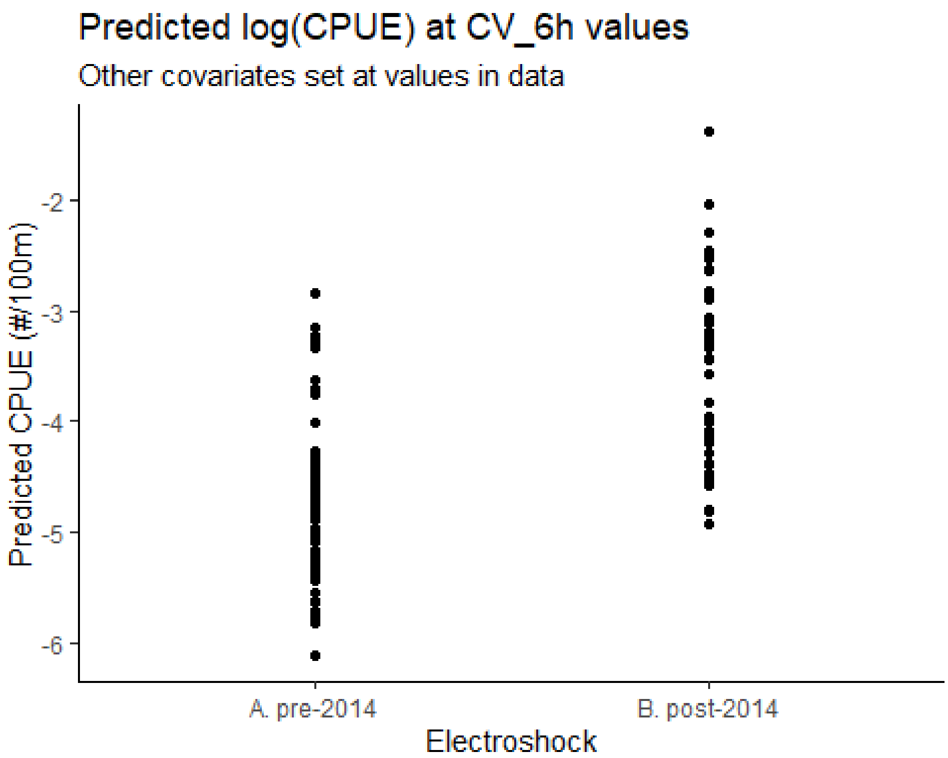

```
car::Anova(fit100m.WSU_5, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                       2.0310  1    0.15412
## Mean.Prev6hDischarge                    1.6074  1    0.20486
## CV.Prev6hDischarge                      0.2007  1    0.65415
## Mean.30DayDischarge                     1.4892  1    0.22234
## CV.30DayDischarge                       0.0458  1    0.83058
## Electroshock                            6.0738  1    0.01372 *
## Mean.1HrDischarge:Mean.Prev6hDischarge 5.8728  1    0.01538 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataWSU5.p <- cbind(dataWSU5, pred_100m.WSU_5=predict(fit100m.WSU_5, newdata=dataWSU5))

# Prev 1 h
ggplot(data=dataWSU5.p, aes(x=Mean.1HrDischarge, y=pred_100m.WSU_5))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```




```
# Mean 6h
ggplot(data=dataWSU5.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.WSU_5))+
    ggtitle("Predicted log(CPUE) at Mean_30d values",subtitle="Other covariates set at values
in data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```

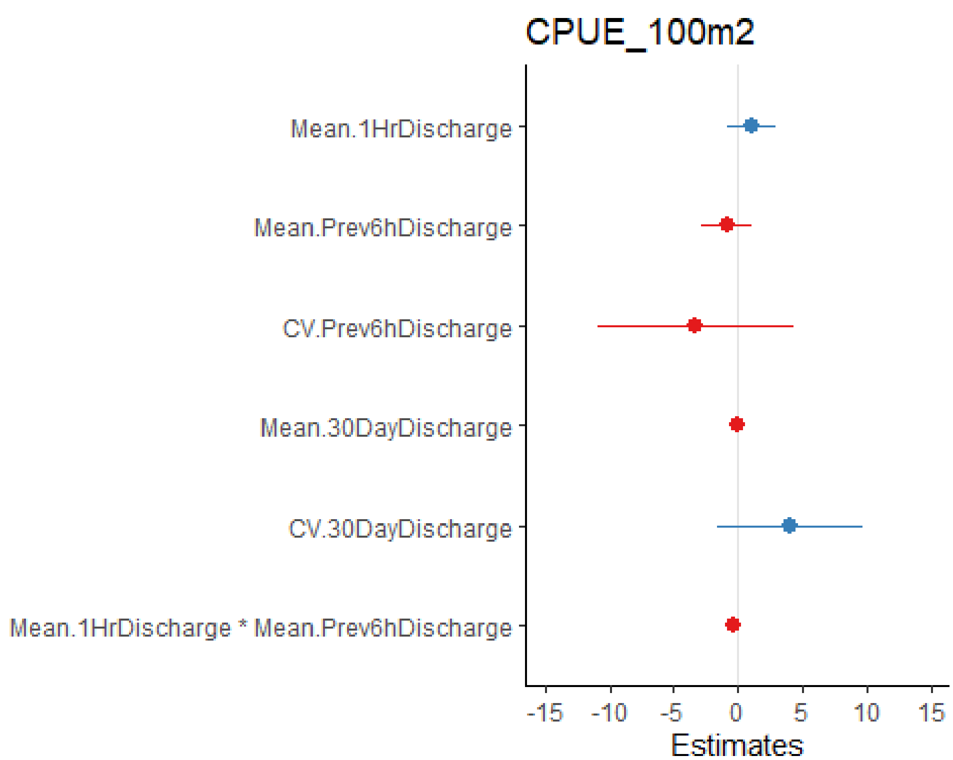



```
#Electroshocking
ggplot(data=dataWSU5.p, aes(x=Electroshock, y=pred_100m.WSU_5))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Electroshock") +
    geom_point()

## Warning: Removed 1 rows containing missing values (geom_point).
```




```
# WSU 6 ---------------------------------------------------------------------------------------------------
summary(fit100m.WSU_6)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataWSU6
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    169.7    185.4    -75.9    151.7       33
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.9780 -0.7270  0.2158  0.7907  1.4352
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.1186   0.3443
##  Residual               2.0719   1.4394
## Number of obs: 42, groups:  SampleYear, 5
##
## Fixed effects:
##                                          Estimate Std. Error       df
## (Intercept)                              -4.81743    0.90376  9.56074
## Mean.1HrDischarge                         1.06896    0.96176 41.14447
## Mean.Prev6hDischarge                     -0.87674    0.98899 38.16188
## CV.Prev6hDischarge                       -3.30061    3.88832 36.12300
```

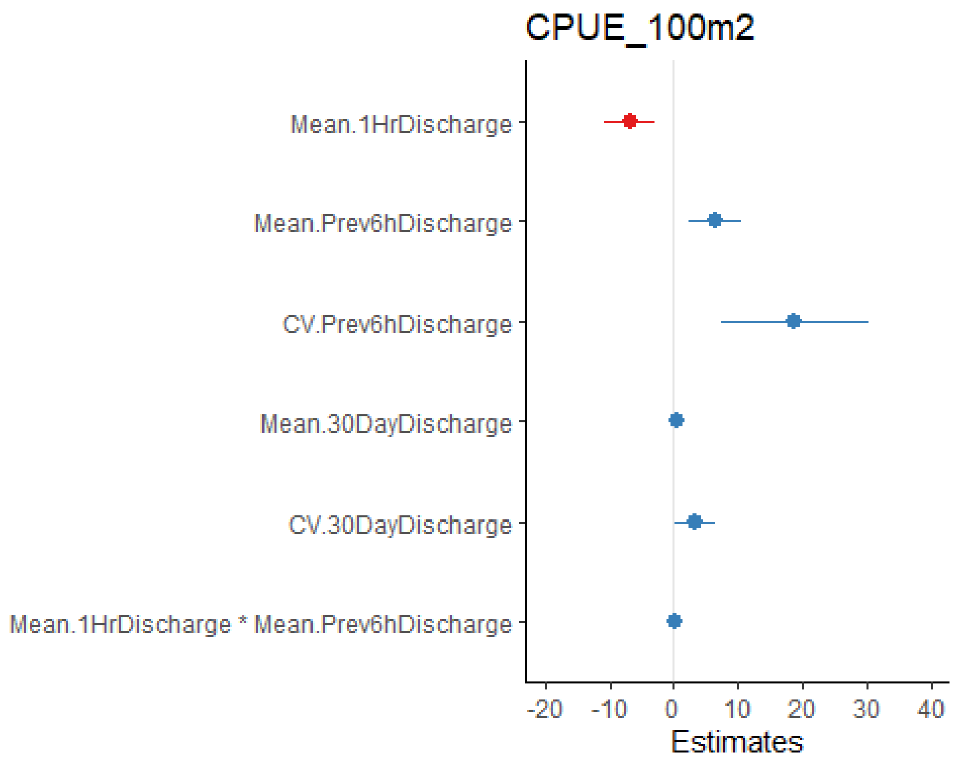
```
## Mean.30DayDischarge                      -0.01687    0.30582  8.25943
## CV.30DayDischarge                         4.03712    2.90667  9.31306
## Mean.1HrDischarge:Mean.Prev6hDischarge -0.33434    0.18329 39.68841
##                                         t value Pr(>|t|)    
## (Intercept)                              -5.330 0.000387 ***
## Mean.1HrDischarge                         1.111 0.272821    
## Mean.Prev6hDischarge                     -0.886 0.380902    
## CV.Prev6hDischarge                       -0.849 0.401553    
## Mean.30DayDischarge                      -0.055 0.957323    
## CV.30DayDischarge                         1.389 0.197173    
## Mean.1HrDischarge:Mean.Prev6hDischarge  -1.824 0.075669 .  
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.153                                   
## Mn.Prv6hDsc -0.203 -0.957                            
## CV.Prv6hDsc -0.186 -0.036  0.087                     
## Mn.30DyDsch -0.048  0.090 -0.203  0.063              
## CV.30DyDsch -0.904 -0.175  0.218 -0.066  0.011       
## M.1HD:M.P6D -0.034  0.117 -0.132  0.227  0.184 -0.205

PlotAndSave(fit100m.WSU_6,"EffectSize_100m_WSU_6.tiff")
```



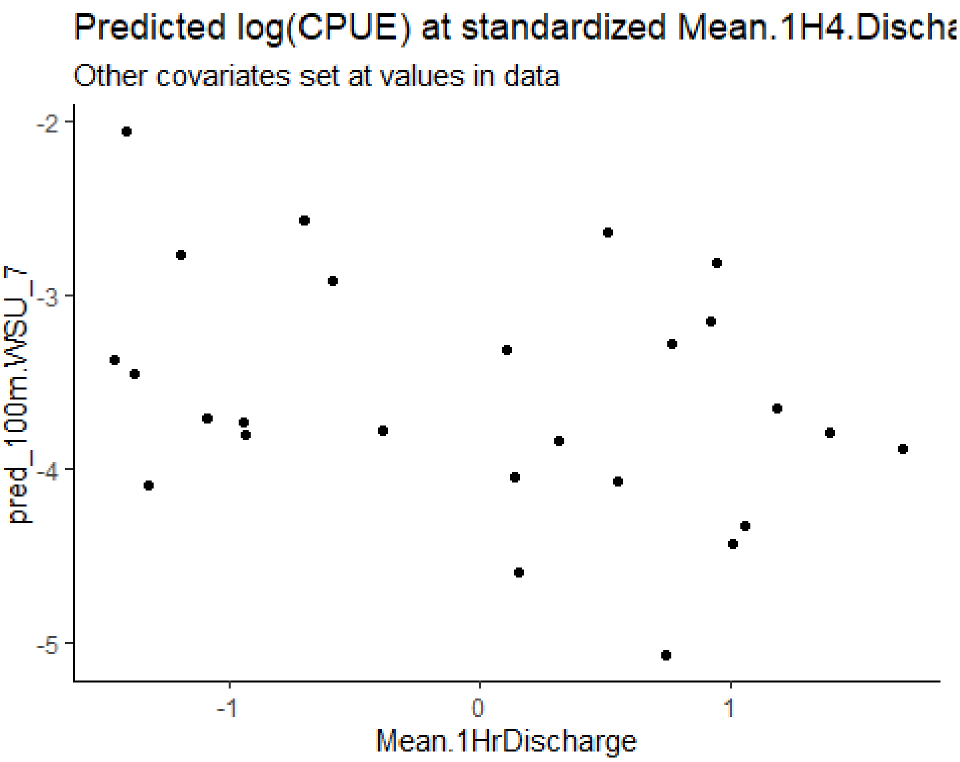

```
car::Anova(fit100m.WSU_6, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
## 
## Response: CPUE_100m2
##                                         Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                      1.7783  1    0.18236
## Mean.Prev6hDischarge                   1.2947  1    0.25518
```

```
## CV.Prev6hDischarge                         0.7206  1    0.39596
## Mean.30DayDischarge                        0.0030  1    0.95601
## CV.30DayDischarge                          1.9291  1    0.16486
## Mean.1HrDischarge:Mean.Prev6hDischarge 3.3274  1    0.06813 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataWSU6.p <- cbind(dataWSU6, pred_100m.WSU_6=predict(fit100m.WSU_6, newdata=dataWSU6))

# NONE

# WSU 7 ---------------------------------------------------------------------------------
-------------------
summary(fit100m.WSU_7)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataWSU7
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##     75.7     87.0    -28.8     57.7       17
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.54773 -0.33721  0.07776  0.55381  2.49565
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.5385   0.7338
## Number of obs: 26, groups:  SampleYear, 5
##
## Fixed effects:
##                                         Estimate Std. Error        df
## (Intercept)                            -5.291913   0.666547 26.000000
## Mean.1HrDischarge                      -6.884590   2.043517 26.000000
## Mean.Prev6hDischarge                    6.494339   2.107139 26.000000
## CV.Prev6hDischarge                     18.808688   5.815419 26.000000
## Mean.30DayDischarge                     0.374252   0.263007 26.000000
## CV.30DayDischarge                       3.276862   1.667244 26.000000
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.007937   0.225334 26.000000
##                                        t value Pr(>|t|)
## (Intercept)                             -7.939 2.04e-08 ***
## Mean.1HrDischarge                       -3.369  0.00236 **
## Mean.Prev6hDischarge                     3.082  0.00482 **
## CV.Prev6hDischarge                       3.234  0.00331 **
## Mean.30DayDischarge                      1.423  0.16663
## CV.30DayDischarge                        1.965  0.06013 .
## Mean.1HrDischarge:Mean.Prev6hDischarge   0.035  0.97217
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr  0.216
```

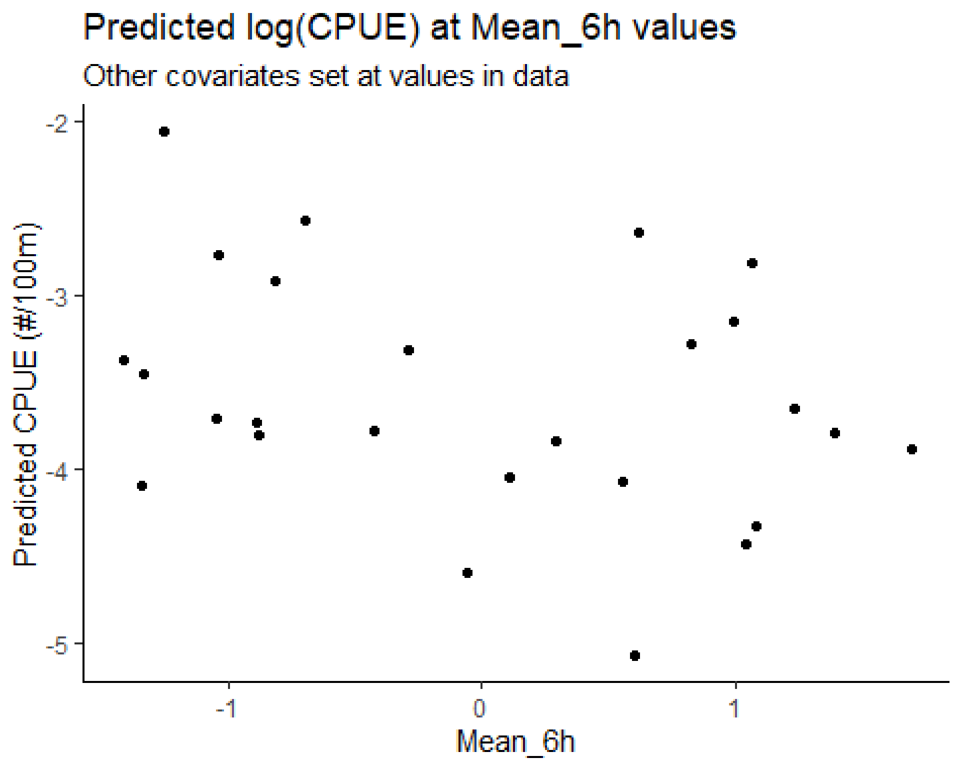
```
## Mn.Prv6hDsc -0.232 -0.993
## CV.Prv6hDsc -0.343 -0.737  0.733
## Mn.30DyDsch  0.251  0.084 -0.173  0.073
## CV.30DyDsch -0.863 -0.072  0.082  0.018 -0.256
## M.1HD:M.P6D -0.454  0.178 -0.150  0.116 -0.196  0.119
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.WSU_7,"EffectSize_100m_WSU_7.tiff")
```



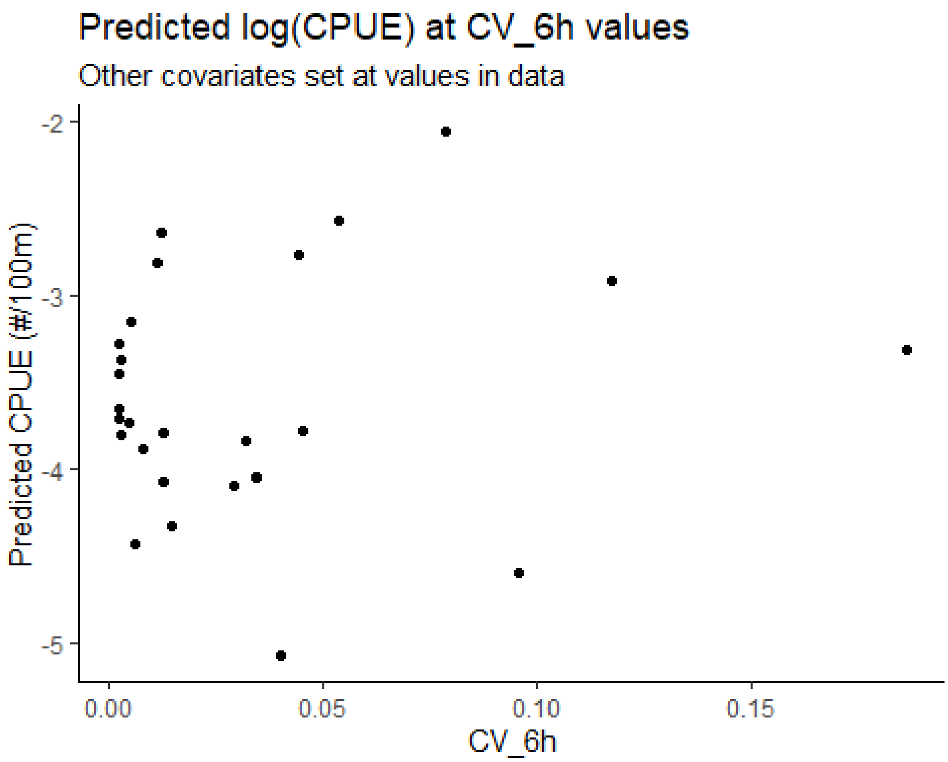

```
car::Anova(fit100m.WSU_7, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                          Chisq Df Pr(>Chisq)
## Mean.1HrDischarge                      11.7632  1  0.0006041 ***
## Mean.Prev6hDischarge                    9.7501  1  0.0017931 **
## CV.Prev6hDischarge                     10.4606  1  0.0012195 **
## Mean.30DayDischarge                     2.0248  1  0.1547448
## CV.30DayDischarge                       3.8629  1  0.0493637 *
## Mean.1HrDischarge:Mean.Prev6hDischarge  0.0012  1  0.9719024
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataWSU7.p <- cbind(dataWSU7, pred_100m.WSU_7=predict(fit100m.WSU_7, newdata=dataWSU7))

ggplot(data=dataWSU7.p, aes(x=Mean.1HrDischarge, y=pred_100m.WSU_7))+
    ggtitle("Predicted log(CPUE) at standardized Mean.1H4.Discharge values",
            subtitle="Other covariates set at values in data")+
    geom_point()
```



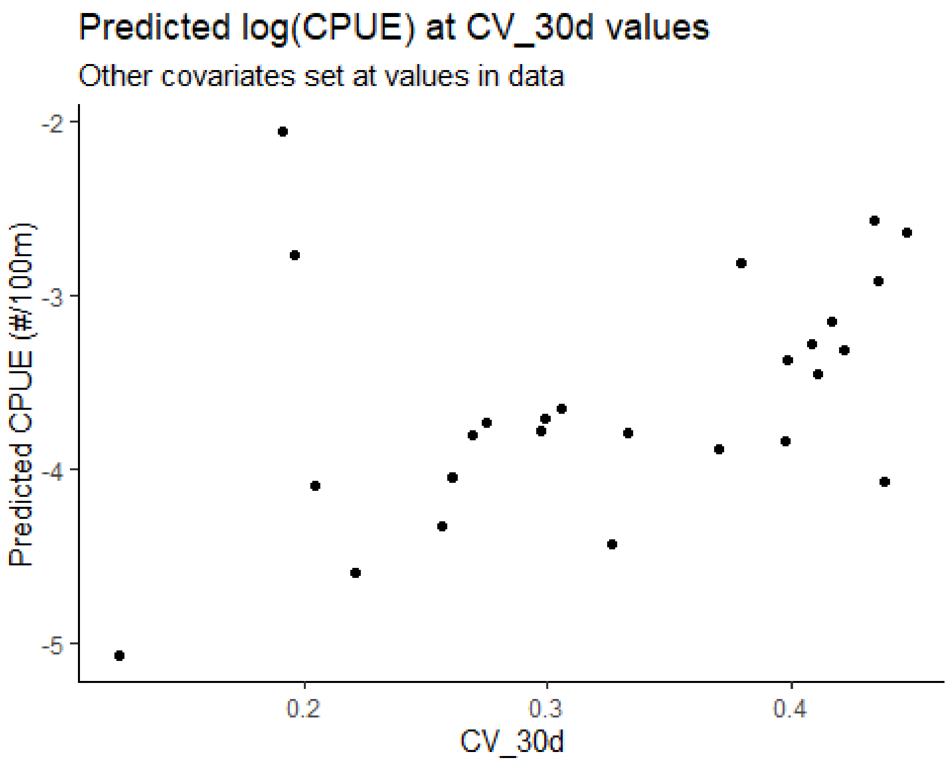

```
# Mean Prev 6
ggplot(data=dataWSU7.p, aes(x=Mean.Prev6hDischarge, y=pred_100m.WSU_7))+
    ggtitle("Predicted log(CPUE) at Mean_6h values",subtitle="Other covariates set at values i
n data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("Mean_6h") +
    geom_point()
```




```
# CV Prev 6 h
ggplot(data=dataWSU7.p, aes(x=CV.Prev6hDischarge, y=pred_100m.WSU_7))+
    ggtitle("Predicted log(CPUE) at CV_6h values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_6h") +
    geom_point()
```

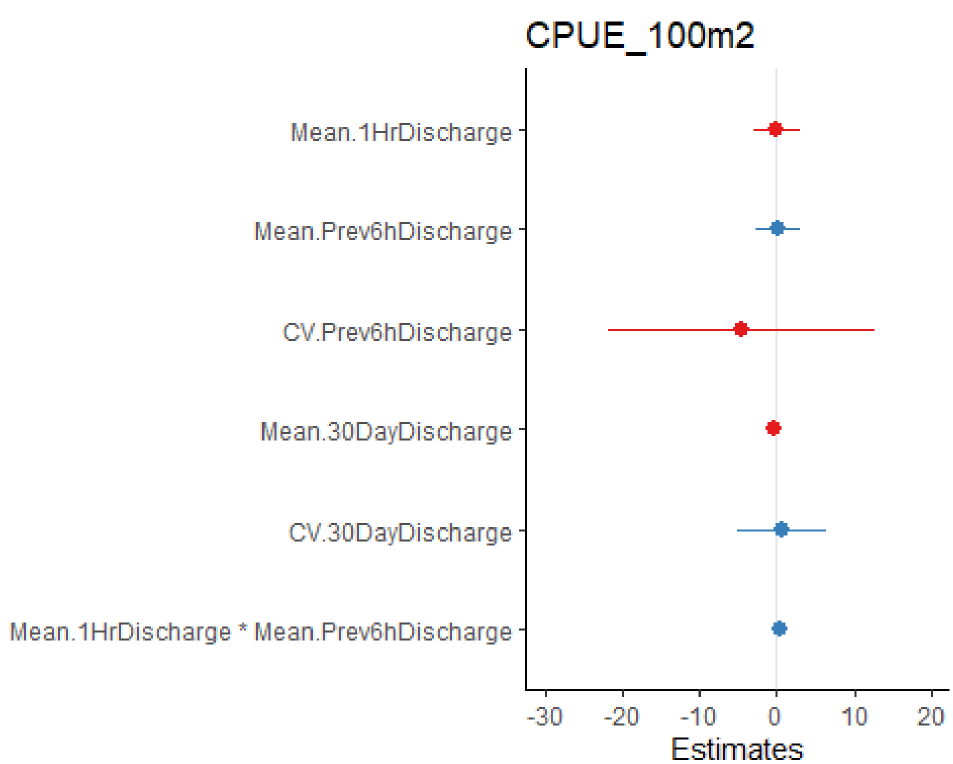



```
# CV Prev 30 Days
ggplot(data=dataWSU7.p, aes(x=CV.30DayDischarge, y=pred_100m.WSU_7))+
    ggtitle("Predicted log(CPUE) at CV_30d values",subtitle="Other covariates set at values in
data") +
    ylab("Predicted CPUE (#/100m)") +
    xlab("CV_30d") +
    geom_point()
```




```
# WSU 9 --------------------------------------------------------------------------------------
-------------------
summary(fit100m.WSU_9)

## Linear mixed model fit by maximum likelihood . t-tests use
##   Satterthwaite's method [lmerModLmerTest]
## Formula:
## CPUE_100m2 ~ Mean.1HrDischarge + Mean.Prev6hDischarge + Mean.1HrDischarge:Mean.Prev6hDischa
rge +
##     CV.Prev6hDischarge + Mean.30DayDischarge + CV.30DayDischarge +
##     (1 | SampleYear)
##    Data: dataWSU9
## Control: lmerControl(optimizer = "Nelder_Mead")
##
##      AIC      BIC   logLik deviance df.resid
##    110.9    124.6    -46.4     92.9       25
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -2.6886 -0.4222  0.3376  0.6737  1.2642
##
## Random effects:
##  Groups     Name        Variance Std.Dev.
##  SampleYear (Intercept) 0.0000   0.0000
##  Residual               0.8992   0.9483
## Number of obs: 34, groups:  SampleYear, 5
##
## Fixed effects:
##                                           Estimate Std. Error        df
## (Intercept)                              -3.865027   0.684840 34.000000
## Mean.1HrDischarge                        -0.009553   1.569797 34.000000
## Mean.Prev6hDischarge                      0.217856   1.470075 34.000000
## CV.Prev6hDischarge                       -4.512235   8.857033 34.000000
```

```
## Mean.30DayDischarge                       -0.358798   0.247116 34.000000
## CV.30DayDischarge                          0.583971   2.936594 34.000000
## Mean.1HrDischarge:Mean.Prev6hDischarge     0.489485   0.281340 34.000000
##                                           t value Pr(>|t|)
## (Intercept)                                -5.644  2.5e-06 ***
## Mean.1HrDischarge                          -0.006   0.9952
## Mean.Prev6hDischarge                        0.148   0.8831
## CV.Prev6hDischarge                         -0.509   0.6137
## Mean.30DayDischarge                        -1.452   0.1557
## CV.30DayDischarge                           0.199   0.8436
## Mean.1HrDischarge:Mean.Prev6hDischarge      1.740   0.0909 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) Mn.1HD Mn.P6D CV.P6D M.30DD CV.30D
## Mn.1HrDschr -0.218
## Mn.Prv6hDsc  0.180 -0.984
## CV.Prv6hDsc -0.264  0.820 -0.786
## Mn.30DyDsch -0.215 -0.280  0.180 -0.327
## CV.30DyDsch -0.772 -0.256  0.244 -0.299  0.508
## M.1HD:M.P6D  0.088  0.458 -0.362  0.516 -0.582 -0.607
## convergence code: 0
## boundary (singular) fit: see ?isSingular

PlotAndSave(fit100m.WSU_9,"EffectSize_100m_WSU_9.tiff")
```




```
car::Anova(fit100m.WSU_9, type=2)

## Analysis of Deviance Table (Type II Wald chisquare tests)
##
## Response: CPUE_100m2
##                                            Chisq Df Pr(>Chisq)
```

```
## Mean.1HrDischarge                       0.8175  1    0.36591
## Mean.Prev6hDischarge                    0.6966  1    0.40393
## CV.Prev6hDischarge                      0.2595  1    0.61044
## Mean.30DayDischarge                     2.1081  1    0.14652
## CV.30DayDischarge                       0.0395  1    0.84237
## Mean.1HrDischarge:Mean.Prev6hDischarge 3.0270  1    0.08189 .
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

dataWSU9.p <- cbind(dataWSU9, pred_100m.WSU_9=predict(fit100m.WSU_9, newdata=dataWSU9))

# NONE
```

APPENDIX B: 2018 JUVENILE OTOLITH DAILY GROWTH ANALYSIS

• **TECHNICAL MEMORANDUM**

DATE 28 August 2019 **Project No.** 19121767-003-TM-RevA-DRAFT

TO Brent Mossop
BC Hydro

CC Nich Burnett, Dustin Ford

FROM David Roscoe **EMAIL droscoe@golder.com**

SITE C FISHERIES AND AQUATIC HABITAT MONITORING AND FOLLOW-UP PROGRAM – MON-17 – 2018 JUVENILE OTOLITH DAILY GROWTH ANALYSIS

1.0 BACKGROUND

The construction and operation of the Site C Clean Energy Project (the Project) is expected to change the typical daily hydrograph for the Peace River downstream of the Project, which could affect fish populations by altering the amount or quality of fish habitat, potentially influencing fish growth or survival. The Peace River Water Level Fluctuations Monitoring Program (Mon-17) of the Site C Fisheries and Aquatic Habitat Monitoring and Follow-up Program (FAHMFP), summarizes how the Project is expected to change Peace River water levels downstream of the Project. Briefly, the Project is expected to result in the following changes during typical operations:

1. Daily peak flows at the Taylor gauging station are expected to shift by approximately 12 hours. Currently, peak flows at Taylor typically occur between 2:00 am and 6:00 am, but during Project operation, peak flows at this location are expected to occur between 2:00 pm and 6:00 pm. Similarly, at the Alces River confluence (approximately 58 km downstream of the Project), peak flows are expected to change from between 7:00 am and 12:00 pm to between 7:00 pm and 12:00 am.
2. At the Site C tailrace, the daily range of water levels is predicted to increase from the 0.5 m experienced under current conditions to 1.0 m during Project operation. Water levels are expected to attenuate with increasing distance from the Project. Specifically, from 0.5 m to 0.8 m near Taylor, and from 0.5 m to 0.9 m near the Alces River confluence.

Within-day changes in discharge result in changes in water depth and velocity that may influence habitat quality and quantity for fish. These changes in habitat could affect the growth of fish in numerous ways, such as changes in the energetic costs of swimming while feeding, seeking new habitat, or maintaining position (Korman and Campana 2009; Puffer et al. 2015). Juvenile fish may be particularly vulnerable to fluctuating flows due to lower swimming abilities than adult fish (Taylor and Cooke 2012). Fluctuating flows could also affect growth through changes to in-river productivity and food availability (Marty et al. 2009).

To help determine the effect of flow variability on fish growth, the widths of daily growth rings (circuli) on otoliths collected from juvenile Peace River fishes in 2014 to 2016 were measured. These data were used to examine the effects of discharge variability (m^3/s) on daily incremental otolith growth (Golder 2018). During the fall of 2018, additional otoliths were collected from juvenile Peace River fishes and this memo presents the results of analyses conducted on the 2014–2016 and 2018 data sets combined.

These activities correspond to Task 2b of Mon-17. Information collected as part of Task 2b will be used to answer the following Mon-17 management question:

- How do changes in the hydrological regime affect fish and fish habitat of the Peace River?

1.1 Objectives

The main objective of Mon-17 is to address uncertainties regarding hydrographic changes in the Peace River as a result of the Project's construction and operation. Task 2b is designed to test the following Mon-17 management hypothesis:

> H_4: Species-specific fish growth of age-0 and age-1 fish among sites in the Peace River is independent of the magnitude and timing of flow fluctuations.

To address this objective, the widths of the most recent daily growth rings on otoliths collected from young (age-0 and age-1) fish of indicator species were measured. Approximately the most recent 50 daily growth rings (i.e., the 50 rings closest to the perimeter of the otolith) were measured, although the number varied from 23 to 69 between fish, because that is the number of rings that are clearly identifiable and can be used to represent daily growth. The incremental growth (i.e., the daily growth) of otoliths was compared to flow data over the corresponding days immediately prior to the fish's capture date to identify relationships between growth and changes in habitat.

2.0 METHODS

2.1 Overview

The daily growth increments on otoliths of juvenile Mountain Whitefish (*Prosopium williamsoni*) and suckers collected from the Peace River were measured and used as an indicator of short-term (daily) variation body growth. The otolith growth increment data were used in statistical models to assess whether variation in growth was related to discharge variability in the Peace River. Details of the field sampling, laboratory analysis, and statistical analysis are provided in the following sections.

2.2 Data Collection

2.2.1 Field Sampling

All fish were collected from the 15 km long portion of the Peace River between the Project and the Pine River's confluence with the Peace River. This section of the river is expected to experience the largest variation in water levels associated with the Project. Fish were captured on 4 November 2016 and on 11 and 12 October 2018. Fish were collected in the fall (i.e., near the end of the growing season) because daily growth rings were expected to be more readily visible on otoliths during the preceding months. During both study years, the field crew collected fish using three different capture methods: a boat electroshocking (a Smith-root Inc. high-output Generator Powered Pulsator [GPP 5.0] in 2016 and a Smith-Root Inc. Type VI electroshocker in 2018); a Smith-Root Inc. LR24 backpack electrofishing unit, and a 5 m wide beach seine with a 3 mm mesh size. For all three capture methods, sampling was limited to portions of the river immediately adjacent to the shoreline, and within the varial zone when possible, as these areas were expected to experience the greatest changes in habitat due to water level fluctuations.

Habitats sampled by each capture method were similar and field crews did not attempt to capture fish at specific water levels. Otoliths from 2014 and 2015 were opportunistically collected from mortalities encountered on the 11 km portion of the Peace River between the Project and the CPR railway bridge during boat electroshocking surveys conducted as part of BC Hydro's Large River Fish Indexing Survey (Mon-2, Task 2a) between mid-August and late September.

In 2016, 6 Arctic Grayling (*Thymallus arcticus*), 4 Longnose Sucker (*Catostomus catostomus*), 77 Mountain Whitefish, 1 Northern Pike (*Esox lucius*) and 1 Rainbow Trout (*Oncorhynchus mykiss*) were collected. In 2018, the crew captured 100 Mountain Whitefish, 11 Longnose Sucker, 6 White Sucker (*Catostomus commersonii*), and 3 Largescale Sucker (*Catostomus macrocheilus*). The number of otoliths from mortalities encountered during the Peace River Large Fish Indexing Program was 4 from Mountain Whitefish in 2014 and one from a Mountain Whitefish in 2015.

After fish were captured, they were euthanized using a diluted clove oil bath. Once mortality was confirmed, each fish was measured for fork length (FL; mm), weighed (g), and stored in labeled plastic bags in a cooler of ice. Sagittal otoliths were removed in the laboratory using the techniques described in Schneidervin and Hubert (1986). Scissors were used to cut the gill arch, isthmus and approximately 75% of the way through the roof of the fish's mouth. The backbone was broken downwards to expose the otoliths and fine-point forceps were used to remove the otoliths. The membranous sac was manually removed from around each otolith and the pair of otoliths was placed in a single labelled envelope and left to dry.

All suckers were small enough to be considered age-0 (<90 mm). Mountain Whitefish were assigned an age based on their fork length. Based on data provided by Golder and Gazey (2018), all captured Mountain Whitefish were considered age-0 if they were less than 130 mm FL and age-1 if they were between 131 and 200 mm FL.

2.2.2 Laboratory Analysis

Otolith samples were provided to the Okanagan Nation Alliance's (ONA) fish ageing laboratory in Penticton, BC for circuli measurements. All Mountain Whitefish otoliths were embedded in epoxy and a central transverse section, approximately 0.5 mm thick, was cut on an Isomet low-speed saw (Buehler; Lake Bluff, Illinois). The sections were mounted on glass slides and a calibrated image was taken under phase-contrast at 40x magnification. Seven of the sucker otoliths (the one sample from 2016 and six of the samples from 2018) were processed using the same method as the Mountain Whitefish samples. The rest of the sucker otoliths were glued (with Crystalbond 509) to a slide and sanded down using a P2000 grit sandpaper. Sanding whole otoliths, rather than cutting a section, was more effective for age-0 sucker otoliths, which were smaller than the age-0 Mountain Whitefish otoliths. Regardless of the otolith preparation method, imaging was completed using the same methods for all samples. The smallest visible growth rings, beginning towards the center and progressing outwards, were marked and measured using Image-Pro Premier 9.3 processing software (Media Cybernetics, MD, USA). The starting point for the measurements was approximately 50 circuli from the outer edge where all circuli were clearly discernable (i.e., outside of any areas where circuli were faint or hard to discern). Thus, the otolith measurement data presented below represent otolith growth extending from day of capture back in time up to approximately 50 days or until no growth increments could be distinguished (range 23 to 69 days; mean = 45 days). The distance measured between circuli is referred to as the daily otolith growth increment. All measurements were conducted by a single laboratory technician.

For the analysis of 2018 otoliths, the laboratory provided a quality ranking (Good, Okay, Poor) for each otolith based on the image quality and distinctiveness of circuli. “Good” samples had easily discernable circuli with no problems in the area analyzed. “Okay” samples had minor problems, with some areas containing hard to distinguish circuli. “Poor” samples had circuli that were not easily distinguished or had large gaps or blurry areas. Based on exploratory data visualization, “Good” and “Okay” samples were used in the analysis and data from “Poor” samples were excluded. The large gaps in the “Poor” samples were likely areas where circuli were not discernable, due to either poor image quality or lack of distinct daily circuli in that portion of the otolith. If used for analysis, then these samples would have large outlying values of the growth increment that would be interpreted as days with very large values of growth, which is likely not the case. In the 2018 data, 34 otoliths were ranked as “Good” (22 Mountain Whitefish and 12 suckers), 62 were ranked as “Okay” (57 Mountain Whiteish and 5 suckers, and 18 were ranked as “Poor” and were excluded from analysis (15 Mountain Whitefish and 3 suckers). For the samples used for analysis, QA/QC consisted of plotting the data for each fish to look for outliers. The last increment was removed for one Mountain Whitefish because of a large value that was likely an error. Data from one of the sucker samples was excluded because of large outliers that were likely measurement errors or areas of indistinct circuli. All other data received from the laboratory were used for analysis.

Data from otoliths in 2014, 2015, 2016 did not have any outlying values that suggested poor sample quality and no data were excluded due to outliers. The data included only one age-0 Mountain Whitefish from each of 2014 and 2015 and these years were excluded from statistical analysis because the sample sizes were too small. Data from Arctic Grayling (*n* = 6), Northern Pike (*n* = 1), and Rainbow Trout (*n* = 1) were excluded from analyses due to the low number of individuals captured. A summary of sample sizes for otoliths used for statistical analysis is provided in Table 1.

Table 13: Number of otolith samples used for statistical analysis by year and age-class.

Species	Age class	Capture year	Number of otolith samples
Largescale Sucker	age-0	2018	3
Longnose Sucker	age-0	2016	1
Longnose Sucker	age-0	2018	10
White Sucker	age-0	2018	3
Mountain Whitefish	age-0	2016	34
Mountain Whitefish	age-0	2018	67
Mountain Whitefish	age-1	2014	3
Mountain Whitefish	age-1	2018	12

2.2.3 Discharge and Water Temperature

Hourly discharge (m^3/s) data were obtained from the Water Survey of Canada’s Peace River above Pine River station (Station Number 07FA004)[9]. This station is located 90 km downstream of Peace Canyon Dam, 5 km downstream of the Project, and within the 15 km long portion of the Peace River where all the fish were captured. Hourly water temperature data collected from the Peace River approximately 2 km downstream of the Moberly River confluence (station mobDN1; Diversified Environmental Services in prep.) were used in analysis.

[9] https://wateroffice.ec.gc.ca/report/real_time_e.html?stn=07FA004

2.3 Data Analysis

2.3.1 Discharge and Water Temperature

Hourly discharge data were used to calculate daily discharge range (the difference between daily maximum and minimum discharges; m^3/s) and the mean daily discharge. Hourly water temperatures were used to calculate mean daily temperature. The interpretation of otolith growth rings is that the first outward opaque ring was deposited the night before capture, and therefore the distance between the first two most outward opaque rings represents the previous day's growth. However, it is not known whether changes in environmental variables affect growth on the same day or whether there is a delay between changes in environmental variables and the deposition of otolith rings. Therefore, the analysis included several sets of candidate models that included different time lags between environmental variables and otolith growth. The mean daily temperature, daily range of discharge, and mean daily discharge were calculated for the same day (0 h offset), as well as data offset by 12 h, 24 h, and 48 h, to account for a time delay in the effect of environmental variability on otolith growth. These three predictor variables (water temperature, mean discharge, and discharge range) and four time lags resulted in a set of 12 statistics that were used as predictor variables in models of otolith growth. This systematic approach assessing the arbitrary time lags of 0, 12, 24, and 48 h was necessary because of uncertainty in the precise timing of when the outer opaque ring of the otolith is deposited, and the unknown time lag between environmental conditions experienced in the river and related changes in otolith growth.

2.3.2 Statistical Analysis

Repeated-measures linear mixed models were used to analyze daily otolith growth increment data. The use of a repeated measures analysis accounted for the individual variability of otolith growth in each sampled fish and incorporated the lack of independence of otolith increment data within specimens. Models were fitted separately for age-0 Mountain Whitefish, age-1 Mountain Whitefish, and all three sucker species combined. Growth rates are expected to differ between fish species and by size and age (Putman et al. 1995) due to many factors such as differences in anatomy, physiology, and habitat use (Baltz and Moyle 1984). However, age-0 suckers of all three species were grouped together for this analysis because of small samples sizes. The resulting assumption is that age-0 individuals of these three sucker species had similar otolith growth rates and responses to discharge and temperature. Model building and selection followed the same approach for age-0 Mountain Whitefish, age-1 Mountain Whitefish, and age-0 sucker species but the predictor variables included in the final models varied slightly between these three groups. Simplified models were used for age-1 Mountain Whitefish and age-0 suckers because of smaller sample sizes or predictor variables and interaction terms that were omitted because they were not necessary for these groups. Details of the modelling are provided below.

2.3.2.1 Age-0 Mountain Whitefish

The response variable, daily growth increment, was transformed using the natural logarithm to better meet model assumptions of normality. Daily discharge range was the fixed predictor variable of main interest to the study objectives. Other continuous predictor variables included as fixed effects were mean daily discharge, mean daily water temperature (as a second order polynomial), and body length. Water temperature needed to be modelled as a second order polynomial because of the dome-shaped relationship observed in 2016 (Golder 2018). The categorical variable year (2016 or 2018) was included as a fixed effect. Interaction effects in the model included the three-way interaction between discharge range, mean discharge, and year, and all possible two-way interactions between these three variables. These interaction terms were selected because interactions with discharge range are of primary interest to the objectives. It was hypothesized that the effect of discharge range might depend on water levels because of hydraulic geometry. For instance, flow fluctuations occurring during periods of low mean discharge may result in greater within-day variability in velocity or depth, compared to during high discharge, which could have a greater impact on bioenergetics or habitat use of fishes. The three-way interaction between year, mean discharge, and discharge range was included because exploratory plotting suggested that the effects of discharge variability, and the interaction between mean discharge and discharge range varied between years. Random effects in the full model included random intercepts by fish and random slopes by fish for discharge range, mean discharge, water temperature, and all two-way interactions described above. All continuous predictor variables were standardized by subtracting the mean and dividing by the standard deviation before including in the model. The full model is represented by the following equation:

$$g_{i,d} = \beta_0 + b_{0i} + (\beta_1 + b_{1i,d})\text{ Discharge Range}_{i,d} + (\beta_2 + b_{2i,d})\text{ Mean Discharge} +$$
$$(\beta_3 + b_{3i,d})\text{ Water Temperature} + (\beta_4 + b_{4i,d})\text{ Water Temperature}^2 + (\beta_5)\text{ Fork Length} + (\beta_6)\text{ Year} +$$
$$(\beta_7 + b_{7i,d})\text{ Discharge Range:Mean Discharge} + (\beta_8 + b_{8i,d})\text{ Discharge Range:Year} +$$
$$(\beta_9 + b_{9i,d})\text{ Mean Discharge:Year} + (\beta_{10})\text{ Discharge Range:Mean Discharge:Year} + \varepsilon_{i,d},$$

where $g_{i,d}$ is the natural logarithm of the otolith growth increment of the *i*-th fish on day *d*, β_0 is the intercept, β_1 to β_{10} are the coefficients of the fixed predictor variables, b_{0i} is a random intercept, b_1 to b_9 are random slopes, and $\varepsilon_{i,d}$ is the error term. Two structures were considered for the error term, $\varepsilon_{i,d}$:

1. A homoscedastic structure assuming a normal distribution with mean of zero and variance of σ^2, which can be noted as $\varepsilon_{i,d}$ ~ normal(0, σ^2).
2. A hetereoscedastic error structure assuming a power variance function where $\sigma^2=v^2$, v is the covariance variate, which is in this case was the fitted values of growth increment in the model, and $\varepsilon_{i,d}$ ~ normal(0, σ).

Model building and selection consisted of the following:

1. **Variance structure selection –** Compare between equal variance structure and a heteroscedastic power variance structure using generalized least squares model with the fixed effects listed above and no random effects. Four comparisons were made, one for each time offset value (0, 12, 24, and 48 h) of the environmental variables.

2. **Fixed effect selection** – Using the selected variance structure, four models with offsets in the environmental variables of 0, 12, 24, and 48 h were compared and the best-

supported time lag between environmental conditions and otolith growth increments was chosen. All models had the same predictor variables and interactions described above.

3. **Random effect selection** – Using the selected variance structure and time offset for fixed effects, models with three different random effect structures were compared:
    a. No random effects (fitted using generalized least squares)
    b. Random intercept by individual fish (fitted using restricted maximum likelihood [REML])
    c. Random intercept and random slope by individual fish for discharge range, mean discharge, water temperature, and all two-way interactions in the model (also fitted using REML).

Model selection for Steps 1 and 2 were conducted using marginal Akaike's Information Criterion, corrected for small sample size (mAICc), where models with the lowest mAICc values were considered to have more support given the collected data. Marginal AICc values can be used for mixed model selection where the goal of the analysis is estimating population-level effects (Vaida and Blanchard 2005). Models were fit using maximum likelihood for comparison of fixed effects. Models were fit using REML for selection of variance structure and random effects, and for final interpretation and prediction. Selection of random effect structure was based on likelihood ratio tests (Zuur et al. 2009).

The fit of the final model was evaluated using visual examination of residual plots for normality, linearity, and heteroscedasticity. Model adequacy was also assessed using scatterplots of residuals versus predictor variables, including variables not selected for inclusion in the final model (e.g., fork length). Multicollinearity was assessed by calculating the variance inflation factor (VIF), which measures how much the variance of a model coefficient is inflated due to collinearity. Predictors with VIFs less than 3.0 were considered acceptable (Zuur et al. 2010). An R^2 statistic was calculated for the final model and describes the proportion of variance explained by the fixed effects in the linear mixed effect model (Jaeger et al. 2017). Semi-partial R^2 was calculated for each fixed effect to assess their relative contribution to the model (Jaeger et al. 2017). To assess how much of the variance was accounted for by the fixed effects alone (marginal R^2), and the fixed and random effects together (conditional R^2), the "r.squaredGLMM" function in the R package "MuMIn" was used, which follows the methods of Nakagawa et al. (2017). Although the response variable in the models was the log-transformed daily growth increment, model results are shown as growth increment on the original, back-transformed scale (µm) for easier interpretation. All analyses were performed in the statistical environment R (v. 3.5.1; R Core Team 2018).

2.3.2.2 Age-1 Mountain Whitefish

Based on exploratory plotting and analysis, the effect of discharge range did not vary between years for age-1 Mountain Whitefish, and the sample size for 2015 (n = 3) was too small for assessment of interactions with year. Therefore, year was included as a fixed categorical effect but the three-way interaction between discharge range, mean discharge, and year was not included. The only interaction included in the model for age-1 Mountain Whitefish was the daily discharge range by mean daily discharge interaction. The full model included all fixed effects other than year and fork length as fish-specific random slopes. The mathematical representation of the model was:

$$g_{i,d} = \beta_0 + b_{0i} + (\beta_1 + b_{1i,d})\text{ Discharge Range}_{i,d} + (\beta_2 + b_{2i,d})\text{ Mean Discharge} +$$

$(\beta_3 + b_{3i,d})$ Water Temperature + $(\beta_4 + b_{4i,d})$ Water Temperature² + (β_5) Fork Length + (β_6) Year +
$(\beta_7 + b_{7i,d})$ Discharge Range:Mean Discharge + $\varepsilon_{i,d,}$

where $g_{i,d}$ is the natural logarithm of the otolith growth increment of the *i*-th fish on day *d*, β_0 is the intercept, β_1 to β_7 are the coefficients of the fixed predictor variables, b_{0i} is a random intercept, b_1 to b_7 are random slopes, and $\varepsilon_{i,d}$ is the error term.

Except where noted above, model building, selection, and diagnostics were the same as described for age-0 Mountain Whitefish (Section 2.3.2.1).

2.3.2.3 Age-0 suckers

As was done for age-1 Mountain Whitefish, interactions between discharge variables and year were not required for age-0 suckers and the only interaction term included in the model was the discharge range by mean discharge interaction. The effect of water temperature was included as a linear, rather than second order polynomial effect, because exploratory plotting showed that the effect was linear. The full model included all fixed effects other than year and fork length as fish-specific random slopes. The mathematical representation of the model was:

$g_{i,d} = \beta_0 + b_{0i} + (\beta_1 + b_{1i,d})$ Discharge Range$_{i,d}$ + $(\beta_2 + b_{2i,d})$ Mean Discharge +
$(\beta_3 + b_{3i,d})$ Water Temperature + (β_4) Fork Length + (β_5) Year +
$(\beta_6 + b_{6i,d})$ Discharge Range:Mean Discharge + $\varepsilon_{i,d,}$

where $g_{i,d}$ is the natural logarithm of the otolith growth increment of the *i*-th fish on day *d*, β_0 is the intercept, β_1 to β_7 are the coefficients of the fixed predictor variables, b_{0i} is a random intercept, b_1 to b_7 are random slopes, and $\varepsilon_{i,d}$ is the error term.

Except where noted above, model building, selection and diagnostics were the same as described for age-0 Mountain Whitefish (Section 2.3.2.1).

2.3.2.4 Assumptions

The following assumptions were made for the analysis and interpretation of the results:

- Within an age-class, individual daily otolith growth increments do not change with fish age, as fish of a certain age-class may have hatched on different days within the year. It is assumed that the size of otolith increments does not depend on fish age within an age-class in the period of interest (August to October).
- Otolith growth rate as a function of temperature or discharge may differ across individuals during the period of interest. This was modeled by the random slopes for temperature and discharge range by individual fish.
- Otolith growth is correlated with fish body growth; therefore, effects of flow fluctuations on otolith growth can be interpreted as effects on fish body growth.
- Otolith growth and its relationship with discharge and temperature did not differ between the three species of sucker.
- The first outward opaque ring on the otoliths was deposited the night before capture and the distance between the first two most outward opaque rings represents the previous day's growth.

The first assumption was required because the age of the captured fish (i.e., days since hatch) could not be determined, and therefore the effect of age on otolith growth rate could not be modeled. While age may strongly influence otolith growth rate in early life stages, the effect decreases with age in the first year of life (e.g., Cotano and Alvarez 2003; Aldanondo et al. 2010).

The analysis included data from otoliths collected in 2014, 2016, and 2018. One otolith from 2014 and one from 2015 were not included in the analysis because the sample sizes were too small to estimate a year effect. Otoliths were collected later in 2016 (4 November) than in 2018 (11–12 October) and 2014 (4–5 September). Therefore, the year effect in the model may represent seasonal differences due to sampling date, as well as other differences in conditions for growth between years.

3.0 RESULTS

3.1 Discharge and Temperature

Mean daily discharge during the study period was greater in 2016, when values were mostly greater than 1000 m^3/s (range: 783 to 1666 m^3/s), than during 2018, when values ranged from 418 to 1621 m^3/s (Figure 19). Daily discharge range was highly variable in both 2016 and 2018, ranging from approximately 10 to 1200 m^3/s (Figure 20). An exception was between 16 and 30 September in 2018, when discharge varied less than 70 m^3/s per day for twelve days. During this period, mean daily discharges were approximately 420 to 480 m^3/s (Figure 19). In 2018, discharge range was greater at intermediate discharges and lower during high and low discharges (Figure 21). In 2016, discharge range was variable (approximately 20 to 1200 m^3/s) during the most common mean discharges of 1000 to 1400 m^3/s, but the discharge range was lower (less than 500 m^3/s) at high mean discharge (Figure 21). Mean daily water temperature was similar between years, despite the later capture dates in 2016 than 2018 (Figure 22). Mean daily water temperature decrease from 14°C to 6°C during the 2018 study period and from 13°C to 6°C during the 2016 study period. Grey, blue, and orange points on Figures 1 to 4 illustrate the discharge and water temperature experienced by fish whose otolith measurements were used in the analysis.

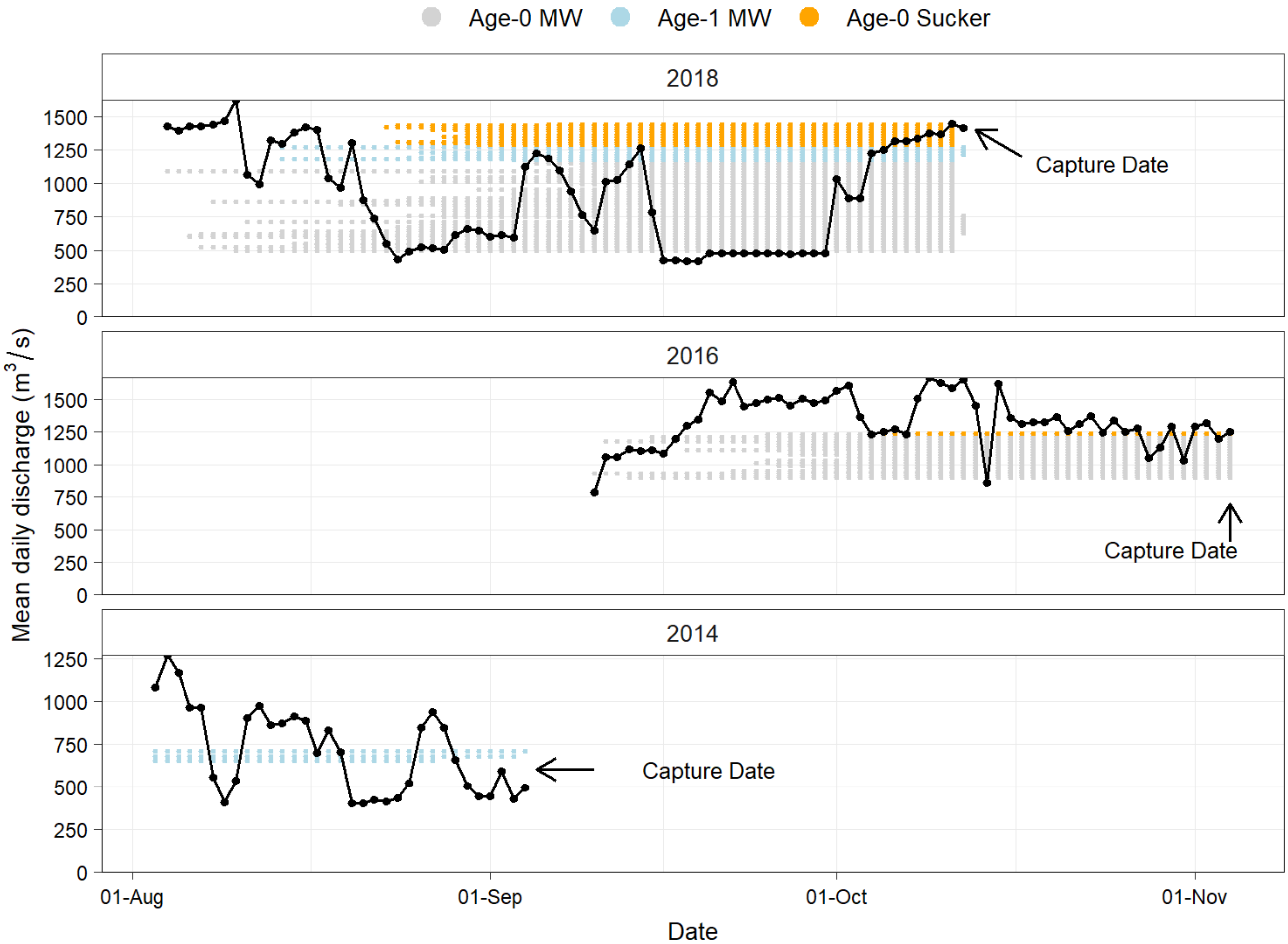


Figure 19: Mean daily discharge for the Peace River above the Pine River confluence during the 2014, 2016, and 2018 study periods. Each row of points (grey, blue, or orange) represents a fish whose otolith was measured, and each point represents a daily growth increment starting at the capture date on the right and extending as far back (left) as circuli were clearly distinguishable.

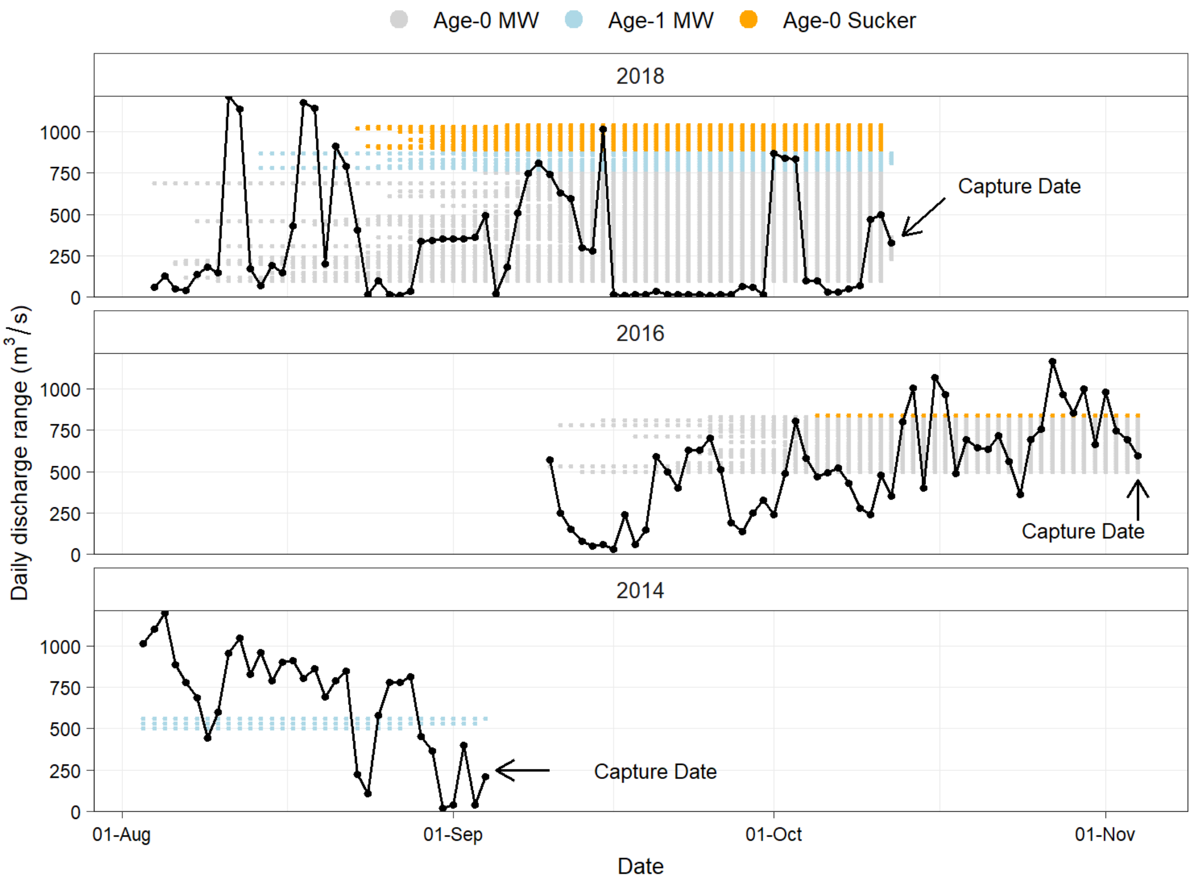


Figure 20: Daily discharge range in the Peace River above the Pine River confluence during the 2014, 2016, and 2018 study periods. Discharge range was calculated as the daily maximum hourly discharge minus the daily minimum hourly discharge. Each row of points (grey, blue, or orange) represents a fish whose otolith was measured, and each point represents a daily growth increment starting at the capture date on the right and extending as far back (left) as circuli were clearly distinguishable.

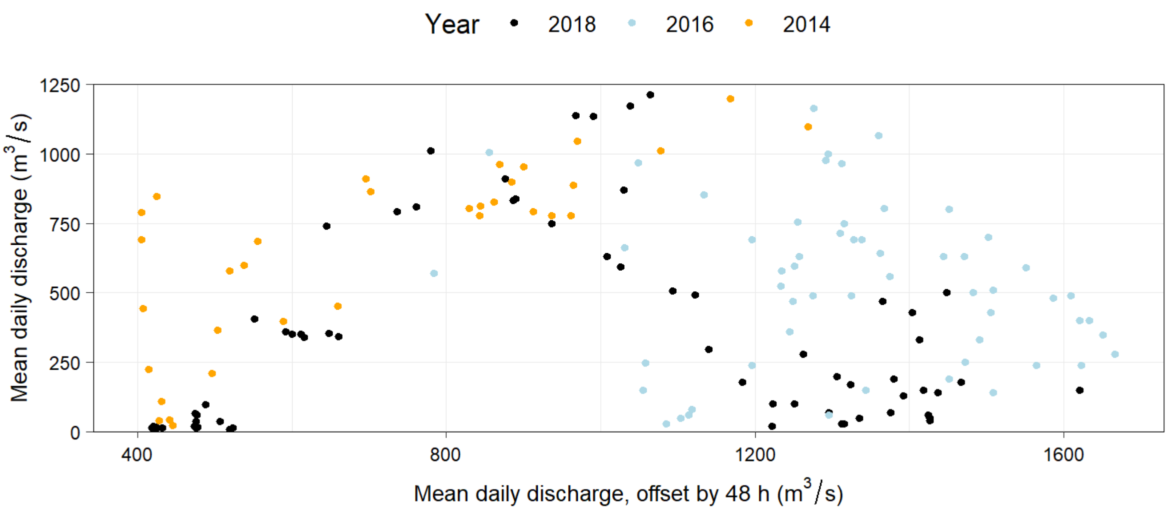


Figure 21: Relationship between mean daily discharge and daily discharge range in the Peace River above the Pine River confluence during the 2014, 2016, and 2018 study periods.

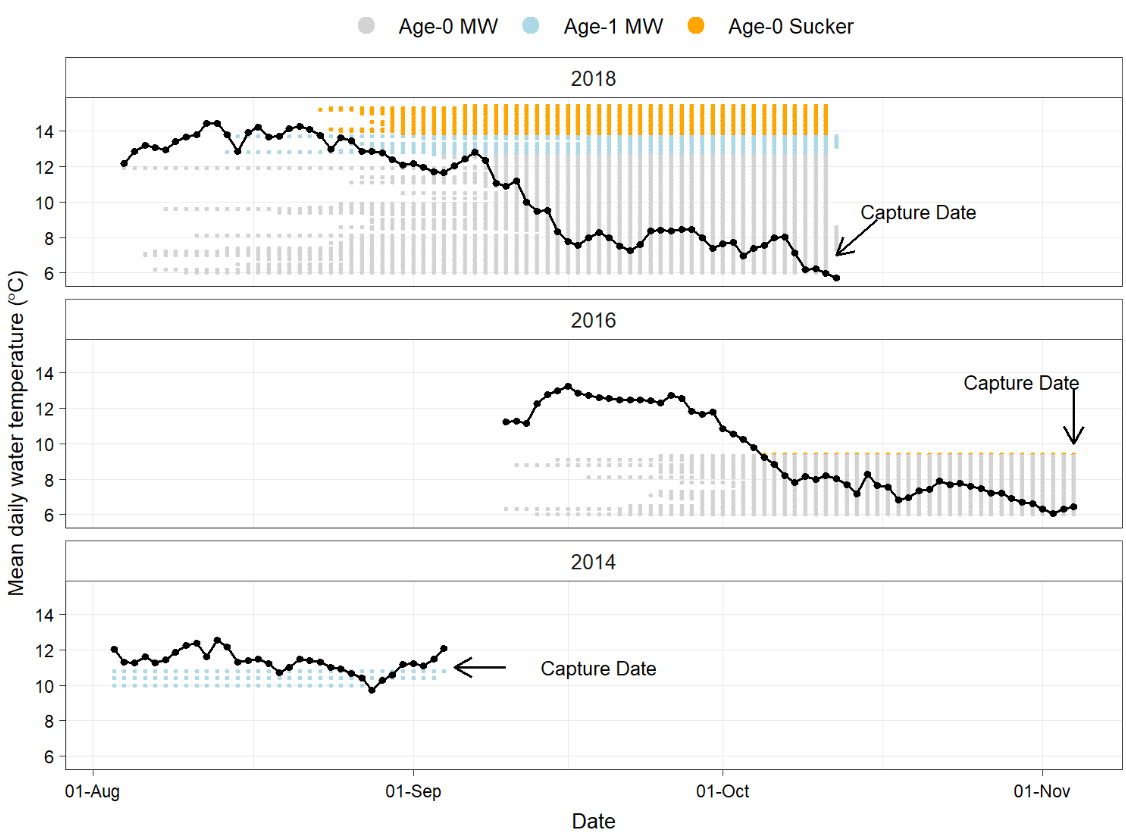


Figure 22: Mean daily water temperatures for the Peace River downstream of the Moberly River confluence (MobDN1) during the 2014, 2016, and 2018 study periods. Each row of points (grey, blue, or orange) represents a fish whose otolith was measured, and each point represents a daily growth increment starting at the capture date on the right and extending as far back (left) as circuli were clearly distinguishable.

3.2 Otolith Samples

Otoliths from 101 age-0 and 15 age-1 Mountain Whitefish were used for analysis. Fork lengths of age-0 Mountain Whitefish ranged from 76 to 120 mm (mean ± SD: 101 mm ± 10 mm). Fork lengths of age-1 Mountain Whitefish ranged from 154 to 174 mm (168 mm ± 6 mm). The number of otolith increments measured per fish ranged between 23 and 69 for age-0 Mountain Whitefish (mean = 41). The number of otolith increments measured per age-1 Mountain Whitefish fish ranged between 25 and 60 (mean = 39). Fish-specific mean otolith increments ranged between 0.012 and 0.063 µm for age-0 Mountain Whitefish (0.031 µm ± 0.009 µm) and between 0.017 and 0.069 µm for age-1 Mountain Whitefish (0.032 µm ± 0.014 µm).

For sucker species, otolith data used for data analysis included 3 Largescale Sucker, 11 Longnose Sucker, and 3 White Sucker. Fork lengths of Largescale Sucker ranged from 45 to 53 mm (49 mm ± 4 mm). Fork lengths of Longnose Sucker ranged from 40 to 53 mm (45 mm ± 4 mm). Fork lengths of White Sucker ranged from 69 to 89 mm (80 mm ± 10 mm). Largescale Sucker, Longnose Sucker, and White Sucker were assumed to be age-0, based on their fork lengths (all less than 90 mm). The number of otolith increments measured per sucker ranged from 29 to 50 (mean = 42). Fish-specific mean otolith increments ranged between 0.015 and 0.068 µm for suckers (0.042 µm ± 0.013 µm).

3.3 Age-0 Mountain Whitefish

In models of age-0 Mountain Whitefish otolith growth increments, an error structure where the variance was a power function of the fitted values to account for heteroscedasticity was supported better than an equal variance structure and was used for all subsequent candidate models. Of the four models with fixed effects that had different time offsets, the model with a 12 h offset was best supported by the data (Table 14). When comparing random effect structures, the model with random intercepts by fish was better supported than a model with no random effects (likelihood ratio test; $P<0.001$). The model with fish-specific random slopes was better supported than models with only random intercepts ($P<0.001$). Therefore, the final model selected for interpretation (Model 2) included a heteroscedastic variance structure, a 12 h offset for environmental variables modeled as fixed effects, and fish-specific random intercepts and slopes for the effects of discharge range and mean water temperature. Estimates of the variance for each of the random effects in the final model are provided in Table 15. The intercept can be interpreted as the variability in growth increment between all sampled fish, whereas the other terms represent the variability in the effect of the predictor variables (i.e., the slopes) between fish (Table 15).

Table 14: Comparisons of model support for models of growth increment of age-0 Mountain Whitefish using different temporal offsets for environmental predictors.

Model	Time Offset (h)	R^2_m	R^2_c	Log-likelihood	K	$mAIC_C$	ΔAIC_C
2	12	0.17	0.66	-236.1	49	571.4	0.0
1	0	0.17	0.67	-261.0	49	621.1	49.8
3	24	0.15	0.58	-266.7	49	632.7	61.3
4	48	0.12	0.51	-284.5	49	668.3	96.9

Notes: R^2_m is for fixed effects only and R^2_c is for the fixed and random effects combined (Nakagawa et al. 2017); K = number of estimated parameters; mAICC is marginal Aikake's Information Criterion corrected for small sample sizes; ΔmAICc is the difference in mAICc between the highest ranked (lowest mAICc) model and each candidate model.

Table 15: Estimates and standard deviation of variance for the random effects in the full model with random intercept and slopes by fish for age-0 Mountain Whitefish.

Random Effect	Variance	Standard Deviation
Intercept	0.095	0.309
Mean Temperature	0.010	0.102
Mean Temperature²	0.007	0.082
Discharge Range	0.002	0.040
Mean Discharge	0.002	0.047
Discharge Range:Year	0.006	0.075
Discharge Range:Mean Discharge	0.004	0.065
Mean Discharge:Year	0.002	0.045
Residual	0.074	0.272

Using the selected model (Model 2), mean daily otolith growth when predictor variables were at their average or reference level values was 0.029 µm. The reference value of the year variable was 2018, so this estimate represents the mean for that year. The interaction between daily discharge range, mean discharge, and year was statistically significant ($P<0.001$). Therefore, the statistical significance of the daily discharge range and mean discharge by themselves (i.e., the main effects) should not be interpreted and is not presented. This supports the idea that the effects of discharge range and mean temperature affected otolith increment differently between years.

The estimate of R^2 suggested that 41.5% of the variance in growth increments was explained by the selected model (Table 16). Semi-partial R^2 for fixed effects showed that mean temperature was the most important predictor of growth increment (R^2=0.240), followed by fork length (R^2=0.039; Table 16). Year, discharge range:mean discharge, and the three-way interaction between discharge range, mean discharge range, and year explained approximately 1% in the variance each. The remaining predictor variables had low values of R^2 (≤0.001), suggesting they were not important predictors of growth increment.

Table 16: Estimated R² with 95% confidence intervals for selected model of otolith growth increment for age-0 Mountain Whitefish. Fixed effects for environmental variables had a 12 h offset in the model.

Effect	R^2		
	Estimate	LCL	UCL
Model	0.415	0.393	0.439
Mean Temperature	0.240	0.216	0.265
Fork Length	0.039	0.027	0.053
Mean Temperature²	0.016	0.008	0.025
Year	0.014	0.007	0.023
Discharge Range:Mean Discharge	0.013	0.006	0.022
Discharge Range:Mean Discharge:Year	0.013	0.006	0.021
Mean Discharge:Year	0.007	0.003	0.015
Discharge Range	0.004	0.001	0.009
Discharge Range:Year	0.002	0.000	0.005
Mean Discharge	0.000	0.000	0.002

Notes: LCL is the lower confidence level and UCL is the upper confidence level. R^2 and semi-partial R^2 for fixed effects were calculated following Jaeger et al. (2017).

The effect size for mean temperature indicated that mean increment would increase 0.007 µm (from a mean of 0.029 to 0.036 µm) for every 1 SD (2.3°C) increase in mean water temperature

(Figure 23). The small effect size for the second-order polynomial for water temperature (-0.001 µm) reflects that the relationship between growth increment and temperature was only dome-shaped for some of the age-0 Mountain Whitefish, mostly in 2016, and was linear for most fish in 2018 (data not shown). The negative value of the year effect indicates 0.005 µm lower mean growth increment in 2016 than in 2018, which was the reference year in the model. The 95% confidence interval (CI) for the year effect was from -0.001 to -0.008 µm. Fork length had a small negative effect, with a 0001 µm decrease (CI: 0.0001 to -0.003 µm) for every 1 SD (10 mm) increase in fork length. Estimated effect sizes of the two-way and three-way interactions between discharge range, mean discharge, and year were small (mean estimates of -0.004 to 0.004 µm) but most their CIs did not overlap zero (except discharge range by year), suggesting a statistically significant effect. Interpreting two- and three-way interactions from coefficient effect sizes is somewhat unintuitive and the effects of these variables are more easily understood by examining plots of predicted values of growth increment versus the predictor variables of interest (Figures 6 and 7).

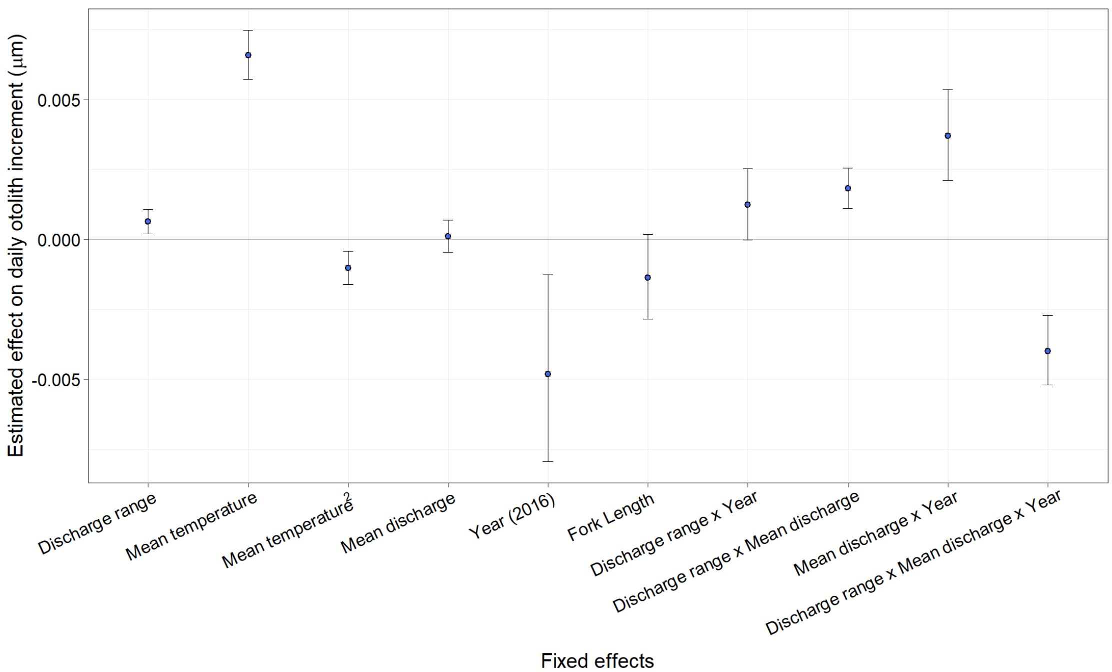


Figure 23: Estimated effect of fixed effect predictor variables on otolith growth increment of age-0 Mountain Whitefish. Values are means with 95% confidence intervals calculated from the estimated coefficients from the linear mixed effect model. As predictor variables were standardized, effect sizes for continuous variables (all variables except year) describe the change in otolith growth with an increase of 1 SD in the value of the respective environmental variable.

Population-level predictions represent the expected growth increment for an average fish at the specified level of the predictor variables. Population-level predicted values of growth increment increased from 0.027 µm at 8°C to 0.036 µm at 12°C, when the other predictor variables were held at their mean values (Figure 24). Predicted values of growth increment versus discharge range show that the effect of discharge range varied by mean discharge and year (Figure 25), reflecting the significant interaction between these variables. In 2018, discharge range was negatively related to growth increment at low discharge but positively related to growth increment at high discharge, although the effect size was small. For example, in 2018 when mean discharge was 1400 m³/s, the predicted growth increment increased from 0.028 µm at a daily discharge range of 100 m³/s to 0.036 µm at a daily discharge range of 1200 m³/s (Figure

25). In 2016, there were no days with low mean discharge (less than 800 m³/s) and there were relatively few data during medium discharges (800 to 1200 m³/s; Figure 25). During high discharge (1400 m³/s) in 2016 (bottom right panel of Figure 25), there was a negative relationship between discharge range and mean discharge, with predicted growth increment decreasing from 0.028 µm at a daily range of 100 m³/s to 0.026 µm at a daily range of 1200 m³/s. Because of the difference in the effect of discharge range between years, the small effect sizes, and small values of semi-partial R^2, the results do not provide strong support for an effect of discharge range on growth increment.

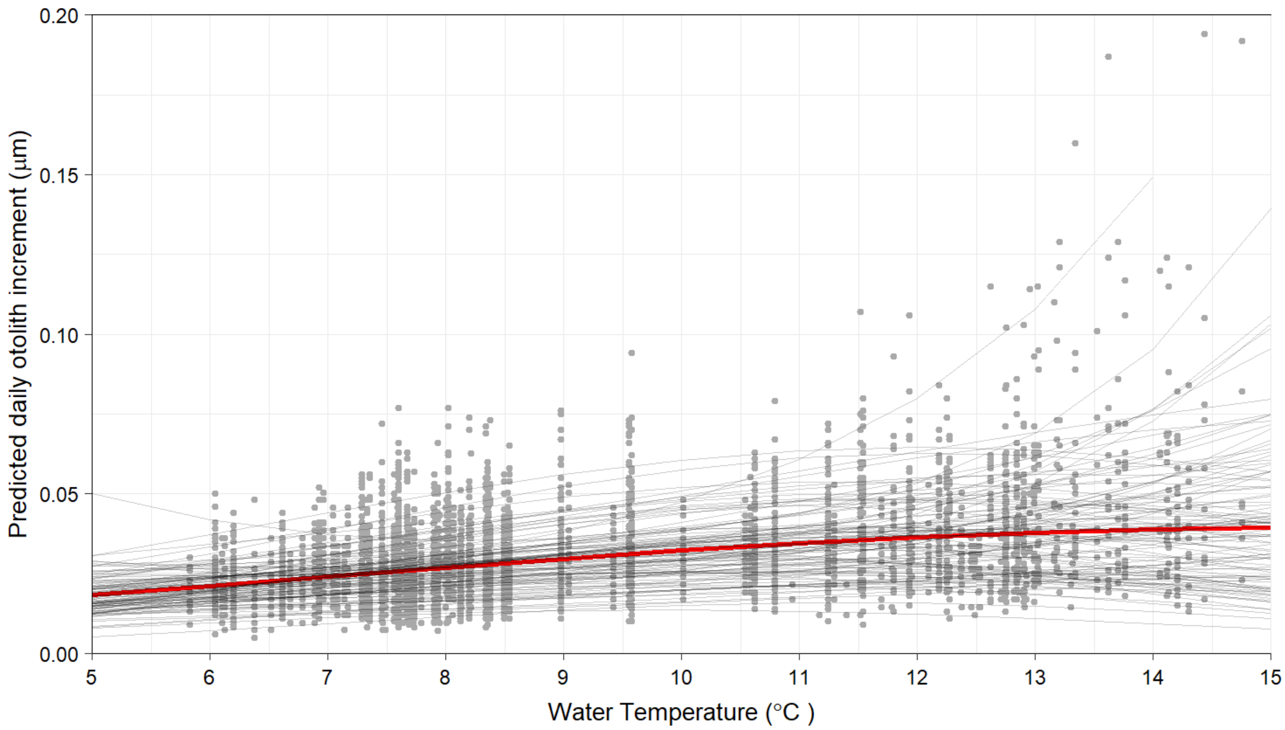


Figure 24: The relationship between daily otolith growth increment and water temperature (offset by 12 h) for age-0 Mountain Whitefish. The red line represents the population-level predicted values (from fixed effects β_{1-10}) and the grey lines are fish-specific predicted values (from fixed and random effects b_{0-9} and β_{1-10}), with the other predictor variables held at their mean or reference level values. Grey points are raw data.

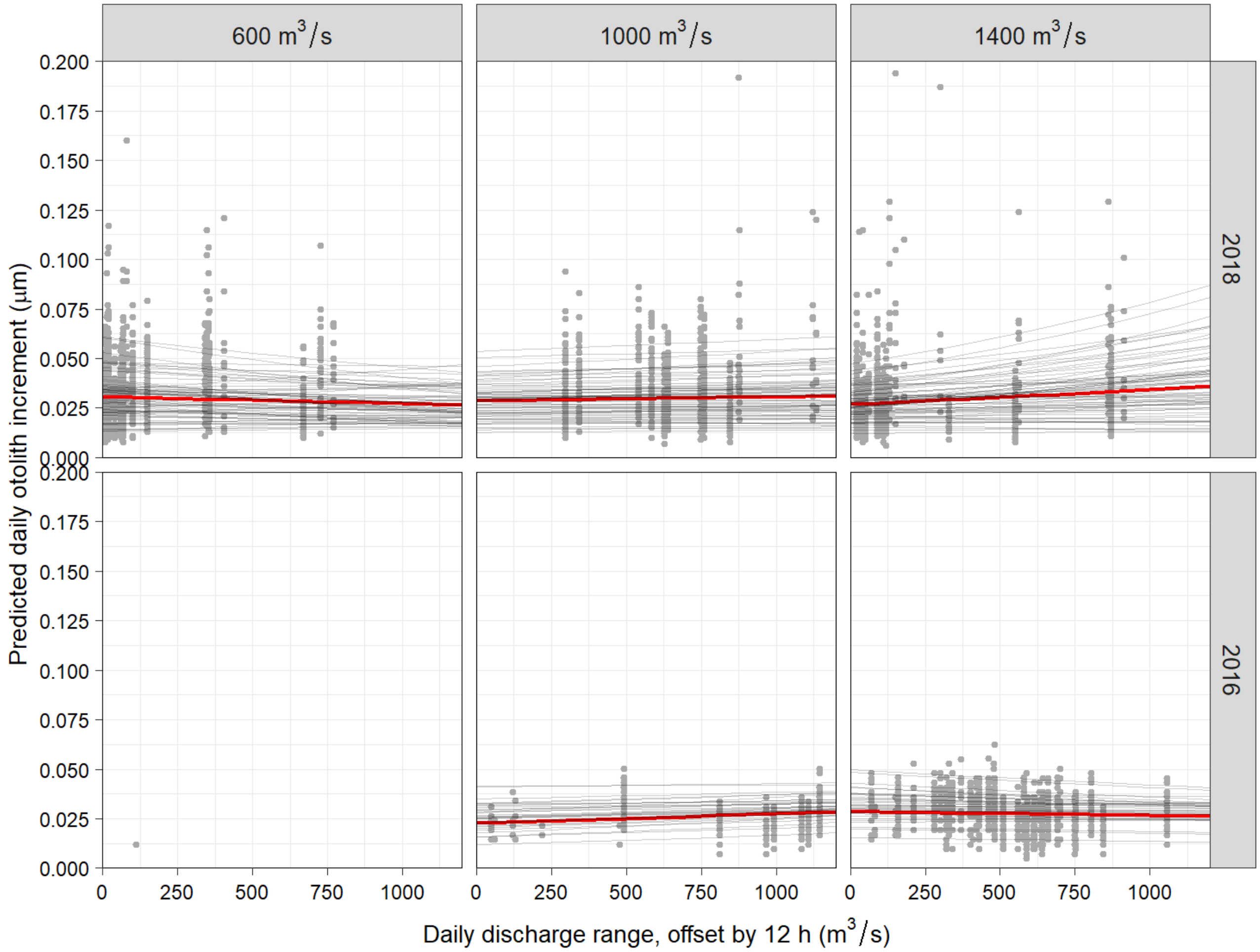


Figure 25: The relationship between daily otolith growth increment for age-0 Mountain Whitefish and daily discharge range (offset by 12 h), at three example levels of mean discharge. The red line represents the population-level predicted values and the grey lines are fish-specific predicted values, with the other predictor variables held at their mean or reference level values. Grey points are raw data and were binned by mean discharge to allow plotting with the predictions. Mean discharge bins for the raw data were 400–800 m³/s for the 600 m³/s panel, 800–1200 m³/s for the 1000 m³/s panel, and 1200–1600 m³/s for the 1400 m³/s panel.

3.4 Age-1 Mountain Whitefish

In models of age-1 Mountain Whitefish otolith growth increments, an error structure where the variance was a power function of the fitted values to account for heteroscedasticity was supported better than an equal variance structure and was used for all subsequent candidate models. Of the four models with fixed effects that had different time offsets, the model with a 12 h offset was best supported by the data (Table 17). When comparing random effect structures, the model with random intercepts by fish was better supported than a model with no random effects (likelihood ratio test; $P<0.001$). The model with fish-specific random slopes was better supported than models with only random intercepts ($P<0.001$). Therefore, the final model selected for interpretation (Model 2) included a heteroscedastic variance structure, a 12 h offset for environmental variables modeled as fixed effects, and fish-specific random intercepts and slopes for the effects of discharge range and mean water temperature. Estimates of the variance for each of the random effects in the final model are provided in Table 18. The intercept can be interpreted as the variability in average growth increment between all sampled fish, whereas the other terms represent the variability in the effect of the predictor variables (i.e., the slopes) between fish (Table 18).

Table 17: Comparisons of model support for models of growth increment of age-1 Mountain Whitefish using different temporal offsets for environmental predictors.

Model	Time Offset (h)	R^2_m	R^2_c	Log-likelihood	K	$mAIC_C$	$\Delta mAIC_C$
2	12	0.04	0.24	-125.2	31	316.0	0.0
4	48	0.02	0.18	-126.6	31	318.9	2.9
1	0	0.06	0.23	-128.4	31	322.3	6.3
3	24	0.03	0.23	-130.1	31	325.9	9.9

Notes: R^2_m is for fixed effects only and R^2_c is for the fixed and random effects combined (Nakagawa et al. 2017); K = number of estimated parameters; $mAIC_C$ is marginal Aikake's Information Criterion corrected for small sample sizes; ΔmAICc is the difference in mAICc between the highest ranked (lowest mAICc) model and each candidate model.

Table 18: Estimates and standard deviation of variance for the random effects in the full model with random intercept and slopes by fish for age-1 Mountain Whitefish.

Random Effect	Variance	Standard Deviation
Intercept	0.126	0.355
Mean Temperature	0.014	0.118
Mean Temperature²	0.012	0.112
Discharge Range	0.007	0.081
Mean Discharge	0.004	0.066
Discharge Range:Mean Discharge	0.008	0.091
Residual	0.652	0.807

Using the selected model (Model 2), mean daily otolith growth, when environmental predictor variables were at their average values, was 0.031 µm. Daily discharge range (P=0.4), mean daily discharge (P=0.6), and their interaction (P=0.2) were not statistically significant predictors of growth increment. The effect sizes for the fixed predictor variables in the model are assessed by semi-partial R^2 values and standardized coefficients below.

The estimate of R^2 suggested that 30.5% of the variance in growth increments was explained by the selected model (Table 19). Semi-partial R^2 for fixed effects showed that year was the most important predictor of growth increment (R^2=0.24), although this could have been related to the small sample size (n = 3) in 2014. Fork length (R^2=0.076) and mean temperature (R^2=0.055) were the next most important predictors of growth increment (Table 19). Discharge range and the interaction between discharge range and mean discharge had R^2 values less than 0.01, suggesting that they had little predictive value.

The effect size for mean temperature indicated that mean increment would increase 0.003 µm (from a mean of 0.031 to 0.034 µm) for every 1 SD (2.2°C) increase in mean water temperature (Figure 26). The estimated effect size for daily discharge range was small (mean: 0.0008 µm; CI: -0.002 to 0.0009 µm), suggesting a 0.0008 µm decrease in growth increment for every 1 SD (328 m³/s) increase in discharge range. The effect size for the interaction between discharge range and mean discharge was 0.001 µm (CI: -0.0004 to 0.003 µm). The 95% CI intervals for discharge range, mean discharge, and their interaction all overlap zero suggesting no statistically significant effect, and the range of likely values shown by these CIs suggests that only very small effects are probable given the available data. For example, the lower 95% confidence interval for daily discharge range was -0.002 µm, which corresponds to a 6% decrease in growth increment from 0.031 to 0.029 µm for every 328 m³/s (1 SD) increase in discharge. This represents the largest possible (with 95% confidence) negative effect, whereas the most likely effect (0.0008 µm) was a 2% decrease in growth increment for a 328 m³/s increase in discharge.

Table 19: Estimated R^2 with 95% confidence intervals for the selected model of otolith growth increment for age-1 Mountain Whitefish. Fixed effects for environmental variables had a 12 h offset in the model.

Effect	R^2 (estimate)	R^2 (LCL)	R^2 (LCL)
Model	0.305	0.254	0.368
Year	0.241	0.185	0.299
Fork Length	0.076	0.040	0.121
Mean Temperature	0.055	0.025	0.095
Discharge Range:Mean Discharge	0.009	0.000	0.030
Discharge Range	0.003	0.000	0.019
Mean Temperature²	0.002	0.000	0.016
Mean Discharge	0.001	0.000	0.012

Notes: LCL is the lower confidence level and UCL is the upper confidence level. R^2 and semi-partial R^2 for fixed effects were calculated following Jaeger et al. (2017).

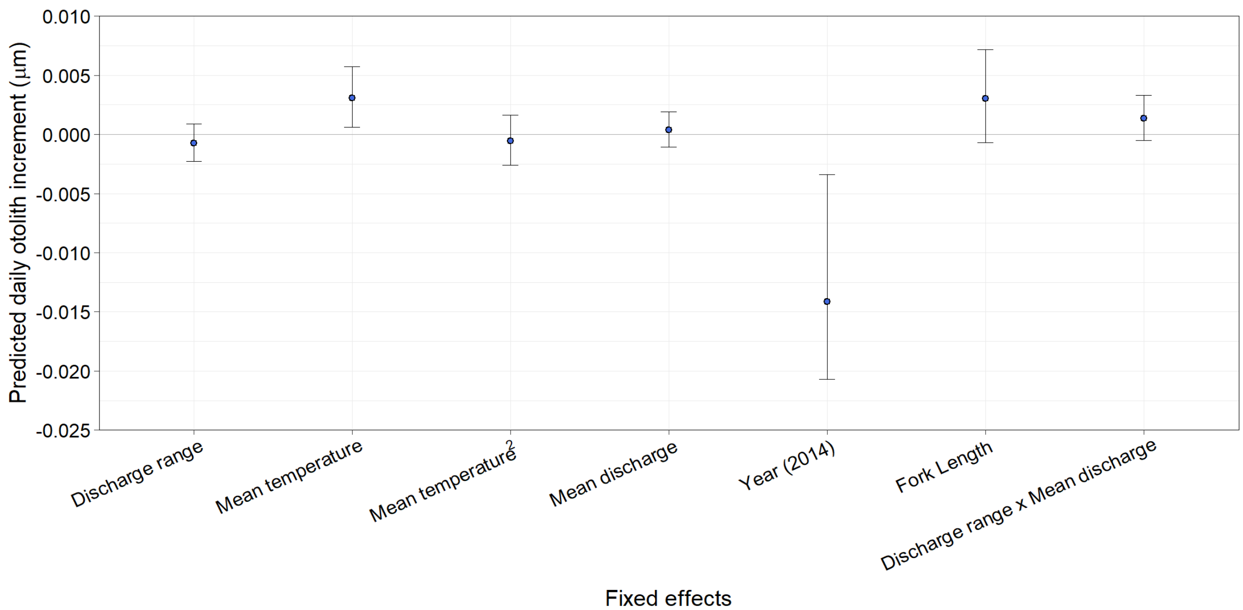


Figure 26: Estimated effect of fixed effect predictor variables on otolith growth increment of age-1 Mountain Whitefish. Values are means with 95% confidence intervals calculated from the estimated coefficients from the linear mixed effect model. As predictor variables were standardized, effect sizes for continuous variables (all variables except year) describe the change in otolith growth with an increase of 1 SD in the value of the respective environmental variable.

Population-level predicted values of growth increment increased from 0.029 µm at 8°C to 0.034 µm at 12°C, when the other predictor variables were held at their mean values (Figure 27). Population-level predicted values (red lines) of growth increment versus discharge range suggest that the effect of discharge range varied by mean discharge (Figure 28); however, the random-level predictions (grey lines) show high variability in the response between fish, and the raw data (grey points) suggest very little relationship between discharge range and growth increment (Figure 28). Because the effect of discharge range was not statistically significant, model-predicted differences in growth increment should not be considered strong evidence of an effect of discharge range. However, as an example of the predicted effect, the growth increment decreased from 0.032 µm at a daily discharge range of 100 m³/s to 0.027 µm at a daily discharge range of 1200 m³/s (i.e., a 15% decrease), when mean daily discharge was 600 m³/s (Figure 28). Because of the large variability in responses, lack of statistical significance, and small values of semi-partial R^2, the results do not provide strong support for an effect of discharge range on growth increment of age-1 Mountain Whitefish.

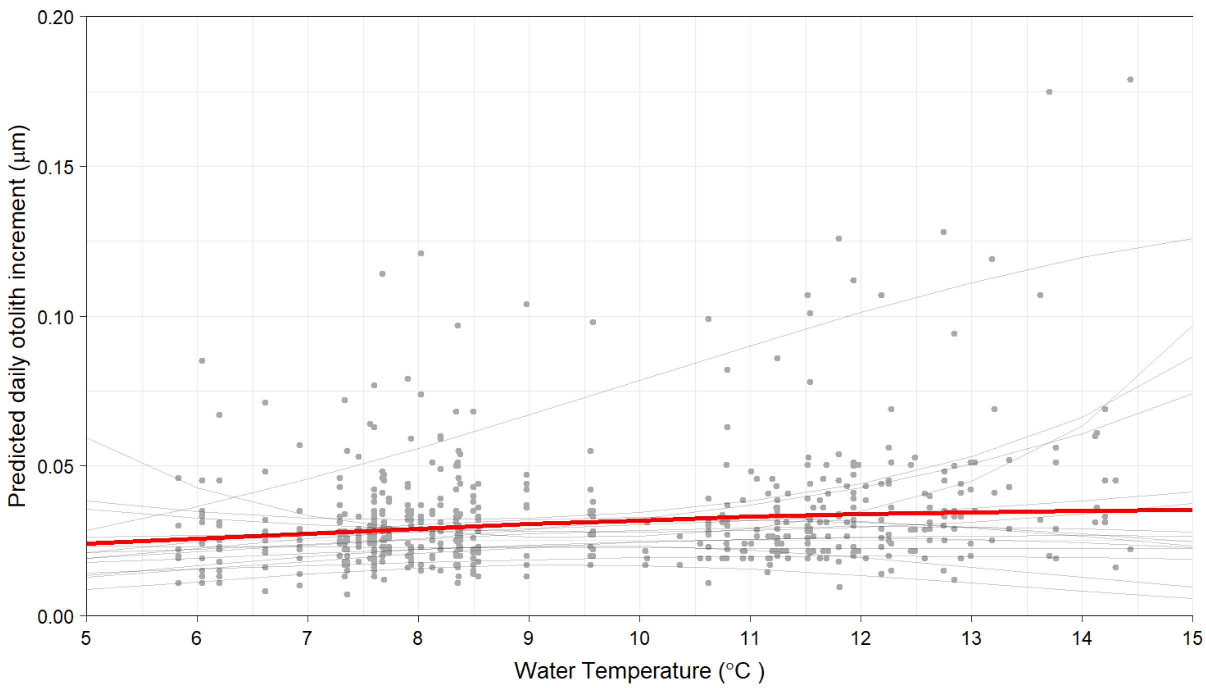


Figure 27: The relationship between daily otolith growth increment and water temperature (offset by 12 h) for age-1 Mountain Whitefish. The red line represents the population-level predicted values (from fixed effects $\beta_{1\text{-}10}$) and the grey lines are fish-specific predicted values (from fixed and random effects $b_{0\text{-}9}$ and $\beta_{1\text{-}10}$), with the other predictor variables held at their mean or reference level values. Grey points are raw data.

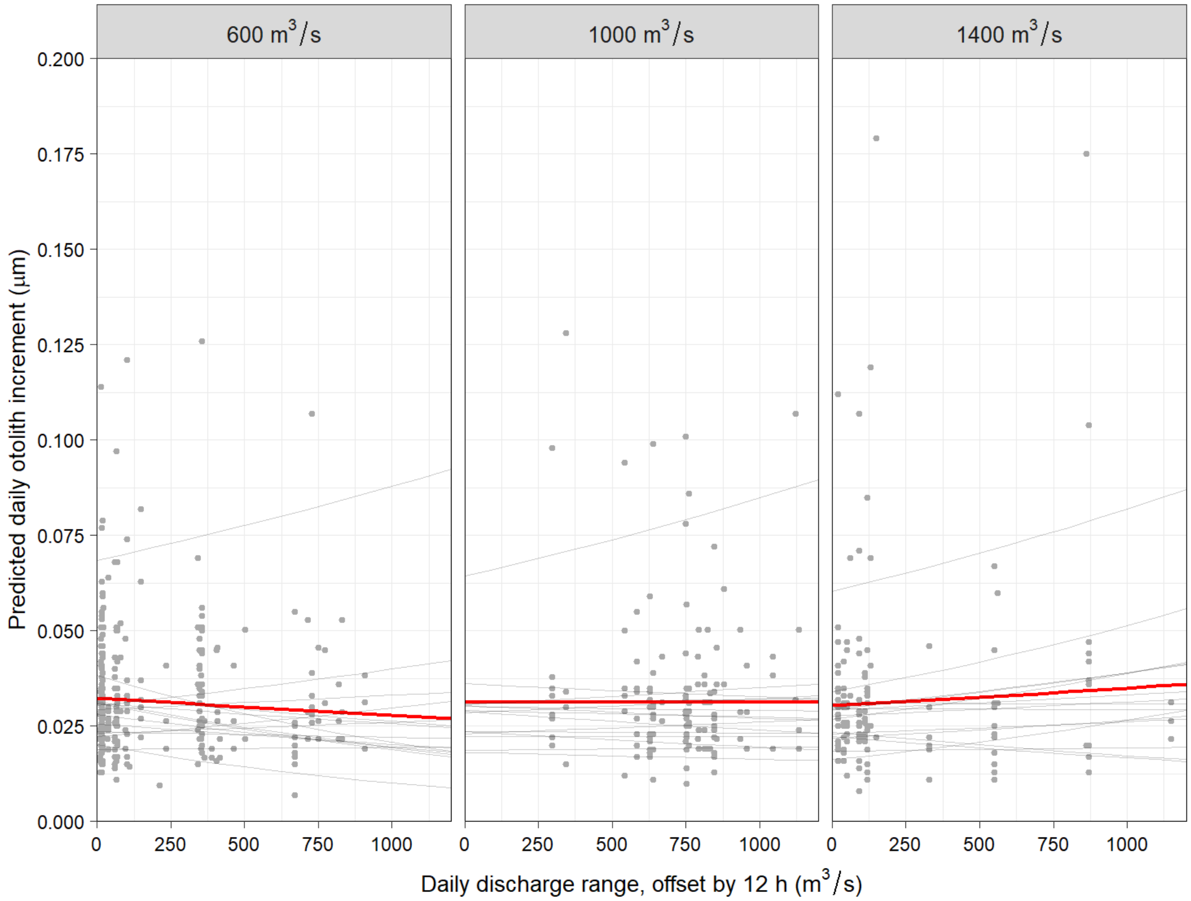


Figure 28: The relationship between daily otolith growth increment and daily discharge range (offset by 12 h) for age-1 Mountain Whitefish at three example levels of mean discharge. The red line represents the population-level predicted values (from fixed effects $\beta_{1\text{-}10}$) and the grey lines are fish-specific predicted values (from fixed and random effects $b_{0\text{-}9}$ and $\beta_{1\text{-}10}$), with the other predictor variables held at their mean or reference level values. Grey points are raw data.

3.5 Suckers

In models of sucker otolith growth increments, an equal variance structure was supported better than a heteroscedastic structure and was used for all subsequent candidate models. Of the four models with fixed effects that had different time offsets, the model with a 48 h offset was best supported by the data (Table 20). When comparing random effect structures, the model with random intercepts by fish was better supported than a model with no random effects (likelihood ratio test; P<0.001). The model with random slopes was better supported than models with only random intercepts (P<0.001). Therefore, the final model selected for interpretation included an equal variance structure, 48 h offset for environmental variables modeled as fixed effects, and fish-specific random intercepts and slopes. Estimates of the variance for each of the random effects in the final model are provided in Table 21. The intercept can be interpreted as the variability in growth increment between all sampled fish, whereas the other terms represent the variability in the effect of the predictor variables (i.e., the slopes) between fish (Table 21). A value close to zero for the random slope of discharge range indicates little variability in the growth response to this variable between fish.

Table 20: Comparisons of model support for models of growth increment of age-0 suckers using different temporal offsets for environmental predictors.

Model	Time Offset (h)	R^2_m	R^2_c	Log-likelihood	K	$mAIC_C$	ΔAIC_C
4	48	0.17	0.62	-157.6	22	360.7	0.0
3	24	0.16	0.62	-163.6	22	372.6	11.9
2	12	0.17	0.62	-171.5	22	388.5	27.9
1	0	0.17	0.61	-174.2	22	393.9	33.3

Notes: R^2_m is for fixed effects only and R^2_c is for the fixed and random effects combined (Nakagawa et al. 2017); K = number of estimated parameters; $mAIC_C$ is marginal Aikake's Information Criterion corrected for small sample sizes; $\Delta mAIC_c$ is the difference in $mAIC_c$ between the highest ranked (lowest $mAIC_c$) model and each candidate model.

Table 21: Estimates and standard deviation of variance for the random effects in the full model with random intercept and slopes by fish for age-0 suckers.

Random Effect	Variance	Standard Deviation
Intercept	0.069	0.262
Discharge Range	0.002	0.040
MeanTemperature	0.018	0.135
Mean Discharge	0.005	0.071
Discharge Range:Mean Discharge	0.002	0.048
Residual	0.076	0.276

Using the selected model (Model 4), mean daily otolith growth, when environmental predictor variables were at their average values, was 0.038 µm. Daily discharge range (P=0.9), and its interaction mean discharge (P=0.8) were not statistically significant predictors of growth increment. Mean water temperature (P<0.0001) and mean discharge (P=0.01) were statistically significant predictors of growth increment. The effect sizes for all these variables (statistically significant or not) are assessed by semi-partial R^2 values and standardized coefficients below.

The estimate of R^2 suggested that 27.6% of the variance in growth increments was explained by the selected model (Table 22). Semi-partial R^2 for fixed effects showed that mean temperature (R^2=0.217) was the most important predictor of growth increment (Table 22). Mean discharge was the second most important predictor (R^2=0.025). Discharge range and its interaction had small values of R^2 (<0.0001).

The effect size for mean temperature indicated that mean growth increment would increase 0.007 µm (from a mean of 0.038 to 0.045 µm) for every 1 SD (3.2°C) increase in mean water temperature (Figure 29). Mean daily discharge had a negative effect on growth increment with an estimated 0.002 µm decrease in growth increment for each 342 m^3/s (1 SD) increase in mean discharge. The effect sizes for daily discharge range, its interaction mean discharge, and fork length all had confidence intervals that overlapped 0, suggesting no significant effect of these variables on growth increment.

Table 22: Estimated R^2 with 95% confidence intervals for selected model of otolith growth increment for sucker species. Fixed effects for environmental variables had a 48 h offset in the model.

Effect	R^2 (estimate)	R^2 (LCL)	R^2 (UCL)
Model	0.276	0.228	0.331
Mean Temperature	0.217	0.168	0.268
Mean Discharge	0.025	0.007	0.052
Fork Length	0.006	0.000	0.022
Discharge Range:Mean Discharge	0.000	0.000	0.008
Discharge Range	0.000	0.000	0.007

Notes: LCL is the lower confidence level and UCL is the upper confidence level. R^2 and semi-partial R^2 for fixed effects were calculated following Jaeger et al. (2017).

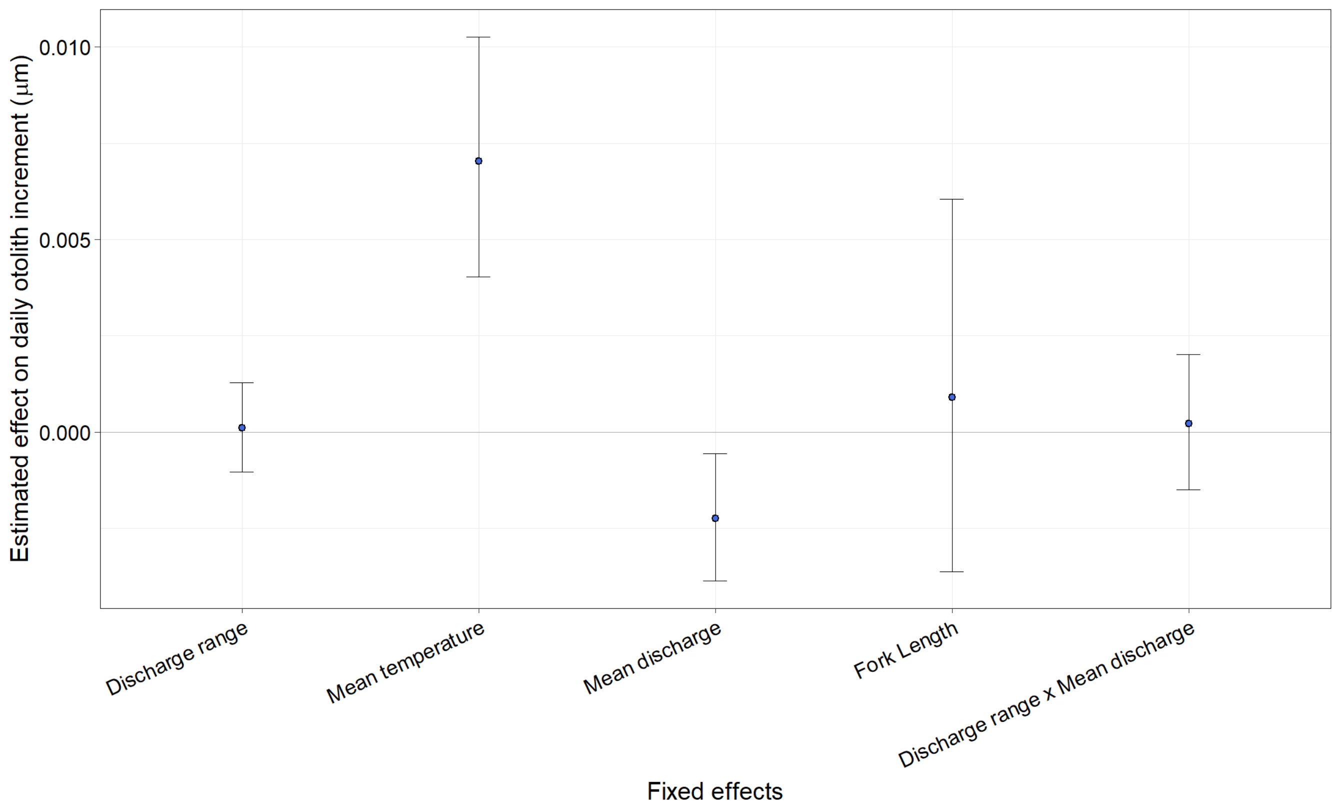


Figure 29: Estimated effect of fixed effect predictor variables on otolith growth increment of sucker species. Values are means with 95% confidence intervals calculated from the estimated coefficients from the linear mixed effect model. As predictor variables were standardized, effect sizes for continuous variables (all variables except year) describe the change in otolith growth with an increase of 1 SD in the value of the respective environmental variable.

Population-level predicted values of growth increment increased from 0.034 µm at 8°C to 0.047 µm at 12°C, when mean discharge,discharge range, and fork length were held at their mean values (Figure 30). Predicted otolith growth increment doubled (from ~0.025 to 0.5 µm) when water temperature increased from 5°C to 13°C (Figure 30). Predicted values of growth increment versus discharge range at three example values of mean discharge illustrate the lack of significant effect of discharge range on growth increment (Figure 31). A decrease in mean discharge from 400 to 1400 m³/s resulted in a decrease in population-level predicted growth increment of 0.041 to 0.034 µm (Figure 32).

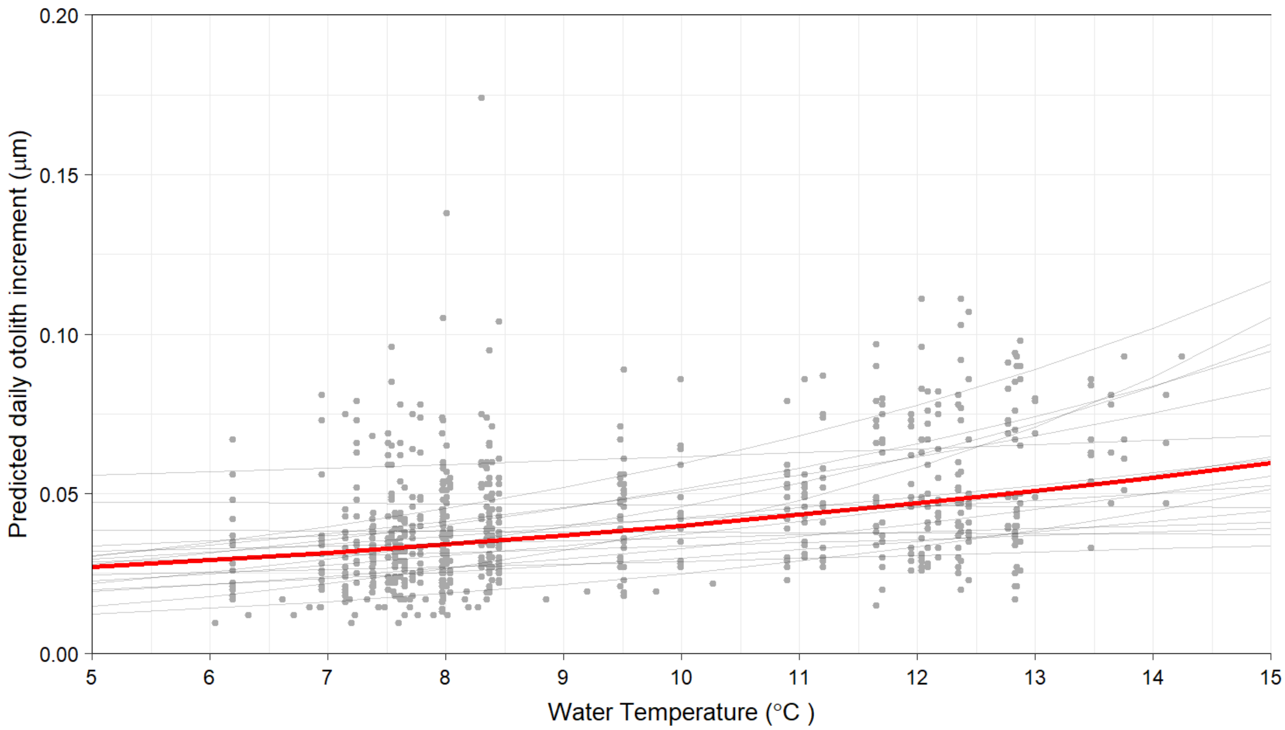


Figure 30: The relationship between daily otolith growth increment and water temperature (offset by 48 h). The red line represents the population-level predicted values (from fixed effects $\beta_{1\text{-}10}$) and the grey lines are fish-specific predicted values (from fixed and random effects $b_{0\text{-}9}$ and $\beta_{1\text{-}10}$), with the other predictor variables held at their mean values. Grey points are raw data.

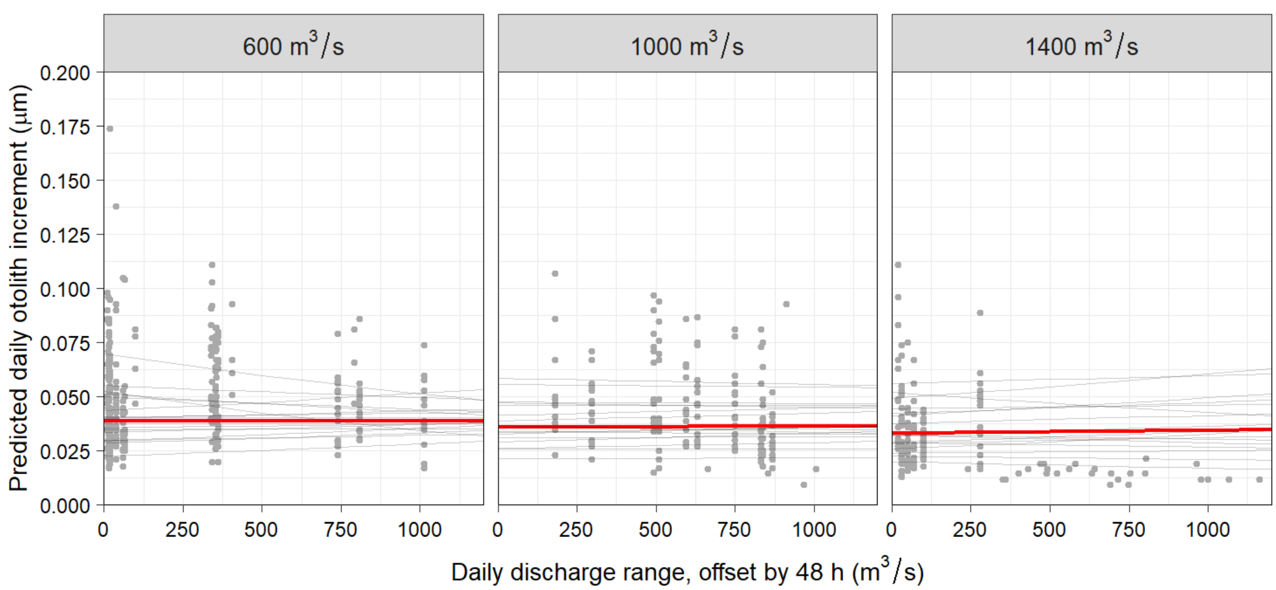


Figure 31: The relationship between daily otolith growth increment and daily discharge range (offset by 48 h), at three example levels of mean discharge. The red line represents the population-level predicted values (from fixed effects $\beta_{1\text{-}10}$) and the grey lines are fish-specific predicted values (from fixed and random effects $b_{0\text{-}9}$ and $\beta_{1\text{-}10}$), with other predictor variables held at their mean values. Grey points are raw data.

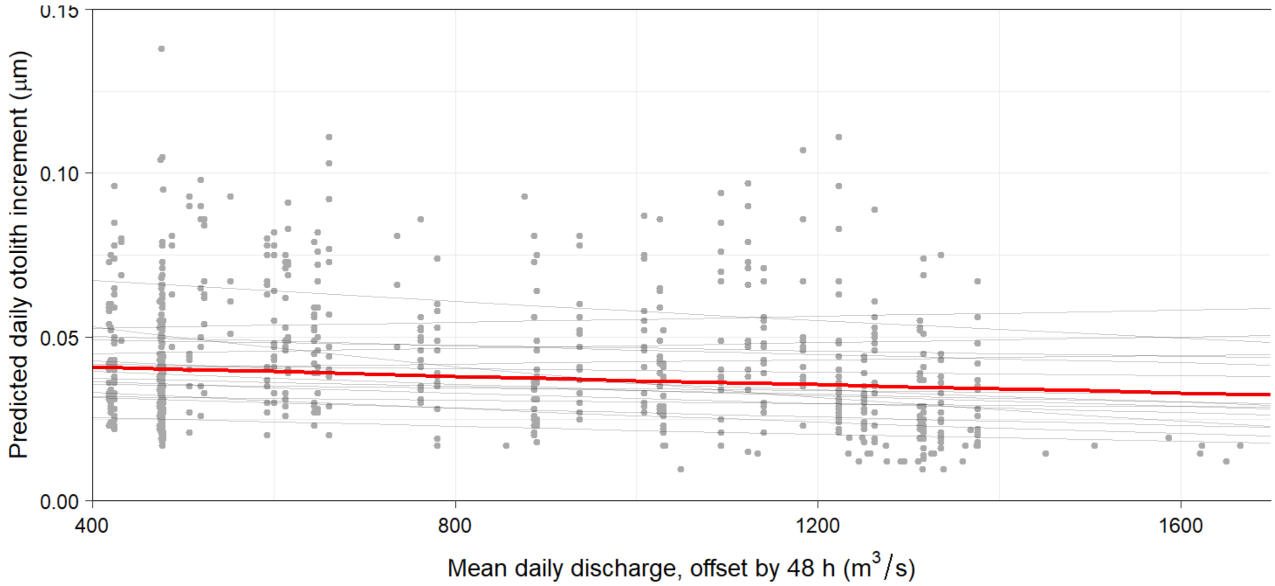


Figure 32: The relationship between daily otolith growth increment and mean daily discharge (offset by 48 h). The red line represents the population-level predicted values (from fixed effects $\beta_{1\text{-}10}$) and the grey lines are fish-specific predicted values (from fixed and random effects $b_{0\text{-}9}$ and $\beta_{1\text{-}10}$), with the other predictor variables held at their mean values. Grey points are raw data.

4.0 DISCUSSION

The main objective of the analysis was to assess the effect of discharge variability in the Peace River on otolith growth increments of juvenile fish. Overall, there was weak evidence that discharge variability had a small effect on growth increment based on the data from 2014, 2016, and 2018. For age-0 Mountain Whitefish, the effect of daily discharge range depended on the year and the mean discharge. In 2018, predicted growth increment decreased with increasing discharge range at low discharge levels (600 m³/s) but increased with discharge variability at high discharge levels (1200 m³/s). As an example of the effect size, the model-predicted growth increment increased from 0.028 μm at a daily discharge range of 100 m³/s to 0.036 μm at a daily discharge range of 1200 m³/s (a 29% increase), when mean discharge was high (1400 m³/s). The same trend of a negative effect of discharge range at low mean discharge and positive effect at high discharge was observed for age-1 Mountain Whitefish, although the effect size was smaller and not statistically significant. In contrast, for age-0 Mountain Whitefish in 2016, there was a negative effect of discharge variability on growth increment during high discharge (1200 m³/s). These opposite effects of discharge variability (negative vs. positive) between years make it difficult to draw conclusions about the overall effect. It may be that other unmeasured factors, such as food availability or competition for food or space, may moderate the influence of discharge variability on growth. Based on the available results, there was a small effect of discharge variability on otolith growth for Mountain Whitefish, but the direction of the effect depended on the mean discharge and differed between years.

Although this program's management hypothesis seeks to identify whether or not fish growth is independent of flow variation, estimates of the effect size and uncertainty in the effect size are necessary to understand the biological significance of flow variation. In this analysis, semi-partial R^2 values suggested a small effect size, with approximately 3% of the variance in growth increment explained by discharge variability and its interaction terms combined (age-0 Mountain Whitefish; Table 4). However, a 29% increase in predicted growth increment over the range of observed discharge ranges (from 100 to 1200 m³/s; Figure 7) suggests a meaningful change in growth. Biological significance would also depend on the relationships between otolith and body growth. The assumption that otolith growth rate is proportional to body growth has not been tested for juvenile Mountain Whitefish and suckers in the Peace River but has been tested for other species in other watersheds (Huuskonen and Karjalainen 1998; Begg et al. 2005).

Juvenile fishes, including Mountain Whitefish and sucker species, prefer low velocity habitats (McPhail 2007). If the effect of discharge variability on growth is negative at low discharge and positive at high discharge, as suggested by the 2018 data for age-0 Mountain Whitefish, then it could be that stable flows are beneficial during low flow when low velocity habitat is abundant. During high flows, less low velocity habitat may be available than during lower flows, and decreases in flows may result in greater availability of low velocity habitat than during stable high flows. Juvenile preference for low velocity habitat is one speculative mechanism for the possible interactive effect of mean and variability in discharge on otolith growth, but additional data would be required to confirm this relationship. A previous study of age-0 Rainbow Trout in the Colorado River found that otolith growth was greater during days with low, stable flows, compared to days with fluctuating flows due to hydropeaking, and that this difference in otolith growth corresponded to a difference in body growth (Korman and Campana 2009).

There was no evidence of an effect of discharge range on growth increments for sucker species. However, otolith growth increment was negatively related to mean daily discharge. The standardized effect size indicated a 0.002 µm decrease in growth increment, compared to the daily mean increment of 0.038 µm, for each 342 m³/s (1 SD) increase in mean daily discharge. This result may also be explained by juvenile preference for low water velocity habitats, which might be more abundant during lower mean discharges.

The models indicated that water temperature is an important predictor of otolith growth rates for both age-classes of Mountain Whitefish and all three species of age-0 sucker. The coefficient of multiple determination (R^2) indicated that water temperature explained more than half of the explained variability in growth increment for age-0 and age-1 Mountain Whitefish, and two thirds of the explained variability for age-0 suckers. Standardized effect sizes suggested that the influence of water temperature was more than twice as large as all the discharge variables combined for age-0 Mountain Whitefish and age-0 suckers. Water temperature is known to be a primary factor influencing growth rates of fishes (Pauly 1979) and is an important covariate to include in future analyses of otolith growth increments. The detection of the effect of flow variability was complicated by the strong effect of temperature on growth and the large range in temperatures during the study period.

As water temperature decreased steadily during the period of interest in both years, water temperature was confounded with the effects of time. Our models included water temperature but did not account for the effects of day of year or the auto-correlation of observations through time. Therefore, part of the explanatory power of water temperature in the analysis could be due to time-related factors and not water temperature. Examples of time-related factors that could influence otolith growth are food availability (Bjornn and Reiser 1991), photoperiod (Boeuf and Le Bail 1999), and fish age (Ashworth et al. 2016). Collecting otolith increment data that correspond to times of year when water temperatures are not steadily decreasing would allow analyses to better separate the effects of time versus water temperature.

The selected time offset between environmental variables and otolith growth increments was greater for sucker species (48 h) than Mountain Whitefish (12 h). This result could be due to real differences between species in the delay between river conditions and their effect on otolith growth, or it could be due to differences in how material is deposited on otoliths as fish grow. Alternatively, the difference could be related to how the otolith samples were processed in the lab. Sucker otoliths were smaller than Mountain Whitefish otoliths and were prepared using a different method. Selecting between different time offsets was necessary to address uncertainties in which date should be associated with the outermost measurement of inter-circuli distances.

The model for age-1 Mountain Whitefish explained less of the variability in otolith growth increments (conditional R^2=0.24) than the model of age-0 Mountain Whitefish (conditional R^2=0.66). This could be partly due to the smaller sample size for age-1 fish (n = 15) than age-0 fish (n = 101). Alternatively, otolith growth of age-1 Mountain Whitefish may be less linked to water temperature and discharge variables and more affected by other factors, compared to age-0 Mountain Whitefish. Both age-classes should be included in future analyses of growth increments. Mountain Whitefish and all three sucker species appear to be suitable indicator species for assessing the effect of discharge variability on otolith growth in juvenile fish.

One assumption of the analysis is that growth rings on the otoliths were deposited daily. This has been validated by other studies for coregonids (Huuskonen and Karjalainen 1998). However, a related potential source of bias is that samples that had areas near the outside of the otolith where growth rings were indistinct or broken were labelled as poor quality by the lab and the data were not used in the statistical analysis. The reason for indistinct circuli in this data set is unknown and could be related to sample processing or a real lack of distinct growth rings. Other studies report increments that become difficult to see or stop being formed daily when larval fish are starved (Eckman and Rey 1987). If areas of indistinct growth rings in samples from the present study were due to slow growth, then excluding these samples from the analysis could be preferentially excluding fish that were the most affected by environmental conditions. Data from these samples cannot be used in the analysis because the areas of indistinct growth rings were measured as large increments (distance between the nearest distinct growth rings), which would be interpreted, likely incorrectly, as a period of rapid growth, if included in the data analysis. Future laboratory analyses should confirm whether poor quality samples are related to sample preparation and imaging, or real differences in growth ring formation. In addition, laboratory analyses should investigate whether greater resolution imaging could allow measurement of smaller or less distinct rings in these areas of the otoliths.

Overall, the results support a measurable but small effect of discharge variability on the otolith growth increment of age-0 and age-1 Mountain Whitefish but the direction of the effect depended on the year and the mean discharge. There was no effect of discharge variability on otolith growth increment of age-0 suckers. These results support a weak effect of discharge variability on otolith growth of juvenile fish but stronger evidence would be required to reject null hypothesis H_4 (Section 1.1), which states that the magnitude of flow fluctuations is independent of the growth of age-0 and age-1 fishes in the study area.

5.0 CLOSURE

We trust that this report meets your current requirements. If you have any further questions, please do not hesitate to contact us.

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