Urosalpinx growth rate (length)

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# The Study

For this part of the study, we measured growth rates of juvenile snails. We measured snails within two days of them hatching, and grew them in tea strainers separated by population for 24 days. Nine replicates per population were distributed in six temperatures, with three groups of three subreplicates in each temperature/population treatment. The end length was recorded, and we substracted the starting length from the beginning length to get the growth rate (over 24 days).

## Metadata

## code

Unique code for each indiviudal snail, corresponding to population, temperature treatment

## pop

Source population of each snail

## temp

Common garden temperature the snails were raised in for 24 hrs. Degrees C

## hatch

hatch date of each snail from it’s egg case

## exp.date

Date on which hatchling snails were placed in the common garden experiment. Not more then 2 days from the hatch date.

## grow.date

End date where growth measurements were taken. 24 days after exp.date, therefore no more then 26 days post hatch

## alive

Tracks if snails survived the experient. m marks missing, n marks no, y marks yes

## rem.oysters

Was there a surplus of food at the end of the experiment? n marks no, y marks yes

## cal.length.start

caliper length of hatchlings upon entering the experment. We took photos of snails before entering snails into the experiment, and then used ImageJ to extract snail sizes. Size in mm

## cal.length.end

caliper length of hatchling at the end of the experiemnt. We took caliper measurements of the snails, as well as verifying the measurements using a subset of photographs in ImageJ. Size in mm

## wt

End weight of snail. Note that no initial starting weight was recorded. Weight in g.

## ran.out

Did the snail ever run out of food during the consumption experiment? 1 for yes, 0 for no

## bin

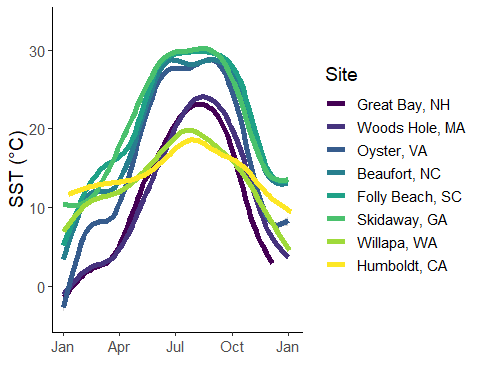
Bin number, controls subreplication

## oce

Ocean

## Environmental Data

## `geom\_smooth()` using method = 'gam' and formula 'y ~ s(x, bs = "cs")'



## site quantile decile max mean summer.mean  
## 1 gbj 22.91100 23.69700 25.96300 12.40097 20.88969  
## 2 wh 23.60000 24.30000 26.00000 12.10044 21.35360  
## 3 oy 28.92496 30.07281 33.56934 17.08424 27.54020  
## 4 bf 29.10000 29.80000 31.00000 19.73769 28.28414  
## 5 fb 29.80000 30.00000 31.30000 20.34944 29.12126  
## 6 nah1516 19.80700 20.43960 26.49120 13.91728 18.73544  
## 7 hmi2 18.77000 19.78000 21.80000 14.43312 17.36318  
## 8 to3 22.14730 22.71100 24.12180 17.90621 20.91789  
## 9 gcsk 30.26200 30.97800 33.47800 21.45739 29.36123

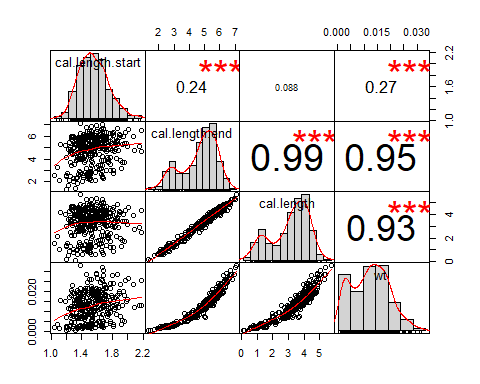
# Data exploration

Do populations differ in their growth rate? Here, ANOVA tells us that growth betwween sites are signficantly different

Should we use end caliper lengths, or do we need to subtract initial caliper length from end caliper length? In other words, do initial caliper lengths differ, requiring us to standardize our growth rate? Here, we find that populations do differ in initial growth. Thus, we must standardize growth by creating a growth rate of Final size - initial size.

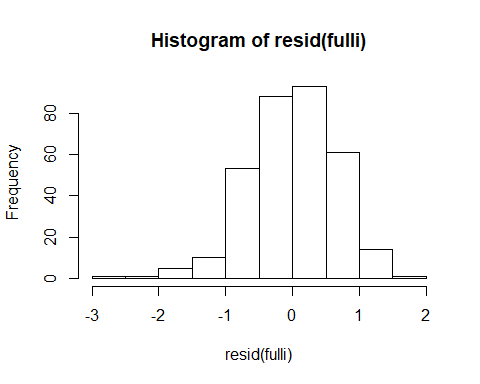
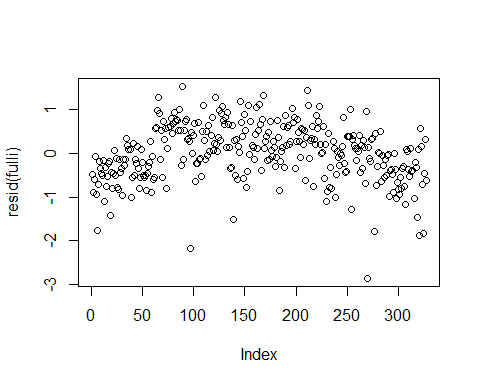
## Df Sum Sq Mean Sq F value Pr(>F)   
## pop 7 1.64 0.23431 6.497 3.57e-07 \*\*\*  
## Residuals 319 11.50 0.03606   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 64 observations deleted due to missingness

## Correlations

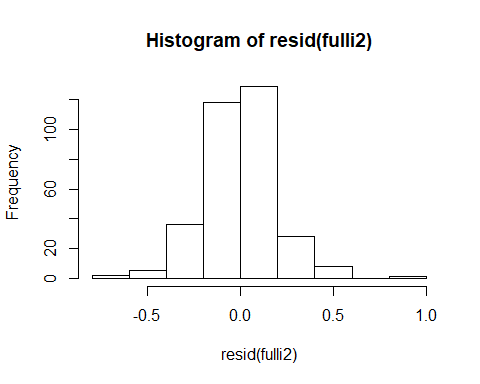
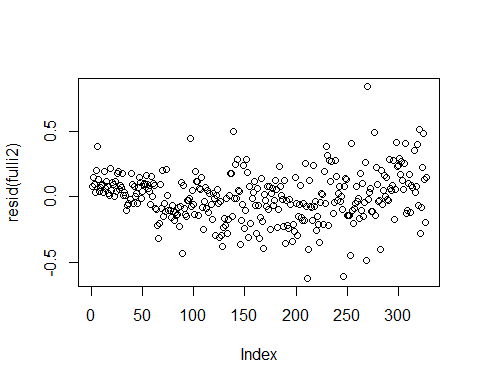
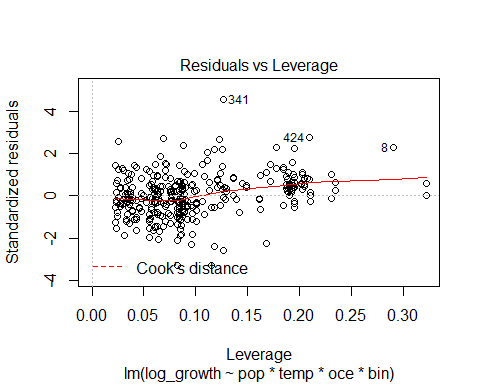
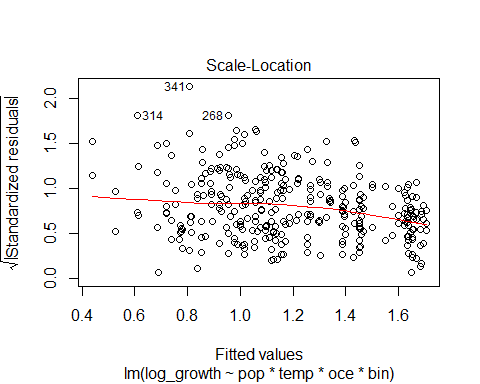
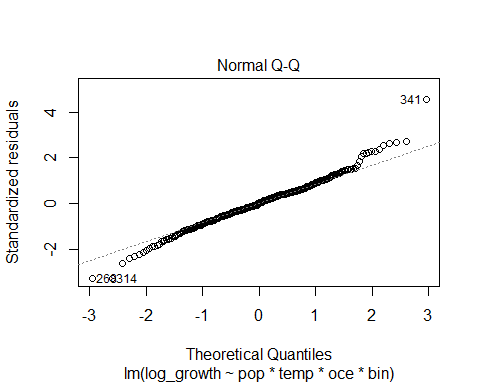
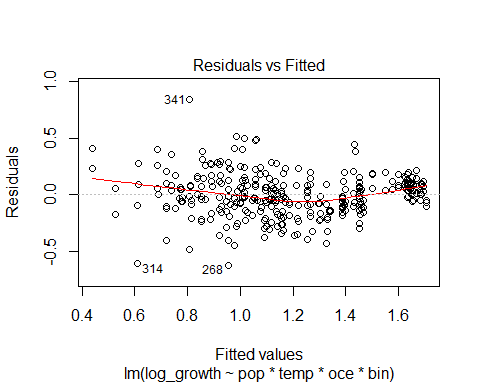
 Here, we see that cal length and weight are both highly correlated. Thus, we will not include weight in any of our models.

## Residuals of full model

Here, we investigate the residuals of the full model.



## [1] -0.627575



## [1] -0.01269512

While the log transformation improves the skewness slightly (silenced but in code), we will assume the distribution of residuals are normal and proceed with untransformed growth rate.

## Coplots

Other than temperature and population, which we control for, do we see different reactions depending on bin? Here, reactions appaer to be the same no matter what bin we used. Note: Margins were too big on this figure to include in the markdown - viewable in R console.

## null device   
## 1

# Data Analysis

## Model predictors

We are going to create TPCs for each population by temperature, using both piecewise (segmented) regression and quadratic regression. What predictors should be used in these models?

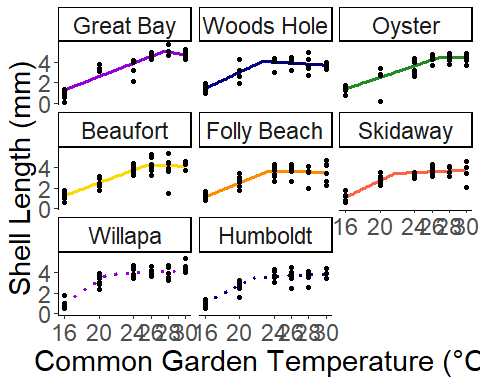
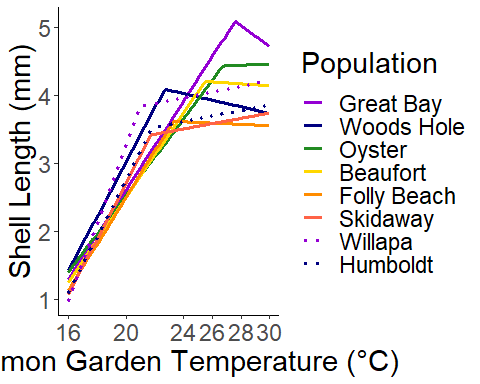
##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## pop.temp.bin 11 690.27 0.00 0.17 0.17 -333.72  
## pop.temp.oce.bin 11 690.27 0.00 0.17 0.34 -333.72  
## pop.temp 10 690.67 0.39 0.14 0.47 -334.98  
## pop.temp.oce 10 690.67 0.39 0.14 0.61 -334.98  
## pop\*temp 17 691.87 1.60 0.08 0.69 -327.94  
## pop\*temp\*oce 17 691.87 1.60 0.08 0.76 -327.94  
## fulla 12 691.96 1.69 0.07 0.83 -333.49  
## pop.temp.out 11 692.48 2.21 0.06 0.89 -334.82  
## pop.temp.oce.out 11 692.48 2.21 0.06 0.94 -334.82  
## pop\*temp\*out 18 693.92 3.65 0.03 0.97 -327.85  
## pop\*temp\*oce\*out 18 693.92 3.65 0.03 1.00 -327.85  
## temp.bin 4 702.99 12.72 0.00 1.00 -347.43  
## temp 3 703.25 12.97 0.00 1.00 -348.59  
## oce 3 703.25 12.97 0.00 1.00 -348.59  
## bin.out.temp 5 704.09 13.81 0.00 1.00 -346.95  
## temp.out 4 704.53 14.26 0.00 1.00 -348.20  
## temp\*out 4 704.53 14.26 0.00 1.00 -348.20  
## oce.temp.bin 5 704.97 14.69 0.00 1.00 -347.39  
## temp\*bin 5 704.98 14.70 0.00 1.00 -347.39  
## temp.oce 4 705.21 14.94 0.00 1.00 -348.54  
## bin\*out\*temp 6 706.03 15.75 0.00 1.00 -346.88  
## temp.oce.bin.out 6 706.09 15.82 0.00 1.00 -346.92  
## oce.temp.out 5 706.53 16.25 0.00 1.00 -348.17  
## temp\*oce 5 706.90 16.63 0.00 1.00 -348.36  
## oce\*temp\*out 6 708.18 17.91 0.00 1.00 -347.96  
## oce\*temp\*bin 9 711.66 21.38 0.00 1.00 -346.54  
## temp\*oce\*bin\*out 10 712.78 22.51 0.00 1.00 -346.04  
## pop\*temp\*bin 33 714.41 24.14 0.00 1.00 -320.38  
## pop\*temp\*oce\*bin 33 714.41 24.14 0.00 1.00 -320.38  
## fulli 34 715.70 25.43 0.00 1.00 -319.78  
## null 2 1074.02 383.75 0.00 1.00 -534.99  
## pop 9 1075.11 384.84 0.00 1.00 -528.27  
## pop.oce 9 1075.11 384.84 0.00 1.00 -528.27  
## pop\*oce 9 1075.11 384.84 0.00 1.00 -528.27  
## bin 3 1075.47 385.20 0.00 1.00 -534.70  
## out 3 1075.69 385.41 0.00 1.00 -534.81  
## pop.out 10 1076.32 386.05 0.00 1.00 -527.81  
## pop\*out 10 1076.32 386.05 0.00 1.00 -527.81  
## pop.bin 10 1076.64 386.37 0.00 1.00 -527.97  
## bin.out 4 1077.21 386.93 0.00 1.00 -534.54  
## bin\*out 4 1077.21 386.93 0.00 1.00 -534.54  
## oce.bin 4 1077.38 387.11 0.00 1.00 -534.63  
## oce.out 4 1077.58 387.30 0.00 1.00 -534.73  
## oce\*out 4 1077.58 387.30 0.00 1.00 -534.73  
## oce\*bin 5 1078.19 387.92 0.00 1.00 -534.00  
## oce.bin.out 5 1079.11 388.84 0.00 1.00 -534.46  
## oce\*bin\*out 6 1079.88 389.61 0.00 1.00 -533.81  
## pop\*bin 17 1087.75 397.48 0.00 1.00 -525.88

Here, we see that a few models are well supported. We choose the interactive pop\*temp model only because 1) the additive model only tells us if populations are different at each temperature, while the additive model also tells us the populations slopes with temperature and gives us a TPC 2) oce adds nothing to the models, so is removed. 3) Looking at our coplots of bin, bin had no effect on growth.

##   
## Call:  
## lm(formula = cal.length ~ pop \* temp, data = growth.alive)  
##   
## Residuals:  
## Min 1Q Median 3Q Max   
## -2.79122 -0.45010 0.04689 0.44438 1.73881   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) -2.164074 0.532857 -4.061 6.18e-05 \*\*\*  
## popFolly Beach 0.799638 0.746989 1.070 0.285   
## popGreat Bay -0.631311 0.764718 -0.826 0.410   
## popHumboldt 0.562630 0.747010 0.753 0.452   
## popOyster 0.012506 0.724360 0.017 0.986   
## popSkidaway 0.500665 0.744551 0.672 0.502   
## popWillapa 0.731032 0.767125 0.953 0.341   
## popWoods Hole 1.229337 0.780359 1.575 0.116   
## temp 0.230618 0.021996 10.485 < 2e-16 \*\*\*  
## popFolly Beach:temp -0.047991 0.031036 -1.546 0.123   
## popGreat Bay:temp 0.039556 0.031818 1.243 0.215   
## popHumboldt:temp -0.032139 0.031132 -1.032 0.303   
## popOyster:temp 0.001835 0.029861 0.061 0.951   
## popSkidaway:temp -0.033517 0.031349 -1.069 0.286   
## popWillapa:temp -0.025905 0.031466 -0.823 0.411   
## popWoods Hole:temp -0.057421 0.031915 -1.799 0.073 .   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.6764 on 311 degrees of freedom  
## Multiple R-squared: 0.7181, Adjusted R-squared: 0.7045   
## F-statistic: 52.83 on 15 and 311 DF, p-value: < 2.2e-16

## Broken Stick regression

It’s hard to compare TPC against one another. One method we’ve settled on is the use of broken stick regression to allow us to quantify the shape of the reaction as well as the thermal optima (x) and the maximal trait performance (y). Here, we used the segmented package to create single-optima broken stick regressions that also allow us to extract optimas



Here, I show the segmented model fits both on a single plot and facetted to show spread of points. Just by eyeballing the results, we see that more or less the northern sites have optima above those of southern sites. We will test for this later. First, how confident are we in these breakpoints? The tests below tell us.

\*P-score: The P-score tests the null hypothesis for no difference in slopes, i.e. no breakpoint. If P is below 0.05, then there is a breakpoint. We see here that all p-scores are signficant, and thus breakpoints do exist in our data

* Davies test: we perform this analysis, but is less powerful for one breakpoint analyses. I am not certain what this means, since the null hypothesis is no breakpoint but we get radically different results this way.
* CI Low/High: Confidence interval of the breakpoint
* Breakpoint: Breakpoint

## site P.Score Davies.Test CI.Low CI.High breakpoint  
## 1 Great Bay 2.951616e-04 0.001510929 25.7432 29.4466 27.5949  
## 2 Woods Hole 1.257784e-05 0.625251077 19.9106 25.4776 22.6941  
## 3 Oyster 2.331936e-02 1.000000000 23.7594 29.8018 26.7806  
## 4 Beaufort 2.276825e-03 0.727819087 23.2719 27.7343 25.5031  
## 5 Folly Beach 3.799425e-05 0.951598239 20.4716 26.0997 23.2857  
## 6 Skidaway 3.514040e-06 0.394912823 19.5362 23.9608 21.7485  
## 7 Willapa 1.190165e-09 0.189487692 19.7224 22.3354 21.0289  
## 8 Humboldt 1.691167e-06 0.500721217 20.0028 23.7666 21.8847

## Breakpoint analysis

To be able to complete statistical analysis of the differences in TPC curves, I extracted the x and y componenets of each curve to give me the thermal optima and maximal trait performance, respectively.

### Breakpoint Y

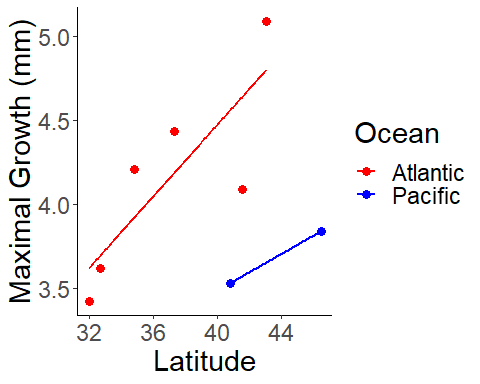
##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## null 2 18.59 0.00 0.89 0.89 -6.09  
## lat 4 23.46 4.88 0.08 0.97 -1.07  
## q.mean 4 27.51 8.92 0.01 0.98 -3.09  
## s.mean 4 27.66 9.08 0.01 0.99 -3.16  
## t.mean 4 28.08 9.49 0.01 1.00 -3.37  
## max 4 30.54 11.95 0.00 1.00 -4.60  
## mean 4 31.77 13.19 0.00 1.00 -5.22  
## \*lat 5 41.62 23.04 0.00 1.00 -0.81  
## \*q.mean 5 45.39 26.80 0.00 1.00 -2.69  
## \*s.mean 5 45.50 26.92 0.00 1.00 -2.75  
## \*t.mean 5 46.18 27.59 0.00 1.00 -3.09  
## \*max 5 47.78 29.19 0.00 1.00 -3.89  
## \*mean 5 50.24 31.65 0.00 1.00 -5.12

One issue here (and actually in literally every one of these analyses I do) is that the null model does a better job then any of the other predictors! I’ve been assuming latitude as the best fit here.

##Maximal trait performance (y)  
  
brkptym<-(lm(brkpty~lat+oce,brkpts))  
summary(brkptym)

##   
## Call:  
## lm(formula = brkpty ~ lat + oce, data = brkpts)  
##   
## Residuals:  
## 1 2 3 4 5 6 7 8   
## -0.1278 0.1278 0.3297 -0.5190 0.2527 0.2699 -0.1014 -0.2318   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.46862 1.17262 0.400 0.7059   
## lat 0.09964 0.03154 3.159 0.0251 \*  
## ocep -1.13467 0.35661 -3.182 0.0245 \*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.3497 on 5 degrees of freedom  
## Multiple R-squared: 0.7155, Adjusted R-squared: 0.6016   
## F-statistic: 6.286 on 2 and 5 DF, p-value: 0.04319

ggplot(brkpts,aes(x=lat,y=brkpty,color=oce,fill=oce),group=oce)+  
 geom\_point(size=3)+theme\_classic()+  
 ylab("Maximal Growth (mm)")+  
 xlab("Latitude")+  
 theme(text=element\_text(family="arial",size=22))+  
 scale\_color\_manual(labels=c("Atlantic","Pacific"),name="Ocean", values=c('red','blue'))+  
 scale\_fill\_manual(labels=c("Atlantic","Pacific"),name="Ocean", values=c('red','blue'))+  
 geom\_smooth(method='lm',se=F)



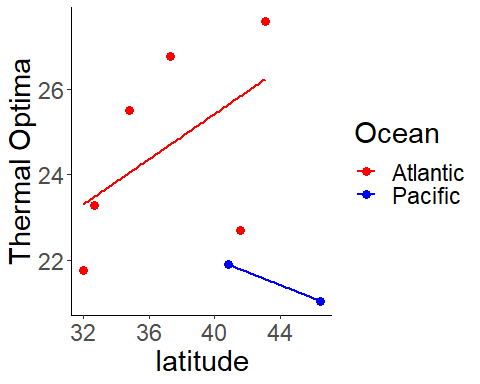
Here, I see that both latitude and ocean significantly describe the trend in maximal trait performance. This means possible countergradient variation! The one weird point in the Atlantic is Woods Hole. Anecdotally, I could attribute this to the very hot local conditions in the estuary, but can’t say for sure.

But what about the thermal optima?

### Breakpoint X

##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## null 2 42.60 0.00 0.97 0.97 -18.10  
## lat 4 52.48 9.88 0.01 0.98 -15.57  
## q.mean 4 53.23 10.63 0.00 0.98 -15.95  
## s.mean 4 53.27 10.67 0.00 0.99 -15.97  
## t.mean 4 53.48 10.89 0.00 0.99 -16.08  
## max 4 53.81 11.21 0.00 1.00 -16.24  
## mean 4 53.88 11.28 0.00 1.00 -16.27  
## \*lat 5 70.26 27.66 0.00 1.00 -15.13  
## \*q.mean 5 71.83 29.24 0.00 1.00 -15.92  
## \*s.mean 5 71.88 29.28 0.00 1.00 -15.94  
## \*t.mean 5 72.07 29.47 0.00 1.00 -16.04  
## \*mean 5 72.45 29.85 0.00 1.00 -16.22  
## \*max 5 72.47 29.87 0.00 1.00 -16.23

##   
## Call:  
## lm(formula = brkptx ~ lat + oce, data = brkpts)  
##   
## Residuals:  
## 1 2 3 4 5 6 7 8   
## -1.0211 1.0211 1.6945 -2.8887 2.0980 1.3390 -0.4253 -1.8175   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 16.8545 7.1891 2.344 0.0660 .  
## lat 0.2099 0.1934 1.086 0.3272   
## ocep -4.5665 2.1863 -2.089 0.0911 .  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 2.144 on 5 degrees of freedom  
## Multiple R-squared: 0.4684, Adjusted R-squared: 0.2557   
## F-statistic: 2.203 on 2 and 5 DF, p-value: 0.2061

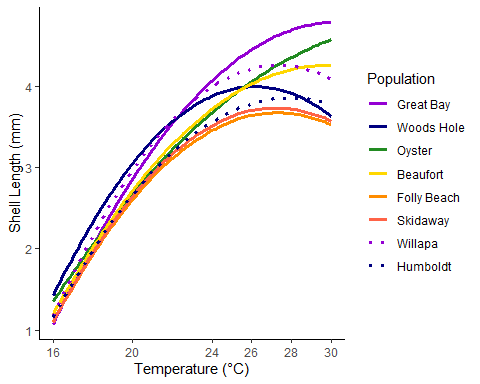
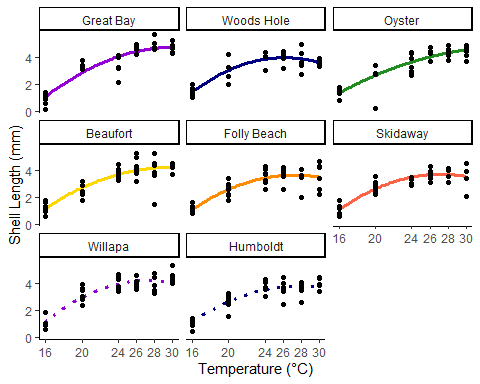
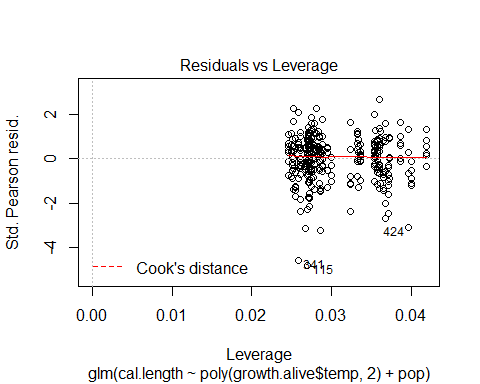
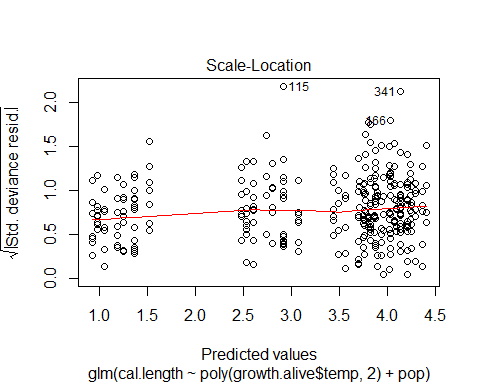
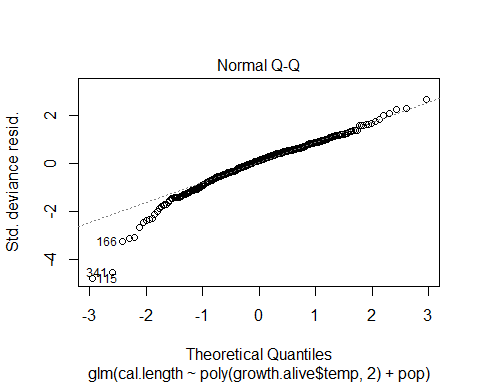
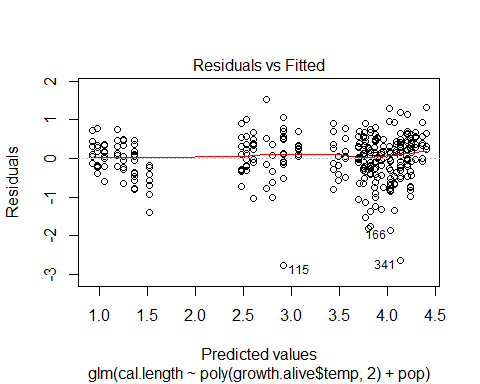
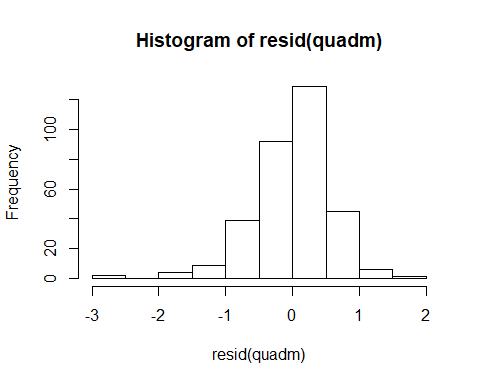


Once again, null model is best! Once again, I go with lat as the best predictor. In this case, however, we see that thermal optima does not trend signficantly upward with latitude. I can attribute this insignicance mostly to the presence of the Woods Hole population. If we remove this, the trend becomes signficant.

##   
## Call:  
## lm(formula = brkptx ~ lat + oce, data = brkpts\_wh)  
##   
## Residuals:  
## 1 2 3 4 5 6 7   
## -1.49490 1.49490 -0.07772 1.29845 0.95346 -0.44890 -1.72529   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 11.4018 5.8987 1.933 0.1254   
## lat 0.3776 0.1628 2.319 0.0812 .  
## ocep -6.4369 1.8354 -3.507 0.0247 \*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.601 on 4 degrees of freedom  
## Multiple R-squared: 0.7548, Adjusted R-squared: 0.6322   
## F-statistic: 6.155 on 2 and 4 DF, p-value: 0.06014

## Quadratic

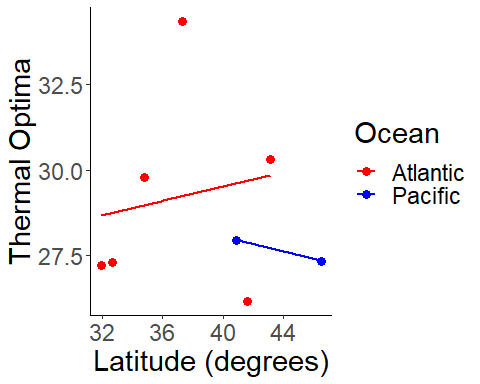
One reason we are checking quadratic is that sometimes the optima isn’t the optima! If you closely examine the segmented regressions, you see that in some cases the second segment’s slope does not appear to be negative. Instead, it plateaus. This raises the question whether we can really define our breakpoint as optima. Potentially, we could interpret the breakpoints as the lowest temperature of maximum growth. At any rate, one idea is to redo all the analysis we just did for segmented regression but with a quadratic model, and seeing if we get a similar result in both the stacking but also the trends of the maximal growth and optima as we did with the segmented regression.

 Here, we see more or less similar patterns of cold pops stacked on warm pops. How do the breakpoints stack up?

### X Breakpoint, Quadratic

##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## null 2 43.53 0.00 0.99 0.99 -18.56  
## mean 4 54.99 11.46 0.00 1.00 -16.83  
## max 4 57.19 13.66 0.00 1.00 -17.93  
## t.mean 4 57.62 14.09 0.00 1.00 -18.14  
## lat 4 57.72 14.19 0.00 1.00 -18.19  
## q.mean 4 57.77 14.25 0.00 1.00 -18.22  
## s.mean 4 57.80 14.27 0.00 1.00 -18.23  
## \*mean 5 73.63 30.10 0.00 1.00 -16.81  
## \*max 5 75.53 32.00 0.00 1.00 -17.77  
## \*t.mean 5 76.24 32.71 0.00 1.00 -18.12  
## \*lat 5 76.27 32.74 0.00 1.00 -18.14  
## \*q.mean 5 76.40 32.87 0.00 1.00 -18.20  
## \*s.mean 5 76.42 32.89 0.00 1.00 -18.21

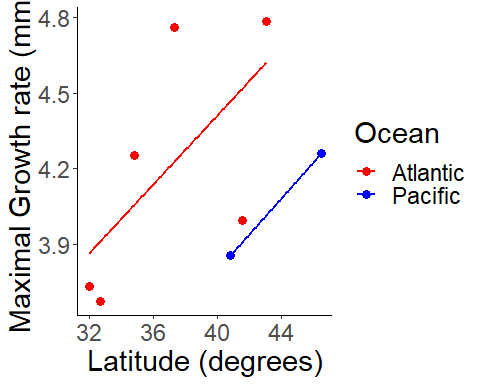
##   
## Call:  
## glm(formula = brkptyq ~ lat + oce, family = "gaussian", data = brkpts)  
##   
## Deviance Residuals:   
## 1 2 3 4 5 6 7 8   
## -0.5247 0.5247 0.6445 -3.3878 5.1318 0.7462 -1.5570 -1.5777   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 26.32998 9.97578 2.639 0.046 \*  
## lat 0.07751 0.26833 0.289 0.784   
## ocep -2.06669 3.03382 -0.681 0.526   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for gaussian family taken to be 8.849778)  
##   
## Null deviance: 48.552 on 7 degrees of freedom  
## Residual deviance: 44.249 on 5 degrees of freedom  
## AIC: 44.386  
##   
## Number of Fisher Scoring iterations: 2

 This is not signficant in the slightest. part of the issue is that the quadratic optima for Oyster site is near 34C. Very unlikely! This is likely due to the very small breakpoint change in Oyster that is interpreted by the quadratic as a single slope. Basically, nothing predicts it well

### Y Breakpoint, Quadratic

##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## null 2 14.65 0.00 0.99 0.99 -4.13  
## lat 4 24.57 9.92 0.01 1.00 -1.62  
## s.mean 4 28.00 13.34 0.00 1.00 -3.33  
## q.mean 4 28.04 13.39 0.00 1.00 -3.35  
## t.mean 4 28.40 13.75 0.00 1.00 -3.53  
## mean 4 29.39 14.74 0.00 1.00 -4.03  
## \*lat 5 43.24 28.59 0.00 1.00 -1.62  
## \*s.mean 5 45.77 31.12 0.00 1.00 -2.88  
## \*q.mean 5 45.85 31.20 0.00 1.00 -2.93  
## \*t.mean 5 46.36 31.71 0.00 1.00 -3.18  
## \*mean 5 47.53 32.88 0.00 1.00 -3.76

##   
## Call:  
## glm(formula = brkptxq ~ lat + oce, family = "gaussian", data = brkpts)  
##   
## Deviance Residuals:   
## 1 2 3 4 5 6 7   
## 0.00715 -0.00715 0.16109 -0.52831 0.53457 0.19771 -0.23558   
## 8   
## -0.12948   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 1.66151 1.25676 1.322 0.2434   
## lat 0.06877 0.03380 2.034 0.0976 .  
## ocep -0.60808 0.38220 -1.591 0.1725   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## (Dispersion parameter for gaussian family taken to be 0.1404571)  
##   
## Null deviance: 1.31387 on 7 degrees of freedom  
## Residual deviance: 0.70229 on 5 degrees of freedom  
## AIC: 11.24  
##   
## Number of Fisher Scoring iterations: 2



Here, we see that the maxima growth rate pattern is more or less preserved. While we don’t trust the quadratic estimates for the optima, I do trust that there is a pattern of increasing growth rate with higher latitude. This is evidence for countergradient variation in growth. We can confirm this by looking further at growth in weight as well as in consumption rate.