TPC Weight

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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 beginning weight of the snails was not recorded, rather, we only have end weight of snails. Therefore, any results of weight analysis should be taken with a grain of salt, since we did not standardize growth rate in weight like we did in length.

## 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

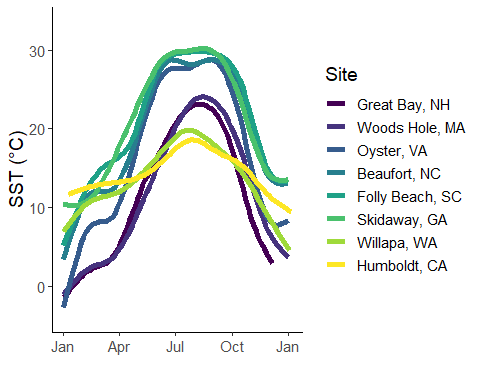
Bin number, controls subreplication

### oce

Ocean

## Environmental Data

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



## site quantile decile max mean summer.mean seasonlength10  
## 1 gbj 22.91100 23.69700 25.96300 12.40097 20.88969 179  
## 2 wh 23.60000 24.30000 26.00000 12.10044 21.35360 197  
## 3 oy 28.92496 30.07281 33.56934 17.08424 27.54020 250  
## 4 bf 29.10000 29.80000 31.00000 19.73769 28.28414 330  
## 5 fb 29.80000 30.00000 31.30000 20.34944 29.12126 310  
## 6 nah1516 19.80700 20.43960 26.49120 13.91728 18.73544 285  
## 7 hmi2 18.77000 19.78000 21.80000 14.43312 17.36318 348  
## 8 to3 22.14730 22.71100 24.12180 17.90621 20.91789 366  
## 9 gcsk 30.26200 30.97800 33.47800 21.45739 29.36123 348  
## seasonlength16  
## 1 137  
## 2 132  
## 3 186  
## 4 224  
## 5 214  
## 6 123  
## 7 113  
## 8 224  
## 9 237

# Data Exploration

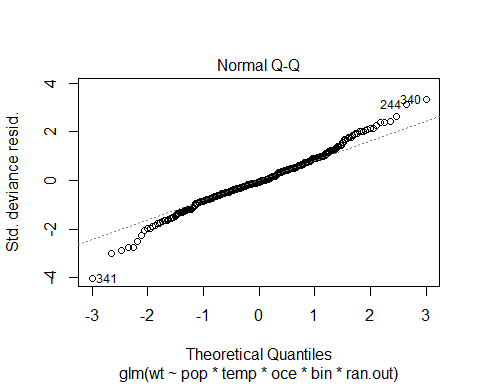
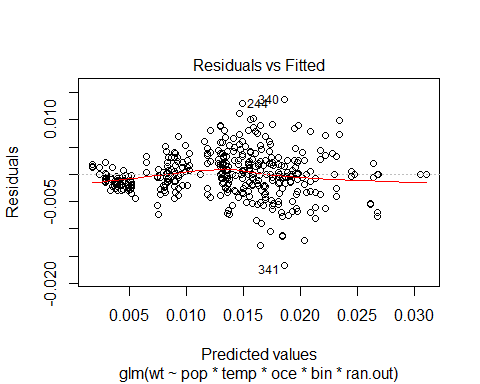
Do populations differ in their weight? Here, ANOVA tells us that growth between sites are signficantly different

## Df Sum Sq Mean Sq F value Pr(>F)   
## pop 7 0.000883 0.000126 6.258 5.95e-07 \*\*\*  
## temp 1 0.011506 0.011506 570.695 < 2e-16 \*\*\*  
## pop:temp 7 0.000588 0.000084 4.164 0.000198 \*\*\*  
## Residuals 373 0.007520 0.000020   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

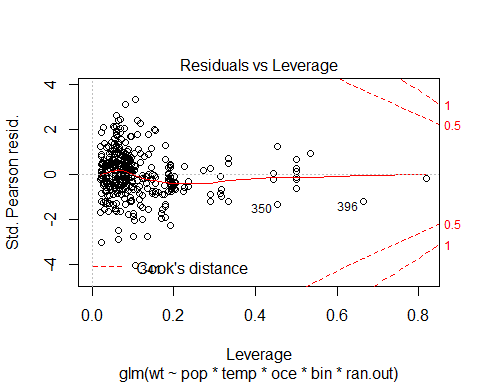
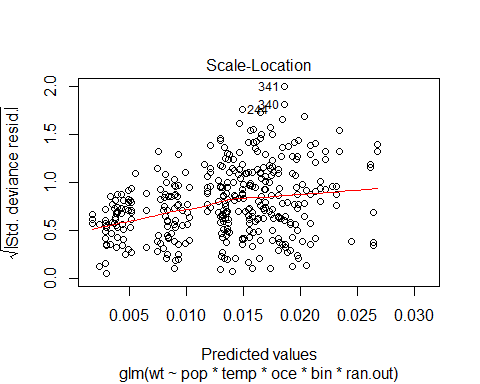
How do the residuals of a full model look? Here, they look acceptable.

weight.model<-glm(wt~pop\*temp\*oce\*bin\*ran.out,growth.alive,family=gaussian)  
plot(weight.model)

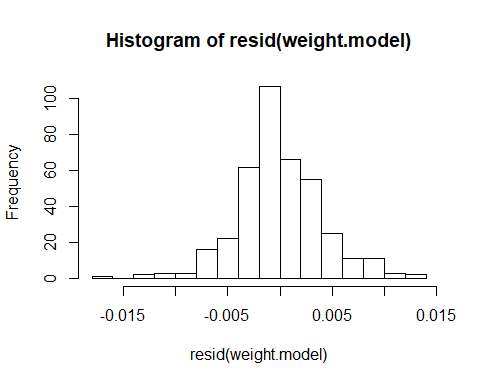
## Warning: not plotting observations with leverage one:  
## 173, 183, 202, 253, 255, 263, 278, 294, 301, 320, 323, 339, 365



## Warning: not plotting observations with leverage one:  
## 173, 183, 202, 253, 255, 263, 278, 294, 301, 320, 323, 339, 365



hist(resid(weight.model),breaks=20)

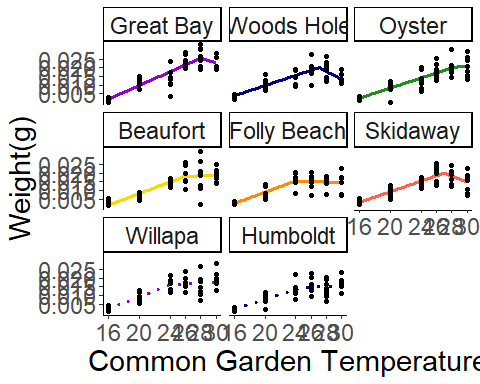
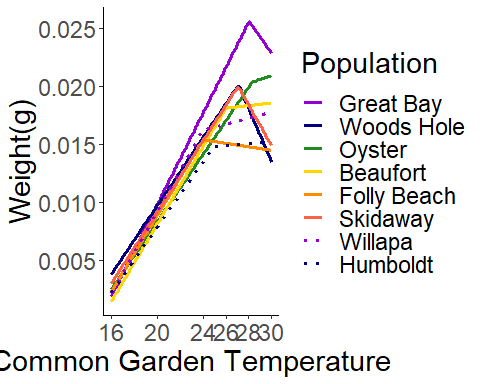
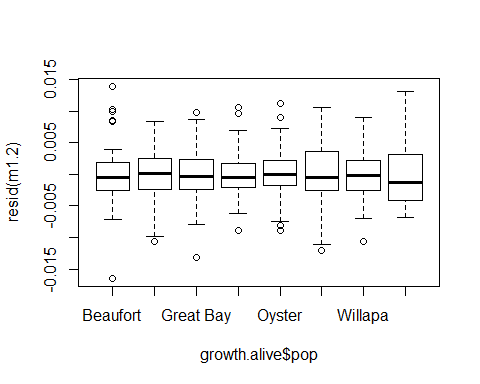
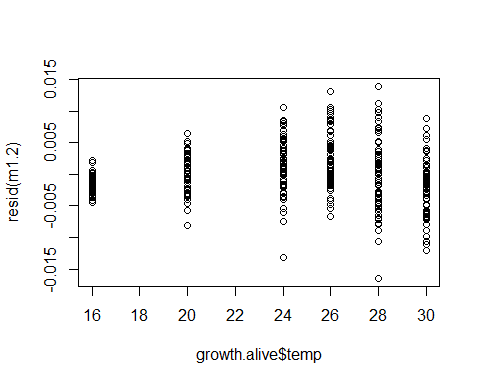
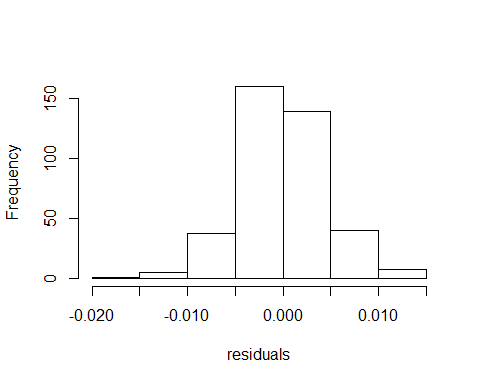


skewness(growth.alive$wt)

## [1] 0.08854404

# Data Analysis

# Breakpoints



Here, we see that the stacking of regressions is not as clear as with length. To see if countergradient variation in still present, we will have to extract breakpoints. First off, how confident are we in our breakpoints?

\*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 not all P-scores are signficant, and therefore we fail to reject the null hypothesis of no change in slope, ie there are no breakpoints

* 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 1.212994e-01 0.2782025 26.6197 29.4530 28.0363  
## 2 Woods Hole 2.167105e-06 0.7936294 25.8551 28.3548 27.1049  
## 3 Oyster 6.479146e-01 0.8215133 24.6512 31.9579 28.3046  
## 4 Beaufort 1.614579e-01 0.2558146 21.0343 30.9658 26.0000  
## 5 Folly Beach 3.051073e-04 0.7489087 20.4235 27.5765 24.0000  
## 6 Skidaway 8.243071e-06 1.0000000 25.6997 28.4468 27.0733  
## 7 Willapa 8.076880e-03 0.1663346 19.2443 28.7548 23.9995  
## 8 Humboldt 1.992216e-02 0.3704263 21.6338 28.2750 24.9544

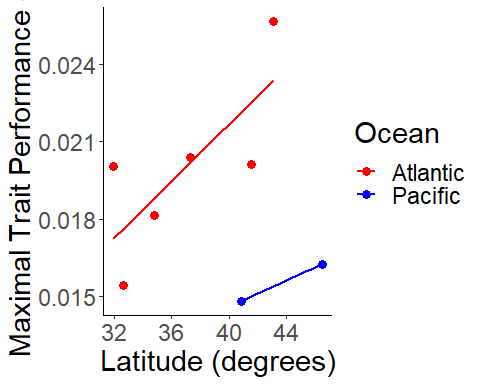
Through these tests, my trust in the accuracy of the breakpoints on the x axis is low. I will remember this as I go through breakpoint analysis

## Breakpoints analysis

### Breakpoint Y

##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## seasonlength10 3 -62.70 0.00 0.41 0.41 37.35  
## nullo 2 -62.32 0.38 0.34 0.74 34.36  
## mean 3 -57.45 5.25 0.03 0.77 34.73  
## lato 4 -57.25 5.45 0.03 0.80 39.29  
## t.mean 3 -56.91 5.79 0.02 0.82 34.45  
## lat 3 -56.87 5.82 0.02 0.84 34.44  
## omax 3 -56.86 5.84 0.02 0.87 34.43  
## q.mean 3 -56.86 5.84 0.02 0.89 34.43  
## s.mean 3 -56.74 5.95 0.02 0.91 34.37  
## seasonlength16 3 -56.72 5.98 0.02 0.93 34.36  
## s.meano 4 -55.96 6.74 0.01 0.94 38.65  
## seasonlengtho10 4 -55.93 6.77 0.01 0.96 38.63  
## q.meano 4 -55.87 6.83 0.01 0.97 38.60  
## meano 4 -55.66 7.04 0.01 0.98 38.50  
## t.meano 4 -55.11 7.59 0.01 0.99 38.22  
## seasonlengtho16 4 -54.55 8.15 0.01 1.00 37.94  
## maxo 4 -52.17 10.53 0.00 1.00 36.75  
## o\*lat 5 -38.98 23.72 0.00 1.00 39.49  
## o\*s.mean 5 -38.02 24.68 0.00 1.00 39.01  
## o\*q.mean 5 -37.86 24.84 0.00 1.00 38.93  
## o\*seasonlength10 5 -37.31 25.38 0.00 1.00 38.66  
## o\*mean 5 -37.16 25.54 0.00 1.00 38.58  
## o\*t.mean 5 -36.89 25.81 0.00 1.00 38.44  
## seasonlength16 5 -36.30 26.40 0.00 1.00 38.15  
## o\*max 5 -34.58 28.12 0.00 1.00 37.29

##   
## Call:  
## lm(formula = brkpty ~ lat + oce, data = brkpts)  
##   
## Residuals:  
## 1 2 3 4 5 6   
## -0.0007310 0.0007310 0.0025255 -0.0022249 0.0002249 -0.0007489   
## 7 8   
## -0.0023740 0.0025975   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 0.0010533 0.0075569 0.139 0.8946   
## lat 0.0005126 0.0002033 2.522 0.0530 .  
## ocep -0.0079022 0.0022982 -3.438 0.0185 \*  
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 0.002254 on 5 degrees of freedom  
## Multiple R-squared: 0.7086, Adjusted R-squared: 0.592   
## F-statistic: 6.078 on 2 and 5 DF, p-value: 0.04586

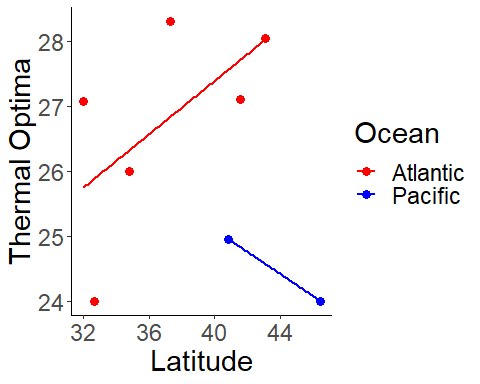


Once again the null model wins out, but when we go with the next best supported model (latitude) we get a well supported, signficant relationship of increasing growth with increasing latitude.

### Breakpoint X

##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## nullo 2 36.69 0.00 0.54 0.54 -15.15  
## seasonlength10 3 39.44 2.75 0.14 0.68 -13.72  
## t.mean 3 41.45 4.75 0.05 0.73 -14.72  
## omax 3 41.64 4.95 0.05 0.77 -14.82  
## q.mean 3 41.65 4.96 0.05 0.82 -14.83  
## s.mean 3 41.98 5.29 0.04 0.85 -14.99  
## mean 3 42.10 5.41 0.04 0.89 -15.05  
## seasonlength16 3 42.20 5.51 0.03 0.92 -15.10  
## lat 3 42.26 5.57 0.03 0.96 -15.13  
## meano 4 45.31 8.62 0.01 0.96 -11.99  
## s.meano 4 45.57 8.88 0.01 0.97 -12.12  
## seasonlengtho16 4 45.69 9.00 0.01 0.98 -12.18  
## lato 4 45.74 9.05 0.01 0.98 -12.20  
## seasonlengtho10 4 45.93 9.24 0.01 0.99 -12.30  
## q.meano 4 45.93 9.24 0.01 0.99 -12.30  
## t.meano 4 46.62 9.93 0.00 1.00 -12.64  
## maxo 4 47.47 10.78 0.00 1.00 -13.07  
## o\*lat 5 62.66 25.97 0.00 1.00 -11.33  
## o\*seasonlength10 5 63.44 26.75 0.00 1.00 -11.72  
## o\*mean 5 63.49 26.80 0.00 1.00 -11.74  
## o\*s.mean 5 64.05 27.35 0.00 1.00 -12.02  
## seasonlength16 5 64.10 27.41 0.00 1.00 -12.05  
## o\*q.mean 5 64.39 27.70 0.00 1.00 -12.20  
## o\*t.mean 5 65.03 28.34 0.00 1.00 -12.52  
## o\*max 5 66.03 29.34 0.00 1.00 -13.01

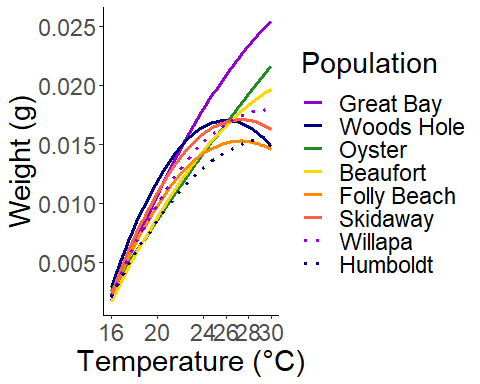
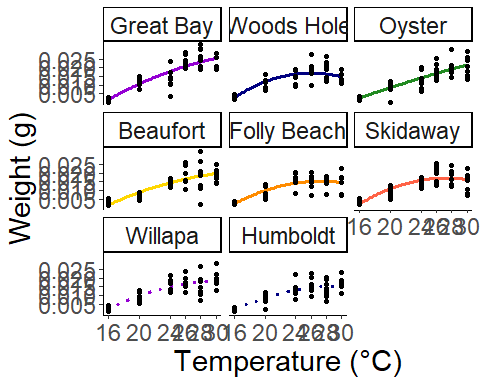
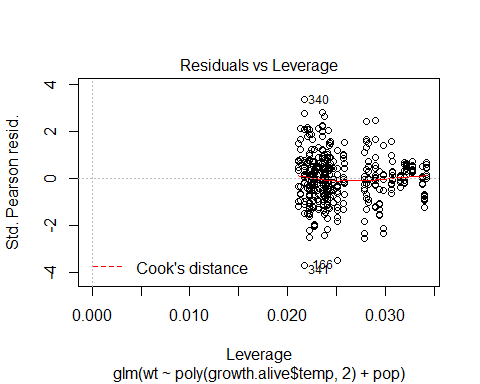
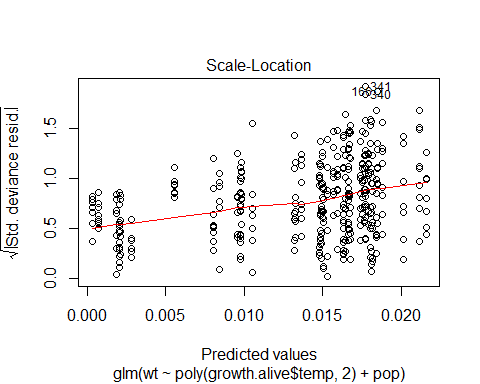
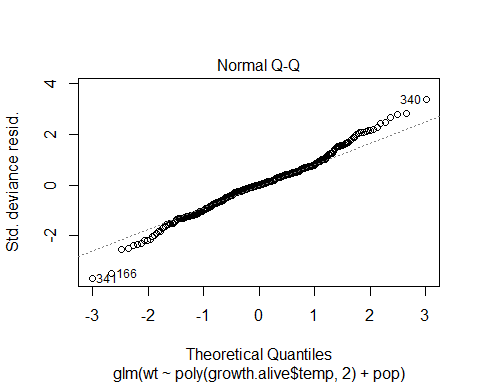
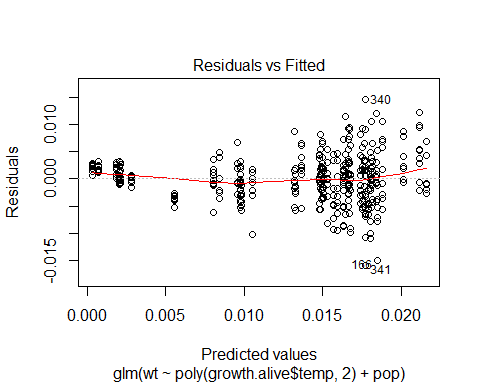
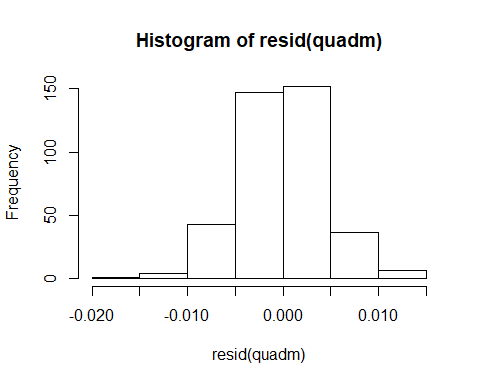
##   
## Call:  
## lm(formula = brkptx ~ lat + oce, data = brkpts)  
##   
## Residuals:  
## 1 2 3 4 5 6 7 8   
## -0.9177 0.9177 0.3188 -0.3769 1.4909 -0.4288 -2.0924 1.0884   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)   
## (Intercept) 21.0030 4.7181 4.452 0.00669 \*\*  
## lat 0.1558 0.1269 1.228 0.27413   
## ocep -3.3318 1.4349 -2.322 0.06788 .   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
##   
## Residual standard error: 1.407 on 5 degrees of freedom  
## Multiple R-squared: 0.5208, Adjusted R-squared: 0.3291   
## F-statistic: 2.717 on 2 and 5 DF, p-value: 0.159



X optima results are not signficant, although we still see a pattern of general increase with habitat temperature. This is more or less the result we found from x optima of length.

## 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 weight 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 weight and optima as we did with the segmented regression.

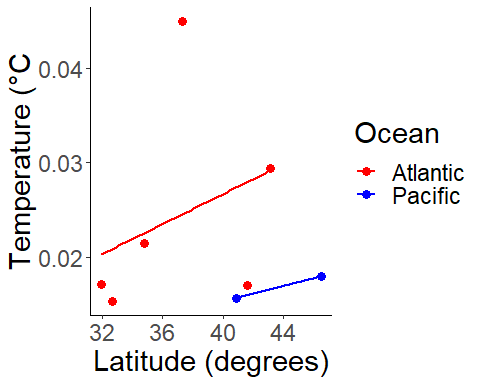


Here, we see that our regressions are more or less stacked with cold populations on top. This is indicative of countergradient variation.

## X Breakpoint, Quadratic

##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## nullo 2 -45.25 0.00 0.59 0.59 25.82  
## seasonlength10 3 -41.29 3.96 0.08 0.68 26.65  
## omax 3 -40.91 4.34 0.07 0.74 26.45  
## t.mean 3 -40.32 4.93 0.05 0.80 26.16  
## q.mean 3 -40.13 5.12 0.05 0.84 26.07  
## s.mean 3 -39.98 5.27 0.04 0.88 25.99  
## mean 3 -39.71 5.54 0.04 0.92 25.85  
## seasonlength16 3 -39.68 5.57 0.04 0.96 25.84  
## lat 3 -39.66 5.58 0.04 0.99 25.83  
## seasonlengtho10 4 -32.38 12.87 0.00 1.00 26.86  
## lato 4 -32.16 13.09 0.00 1.00 26.75  
## meano 4 -31.76 13.49 0.00 1.00 26.55  
## maxo 4 -31.69 13.56 0.00 1.00 26.51  
## seasonlengtho16 4 -31.68 13.57 0.00 1.00 26.51  
## s.meano 4 -31.32 13.93 0.00 1.00 26.33  
## q.meano 4 -31.29 13.96 0.00 1.00 26.31  
## t.meano 4 -31.28 13.97 0.00 1.00 26.31  
## o\*seasonlength10 5 -13.72 31.53 0.00 1.00 26.86  
## o\*lat 5 -13.52 31.73 0.00 1.00 26.76  
## o\*mean 5 -13.12 32.13 0.00 1.00 26.56  
## seasonlength16 5 -13.07 32.18 0.00 1.00 26.53  
## o\*max 5 -13.03 32.22 0.00 1.00 26.51  
## o\*s.mean 5 -12.70 32.55 0.00 1.00 26.35  
## o\*q.mean 5 -12.67 32.58 0.00 1.00 26.33  
## o\*t.mean 5 -12.64 32.61 0.00 1.00 26.32

##   
## Call:  
## glm(formula = brkptyq ~ lat + oce, family = "gaussian", data = brkpts)  
##   
## Deviance Residuals:   
## 1 2 3 4 5 6   
## -0.0009565 0.0009565 0.0005695 -0.0106849 0.0205292 -0.0012252   
## 7 8   
## -0.0057551 -0.0034335   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## (Intercept) -0.0033550 0.0362468 -0.093 0.930  
## lat 0.0007473 0.0009750 0.767 0.478  
## ocep -0.0124964 0.0110233 -1.134 0.308  
##   
## (Dispersion parameter for gaussian family taken to be 0.0001168364)  
##   
## Null deviance: 0.00073572 on 7 degrees of freedom  
## Residual deviance: 0.00058418 on 5 degrees of freedom  
## AIC: -45.495  
##   
## Number of Fisher Scoring iterations: 2

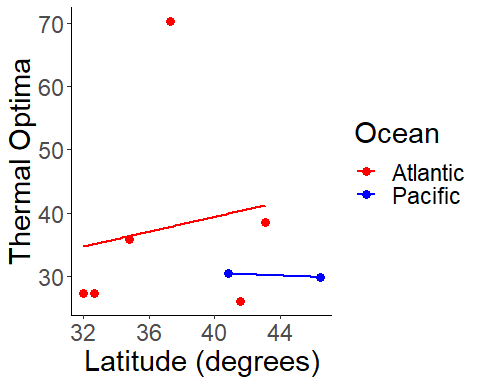


This is clearly not a signficant reaction. The thermal optimas given by quadratics are absurdly high. We should put more trust (but not a lot more) in those produced by segmented regression.

### Y Breakpoints, Quadratic

##   
## Model selection based on AICc:  
##   
## K AICc Delta\_AICc AICcWt Cum.Wt LL  
## nullo 2 70.98 0.00 0.61 0.61 -32.29  
## omax 3 75.17 4.19 0.08 0.69 -31.58  
## t.mean 3 75.83 4.85 0.05 0.74 -31.91  
## q.mean 3 76.03 5.06 0.05 0.79 -32.02  
## seasonlength10 3 76.04 5.06 0.05 0.84 -32.02  
## s.mean 3 76.14 5.16 0.05 0.88 -32.07  
## seasonlength16 3 76.51 5.53 0.04 0.92 -32.25  
## lat 3 76.57 5.59 0.04 0.96 -32.29  
## mean 3 76.58 5.60 0.04 1.00 -32.29  
## maxo 4 84.48 13.51 0.00 1.00 -31.58  
## seasonlengtho10 4 85.15 14.18 0.00 1.00 -31.91  
## t.meano 4 85.16 14.19 0.00 1.00 -31.91  
## lato 4 85.28 14.31 0.00 1.00 -31.97  
## q.meano 4 85.35 14.37 0.00 1.00 -32.01  
## meano 4 85.39 14.42 0.00 1.00 -32.03  
## s.meano 4 85.40 14.42 0.00 1.00 -32.03  
## seasonlengtho16 4 85.40 14.43 0.00 1.00 -32.04  
## o\*max 5 102.93 31.95 0.00 1.00 -31.46  
## o\*seasonlength10 5 103.78 32.81 0.00 1.00 -31.89  
## o\*t.mean 5 103.82 32.85 0.00 1.00 -31.91  
## o\*lat 5 103.91 32.94 0.00 1.00 -31.96  
## o\*q.mean 5 104.01 33.03 0.00 1.00 -32.01  
## o\*mean 5 104.06 33.08 0.00 1.00 -32.03  
## o\*s.mean 5 104.06 33.08 0.00 1.00 -32.03  
## seasonlength16 5 104.07 33.09 0.00 1.00 -32.04

##   
## Call:  
## glm(formula = brkptxq ~ lat + oce, family = "gaussian", data = brkpts)  
##   
## Deviance Residuals:   
## 1 2 3 4 5 6 7 8   
## -1.674 1.674 -2.095 -13.826 32.529 -0.628 -8.167 -7.813   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## (Intercept) 19.2412 55.8593 0.344 0.745  
## lat 0.4964 1.5025 0.330 0.754  
## ocep -10.7928 16.9879 -0.635 0.553  
##   
## (Dispersion parameter for gaussian family taken to be 277.4787)  
##   
## Null deviance: 1500.5 on 7 degrees of freedom  
## Residual deviance: 1387.4 on 5 degrees of freedom  
## AIC: 71.949  
##   
## Number of Fisher Scoring iterations: 2



Here, we see a similar trend of increasing weight with latitude as we saw in segmented regression and with any caliper length regression. One outlier of Woods Hole exists, similar to what we saw in growth rate with length. Upon removing this one site, we see a significant relationship. This evidence, taken together with that of the segmented regression and both the quadratic and segmented regressions for caliper length, point to a pattern of countergradient variation in growth.

##   
## Call:  
## lm(formula = brkptxq ~ lat + oce, data = brkptsq\_wh)  
##   
## Residuals:  
## 1 2 3 4 5 6 7   
## -3.941 3.941 -10.577 28.702 -2.473 -8.280 -7.372   
##   
## Coefficients:  
## Estimate Std. Error t value Pr(>|t|)  
## (Intercept) -6.857 60.993 -0.112 0.916  
## lat 1.299 1.683 0.772 0.483  
## ocep -19.745 18.978 -1.040 0.357  
##   
## Residual standard error: 16.55 on 4 degrees of freedom  
## Multiple R-squared: 0.214, Adjusted R-squared: -0.1789   
## F-statistic: 0.5446 on 2 and 4 DF, p-value: 0.6177

