Vulnerability master

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##Calculating perceptions of vulnerability based upon the exposure, sensitivity, and adaptive capacity of survey participants. ##saves figures into folder ("../figures/vulnerability)

#load data with state code additions

##functions to get likert answers to a 0 to 1 scale

##exposure ##changing from likert responses to numbers in order to calculate exposure index ##modify for different fisheries depending on survey region

##Exposure based on perceptions of how will climate affect all fisheries

##Exposure based upon perceptions of how climate will affect only the fisheries you participate in ##calling other Rmd file with code that calculates exposure that way and adds it to responses as a column called fishery\_specific\_exposure

##sensitivity index

##adaptive capacity

##individual vulnerability

Looking at the correlation between risk and vulnerability ranks when calculated following Cinner (2012), where r = e + s and v = e + s - ac versus using the euclidean distance method (Levin and Samhouri 2012) risk = sqrt(e^2 + s^2) and v = sqrt(e^2 + s^2 (1-ac)^2).

## risk\_rank risk\_euc\_rank vuln\_rank vuln\_euc\_rank  
## risk\_rank 1.0000000 0.9886228 0.9369983 0.9356901  
## risk\_euc\_rank 0.9886228 1.0000000 0.9287217 0.9464840  
## vuln\_rank 0.9369983 0.9287217 1.0000000 0.9865929  
## vuln\_euc\_rank 0.9356901 0.9464840 0.9865929 1.0000000

Components of vulnerability when we subset by each unique combination of fisheries. #subseting by fishery

## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 62 x 7  
## listoffisheries exposure\_avg sensitivity\_avg adaptive\_avg vuln\_avg  
## <chr> <dbl> <dbl> <dbl> <dbl>  
## 1 CPS 0.75 0.639 0.625 0.764   
## 2 CPS, dungeness~ 0.333 0.5 0.528 0.306   
## 3 CPS, groundfis~ 0.5 0.167 0.556 0.111   
## 4 CPS, salmon 1 0.528 0.25 1.28   
## 5 CPS, salmon, s~ 0.688 0.569 0.542 0.715   
## 6 crawfish 0.5 0.5 0.528 0.472   
## 7 dungeness crab 0.438 0.469 0.507 0.400   
## 8 dungeness crab~ 0.5 0.5 0.556 0.444   
## 9 dungeness crab~ 0.167 0.472 0.583 0.0556  
## 10 dungeness crab~ 0.5 0.389 0.5 0.389   
## # ... with 52 more rows, and 2 more variables: vuln\_euc\_avg <dbl>, count <int>

Or we can look at vulnerability based upon everyone that participates in a particular fishery regardless of what else they fish for.

##average vulnerability by fishery

## fishery avg\_exposure avg\_sensitivity avg\_ac ac\_sd avg\_risk  
## 1 CPS 0.6726190 0.5158730 0.5238095 0.12972408 1.1884921  
## 2 dungeness crab 0.6200893 0.5362261 0.4670139 0.16819370 1.1479368  
## 3 groundfish 0.6571581 0.5027804 0.4387464 0.15599087 1.1470467  
## 4 hake 0.5138889 0.4074074 0.5277778 0.14698618 0.9212963  
## 5 HMS 0.6686699 0.5107792 0.4397275 0.15540055 1.1571953  
## 6 salmon 0.7272007 0.5320901 0.4181548 0.16324649 1.2350615  
## 7 scallops 0.6845238 0.5243056 0.3888889 0.11785113 1.2088294  
## 8 sea urchin 0.7744048 0.5502451 0.3758170 0.15593878 1.3246499  
## 9 shrimp 0.6055195 0.5233586 0.4494949 0.14099415 1.1288781  
## 10 squid 0.6375000 0.5388889 0.5500000 0.02324056 1.1763889  
## risk\_sd avg\_risk\_euc avg\_vulnerability avg\_vulnerabilty\_euc  
## 1 0.34376587 0.8622131 0.6646825 0.9926085  
## 2 0.36204360 0.8462016 0.6809229 1.0145188  
## 3 0.40943182 0.8550908 0.7083003 1.0319710  
## 4 0.50122022 0.6898330 0.3935185 0.8694036  
## 5 0.38038232 0.8625254 0.7174678 1.0371500  
## 6 0.38032628 0.9268187 0.8169067 1.1084252  
## 7 0.02034335 0.8720676 0.8199405 1.0681751  
## 8 0.34943750 0.9657288 0.9488329 1.1573814  
## 9 0.21483590 0.8222721 0.6793831 0.9972798  
## 10 0.30164799 0.8437116 0.6263889 0.9607559

Components of vulnerability based upon the unique combination of regions someone fishes in.

#use the same method to look at regions #subseting by region

## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 30 x 7  
## listofregions exposure\_avg sensitivity\_avg adaptive\_avg vuln\_avg vuln\_euc\_avg  
## <chr> <dbl> <dbl> <dbl> <dbl> <dbl>  
## 1 Cen Cal 0.667 0.699 0.417 0.949 1.15   
## 2 Cen Cal, So ~ 0.812 0.361 0.583 0.590 0.982  
## 3 Columbia Riv~ 0.785 0.557 0.366 0.976 1.18   
## 4 Columbia Riv~ 0.656 0.472 0.549 0.580 0.943  
## 5 Columbia Riv~ 0.625 0.417 0.611 0.431 0.846  
## 6 Columbia Riv~ 0.812 0.694 0.306 1.20 1.28   
## 7 Nor Cal 0.819 0.676 0.287 1.21 1.29   
## 8 Nor Cal, Cen~ 0.716 0.514 0.493 0.736 1.03   
## 9 OR coast 0.738 0.511 0.547 0.636 1.08   
## 10 OR coast, No~ 0.75 0.681 0.361 1.07 1.20   
## # ... with 20 more rows, and 1 more variable: count <int>

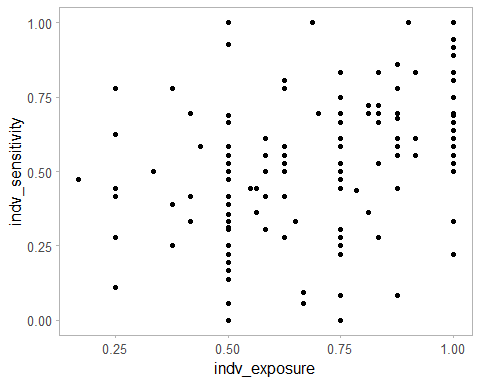
Or if we average by anyone that fishes in a particular region. ##average vulnerability by region

## region avg\_exposure avg\_sensitivity avg\_ac avg\_risk  
## 1 Puget Sound SJF 0.6743552 0.4925079 0.4375000 1.166863  
## 2 WA coast 0.6521577 0.4857891 0.4590395 1.088319  
## 3 Columbia River 0.7265625 0.5217476 0.4057734 1.205571  
## 4 OR coast 0.7060673 0.5291804 0.4643519 1.182305  
## 5 Nor Cal 0.7535417 0.5542328 0.4047619 1.271892  
## 6 Cen Cal 0.7416667 0.5504386 0.4298246 1.292105  
## 7 So Cal 0.7379167 0.4722222 0.4416667 1.210139  
## avg\_vulnerability avg\_risk\_euc avg\_vulnerability\_euc  
## 1 0.7293630 0.8524451 1.032274  
## 2 0.6292793 0.8384260 1.010961  
## 3 0.7997977 0.9173103 1.110672  
## 4 0.7179530 0.9153840 1.078470  
## 5 0.8671296 0.9495312 1.128262  
## 6 0.8622807 0.9378559 1.102743  
## 7 0.7684722 0.8984959 1.067630

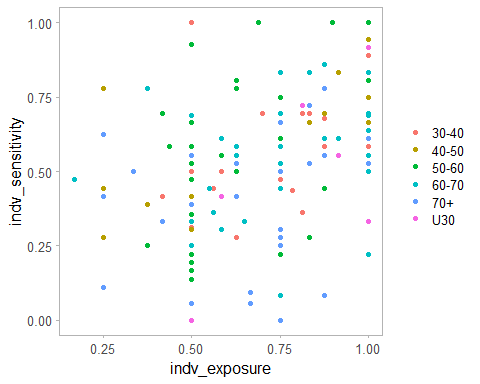
#save with vulnerability calculations

##exploratory figures

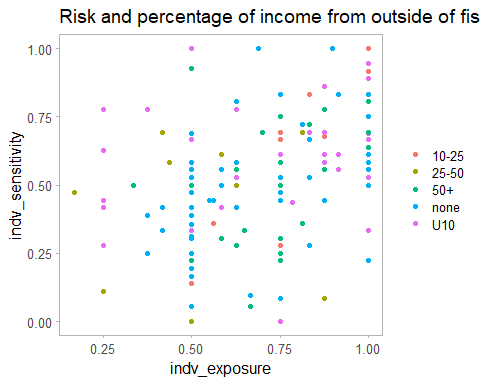
Visualizing risk.

##visualizing individual risk (exposure v sensitivity) 

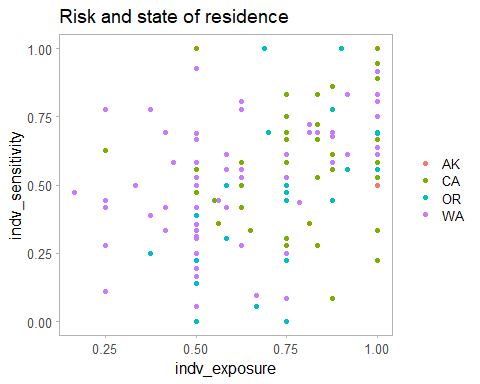
## Saving 5 x 4 in image



## Saving 5 x 4 in image



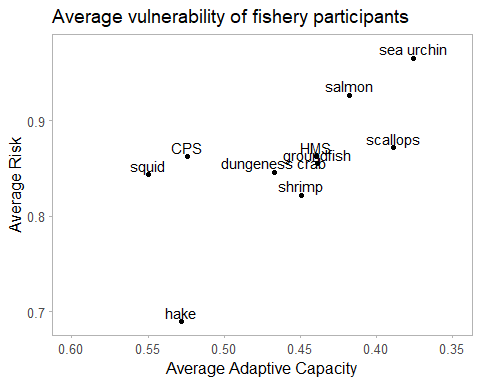
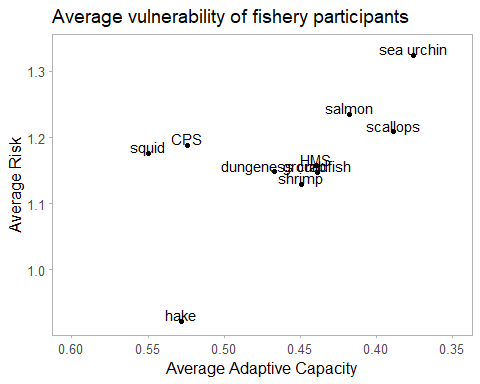
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## Saving 5 x 4 in image

First plot is additive risk, second is euclidean distance. ##considering average vulnerability based upon fishery participation

## Saving 5 x 4 in image  
## Saving 5 x 4 in image

 ##considering average vulnerability based upon region fished

##3d plot

##exploring and visualizing differences in vulnerability and adaptive capacity between groups

##anova of vulnerability for vessel length

#may need to adjust for different surveys  
  
responses$vessel <- factor(responses$vessel, levels = c("U25", "26-35", "36-45", "46-55", "56-65", "66+"))  
  
responses %>%  
 group\_by(vessel) %>%  
 dplyr::summarise(mean = mean(indv\_vulnerability),  
 count = n(),  
 sd = sd(indv\_vulnerability)  
 )

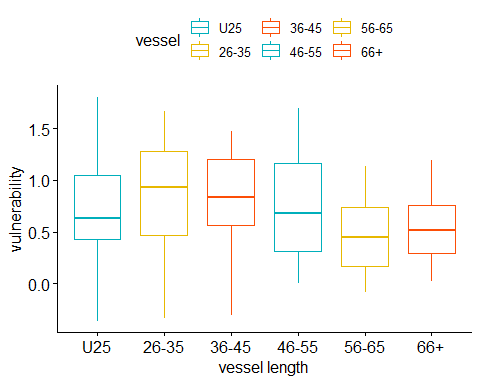
## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 6 x 4  
## vessel mean count sd  
## <fct> <dbl> <int> <dbl>  
## 1 U25 0.687 30 0.515  
## 2 26-35 0.880 53 0.484  
## 3 36-45 0.842 24 0.451  
## 4 46-55 0.773 24 0.499  
## 5 56-65 0.495 19 0.398  
## 6 66+ 0.540 12 0.355

# Box plots  
# Plot weight by group and color by group  
  
vessel\_vulnerability<-ggboxplot(responses, x = "vessel", y = "indv\_vulnerability",  
 color = "vessel", palette = c("#00AFBB", "#E7B800", "#FC4E07", "#00AFBB", "#E7B800", "#FC4E07"),  
 order = c("U25", "26-35", "36-45", "46-55", "56-65", "66+"),  
 ylab = "vulnerability", xlab = "vessel length")  
  
ggsave(plot = vessel\_vulnerability, file = paste0("../figures/vulnerability/vesselvuln.png"))

## Saving 5 x 4 in image

vessel\_vulnerability



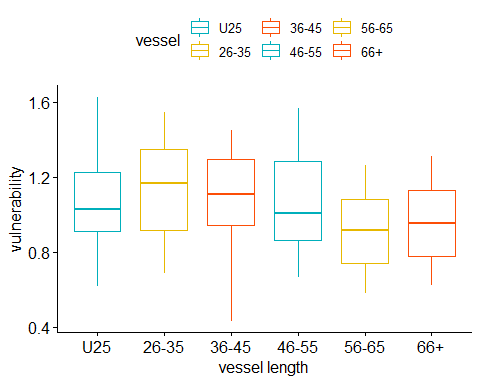
#anova  
vessel\_aov<-aov(indv\_vulnerability ~ vessel, data = responses)  
summary(vessel\_aov)

## Df Sum Sq Mean Sq F value Pr(>F)   
## vessel 5 2.99 0.5982 2.704 0.0226 \*  
## Residuals 156 34.51 0.2212   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

#repeat but use the euclidean distance calc of vulnerabilty  
vessel\_eucvulnerability<-ggboxplot(responses, x = "vessel", y = "indv\_vulnerability\_euc",  
 color = "vessel", palette = c("#00AFBB", "#E7B800", "#FC4E07", "#00AFBB", "#E7B800", "#FC4E07"),  
 order = c("U25", "26-35", "36-45", "46-55", "56-65", "66+"),  
 ylab = "vulnerability", xlab = "vessel length")  
  
ggsave(plot = vessel\_eucvulnerability, file = paste0("../figures/vulnerability/vesselvuln\_euc.png"))

## Saving 5 x 4 in image

vessel\_eucvulnerability



#anova  
euc\_vessel\_aov<-aov(indv\_vulnerability\_euc ~ vessel, data = responses)  
summary(euc\_vessel\_aov)

## Df Sum Sq Mean Sq F value Pr(>F)   
## vessel 5 0.872 0.17446 2.865 0.0168 \*  
## Residuals 149 9.073 0.06089   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 7 observations deleted due to missingness

#tukeys  
TukeyHSD(vessel\_aov)

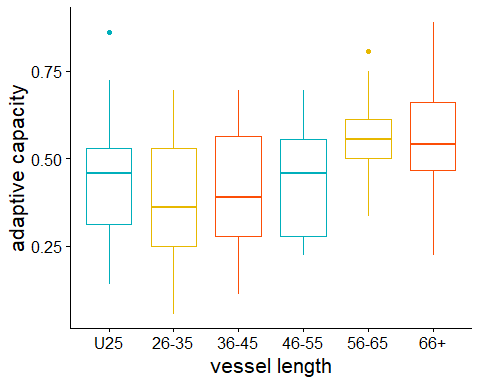
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_vulnerability ~ vessel, data = responses)  
##   
## $vessel  
## diff lwr upr p adj  
## 26-35-U25 0.19332659 -0.1167601 0.50341325 0.4694270  
## 36-45-U25 0.15484623 -0.2168372 0.52652968 0.8352893  
## 46-55-U25 0.08674934 -0.2849341 0.45843279 0.9846117  
## 56-65-U25 -0.19131475 -0.5892416 0.20661207 0.7346273  
## 66+-U25 -0.14681548 -0.6103862 0.31675523 0.9424826  
## 36-45-26-35 -0.03848036 -0.3724019 0.29544115 0.9994527  
## 46-55-26-35 -0.10657726 -0.4404988 0.22734426 0.9406272  
## 56-65-26-35 -0.38464134 -0.7475473 -0.02173538 0.0308612  
## 66+-26-35 -0.34014207 -0.7740232 0.09373901 0.2161028  
## 46-55-36-45 -0.06809689 -0.4598856 0.32369187 0.9960554  
## 56-65-36-45 -0.34616098 -0.7629290 0.07060706 0.1638069  
## 66+-36-45 -0.30166171 -0.7815030 0.17817957 0.4598078  
## 56-65-46-55 -0.27806408 -0.6948321 0.13870395 0.3908212  
## 66+-46-55 -0.23356481 -0.7134061 0.24627646 0.7242762  
## 66+-56-65 0.04449927 -0.4559453 0.54494388 0.9998464

TukeyHSD(euc\_vessel\_aov)

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_vulnerability\_euc ~ vessel, data = responses)  
##   
## $vessel  
## diff lwr upr p adj  
## 26-35-U25 0.069777351 -0.09978763 0.23934233 0.8419579  
## 36-45-U25 0.021163365 -0.17870931 0.22103604 0.9996366  
## 46-55-U25 -0.005108551 -0.20726846 0.19705136 0.9999997  
## 56-65-U25 -0.154944606 -0.37173696 0.06184774 0.3122078  
## 66+-U25 -0.122851068 -0.37003238 0.12433024 0.7056943  
## 36-45-26-35 -0.048613987 -0.22497223 0.12774425 0.9678457  
## 46-55-26-35 -0.074885902 -0.25383219 0.10406038 0.8322837  
## 56-65-26-35 -0.224721957 -0.42004750 -0.02939642 0.0140737  
## 66+-26-35 -0.192628419 -0.42121482 0.03595798 0.1517119  
## 46-55-36-45 -0.026271915 -0.23416269 0.18161886 0.9991397  
## 56-65-36-45 -0.176107971 -0.39825402 0.04603808 0.2051840  
## 66+-36-45 -0.144014433 -0.39590438 0.10787552 0.5664652  
## 56-65-46-55 -0.149836055 -0.37404224 0.07437013 0.3884288  
## 66+-46-55 -0.117742518 -0.37145119 0.13596615 0.7623003  
## 66+-56-65 0.032093538 -0.23342178 0.29760886 0.9993069

##anova for ac by vessel length

vessel\_ac<-ggboxplot(responses, x = "vessel", y = "indv\_ac",  
 color = "vessel", palette = c("#00AFBB", "#E7B800", "#FC4E07", "#00AFBB", "#E7B800", "#FC4E07"),  
 order = c("U25", "26-35", "36-45", "46-55", "56-65", "66+"),  
 ylab = "adaptive capacity", xlab = "vessel length") +  
 theme(plot.title = element\_text(size = 22), axis.title = element\_text(size = 16), legend.position = "none")  
   
vessel\_ac



ggsave(plot = vessel\_ac, file = paste0("../figures/vulnerability/vesselac.png"))

## Saving 5 x 4 in image

#anova  
ac\_vessel\_aov<-aov(indv\_ac ~ vessel, data = responses)  
summary(ac\_vessel\_aov)

## Df Sum Sq Mean Sq F value Pr(>F)   
## vessel 5 0.685 0.13690 5.58 0.0000929 \*\*\*  
## Residuals 156 3.828 0.02454   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

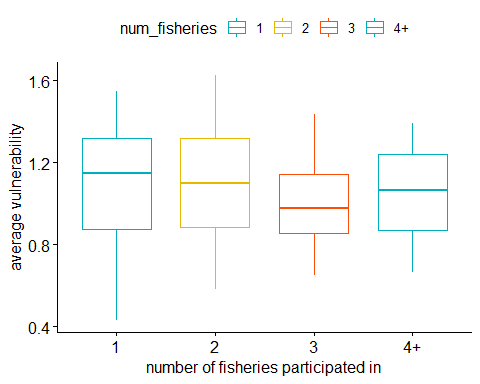
#tukey HSD of anova  
ac\_vessel\_tukey<-TukeyHSD(ac\_vessel\_aov)  
ac\_vessel\_tukey

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_ac ~ vessel, data = responses)  
##   
## $vessel  
## diff lwr upr p adj  
## 26-35-U25 -0.07872117 -0.181986940 0.02454459 0.2438661  
## 36-45-U25 -0.04583333 -0.169612205 0.07794554 0.8931526  
## 46-55-U25 -0.02615741 -0.149936279 0.09762146 0.9902016  
## 56-65-U25 0.09853801 -0.033980485 0.23105651 0.2696914  
## 66+-U25 0.11157407 -0.042805302 0.26595345 0.3003272  
## 36-45-26-35 0.03288784 -0.078315464 0.14409115 0.9567394  
## 46-55-26-35 0.05256377 -0.058639538 0.16376707 0.7484257  
## 56-65-26-35 0.17725919 0.056403413 0.29811496 0.0005552  
## 66+-26-35 0.19029525 0.045803180 0.33478732 0.0027968  
## 46-55-36-45 0.01967593 -0.110798461 0.15015031 0.9979914  
## 56-65-36-45 0.14437135 0.005578303 0.28316439 0.0362942  
## 66+-36-45 0.15740741 -0.002390429 0.31720524 0.0561265  
## 56-65-46-55 0.12469542 -0.014097623 0.26348846 0.1052600  
## 66+-46-55 0.13773148 -0.022066355 0.29752932 0.1343082  
## 66+-56-65 0.01303606 -0.153623144 0.17969527 0.9999184

##how many fisheries are people participating in and how does that affect vulnerability and adpative capacity

## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 4 x 4  
## num\_fisheries mean count sd  
## <chr> <dbl> <int> <dbl>  
## 1 1 1.09 60 0.278  
## 2 2 1.12 45 0.261  
## 3 3 0.996 39 0.210  
## 4 4+ 1.07 18 0.228



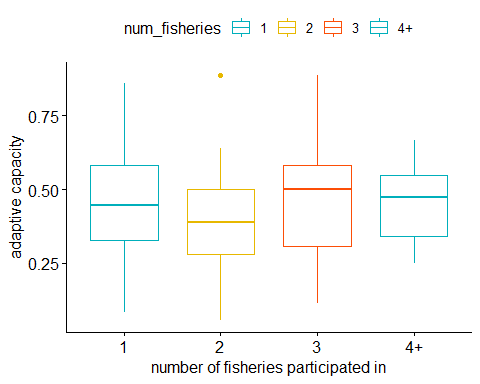
## Saving 5 x 4 in image

## Df Sum Sq Mean Sq F value Pr(>F)  
## num\_fisheries 3 0.348 0.11611 1.827 0.145  
## Residuals 151 9.597 0.06356   
## 7 observations deleted due to missingness

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_vulnerability\_euc ~ num\_fisheries, data = responses)  
##   
## $num\_fisheries  
## diff lwr upr p adj  
## 2-1 0.03492443 -0.09726983 0.16711870 0.9021786  
## 3-1 -0.09077479 -0.22840395 0.04685436 0.3202915  
## 4+-1 -0.01747149 -0.19961177 0.16466878 0.9945450  
## 3-2 -0.12569923 -0.26898373 0.01758528 0.1075291  
## 4+-2 -0.05239593 -0.23884631 0.13405445 0.8849056  
## 4+-3 0.07330330 -0.11703904 0.26364564 0.7493411

## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 4 x 4  
## num\_fisheries mean count sd  
## <chr> <dbl> <int> <dbl>  
## 1 1 0.450 60 0.175  
## 2 2 0.406 45 0.158  
## 3 3 0.455 39 0.180  
## 4 4+ 0.448 18 0.134



## Saving 5 x 4 in image

## Df Sum Sq Mean Sq F value Pr(>F)  
## num\_fisheries 3 0.068 0.02261 0.804 0.493  
## Residuals 158 4.444 0.02813

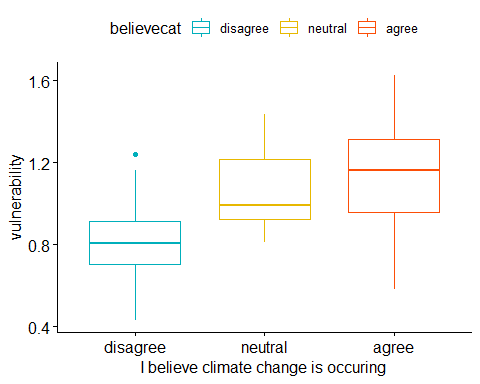
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_ac ~ num\_fisheries, data = responses)  
##   
## $num\_fisheries  
## diff lwr upr p adj  
## 2-1 -0.044290123 -0.13016902 0.04158877 0.5394905  
## 3-1 0.004665242 -0.08490904 0.09423953 0.9991137  
## 4+-1 -0.002932099 -0.11996531 0.11410111 0.9999008  
## 3-2 0.048955366 -0.04631871 0.14422945 0.5425960  
## 4+-2 0.041358025 -0.08009307 0.16280912 0.8130546  
## 4+-3 -0.007597341 -0.13168899 0.11649431 0.9985641

##varibility in vulnerability depending on if you think climate change is happening or not

## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 3 x 6  
## believecat meanex meansen meanac meanvuln count  
## <chr> <dbl> <dbl> <dbl> <dbl> <int>  
## 1 agree 0.752 0.560 0.425 1.13 107  
## 2 disagree 0.543 0.311 0.490 0.824 26  
## 3 neutral 0.641 0.541 0.443 1.06 29

## Warning: Removed 7 rows containing non-finite values (stat\_boxplot).



## Saving 5 x 4 in image

## Warning: Removed 7 rows containing non-finite values (stat\_boxplot).

## Df Sum Sq Mean Sq F value Pr(>F)   
## believecat 2 1.756 0.8780 16.3 0.000000387 \*\*\*  
## Residuals 152 8.189 0.0539   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 7 observations deleted due to missingness

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_vulnerability\_euc ~ believecat, data = responses)  
##   
## $believecat  
## diff lwr upr p adj  
## disagree-agree -0.30437815 -0.43075310 -0.17800320 0.0000002  
## neutral-agree -0.06957956 -0.18981440 0.05065529 0.3593574  
## neutral-disagree 0.23479859 0.07753418 0.39206299 0.0015664

## Df Sum Sq Mean Sq F value Pr(>F)   
## believecat 2 0.970 0.4849 11.18 0.0000292 \*\*\*  
## Residuals 155 6.725 0.0434   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 4 observations deleted due to missingness

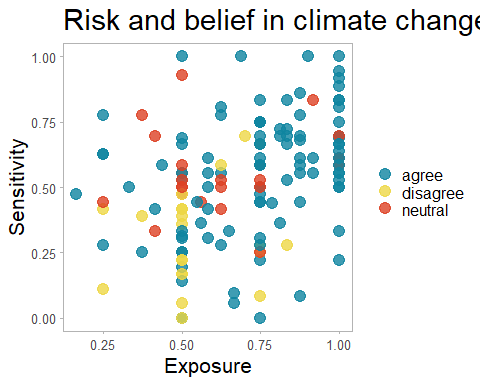
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_exposure ~ believecat, data = responses)  
##   
## $believecat  
## diff lwr upr p adj  
## disagree-agree -0.20860221 -0.31993009 -0.097274331 0.0000516  
## neutral-agree -0.11045406 -0.21661003 -0.004298091 0.0393354  
## neutral-disagree 0.09814815 -0.04013313 0.236429426 0.2162568

## Df Sum Sq Mean Sq F value Pr(>F)   
## believecat 2 1.270 0.6349 14.52 0.00000165 \*\*\*  
## Residuals 156 6.823 0.0437   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 3 observations deleted due to missingness

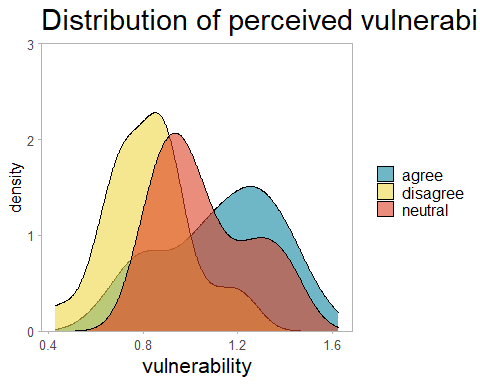
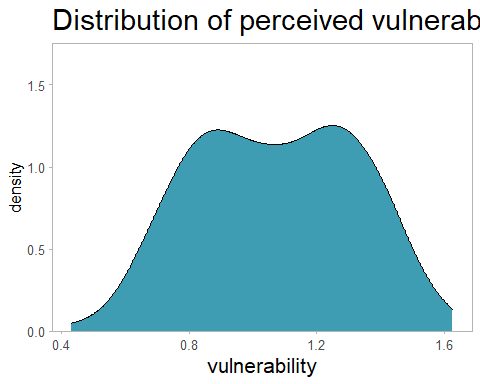
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_sensitivity ~ believecat, data = responses)  
##   
## $believecat  
## diff lwr upr p adj  
## disagree-agree -0.24861354 -0.3586407 -0.13858641 0.0000009  
## neutral-agree -0.01846615 -0.1236157 0.08668342 0.9092657  
## neutral-disagree 0.23014739 0.0939791 0.36631568 0.0002869

## Df Sum Sq Mean Sq F value Pr(>F)  
## believecat 2 0.090 0.04476 1.609 0.203  
## Residuals 159 4.423 0.02782

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_ac ~ believecat, data = responses)  
##   
## $believecat  
## diff lwr upr p adj  
## disagree-agree 0.06515097 -0.02112254 0.15142448 0.1773510  
## neutral-agree 0.01825295 -0.06435252 0.10085841 0.8603254  
## neutral-disagree -0.04689803 -0.15346579 0.05966974 0.5520752

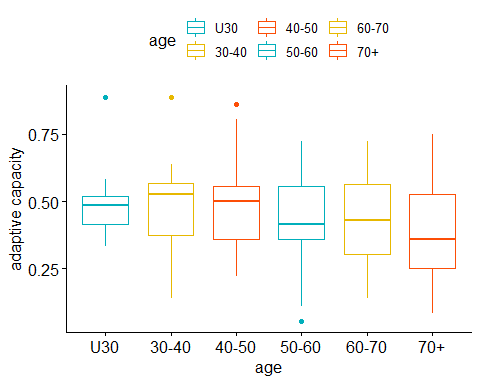
##scatterplot of risk depending on your belief in climate change 

## Saving 5 x 4 in image

##distribution of vulnerability ##vulnerability plots used in tnc talk 

##anova for adaptive capacity by age

## Saving 5 x 4 in image



## Df Sum Sq Mean Sq F value Pr(>F)  
## age 5 0.198 0.03969 1.436 0.214  
## Residuals 156 4.314 0.02765

## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_ac ~ age, data = responses)  
##   
## $age  
## diff lwr upr p adj  
## 40-50-30-40 0.004873294 -0.14704803 0.15679462 0.9999990  
## 50-60-30-40 -0.042264753 -0.18044408 0.09591458 0.9501919  
## 60-70-30-40 -0.040370813 -0.17208796 0.09134633 0.9497656  
## 70+-30-40 -0.088470049 -0.22389277 0.04695267 0.4152332  
## U30-30-40 0.030336257 -0.17188894 0.23256146 0.9980413  
## 50-60-40-50 -0.047138047 -0.18107655 0.08680046 0.9121852  
## 60-70-40-50 -0.045244108 -0.17250527 0.08201705 0.9086438  
## 70+-40-50 -0.093343343 -0.22443609 0.03774941 0.3167722  
## U30-40-50 0.025462963 -0.17388855 0.22481448 0.9990975  
## 60-70-50-60 0.001893939 -0.10859969 0.11238757 1.0000000  
## 70+-50-60 -0.046205296 -0.16109110 0.06868051 0.8547704  
## U30-50-60 0.072601010 -0.11648750 0.26168952 0.8775190  
## 70+-60-70 -0.048099236 -0.15512553 0.05892706 0.7864466  
## U30-60-70 0.070707071 -0.11371187 0.25512601 0.8781693  
## U30-70+ 0.118806306 -0.06827724 0.30588985 0.4481196