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 0.9879716 0.9328855 0.9297814  
## risk\_euc\_rank 0.9879716 1.0000000 0.9251386 0.9420433  
## vuln\_rank 0.9328855 0.9251386 1.0000000 0.9862465  
## vuln\_euc\_rank 0.9297814 0.9420433 0.9862465 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 0.451 0.507 0.382   
## 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 0.5251736 0.4670139 0.16819370 1.1452629  
## 3 groundfish 0.6571581 0.4957265 0.4387464 0.15599087 1.1528846  
## 4 hake 0.5138889 0.4074074 0.5277778 0.14698618 0.9212963  
## 5 HMS 0.6686699 0.5041929 0.4397275 0.15540055 1.1602463  
## 6 salmon 0.7272007 0.5250496 0.4181548 0.16324649 1.2327718  
## 7 scallops 0.6845238 0.5277778 0.3888889 0.11785113 1.2123016  
## 8 sea urchin 0.7744048 0.5506536 0.3758170 0.15593878 1.3250584  
## 9 shrimp 0.6055195 0.5227273 0.4494949 0.14099415 1.1282468  
## 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 0.34286001 0.8351618 0.6782490 1.0055760  
## 3 0.38419597 0.8453758 0.7141382 1.0251769  
## 4 0.50122022 0.6898330 0.3935185 0.8694036  
## 5 0.36085350 0.8547224 0.7205189 1.0316260  
## 6 0.37152834 0.9192898 0.8146170 1.1020876  
## 7 0.02525381 0.8737670 0.8234127 1.0696414  
## 8 0.34931555 0.9659288 0.9492414 1.1575540  
## 9 0.21682799 0.8214106 0.6787518 0.9966836  
## 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)

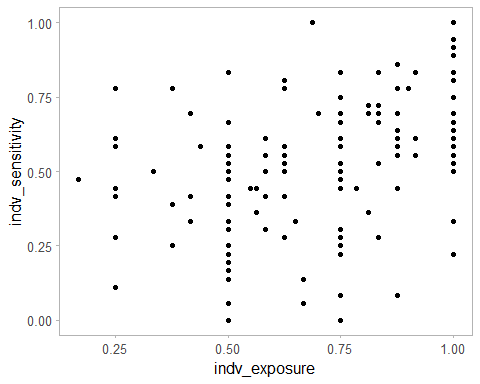
## # A tibble: 30 x 7  
## listofregions exposure\_avg sensitivity\_avg adaptive\_avg vuln\_avg vuln\_euc\_avg  
## <chr> <dbl> <dbl> <dbl> <dbl> <dbl>  
## 1 Cen Cal 0.667 0.685 0.417 0.935 1.14   
## 2 Cen Cal, So ~ 0.812 0.361 0.583 0.590 0.982  
## 3 Columbia Riv~ 0.785 0.554 0.366 0.973 1.18   
## 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 0.481 0.547 0.634 1.04   
## 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

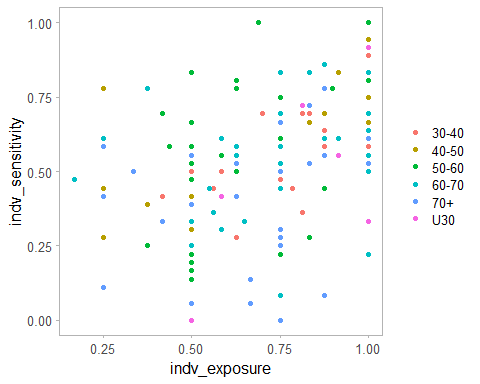
## region avg\_exposure avg\_sensitivity avg\_ac avg\_risk  
## 1 Puget Sound SJF 0.6743552 0.4878472 0.4375000 1.162202  
## 2 WA coast 0.6521577 0.4849341 0.4590395 1.103931  
## 3 Columbia River 0.7265625 0.5174292 0.4057734 1.201253  
## 4 OR coast 0.7060673 0.5152778 0.4643519 1.186042  
## 5 Nor Cal 0.7535417 0.5542328 0.4047619 1.271892  
## 6 Cen Cal 0.7416667 0.5482456 0.4298246 1.289912  
## 7 So Cal 0.7379167 0.4722222 0.4416667 1.210139  
## avg\_vulnerability avg\_risk\_euc avg\_vulnerability\_euc  
## 1 0.7247024 0.8484925 1.028820  
## 2 0.6448917 0.8355693 1.009123  
## 3 0.7954793 0.9143038 1.108261  
## 4 0.7216898 0.8972544 1.060431  
## 5 0.8671296 0.9495312 1.128262  
## 6 0.8600877 0.9358297 1.101002  
## 7 0.7684722 0.8984959 1.067630

##exploratory figures

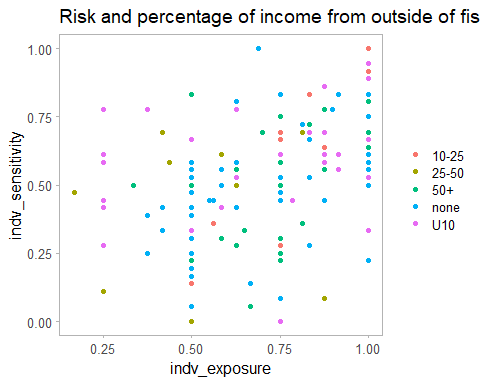
Visualizing risk.

##visualizing individual risk (exposure v sensitivity) 

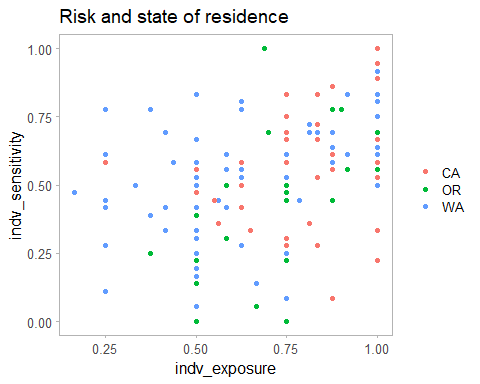
## Saving 5 x 4 in image



## Saving 5 x 4 in image



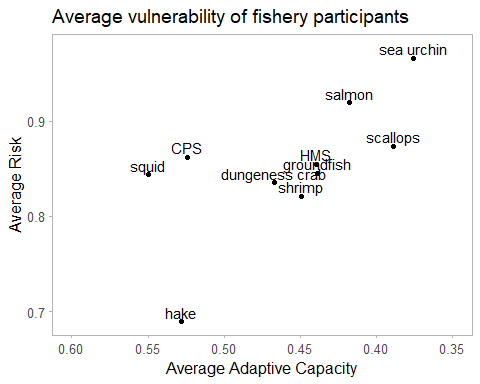
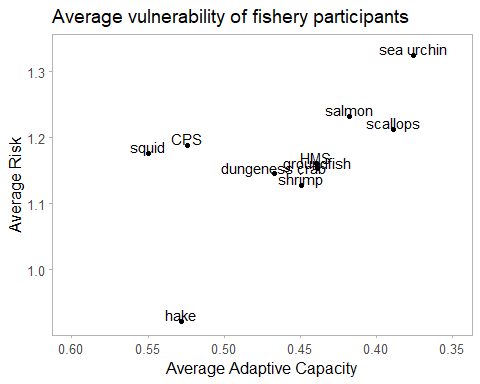
## Saving 5 x 4 in image



## 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)  
 )

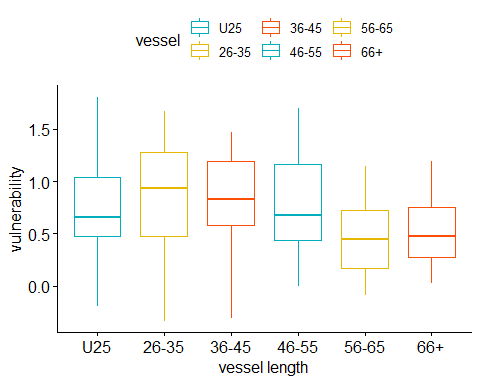
## `summarise()` ungrouping output (override with `.groups` argument)

## # A tibble: 6 x 4  
## vessel mean count sd  
## <fct> <dbl> <int> <dbl>  
## 1 U25 0.719 30 0.481  
## 2 26-35 0.878 53 0.483  
## 3 36-45 0.834 24 0.434  
## 4 46-55 0.793 24 0.481  
## 5 56-65 0.486 19 0.383  
## 6 66+ 0.503 12 0.352

# 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



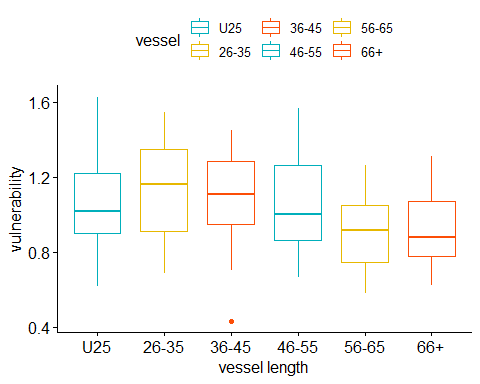
#anova  
vessel\_aov<-aov(indv\_vulnerability ~ vessel, data = responses)  
summary(vessel\_aov)

## Df Sum Sq Mean Sq F value Pr(>F)   
## vessel 5 3.16 0.6319 3.031 0.0122 \*  
## Residuals 156 32.52 0.2084   
## ---  
## 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 0.985 0.1971 3.335 0.00691 \*\*  
## Residuals 152 8.983 0.0591   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1  
## 4 observations deleted due to missingness

#tukeys  
TukeyHSD(vessel\_aov)

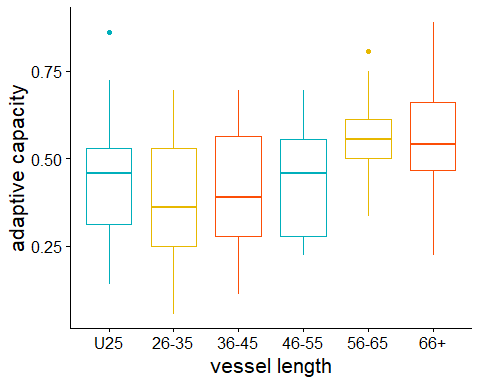
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_vulnerability ~ vessel, data = responses)  
##   
## $vessel  
## diff lwr upr p adj  
## 26-35-U25 0.15909167 -0.1418931 0.46007640 0.6486194  
## 36-45-U25 0.11510582 -0.2456677 0.47587931 0.9407152  
## 46-55-U25 0.07453869 -0.2862348 0.43531218 0.9911668  
## 56-65-U25 -0.23281085 -0.6190574 0.15343569 0.5081486  
## 66+-U25 -0.21544974 -0.6654133 0.23451386 0.7379968  
## 36-45-26-35 -0.04398585 -0.3681058 0.28013412 0.9987902  
## 46-55-26-35 -0.08455298 -0.4086729 0.23956699 0.9747757  
## 56-65-26-35 -0.39190252 -0.7441562 -0.03964887 0.0196868  
## 66+-26-35 -0.37454140 -0.7956868 0.04660404 0.1119773  
## 46-55-36-45 -0.04056713 -0.4208558 0.33972152 0.9996247  
## 56-65-36-45 -0.34791667 -0.7524514 0.05661804 0.1359463  
## 66+-36-45 -0.33055556 -0.7963121 0.13520101 0.3204119  
## 56-65-46-55 -0.30734954 -0.7118842 0.09718517 0.2472919  
## 66+-46-55 -0.28998843 -0.7557450 0.17576814 0.4709867  
## 66+-56-65 0.01736111 -0.4683940 0.50311625 0.9999983

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 0.083841079 -0.0793536 0.247035758 0.6756885  
## 36-45-U25 0.030063974 -0.1635686 0.223696541 0.9976863  
## 46-55-U25 0.005608143 -0.1880244 0.199240711 0.9999994  
## 56-65-U25 -0.146565273 -0.3571170 0.063986434 0.3419511  
## 66+-U25 -0.136163302 -0.3770137 0.104687111 0.5788817  
## 36-45-26-35 -0.053777105 -0.2274712 0.119916973 0.9475275  
## 46-55-26-35 -0.078232935 -0.2519270 0.095461143 0.7846318  
## 56-65-26-35 -0.230406352 -0.4227812 -0.038031502 0.0090940  
## 66+-26-35 -0.220004381 -0.4451376 0.005128875 0.0595679  
## 46-55-36-45 -0.024455830 -0.2270162 0.178104532 0.9993119  
## 56-65-36-45 -0.176629247 -0.3954194 0.042160951 0.1885099  
## 66+-36-45 -0.166227276 -0.4143120 0.081857489 0.3856255  
## 56-65-46-55 -0.152173417 -0.3709636 0.066616781 0.3428935  
## 66+-46-55 -0.141771446 -0.3898562 0.106313320 0.5672291  
## 66+-56-65 0.010401971 -0.2511023 0.271906275 0.9999972

##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

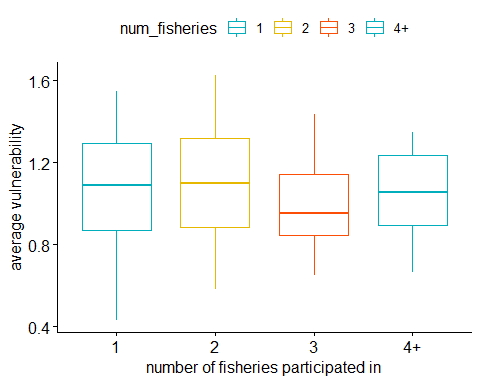
#tukey HSD of anova  
ac\_vessel\_tukey<-TukeyHSD(ac\_vessel\_aov)  
ac\_vessel\_tukey

## 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 1.08 60 0.276  
## 2 2 1.12 45 0.260  
## 3 3 0.986 39 0.208  
## 4 4+ 1.06 18 0.212



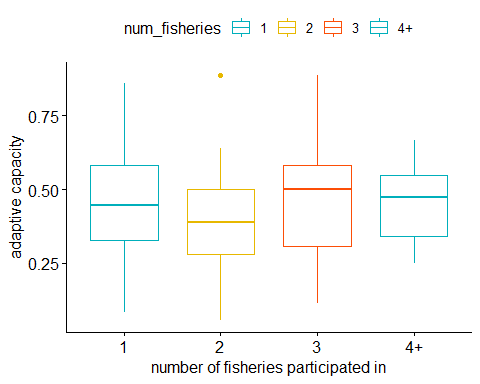
## Saving 5 x 4 in image

## Df Sum Sq Mean Sq F value Pr(>F)  
## num\_fisheries 3 0.389 0.1297 2.085 0.105  
## Residuals 154 9.579 0.0622   
## 4 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 0.04445680 -0.08522826 0.174141865 0.8098660  
## 3-1 -0.08981934 -0.22492235 0.045283671 0.3133963  
## 4+-1 -0.02057414 -0.19608950 0.154941218 0.9901673  
## 3-2 -0.13427614 -0.27599597 0.007443686 0.0702841  
## 4+-2 -0.06503094 -0.24568899 0.115627097 0.7861181  
## 4+-3 0.06924520 -0.11534065 0.253831046 0.7642469

## `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

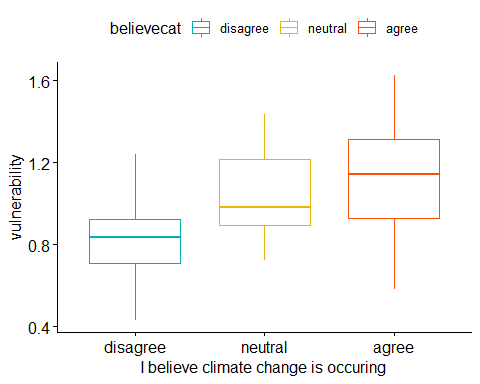
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_ac ~ num\_fisheries, data = responses)  
##   
## $num\_fisheries  
## diff lwr upr p adj  
## 2-1 -0.044290123 -0.13016902 0.04158877 0.5394905  
## 3-1 0.004665242 -0.08490904 0.09423953 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 0.551 0.425 1.12 107  
## 2 disagree 0.543 0.319 0.490 0.831 26  
## 3 neutral 0.641 0.534 0.443 1.04 29

## Warning: Removed 4 rows containing non-finite values (stat\_boxplot).



## Saving 5 x 4 in image

## Warning: Removed 4 rows containing non-finite values (stat\_boxplot).

## Df Sum Sq Mean Sq F value Pr(>F)   
## believecat 2 1.668 0.8341 15.58 0.000000685 \*\*\*  
## Residuals 155 8.300 0.0535   
## ---  
## 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\_vulnerability\_euc ~ believecat, data = responses)  
##   
## $believecat  
## diff lwr upr p adj  
## disagree-agree -0.29049234 -0.41417479 -0.16680988 0.0000003  
## neutral-agree -0.07829022 -0.19622681 0.03964638 0.2613115  
## neutral-disagree 0.21220212 0.05857512 0.36582912 0.0037866

## 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

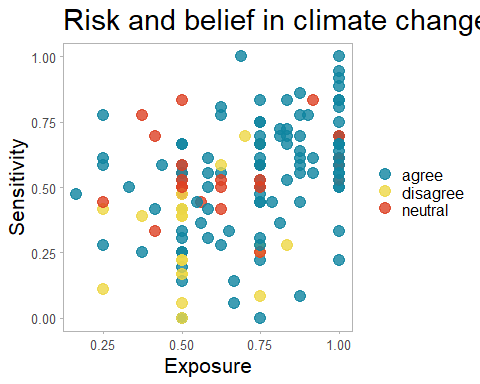
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_exposure ~ believecat, data = responses)  
##   
## $believecat  
## diff lwr upr p adj  
## disagree-agree -0.20860221 -0.31993009 -0.097274331 0.0000516  
## neutral-agree -0.11045406 -0.21661003 -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 1.142 0.5712 14.39 0.0000018 \*\*\*  
## Residuals 159 6.310 0.0397   
## ---  
## Signif. codes: 0 '\*\*\*' 0.001 '\*\*' 0.01 '\*' 0.05 '.' 0.1 ' ' 1

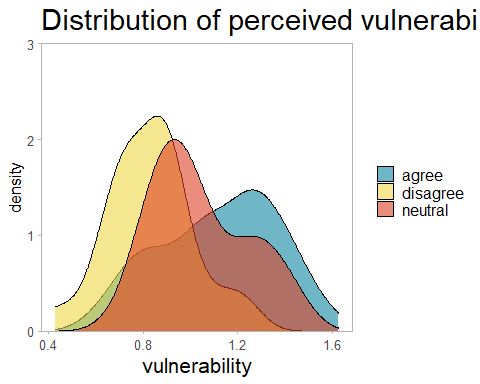
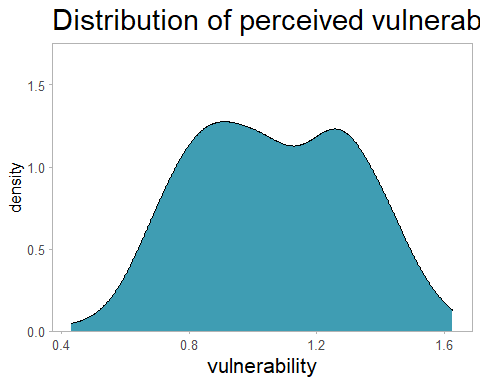
## Tukey multiple comparisons of means  
## 95% family-wise confidence level  
##   
## Fit: aov(formula = indv\_sensitivity ~ believecat, data = responses)  
##   
## $believecat  
## diff lwr upr p adj  
## disagree-agree -0.23169782 -0.33475143 -0.12864421 0.0000010  
## neutral-agree -0.01665951 -0.11533164 0.08201263 0.9158617  
## neutral-disagree 0.21503831 0.08774323 0.34233340 0.0002878

## 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

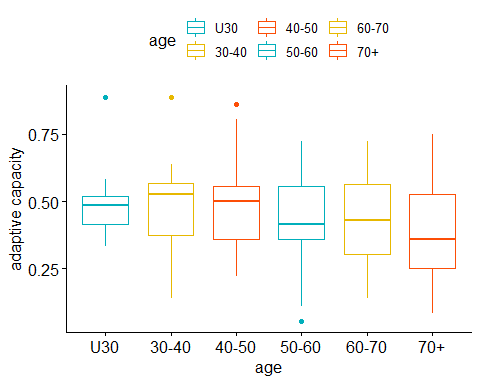
##scatterplot of risk depending on your belief in climate change 

## 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

#save with vulnerability calculations