IUCN_dat_intro

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Read Data

```
data = read_csv('iucn_dat.csv')

# make data set smaller to just columns interested in
imp_data = data %>% select(scientificName, redlistCategory, populationTrend, BodyMass)
imp_data2 = data %>% select(redlistCategory, populationTrend, BodyMass, cat_change, cat_change_bi, syst
```

Data Set Basics

- there are 35451 total species in the data set
- there are 13400 species with body mass data

How many species are in each distinct category?

```
imp_data %>% group_by(redlistCategory) %>% summarize(Sum = n()) %>% arrange(-Sum)
```

```
## # A tibble: 10 x 2
##
     redlistCategory
                                          Sum
##
      <chr>>
                                        <int>
## 1 Least Concern
                                        20473
## 2 Data Deficient
                                         5152
## 3 Vulnerable
                                         2928
## 4 Endangered
                                         2740
## 5 Near Threatened
                                         2333
## 6 Critically Endangered
                                         1521
## 7 Extinct
                                          285
## 8 Extinct in the Wild
                                           15
## 9 Lower Risk/least concern
                                            3
## 10 Lower Risk/conservation dependent
                                            1
```

imp_data %>% group_by(populationTrend) %>% summarize(Sum = n()) %>% arrange(-Sum)

```
9848
## 3 Stable
                       900
## 4 Increasing
## 5 <NA>
                       441
imp_data2 %>% group_by(cat_change) %% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 10 x 2
##
      cat_change
                   Sum
           <dbl> <int>
##
##
              NA 32749
  1
##
              1 1011
                  881
## 3
              -1
## 4
               2
                   352
## 5
              -2
                  311
## 6
              3
                  69
## 7
              -3
                    35
               0
                    27
## 8
## 9
               4
                    10
## 10
                     6
              -4
imp_data2 %>% group_by(cat_change_bi) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 3 x 2
##
     cat_change_bi
                     Sum
##
     <chr>
                   <int>
## 1 <NA>
                   32776
## 2 decline
                    1442
## 3 improve
                    1233
imp_data2 %>% group_by(systems) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 10 x 2
                                                        Sum
##
      systems
##
      <chr>
                                                      <int>
## 1 Terrestrial
                                                      19595
## 2 Terrestrial|Freshwater (=Inland waters)
                                                       6712
## 3 Marine
                                                      5202
## 4 Freshwater (=Inland waters)
                                                       2851
## 5 Terrestrial|Freshwater (=Inland waters)|Marine
                                                       494
## 6 Terrestrial | Marine
                                                        408
## 7 Freshwater (=Inland waters)|Marine
                                                        171
## 8 <NA>
                                                        10
## 9 Marine | Marine
                                                         7
## 10 Freshwater (=Inland waters)|Marine|Marine
                                                         1
imp_data2 %>% group_by(realm) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 128 x 2
##
     realm
                               Sum
##
      <chr>
                             <int>
## 1 Neotropical
                             10608
```

```
##
   2 Afrotropical
                              5200
## 3 Indomalayan
                              4719
## 4 <NA>
                              2789
## 5 Australasian
                              2288
## 6 Oceanian
                              1842
## 7 Nearctic
                              1684
## 8 Palearctic
                              1680
## 9 Indomalayan|Palearctic 1446
## 10 Nearctic|Neotropical
                              1003
## # ... with 118 more rows
imp_data2 %>% group_by(kingdomName) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 2 x 2
    kingdomName
##
                   Sum
##
     <chr>
                 <int>
## 1 animalia
                 32286
## 2 plantae
                  3165
imp_data2 %>% group_by(phylumName) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 4 x 2
##
     phylumName
                    Sum
##
     <chr>
                  <int>
## 1 chordata
                  27968
## 2 tracheophyta 3165
## 3 arthropoda
                   2935
## 4 mollusca
                   1383
imp_data2 %>% group_by(orderName) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 106 x 2
##
      orderName
                       Sum
##
      <chr>
                     <int>
##
  1 passeriformes
                      6659
##
   2 anura
                      6098
## 3 decapoda
                      2864
## 4 rodentia
                      2364
## 5 perciformes
                      1684
##
   6 caryophyllales
                      1477
## 7 chiroptera
                      1304
## 8 neogastropoda
                       633
## 9 caudata
                       611
## 10 pinales
                       610
## # ... with 96 more rows
imp_data2 %>% group_by(className) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 13 x 2
##
      className
                       Sum
##
      <chr>
                     <int>
```

```
## 1 aves
                    11147
## 2 amphibia
                     6892
## 3 mammalia
                     5899
## 4 malacostraca
                     2935
## 5 actinopterygii
                     2595
## 6 magnoliopsida
                     2248
## 7 chondrichthyes
                     1134
## 8 cephalopoda
                      750
## 9 gastropoda
                      633
## 10 pinopsida
                      610
## 11 cycadopsida
                      307
## 12 reptilia
                      225
## 13 myxini
                       76
```

Number of species in each category of population trend for each category of red list

```
list_pop = imp_data %>% group_by(populationTrend, redlistCategory) %>% summarize(Sum = n())
df = as.data.frame(list_pop)

df %>% pivot_wider(names_from=populationTrend, values_from=Sum)
```

## # A tibble: 10 x 6									
##		redlistCategory	Decreasing	Increasing	${\tt Stable}$	Unknown	'NA'		
##		<chr></chr>	<int></int>	<int></int>	<int></int>	<int></int>	<int></int>		
##	1	Critically Endangered	1108	19	42	343	9		
##	2	Data Deficient	228	NA	72	4834	18		
##	3	Endangered	2197	28	81	427	7		
##	4	Extinct	1	NA	1	4	279		
##	5	Extinct in the Wild	1	NA	NA	NA	14		
##	6	Least Concern	4469	775	9013	6170	46		
##	7	Near Threatened	1558	36	314	424	1		
##	8	Vulnerable	1946	42	325	552	63		
##	9	Lower Risk/conservation dependent	NA	NA	NA	NA	1		
##	10	Lower Risk/least concern	NA	NA	NA	NA	3		

Species in each category for each category of red list and class

```
list_order = imp_data2 %>% group_by(redlistCategory, className) %>% summarize(Sum = n())
df2 = as.data.frame(list_order)

df3 = df2 %>% pivot_wider(names_from=redlistCategory, values_from=Sum)

knitr::kable(df3)
```

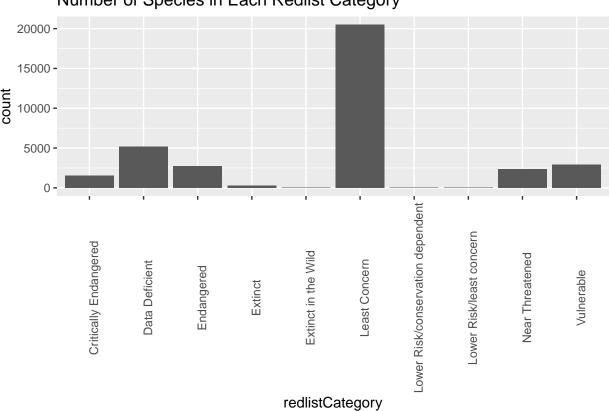
					Extinct		Lower	Lower		
Cr	Data			in the	Least	Risk/conservation	Risk/least	Near	ļ	
${\it className} Endangered$		Deficient	Endang	ge Fed inct	Wild	Concern	dependent	concern	Threatene	èWulnerab
actinopterygii	10	444	34	NA	NA	1953	NA	NA	49	105
amphibia	610	1336	993	35	2	2856	NA	NA	387	673
aves	225	53	461	159	5	8427	NA	NA	1017	800
cephalopoda	1	419	2	NA	NA	324	NA	NA	2	2
chondrichthyes	43	420	62	NA	NA	382	NA	NA	115	112

					Extinct		Lower	Lower		
$ \begin{array}{c} {\rm Critically} \\ {\rm classNameEndangered} \end{array}$		Data Deficient	Endang	ge Eed inct	in the Wild	Least Concern	Risk/conservation dependent	Risk/least concern	Near Threatene	e W ulneral
cycadopsida	53	3	65	NA	4	45	NA	NA	63	74
gastropoda	3	88	11	NA	NA	478	NA	NA	26	27
magnoliopsida	185	348	297	NA	2	1107	NA	NA	110	199
malacostraca	122	1124	143	7	NA	1189	NA	NA	71	279
mammalia	222	869	532	84	2	3292	NA	NA	353	545
myxini	1	30	2	NA	NA	35	NA	NA	2	6
pinopsida	29	8	96	NA	NA	298	NA	NA	99	80
reptilia	17	10	42	NA	NA	87	1	3	39	26

Redlist Categories

```
# redlist distribution
ggplot(imp_data, aes(x=redlistCategory)) + geom_bar() + theme(axis.text.x = element_text(angle = 90)) +
```

Number of Species in Each Redlist Category

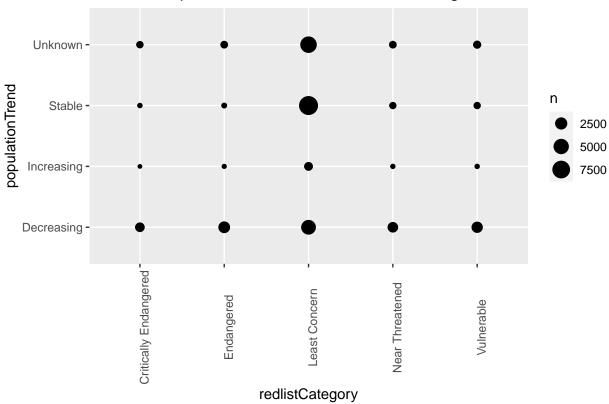


```
# filter data for high risk species
vul_data = imp_data %>% filter(redlistCategory == 'Vulnerable' | redlistCategory == 'Near Threatened' |
```

Compare populationTrend and redlistCategory

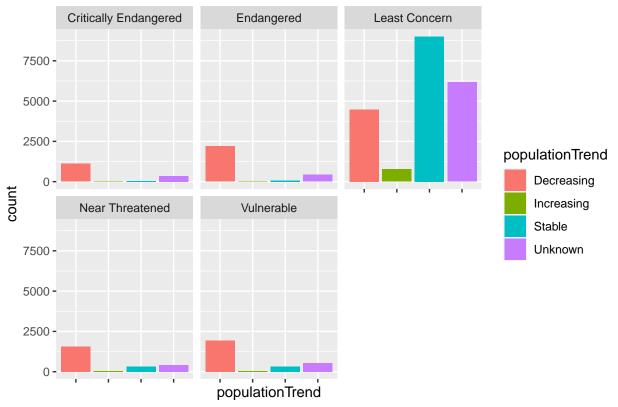
pop = imp_data %>% filter(populationTrend != 'NA') %>% filter(redlistCategory != 'Data Deficient') %>% ggplot(pop, aes(redlistCategory, populationTrend)) + geom_count() + theme(axis.text.x = element_text(and text))

Count of Population Trend and Vulnerable Categories



ggplot(pop, aes(x=populationTrend, fill=populationTrend)) + geom_bar() + facet_wrap(~redlistCategory) +





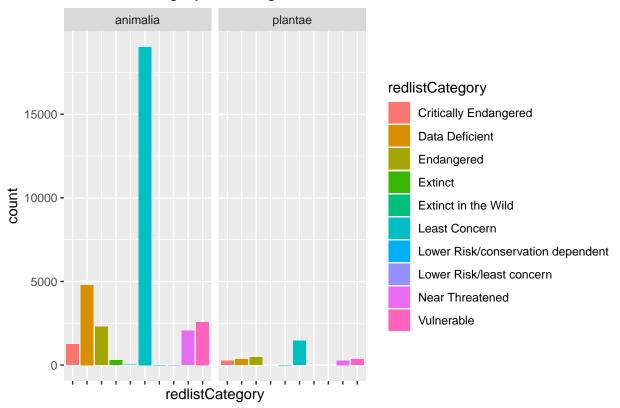
The largest redlistCategory is Least Concern, of which the population trends are more stable or decreasing (unknown excluded). Of the other redlist categories, greater numbers have decreasing population trends than stable/increasing.

Of the populations decreasing, the categories affected in order are least concern, endangered, vulnerable, near threatened, and critically endangered. The majority of populations that are stable or increasing are in the least concern category.

Comparison of redlistCategory and taxonomy

```
# comparison with kingdom
ggplot(imp_data2, aes(x=redlistCategory, fill=redlistCategory)) + geom_bar() + facet_wrap(~kingdomName)
```

Red List Category and Kingdom



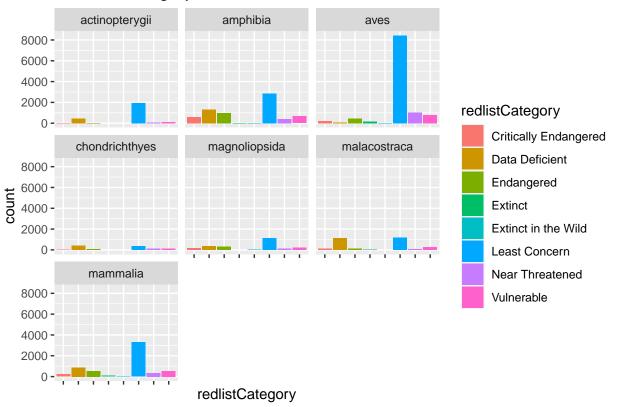
comparison with phylum
ggplot(imp_data2, aes(x=redlistCategory, fill=redlistCategory)) + geom_bar() + facet_wrap(~phylumName)

Red List Category and Phylum



```
# comparison with classes that have over 1000 species in the dataset
class_data = imp_data2 %>% filter(className != 'cephalopoda') %>% filter(className != 'gastropoda') %>%
ggplot(class_data, aes(x=redlistCategory, fill=redlistCategory)) + geom_bar() + facet_wrap(~className) fill=redlistCategory)
```

Red List Category and Class

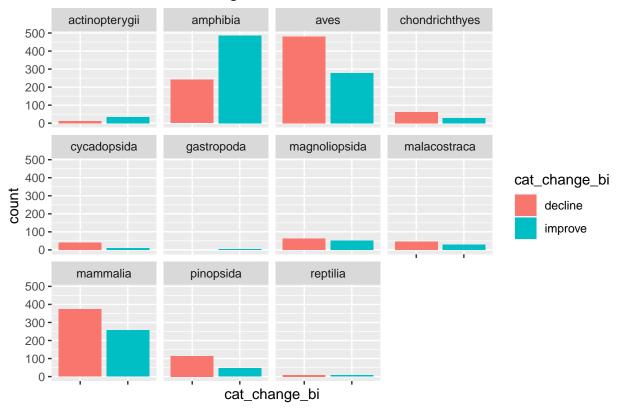


Amphibians (and mammals second) have the highest proportions with critically endangered, endangered, and vulnerable populations. Birds have high proportions of near threatened and vulnerable populations, but they also hav the highest count of species in the least concern category.

Status Change variables

```
# binary change (NA removed)
change_bi = imp_data2 %>% filter(cat_change_bi != 'NA')
ggplot(change_bi, aes(x=cat_change_bi, fill=cat_change_bi)) + geom_bar() + facet_wrap(~className) + then
```

Class and Status Change

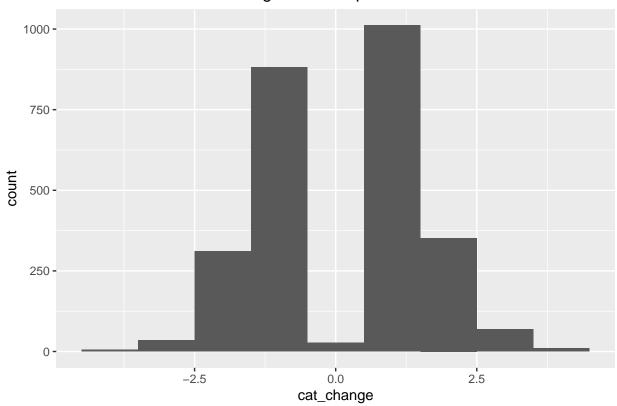


For binary changes, more amphibian and ray-finned fish (actinopterygii) species improved than declined. More bird, mammal, conifer, cycad, and cartilaginous fish species declined than improved (in decreasing order).

```
# non-binary change
change = imp_data2 %>% filter(cat_change != 'NA')

ggplot(change, aes(x=cat_change)) + geom_histogram(binwidth=1) + ggtitle("Distribution of Status Change")
```

Distribution of Status Change Across Species



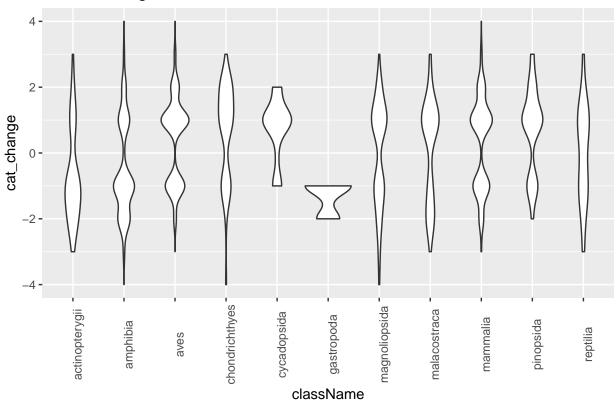
 ${\tt ggplot(change, aes(x=className, y=cat_change)) + geom_boxplot() + theme(\underbrace{axis.text.x} = element_text(\underbrace{angleto.pdf}) + \underbrace{aes(x=className, y=cat_change)}) + \underbrace{aes(x=className, y=cat_change)})$

Status Change Across Class and a magnoliopsida magnoliopsida magnoliopsida pinopsida pinopsida magnoliopsida magn

ggplot(change, aes(x=className, y=cat_change)) + geom_violin() + theme(axis.text.x = element_text(angle

className

Status Change Across Class



For nonbinary changes, the classes with the median cat_change below 0 (improve, downlisting) are ray-finned fish, amphibians, and gastropoda. The remaining species have a median change above 0. However, it is notable that all species have an interquartile range that encompasses 0 except for cycadopsida and gastropoda. Birds, mammals, reptiles, and most plants have the median at the upper end of the IQR and above 0 (decline, uplisting).

Body Mass Calculations

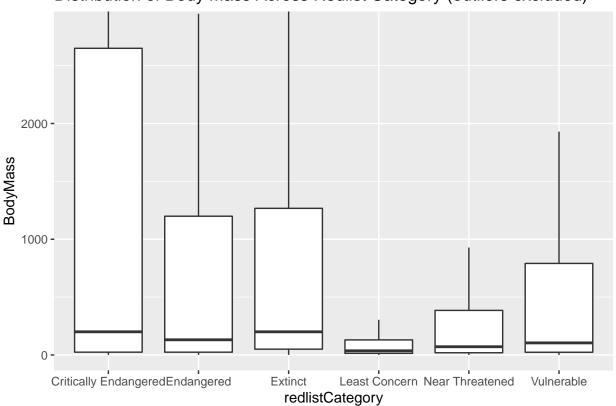
```
# average body mass of each red list category and overall
mass = imp_data2 %>% filter(BodyMass != 'NA')
mean(mass$BodyMass)
## [1] 55947.81
```

mass_list = mass %>% group_by(redlistCategory) %>% summarize(AvgMass = mean(BodyMass), MedMass = median
mass_list

```
# A tibble: 8 x 3
##
##
     redlistCategory
                            AvgMass MedMass
##
     <chr>>
                                       <dbl>
                               <dbl>
## 1 Endangered
                            299307.
                                       131
## 2 Data Deficient
                            116923.
                                        33.4
## 3 Extinct in the Wild
                              87280. 74531.
## 4 Critically Endangered
                              86282.
                                       200.
```

```
## 5 Vulnerable
                             80451.
                                      104.
## 6 Near Threatened
                             41419.
                                       71
                             29065.
## 7 Least Concern
                                       36.0
## 8 Extinct
                             8582.
                                      200
# same but with population trend
mass_pop = mass %>% group_by(populationTrend) %>% summarize(AvgMass = mean(BodyMass), MedMass = median(
mass_pop
## # A tibble: 5 x 3
     populationTrend AvgMass MedMass
##
     <chr>
                        <dbl>
                                <dbl>
                     667111.
                                 78.5
## 1 Increasing
                                 37.3
## 2 Unknown
                      91307.
                                200
## 3 <NA>
                       13426.
## 4 Decreasing
                       9422.
                                 69
                                 30.0
## 5 Stable
                        8280.
# body mass boxplot without outliers
body_out = imp_data %>% filter(BodyMass != 'NA') %% filter(redlistCategory != 'Data Deficient') %>% fi
ggplot(body_out, aes(x=redlistCategory, y=BodyMass)) + geom_boxplot(outlier.shape = NA) + coord_cartesi
```

Distribution of Body Mass Across Redlist Category (outliers excluded)



The average body mass is generally higher for uplisted species on the red list. The average body mass is generally higher for species who have increasing population trends as compared to those with decreasing or stable trends (this may be in part due to differences in sample size).

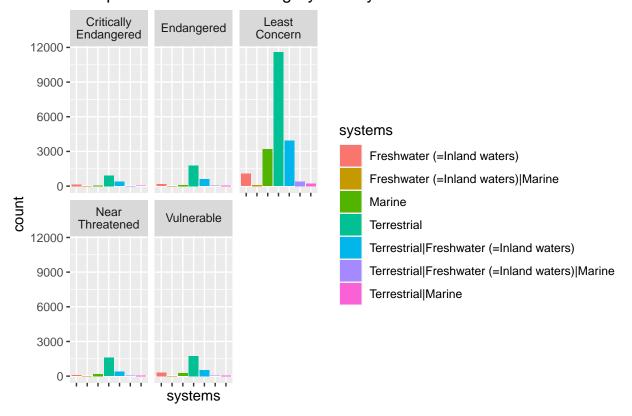
The median body mass is lower for species of least concern and near threatened as compared to the median body mass of other categories. (when outliers are ignored)

Systems

I thought this might be interesting, even though you didn't mention looking at it.

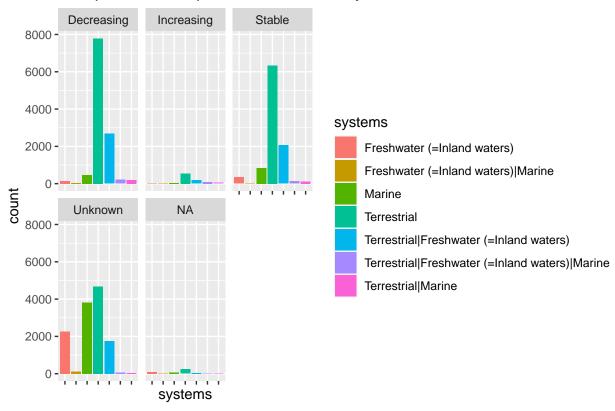
```
# filter out small, NA systems
system = imp_data2 %>% filter(systems != '<NA>') %>% filter(systems != 'Marine|Marine') %>% filter(syst
# filter irrelevant categories
system2 = system %>% filter(redlistCategory == 'Critically Endangered' | redlistCategory == 'Endangered
# compare system and redlistCategory
ggplot(system2, aes(x=systems, fill=systems)) + geom_bar() + facet_wrap(~redlistCategory, labeller = labeller = labeller)
```

Comparison of Redlist Category and System



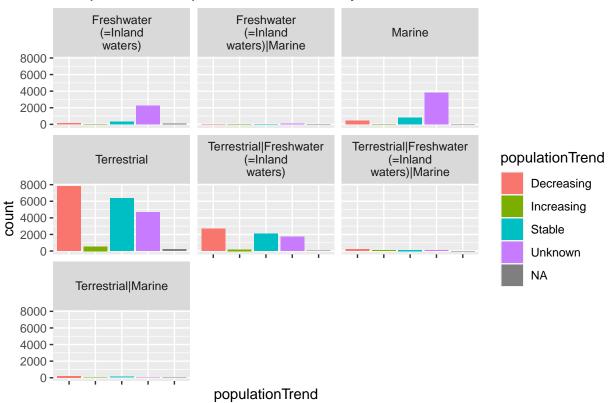
```
# compare system and populationTrend
ggplot(system, aes(x=systems, fill=systems)) + geom_bar() + facet_wrap(~populationTrend) + theme(axis.t
```

Comparison of Population Trend and System



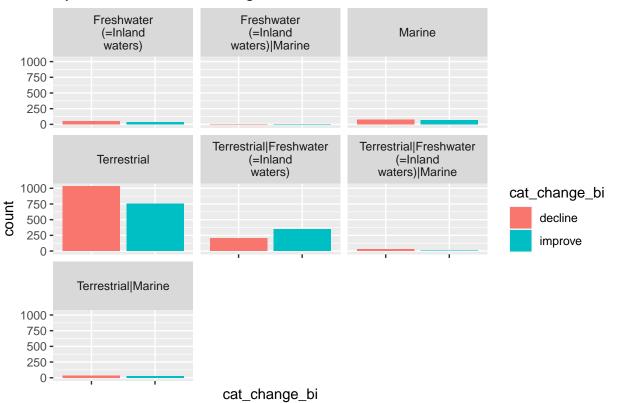
ggplot(system, aes(x=populationTrend, fill=populationTrend)) + geom_bar() + facet_wrap(~systems, labell

Comparison of Population Trend and System

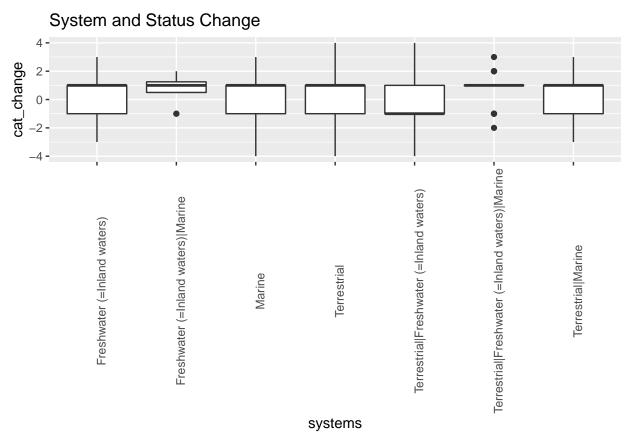


```
# compare system and cat_change_bi
system_bi = system %>% filter(cat_change_bi != 'NA')
ggplot(system_bi, aes(x=cat_change_bi, fill=cat_change_bi)) + geom_bar() + facet_wrap(~systems, labelle
```

System and Status Change



```
# system and cat_change
system_change = system %>% filter(cat_change != 'NA')
ggplot(system_change, aes(x=systems, y=cat_change)) + geom_boxplot() + theme(axis.text.x = element_text
```



The majority of systems are in the least concern category. However, of the categories that are not least concern, the systems with the most species are terrestrial and freshwater inland waters. A small portion of Near Threatened and Vulnerable are marine.

Similarly, terrestrial and freshwater inland water systems have the highest number of species with decreasing population trends. The systems with stable species are in decreasing order: terrestrial, terrestrial freshwater inland, marine, freshwater. Only terrestrial has a noticeable number of species that have increasing trends.

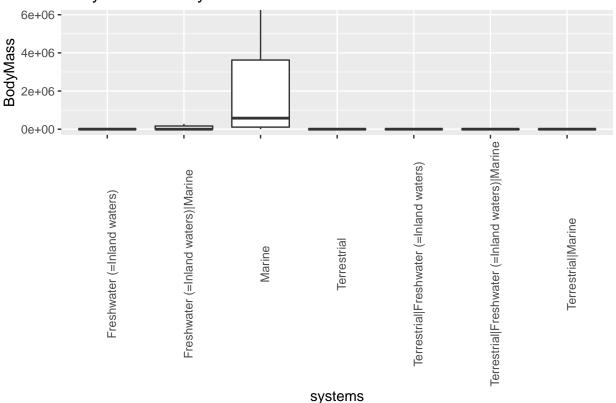
Within the binary change categories, terrestrial had the most change, with more species in decline than improving. Terrestrial freshwater inland had more improved than decline. Marine systems were relatively equal.

Within nonbinary change, the species with median negative -1 change were terrestrial inland freshwater. The remaining systems had a median positive +1 change. ALL IQRs were from -1 to 1 except for freshwater/marine and terrestrial/freshwater/marine, which both had IQRs above 0 cat_change.

For fun

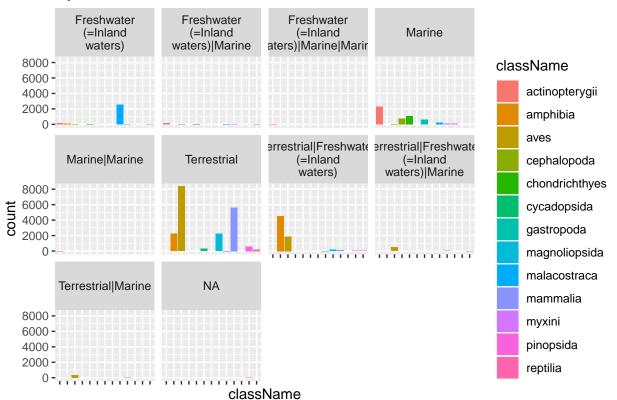
```
# compare system and class, bodymass
ggplot(system, aes(x=systems, y=BodyMass)) + geom_boxplot(outlier.shape = NA) + coord_cartesian(ylim = outlier.shape)
```

Body Mass and System

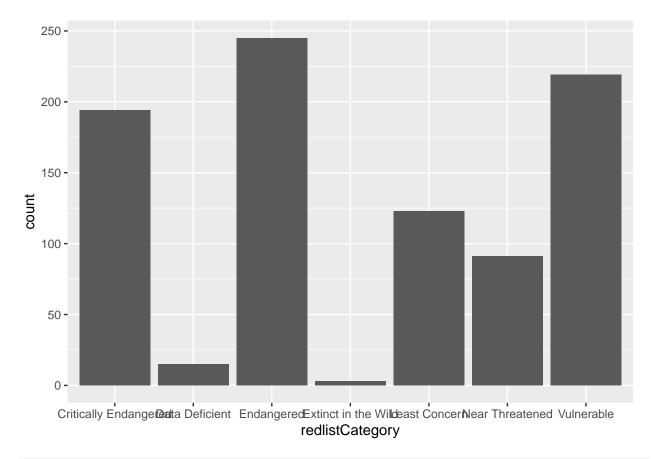


```
# average body mass of each system
mass_system = mass %>% group_by(systems) %>% summarize(AvgMass = mean(BodyMass), MedMass = median(BodyM
mass_system
## # A tibble: 7 x 3
     systems
                                                       AvgMass MedMass
##
     <chr>
                                                         <dbl>
##
                                                                  <dbl>
## 1 Marine
                                                     8676310. 578750
## 2 Freshwater (=Inland waters)|Marine
                                                       104567.
                                                                 1156.
## 3 Freshwater (=Inland waters)
                                                        27856.
                                                                  681.
                                                                  490.
## 4 Terrestrial | Marine
                                                        25999.
## 5 Terrestrial|Freshwater (=Inland waters)|Marine
                                                        5061.
                                                                  323.
## 6 Terrestrial
                                                         3650.
                                                                   39.9
## 7 Terrestrial|Freshwater (=Inland waters)
                                                         2300.
                                                                   34.9
# turns out marine is like wayyyyy bigger !!
# class
ggplot(imp_data2, aes(x=className, fill=className)) + geom_bar() + facet_wrap(~systems, labeller = labe
```

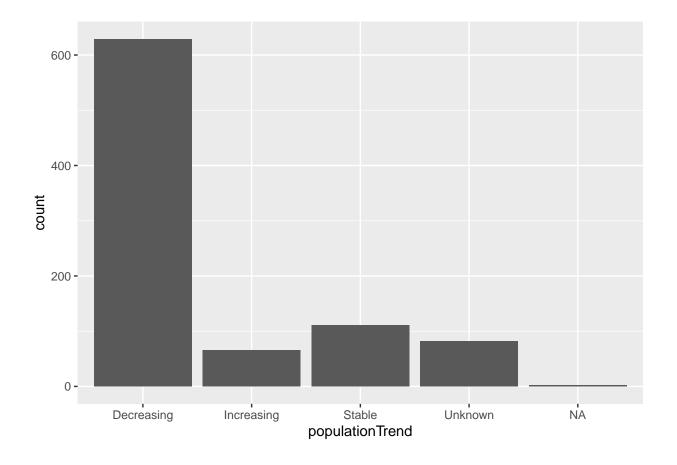
System and Class



```
# education
# it seems education is focused on more threatened species
edu = data %>% filter(education == TRUE)
ggplot(edu, aes(x=redlistCategory)) + geom_bar()
```



ggplot(edu, aes(x=populationTrend)) + geom_bar()



Amphibian Study

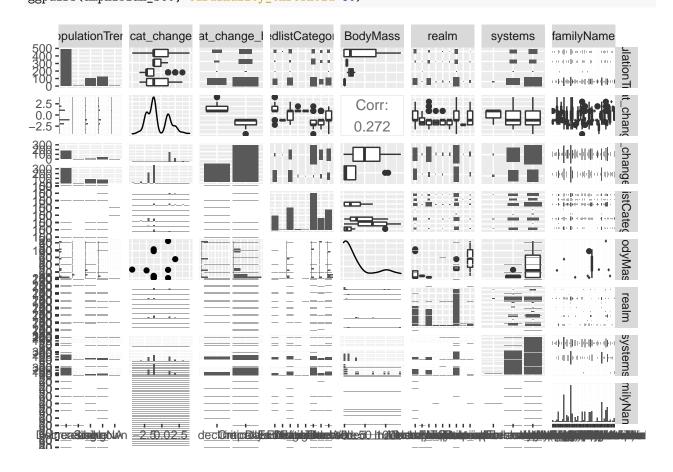
```
amphibian = data %>% filter(className == 'amphibia') %>% filter(cat_change_bi != 'NA')
amphibian %>% group_by(familyName) %>% summarize(Sum = n()) %>% arrange(-Sum)
```

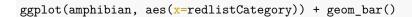
```
## # A tibble: 45 x 2
      familyName
##
                      Sum
      <chr>
                    <int>
##
## 1 craugastoridae
                      113
## 2 bufonidae
                       83
## 3 plethodontidae
## 4 rhacophoridae
                       45
## 5 ranidae
## 6 microhylidae
                       33
## 7 hyperoliidae
                       32
## 8 arthroleptidae
## 9 hylidae
                       31
## 10 mantellidae
## # ... with 35 more rows
amphibian %>% group_by(systems) %>% summarize(Sum = n()) %>% arrange(-Sum)
```

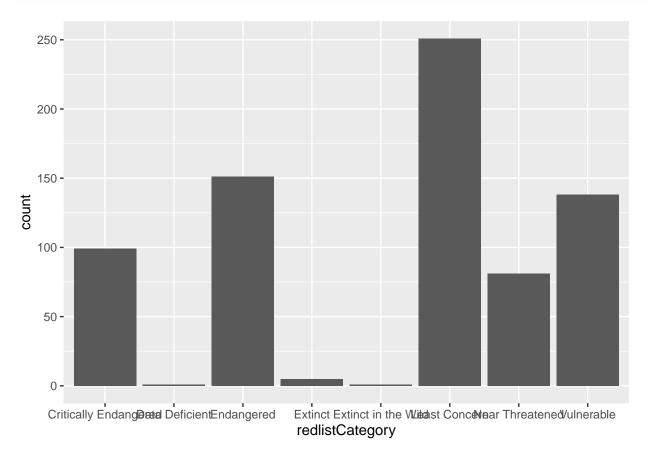
```
## # A tibble: 3 x 2
##
     systems
                                                 Sum
     <chr>
##
                                               <int>
## 1 Terrestrial|Freshwater (=Inland waters)
                                                 441
## 2 Terrestrial
                                                 280
## 3 Freshwater (=Inland waters)
                                                   6
amphibian %>% group_by(realm) %>% summarize(Sum = n()) %>% arrange(-Sum)
## # A tibble: 9 x 2
##
     realm
                               Sum
```

<chr> <int> ## ## 1 Neotropical 337 ## 2 Afrotropical 181 ## 3 Indomalayan 157 ## 4 Palearctic 25 ## 5 Nearctic 9 7 ## 6 Nearctic|Neotropical ## 7 Indomalayan|Palearctic 6 ## 8 Australasian 4 ## 9 Oceanian 1

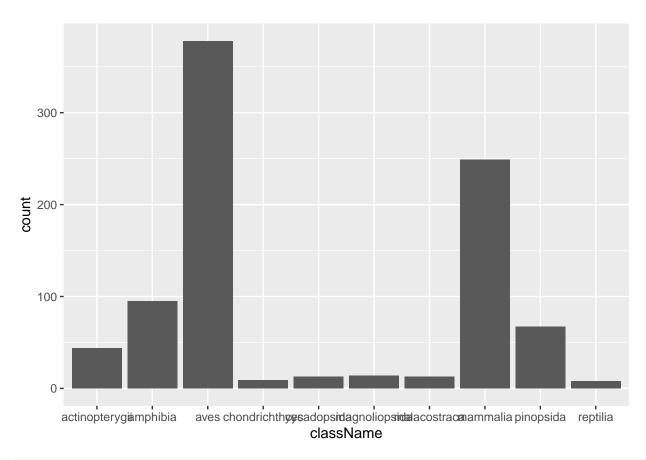
pull out population trend, cat_change, cat_change_bi, redlistCategory, bodymass, realm, systems, fami
amphibian_set = amphibian %>% select(populationTrend, cat_change, cat_change_bi, redlistCategory, BodyM
ggpairs(amphibian_set, cardinality_threshold=80)



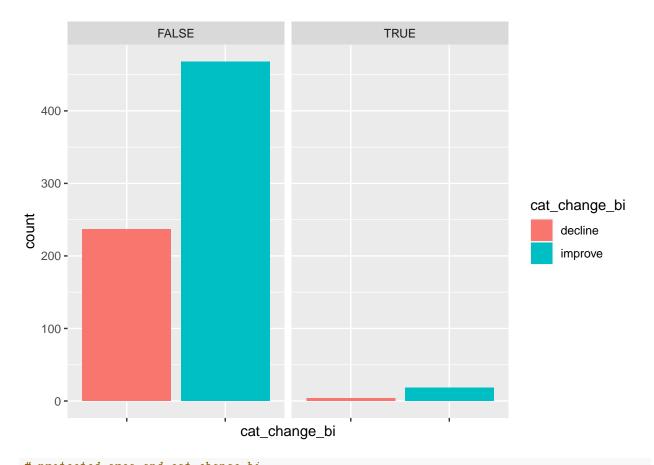




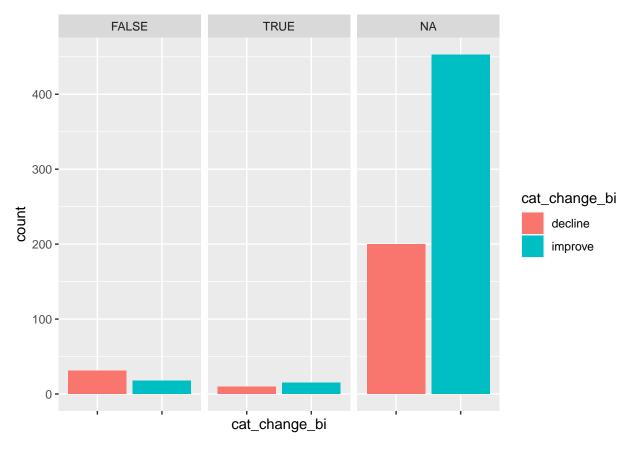
```
# education and cat_change_bi
education = data %>% filter(education == TRUE)
ggplot(education, aes(x=className)) + geom_bar()
```



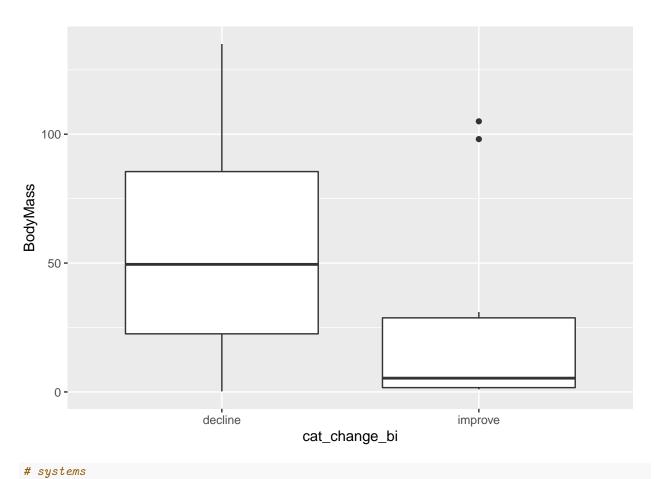
ggplot(amphibian, aes(x=cat_change_bi, fill=cat_change_bi)) + geom_bar() + facet_wrap(~education) + the



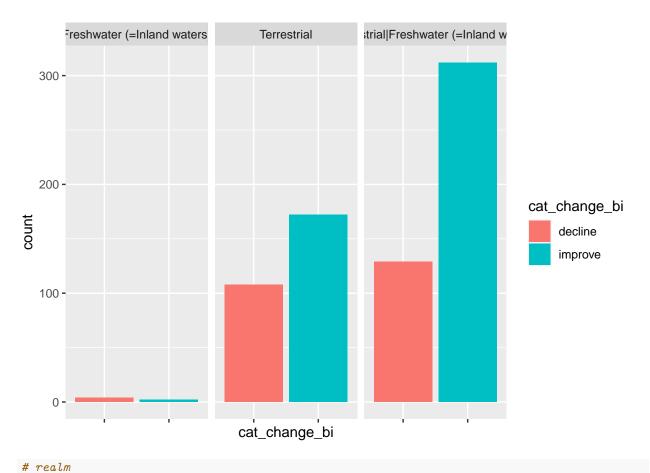
protected area and cat_change_bi
ggplot(amphibian, aes(x=cat_change_bi, fill=cat_change_bi)) + geom_bar() + facet_wrap(~aohPA_prop) + th



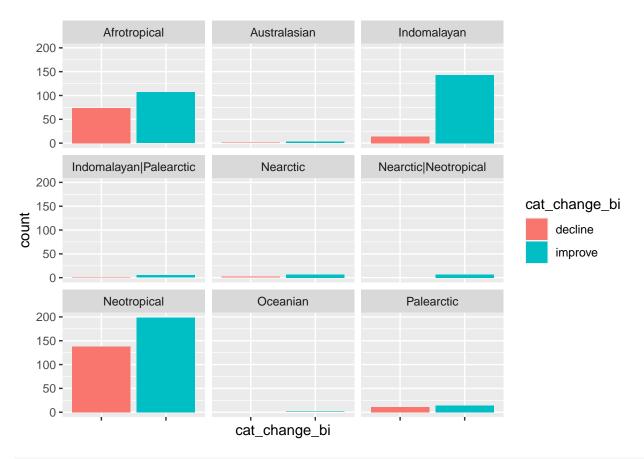
```
# body mass and cat_change_bi
# improving species have smaller body mass
ggplot(amphibian, aes(x=cat_change_bi, y=BodyMass)) + geom_boxplot()
```



```
# systems
# improving more in terrestrial - associated lands
ggplot(amphibian, aes(x=cat_change_bi, fill=cat_change_bi)) + geom_bar() + facet_wrap(~systems) + theme
```



realm
doesn't seem to have much of a correlation with realm, although indomalayan notably has a large diffe
ggplot(amphibian, aes(x=cat_change_bi, fill=cat_change_bi)) + geom_bar() + facet_wrap(~realm) + theme(a



```
# red list category
# critically endangered and endangered are declining
# up listed categories are improving
ggplot(amphibian, aes(x=realm, fill=cat_change_bi)) + geom_bar() + facet_wrap(~redlistCategory) + theme
```



most endangered and critically endangered species are neotropical (which is improving!) and afrotropi
largest population in least concern is indomalayn (which are also improving)

Largest factors affecting cat_change_bi seem to be body mass and redlistCategory.