Semester Project: Endangered Species Across the United States

Loading Packages and Datasets

In [322…]
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
from scipy import stats
from sklearn.preprocessing import LabelEncoder
from sklearn.feature_selection import chi2
from sklearn.model_selection import train_test_split, cross_val_score
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, confusion_matrix, accuracy_score
from yellowbrick.classifier import ConfusionMatrix
from yellowbrick.classifier import ClassificationReport
from yellowbrick.classifier import ROCAUC
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import RandomForestRegressor
from pprint import pprint
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
from scipy.stats import chi2_contingency
from sklearn import neighbors
```

In [2]:
```
parks = pd.read_csv(r"C:\Users\datre\OneDrive\Documents\Graduate School\Winter '20\parks.csv")
species = pd.read_csv(r"C:\Users\datre\OneDrive\Documents\Graduate School\Winter '20\species.csv")
```

```
C:\Users\datre\Anaconda3\lib\site-packages\IPython\core\interactiveshell.py:3147: DtypeWarning: Columns (13) have m
ixed types.Specify dtype option on import or set low_memory=False.
  interactivity=interactivity, compiler=compiler, result=result)
```

Data Wrangling

In [3]:
```
# Looking at shape of park dataset
print(parks.shape)
parks.head(3)
```

```
(56, 6)
```

Out[3]:

	Park Code	Park Name	State	Acres	Latitude	Longitude
0	ACAD	Acadia National Park	ME	47390	44.35	-68.21
1	ARCH	Arches National Park	UT	76519	38.68	-109.57
2	BADL	Badlands National Park	SD	242756	43.75	-102.50

In [4]:
```
# Looking at shape of species dataset
print(species.shape)
species.head(3)
```

```
(119248, 14)
```

Out[4]:

	Species ID	Park Name	Category	Order	Family	Scientific Name	Common Names	Record Status	Occurrence	Nativeness	Abundance	Seasonality
0	ACAD-1000	Acadia National Park	Mammal	Artiodactyla	Cervidae	Alces alces	Moose	Approved	Present	Native	Rare	Resident
1	ACAD-1001	Acadia National Park	Mammal	Artiodactyla	Cervidae	Odocoileus virginianus	Northern White-Tailed Deer, Virginia Deer, Whi...	Approved	Present	Native	Abundant	NaN

	Species ID	Park Name	Category	Order	Family	Scientific Name	Common Names	Record Status	Occurrence	Nativeness	Abundance	Seasonality
2	ACAD-1002	Acadia National Park	Mammal	Carnivora	Canidae	Canis latrans	Coyote, Eastern Coyote	Approved	Present	Not Native	Common	NaN

In [5]:
```
# Merging on park name to overlay state, acres, and latitude/longitude
sp = pd.merge(parks, species, on="Park Name")
print(sp.shape)
sp.head()
```

```
(119248, 19)
```

Out[5]:

	Park Code	Park Name	State	Acres	Latitude	Longitude	Species ID	Category	Order	Family	Scientific Name	Common Names	Record Status	Occurr
0	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1000	Mammal	Artiodactyla	Cervidae	Alces alces	Moose	Approved	Pr
1	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1001	Mammal	Artiodactyla	Cervidae	Odocoileus virginianus	Northern White-Tailed Deer, Virginia Deer, Whi...	Approved	Pr
2	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1002	Mammal	Carnivora	Canidae	Canis latrans	Coyote, Eastern Coyote	Approved	Pr
3	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1003	Mammal	Carnivora	Canidae	Canis lupus	Eastern Timber Wolf, Gray Wolf, Timber Wolf	Approved	Confi
4	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1004	Mammal	Carnivora	Canidae	Vulpes vulpes	Black Fox, Cross Fox, Eastern Red Fox, Fox, Re...	Approved	Pr

In [6]:
```
# Taking out non-final conservation status such as proposed or unknown
sp_danger = sp[sp["Conservation Status"].isin(["Endangered", "Threatened","In Recovery", "Species of Concern"])]
print(sp_danger.shape)
sp_danger.head(3)
```

```
(4478, 19)
```

Out[6]:

	Park Code	Park Name	State	Acres	Latitude	Longitude	Species ID	Category	Order	Family	Scientific Name	Common Names	Record Status	C
2	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1002	Mammal	Carnivora	Canidae	Canis latrans	Coyote, Eastern Coyote	Approved	
3	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1003	Mammal	Carnivora	Canidae	Canis lupus	Eastern Timber Wolf, Gray Wolf, Timber Wolf	Approved	

	Park Code	Park Name	State	Acres	Latitude	Longitude	Species ID	Category	Order	Family	Scientific Name	Common Names	Record Status	C
20	ACAD	Acadia National Park	ME	47390	44.35	-68.21	ACAD-1020	Mammal	Chiroptera	Vespertilionidae	Eptesicus fuscus	Big Brown Bat, Common Brown Bat	Approved	

For consistency, I chose the conservation status rows that have a definite label, versus NaN or proposed labels.

In [7]:
```
# Examining the labels and types of data in dataset
sp_danger.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 4478 entries, 2 to 118992
Data columns (total 19 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   Park Code            4478 non-null   object
 1   Park Name            4478 non-null   object
 2   State                4478 non-null   object
 3   Acres                4478 non-null   int64
 4   Latitude             4478 non-null   float64
 5   Longitude            4478 non-null   float64
 6   Species ID           4478 non-null   object
 7   Category             4478 non-null   object
 8   Order                4473 non-null   object
 9   Family               4473 non-null   object
 10  Scientific Name      4478 non-null   object
 11  Common Names         4478 non-null   object
 12  Record Status        4478 non-null   object
 13  Occurrence           4254 non-null   object
 14  Nativeness           4218 non-null   object
 15  Abundance            3427 non-null   object
 16  Seasonality          2646 non-null   object
 17  Conservation Status  4478 non-null   object
 18  Unnamed: 13          0 non-null      object
dtypes: float64(2), int64(1), object(16)
memory usage: 699.7+ KB
```

Off of knowledge, features we will not need in the project include: Park Code, Species ID, Order, Family, Common Names, Record Status, Seasonality, and Unnammed: 13.

In [8]:
```
# Taking out featuers that are redundant
sp = sp_danger[["Park Name", "State", "Acres", "Latitude", "Longitude", "Category", "Occurrence", "Nativeness", "Co
sp
```

Out[8]:

	Park Name	State	Acres	Latitude	Longitude	Category	Occurrence	Nativeness	Conservation Status
2	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Not Native	Species of Concern
3	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Not Confirmed	Native	Endangered
20	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Native	Species of Concern
21	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Native	Species of Concern
24	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Native	Species of Concern
...	...	...	...	...	...	...	...	...	...
118628	Zion National Park	UT	146598	37.30	-113.05	Vascular Plant	Not Present (False Report)	Native	Species of Concern
118840	Zion National Park	UT	146598	37.30	-113.05	Vascular Plant	Present	Native	Species of Concern

	Park Name	State	Acres	Latitude	Longitude	Category	Occurrence	Nativeness	Conservation Status
118855	Zion National Park	UT	146598	37.30	-113.05	Vascular Plant	Present	Native	Species of Concern
118894	Zion National Park	UT	146598	37.30	-113.05	Vascular Plant	Present	Native	Species of Concern
118992	Zion National Park	UT	146598	37.30	-113.05	Vascular Plant	Present	Native	Species of Concern

4478 rows × 9 columns

In [9]:

```
sns.set(style = "darkgrid")
sns.set_palette("hls", 3)
# Setting figure size
plt.figure(figsize=(15,7))
# Using stack to combine categories and see total number of species per state
g1 = sns.histplot(data = sp_danger, x = "State", hue = "Category", multiple = "stack")
# Rotate labels for ease of reading
plt.setp(g1.get_xticklabels(), rotation=45)
```

Out[9]:

```
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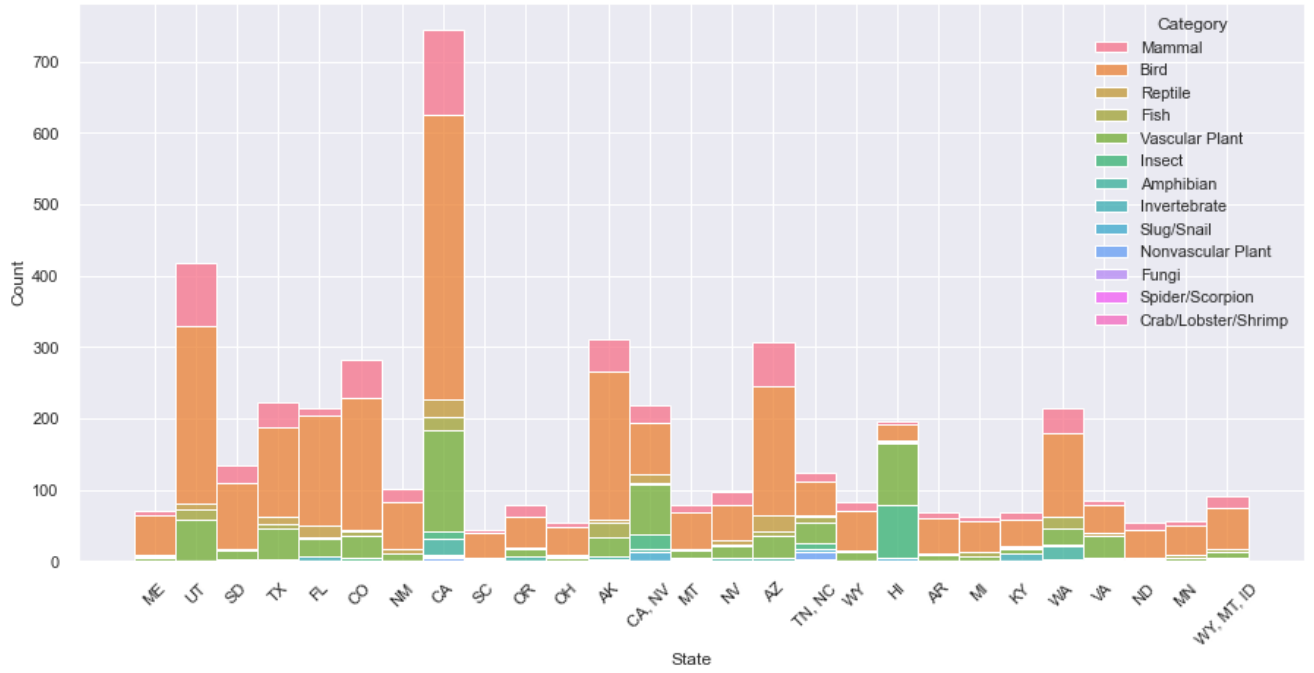
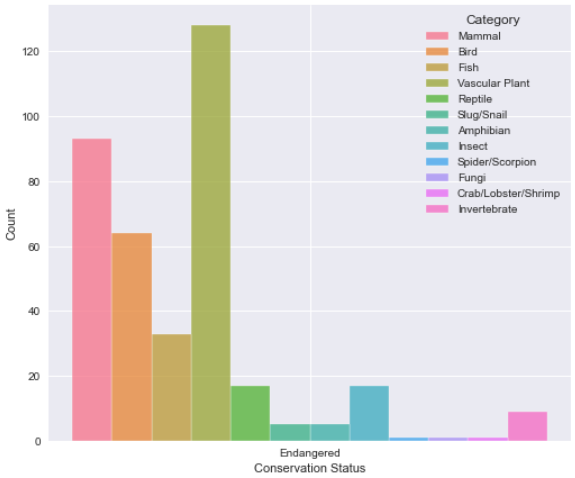
```

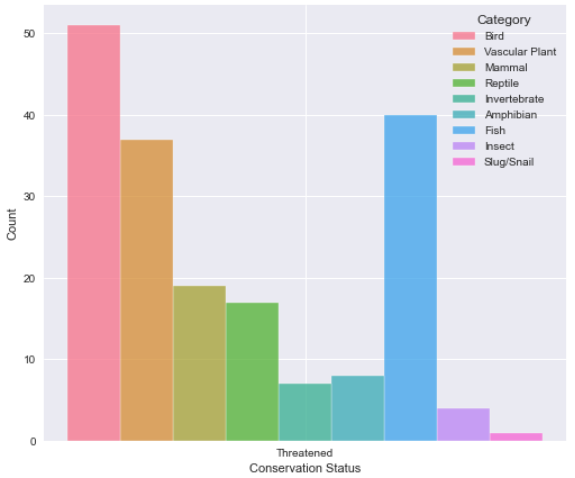


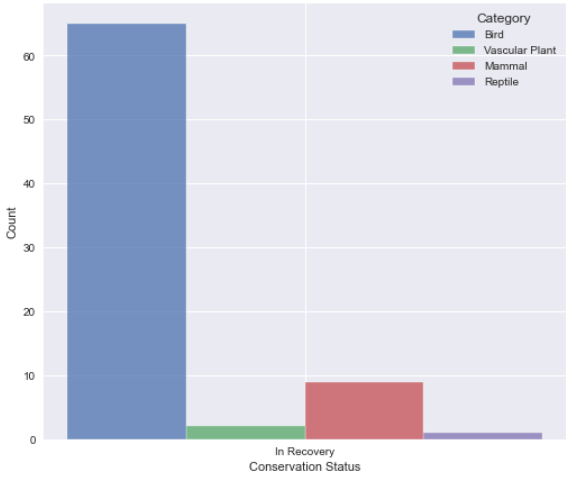
In [10]:
```
# Creating a mini dataset for each conservation status type to graph easier
end = sp[sp["Conservation Status"].isin(["Endangered"])]
threat = sp[sp["Conservation Status"].isin(["Threatened"])]
recov = sp[sp["Conservation Status"].isin(["In Recovery"])]
SOC = sp[sp["Conservation Status"].isin(["Species of Concern"])]
```

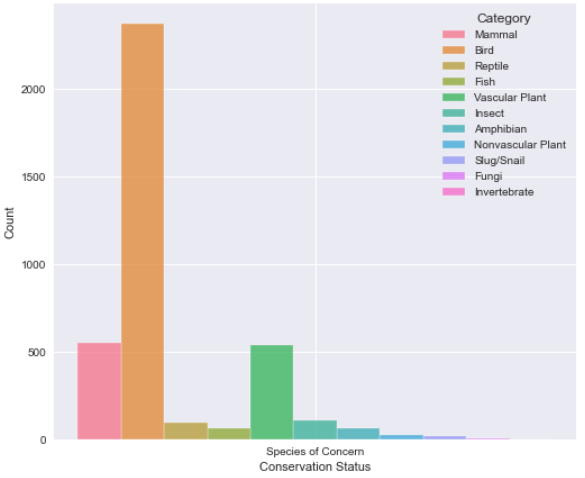
In [11]:
```
sns.set_palette("hls", 3)
plt.style.use('seaborn')
# asking for two rows and two columns of graphs
fig, axis = plt.subplots(nrows = 2, ncols = 2)
# setting size for graphs
fig.set_size_inches(20,20)
fig.subplots_adjust(wspace = 0.4, hspace = 0.8)

# plot 1
# dodge so bars are next to each other
h1 = sns.histplot(data = end, x = "Conservation Status", hue = "Category", multiple = "dodge", ax = axis[0,0])
# plot 2
h2 = sns.histplot(data = threat, x = "Conservation Status", hue = "Category", multiple = "dodge", ax = axis[0,1])
# plot 3
h3 = sns.histplot(data = recov, x = "Conservation Status", hue = "Category", multiple = "dodge", ax = axis[1,0])
# plot 4
h4 = sns.histplot(data = SOC, x = "Conservation Status", hue = "Category", multiple = "dodge", ax = axis[1,1])
```









Correlation and Heat Map

One-Hot Encoding

In [12]:
```
sp1 = sp.copy()
```

In [13]:
```
# creates column for each type in feature to give binomial data
for column in ["Category", "Nativeness"]:
    dummies = pd.get_dummies(sp1[column])
    # adding back to the dataset
    sp1[dummies.columns] = dummies
```

In [14]:
```
# seeing the added dummy columns
for col in sp1.columns:
    print(col, ":", len(sp1[col].unique()), "labels")
```

```
Park Name : 56 labels
State : 27 labels
Acres : 55 labels
Latitude : 53 labels
Longitude : 55 labels
Category : 13 labels
Occurrence : 6 labels
```

```
Nativeness : 4 labels
Conservation Status : 4 labels
Amphibian : 2 labels
Bird : 2 labels
Crab/Lobster/Shrimp : 2 labels
Fish : 2 labels
Fungi : 2 labels
Insect : 2 labels
Invertebrate : 2 labels
Mammal : 2 labels
Nonvascular Plant : 2 labels
Reptile : 2 labels
Slug/Snail : 2 labels
Spider/Scorpion : 2 labels
Vascular Plant : 2 labels
Native : 2 labels
Not Native : 2 labels
Unknown : 2 labels
```

In [15]:
```
sp1.head(3)
```

Out[15]:

	Park Name	State	Acres	Latitude	Longitude	Category	Occurrence	Nativeness	Conservation Status	Amphibian	...	Invertebrate	Mamma
2	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Not Native	Species of Concern	0	...	0	
3	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Not Confirmed	Native	Endangered	0	...	0	
20	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Native	Species of Concern	0	...	0	

3 rows × 25 columns

In [16]:
```
# taking out the columns that we dummied, as well as occurrence which I felt was not needed
sp1 = sp1.drop(["Category", "Nativeness", "Occurrence"], axis = 1)
sp1.head(3)
```

Out[16]:

	Park Name	State	Acres	Latitude	Longitude	Conservation Status	Amphibian	Bird	Crab/Lobster/Shrimp	Fish	...	Invertebrate	Mammal
2	Acadia National Park	ME	47390	44.35	-68.21	Species of Concern	0	0	0	0	...	0	1
3	Acadia National Park	ME	47390	44.35	-68.21	Endangered	0	0	0	0	...	0	1
20	Acadia National Park	ME	47390	44.35	-68.21	Species of Concern	0	0	0	0	...	0	1

3 rows × 22 columns

In [17]:
```
# I like to copy the dataset so I don't mess up the original
sp_corr = sp1.copy()
# Creating numerical values for each type of entry in features with categorical data
label_encoder = LabelEncoder()
sp_corr["Park Name"] = label_encoder.fit_transform(sp_corr["Park Name"])
sp_corr["State"] = label_encoder.fit_transform(sp_corr["State"])
sp_corr["Conservation Status"] = label_encoder.fit_transform(sp_corr["Conservation Status"])
```

In [18]:
```
corr_matrix = sp_corr.corr()
corr_matrix
```

Out[18]:

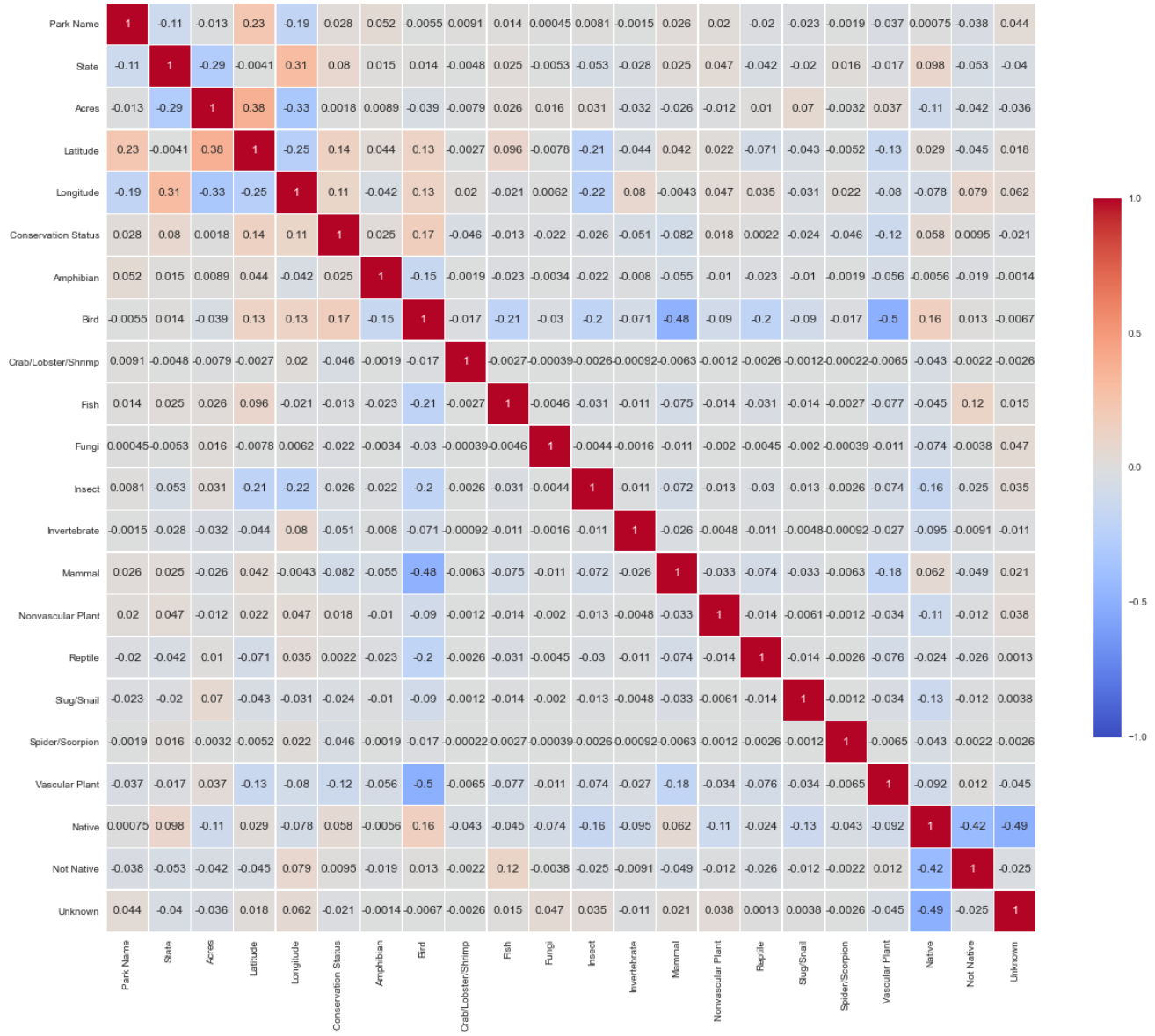
	Park Name	State	Acres	Latitude	Longitude	Conservation Status	Amphibian	Bird	Crab/Lobster/Shrimp
Park Name	1.000000	-0.111757	-0.012628	0.227961	-0.189064	0.028289	0.051610	-0.005474	0.009141
State	-0.111757	1.000000	-0.288115	-0.004090	0.308933	0.080314	0.015107	0.013818	-0.004797
Acres	-0.012628	-0.288115	1.000000	0.382716	-0.327344	0.001823	0.008941	-0.039306	-0.007916
Latitude	0.227961	-0.004090	0.382716	1.000000	-0.250196	0.135262	0.044278	0.127081	-0.002739
Longitude	-0.189064	0.308933	-0.327344	-0.250196	1.000000	0.106659	-0.042402	0.128564	0.019785
Conservation Status	0.028289	0.080314	0.001823	0.135262	0.106659	1.000000	0.024683	0.165054	-0.045508
Amphibian	0.051610	0.015107	0.008941	0.044278	-0.042402	0.024683	1.000000	-0.149144	-0.001937
Bird	-0.005474	0.013818	-0.039306	0.127081	0.128564	0.165054	-0.149144	1.000000	-0.017196
Crab/Lobster/Shrimp	0.009141	-0.004797	-0.007916	-0.002739	0.019785	-0.045508	-0.001937	-0.017196	1.000000
Fish	0.013780	0.025182	0.025835	0.095829	-0.021016	-0.012887	-0.023201	-0.205933	-0.002675
Fungi	0.000452	-0.005306	0.016361	-0.007763	0.006157	-0.022228	-0.003356	-0.029791	-0.000387
Insect	0.008127	-0.053347	0.030601	-0.207982	-0.222343	-0.025663	-0.022236	-0.197367	-0.002564
Invertebrate	-0.001527	-0.027820	-0.031545	-0.043933	0.080425	-0.051012	-0.008002	-0.071027	-0.000923
Mammal	0.026259	0.024837	-0.025839	0.042490	-0.004308	-0.081636	-0.054516	-0.483888	-0.006285
Nonvascular Plant	0.019621	0.046635	-0.012152	0.022015	0.046666	0.018282	-0.010096	-0.089612	-0.001164
Reptile	-0.019615	-0.042112	0.010408	-0.070895	0.035440	0.002240	-0.022679	-0.201301	-0.002615
Slug/Snail	-0.022755	-0.019977	0.069785	-0.043225	-0.030691	-0.024291	-0.010096	-0.089612	-0.001164
Spider/Scorpion	-0.001883	0.016014	-0.003159	-0.005235	0.021764	-0.045508	-0.001937	-0.017196	-0.000223
Vascular Plant	-0.036952	-0.017459	0.036893	-0.134650	-0.079653	-0.120953	-0.055986	-0.496935	-0.006455
Native	0.000753	0.097603	-0.105499	0.029234	-0.077660	0.058418	-0.005554	0.158619	-0.042883
Not Native	-0.037980	-0.053411	-0.041709	-0.045026	0.079238	0.009461	-0.019186	0.013425	-0.002212
Unknown	0.043953	-0.039632	-0.035695	0.018379	0.061806	-0.020874	-0.001380	-0.006709	-0.002574

22 rows × 22 columns

In [19]:

```
# setting figure size
f, ax = plt.subplots(figsize=(21,25))
heatmap = sns.heatmap(corr_matrix,
                      square = True,
                      linewidths = .5,
                      cmap = "coolwarm", # choosing color type for graph
                      cbar_kws = {"shrink": .4,
                                  "ticks" : [-1, -.5, 0, 0.5, 1]},
                      vmin = -1,
                      vmax = 1,
                      annot = True,
                      annot_kws = {"size": 12})

#add the column names as labels
ax.set_yticklabels(corr_matrix.columns, rotation = 0)
ax.set_xticklabels(corr_matrix.columns)
sns.set_style({'xtick.bottom': True}, {'ytick.left': True})
```



Chi-Squared Test

H0: Two variables are independent

HA: Two variables are not indenpendent

In [20]:
```
# same as above, copying dataset
sp_cs = sp.copy()
sp_cs.head(3)
```

Out[20]:

	Park Name	State	Acres	Latitude	Longitude	Category	Occurrence	Nativeness	Conservation Status
2	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Not Native	Species of Concern
3	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Not Confirmed	Native	Endangered
20	Acadia National Park	ME	47390	44.35	-68.21	Mammal	Present	Native	Species of Concern

In [21]:
```
#creating numerical values for categorical data
label_encoder = LabelEncoder()
sp_cs["Park Name"] = label_encoder.fit_transform(sp_cs["Park Name"])
sp_cs["State"] = label_encoder.fit_transform(sp_cs["State"])
sp_cs["Conservation Status"] = label_encoder.fit_transform(sp_cs["Conservation Status"])
```

In [22]:
```
#creating binomial data for certain features
for column in ["Category", "Nativeness"]:
```

```
    dummies = pd.get_dummies(sp_cs[column])
    sp_cs[dummies.columns] = dummies
```

In [23]:
```
#dropping lat and lon because they have negatives, occurrence because not needed, and dummied features
sp_cs = sp_cs.drop(["Latitude", "Longitude", "Occurrence", "Category", "Nativeness"], axis = 1)
```

In [24]:
```
sp_cs.head(3)
```

Out[24]:

	Park Name	State	Acres	Conservation Status	Amphibian	Bird	Crab/Lobster/Shrimp	Fish	Fungi	Insect	Invertebrate	Mammal	Nonvascular Plant
2	0	9	47390	2	0	0	0	0	0	0	0	1	0
3	0	9	47390	0	0	0	0	0	0	0	0	1	0
20	0	9	47390	2	0	0	0	0	0	0	0	1	0

In [25]:
```
# taking out conservation status as variable to compare to all others
X = sp_cs.drop("Conservation Status",axis=1)
y = sp_cs["Conservation Status"]
```

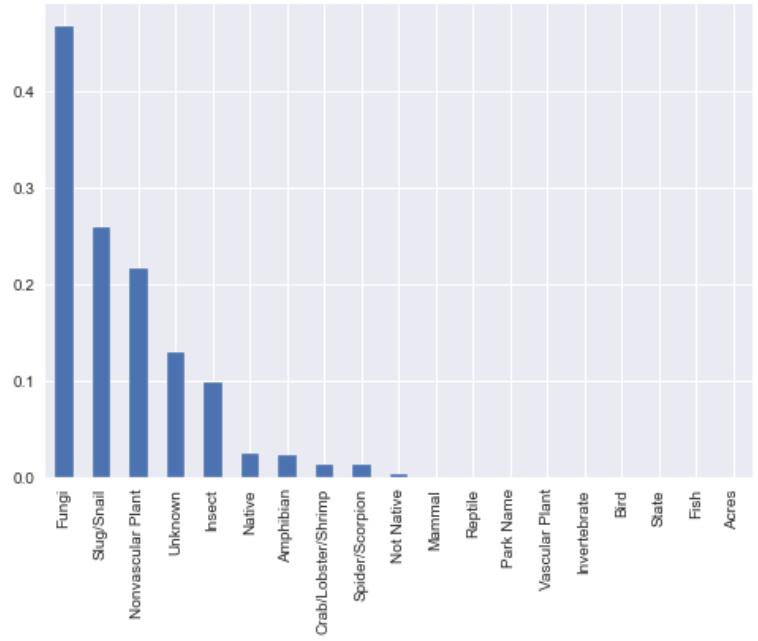
In [26]:
```
chi_scores = chi2(X,y)
chi_scores
```

Out[26]:
```
(array([4.66406416e+01, 2.39688979e+02, 1.21409893e+07, 9.68564916e+00,
        1.57187758e+02, 1.09732620e+01, 2.71458839e+02, 2.54473467e+00,
        6.30035306e+00, 1.10265314e+02, 2.84932001e+01, 4.46135831e+00,
        3.04791781e+01, 4.01990221e+00, 1.09732620e+01, 9.96045964e+01,
        9.44775324e+00, 1.42196182e+01, 5.67884800e+00]),
 array([4.14442865e-10, 1.11112871e-51, 0.00000000e+00, 2.14362146e-02,
        7.41307802e-34, 1.18713400e-02, 1.49226269e-58, 4.67260746e-01,
        9.78775041e-02, 9.62137895e-24, 2.86154886e-06, 2.15763044e-01,
        1.09415314e-06, 2.59323055e-01, 1.18713400e-02, 1.89022191e-21,
        2.38937234e-02, 2.62095610e-03, 1.28324360e-01]))
```

In [27]:
```
# pulling out p-values of chi-squared test
p_values = pd.Series(chi_scores[1],index = X.columns)
p_values.sort_values(ascending = False , inplace = True)
```

In [28]:
```
# plotting p-values for ease of understanding and interpretation
p_values.plot.bar()
```

Out[28]:
```
<AxesSubplot:>
```



Since Insect, Unknown, Nonvascular Plant, Slug/Snail, and Fungi have high p-values (above 0.05), they should be removed since they are independent of Conservation Status.

Creating dataset for test train splits

In [224…
```
# Dropping features from the chi-squared test results that are independent of Conservation Status
sp_tt = sp_cs.drop(["Fungi", "Slug/Snail", "Nonvascular Plant", "Unknown", "Insect"],axis=1)
```

In [225…
```
# Confirming features dropped
print(sp_tt.shape)
sp_tt.head(3)
```

```
(4478, 15)
```

Out[225…

	Park Name	State	Acres	Conservation Status	Amphibian	Bird	Crab/Lobster/Shrimp	Fish	Invertebrate	Mammal	Reptile	Spider/Scorpion
2	0	9	47390	2	0	0	0	0	0	1	0	0
3	0	9	47390	0	0	0	0	0	0	1	0	0
20	0	9	47390	2	0	0	0	0	0	1	0	0

In [226…
```
# Create dataset without target value, conservation status
data_model_x = sp_tt.drop(["Conservation Status"], axis = 1)
data_model_x.head(3)
```

Out[226…

	Park Name	State	Acres	Amphibian	Bird	Crab/Lobster/Shrimp	Fish	Invertebrate	Mammal	Reptile	Spider/Scorpion	Vascular Plant	Nativ
2	0	9	47390	0	0	0	0	0	1	0	0	0	
3	0	9	47390	0	0	0	0	0	1	0	0	0	
20	0	9	47390	0	0	0	0	0	1	0	0	0	

In [227…
```
# The target of this dataset is predicting conservation status
data_model_y = sp_tt["Conservation Status"]
data_model_y.head(3)
```

Out[227…
```
2    2
3    0
```

```
20    2
Name: Conservation Status, dtype: int32
```

In [228…

```
# Splitting into test and train sets
X_train, X_val, y_train, y_val = train_test_split(data_model_x, data_model_y, test_size =0.3, random_state=11)
print("No. of samples in training set: ", X_train.shape[0])
print("No. of samples in validation set:", X_val.shape[0])
```

```
No. of samples in training set:  3134
No. of samples in validation set: 1344
```

In [229…

```
# Stating how many of each conservation level there are
print('\n')
print('No. of each Conservation Status in training set:')
print(y_train.value_counts())

print('\n')
print('No. of each Conservation Status in the validation set:')
print(y_val.value_counts())
```

```
No. of each Conservation Status in training set:
2    2693
0     266
3     123
1      52
Name: Conservation Status, dtype: int64


No. of each Conservation Status in the validation set:
2    1150
0     108
3      61
1      25
Name: Conservation Status, dtype: int64
```

0: Endangered

1: In Recovery

2: Species of Concern

3: Threatened

Perform Logistic Regression Model

In [230…

```
# Calling logistic regression model
model = LogisticRegression()
```

In [231…

```
# Taxing model with confushion matrix
classes = ["Endangered", "In Recovery", "Species of Concern", "Threatened"]
cm = ConfusionMatrix(model, classes=classes, percent=False)

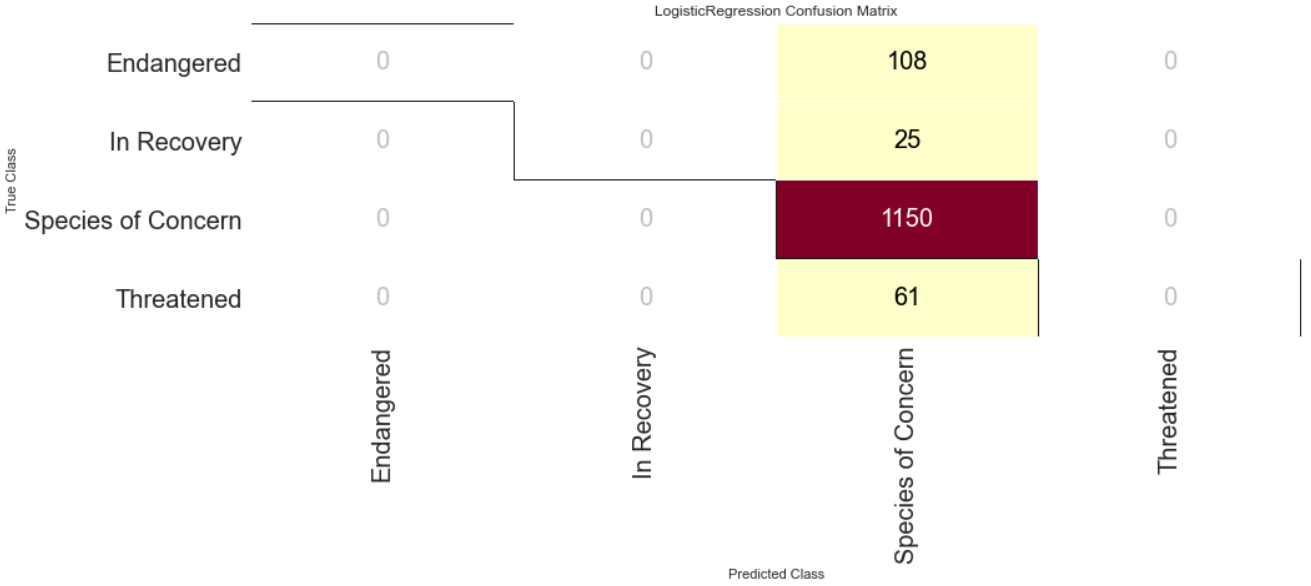
# Fitting the logistic regression model
cm.fit(X_train, y_train)

# Entering test data into mix
cm.score(X_val, y_val)

# Changing font size
for label in cm.ax.texts:
    label.set_size(20)

cm.poof()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



Out[231… <AxesSubplot:title={'center':'LogisticRegression Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Class'>

In [232…

```
%matplotlib inline
plt.rcParams['figure.figsize'] = (15, 7)
plt.rcParams['font.size'] = 20

visualizer = ClassificationReport(model, classes=classes)

# Fitting training data to visualizer
visualizer.fit(X_train, y_train)
# Entering test data to model
visualizer.score(X_val, y_val)

g = visualizer.poof()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\metrics\_classification.py:1221: UndefinedMetricWarning: Precisi
on and F-score are ill-defined and being set to 0.0 in labels with no predicted samples. Use `zero_division` parame
ter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

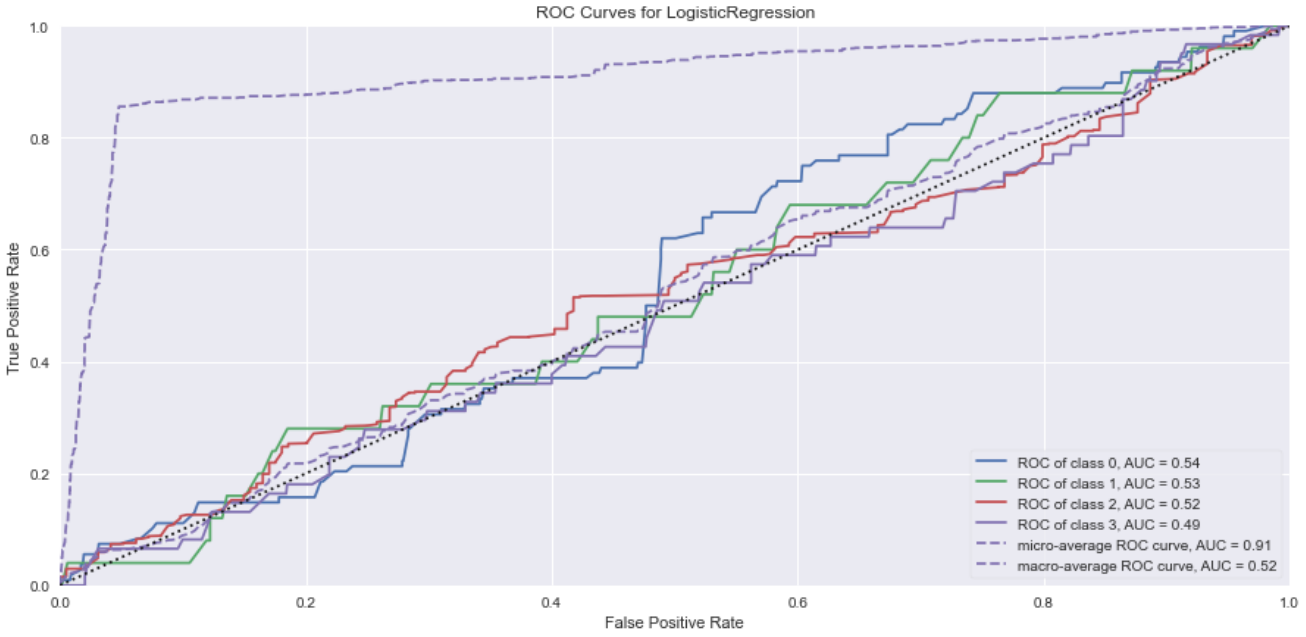
In [233…

```
visualizer = ROCAUC(model)
```

```
# Fitting training data to visualizer
visualizer.fit(X_train, y_train)
# Entering test data to model
visualizer.score(X_val, y_val)

g = visualizer.poof()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



Performing Random Forest Model

In [234…
```
rf = RandomForestClassifier(n_estimators = 1000, random_state = 42, bootstrap=True)
rf.fit(X_train, y_train)
```

Out[234… `RandomForestClassifier(n_estimators=1000, random_state=42)`

In [239…
```
# Creating predictions
y_pred = rf.predict(X_val)
```

In [242…
```
# Printing the confusion matrix, report, and accuracy to examine before visualizing
print(confusion_matrix(y_val,y_pred))
print(classification_report(y_val,y_pred))
print(accuracy_score(y_val, y_pred))
```

```
[[  45    0   60    3]
 [   1    0   24    0]
 [  23    1 1124    2]
 [   5    0   45   11]]
              precision    recall  f1-score   support

           0       0.61      0.42      0.49       108
           1       0.00      0.00      0.00        25
           2       0.90      0.98      0.94      1150
           3       0.69      0.18      0.29        61

    accuracy                           0.88      1344
   macro avg       0.55      0.39      0.43      1344
weighted avg       0.85      0.88      0.85      1344

0.8779761904761905
```

Accuracy of this prediction model is 87.79%

In [248…
```
model = RandomForestClassifier(n_estimators = 1000, random_state = 42, bootstrap = True)
```

```
# Taxing model with confushion matrix
classes = ["Endangered", "In Recovery", "Species of Concern", "Threatened"]
cm = ConfusionMatrix(model, classes=classes, percent=False)

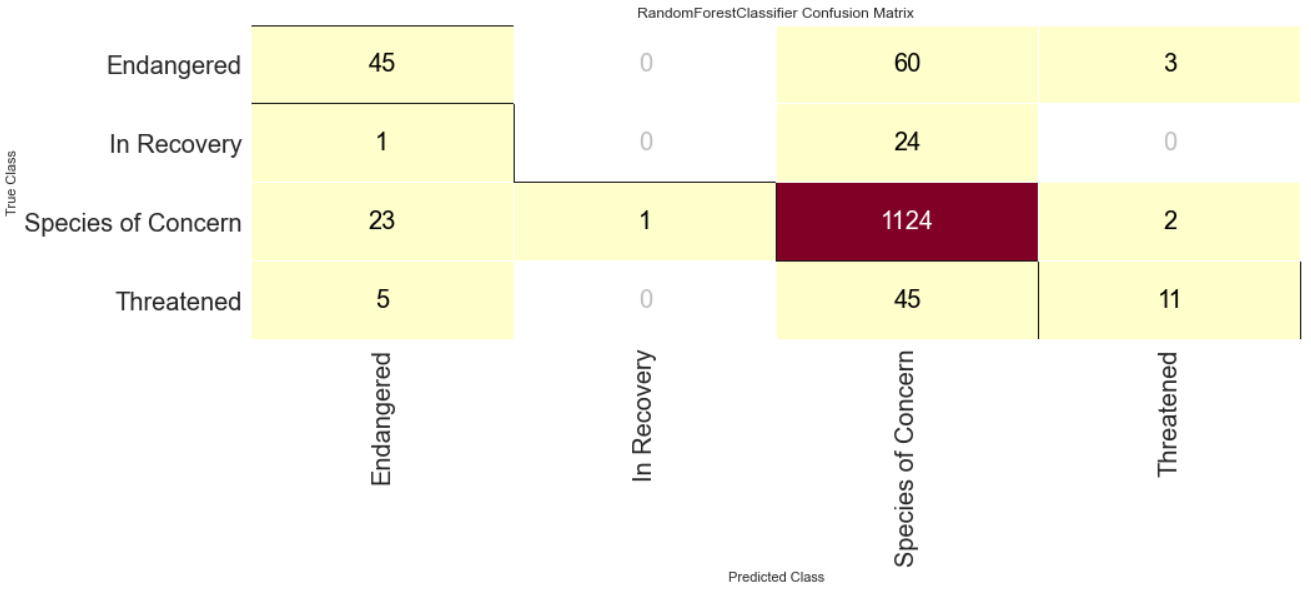
# Fitting the random forest model
cm.fit(X_train, y_train)

# Entering test data into mix
cm.score(X_val, y_val)

# Changing font size
for label in cm.ax.texts:
    label.set_size(20)

cm.poof()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



Out[248… `<AxesSubplot:title={'center':'RandomForestClassifier Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Cla
ss'>`

In [249…

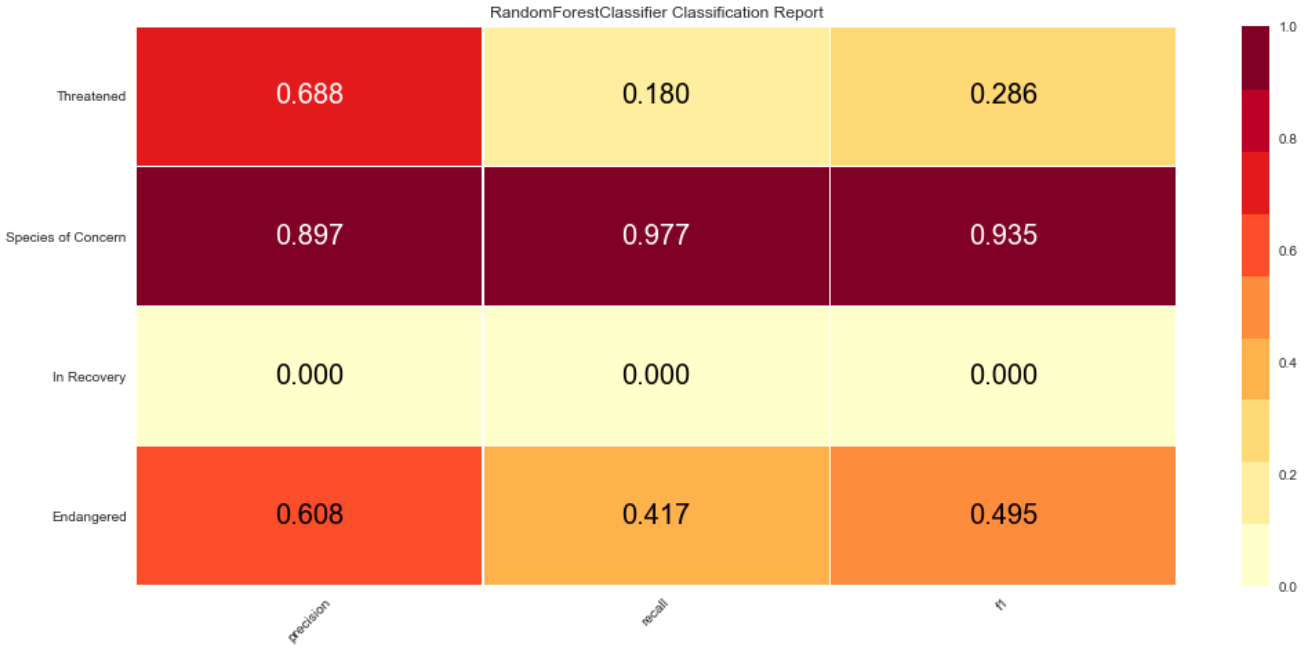
```
%matplotlib inline
plt.rcParams['figure.figsize'] = (15, 7)
plt.rcParams['font.size'] = 20

visualizer = ClassificationReport(model, classes=classes)

# Fitting training data to visualizer
visualizer.fit(X_train, y_train)
# Entering test data to model
visualizer.score(X_val, y_val)

g = visualizer.poof()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



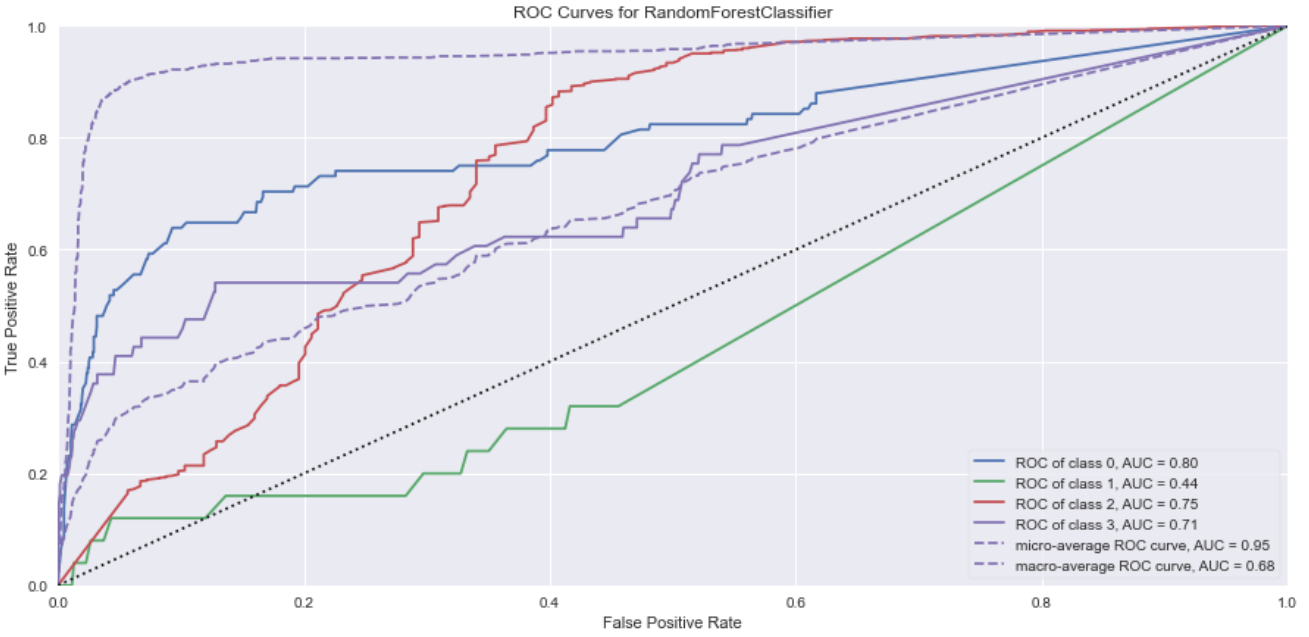
In [250…

```
visualizer = ROCAUC(model)

# Fitting training data to visualizer
visualizer.fit(X_train, y_train)
# Entering test data to model
visualizer.score(X_val, y_val)

visualizer.show()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



Out[250… `<AxesSubplot:title={'center':'ROC Curves for RandomForestClassifier'}, xlabel='False Positive Rate', ylabel='True P
ositive Rate'>`

Using Random Search for hyperparameter tuning

In [251…

```
# Look at parameters used by our current forest
print('Parameters currently in use:\n')
pprint(model.get_params())
```

```
Parameters currently in use:
```

```
{'bootstrap': True,
 'ccp_alpha': 0.0,
 'class_weight': None,
 'criterion': 'gini',
 'max_depth': None,
 'max_features': 'auto',
 'max_leaf_nodes': None,
 'max_samples': None,
 'min_impurity_decrease': 0.0,
 'min_impurity_split': None,
 'min_samples_leaf': 1,
 'min_samples_split': 2,
 'min_weight_fraction_leaf': 0.0,
 'n_estimators': 1000,
 'n_jobs': None,
 'oob_score': False,
 'random_state': 42,
 'verbose': 0,
 'warm_start': False}
```

In [87]:

```
# Number of trees in random forest
n_estimators = [int(x) for x in np.linspace(start = 200, stop = 2000, num = 10)]
# Number of features to consider at every split
max_features = ['auto', 'sqrt']
# Maximum number of levels in tree
max_depth = [int(x) for x in np.linspace(10, 110, num = 11)]
max_depth.append(None)
# Minimum number of samples required to split a node
min_samples_split = [2, 5, 10]
# Minimum number of samples required at each leaf node
min_samples_leaf = [1, 2, 4]
# Method of selecting samples for training each tree
bootstrap = [True, False]
# Create the random grid
random_grid = {'n_estimators': n_estimators,
               'max_features': max_features,
               'max_depth': max_depth,
               'min_samples_split': min_samples_split,
               'min_samples_leaf': min_samples_leaf,
               'bootstrap': bootstrap}
pprint(random_grid)
```

```
{'bootstrap': [True, False],
 'max_depth': [10, 20, 30, 40, 50, 60, 70, 80, 90, 100, 110, None],
 'max_features': ['auto', 'sqrt'],
 'min_samples_leaf': [1, 2, 4],
 'min_samples_split': [2, 5, 10],
 'n_estimators': [200, 400, 600, 800, 1000, 1200, 1400, 1600, 1800, 2000]}
```

In [88]:

```
# Use the random grid to search for best hyperparameters
# First create the base model to tune
rf = RandomForestClassifier()
# Random search of parameters, using 3 fold cross validation,
# search across 100 different combinations, and use all available cores
rf_random = RandomizedSearchCV(estimator = rf, param_distributions = random_grid, n_iter = 100, cv = 3, verbose=2,
# Fit the random search model
rf_random.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   44.7s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  3.0min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  5.9min finished
```

Out[88]:

```
RandomizedSearchCV(cv=3, estimator=RandomForestClassifier(), n_iter=100,
                   n_jobs=-1,
                   param_distributions={'bootstrap': [True, False],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      None],
                                        'max_features': ['auto', 'sqrt'],
                                        'min_samples_leaf': [1, 2, 4],
                                        'min_samples_split': [2, 5, 10],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 1600,
                                                         1800, 2000]},
                   random_state=42, verbose=2)
```

In [89]:
```
# Asking for best parameters from random search
rf_random.best_params_
```

Out[89]:
```
{'n_estimators': 600,
 'min_samples_split': 2,
 'min_samples_leaf': 4,
 'max_features': 'sqrt',
 'max_depth': 30,
 'bootstrap': False}
```

Using Grid Search for hyperparameter tuning

In [92]:
```
# creating grid of hyperparameters based off random grid
param_grid = {
    "bootstrap": [False],
    "max_depth": [20, 30, 40, 50, 60],
    "max_features": ["sqrt"],
    "min_samples_split": [2, 4, 6, 8],
    "n_estimators": [200, 400, 600, 800, 1000]
}
```

In [93]:
```
rf = RandomForestClassifier()
```

In [94]:
```
# using Grid Search to narrow best hyperparameters
grid_search = GridSearchCV(estimator = rf, param_grid = param_grid, cv = 3, n_jobs = -1, verbose = 2)
grid_search.fit(X_train, y_train)
```

```
Fitting 3 folds for each of 100 candidates, totalling 300 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent workers.
[Parallel(n_jobs=-1)]: Done  33 tasks      | elapsed:   24.4s
[Parallel(n_jobs=-1)]: Done 154 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 300 out of 300 | elapsed:  3.8min finished
```

Out[94]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [False],
                         'max_depth': [20, 30, 40, 50, 60],
                         'max_features': ['sqrt'],
                         'min_samples_split': [2, 4, 6, 8],
                         'n_estimators': [200, 400, 600, 800, 1000]},
             verbose=2)
```

In [95]:
```
# Asking for best parameters found in grid search
grid_search.best_params_
```

Out[95]:
```
{'bootstrap': False,
 'max_depth': 20,
 'max_features': 'sqrt',
 'min_samples_split': 8,
 'n_estimators': 800}
```

Running Random Forest with tuned hyperparameters

In [245…
```
# Creating tuned classifier using hyperparameters from grid search
rf_tuned = RandomForestClassifier(n_estimators = 800, min_samples_split = 8, max_features = "sqrt", max_depth = 20,
rf_tuned.fit(X_train, y_train)
```

Out[245…
```
RandomForestClassifier(bootstrap=False, max_depth=20, max_features='sqrt',
                       min_samples_split=8, n_estimators=800)
```

In [246…
```
# Creating new predictions
y_pred2 = rf_tuned.predict(X_val)
```

In [247…
```
# Printing resulting information before visualization
print(confusion_matrix(y_val,y_pred2))
print(classification_report(y_val,y_pred2))
print(accuracy_score(y_val, y_pred2))
```

```
[[  40    0   63    5]
 [   1    0   24    0]
 [  23    1 1124    2]
 [   4    0   45   12]]
```

```
              precision    recall  f1-score   support

           0       0.59      0.37      0.45       108
           1       0.00      0.00      0.00        25
           2       0.89      0.98      0.93      1150
           3       0.63      0.20      0.30        61

    accuracy                           0.88      1344
   macro avg       0.53      0.39      0.42      1344
weighted avg       0.84      0.88      0.85      1344

0.875
```

The accuracy dropped slightly from 87.79% to 87.5%

In [179…

```
# Taxing model with confushion matrix
classes = ["Endangered", "In Recovery", "Species of Concern", "Threatened"]
cm = ConfusionMatrix(rf_tuned, classes=classes, percent=False)

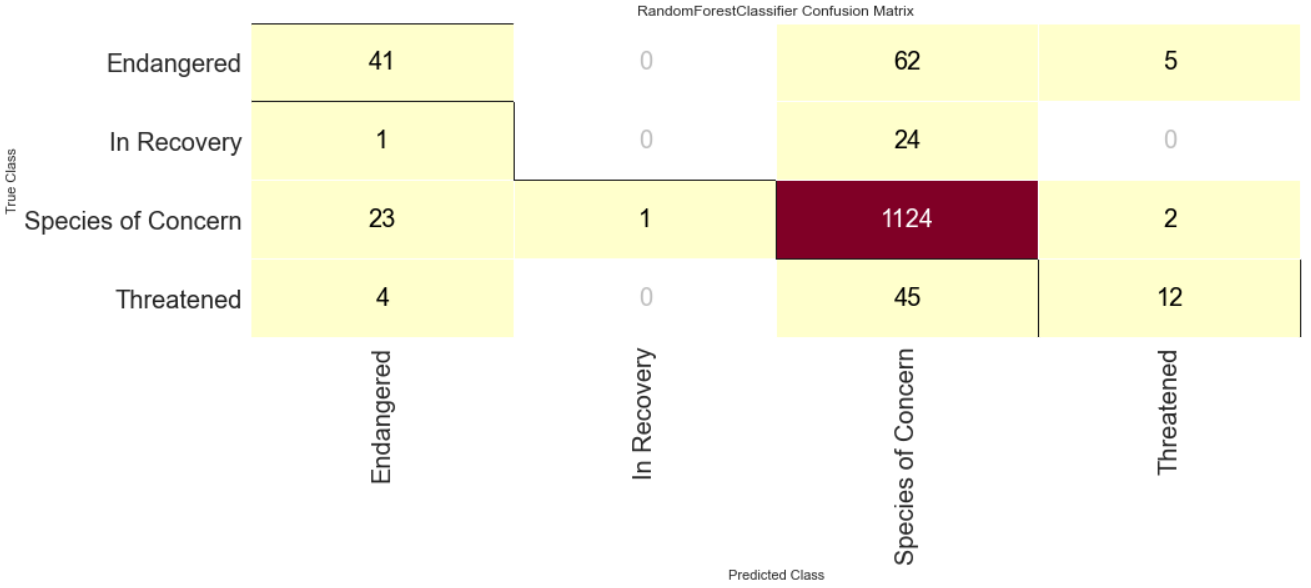
# Fitting the random forest model
cm.fit(X_train, y_train)

# Entering test data into mix
cm.score(X_val, y_val)

# Changing font size
for label in cm.ax.texts:
    label.set_size(20)

cm.poof()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



Out[179…

```
<AxesSubplot:title={'center':'RandomForestClassifier Confusion Matrix'}, xlabel='Predicted Class', ylabel='True Cla
ss'>
```

In [180…

```
%matplotlib inline
plt.rcParams['figure.figsize'] = (15, 7)
plt.rcParams['font.size'] = 20

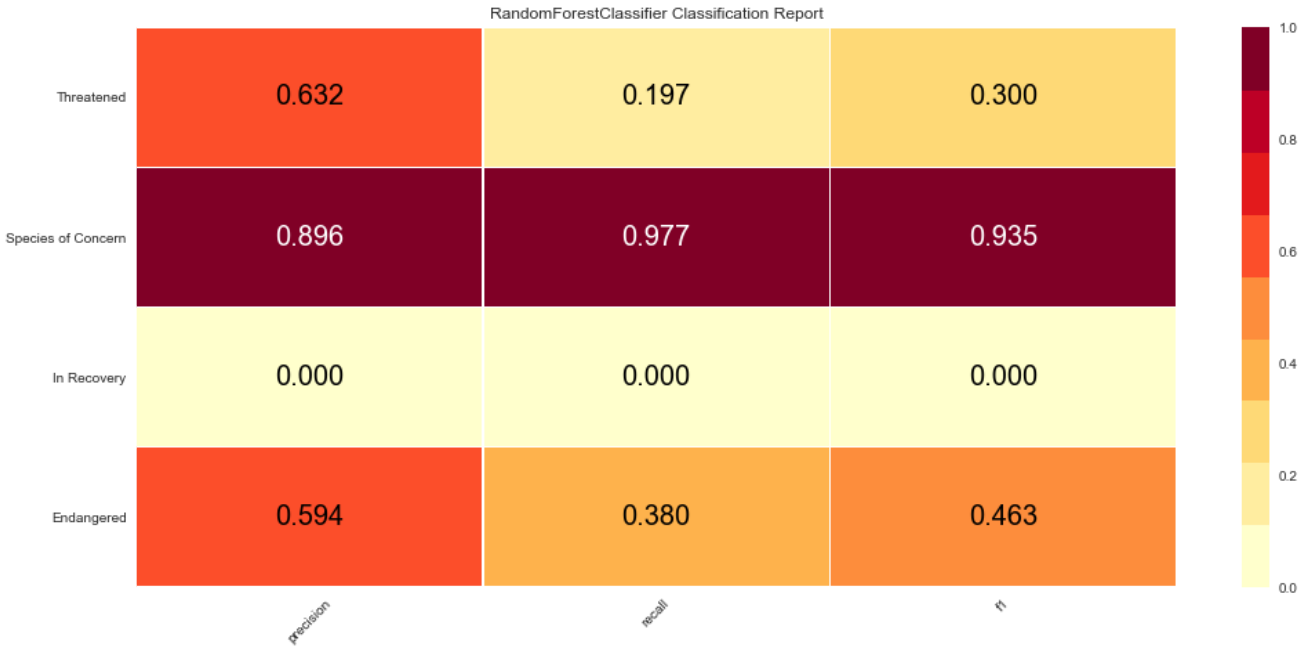
visualizer = ClassificationReport(rf_tuned, classes=classes)

# Fitting training data to visualizer
visualizer.fit(X_train, y_train)
# Entering test data to model
visualizer.score(X_val, y_val)

g = visualizer.poof()
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
```

```
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



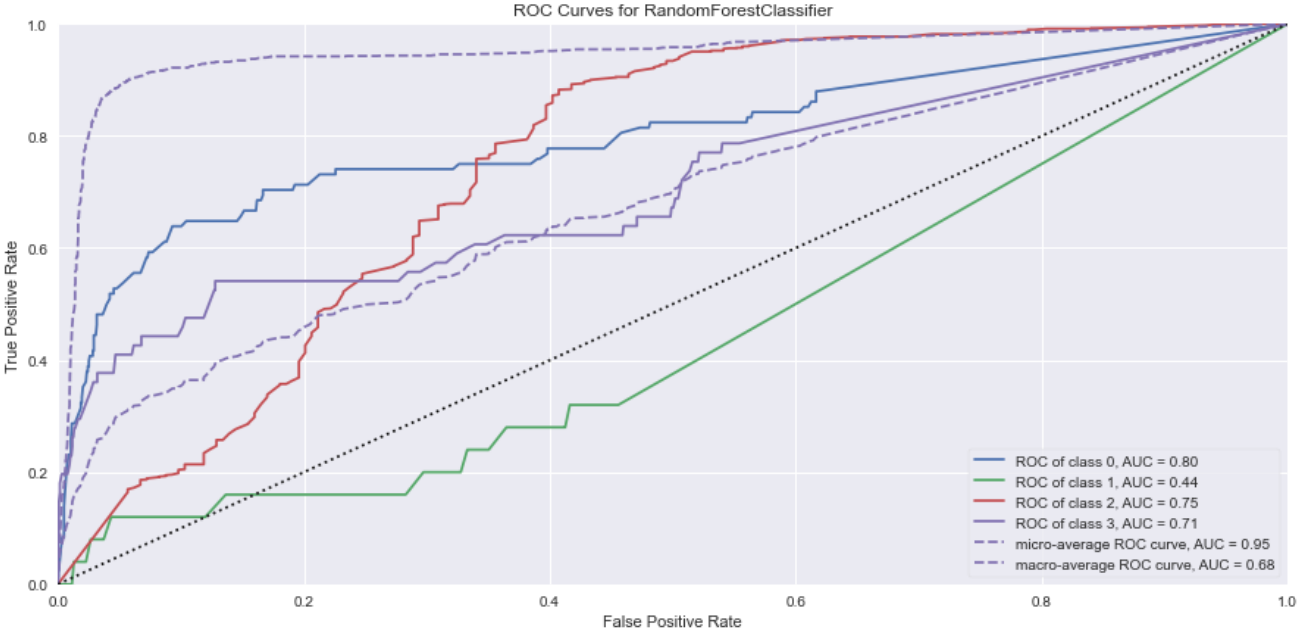
In [181…

```
visualizer = ROCAUC(model)

# Fitting training data to visualizer
visualizer.fit(X_train, y_train)
# Entering test data to model
visualizer.score(X_val, y_val)

g = visualizer.poof()
g
```

```
C:\Users\datre\Anaconda3\lib\site-packages\sklearn\base.py:213: FutureWarning: From version 0.24, get_params will r
aise an AttributeError if a parameter cannot be retrieved as an instance attribute. Previously it would return Non
e.
  FutureWarning)
```



Out[181…

```
<AxesSubplot:title={'center':'ROC Curves for RandomForestClassifier'}, xlabel='False Positive Rate', ylabel='True P
ositive Rate'>
```

The hypertuning did help in the endangered category but reduced scores in the threatened category

Separating by Category

In [281…
```
sp_category = sp.copy()
pd.crosstab(sp_category["Category"], sp_category["Conservation Status"])
```

Out[281…

Category	Endangered	In Recovery	Species of Concern	Threatened
Amphibian	5	0	61	8
Bird	64	65	2371	51
Crab/Lobster/Shrimp	1	0	0	0
Fish	33	0	66	40
Fungi	1	0	2	0
Insect	17	0	107	4
Invertebrate	9	0	1	7
Mammal	93	9	552	19
Nonvascular Plant	0	0	27	0
Reptile	17	1	98	17
Slug/Snail	5	0	21	1
Spider/Scorpion	1	0	0	0
Vascular Plant	128	2	537	37

In [284…
```
chi2_contingency(pd.crosstab(sp_category["Category"], sp_category["Conservation Status"]))
```

Out[284…
```
(746.447405976747,
 1.269410315755824e-133,
 36,
 array([[6.18043770e+00, 1.27244305e+00, 6.35064761e+01, 3.04064314e+00],
        [2.13058062e+02, 4.38648950e+01, 2.18925703e+03, 1.04820009e+02],
        [8.35194283e-02, 1.71951764e-02, 8.58195623e-01, 4.10897722e-02],
        [1.16092005e+01, 2.39012952e+00, 1.19289192e+02, 5.71147834e+00],
        [2.50558285e-01, 5.15855293e-02, 2.57458687e+00, 1.23269317e-01],
        [1.06904868e+01, 2.20098258e+00, 1.09849040e+02, 5.25949084e+00],
        [1.41983028e+00, 2.92317999e-01, 1.45893256e+01, 6.98526128e-01],
        [5.62085753e+01, 1.15723537e+01, 5.77565654e+02, 2.76534167e+01],
        [2.25502456e+00, 4.64269763e-01, 2.31712818e+01, 1.10942385e+00],
        [1.11080840e+01, 2.28695846e+00, 1.14140018e+02, 5.46493971e+00],
        [2.25502456e+00, 4.64269763e-01, 2.31712818e+01, 1.10942385e+00],
        [8.35194283e-02, 1.71951764e-02, 8.58195623e-01, 4.10897722e-02],
        [5.87976775e+01, 1.21054042e+01, 6.04169719e+02, 2.89271996e+01]]))
```

Separating by State

In [286…
```
sp_state = sp.copy()
pd.crosstab(sp_state["State"], sp_state["Conservation Status"])
```

Out[286…

State	Endangered	In Recovery	Species of Concern	Threatened
AK	31	2	263	14
AR	4	1	61	2
AZ	16	5	279	7
CA	67	20	627	31
CA, NV	24	2	177	16
CO	10	4	261	7
FL	33	5	159	18
HI	84	0	103	8
KY	13	2	53	1
ME	3	2	65	1

Conservation Status	Endangered	In Recovery	Species of Concern	Threatened
State				
MI	2	1	58	2
MN	1	1	52	2
MT	0	2	75	2
ND	3	1	49	1
NM	4	1	94	2
NV	2	1	89	5
OH	1	1	52	1
OR	4	3	66	5
SC	4	1	37	1
SD	5	2	125	2
TN, NC	13	1	104	6
TX	13	3	199	7
UT	22	6	376	14
VA	4	1	74	6
WA	6	4	184	20
WY	3	2	77	1
WY, MT, ID	2	3	84	2

In [287…
```
chi2_contingency(pd.crosstab(sp_state["State"], sp_state["Conservation Status"]))
```

Out[287…
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(474.04294821280064,
 4.589547088753656e-58,
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        [ 10.35640911,   2.13220188, 106.41625726,   5.09513176],
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        [  7.09915141,   1.46159   ,  72.94662796,   3.49263064],
        [ 17.87315766,   3.67976775, 183.65386333,   8.79321126],
        [  6.93211255,   1.42719964,  71.23023671,   3.41045109],
        [  7.60026798,   1.56476105,  78.0958017 ,   3.73916927]]))
```

In [ ]:
```

```