In [1]:

```
#Importing libraries needed
import pandas as pd
import numpy as np


#For visualization
import matplotlib.pyplot as plt
from matplotlib import pyplot
%matplotlib inline
import seaborn as sns
import shap

# For our modeling steps
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import normalize
from sklearn.linear_model import LinearRegression, LogisticRegression
from sklearn.metrics import log_loss
from sklearn.metrics import precision_recall_fscore_support
from sklearn.preprocessing import StandardScaler
from sklearn.svm import SVC
from sklearn.metrics import confusion_matrix
from sklearn.metrics import precision_score, recall_score, f1_score, a
from sklearn.model_selection import GridSearchCV, cross_val_score
import xgboost as xgb
from xgboost import XGBClassifier, plot_importance
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_
from sklearn import svm, datasets
from sklearn import metrics


# For demonstrative purposes
from scipy.special import logit, expit

import warnings
warnings.filterwarnings('ignore')
```

```
pandas.Int64Index is deprecated and will be removed from pandas in a futu
re version. Use pandas.Index with the appropriate dtype instead.
```

How Do Wind Speed Features Impact Model Performance

For the scope of this project we are particularly interested in how hurricane's impact real estate value. Using wind speed we were able to gauge how much damage a hurricane had on a certain area. The most important feature for our best model was the fastest 2 minute wind gust and SizeRank. When we drop the wind features from the model the accuracy drops to 0.98 and the F1 score drops to 0.96. Meaning that wind features do improve model performance.

Model	Accuracy	F1	AUC
No Wind	0.98	0.96	0.99
Just Wind	0.96	0.91	0.98

Model	Accuracy	F1	AUC

Obtaining the Data

For this part of the process I will use the dataset containing all homes.

In [2]:
```
#opening dataset
all_df = pd.read_csv(r'data\wind_modeling.csv')
all_df.describe()
```

Out[2]:

	AWND	WSF2	SizeRank	before	after	percent	i
count	344.000000	344.000000	344.000000	344.000000	344.000000	344.000000	344
mean	14.046948	27.354942	1359.034884	196091.514509	219108.234733	13.783402	(
std	7.013264	12.690591	3021.571059	118770.632169	126637.076629	8.838321	(
min	2.910000	0.000000	12.000000	44457.567490	52157.021900	-4.161603	(
25%	8.720000	18.100000	106.000000	101212.031625	122666.923050	6.526272	(
50%	12.750000	23.900000	233.000000	168065.082200	188091.092300	11.638427	(
75%	17.220000	31.325000	916.000000	257806.739650	286217.803975	19.627916	(
max	40.710000	79.000000	12877.000000	638691.713200	669502.004200	38.720009	1

Running the Model Without Wind Features

In [3]:
```
#initiating model
xgb = XGBClassifier(random_state=56)
```

Selecting Our Target Variable and Features

In [4]:
```
#y is prediction variable
#X is features
y_boost = all_df['increase']
X_boost = all_df.drop(['City', 'HurricaneName', 'DATE', 'after', 'perc

```

Train/Test Split

In [5]:
```
#train/test splits with 30% test size
XG_X_train, XG_X_test, XG_y_train, XG_y_test = train_test_split(X_boos
```

Training Data

In [6]:
```
#fitting the model
xgb.fit(XG_X_train, XG_y_train);
```

In [7]:
```
#getting predictions
y_pred_train = xgb.predict(XG_X_train)
```

In [8]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(XG_y_train, y_pred_train))
```

```
Accuracy: 0.996
```

In [9]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(XG_y_train, y_pred_train))
```

```
F1 Score: 0.992
```

Testing Data

In [10]:
```
#fitting the model
xgb.fit(XG_X_test, XG_y_test);
```

In [11]:
```
#getting predictions
y_pred_test = xgb.predict(XG_X_test)
```

In [12]:
```
#Printing Accuracy
accuracy_XG_nowind = accuracy_score(XG_y_test, y_pred_test)
print(accuracy_XG_nowind)
```

```
0.9807692307692307
```

In [13]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
F1_XG_nowind = f1_score(XG_y_test, y_pred_test)
print(F1_XG_nowind)
```

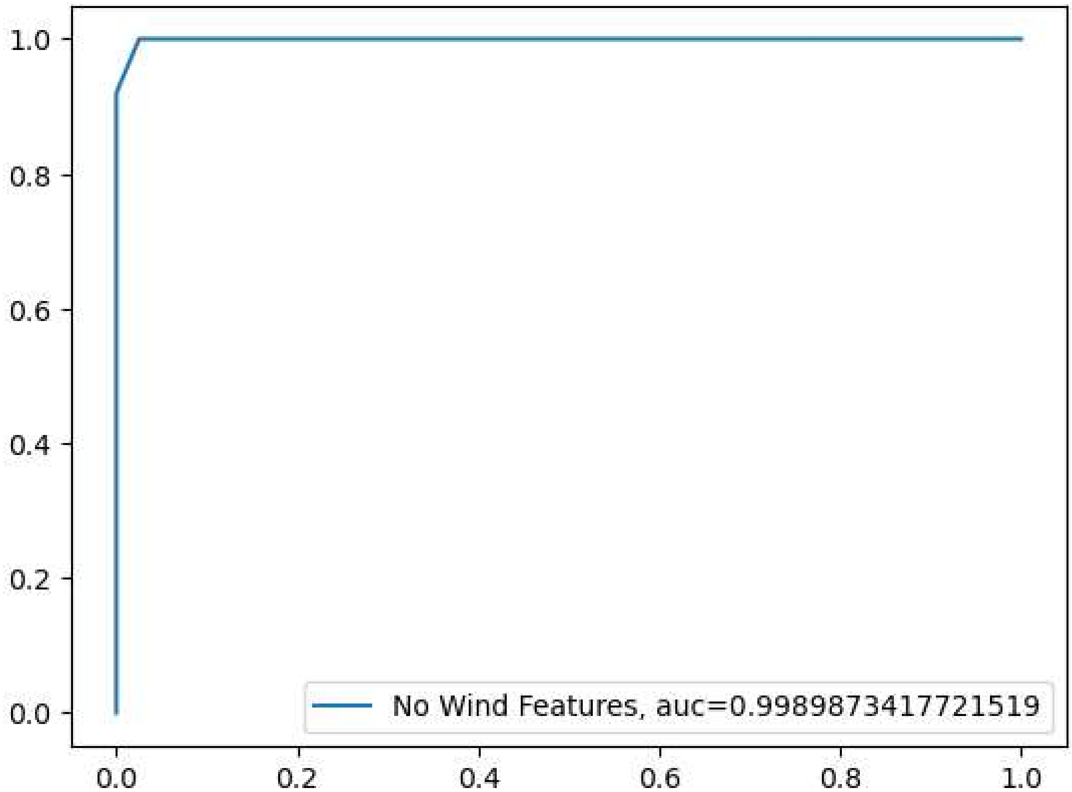
```
0.96
```

In [14]:
```
model_dict = {}
model_dict['XGBoost Accuracy No Wind'] = accuracy_XG_nowind
model_dict['XGBoost F1 No Wind'] = F1_XG_nowind
model_dict
```

Out[14]:
```
{'XGBoost Accuracy No Wind': 0.9807692307692307, 'XGBoost F1 No Wind': 0.
96}
```

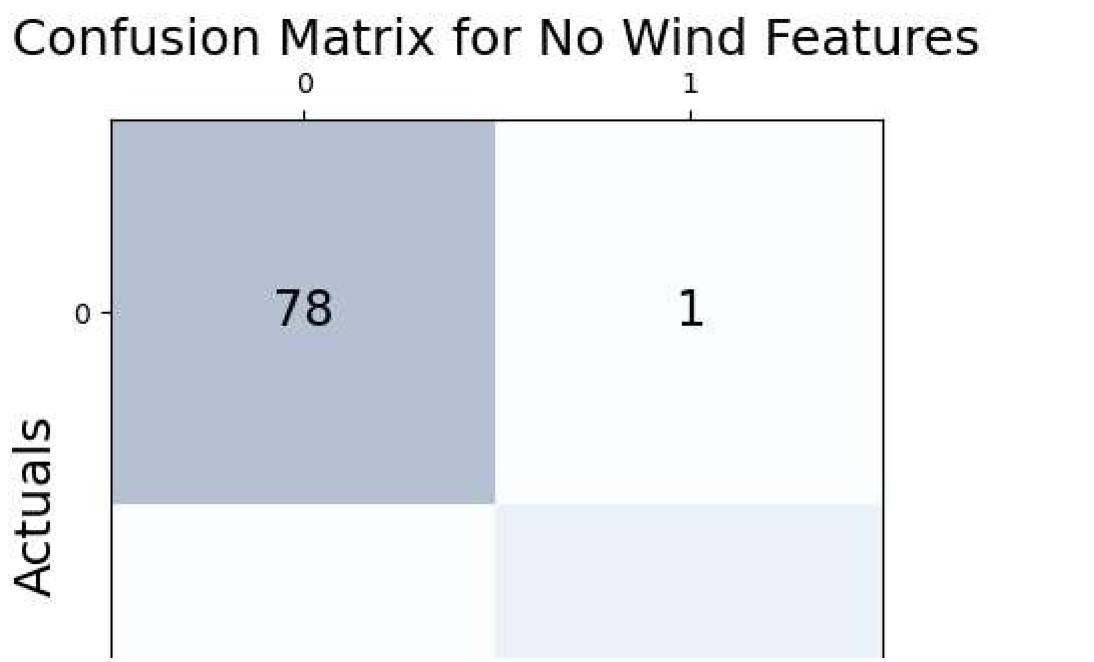
In [15]:

```
#Let's check out the AUC curve
#getting probability
y_pred_prob = xgb.predict_proba(XG_X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(XG_y_test,  y_pred_prob)
auc = metrics.roc_auc_score(XG_y_test, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="No Wind Features, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```

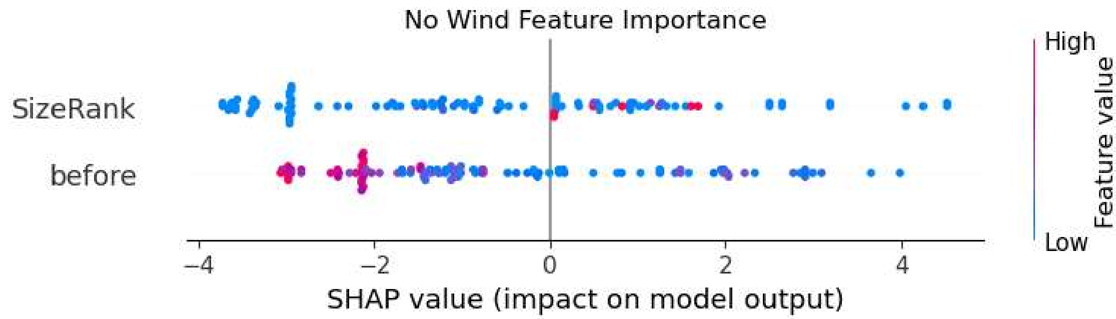


In [16]:

```
#plotting confusion matrix
conf_matrix = confusion_matrix(y_true=XG_y_test, y_pred=y_pred_test)

fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix for No Wind Features', fontsize=18)
plt.show()
```



In [17]:
```
#Using SHAP to assess feature importance
# creating an explainer for our model
explainer = shap.TreeExplainer(xgb)

# finding out the shap values using the explainer
shap_values = explainer.shap_values(XG_X_test)

#creating a beeswarm plot
shap.initjs()
plt.title("No Wind Feature Importance", y=1)
shap.summary_plot(shap_values, XG_X_test)
```



XGBoost on Just Wind Features

Let's see our results using just wind as a feature.

Selecting Our Target Variable and Features

In [18]:
```
#y is prediction variable
#X is features
y_boost = all_df['increase']
X_boost = all_df.drop(['City', 'HurricaneName', 'DATE', 'after', 'perc

```

Train/Test Split

In [19]:
```
#train/test splits with 30% test size
XG_X_train, XG_X_test, XG_y_train, XG_y_test = train_test_split(X_boos
```

Training Data

In [20]:
```
#fitting model
xgb.fit(XG_X_train, XG_y_train);
```

In [21]:
```
#getting predictions
y_pred_train = xgb.predict(XG_X_train)
```

In [22]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(XG_y_train, y_pred_train))
```

```
Accuracy: 0.933
```

In [23]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(XG_y_train, y_pred_train))
```

```
F1 Score: 0.857
```

Testing Data

In [24]:
```
#fitting the model
xgb.fit(XG_X_test, XG_y_test);
```

In [25]:
```
#getting predictions
y_pred_test = xgb.predict(XG_X_test)
```

In [26]:
```
#Printing Accuracy
accuracy_XG_justwind = accuracy_score(XG_y_test, y_pred_test)
print(accuracy_XG_justwind)
```

```
0.9615384615384616
```

In [27]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
F1_XG_justwind = f1_score(XG_y_test, y_pred_test)
print(F1_XG_justwind)
```

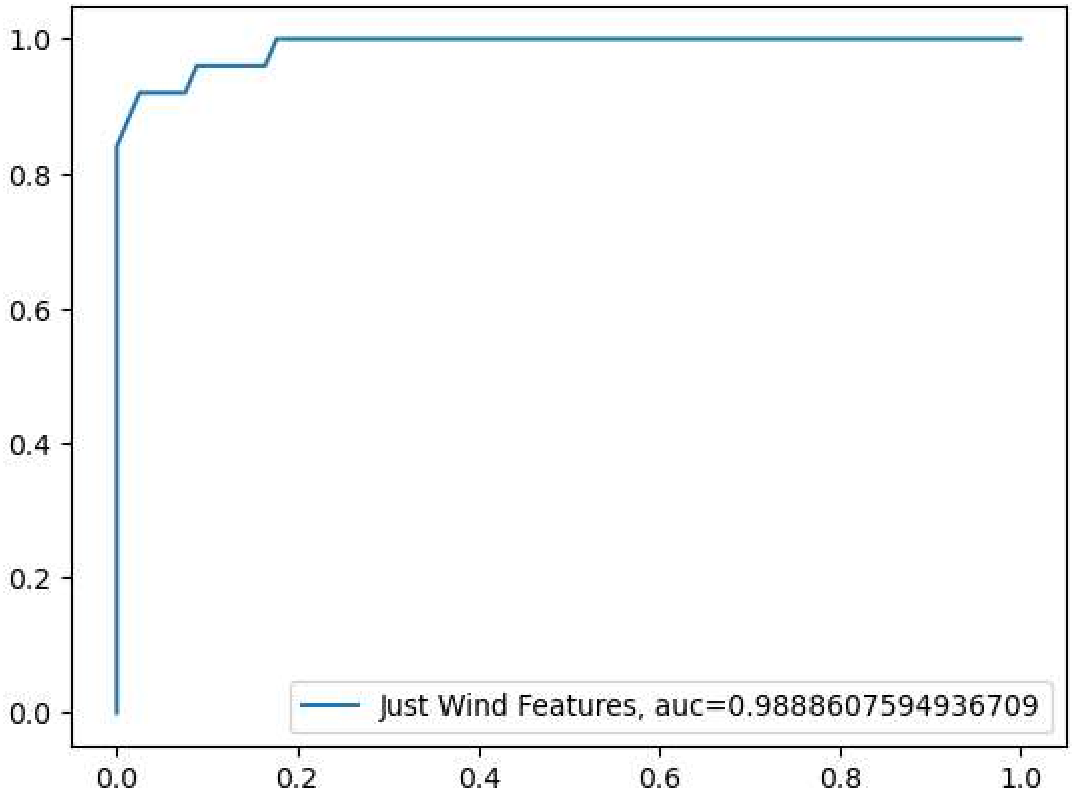
```
0.9166666666666666
```

In [28]:
```
model_dict['XGBoost Accuracy Just Wind'] = accuracy_XG_justwind
model_dict['XGBoost F1 Just Wind'] = F1_XG_justwind
model_dict
```

Out[28]:
```
{'XGBoost Accuracy No Wind': 0.9807692307692307,
 'XGBoost F1 No Wind': 0.96,
 'XGBoost Accuracy Just Wind': 0.9615384615384616,
 'XGBoost F1 Just Wind': 0.9166666666666666}
```

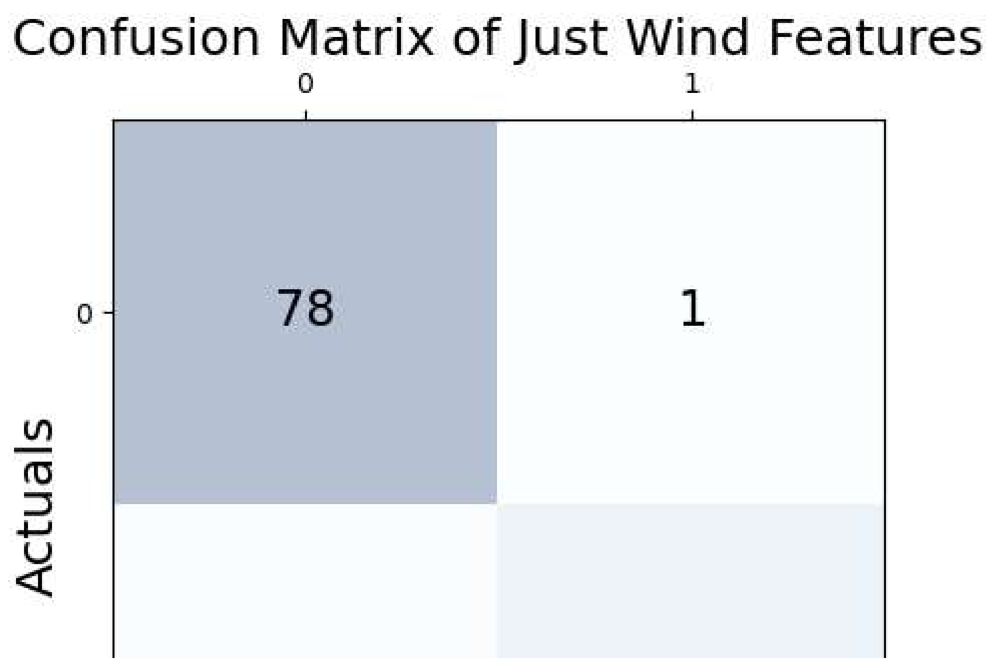
In [29]:

```
#Let's check out the AUC curve
#getting probability
y_pred_prob = xgb.predict_proba(XG_X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(XG_y_test,  y_pred_prob)
auc = metrics.roc_auc_score(XG_y_test, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="Just Wind Features, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



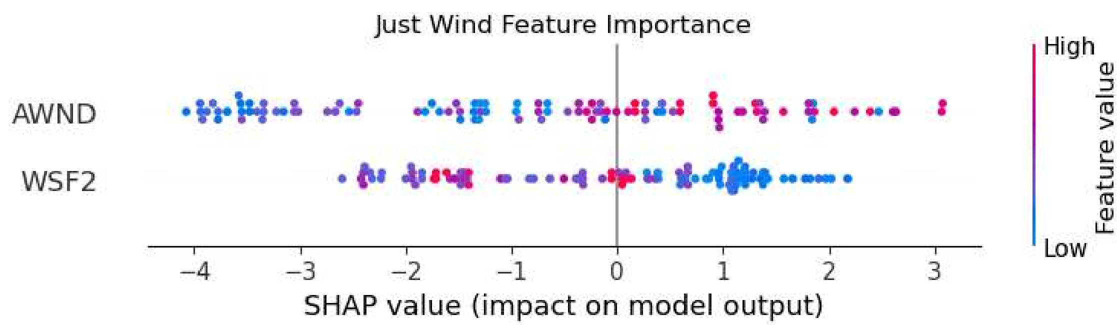
In [30]:

```
#plotting confusion matrix
conf_matrix = confusion_matrix(y_true=XG_y_test, y_pred=y_pred_test)

fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix of Just Wind Features', fontsize=18)
plt.show()
```



In [31]:

```
#Using SHAP to assess feature importance
# creating an explainer for our model
explainer = shap.TreeExplainer(xgb)

# finding out the shap values using the explainer
shap_values = explainer.shap_values(XG_X_test)

#creating a beeswarm plot
shap.initjs()
plt.title("Just Wind Feature Importance", y=1)
shap.summary_plot(shap_values, XG_X_test)
```



XG Boost Tuning

Let's see if we can improve our results using just wind features with model tuning. The optimal parameters according to the gridsearch are:

Best Parameters for Our XGBoost Model:
{'gamma': 0,
'learning_rate': 0.01,
'max_depth': 2,
'min_child_weight': 1,
'n_estimators': 10,
'subsample': 0.5}

Selecting Our Target Variable and Features

In [32]:

```
#y is prediction variable
#X is features
y_boost = all_df['increase']
X_boost = all_df.drop(['City', 'HurricaneName', 'DATE', 'after', 'perc

```

Train/Test/Tune Split

In order to properly tune our model it should be done on data that is not seen during the training or testing process. This will help assure an unbiased model. 70% of our data will be used for training, 15% for testing, and 15% for tuning.

Works Cited:

1.Training, Tuning, and Test Datasets. onepager.togaware.com. Accessed July 6, 2023. https://onepager.togaware.com/Training_Tuning_Test_Datase.html (https://onepager.togaware.com/Training_Tuning_Test_Datase.html)

In [33]:
```
#train/test splits with 30% test size
#half of the test set will be used to create the set we will be tuning
XG_X_train, XG_X_test_tune, XG_y_train, XG_y_test_tune = train_test_sp
```

In [34]:
```
#train/test splits with 30% test size
XG_X_test, XG_X_tune, XG_y_test, XG_y_tune = train_test_split(XG_X_tes
```

```
#skipping this cell from running since we know the parameters

#hypertuning the model using GridSearch
#the parameters that will be searched
xgb_grid = {
            'learning_rate': [0.01, 0.1, 0.5],
            'gamma': [0, 0.01, 0.1],
            'max_depth': [2, 5, 6, 10],
            'min_child_weight': [0.1, 1, 10],
            'subsample': [0.5, 0.7, 0.9],
            'n_estimators': [5, 10, 20, 100]
           }
#runninig GridSearch
xgb_gridsearch = GridSearchCV(estimator=xgb,
                              param_grid=xgb_grid,
                              cv=5,
                              return_train_score=True)
#fitting the gridsearch
xgb_gridsearch.fit(XG_X_tune, XG_y_tune)

#printing the best parameters
print('Best Parameters for Our XGBoost Model:')
xgb_gridsearch.best_params_

```

In [35]:
```
#initiating the model
xgb_gs = XGBClassifier(gamma= 0, learning_rate= 0.01, max_depth= 2, mi
```

Training Data

In [36]:
```
#fitting the model
xgb_gs.fit(XG_X_train, XG_y_train);
```

In [37]:
```
#predicting
y_pred_train = xgb_gs.predict(XG_X_train)
```

In [38]:
```
#Printing Accuracy
print('Accuracy: %.3f' % accuracy_score(XG_y_train, y_pred_train))
```

```
Accuracy: 0.746
```

In [39]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
print('F1 Score: %.3f' % f1_score(XG_y_train, y_pred_train))
```

```
F1 Score: 0.000
```

Testing Data

In [40]:
```
#fitting the model
xgb_gs.fit(XG_X_test, XG_y_test);
```

In [41]:
```
#getting predictions
y_pred_test = xgb_gs.predict(XG_X_test)
```

In [42]:
```
#Printing Accuracy
accuracy_XG_justwind_tuned = accuracy_score(XG_y_test, y_pred_test)
print(accuracy_XG_justwind_tuned)
```

```
0.7884615384615384
```

In [43]:
```
#using F-1 score to see how it performs
#F1 Score = 2* Precision Score * Recall Score/ (Precision Score + Reca
F1_XG_justwind_tuned = f1_score(XG_y_test, y_pred_test)
print(F1_XG_justwind_tuned)
```

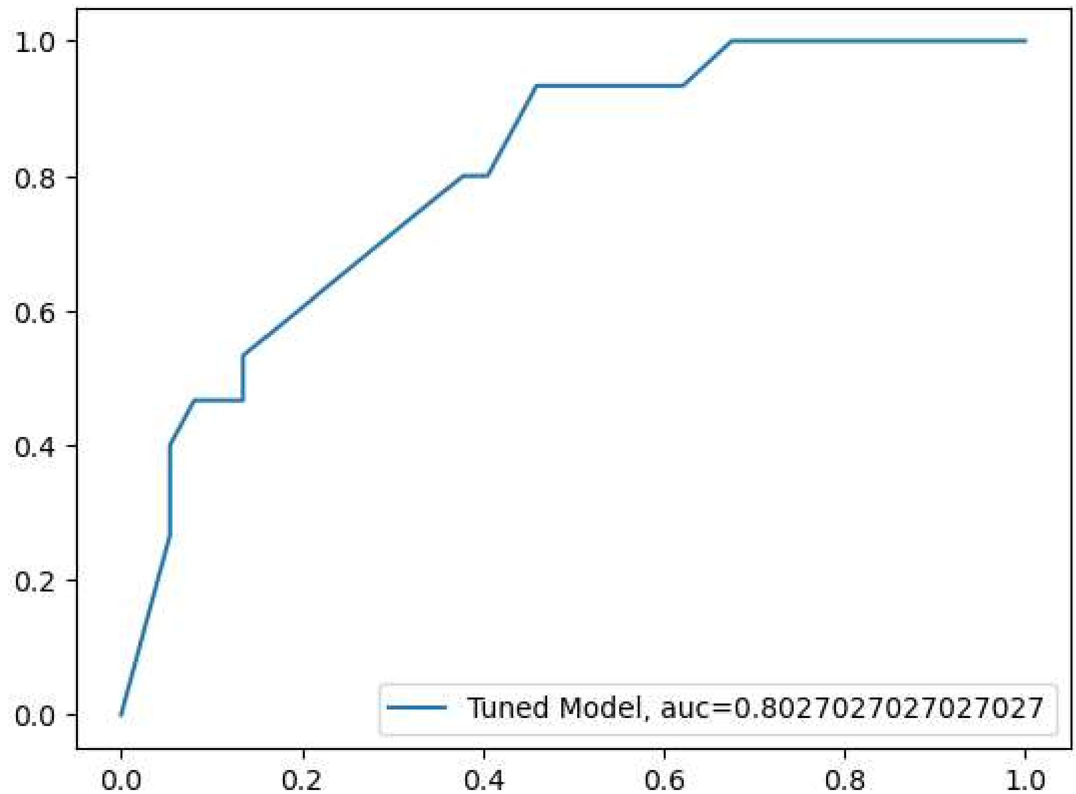
```
0.56
```

In [44]:
```
#adding values to model dictionary
model_dict['XGBoost Accuracy Just Wind Tuned'] = accuracy_XG_justwind_
model_dict['XGBoost F1 Just Wind Tuned'] = F1_XG_justwind_tuned
model_dict
```

Out[44]:
```
{'XGBoost Accuracy No Wind': 0.9807692307692307,
 'XGBoost F1 No Wind': 0.96,
 'XGBoost Accuracy Just Wind': 0.9615384615384616,
 'XGBoost F1 Just Wind': 0.9166666666666666,
 'XGBoost Accuracy Just Wind Tuned': 0.7884615384615384,
 'XGBoost F1 Just Wind Tuned': 0.56}
```

In [45]:

```
#Let's check out the AUC curve
#getting probability
y_pred_prob = xgb_gs.predict_proba(XG_X_test)[::,1]
fpr, tpr, _ = metrics.roc_curve(XG_y_test,  y_pred_prob)
auc = metrics.roc_auc_score(XG_y_test, y_pred_prob)

#plotting
plt.plot(fpr,tpr,label="Tuned Model, auc="+str(auc))
plt.legend(loc=4)
plt.show()
```



In [46]:

```
#plotting confusion matrix
conf_matrix = confusion_matrix(y_true=XG_y_test, y_pred=y_pred_test)

fig, ax = plt.subplots(figsize=(5, 5))
ax.matshow(conf_matrix, cmap=plt.cm.Blues, alpha=0.3)
for i in range(conf_matrix.shape[0]):
    for j in range(conf_matrix.shape[1]):
        ax.text(x=j, y=i,s=conf_matrix[i, j], va='center', ha='center'

plt.xlabel('Predictions', fontsize=18)
plt.ylabel('Actuals', fontsize=18)
plt.title('Confusion Matrix for Tuned Model', fontsize=18)
plt.show()
```