In [ ]:

```python
import pandas as pd
import threadpoolctl
import StandardScaler
import matplotlib.pyplot as plt
from statsmodels.stats.multicomp import pairwise_tukeyhsd
import matplotlib
from sklearn.cluster import KMeans
import seaborn as sns
from sklearn.preprocessing import StandardScaler
from scipy.stats import f_oneway
import statsmodels.api as sm
from statsmodels.formula.api import ols
import itertools
import statsmodels.formula.api as smf
from statsmodels.stats.multitest import multipletests
from statsmodels.stats.anova import anova_lm
from itertools import combinations
from statsmodels.tsa.arima.model import ARIMA
from sklearn.metrics import mean_absolute_error, mean_squared_error
import numpy as np
from sklearn.linear_model import LinearRegression
```

In [8]:

```python
###########################################################################

#Data set Book1. is a data set about 18 diferent sites (plots) from the Amaz
#These 18 transects are the same size, a radius of 2km, but each have a diff
#Each of them can have a different combination between 11 habitat types. Hav
#The measurements from the different habitat types in each transect was obta

df = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Docum

##############################              First, I am going to use some c

# Group by BufferID and calculate the average area
df_avg_area = df.groupby('BufferID')['Area_m2'].mean().reset_index()
# Standardize the data
scaler = StandardScaler()
df_avg_area_scaled = scaler.fit_transform(df_avg_area[['Area_m2']])

# Apply K-Means clustering
kmeans = KMeans(n_clusters=4, random_state=0)
df_avg_area['Cluster'] = kmeans.fit_predict(df_avg_area_scaled)

# Plot the clusters

plt.figure(figsize=(10, 6))
sns.scatterplot(x='BufferID', y='Area_m2', hue='Cluster', data=df_avg_area,
plt.title('K-Means Clustering of each Plot by Average Area')
plt.xlabel('Plot')
plt.ylabel('Average Area (m²)')
plt.legend(title='Cluster')
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig('K-Means Clustering of Buffer Zones by Average Area (18plots).pr
```

```
plt.show()
#This plot should plot the 4 clusters of the Area in squared meters of each
#But since each of the transects have the same Area and only changes the typ
#homogenity or heterogenity of the plot.
#Cluster 1 are the more homogenous so they have more area because its only c
#Cluster 0 are plots that have their area divided in 5 or 6 habitat types
#Cluster 2, 3-4 habitat types
#Cluster 3, 2-3 habitat types



###########################################################          HEATMAP

#Actually the cluster plot is not very specific, so it would be better to ha

#########   HEAT MAP FOR HABITAT TYPE PER PLOT

# Aggregate by BufferID and Areas to calculate the average proportion across
df_avg_proportion = df.groupby(['BufferID', 'Type'])['Area_m2'].sum().reset_
# Calculate the proportion of Area_m2 for each Area within each Plot
df_avg_proportion['Proportion'] = df_avg_proportion.groupby('BufferID')['Are
# Pivot the data for heatmap
df_pivot_avg = df_avg_proportion.pivot_table(values='Proportion', index='Buf

#Plot the heatmap
#In the heatmap we can see that our main habitat type is "Forest formation"
#We can also observed than a lot of the other habitat types contribute with
plt.figure(figsize=(12, 8))
sns.heatmap(df_pivot_avg, cmap='PiYG', annot=True, fmt='.2f', linewidths=0.5
plt.title('Average Proportion of Total Area by Habitat Type for Each Plot')
plt.xlabel('Habitat Type')
plt.ylabel('Plot')
plt.xticks(rotation=45)
plt.tight_layout()
plt.savefig('HEAT MAP FOR HABITAT TYPE PER PLOT (18plots).png')
plt.show()


#########   HEAT MAP FOR HABITAT TYPE PER YEAR

# Aggregate by BufferID and Areas to calculate the average proportion across
df_avg_proportion = df.groupby(['Date', 'Type'])['Area_m2'].sum().reset_inde
# Calculate the proportion of Area_m2 for each Area within each Plot
df_avg_proportion['Proportion'] = df_avg_proportion.groupby('Date')['Area_m2
# Pivot the data for heatmap
df_pivot_avg = df_avg_proportion.pivot_table(values='Proportion', index='Dat

#Plot the heatmap
#In the heatmap we can see that our main habitat type is "Forest formation"
#The percentages dont really change across the years.
plt.figure(figsize=(12, 8))
sns.heatmap(df_pivot_avg, cmap='PiYG', annot=True, fmt='.2f', linewidths=0.5
plt.title('Average Proportion of Total Area by Habitat Type for Each Year')
plt.xlabel('Habitat Type')
plt.ylabel('Year')
plt.xticks(rotation=45)
```

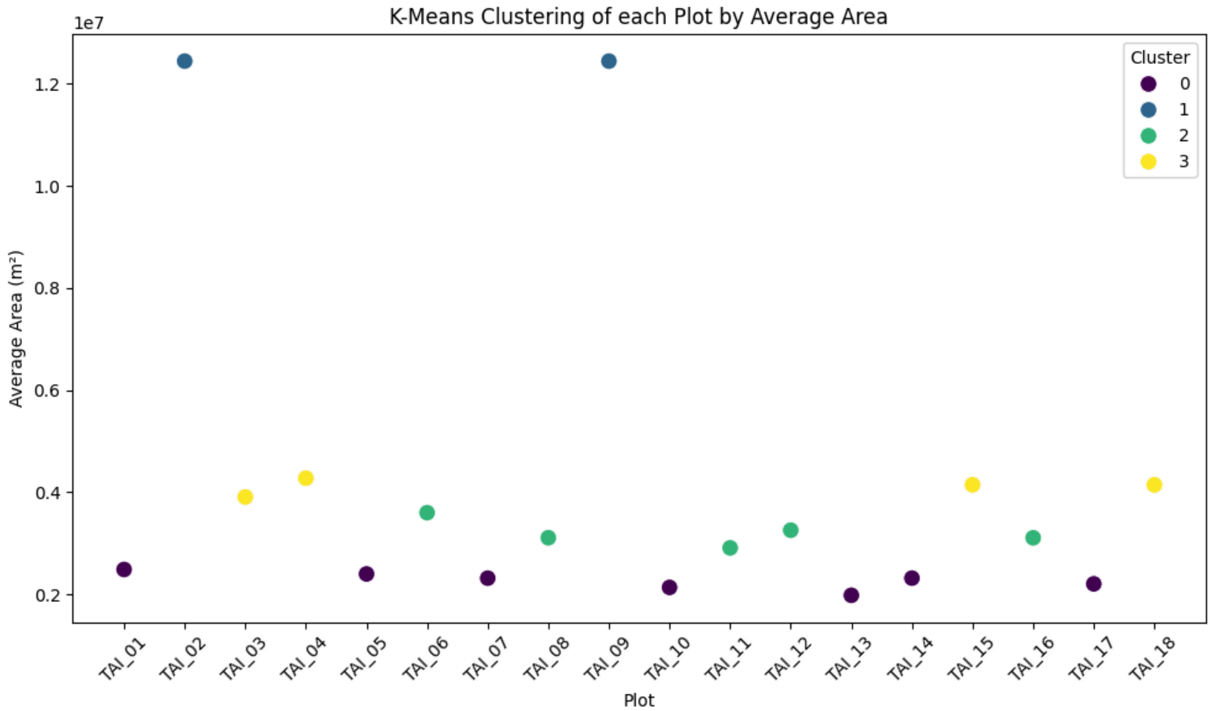
```
plt.tight_layout()
plt.savefig('HEAT MAP FOR HABITAT TYPE PER YEAR (18plots).png')
plt.show()





##############################                     ARE THE DIFFERENCES IN TH

#################       ANOVA for Plot (BufferID)

buffer_groups = [df[df['BufferID'] == buffer]['Area_m2'].values for buffer i
anova_buffer = f_oneway(*buffer_groups)
print("ANOVA for BufferID:")
print(f"F-statistic: {anova_buffer.statistic}, p-value: {anova_buffer.pvalue

# Perform Tukey's HSD test for BufferID
tukey_type = pairwise_tukeyhsd(endog=df['Area_m2'], groups=df['BufferID'], a
# Display the results
print("\nTukey HSD Test for PLot:")
print(tukey_type)
# Visualize the Tukey HSD results
tukey_type.plot_simultaneous()
plt.title("Tukey HSD Test for Plot")
plt.xlabel('Mean Difference')
plt.grid(True)
plt.savefig('Tukey plot (18plots).png')
plt.show()
#There is a significant difference between the plots, being plot TAI_02 and
#Plot TAI_02 and TAI_09 are the plots that are compound by only one habitat

############################################################################
#################         ANOVA for Type

type_groups = [df[df['Type'] == buffer]['Area_m2'].values for buffer in df['
anova_type = f_oneway(*type_groups)
print("ANOVA for Type:")
print(f"F-statistic: {anova_type.statistic}, p-value: {anova_type.pvalue}")

# Perform Tukey's HSD test for Type
tukey_type = pairwise_tukeyhsd(endog=df['Area_m2'], groups=df['Type'], alpha
# Display the results
print("\nTukey HSD Test for Type:")
print(tukey_type)
# Visualize the Tukey HSD results
tukey_type.plot_simultaneous()
plt.title("Tukey HSD Test for Habitat Type")
plt.xlabel('Mean Difference')
plt.grid(True)
plt.savefig('Tukey type (18plots).png')
plt.show()
#There is a significant difference between the Habitat types, being ForestFo
#Both types are the one with the largest area_m2

############################################################################
```

```python
#################      ANOVA for Year
year_groups = [df[df['Date'] == year]['Area_m2'].values for year in df['Date
anova_year = f_oneway(*year_groups)
print("\nANOVA for Year:")
print(f"F-statistic: {anova_year.statistic}, p-value: {anova_year.pvalue}")

# Perform Tukey's HSD test for Year
tukey_type = pairwise_tukeyhsd(endog=df['Area_m2'], groups=df['Date'], alpha
# Display the results
print("\nTukey HSD Test for Year:")
print(tukey_type)
# Visualize the Tukey HSD results
tukey_type.plot_simultaneous()
plt.title("Tukey HSD Test for Year")
plt.xlabel('Mean Difference')
plt.grid(True)
plt.savefig('Tukey date (18plots).png')
plt.show()
#There was no a significant in the area differences between the 11 years

#############################################################################
##########################################
##############
#                                                                 TIME SERIES
# Load the dataset
df = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Docum
#Identify unique BufferIDs and Area
unique_dates = df['Date'].unique()
unique_buffer_ids = df['BufferID'].unique()
unique_areas = df['Type'].unique()

#Create a complete DataFrame with all combinations
all_combinations = pd.DataFrame(
    list(itertools.product(unique_dates, unique_buffer_ids, unique_areas)),
    columns=['Date', 'BufferID', 'Type'])
# Merge with the original DataFrame and fill missing values with 0
df_complete = pd.merge(all_combinations, df, on=['Date', 'BufferID', 'Type']

# Time series analysis for a specific BufferID
buffer_id = 'TAI_01'  # Example BufferID
area = 'ForestFormation'       # Example Area
df_filtered = df_complete[(df_complete['BufferID'] == buffer_id) & (df_compl

# Convert Date to numeric index for time series modeling
#df_filtered['Date'] = pd.to_datetime(df_filtered['Date'], errors='coerce')
df_filtered['Date'] = pd.to_numeric(df_filtered['Date'])
df_filtered.sort_values('Date', inplace=True)
df_filtered.set_index('Date', inplace=True)

# Define the model with specified order (p, d, q)
model = ARIMA(df_filtered['Area_m2'], order=(1, 2, 1))
# Fit the model
model_fit = model.fit()

#Forecasting
steps = 5
```

```python
forecast = model_fit.forecast(steps=steps)
forecast_years = range(df_filtered.index[-1] + 1, df_filtered.index[-1] + 1
forecast_df = pd.DataFrame({'Date': forecast_years, 'Forecasted_Area_m2': fo

plt.figure(figsize=(12, 6))
plt.plot(df_filtered.index, df_filtered['Area_m2'], label='Observed', color=
plt.plot(forecast_df['Date'], forecast_df['Forecasted_Area_m2'], label='Fore
plt.xlabel('Date')
plt.ylabel('Area_m2')
plt.title(f'Time Series Forecast for Plot: {buffer_id}, Area: {area}')
plt.legend()
plt.grid(True)
plt.savefig('Time Series Forecast for BufferID (18plots) TAI_01.png')
plt.show()

print(forecast_df)

#####   test if forecast is correct or good

# Split data into training and testing sets (e.g., last 5 years for testing)
train_size = int(len(df_filtered) * 0.6)
train_data, test_data = df_filtered.iloc[:train_size], df_filtered.iloc[trai

# Fit SARIMA model on the training data
arima_model_train = ARIMA(train_data['Area_m2'], order=(1, 2, 1))
arima_fit_train = arima_model_train.fit()

# Forecast for the test period
forecast_test = arima_fit_train.get_forecast(steps=len(test_data))
forecasted_values = forecast_test.predicted_mean
confidence_intervals = forecast_test.conf_int()

# Evaluation metrics
mae = mean_absolute_error(test_data['Area_m2'], forecasted_values)
mse = mean_squared_error(test_data['Area_m2'], forecasted_values)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((test_data['Area_m2'] - forecasted_values) / test_data

# Print evaluation metrics
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
print(f"MAPE: {mape}%")

# Plot the forecast with confidence intervals
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data['Area_m2'], label='Training Data', col
plt.plot(test_data.index, test_data['Area_m2'], label='Actual Test Data', co
plt.plot(test_data.index, forecasted_values, label='Forecast', color='red',
plt.fill_between(test_data.index, confidence_intervals.iloc[:, 0], confidenc
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title('ARIMA Forecast vs Actuals with Confidence Intervals')
plt.legend()
plt.grid(True)
```

```
plt.savefig('ARIMA book1 Forecast vs Actuals with Confidence Intervals.png')
plt.show()
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\sklearn\cluster
\_kmeans.py:1411: UserWarning: KMeans is known to have a memory leak on Wind
ows with MKL, when there are less chunks than available threads. You can avo
id it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```



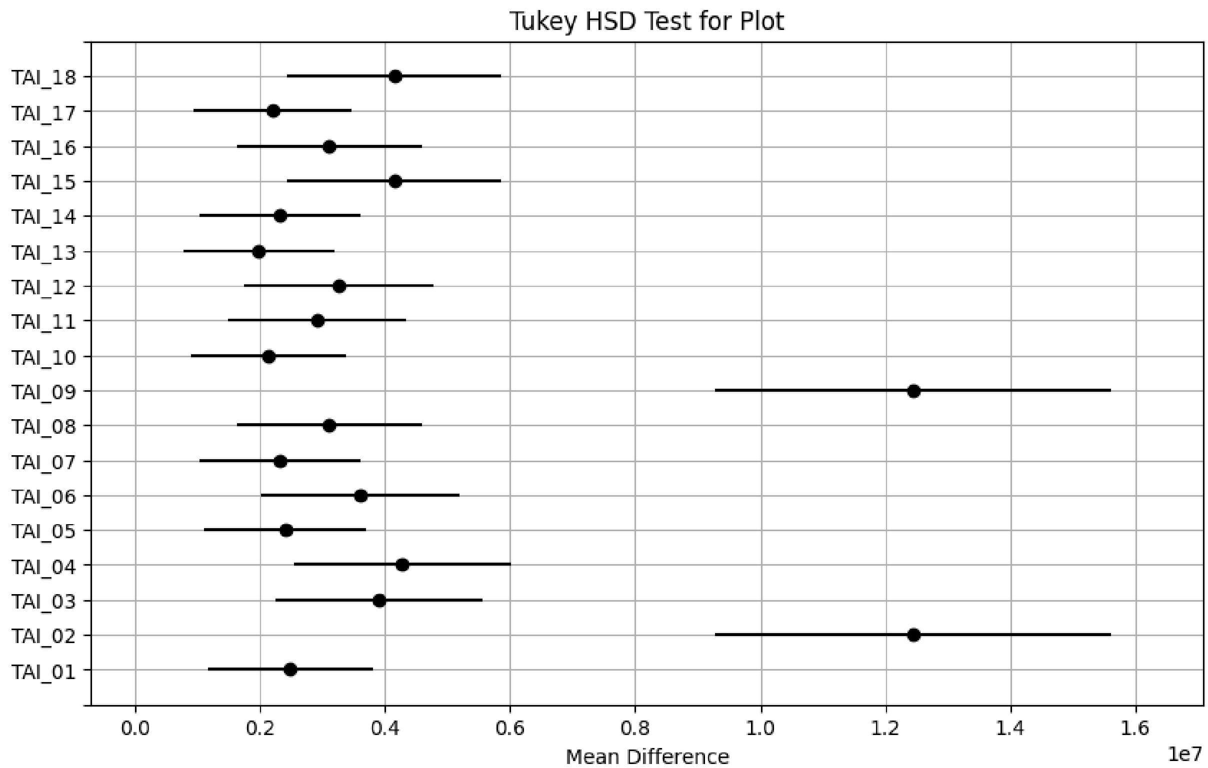
Average Proportion of Total Area by Habitat Type for Each Year
Year
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Habitat Type
Floodplains
ForestFormation
ForestPlantation
Grassland
MosaicofCrops
OilPalm
Pasture
RiverLakeandOcean
Soybeans
UrbanInfrastructure
Wetland
0.05 0.80 0.00 0.00 0.00 0.09 0.05 0.00 0.00 0.00 0.00
0.05 0.80 0.00 0.00 0.00 0.10 0.05 0.00 0.00 0.00 0.00
0.05 0.80 0.00 0.00 0.00 0.10 0.05 0.00 0.00 0.00 0.00
0.05 0.80 0.00 0.00 0.00 0.10 0.05 0.00 0.00 0.00 0.00
0.05 0.80 0.00 0.00 0.00 0.10 0.05 0.00 0.00 0.00 0.00
0.05 0.79 0.00 0.00 0.00 0.10 0.05 0.00 0.00 0.00 0.00
0.05 0.79 0.00 0.00 0.00 0.10 0.05 0.00 0.00 0.00 0.00
0.05 0.79 0.00 0.00 0.00 0.11 0.05 0.00 0.00 0.00 0.00
0.05 0.80 0.00 0.00 0.00 0.11 0.04 0.00 0.00 0.00 0.00
0.05 0.80 0.00 0.00 0.00 0.11 0.04 0.00 0.00 0.00 0.00
0.05 0.79 0.00 0.00 0.00 0.11 0.05 0.00 0.00 0.00 0.00
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7

```
ANOVA for BufferID:
F-statistic: 9.00751058069251, p-value: 1.3372846720700188e-21

Tukey HSD Test for PLot:
          Multiple Comparison of Means - Tukey HSD, FWER=0.05
=======================================================================
group1 group2    meandiff    p-adj      lower          upper     reject
-----------------------------------------------------------------------
TAI_01 TAI_02   9952017.1729    0.0   5388010.0773 14516024.2686   True
TAI_01 TAI_03   1419641.5462 0.9727  -1568202.4521  4407485.5445  False
TAI_01 TAI_04   1787849.2717 0.8503  -1284392.0272  4860090.5705  False
TAI_01 TAI_05    -87312.9164    1.0  -2699127.0593  2524501.2265  False
TAI_01 TAI_06   1111634.6378 0.9975  -1803243.2233  4026512.4989  False
TAI_01 TAI_07   -169888.1874    1.0  -2759872.3331  2420095.9582  False
TAI_01 TAI_08    621840.5455    1.0  -2173031.5962  3416712.6871  False
TAI_01 TAI_09   9951530.1225    0.0   5387523.0268 14515537.2181   True
TAI_01 TAI_10   -350639.2941    1.0  -2891343.9267  2190065.3384  False
TAI_01 TAI_11    423092.1702    1.0  -2321778.2219  3167962.5623  False
TAI_01 TAI_12    769307.6807    1.0  -2062292.3456  3600907.7069  False
TAI_01 TAI_13   -505275.0997    1.0  -3003071.1985   1992520.999  False
TAI_01 TAI_14   -169099.8126    1.0  -2759083.9582  2420884.3331  False
TAI_01 TAI_15   1658171.2941 0.9084   -1384500.103  4700842.6912  False
TAI_01 TAI_16    620587.7647    1.0   -2174284.377  3415459.9064  False
TAI_01 TAI_17   -281493.3359    1.0  -2841067.8185  2278081.1468  False
TAI_01 TAI_18   1656872.4706  0.909  -1385798.9265  4699543.8677  False
TAI_02 TAI_03  -8532375.6267    0.0  -13308774.438 -3755976.8155   True
TAI_02 TAI_04  -8164167.9013    0.0 -12993809.7559 -3334526.0466   True
TAI_02 TAI_05 -10039330.0893    0.0 -14589972.5674 -5488687.6113   True
TAI_02 TAI_06  -8840382.5352    0.0 -13571480.3772 -4109284.6931   True
TAI_02 TAI_07 -10121905.3604    0.0 -14660053.8507   -5583756.87   True
TAI_02 TAI_08  -9330176.6275    0.0 -13988296.8636 -4672056.3914   True
TAI_02 TAI_09      -487.0505    1.0  -5892594.8749  5891620.7739  False
TAI_02 TAI_10 -10302656.4671    0.0 -14812861.9918 -5792450.9423   True
TAI_02 TAI_11  -9528925.0027    0.0 -14157217.0544 -4900632.9511   True
TAI_02 TAI_12  -9182709.4923    0.0 -13862958.6902 -4502460.2944   True
TAI_02 TAI_13 -10457292.2727    0.0 -14943466.4999 -5971118.0455   True
TAI_02 TAI_14 -10121116.9855    0.0 -14659265.4759 -5582968.4951   True
TAI_02 TAI_15  -8293845.8788    0.0 -13104731.7719 -3482959.9857   True
TAI_02 TAI_16  -9331429.4082    0.0 -13989549.6444 -4673309.1721   True
TAI_02 TAI_17 -10233510.5088    0.0 -14754372.7471 -5712648.2705   True
TAI_02 TAI_18  -8295144.7024    0.0 -13106030.5955 -3484258.8093   True
TAI_03 TAI_04    368207.7255    1.0  -3011509.9304  3747925.3814  False
TAI_03 TAI_05  -1506954.4626 0.9494  -4474343.5427  1460434.6174  False
TAI_03 TAI_06   -308006.9084    1.0  -3545341.8896  2929328.0727  False
TAI_03 TAI_07  -1589529.7337  0.916  -4537722.8599  1358663.3926  False
TAI_03 TAI_08   -797801.0008    1.0  -3927519.0589  2331917.0574  False
TAI_03 TAI_09   8531888.5762    0.0    3755489.765 13308287.3875   True
TAI_03 TAI_10  -1770280.8403  0.796  -4675277.3748  1134715.6941  False
TAI_03 TAI_11    -996549.376 0.9997  -4081697.3959  2088598.6439  False
TAI_03 TAI_12   -650333.8655    1.0  -3812893.5162  2512225.7851  False
TAI_03 TAI_13   -1924916.646 0.6462  -4792460.9239    942627.632  False
TAI_03 TAI_14  -1588741.3588 0.9163  -4536934.4851  1359451.7675  False
TAI_03 TAI_15    238529.7479    1.0  -3114330.8316  3591390.3274  False
TAI_03 TAI_16   -799053.7815    1.0  -3928771.8396  2330664.2766  False
TAI_03 TAI_17  -1701134.8821 0.8497  -4622649.2783  1220379.5141  False
TAI_03 TAI_18    237230.9244    1.0  -3115629.6551  3590091.5039  False
```

TAI_04	TAI_05	-1875162.1881	0.7853	-4927514.1981	1177189.8219	False
TAI_04	TAI_06	-676214.6339	1.0	-3991601.8844	2639172.6166	False
TAI_04	TAI_07	-1957737.4591	0.7127	-4991431.1731	1075956.2548	False
TAI_04	TAI_08	-1166008.7262	0.9986	-4376396.5476	2044379.0952	False
TAI_04	TAI_09	8163680.8508	0.0	3334038.9961	12993322.7054	True
TAI_04	TAI_10	-2138488.5658	0.5293	-5130220.4564	853243.3248	False
TAI_04	TAI_11	-1364757.1015	0.9899	-4531710.3921	1802196.1891	False
TAI_04	TAI_12	-1018541.591	0.9998	-4260954.0238	2223870.8417	False
TAI_04	TAI_13	-2293124.3714	0.3708	-5248503.3702	662254.6274	False
TAI_04	TAI_14	-1956949.0843	0.7133	-4990642.7982	1076744.6297	False
TAI_04	TAI_15	-129677.9776	1.0	-3557961.6452	3298605.6901	False
TAI_04	TAI_16	-1167261.507	0.9986	-4377649.3284	2043126.3144	False
TAI_04	TAI_17	-2069342.6076	0.6017	-5077116.071	938430.8559	False
TAI_04	TAI_18	-130976.8011	1.0	-3559260.4688	3297306.8666	False
TAI_05	TAI_06	1198947.5542	0.9935	-1694959.6903	4092854.7986	False
TAI_05	TAI_07	-82575.271	1.0	-2648935.3527	2483784.8107	False
TAI_05	TAI_08	709153.4619	1.0	-2063840.6749	3482147.5986	False
TAI_05	TAI_09	10038843.0389	0.0	5488200.5608	14589485.5169	True
TAI_05	TAI_10	-263326.3777	1.0	-2779944.3909	2253291.6355	False
TAI_05	TAI_11	510405.0866	1.0	-2212185.5297	3232995.7029	False
TAI_05	TAI_12	856620.5971	0.9999	-1953387.3928	3666628.5869	False
TAI_05	TAI_13	-417962.1833	1.0	-2891253.8251	2055329.4585	False
TAI_05	TAI_14	-81786.8962	1.0	-2648146.9779	2484573.1856	False
TAI_05	TAI_15	1745484.2105	0.8582	-1277103.3275	4768071.7485	False
TAI_05	TAI_16	707900.6811	1.0	-2065093.4557	3480894.8179	False
TAI_05	TAI_17	-194180.4195	1.0	-2729847.5361	2341486.6972	False
TAI_05	TAI_18	1744185.387	0.859	-1278402.151	4766772.925	False
TAI_06	TAI_07	-1281522.8252	0.9856	-4155743.3973	1592697.7469	False
TAI_06	TAI_08	-489794.0923	1.0	-3549930.7413	2570342.5567	False
TAI_06	TAI_09	8839895.4847	0.0	4108797.6426	13570993.3267	True
TAI_06	TAI_10	-1462273.9319	0.9411	-4292168.9922	1367621.1284	False
TAI_06	TAI_11	-688542.4676	1.0	-3703080.4905	2325995.5554	False
TAI_06	TAI_12	-342326.9571	1.0	-3436043.9336	2751390.0194	False
TAI_06	TAI_13	-1616909.7375	0.8551	-4408345.0983	1174525.6232	False
TAI_06	TAI_14	-1280734.4503	0.9857	-4154955.0224	1593486.1217	False
TAI_06	TAI_15	546536.6563	1.0	-2741468.0962	3834541.4089	False
TAI_06	TAI_16	-491046.8731	1.0	-3551183.5221	2569089.7759	False
TAI_06	TAI_17	-1393127.9736	0.9639	-4239976.6795	1453720.7323	False
TAI_06	TAI_18	545237.8328	1.0	-2742766.9197	3833242.5854	False
TAI_07	TAI_08	791728.7329	0.9999	-1960714.044	3544171.5098	False
TAI_07	TAI_09	10121418.3099	0.0	5583269.8195	14659566.8003	True
TAI_07	TAI_10	-180751.1067	1.0	-2674705.9943	2313203.781	False
TAI_07	TAI_11	592980.3577	1.0	-2108675.5089	3294636.2242	False
TAI_07	TAI_12	939195.8681	0.9995	-1850533.4486	3728925.1848	False
TAI_07	TAI_13	-335386.9123	1.0	-2785614.7186	2114840.894	False
TAI_07	TAI_14	788.3749	1.0	-2543351.7208	2544928.4706	False
TAI_07	TAI_15	1828059.4816	0.7977	-1175684.8788	4831803.8419	False
TAI_07	TAI_16	790475.9521	0.9999	-1961966.8247	3542918.729	False
TAI_07	TAI_17	-111605.1484	1.0	-2624780.925	2401570.6281	False
TAI_07	TAI_18	1826760.658	0.7986	-1176983.7023	4830505.0184	False
TAI_08	TAI_09	9329689.577	0.0	4671569.3409	13987809.8131	True
TAI_08	TAI_10	-972479.8396	0.9988	-3678603.1544	1733643.4753	False
TAI_08	TAI_11	-198748.3752	1.0	-3097409.5895	2699912.839	False
TAI_08	TAI_12	147467.1352	1.0	-2833452.5339	3128386.8044	False
TAI_08	TAI_13	-1127115.6452	0.9918	-3792994.2464	1538762.956	False
TAI_08	TAI_14	-790940.358	0.9999	-3543383.1349	1961502.4189	False

TAI_08	TAI_15	1036330.7487	0.9997	-2145771.1661	4218432.6634	False
TAI_08	TAI_16	-1252.7807	1.0	-2947306.693	2944801.1315	False
TAI_08	TAI_17	-903333.8813	0.9996	-3627181.3252	1820513.5626	False
TAI_08	TAI_18	1035031.9251	0.9997	-2147069.9896	4217133.8399	False
TAI_09	TAI_10	-10302169.4166	0.0	-14812374.9414	-5791963.8918	True
TAI_09	TAI_11	-9528437.9522	0.0	-14156730.0039	-4900145.9006	True
TAI_09	TAI_12	-9182222.4418	0.0	-13862471.6397	-4501973.2439	True
TAI_09	TAI_13	-10456805.2222	0.0	-14942979.4494	-5970630.995	True
TAI_09	TAI_14	-10120629.935	0.0	-14658778.4254	-5582481.4447	True
TAI_09	TAI_15	-8293358.8283	0.0	-13104244.7214	-3482472.9352	True
TAI_09	TAI_16	-9330942.3578	0.0	-13989062.5939	-4672822.1216	True
TAI_09	TAI_17	-10233023.4583	0.0	-14753885.6967	-5712161.22	True
TAI_09	TAI_18	-8294657.6519	0.0	-13105543.545	-3483771.7588	True
TAI_10	TAI_11	773731.4643	0.9999	-1880718.8698	3428181.7985	False
TAI_10	TAI_12	1119946.9748	0.9945	-1624092.3499	3863986.2995	False
TAI_10	TAI_13	-154635.8056	1.0	-2552713.8815	2243442.2703	False
TAI_10	TAI_14	181539.4816	1.0	-2312415.4061	2675494.3692	False
TAI_10	TAI_15	2008810.5882	0.6275	-952547.6031	4970168.7796	False
TAI_10	TAI_16	971227.0588	0.9988	-1734896.256	3677350.3737	False
TAI_10	TAI_17	69145.9583	1.0	-2393213.6091	2531505.5256	False
TAI_10	TAI_18	2007511.7647	0.6287	-953846.4267	4968869.9561	False
TAI_11	TAI_12	346215.5105	1.0	-2587874.6816	3280305.7025	False
TAI_11	TAI_13	-928367.27	0.9989	-3541777.2833	1685042.7434	False
TAI_11	TAI_14	-592191.9828	1.0	-3293847.8493	2109463.8838	False
TAI_11	TAI_15	1235079.1239	0.9964	-1903196.8004	4373355.0482	False
TAI_11	TAI_16	197495.5945	1.0	-2701165.6197	3096156.8087	False
TAI_11	TAI_17	-704585.5061	1.0	-3377102.6863	1967931.6742	False
TAI_11	TAI_18	1233780.3004	0.9964	-1904495.624	4372056.2247	False
TAI_12	TAI_13	-1274582.7804	0.9748	-3978941.6946	1429776.1338	False
TAI_12	TAI_14	-938407.4932	0.9995	-3728136.8099	1851321.8235	False
TAI_12	TAI_15	888863.6134	1.0	-2325544.7328	4103271.9597	False
TAI_12	TAI_16	-148719.916	1.0	-3129639.5851	2832199.7532	False
TAI_12	TAI_17	-1050801.0165	0.9976	-3812321.1265	1710719.0934	False
TAI_12	TAI_18	887564.7899	1.0	-2326843.5563	4101973.1361	False
TAI_13	TAI_14	336175.2872	1.0	-2114052.5191	2786403.0935	False
TAI_13	TAI_15	2163446.3939	0.4627	-761181.3874	5088074.1751	False
TAI_13	TAI_16	1125862.8645	0.9919	-1540015.7368	3791741.4657	False
TAI_13	TAI_17	223781.7639	1.0	-2194279.4347	2641842.9625	False
TAI_13	TAI_18	2162147.5703	0.4638	-762480.2109	5086775.3516	False
TAI_14	TAI_15	1827271.1067	0.7982	-1176473.2537	4831015.467	False
TAI_14	TAI_16	789687.5773	0.9999	-1962755.1996	3542130.3542	False
TAI_14	TAI_17	-112393.5233	1.0	-2625569.2999	2400782.2533	False
TAI_14	TAI_18	1825972.2832	0.7992	-1177772.0772	4829716.6435	False
TAI_15	TAI_16	-1037583.5294	0.9997	-4219685.4442	2144518.3854	False
TAI_15	TAI_17	-1939664.63	0.6974	-4917228.0365	1037898.7765	False
TAI_15	TAI_18	-1298.8235	1.0	-3403108.8621	3400511.215	False
TAI_16	TAI_17	-902081.1006	0.9996	-3625928.5444	1821766.3433	False
TAI_16	TAI_18	1036284.7059	0.9997	-2145817.2089	4218386.6206	False
TAI_17	TAI_18	1938365.8065	0.6985	-1039197.6001	4915929.213	False

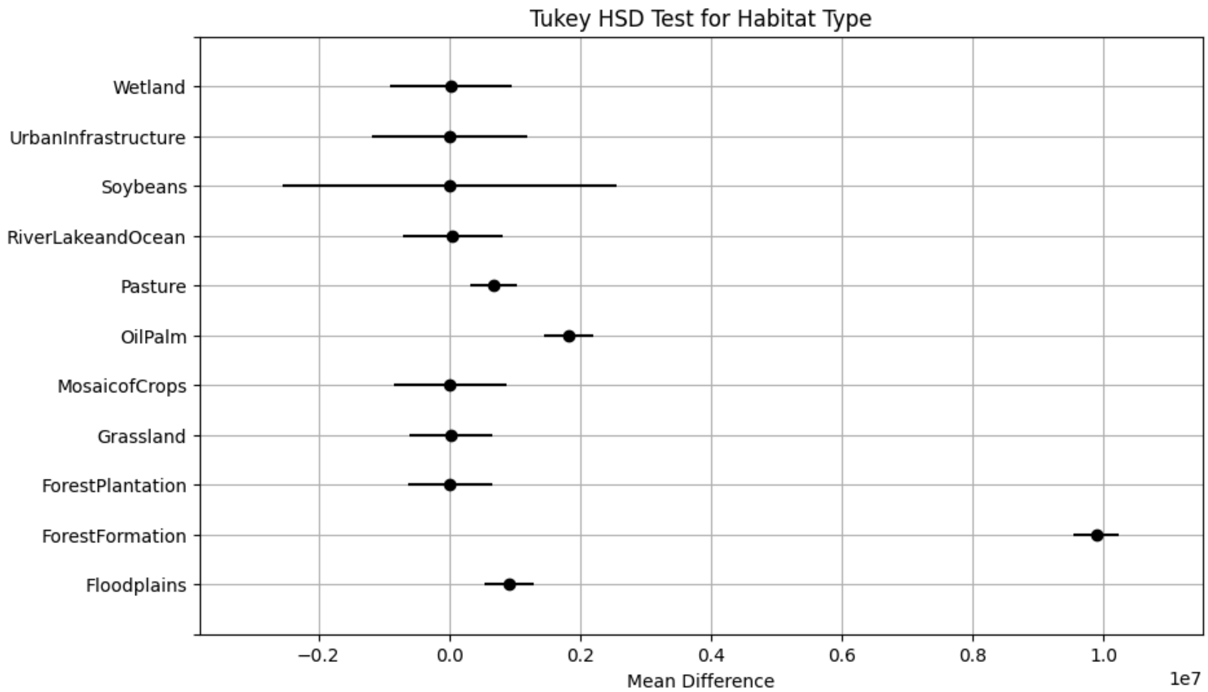
----


Tukey HSD Test for Plot
TAI_18
TAI_17
TAI_16
TAI_15
TAI_14
TAI_13
TAI_12
TAI_11
TAI_10
TAI_09
TAI_08
TAI_07
TAI_06
TAI_05
TAI_04
TAI_03
TAI_02
TAI_01
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1.6
1e7
Mean Difference

```
ANOVA for Type:
F-statistic: 464.7582383256251, p-value: 1.64e-321

Tukey HSD Test for Type:
                      Multiple Comparison of Means - Tukey HSD, FWER=0.05
============================================================================
====================
       group1             group2          meandiff   p-adj      lower
upper     reject
----------------------------------------------------------------------------
--------------------
        Floodplains     ForestFormation  8977324.9034    0.0   8398617.0403
9556032.7665   True
        Floodplains    ForestPlantation  -901621.7277 0.1387  -1920011.7905
116768.3351  False
        Floodplains           Grassland  -888500.2429 0.1412  -1894648.4639
117647.978  False
        Floodplains       MosaicofCrops  -898134.2805 0.4686  -2185777.3532
389508.7923  False
        Floodplains             OilPalm   910244.7248 0.0002    282140.1697
1538349.28   True
        Floodplains             Pasture  -240545.7901  0.968   -835755.2101
354663.63  False
        Floodplains   RiverLakeandOcean  -865295.8052 0.3669  -2028530.6518
297939.0413  False
        Floodplains            Soybeans   -908085.364 0.9971  -3984398.8511
2168228.123  False
        Floodplains UrbanInfrastructure  -907238.3052 0.7947   -2557218.787
742742.1765  False
        Floodplains             Wetland  -888098.9281 0.5638  -2240951.0265
464753.1703  False
    ForestFormation    ForestPlantation -9878946.6311    0.0 -10870461.5028
-8887431.7593   True
    ForestFormation           Grassland -9865825.1463    0.0 -10844762.1532
-8886888.1395   True
    ForestFormation       MosaicofCrops -9875459.1838    0.0  -11141953.599
-8608964.7687   True
    ForestFormation             OilPalm -8067080.1786    0.0  -8650602.8885
-7483557.4686   True
    ForestFormation             Pasture -9217870.6935    0.0  -9765828.4241
-8669912.9628   True
    ForestFormation   RiverLakeandOcean -9842620.7086    0.0 -10982400.8317
-8702840.5855   True
    ForestFormation            Soybeans -9885410.2674    0.0 -12952931.7574
-6817888.7775   True
    ForestFormation UrbanInfrastructure -9884563.2086    0.0  -11518092.826
-8251033.5912   True
    ForestFormation             Wetland -9865423.8315    0.0 -11198162.4483
-8532685.2146   True
   ForestPlantation           Grassland    13121.4847    1.0  -1275495.2902
1301738.2597  False
   ForestPlantation       MosaicofCrops     3487.4472    1.0  -1515138.1264
1522113.0208  False
   ForestPlantation             OilPalm  1811866.4525    0.0    790732.6306
2833000.2744   True
   ForestPlantation             Pasture   661075.9376 0.5549   -340159.9006
```

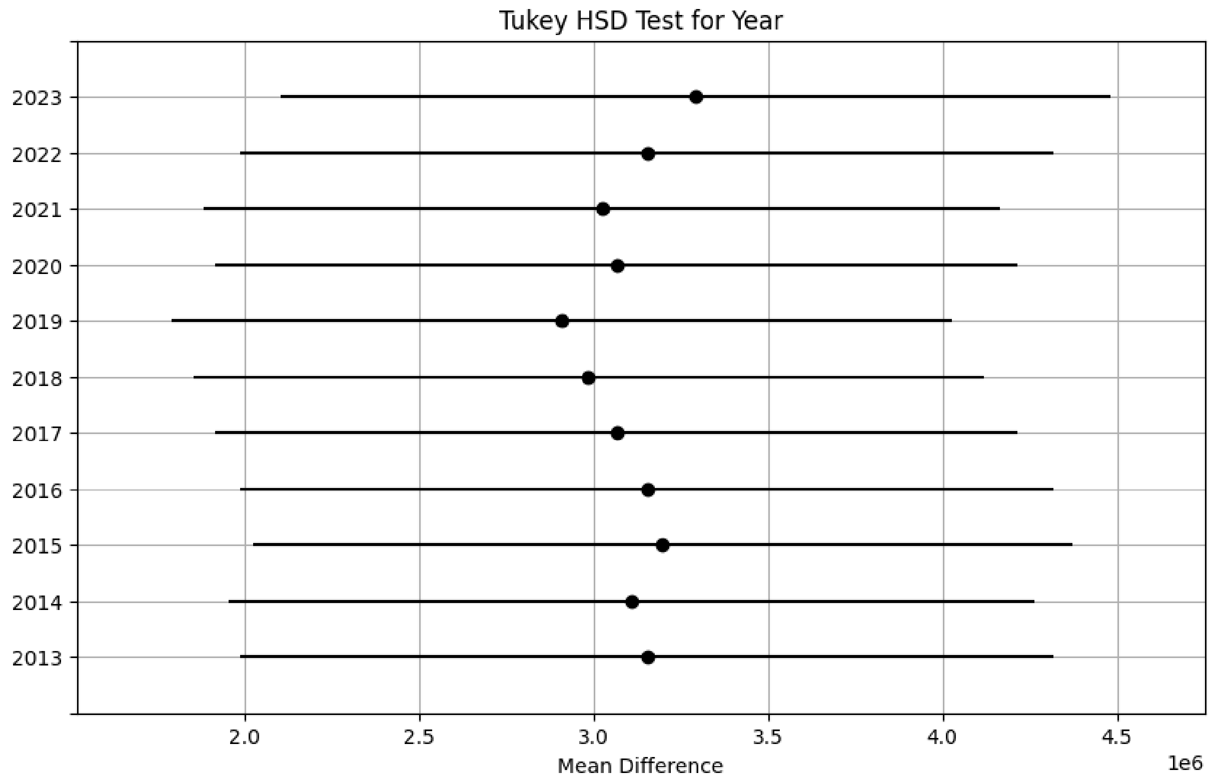
					1662311.7759	False
ForestPlantation	RiverLakeandOcean	36325.9225	1.0	-1378352.2241	1451004.069	False
ForestPlantation	Soybeans	-6463.6364	1.0	-3186385.5883	3173458.3156	False
ForestPlantation	UrbanInfrastructure	-5616.5775	1.0	-1841545.3725	1830312.2174	False
ForestPlantation	Wetland	13522.7996	1.0	-1560773.1542	1587818.7534	False
Grassland	MosaicofCrops	-9634.0375	1.0	-1520077.5337	1500809.4587	False
Grassland	OilPalm	1798744.9678	0.0	789819.6956	2807670.2399	True
Grassland	Pasture	647954.4529	0.5665	-340827.1844	1636736.0902	False
Grassland	RiverLakeandOcean	23204.4377	1.0	-1382686.803	1429095.6784	False
Grassland	Soybeans	-19585.1211	1.0	-3195607.7191	3156437.4769	False
Grassland	UrbanInfrastructure	-18738.0623	1.0	-1847904.6656	1810428.541	False
Grassland	Wetland	401.3149	1.0	-1566003.3814	1566806.0112	False
MosaicofCrops	OilPalm	1808379.0053	0.0004	518564.8152	3098193.1953	True
MosaicofCrops	Pasture	657588.4904	0.8524	-616530.6431	1931707.6239	False
MosaicofCrops	RiverLakeandOcean	32838.4752	1.0	-1586488.7372	1652165.6877	False
MosaicofCrops	Soybeans	-9951.0836	1.0	-3286047.844	3266145.6768	False
MosaicofCrops	UrbanInfrastructure	-9104.0248	1.0	-2006988.1312	1988780.0817	False
MosaicofCrops	Wetland	10035.3524	1.0	-1750451.5441	1770522.2489	False
OilPalm	Pasture	-1150790.5149	0.0	-1750682.3517	-550898.6781	True
OilPalm	RiverLakeandOcean	-1775540.53	0.0001	-2941178.2398	-609902.8203	True
OilPalm	Soybeans	-1818330.0889	0.7123	-4895552.9656	1258892.7878	False
OilPalm	UrbanInfrastructure	-1817483.03	0.0176	-3469158.4075	-165807.6526	True
OilPalm	Wetland	-1798343.6529	0.001	-3153262.3819	-443424.9239	True
Pasture	RiverLakeandOcean	-624750.0152	0.8052	-1772996.5879	523496.5576	False
Pasture	Soybeans	-667539.574	0.9998	-3738216.9511	2403137.8031	False
Pasture	UrbanInfrastructure	-666692.5152	0.9666	-2306140.7375	972755.7072	False
Pasture	Wetland	-647553.138	0.8984	-1987539.5871	692433.3111	False
RiverLakeandOcean	Soybeans	-42789.5588	1.0	-3272015.5665	3186436.4489	False
RiverLakeandOcean	UrbanInfrastructure	-41942.5	1.0	-1962002.7929		

```
1878117.7929  False
  RiverLakeandOcean             Wetland   -22803.1228    1.0  -1694450.4356
1648844.1899  False
           Soybeans UrbanInfrastructure      847.0588    1.0  -3433861.2098
3435555.3275  False
           Soybeans             Wetland     19986.436    1.0   -3282284.616
3322257.488  False
UrbanInfrastructure             Wetland    19139.3772    1.0  -2021381.3947
2059660.149  False
----------------------------------------------------------------------------
-------------------
```

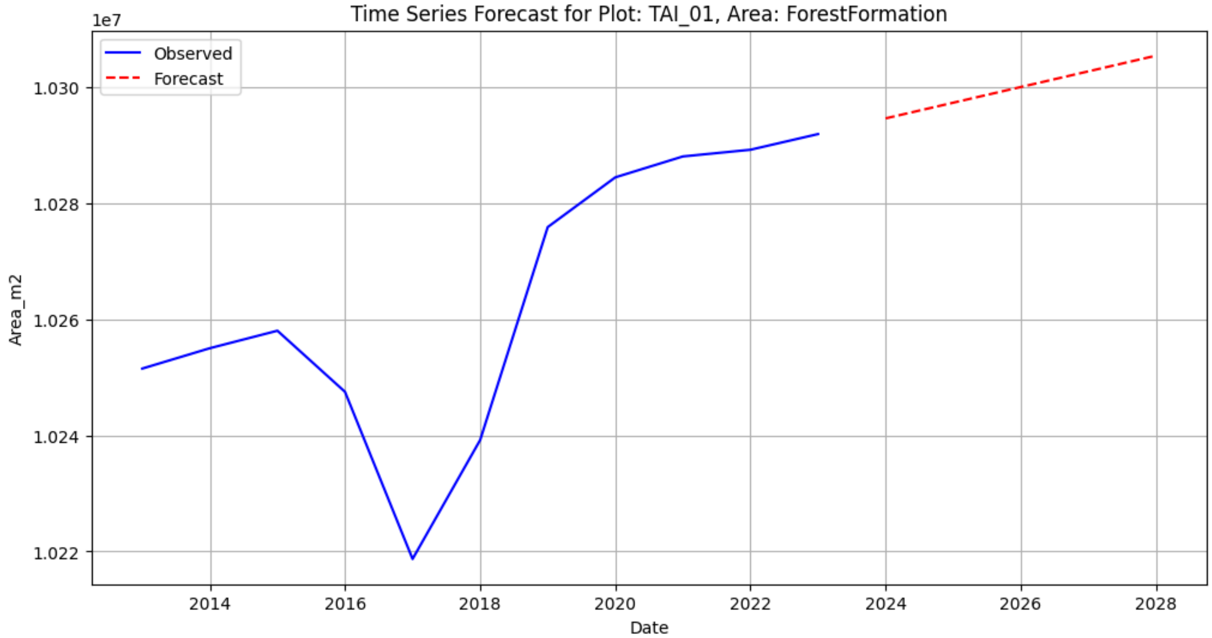


```
ANOVA for Year:
F-statistic: 0.04438257860079598, p-value: 0.9999961834517294

Tukey HSD Test for Year:
       Multiple Comparison of Means - Tukey HSD, FWER=0.05
==================================================================
group1 group2   meandiff   p-adj     lower        upper     reject
------------------------------------------------------------------
  2013   2014  -43796.5437   1.0 -2364596.2714  2277003.184  False
  2013   2015   45047.8736   1.0 -2292155.1025 2382250.8497  False
  2013   2016          0.0   1.0 -2328900.2749  2328900.275  False
  2013   2017  -86393.1822   1.0   -2399287.08 2226500.7157  False
  2013   2018  -168178.728   1.0 -2465817.1789 2129459.7229  False
  2013   2019  -245231.778   1.0 -2528313.1439  2037849.588  False
  2013   2020  -86393.1822   1.0   -2399287.08 2226500.7157  False
  2013   2021 -127838.5601   1.0 -2433014.2748 2177337.1545  False
  2013   2022       0.0001   1.0 -2328900.2749  2328900.275  False
  2013   2023  139118.4332   1.0   -2215328.13 2493564.9965  False
  2014   2015   88844.4173   1.0 -2240286.8879 2417975.7225  False
  2014   2016   43796.5437   1.0  -2277003.184 2364596.2715  False
  2014   2017  -42596.6384   1.0 -2347333.7315 2262140.4546  False
  2014   2018 -124382.1843   1.0 -2413809.4787 2165045.1101  False
  2014   2019 -201435.2342   1.0 -2476252.8992 2073382.4308  False
  2014   2020  -42596.6384   1.0 -2347333.7315 2262140.4546  False
  2014   2021  -84042.0164   1.0 -2381033.5185 2212949.4857  False
  2014   2022   43796.5438   1.0 -2277003.1839 2364596.2715  False
  2014   2023   182914.977   1.0 -2163519.2336 2529349.1876  False
  2015   2016  -45047.8736   1.0 -2382250.8497 2292155.1025  False
  2015   2017 -131441.0558   1.0 -2452694.9073 2189812.7958  False
  2015   2018 -213226.6016   1.0 -2519280.3112  2092827.108  False
  2015   2019 -290279.6516   1.0 -2581829.7349 2001270.4317  False
  2015   2020 -131441.0558   1.0 -2452694.9073 2189812.7958  False
  2015   2021 -172886.4337   1.0 -2486449.9915 2140677.1241  False
  2015   2022  -45047.8735   1.0 -2382250.8496 2292155.1025  False
  2015   2023   94070.5596   1.0 -2268588.9334 2456730.0526  False
  2016   2017  -86393.1822   1.0   -2399287.08 2226500.7157  False
  2016   2018  -168178.728   1.0 -2465817.1789 2129459.7229  False
  2016   2019  -245231.778   1.0 -2528313.1439  2037849.588  False
  2016   2020  -86393.1822   1.0   -2399287.08 2226500.7157  False
  2016   2021 -127838.5601   1.0 -2433014.2748 2177337.1545  False
  2016   2022       0.0001   1.0 -2328900.2749  2328900.275  False
  2016   2023  139118.4332   1.0   -2215328.13 2493564.9965  False
  2017   2018  -81785.5459   1.0 -2363198.2974 2199627.2057  False
  2017   2019 -158838.5958   1.0 -2425590.0633 2107912.8717  False
  2017   2020          0.0   1.0 -2296775.9739 2296775.9739  False
  2017   2021   -41445.378   1.0 -2330448.8221 2247558.0662  False
  2017   2022   86393.1822   1.0 -2226500.7156 2399287.0801  False
  2017   2023  225511.6154   1.0 -2113103.4258 2564126.6566  False
  2018   2019    -77053.05   1.0 -2328236.4018 2174130.3019  False
  2018   2020   81785.5459   1.0 -2199627.2057 2363198.2974  False
  2018   2021   40340.1679   1.0 -2233247.5334 2313927.8692  False
  2018   2022  168178.7281   1.0 -2129459.7228  2465817.179  False
  2018   2023  307297.1612   1.0 -2016231.3149 2630825.6374  False
  2019   2020  158838.5958   1.0 -2107912.8717 2425590.0633  False
  2019   2021  117393.2178   1.0 -2141482.4113  2376268.847  False
  2019   2022   245231.778   1.0 -2037849.5879  2528313.144  False
```

```
  2019   2023  384350.2112   1.0 -1924784.3999 2693484.8223  False
  2020   2021   -41445.378   1.0 -2330448.8221 2247558.0662  False
  2020   2022   86393.1822   1.0 -2226500.7156 2399287.0801  False
  2020   2023  225511.6154   1.0 -2113103.4258 2564126.6566  False
  2021   2022  127838.5602   1.0 -2177337.1544 2433014.2748  False
  2021   2023  266956.9934   1.0 -2064025.0323  2597939.019  False
  2022   2023  139118.4332   1.0 -2215328.1301 2493564.9964  False
-----------------------------------------------------------------
```

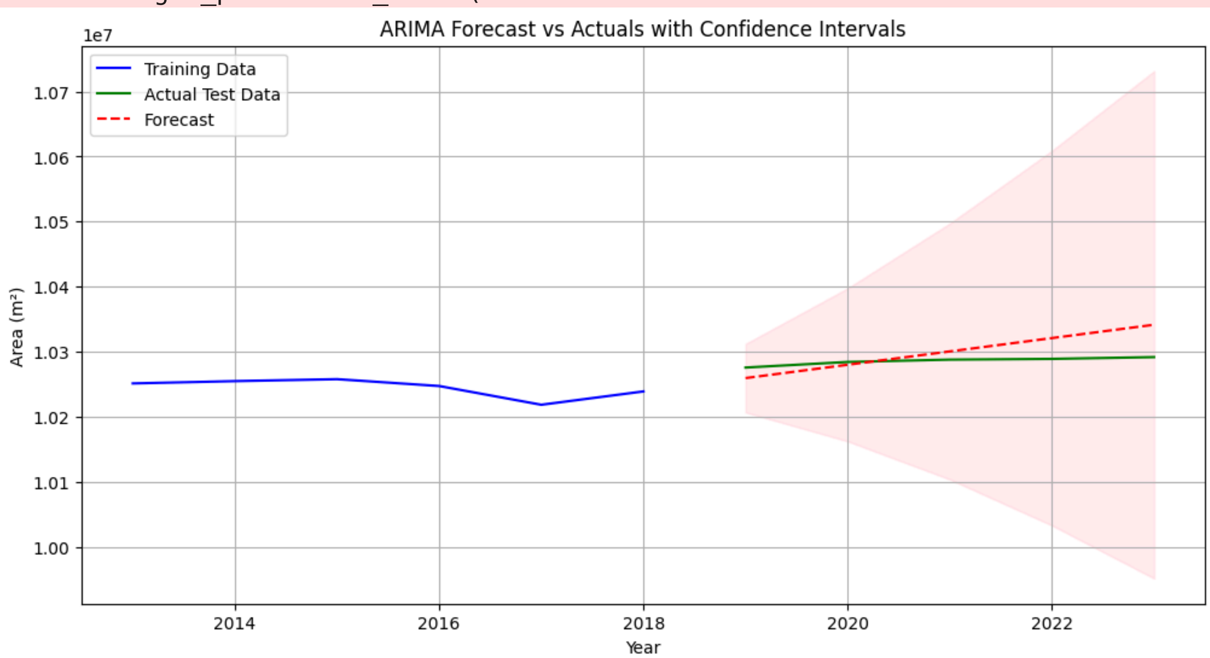



```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
ction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```




```
    Date  Forecasted_Area_m2
11  2024        1.029459e+07
12  2025        1.029729e+07
13  2026        1.029999e+07
14  2027        1.030269e+07
15  2028        1.030539e+07
MAE: 22952.759128947928
MSE: 786893609.4934272
RMSE: 28051.624008128783
MAPE: nan%
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:966: UserWarning: Non-stationary starting autoregress
ive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
ction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```



In [9]:
```
################################################################################
###############################                                 SECOND DATA BA

# I used a second data base to explore a bigger area than contains all 18 pl
# I found important to also analize this data base, because it can contain i
# in the whole area and not only snips of it
```

```
center = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\D

##############################              First, I am going to use some c

# Group by BufferID and calculate the average area
center_avg_area = center.groupby('Type')['Area_m2'].mean().reset_index()
# Standardize the data
scaler = StandardScaler()
center_avg_area_scaled = scaler.fit_transform(center_avg_area[['Area_m2']])

# Apply K-Means clustering
kmeans = KMeans(n_clusters=4, random_state=0)
center_avg_area['Cluster'] = kmeans.fit_predict(center_avg_area_scaled)

# Plot the clusters
# Here the cluster plot indicates which habitat type has more area in total,
# We can see that in the big area "ForestFormation" has the biggest squared

plt.figure(figsize=(10, 6))
sns.scatterplot(x='Type', y='Area_m2', hue='Cluster', data=center_avg_area,
plt.title('K-Means Clustering of Habitat Type by Average Area m2')
plt.xlabel('Type')
plt.ylabel('Average Area (m²)')
plt.legend(title='Cluster')
plt.xticks(rotation=90)
plt.tight_layout()
plt.savefig('K-Means Clustering of Habitat Type by Average Area m2 center.pr
plt.show()

#########   HEAT MAP FOR HABITAT TYPE PER YEAR

# Aggregate by BufferID and Areas to calculate the average proportion across
center_avg_proportion = center.groupby(['Date', 'Type'])['Area_m2'].sum().re
# Calculate the proportion of Area_m2 for each Area within each Plot
center_avg_proportion['Proportion'] = center_avg_proportion.groupby('Date')[
# Pivot the data for heatmap
center_pivot_avg = center_avg_proportion.pivot_table(values='Proportion', ir

#Plot the heatmap
#In the heatmap we can see that our main habitat type is "Forest formation"
#The percentages dont really change across the years.
plt.figure(figsize=(12, 8))
sns.heatmap(center_pivot_avg, cmap='PiYG', annot=True, fmt='.2f', linewidths
plt.title('Average Proportion of Total Area by Habitat Type for Each Year')
plt.xlabel('Habitat Type')
plt.ylabel('Year')
plt.xticks(rotation=80)
plt.tight_layout()
plt.savefig('Average Proportion of Total Area by Habitat Type for Each Year.
plt.show()

##############################              ARE THE DIFFERENCES IN THE HEAT


#################       ANOVA for Type
```

```
Type_cent_groups = [center[center['Type'] == Type]['Area_m2'].values for Typ
anova_cent_Type = f_oneway(*Type_cent_groups)
print("ANOVA for Type:")
print(f"F-statistic: {anova_cent_Type.statistic}, p-value: {anova_cent_Type.

# Perform Tukey's HSD test for Type
tukey_type = pairwise_tukeyhsd(endog=center['Area_m2'], groups=center['Type'
# Display the results
print("\nTukey HSD Test for PLot:")
print(tukey_type)
# Visualize the Tukey HSD results
tukey_type.plot_simultaneous()
plt.title("Tukey HSD Test for Habitat Type")
plt.xlabel('Mean Difference')
plt.grid(True)
plt.savefig('Tukey HSD Test for Type center.png')
plt.show()
#There is a significant difference between the Habitat types, being ForestFo
#These types are the one with the largest area_m2
# A difference can be noted between the whole area of the experiment and the
# If only we take only the plots under accountance we get a false overview o
# But ForestFormation has by far the largest area. If we take also the whole
# heterogenic, having a high area disturbance type habitats, like Pasture an

##########################################################################
#################      ANOVA for Year
year_groups = [center[center['Date'] == year]['Area_m2'].values for year in 
anova_year = f_oneway(*year_groups)
print("\nANOVA for Year:")
print(f"F-statistic: {anova_year.statistic}, p-value: {anova_year.pvalue}")

# Perform Tukey's HSD test for Year
tukey_Year = pairwise_tukeyhsd(endog=center['Area_m2'], groups=center['Date'
# Display the results
print("\nTukey HSD Test for Year:")
print(tukey_Year)
# Visualize the Tukey HSD results
tukey_Year.plot_simultaneous()
plt.title("Tukey HSD Test for Year")
plt.xlabel('Mean Difference')
plt.grid(True)
plt.savefig('Tukey HSD Test for Year center.png')
plt.show()
#There was no a significant in the area differences between the 11 years

##########################################################################
##########################################################################
#####                                                    TIME SERIES AND FOR

####    PASTURES
# Load the dataset
df = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Docum

# Identify unique BufferIDs and Area
unique_dates = df['Date'].unique()
unique_buffer_ids = df['BufferID'].unique()
```

```python
unique_areas = df['Type'].unique()

# Create a complete DataFrame with all combinations
all_combinations = pd.DataFrame(
    list(itertools.product(unique_dates, unique_buffer_ids, unique_areas)),
    columns=['Date', 'BufferID', 'Type'])
# Step 3: Merge with the original DataFrame and fill missing values with 0
df_complete = pd.merge(all_combinations, df, on=['Date', 'BufferID', 'Type']

# Time series analysis for a specific BufferID
area = 'Pasture'# Example Area
df_filtered = df[(df['Type'] == area)].copy()

# Convert Date to numeric index for time series modeling
df_filtered['Date'] = pd.to_numeric(df_filtered['Date'])
df_filtered.sort_values('Date', inplace=True)
df_filtered.set_index('Date', inplace=True)

# Define the model with specified order (p, d, q)
model = ARIMA(df_filtered['Area_m2'], order=(1, 2, 1))
# Fit the model
model_fit = model.fit()
#print(model_fit.summary())

#Forecast
steps = 5
forecast = model_fit.forecast(steps=steps)
forecast_years = range(df_filtered.index[-1] + 1, df_filtered.index[-1] + 1
forecast_df = pd.DataFrame({'Date': forecast_years, 'Forecasted_Area_m2': fo

#Plot and forecast
plt.figure(figsize=(12, 6))
plt.plot(df_filtered.index, df_filtered['Area_m2'], label='Observed', color=
plt.plot(forecast_df['Date'], forecast_df['Forecasted_Area_m2'], label='Fore
plt.xlabel('Date')
plt.ylabel('Area (m2)')
plt.title(f'Time Series Forecast for Area: {area} in the Tailandia(Pará, Bra
plt.legend()
plt.grid(True)
plt.savefig('time series forecast pasture tailandia.png')
plt.show()

print(forecast_df)

# The area m2 of Pasture habitat type in the site (Tailandia-Brazil), are ex
#I Checked the forecast using "ARIMA" and the forecast looks plausible


################################################################################

#####                                                    test if forecast is



# Split data into training and testing sets (e.g., last 5 years for testing)
train_size = int(len(df_filtered) * 0.6)
```

```
train_data, test_data = df_filtered.iloc[:train_size], df_filtered.iloc[trai

# Fit ARIMA model on the training data
arima_model_train = ARIMA(train_data['Area_m2'], order=(1, 2, 1))
arima_fit_train = arima_model_train.fit()

# Forecast for the test period
forecast_test = arima_fit_train.get_forecast(steps=len(test_data))
forecasted_values = forecast_test.predicted_mean
confidence_intervals = forecast_test.conf_int()

# Evaluation metrics
mae = mean_absolute_error(test_data['Area_m2'], forecasted_values)
mse = mean_squared_error(test_data['Area_m2'], forecasted_values)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((test_data['Area_m2'] - forecasted_values) / test_data

# Print evaluation metrics
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
print(f"MAPE: {mape}%")

# Plot the forecast with confidence intervals
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data['Area_m2'], label='Training Data', col
plt.plot(test_data.index, test_data['Area_m2'], label='Actual Test Data', co
plt.plot(test_data.index, forecasted_values, label='Forecast', color='red', 
plt.fill_between(test_data.index, confidence_intervals.iloc[:, 0], confidenc
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title('ARIMA Pastures Forecast vs Actuals with Confidence Intervals')
plt.legend()
plt.grid(True)
plt.savefig('ARIMA Pastures Forecast vs Actuals with Confidence Intervals.pr
plt.show()


##########################################################################

####    ForestFormation

# Load the dataset
df = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Docum
print(df)

# Step 1: Identify unique BufferIDs and Area
unique_dates = df['Date'].unique()
unique_buffer_ids = df['BufferID'].unique()
unique_areas = df['Type'].unique()

# Step 2: Create a complete DataFrame with all combinations
import itertools
all_combinations = pd.DataFrame(
    list(itertools.product(unique_dates, unique_buffer_ids, unique_areas)),
    columns=['Date', 'BufferID', 'Type'])
```

```
# Step 3: Merge with the original DataFrame and fill missing values with 0
df_complete = pd.merge(all_combinations, df, on=['Date', 'BufferID', 'Type']

# Time series analysis for a specific BufferID
area = 'ForestFormation'# Example Area
df_filtered = df[(df['Type'] == area)].copy()

# Convert Date to numeric index for time series modeling
df_filtered['Date'] = pd.to_numeric(df_filtered['Date'])
df_filtered.sort_values('Date', inplace=True)
df_filtered.set_index('Date', inplace=True)

# Define the model with specified order (p, d, q)
model = ARIMA(df_filtered['Area_m2'], order=(1, 2, 1))
# Fit the model
model_fit = model.fit()
#print(model_fit.summary())

#Forecast
steps = 5
forecast = model_fit.forecast(steps=steps)
forecast_years = range(df_filtered.index[-1] + 1, df_filtered.index[-1] + 1
forecast_df = pd.DataFrame({'Date': forecast_years, 'Forecasted_Area_m2': fo

#Plot and forecast
plt.figure(figsize=(12, 6))
plt.plot(df_filtered.index, df_filtered['Area_m2'], label='Observed', color=
plt.plot(forecast_df['Date'], forecast_df['Forecasted_Area_m2'], label='Fore
plt.xlabel('Date')
plt.ylabel('Area (m2)')
plt.title(f'Time Series Forecast for Area: {area} in the Tailandia(Pará, Bra
plt.legend()
plt.grid(True)
plt.savefig('Forest formation Forecast tailandia.png')
plt.show()

print(forecast_df)

# The area m2 of ForestFormation habitat type in the site (Tailandia-Brazil)
#I Checked the forecast using "ARIMA" and the forecast looks plausible, beac

#############################################################################

#####                                                  test if forecast is

# Split data into training and testing sets (e.g., last 5 years for testing)
train_size = int(len(df_filtered) * 0.5)
train_data, test_data = df_filtered.iloc[:train_size], df_filtered.iloc[trai

# Fit SARIMA model on the training data
arima_model_train = ARIMA(train_data['Area_m2'], order=(1, 2, 1))
arima_fit_train = arima_model_train.fit()

# Forecast for the test period
forecast_test = arima_fit_train.get_forecast(steps=len(test_data))
forecasted_values = forecast_test.predicted_mean
```

```python
confidence_intervals = forecast_test.conf_int()

# Evaluation metrics
mae = mean_absolute_error(test_data['Area_m2'], forecasted_values)
mse = mean_squared_error(test_data['Area_m2'], forecasted_values)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((test_data['Area_m2'] - forecasted_values) / test_data

# Print evaluation metrics
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
print(f"MAPE: {mape}%")

# Plot the forecast with confidence intervals
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data['Area_m2'], label='Training Data', col
plt.plot(test_data.index, test_data['Area_m2'], label='Actual Test Data', co
plt.plot(test_data.index, forecasted_values, label='Forecast', color='red',
plt.fill_between(test_data.index, confidence_intervals.iloc[:, 0], confidenc
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title('ARIMA ForestFormation Forecast vs Actuals with Confidence Interva
plt.legend()
plt.grid(True)
plt.savefig('ARIMA ForestFormation Forecast vs Actuals with Confidence Inter
plt.show()


#############################################################################

####    OilPalm

# Load the dataset
df = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Docum
print(df)

# Identify unique BufferIDs and Area
unique_dates = df['Date'].unique()
unique_buffer_ids = df['BufferID'].unique()
unique_areas = df['Type'].unique()

# Create a complete DataFrame with all combinations
import itertools
all_combinations = pd.DataFrame(
    list(itertools.product(unique_dates, unique_buffer_ids, unique_areas)),
    columns=['Date', 'BufferID', 'Type'])
# Merge with the original DataFrame and fill missing values with 0
df_complete = pd.merge(all_combinations, df, on=['Date', 'BufferID', 'Type']

# Time series analysis for a specific BufferID
area = 'OilPalm'# Example Area
df_filtered = df[(df['Type'] == area)].copy()

# Convert Date to numeric index for time series modeling
df_filtered['Date'] = pd.to_numeric(df_filtered['Date'])
```

```
df_filtered.sort_values('Date', inplace=True)
df_filtered.set_index('Date', inplace=True)

# Define the model with specified order (p, d, q)
model = ARIMA(df_filtered['Area_m2'], order=(1, 2, 1))
# Fit the model
model_fit = model.fit()
#print(model_fit.summary())

#Forecast
steps = 5
forecast = model_fit.forecast(steps=steps)
forecast_years = range(df_filtered.index[-1] + 1, df_filtered.index[-1] + 1
forecast_df = pd.DataFrame({'Date': forecast_years, 'Forecasted_Area_m2': fo

#Plot and forecast
plt.figure(figsize=(12, 6))
plt.plot(df_filtered.index, df_filtered['Area_m2'], label='Observed', color=
plt.plot(forecast_df['Date'], forecast_df['Forecasted_Area_m2'], label='Fore
plt.xlabel('Date')
plt.ylabel('Area (m2)')
plt.title(f'Time Series Forecast for Area: {area} in the Tailandia(Pará, Bra
plt.legend()
plt.grid(True)
plt.savefig('OilPalm Forecast tailandia.png')
plt.show()
print(forecast_df)


# The area m2 of OilPalm habitat type in the site (Tailandia-Brazil), is exp
# the forecast using "ARIMA" it seems to be increasing, I think that the dis
# so the train data only shows an increasing (80%) and the test data is decr
# a expected increase


############################################################################

#####                                                   test if forecast is 

# Split data into training and testing sets (e.g., last 5 years for testing)
train_size = int(len(df_filtered) * 0.8)
train_data, test_data = df_filtered.iloc[:train_size], df_filtered.iloc[trai

# Fit SARIMA model on the training data
arima_model_train = ARIMA(train_data['Area_m2'], order=(1, 2, 1))
arima_fit_train = arima_model_train.fit()

# Forecast for the test period
forecast_test = arima_fit_train.get_forecast(steps=len(test_data))
forecasted_values = forecast_test.predicted_mean
confidence_intervals = forecast_test.conf_int()

# Evaluation metrics
mae = mean_absolute_error(test_data['Area_m2'], forecasted_values)
mse = mean_squared_error(test_data['Area_m2'], forecasted_values)
rmse = np.sqrt(mse)
```

```
mape = np.mean(np.abs((test_data['Area_m2'] - forecasted_values) / test_data

# Print evaluation metrics
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
print(f"MAPE: {mape}%")

# Plot the forecast with confidence intervals
plt.figure(figsize=(12, 6))
plt.plot(train_data.index, train_data['Area_m2'], label='Training Data', col
plt.plot(test_data.index, test_data['Area_m2'], label='Actual Test Data', co
plt.plot(test_data.index, forecasted_values, label='Forecast', color='red',
plt.fill_between(test_data.index, confidence_intervals.iloc[:, 0], confidenc
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title('ARIMA Oilpalm Forecast vs Actuals with Confidence Intervals')
plt.legend()
plt.grid(True)
plt.savefig('ARIMA Oilpalm Forecast vs Actuals with Confidence Intervals cer
plt.show()



############################################################################

####    Floodplains

# Load the dataset
df = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Docum
# Identify unique BufferIDs and Area
unique_dates = df['Date'].unique()
unique_buffer_ids = df['BufferID'].unique()
unique_areas = df['Type'].unique()

# Create a complete DataFrame with all combinations
import itertools
all_combinations = pd.DataFrame(
    list(itertools.product(unique_dates, unique_buffer_ids, unique_areas)),
    columns=['Date', 'BufferID', 'Type'])
# Merge with the original DataFrame and fill missing values with 0
df_complete = pd.merge(all_combinations, df, on=['Date', 'BufferID', 'Type']

# Time series analysis for a specific BufferID
area = 'Floodplains'# Example Area
df_filtered = df[(df['Type'] == area)].copy()

# Convert Date to numeric index for time series modeling
df_filtered['Date'] = pd.to_numeric(df_filtered['Date'])
df_filtered.sort_values('Date', inplace=True)
df_filtered.set_index('Date', inplace=True)

# Define the model with specified order (p, d, q)
model = ARIMA(df_filtered['Area_m2'], order=(1, 2, 1))
# Fit the model
model_fit = model.fit()
```

```
#print(model_fit.summary())

#Forecast
steps = 5
forecast = model_fit.forecast(steps=steps)
forecast_years = range(df_filtered.index[-1] + 1, df_filtered.index[-1] + 1
forecast_df = pd.DataFrame({'Date': forecast_years, 'Forecasted_Area_m2': fo

#Plot and forecast
plt.figure(figsize=(12, 6))
plt.plot(df_filtered.index, df_filtered['Area_m2'], label='Observed', color=
plt.plot(forecast_df['Date'], forecast_df['Forecasted_Area_m2'], label='Fore
plt.xlabel('Date')
plt.ylabel('Area (m2)')
plt.title(f'Time Series Forecast for Habitat: {area} in the Tailandia(Pará,
plt.legend()
plt.grid(True)
plt.savefig('Floodplains Forecast tailandia.png')
plt.show()
print(forecast_df)


# The area m2 of Floodplains habitat type in the site (Tailandia-Brazil), is
# the forecast using "ARIMA" I can conlude is accurate, since the forecast i

############################################################################

#####                                                    test if forecast is

# Split data into training and testing sets (e.g., last 5 years for testing)
train_size = int(len(df_filtered) * 0.8)
train_data, test_data = df_filtered.iloc[:train_size], df_filtered.iloc[trai

# Fit SARIMA model on the training data
arima_model_train = ARIMA(train_data['Area_m2'], order=(1, 2, 1))
arima_fit_train = arima_model_train.fit()

# Forecast for the test period
forecast_test = arima_fit_train.get_forecast(steps=len(test_data))
forecasted_values = forecast_test.predicted_mean
confidence_intervals = forecast_test.conf_int()

# Evaluation metrics
mae = mean_absolute_error(test_data['Area_m2'], forecasted_values)
mse = mean_squared_error(test_data['Area_m2'], forecasted_values)
rmse = np.sqrt(mse)
mape = np.mean(np.abs((test_data['Area_m2'] - forecasted_values) / test_data

# Print evaluation metrics
print(f"MAE: {mae}")
print(f"MSE: {mse}")
print(f"RMSE: {rmse}")
print(f"MAPE: {mape}%")

# Plot the forecast with confidence intervals
plt.figure(figsize=(12, 6))
```

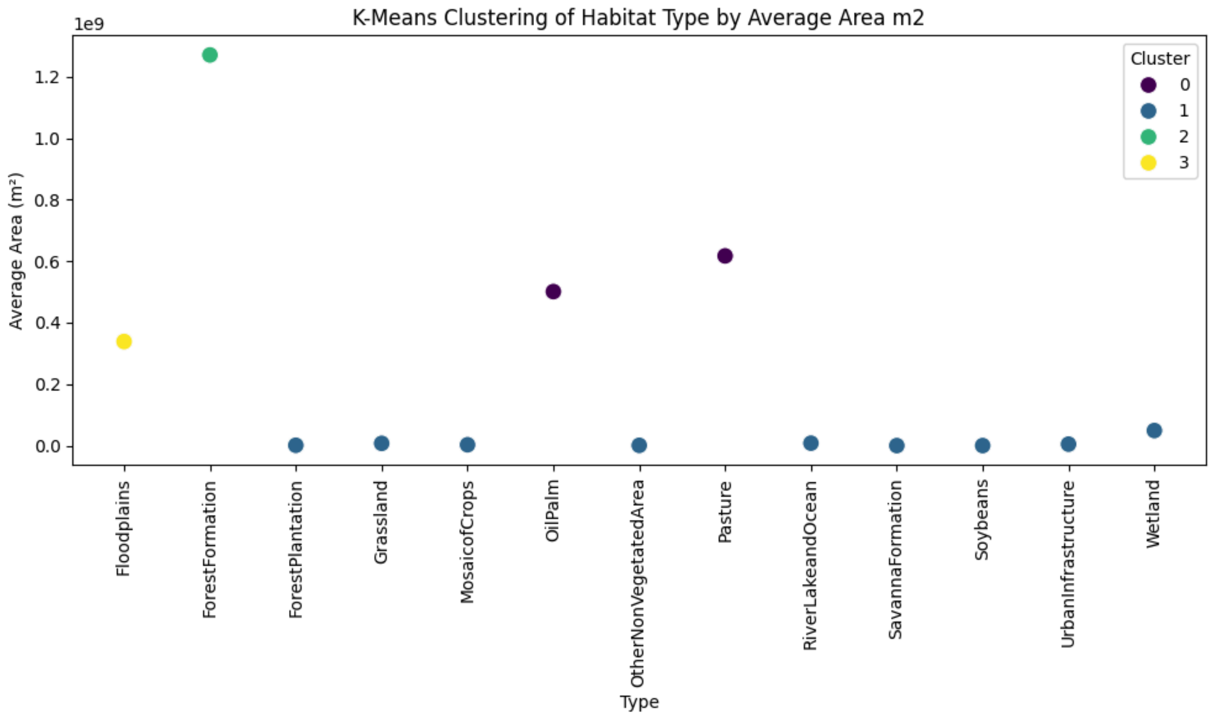
```python
plt.plot(train_data.index, train_data['Area_m2'], label='Training Data', col
plt.plot(test_data.index, test_data['Area_m2'], label='Actual Test Data', co
plt.plot(test_data.index, forecasted_values, label='Forecast', color='red',
plt.fill_between(test_data.index, confidence_intervals.iloc[:, 0], confidenc
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title('ARIMA Floodplains Forecast vs Actuals with Confidence Intervals')
plt.legend()
plt.grid(True)
plt.savefig('ARIMA Floodplains Forecast vs Actuals with Confidence Intervals
plt.show()



###########################################################################

#########                                         LINEAR REGRESSION

# ForestFormation

# Load the data
data = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Doc

# Filter data for 'ForestFormation'
forest_data = data[data['Type'] == 'ForestFormation'].copy()

# Encode 'BufferID' as numerical for plotting and regression
forest_data.loc[:, 'BufferID_encoded'] = pd.factorize(forest_data['Date'])[0

# Prepare data for regression
X = sm.add_constant(forest_data['BufferID_encoded'])  # Add constant for int
y = forest_data['Area_m2']
# Fit the regression model using statsmodels
model = sm.OLS(y, X).fit()
# Get the model summary
model_summary = model.summary()

# Predict area for plotting the regression line
forest_data.loc[:, 'Predicted_Area'] = model.predict(X)

# Plot the scatter plot with regression line
plt.figure(figsize=(12, 6))
sns.scatterplot(x='BufferID_encoded', y='Area_m2', data=forest_data, label='
plt.plot(forest_data['BufferID_encoded'], forest_data['Predicted_Area'], col
plt.xticks(np.arange(len(forest_data['Date'].unique())), forest_data['Date']
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title("Scatter Plot with Regression Line: Area by Year for 'ForestFormat
plt.legend()
plt.grid(True)
plt.savefig("Scatter Plot with Regression Line: Area by Year for 'ForestForm
plt.show()
print(model_summary)

# The linear regression indicates a signficative increase of 1.528e+07 m2 ev
# The R-squared is high, so the variance can be explain by this model
```

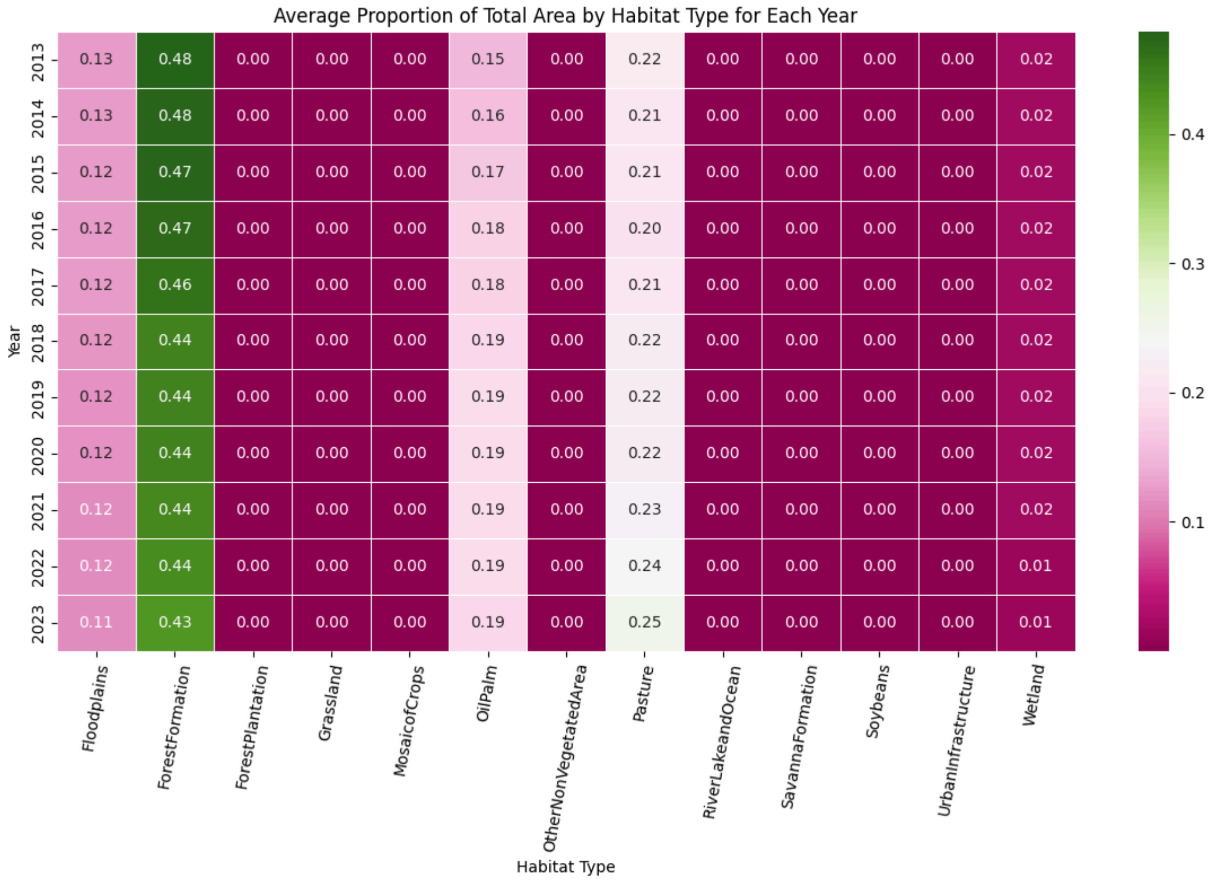
```
#################################################################
# OilPalm

# Load the data
data = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Doc

# Filter data for 'ForestFormation'
forest_data = data[data['Type'] == 'OilPalm'].copy()

# Encode 'BufferID' as numerical for plotting and regression
forest_data.loc[:, 'BufferID_encoded'] = pd.factorize(forest_data['Date'])[0

# Prepare data for regression
X = sm.add_constant(forest_data['BufferID_encoded'])  # Add constant for int
y = forest_data['Area_m2']
# Fit the regression model using statsmodels
model = sm.OLS(y, X).fit()
# Get the model summary
model_summary = model.summary()

# Predict area for plotting the regression line
forest_data.loc[:, 'Predicted_Area'] = model.predict(X)

# Plot the scatter plot with regression line
plt.figure(figsize=(12, 6))
sns.scatterplot(x='BufferID_encoded', y='Area_m2', data=forest_data, label='
plt.plot(forest_data['BufferID_encoded'], forest_data['Predicted_Area'], col
plt.xticks(np.arange(len(forest_data['Date'].unique())), forest_data['Date']
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title("Scatter Plot with Regression Line: Area by Year for 'Oilpalm' hab
plt.legend()
plt.grid(True)
plt.savefig("Scatter Plot with Regression Line: Area by Year for 'Oilpalm' h
plt.show()
print(model_summary)
# The linear regression indicates a signficative increase of 9.968e+06 m2 ev
# The R-squared is not that high, so  the variance cannot be fully explain b



# Pasture

# Load the data
data = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Doc

# Filter data for 'ForestFormation'
forest_data = data[data['Type'] == 'Pasture'].copy()

# Encode 'BufferID' as numerical for plotting and regression
forest_data.loc[:, 'BufferID_encoded'] = pd.factorize(forest_data['Date'])[0

# Prepare data for regression
X = sm.add_constant(forest_data['BufferID_encoded'])  # Add constant for int
```

```
y = forest_data['Area_m2']
# Fit the regression model using statsmodels
model = sm.OLS(y, X).fit()
# Get the model summary
model_summary = model.summary()

# Predict area for plotting the regression line
forest_data.loc[:, 'Predicted_Area'] = model.predict(X)

# Plot the scatter plot with regression line
plt.figure(figsize=(12, 6))
sns.scatterplot(x='BufferID_encoded', y='Area_m2', data=forest_data, label='
plt.plot(forest_data['BufferID_encoded'], forest_data['Predicted_Area'], col
plt.xticks(np.arange(len(forest_data['Date'].unique())), forest_data['Date']
plt.xlabel('Year')
plt.ylabel('Area (m²)')
plt.title("Scatter Plot with Regression Line: Area by Year for 'Pasture' hab
plt.legend()
plt.grid(True)
plt.savefig("Scatter Plot with Regression Line: Area by Year for 'Pasture' h
plt.show()
print(model_summary)
# The linear regression indicates a signficative increase of 9.929e+06 m2 ev
# The R-squared is not that high, so  the variance cannot be fully explain b


##################################################
# Floodplain

# Load the data
data = pd.read_excel(r"C:\Users\vs24904\OneDrive - University of Bristol\Doc

# Filter data for 'ForestFormation'
forest_data = data[data['Type'] == 'Floodplains'].copy()

# Encode 'BufferID' as numerical for plotting and regression
forest_data.loc[:, 'BufferID_encoded'] = pd.factorize(forest_data['Date'])[0

# Prepare data for regression
X = sm.add_constant(forest_data['BufferID_encoded'])  # Add constant for int
y = forest_data['Area_m2']
# Fit the regression model using statsmodels
model = sm.OLS(y, X).fit()
# Get the model summary
model_summary = model.summary()

# Predict area for plotting the regression line
forest_data.loc[:, 'Predicted_Area'] = model.predict(X)

# Plot the scatter plot with regression line
plt.figure(figsize=(12, 6))
sns.scatterplot(x='BufferID_encoded', y='Area_m2', data=forest_data, label='
plt.plot(forest_data['BufferID_encoded'], forest_data['Predicted_Area'], col
plt.xticks(np.arange(len(forest_data['Date'].unique())), forest_data['Date']
plt.xlabel('Year')
plt.ylabel('Area (m²)')
```

```
plt.title("Scatter Plot with Regression Line: Area by Year for 'FloodPlains'
plt.legend()
plt.grid(True)
plt.savefig("Scatter Plot with Regression Line: Area by Year for 'Floodplair
plt.show()
print(model_summary)

# The linear regression indicates a signficative decrease of Floofplains are
#The high R-squared indicates that the variance can be explain by this model
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\sklearn\cluster
\_kmeans.py:1411: UserWarning: KMeans is known to have a memory leak on Wind
ows with MKL, when there are less chunks than available threads. You can avo
id it by setting the environment variable OMP_NUM_THREADS=1.
  warnings.warn(
```





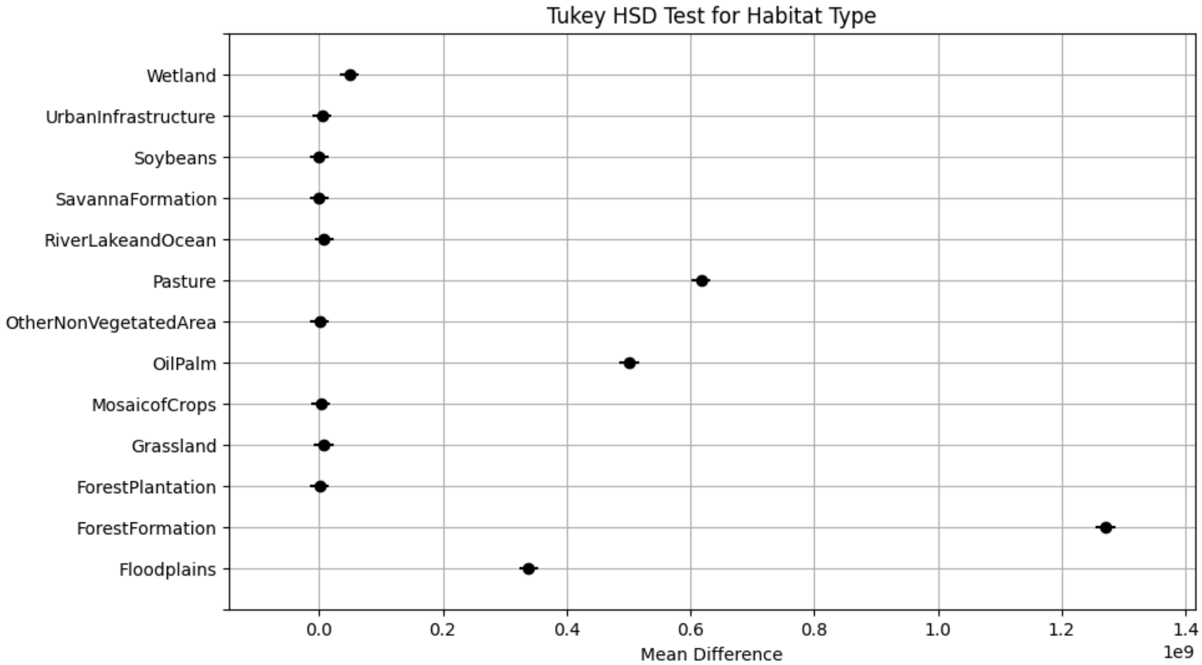
Average Proportion of Total Area by Habitat Type for Each Year
Year
Habitat Type
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Floodplains
ForestFormation
ForestPlantation
Grassland
MosaicofCrops
OilPalm
OtherNonVegetatedArea
Pasture
RiverLakeandOcean
SavannaFormation
Soybeans
UrbanInfrastructure
Wetland
0.1
0.2
0.3
0.4

```
ANOVA for Type:
F-statistic: 3518.154323541889, p-value: 5.477677187641807e-157

Tukey HSD Test for PLot:
                            Multiple Comparison of Means - Tukey HSD, FWER=
0.05
============================================================================
================================
        group1                group2             meandiff     p-adj       low
er            upper       reject
----------------------------------------------------------------------------
--------------------------------
          Floodplains       ForestFormation   931911605.1337    0.0   901097
892.8823   962725317.3851   True
          Floodplains      ForestPlantation  -337407734.4385    0.0  -368221
446.6899  -306594022.1871   True
          Floodplains             Grassland  -331212437.3262    0.0  -362026
149.5776  -300398725.0748   True
          Floodplains         MosaicofCrops  -335764870.5882    0.0  -366578
582.8396  -304951158.3369   True
          Floodplains               OilPalm   162326971.4439    0.0   131513
259.1925   193140683.6952   True
          Floodplains OtherNonVegetatedArea  -337603459.2513    0.0  -368417
171.5027     -306789747.0   True
          Floodplains               Pasture   278428724.5989    0.0   247615
012.3476   309242436.8503   True
          Floodplains     RiverLakeandOcean  -330588565.6684    0.0  -361402
277.9198  -299774853.4171   True
          Floodplains      SavannaFormation  -338442160.7487    0.0     -369
255873.0  -307628448.4973   True
          Floodplains              Soybeans  -338372746.8449    0.0  -369186
459.0963  -307559034.5935   True
          Floodplains   UrbanInfrastructure  -333717815.2941    0.0  -364531
527.5455  -302904103.0427   True
          Floodplains               Wetland  -289465026.0963    0.0  -320278
738.3476  -258651313.8449   True
      ForestFormation      ForestPlantation -1269319339.5722    0.0 -1300133
051.8236 -1238505627.3208   True
      ForestFormation             Grassland -1263124042.4599    0.0 -1293937
754.7113 -1232310330.2085   True
      ForestFormation         MosaicofCrops -1267676475.7219    0.0 -1298490
187.9733 -1236862763.4705   True
      ForestFormation               OilPalm  -769584633.6898    0.0  -800398
345.9412  -738770921.4385   True
      ForestFormation OtherNonVegetatedArea  -1269515064.385    0.0 -1300328
776.6364 -1238701352.1337   True
      ForestFormation               Pasture  -653482880.5348    0.0  -684296
592.7861  -622669168.2834   True
      ForestFormation     RiverLakeandOcean -1262500170.8021    0.0 -1293313
883.0535 -1231686458.5508   True
      ForestFormation      SavannaFormation -1270353765.8823    0.0 -1301167
478.1337  -1239540053.631   True
      ForestFormation              Soybeans -1270284351.9786    0.0   -13010
98064.23 -1239470639.7272   True
      ForestFormation   UrbanInfrastructure -1265629420.4278    0.0 -1296443
132.6792 -1234815708.1764   True
```

```
      ForestFormation              Wetland -1221376631.2299    0.0 -1252190
343.4813 -1190562918.9786   True
     ForestPlantation            Grassland     6195297.1123    1.0   -24618
415.1391    37009009.3637  False
     ForestPlantation        MosaicofCrops     1642863.8503    1.0   -29170
848.4011    32456576.1016  False
     ForestPlantation              OilPalm   499734705.8824    0.0    46892
0993.631   530548418.1337   True
     ForestPlantation OtherNonVegetatedArea     -195724.8128    1.0   -31009
437.0642    30617987.4385  False
     ForestPlantation              Pasture   615836459.0374    0.0   585022
746.7861   646650171.2888   True
     ForestPlantation    RiverLakeandOcean     6819168.7701 0.9999   -23994
543.4813    37632881.0214  False
     ForestPlantation     SavannaFormation    -1034426.3102    1.0   -31848
138.5615    29779285.9412  False
     ForestPlantation             Soybeans     -965012.4064    1.0   -31778
724.6578     29848699.845  False
     ForestPlantation   UrbanInfrastructure     3689919.1444    1.0    -2712
3793.107    34503631.3958  False
     ForestPlantation              Wetland    47942708.3422    0.0    17128
996.0909    78756420.5936   True
            Grassland        MosaicofCrops     -4552433.262    1.0   -35366
145.5134    26261278.9893  False
            Grassland              OilPalm   493539408.7701    0.0   462725
696.5187   524353121.0214   True
            Grassland OtherNonVegetatedArea    -6391021.9251    1.0   -37204
734.1765    24422690.3262  False
            Grassland              Pasture   609641161.9251    0.0   578827
449.6738   640454874.1765   True
            Grassland    RiverLakeandOcean      623871.6578    1.0   -30189
840.5936    31437583.9091  False
            Grassland     SavannaFormation    -7229723.4225 0.9999   -38043
435.6738    23583988.8289  False
            Grassland             Soybeans    -7160309.5187 0.9999   -37974
021.7701    23653402.7327  False
            Grassland   UrbanInfrastructure    -2505377.9679    1.0   -33319
090.2193    28308334.2835  False
            Grassland              Wetland    41747411.2299 0.0008    10933
698.9786    72561123.4813   True
        MosaicofCrops              OilPalm   498091842.0321    0.0   467278
129.7807   528905554.2835   True
        MosaicofCrops OtherNonVegetatedArea    -1838588.6631    1.0   -32652
300.9145    28975123.5883  False
        MosaicofCrops              Pasture   614193595.1872    0.0   583379
882.9358   645007307.4385   True
        MosaicofCrops    RiverLakeandOcean     5176304.9198    1.0   -25637
407.3316    35990017.1712  False
        MosaicofCrops     SavannaFormation    -2677290.1604    1.0   -33491
002.4118    28136422.0909  False
        MosaicofCrops             Soybeans    -2607876.2567    1.0   -33421
588.5081    28205835.9947  False
        MosaicofCrops   UrbanInfrastructure     2047055.2941    1.0   -28766
656.9573    32860767.5455  False
        MosaicofCrops              Wetland     46299844.492 0.0001    15486
132.2406    77113556.7434   True
```

```
              OilPalm OtherNonVegetatedArea  -499930430.6952    0.0  -530744
142.9466  -469116718.4438   True
              OilPalm               Pasture   116101753.1551    0.0    85288
040.9037   146915465.4065   True
              OilPalm     RiverLakeandOcean  -492915537.1123    0.0  -523729
249.3637  -462101824.8609   True
              OilPalm      SavannaFormation  -500769132.1925    0.0  -531582
844.4439  -469955419.9411   True
              OilPalm              Soybeans  -500699718.2888    0.0  -531513
430.5401  -469886006.0374   True
              OilPalm   UrbanInfrastructure   -496044786.738    0.0  -526858
498.9893  -465231074.4866   True
              OilPalm               Wetland  -451791997.5401    0.0  -482605
709.7915  -420978285.2887   True
OtherNonVegetatedArea               Pasture   616032183.8503    0.0   585218
471.5989   646845896.1016   True
OtherNonVegetatedArea     RiverLakeandOcean     7014893.5829 0.9999   -23798
818.6685    37828605.8343  False
OtherNonVegetatedArea      SavannaFormation     -838701.4973    1.0   -31652
413.7487     29975010.754  False
OtherNonVegetatedArea              Soybeans     -769287.5936    1.0    -3158
2999.845    30044424.6578  False
OtherNonVegetatedArea   UrbanInfrastructure     3885643.9572    1.0   -26928
068.2942    34699356.2086  False
OtherNonVegetatedArea               Wetland    48138433.1551    0.0    17324
720.9037    78952145.4065   True
              Pasture     RiverLakeandOcean  -609017290.2674    0.0  -639831
002.5188   -578203578.016   True
              Pasture      SavannaFormation  -616870885.3476    0.0   -64768
4597.599  -586057173.0962   True
              Pasture              Soybeans  -616801471.4438    0.0  -647615
183.6952  -585987759.1925   True
              Pasture   UrbanInfrastructure   -612146539.893    0.0  -642960
252.1444  -581332827.6417   True
              Pasture               Wetland  -567893750.6952    0.0  -598707
462.9466  -537080038.4438   True
    RiverLakeandOcean      SavannaFormation    -7853595.0802 0.9997   -38667
307.3316    22960117.1712  False
    RiverLakeandOcean              Soybeans    -7784181.1765 0.9997   -38597
893.4278    23029531.0749  False
    RiverLakeandOcean   UrbanInfrastructure    -3129249.6257    1.0    -3394
2961.877    27684462.6257  False
    RiverLakeandOcean               Wetland    41123539.5722  0.001    10309
827.3208    71937251.8236   True
     SavannaFormation              Soybeans       69413.9037    1.0   -30744
298.3476    30883126.1551  False
     SavannaFormation   UrbanInfrastructure     4724345.4545    1.0   -26089
366.7968    35538057.7059  False
     SavannaFormation               Wetland    48977134.6524    0.0     1816
3422.401    79790846.9038   True
             Soybeans   UrbanInfrastructure     4654931.5508    1.0   -26158
780.7006    35468643.8022  False
             Soybeans               Wetland    48907720.7487    0.0    18094
008.4973       79721433.0   True
  UrbanInfrastructure               Wetland    44252789.1979 0.0003    13439
076.9465    75066501.4492   True
```

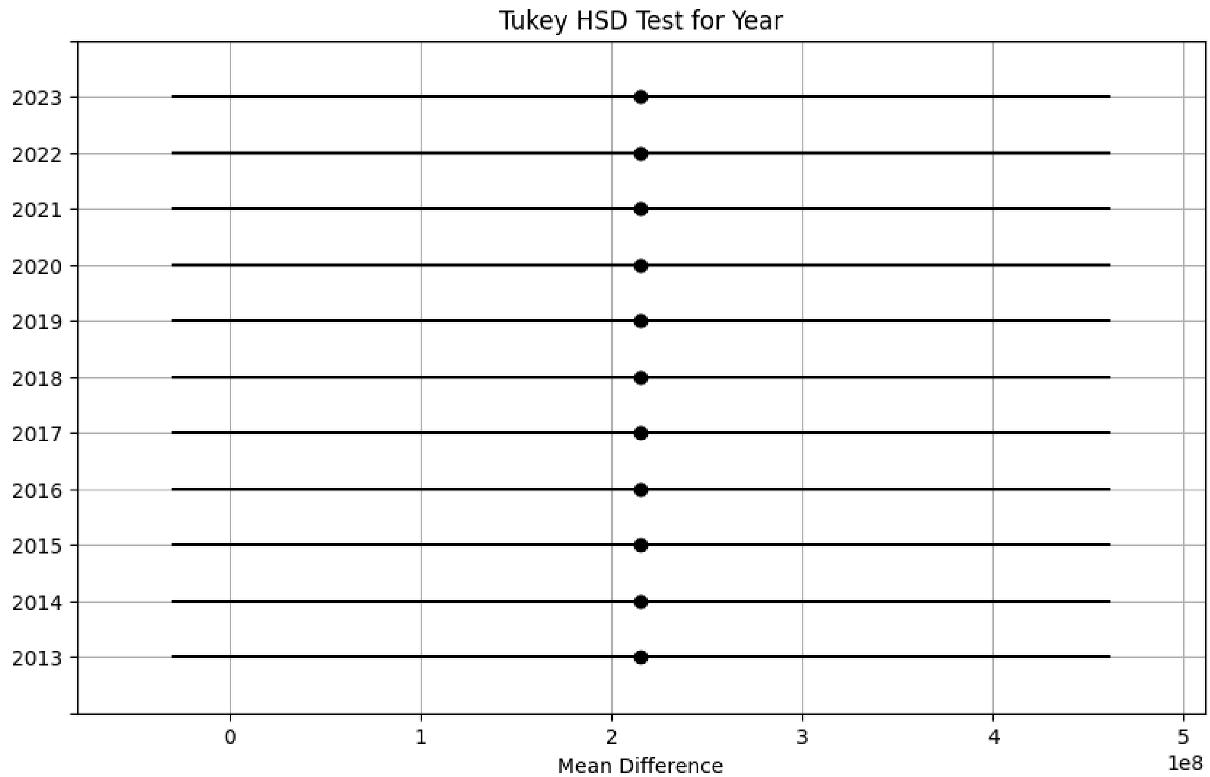
- -



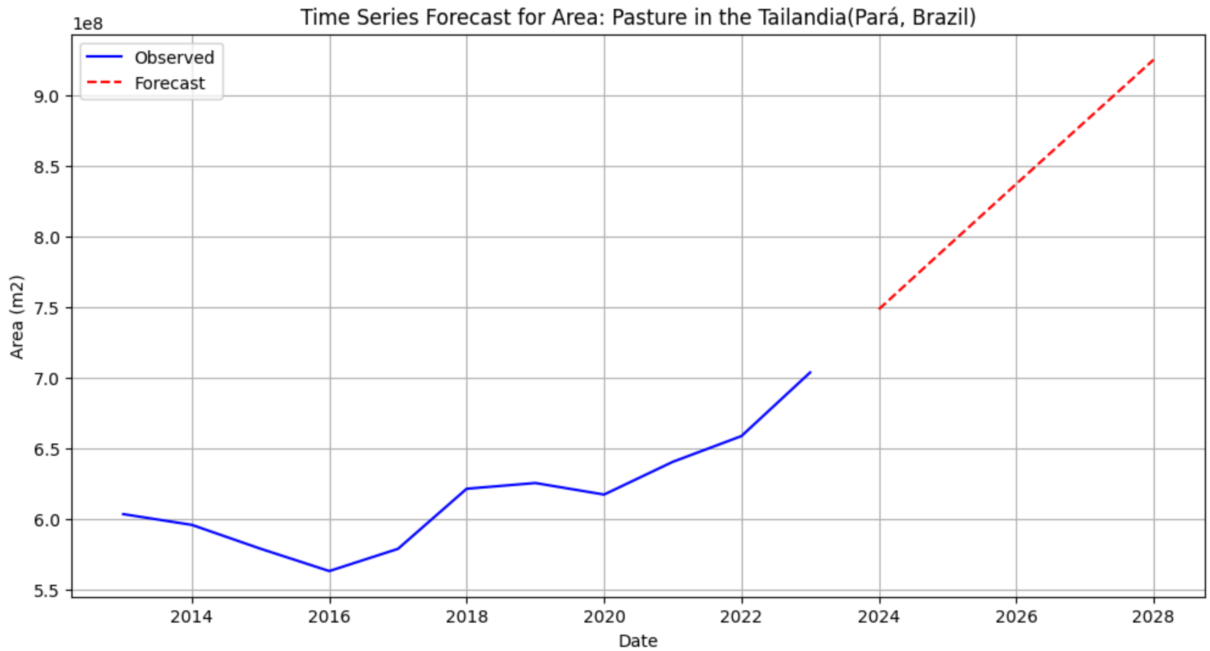
Tukey HSD Test for Habitat Type
Wetland
UrbanInfrastructure
Soybeans
SavannaFormation
RiverLakeandOcean
Pasture
OtherNonVegetatedArea
OilPalm
MosaicofCrops
Grassland
ForestPlantation
ForestFormation
Floodplains
0.0
0.2
0.4
0.6
0.8
1.0
1.2
1.4
1e9
Mean Difference

```
ANOVA for Year:
F-statistic: 4.867223506960202e-30, p-value: 1.0

Tukey HSD Test for Year:
       Multiple Comparison of Means - Tukey HSD, FWER=0.05
==================================================================
group1 group2 meandiff p-adj      lower          upper      reject
------------------------------------------------------------------
  2013   2014      0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2015      0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2016     -0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2017     -0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2018      0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2019     -0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2020     -0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2021     -0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2022     -0.0   1.0 -492736391.7088 492736391.7088  False
  2013   2023      0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2015      0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2016     -0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2017     -0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2018      0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2019     -0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2020     -0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2021     -0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2022     -0.0   1.0 -492736391.7088 492736391.7088  False
  2014   2023      0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2016     -0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2017     -0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2018      0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2019     -0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2020     -0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2021     -0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2022     -0.0   1.0 -492736391.7088 492736391.7088  False
  2015   2023     -0.0   1.0 -492736391.7088 492736391.7088  False
  2016   2017     -0.0   1.0 -492736391.7088 492736391.7088  False
  2016   2018      0.0   1.0 -492736391.7088 492736391.7088  False
  2016   2019     -0.0   1.0 -492736391.7088 492736391.7088  False
  2016   2020     -0.0   1.0 -492736391.7088 492736391.7088  False
  2016   2021     -0.0   1.0 -492736391.7088 492736391.7088  False
  2016   2022      0.0   1.0 -492736391.7088 492736391.7088  False
  2016   2023      0.0   1.0 -492736391.7088 492736391.7088  False
  2017   2018      0.0   1.0 -492736391.7088 492736391.7088  False
  2017   2019      0.0   1.0 -492736391.7088 492736391.7088  False
  2017   2020      0.0   1.0 -492736391.7088 492736391.7088  False
  2017   2021      0.0   1.0 -492736391.7088 492736391.7088  False
  2017   2022      0.0   1.0 -492736391.7088 492736391.7088  False
  2017   2023      0.0   1.0 -492736391.7088 492736391.7088  False
  2018   2019     -0.0   1.0 -492736391.7088 492736391.7088  False
  2018   2020     -0.0   1.0 -492736391.7088 492736391.7088  False
  2018   2021     -0.0   1.0 -492736391.7088 492736391.7088  False
  2018   2022     -0.0   1.0 -492736391.7088 492736391.7088  False
  2018   2023     -0.0   1.0 -492736391.7088 492736391.7088  False
  2019   2020     -0.0   1.0 -492736391.7088 492736391.7088  False
  2019   2021      0.0   1.0 -492736391.7088 492736391.7088  False
  2019   2022      0.0   1.0 -492736391.7088 492736391.7088  False
```

```
  2019   2023      0.0   1.0 -492736391.7088 492736391.7088  False
  2020   2021      0.0   1.0 -492736391.7088 492736391.7088  False
  2020   2022      0.0   1.0 -492736391.7088 492736391.7088  False
  2020   2023      0.0   1.0 -492736391.7088 492736391.7088  False
  2021   2022      0.0   1.0 -492736391.7088 492736391.7088  False
  2021   2023      0.0   1.0 -492736391.7088 492736391.7088  False
  2022   2023      0.0   1.0 -492736391.7088 492736391.7088  False
-------------------------------------------------------------------
```

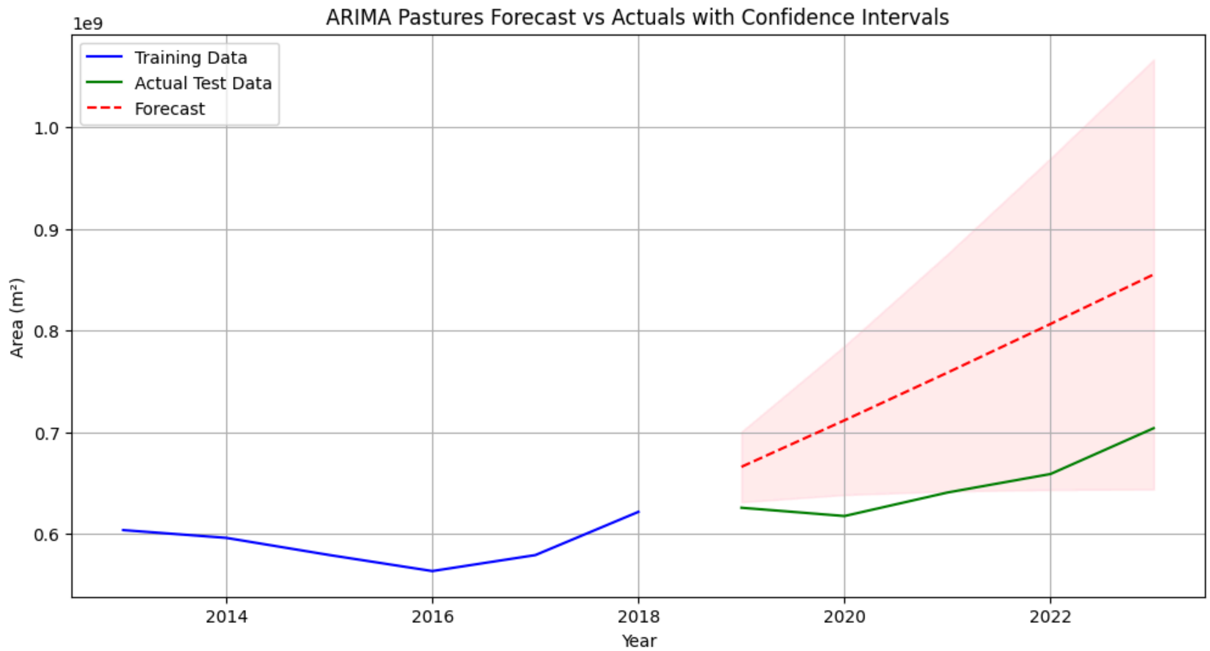



```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
ction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```



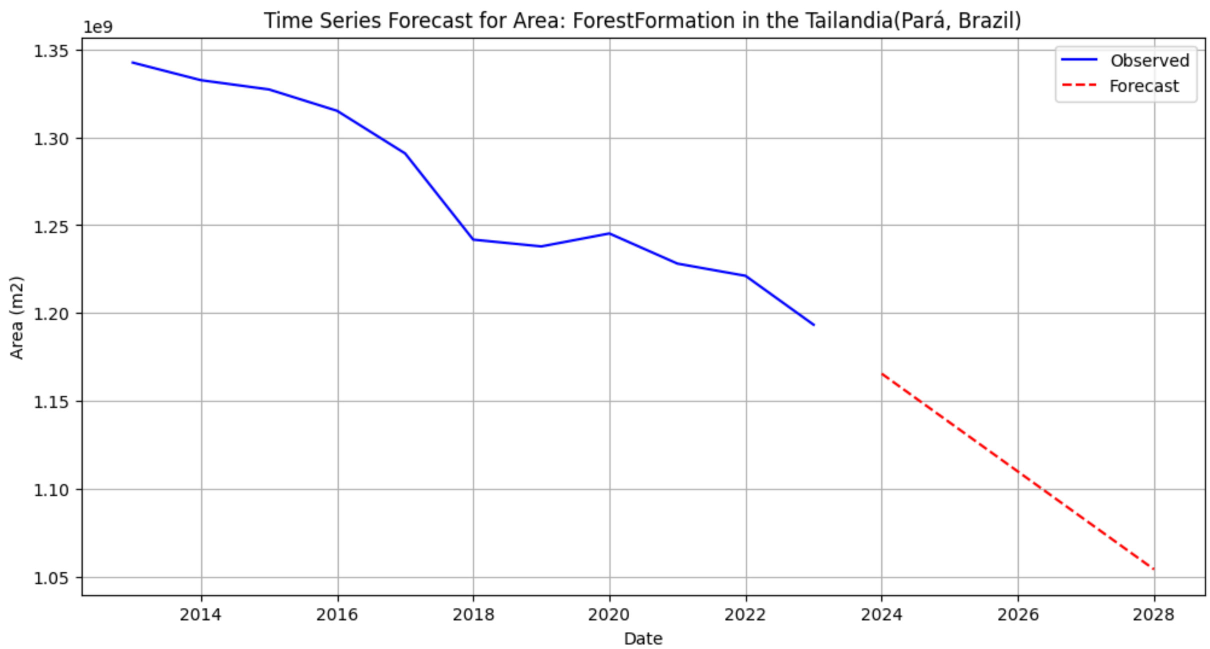

```
    Date  Forecasted_Area_m2
11  2024        7.484357e+08
12  2025        7.928831e+08
13  2026        8.371145e+08
14  2027        8.811696e+08
15  2028        9.250809e+08
MAE: 110300072.24824476
MSE: 1.3826009542965576e+16
RMSE: 117584053.09805228
MAPE: nan%
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
ction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```



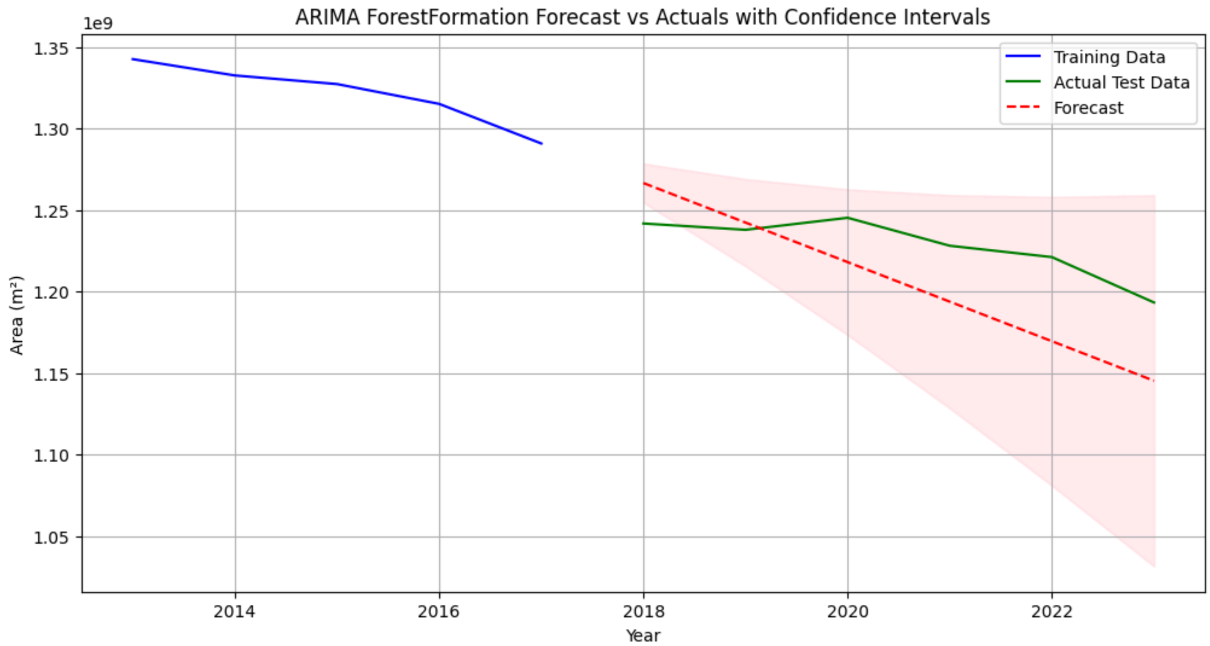

```
     Date BufferID                   Type        Area_m2
0    2013   center                Wetland   5.228134e+07
1    2013  center               Grassland   7.807045e+06
2    2013  center                 Pasture   6.034558e+08
3    2013  center     UrbanInfrastructure   4.611600e+06
4    2013  center   OtherNonVegetatedArea   1.161000e+05
..    ...      ...                    ...            ...
138  2023   center               Soybeans   7.334294e+05
139  2023   center      SavannaFormation   1.215000e+05
140  2023   center         MosaicofCrops   1.465211e+06
141  2023   center           Floodplains   3.191143e+08
142  2023   center      ForestPlantation   1.186906e+06

[143 rows x 4 columns]
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:978: UserWarning: Non-invertible starting MA paramete
rs found. Using zeros as starting parameters.
  warn('Non-invertible starting MA parameters found.'
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
ction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```



```
    Date  Forecasted_Area_m2
11  2024        1.165483e+09
12  2025        1.137640e+09
13  2026        1.109796e+09
14  2027        1.081950e+09
15  2028        1.054104e+09
MAE: 31708128.052738428
MSE: 1251817592692463.8
RMSE: 35381034.364366226
MAPE: nan%
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:866: UserWarning: Too few observations to estimate st
arting parameters for ARMA and trend. All parameters except for variances wi
ll be set to zeros.
  warn('Too few observations to estimate starting parameters%s.'
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
ction results will be given with an integer index beginning at `start`.
  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```




```
     Date BufferID                   Type       Area_m2
0    2013   center                Wetland  5.228134e+07
1    2013  center               Grassland  7.807045e+06
2    2013  center                 Pasture  6.034558e+08
3    2013  center     UrbanInfrastructure  4.611600e+06
4    2013  center   OtherNonVegetatedArea  1.161000e+05
..    ...      ...                    ...           ...
138  2023   center               Soybeans  7.334294e+05
139  2023   center       SavannaFormation  1.215000e+05
140  2023   center          MosaicofCrops  1.465211e+06
141  2023   center            Floodplains  3.191143e+08
142  2023   center       ForestPlantation  1.186906e+06

[143 rows x 4 columns]
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
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\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
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se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:966: UserWarning: Non-stationary starting autoregress
ive parameters found. Using zeros as starting parameters.
  warn('Non-stationary starting autoregressive parameters'
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:978: UserWarning: Non-invertible starting MA paramete
rs found. Using zeros as starting parameters.
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```

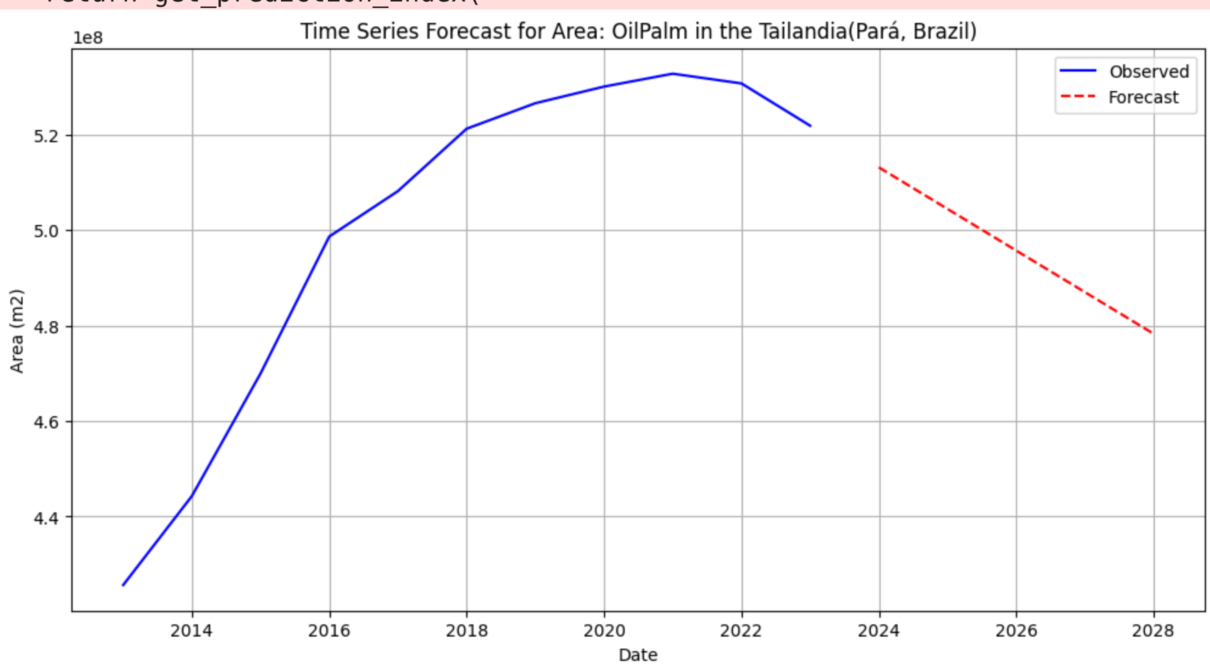

```
    Date  Forecasted_Area_m2
11  2024        5.131608e+08
12  2025        5.044460e+08
13  2026        4.957316e+08
14  2027        4.870173e+08
15  2028        4.783029e+08
MAE: 8671598.79203401
MSE: 131579802076476.12
RMSE: 11470823.94932797
MAPE: nan%
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:966: UserWarning: Non-stationary starting autoregress
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  warn('Non-stationary starting autoregressive parameters'
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:978: UserWarning: Non-invertible starting MA paramete
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  warn('Non-invertible starting MA parameters found.'
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
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  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```

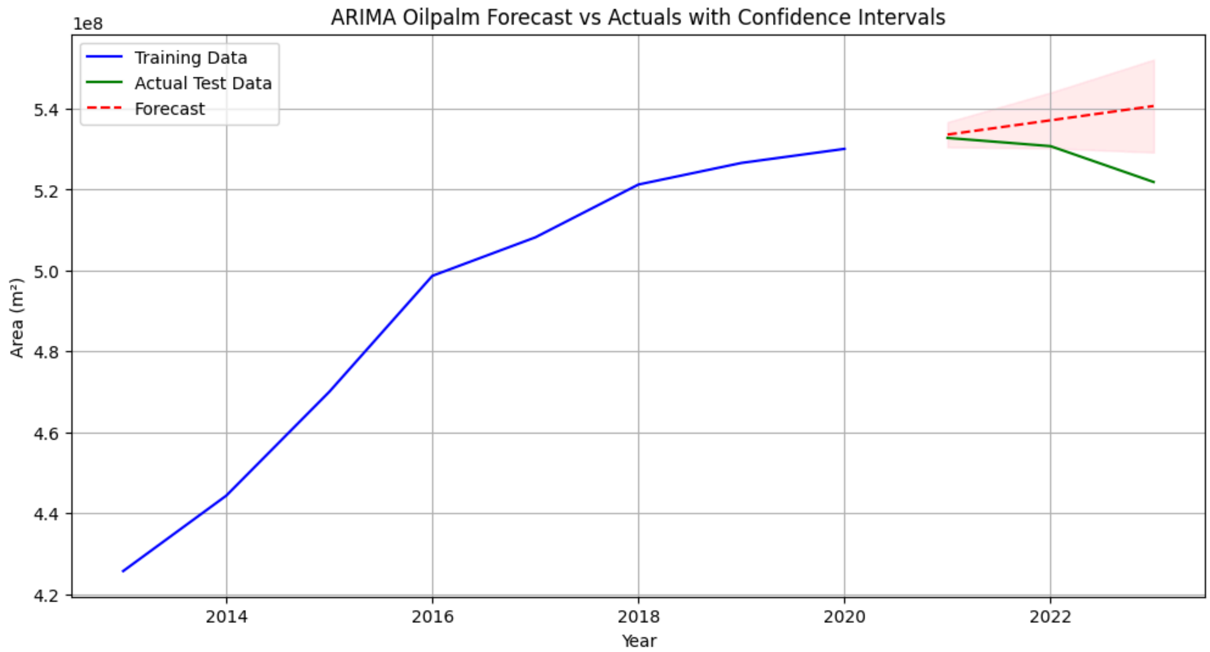


```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
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  self._init_dates(dates, freq)
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  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: ValueWarning: No supported index is available. Predi
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```

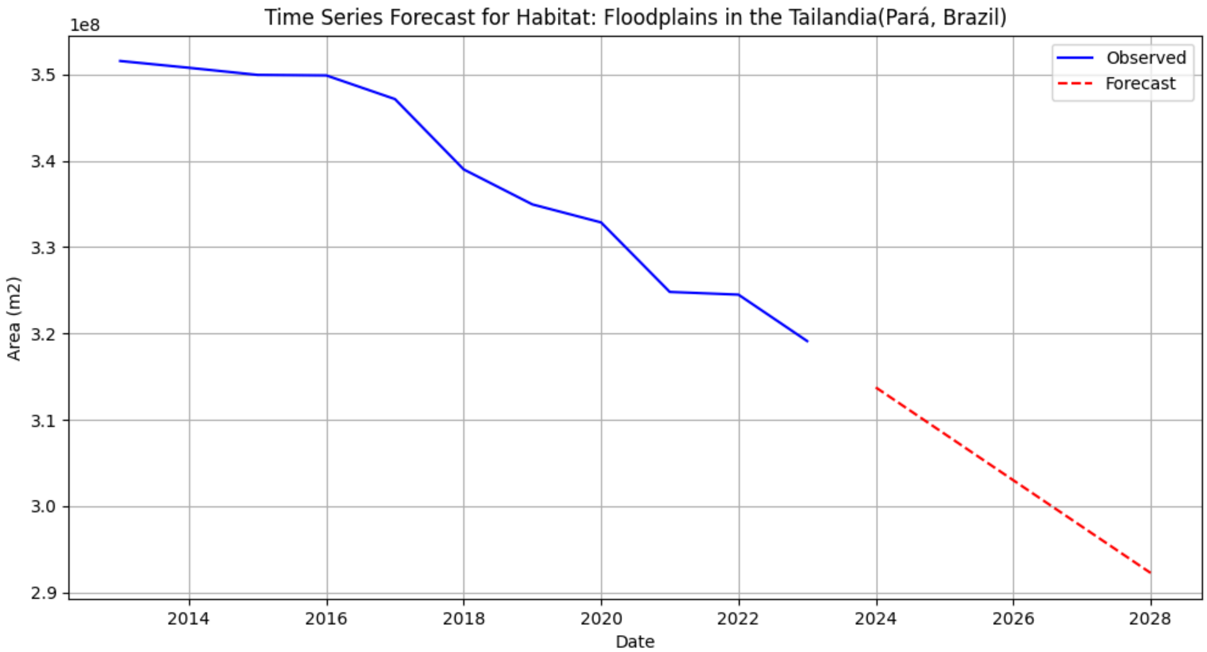

	Date	Forecasted_Area_m2
11	2024	3.137402e+08
12	2025	3.083666e+08
13	2026	3.029931e+08
14	2027	2.976197e+08
15	2028	2.922462e+08

MAE: 5666639.169054608
MSE: 33763819493611.793
RMSE: 5810664.2902177535
MAPE: nan%

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
se one of the supported classes of index.
  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
a result, forecasts cannot be generated. To use the model for forecasting, u
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  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:473: ValueWarning: An unsupported index was provided. As
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  self._init_dates(dates, freq)
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\statespace\sarimax.py:978: UserWarning: Non-invertible starting MA paramete
rs found. Using zeros as starting parameters.
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C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
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  return get_prediction_index(
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\statsmodels\tsa
\base\tsa_model.py:837: FutureWarning: No supported index is available. In t
he next version, calling this method in a model without a supported index wi
ll result in an exception.
  return get_prediction_index(
```
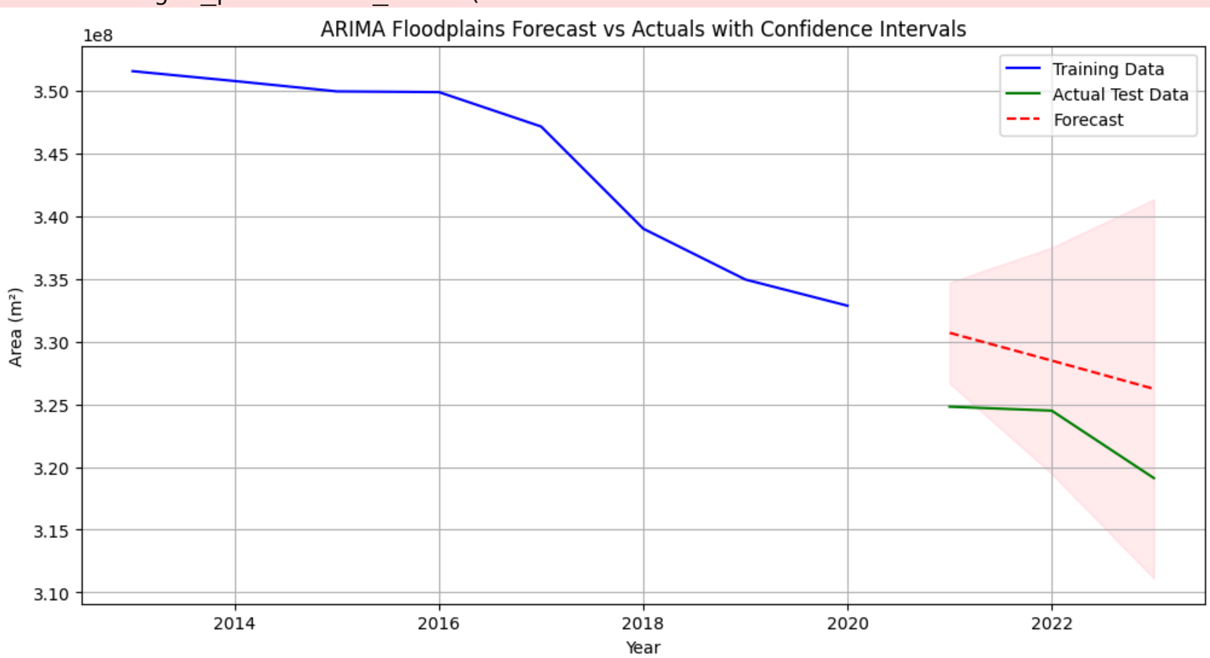
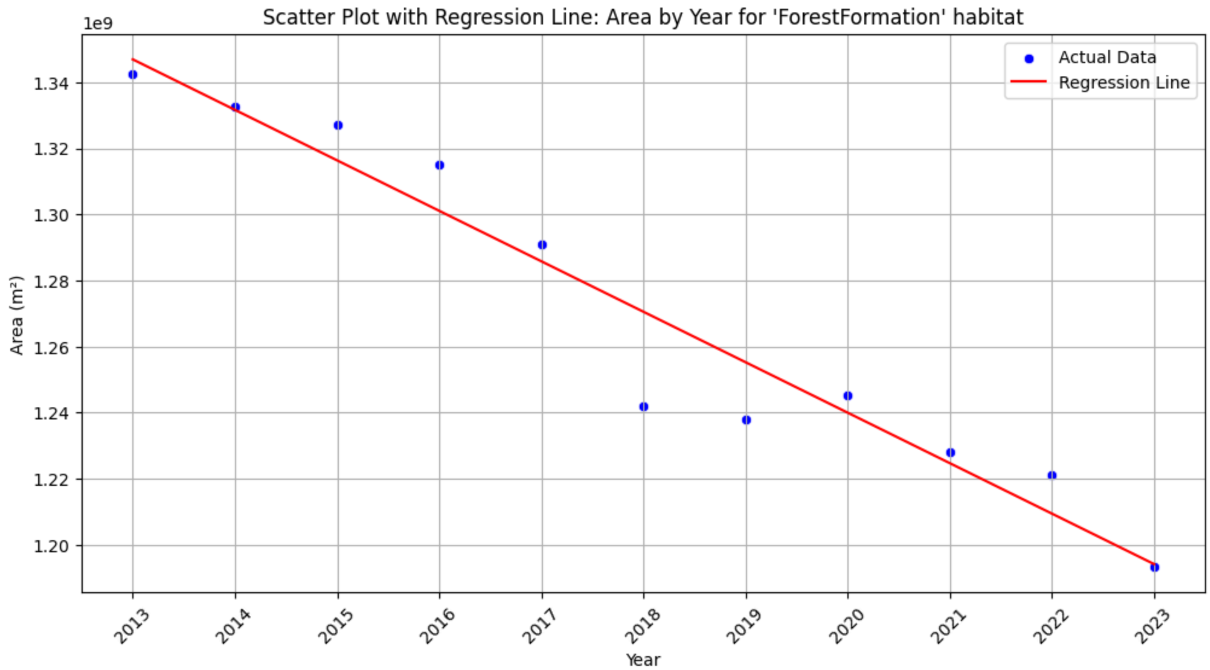
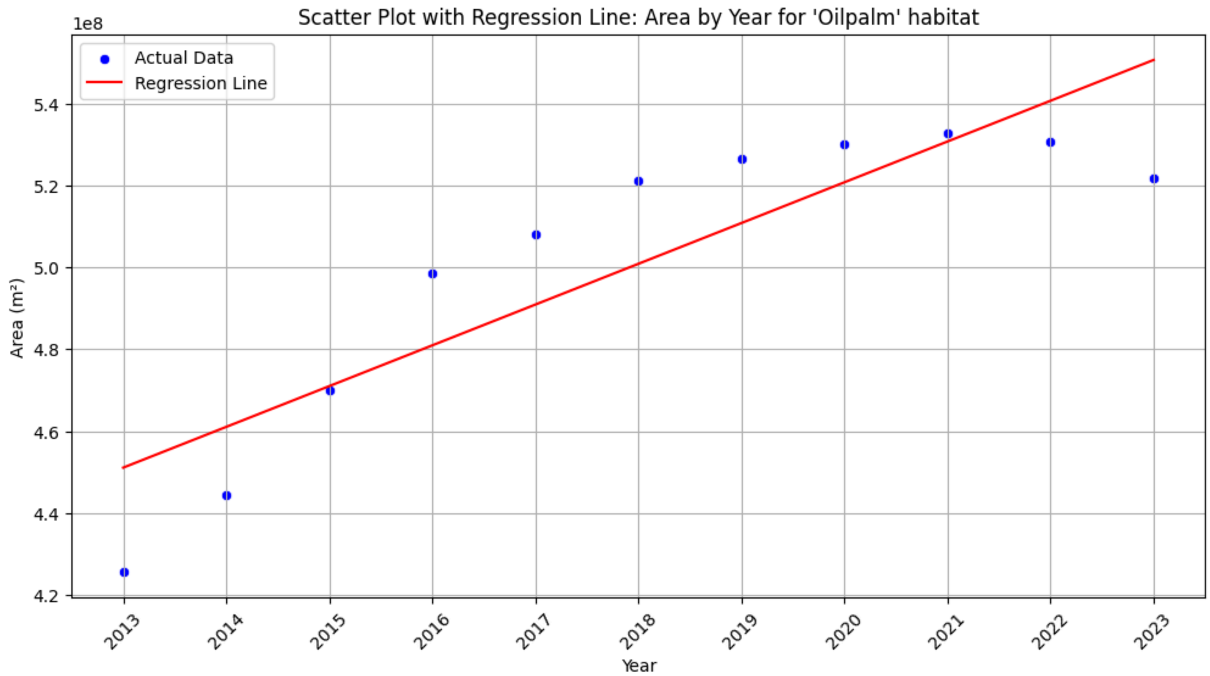




```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\scipy\stats\_axi
s_nan_policy.py:430: UserWarning: `kurtosistest` p-value may be inaccurate w
ith fewer than 20 observations; only n=11 observations were given.
  return hypotest_fun_in(*args, **kwds)
```


Scatter Plot with Regression Line: Area by Year for 'ForestFormation' habitat
1e9
1.34
1.32
1.30
1.28
1.26
1.24
1.22
1.20
Area (m²)
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Year
Actual Data
Regression Line

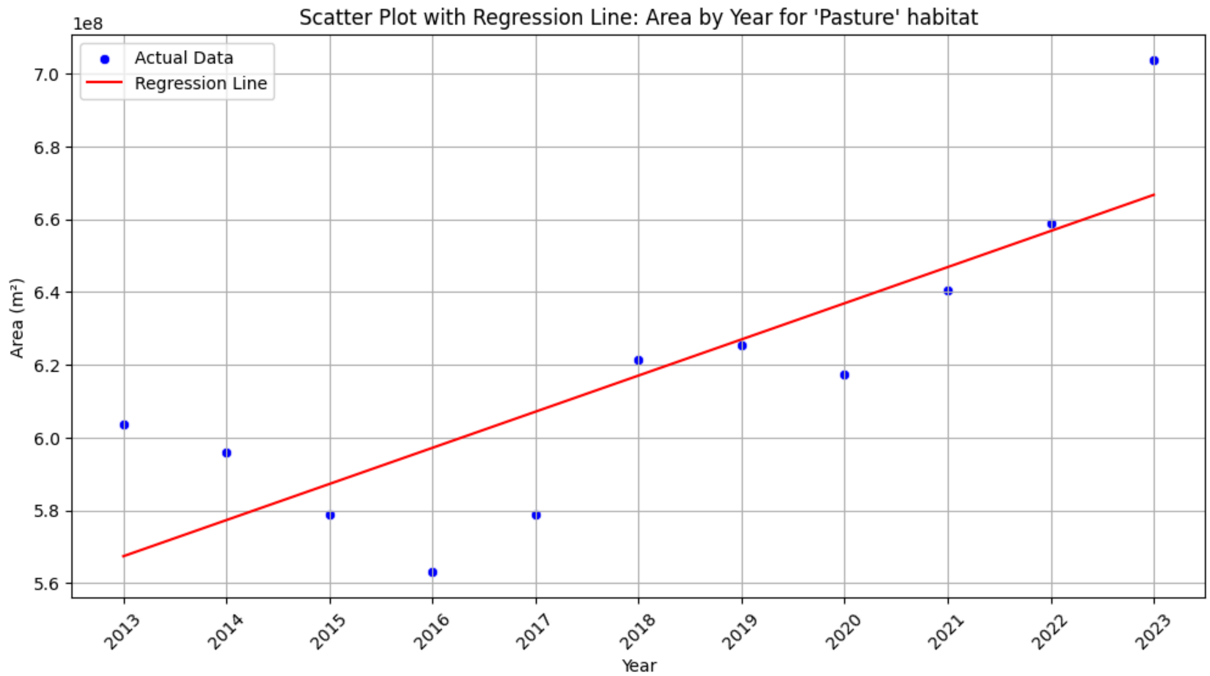
```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:                Area_m2   R-squared:                       0.9
39
Model:                            OLS   Adj. R-squared:                  0.9
32
Method:                 Least Squares   F-statistic:                     13
8.8
Date:                Tue, 14 Jan 2025   Prob (F-statistic):           9.02e-
07
Time:                        12:51:59   Log-Likelihood:                -195.
19
No. Observations:                  11   AIC:                             39
4.4
Df Residuals:                       9   BIC:                             39
5.2
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
========
                       coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const             1.347e+09   7.68e+06    175.484      0.000    1.33e+09
1.36e+09
BufferID_encoded -1.528e+07    1.3e+06    -11.780      0.000   -1.82e+07   -
1.23e+07
==============================================================================
==
Omnibus:                        5.232   Durbin-Watson:                   1.3
40
Prob(Omnibus):                  0.073   Jarque-Bera (JB):                2.3
80
Skew:                          -1.125   Prob(JB):                        0.3
04
Kurtosis:                       3.357   Cond. No.                         1
1.3
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\scipy\stats\_axi
s_nan_policy.py:430: UserWarning: `kurtosistest` p-value may be inaccurate w
ith fewer than 20 observations; only n=11 observations were given.
  return hypotest_fun_in(*args, **kwds)
```


Scatter Plot with Regression Line: Area by Year for 'Oilpalm' habitat
1e8
Actual Data
Regression Line
5.4
5.2
5.0
4.8
4.6
4.4
4.2
Area (m²)
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Year

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:                Area_m2   R-squared:                       0.7
72
Model:                            OLS   Adj. R-squared:                  0.7
47
Method:                 Least Squares   F-statistic:                     30.
53
Date:                Tue, 14 Jan 2025   Prob (F-statistic):           0.0003
68
Time:                        12:51:59   Log-Likelihood:                -198.
82
No. Observations:                  11   AIC:                             40
1.6
Df Residuals:                       9   BIC:                             40
2.4
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
========
                       coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const             4.511e+08   1.07e+07     42.268      0.000    4.27e+08
4.75e+08
BufferID_encoded  9.968e+06    1.8e+06      5.526      0.000    5.89e+06
1.4e+07
==============================================================================
==
Omnibus:                        1.989   Durbin-Watson:                   0.4
03
Prob(Omnibus):                  0.370   Jarque-Bera (JB):                1.0
51
Skew:                          -0.408   Prob(JB):                        0.5
91
Kurtosis:                       1.725   Cond. No.                         1
1.3
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

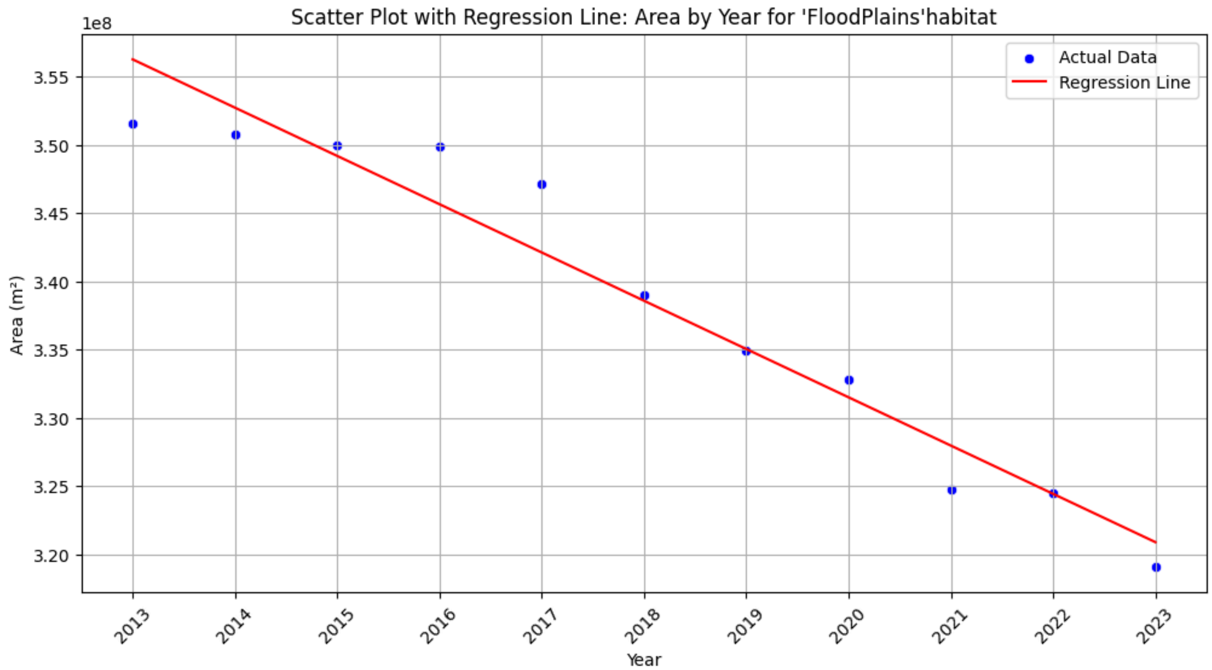
```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\scipy\stats\_axi
s_nan_policy.py:430: UserWarning: `kurtosistest` p-value may be inaccurate w
ith fewer than 20 observations; only n=11 observations were given.
  return hypotest_fun_in(*args, **kwds)
```



Scatter Plot with Regression Line: Area by Year for 'Pasture' habitat
1e8
Actual Data
Regression Line
7.0
6.8
6.6
6.4
6.2
6.0
5.8
5.6
Area (m²)
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Year

```
                            OLS Regression Results
==============================================================================
==
Dep. Variable:                Area_m2   R-squared:                       0.6
64
Model:                            OLS   Adj. R-squared:                  0.6
27
Method:                 Least Squares   F-statistic:                     17.
78
Date:                Tue, 14 Jan 2025   Prob (F-statistic):            0.002
25
Time:                        12:51:59   Log-Likelihood:                -201.
75
No. Observations:                  11   AIC:                             40
7.5
Df Residuals:                       9   BIC:                             40
8.3
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
========
                      coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
const             5.674e+08   1.39e+07     40.728      0.000    5.36e+08
5.99e+08
BufferID_encoded  9.929e+06   2.35e+06      4.217      0.002     4.6e+06
1.53e+07
==============================================================================
==
Omnibus:                        0.401   Durbin-Watson:                   0.8
42
Prob(Omnibus):                  0.818   Jarque-Bera (JB):                0.4
92
Skew:                           0.278   Prob(JB):                        0.7
82
Kurtosis:                       2.126   Cond. No.                         1
1.3
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```

```
C:\Users\vs24904\AppData\Local\anaconda32\Lib\site-packages\scipy\stats\_axi
s_nan_policy.py:430: UserWarning: `kurtosistest` p-value may be inaccurate w
ith fewer than 20 observations; only n=11 observations were given.
  return hypotest_fun_in(*args, **kwds)
```


Scatter Plot with Regression Line: Area by Year for 'FloodPlains'habitat
1e8
3.55
3.50
3.45
3.40
3.35
3.30
3.25
3.20
Area (m²)
2013
2014
2015
2016
2017
2018
2019
2020
2021
2022
2023
Year
Actual Data
Regression Line

```
                            OLS Regression Results                            
==============================================================================
==
Dep. Variable:                Area_m2   R-squared:                       0.9
42
Model:                            OLS   Adj. R-squared:                  0.9
35
Method:                 Least Squares   F-statistic:                     14
5.8
Date:                Tue, 14 Jan 2025   Prob (F-statistic):           7.30e-
07
Time:                        12:52:00   Log-Likelihood:                -178.
82
No. Observations:                  11   AIC:                             36
1.6
Df Residuals:                       9   BIC:                             36
2.4
Df Model:                           1                                         
Covariance Type:            nonrobust                                         
==============================================================================
========
                       coef    std err          t      P>|t|      [0.025      
0.975]
------------------------------------------------------------------------------
--------
const             3.563e+08   1.73e+06    205.574      0.000    3.52e+08      
3.6e+08
BufferID_encoded -3.537e+06   2.93e+05    -12.074      0.000    -4.2e+06   -
2.87e+06
==============================================================================
==
Omnibus:                        0.179   Durbin-Watson:                   1.0
05
Prob(Omnibus):                  0.914   Jarque-Bera (JB):                0.2
58
Skew:                           0.228   Prob(JB):                        0.8
79
Kurtosis:                       2.403   Cond. No.                         1
1.3
==============================================================================
==

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is corre
ctly specified.
```