WATER BAG CLUSTERS IN RIO DE JANEIRO - MEANSHIFT HYPERPARAMETER TUNING

Notebook Sections:

1. Utility functions
2. Data Cleaning
3. Hyperparameter Tuning
4. Final Model
5. Cluster Result Analysis

Import modules and functions

In [1]:
```
import os, sys, pandas as pd, numpy as np, matplotlib.pyplot as plt, seaborn as sns; sns.set()
from IPython.display import clear_output as co

### Define data class to host data paths
class DATA:
    project = 'Desktop/Repositories/Data Science Projects/Hackaton COR IV - Centro de Operações do RJ/ACELERAÇÃO/Modulos'
    path = r'C:\Users\luisr\Desktop\Repositories\Dados\Desafio COR-Rio IV\\'
    AlertaAPI = r'http://websempre.rio.rj.gov.br/json/chuvas'
```

Change project root folder

In [2]:
```
cd ../
```

```
C:\Users\luisr\Desktop\Repositories\Data Science Projects\Hackaton COR IV - Centro de Operações do RJ\ACELERAÇÃO
```

Load data

In [3]:
```
catalog = pd.read_csv('Dados/Catalog/water_bag_catalog_google.csv'); data = catalog.copy()
data[['EVENTO_ID', 'EVENTO_TITULO', 'EVENTO_DESCRICAO', 'EVENTO_LATITUDE', 'EVENTO_LONGITUDE', 'EVENTO_INICIO']].head()
```

Out[3]:

	EVENTO_ID	EVENTO_TITULO	EVENTO_DESCRICAO	EVENTO_LATITUDE	EVENTO_LONGITUDE	EVENTO_INICIO
0	1258	Bolsão d'agua	R. Pinheiro Machado com Muniz Barreto - Botafogo	-22.944774	-43.183917	2015-09-12 20:12:00
1	1259	Bolsão	Av. Novo Rio, 3131 - Bonsucesso	-22.871684	-43.256200	2015-09-12 22:13:00
2	1260	Bolsão	Av. Ataulfo de Paiva, 752 - Leblon	-22.984337	-43.223100	2015-09-12 22:15:00
3	1261	Bolsão	Avenida General San Martin / Praça Antero de Q...	-22.984337	-43.223100	2015-09-12 22:16:00
4	1263	Bolsão d'água	Av. Brasil, 40 - São Cristóvão	-22.892179	-43.216400	2015-09-13 06:30:00

---

0. Utility functions

Unsupervised learning algorithms, evaluation metrics and preprocessing functions

In [4]:
```
from sklearn import cluster, mixture, metrics
from sklearn.preprocessing import MinMaxScaler as mms, LabelEncoder as le
```

Plot colored and connected coordinates in 2D plane

In [5]:
```
from Modulos.coord_plot import (
    cmaps, filter_group_size,
    cluster_algo_comparison,
    connect_coordinates_colored,
    min_group_size_progression_plot,
    atemporal_evolution_plot
)
```

Cluster hyperparameter tunning module

In [6]:
```
from Modulos.cluster_tunning import (
    labels_size_stats,
    log_range,
    cluster_grid_search,
```

```
    evaluate_labels,
    min_samples_analysis,
    rotate_3d_plot
)
```

---

1. Data Cleaning

Data type conversion

In [7]:
```
float_cols = ['EVENTO_LATITUDE', 'EVENTO_LONGITUDE', 'search_lat', 'search_lng']

data[float_cols] = data[float_cols].astype(float)
```

---

2. Meanshift Cluster Model Hyperparameter Tunning

Scale algorithm input data

In [8]:
```
# Fit algotihm on incidents coordintes
profile_cols = ['EVENTO_LONGITUDE', 'EVENTO_LATITUDE']

coords = pd.DataFrame(mms().fit_transform(data[profile_cols]), columns=profile_cols, index=data.index)
```

Hyperparameter grid search settings

In [9]:
```
# Set base algorithm for evaluation
alg = meanshift = cluster.MeanShift(
    bandwidth=None, cluster_all=False,
    max_iter=1000, n_jobs=-1
)

# Set parameters for grid search
param_name = 'bandwidth'
min_value = 0.001
max_value = 0.02
n_params = 20
params= np.linspace(min_value, max_value, n_params); params
```

Out[9]:
```
array([0.001, 0.002, 0.003, 0.004, 0.005, 0.006, 0.007, 0.008, 0.009,
       0.01 , 0.011, 0.012, 0.013, 0.014, 0.015, 0.016, 0.017, 0.018,
       0.019, 0.02 ])
```

Build and evaluate model with grid search in parameter space

In [27]:
```
# Perform parameter space grid search
labels = cluster_grid_search(coords, alg, param_name, params)

# Evaluate parameter search results
scrs = evaluate_labels(coords, labels, param_name, min_samples=10)

# Evaluate parameter search results
min_samples = min_samples_analysis(coords, labels, param_name, min_samples=0, max_samples=25)
```

```
20/20 Search grid evaluation...
```

Save grid search result

In [12]:
```
res_path = 'Dados/Cluster Tunning/'

results = {
#     'Grid Search Labels': pd.DataFrame(labels, index=catalog['EVENTO_ID']),
#     'Grid Search Results': scrs,
#     'Grid Search Min Samples Analysis': min_samples
}

# Save results
for i, (key, res) in enumerate(results.items()):
    co(wait=True); print(f'{i+1}/{len(results)} - Saving result: {key}...')
#     res.to_csv(res_path + key + '.csv', index=True)
```

Reload grid search results

In [13]:
```
from Modules.data import read_csv_folder

res_path = 'Dados/Cluster Tunning/'

# Reload results
labels, min_samples, scrs = read_csv_folder(res_path, index_col=0)
labels = {label: labels[label].values for label in labels}
```

---

3. Visualize Hyperparameter Grid Search

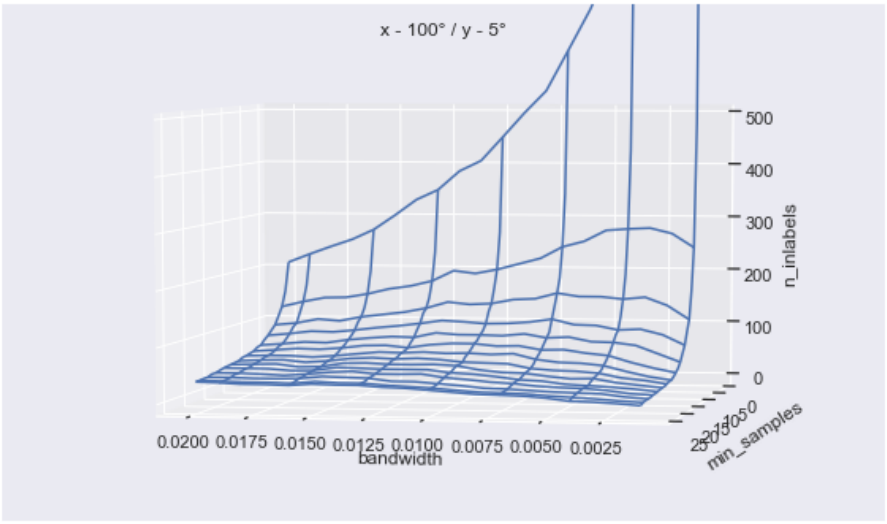
2D Grid search result

In [ ]:
```
band_scrs = scrs.set_index('bandwidth')

fig, axs = plt.subplots(1, 2, figsize=(14, 3.5))
band_scrs[['n_labels', 'n_outlabels']].plot(marker='o', ax=axs[0])
band_scrs[['n_inlabels']].plot(marker='o', ax=axs[1])
# ax.set(xlim=(0, 0.1))

fig, axs = plt.subplots(1, 2, figsize=(14, 3.5))
band_scrs[['n_in', 'n_out', 'n_non_outliers', 'n_outliers_label']].plot(marker='o', ax=axs[0])
band_scrs[['n_outliers']].plot(marker='o', ax=axs[1])

fig, axs = plt.subplots(1, 2, figsize=(14, 3.5))
pd.DataFrame(
    mms().fit_transform(band_scrs[['silhouette', 'bouldin']]),
    columns=['silhouette', 'bouldin'], index=band_scrs.index
).plot(marker='o', ax=axs[0])
band_scrs[['inertia']].plot(marker='o', ax=axs[1])

plt.show()
```

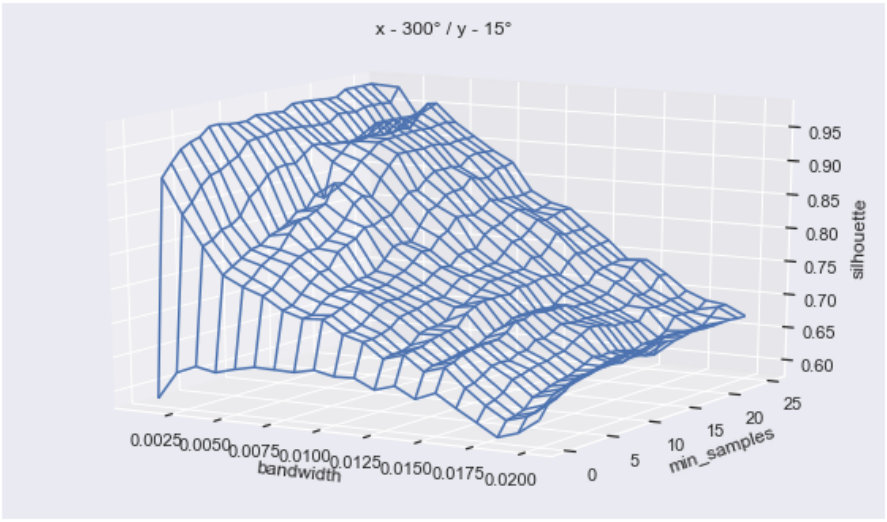
3D Grid search result

In [29]:
```
x = 'bandwidth'
y = 'min_samples'
z = 'n_inlabels'
zz = 'n_outliers'
w = 'inertia'
ww = 'silhouette'
www = 'bouldin'
wwww = 'calinski'
```

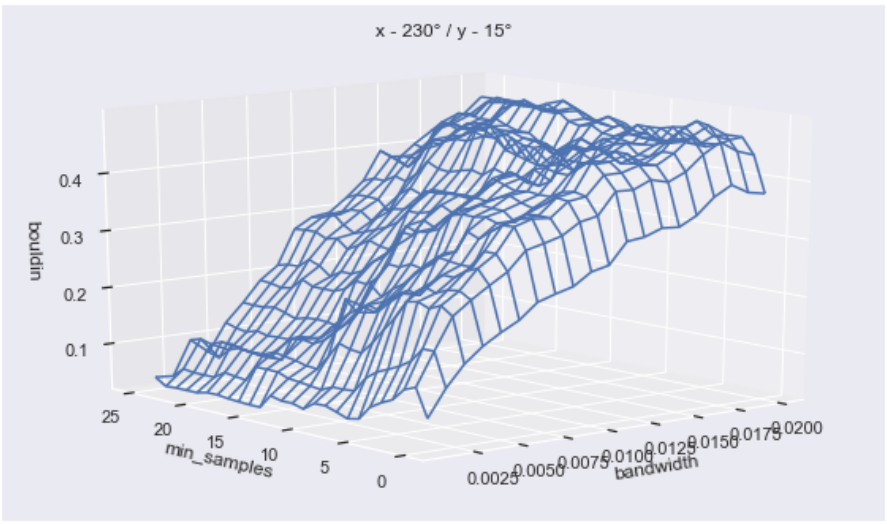
In [30]:
```
rotate_3d_plot(min_samples, x, y, z, xy_start=0, xy_end=5, z_start=0, z_end=100, frames=15, zlim=(-10, 500), cstride=2, rs
```



In [31]:
```
rotate_3d_plot(min_samples, x, y, ww, xy_start=0, xy_end=15, z_start=0, z_end=300, frames=15, zlim=None)
```

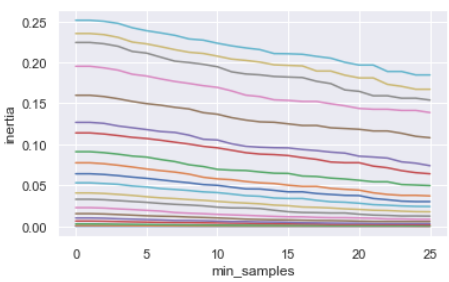


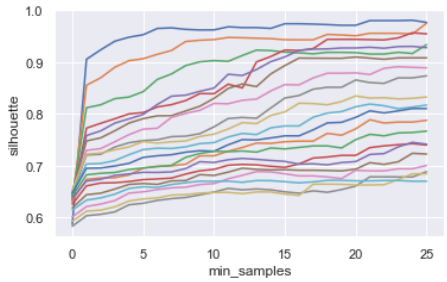
In [32]:
```
rotate_3d_plot(min_samples, x, y, www, xy_start=0, xy_end=15, z_start=0, z_end=230, frames=15, zlim=None)
```

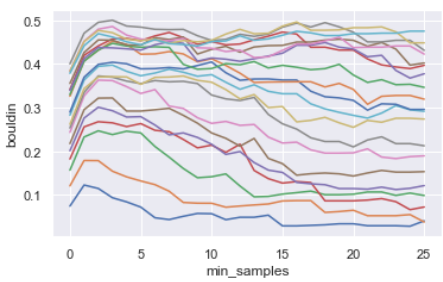


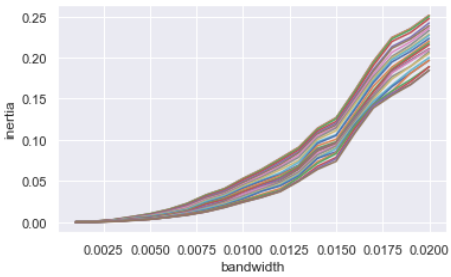
2D Orthogonal views

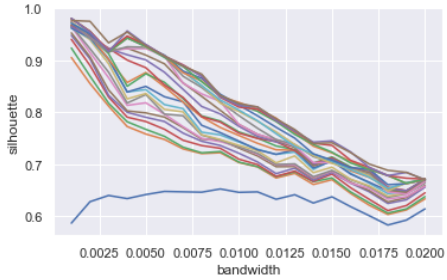
In [33]:
```
fig, axs = plt.subplots(1, 3, figsize=(20, 3.5))
for W, ax in zip([w, ww, www], axs):
    for index, df in min_samples.groupby(x):
        df.set_index(y)[W].plot(ax=ax)
    ax.set(xlabel=y, ylabel=W)

fig, axs = plt.subplots(1, 3, figsize=(20, 3.5))
for W, ax in zip([w, ww, www], axs):
    for index, df in min_samples.groupby(y):
        df.set_index(x)[W].plot(ax=ax)
    ax.set(xlabel=x, ylabel=W)

fig, axs = plt.subplots(1, 2, figsize=(14, 3.5))
for X, Y, ax in zip([x, y], [y, x], axs):
    for index, df in min_samples.groupby(X):
        df.set_index(Y)[z].plot(ax=ax)
    ax.set(xlabel=Y, ylabel=z, ylim=(-10, 500))
```

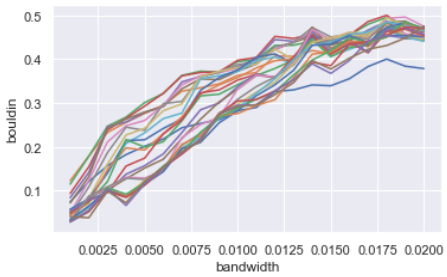


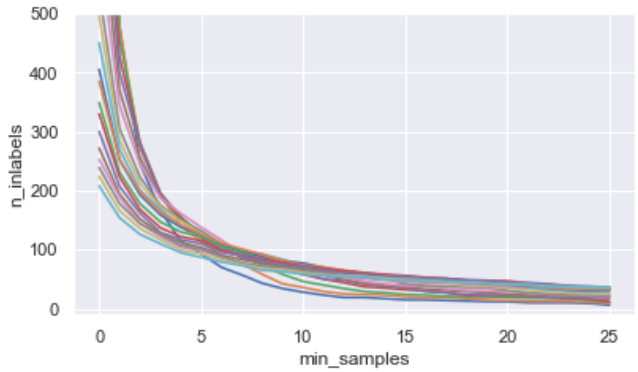


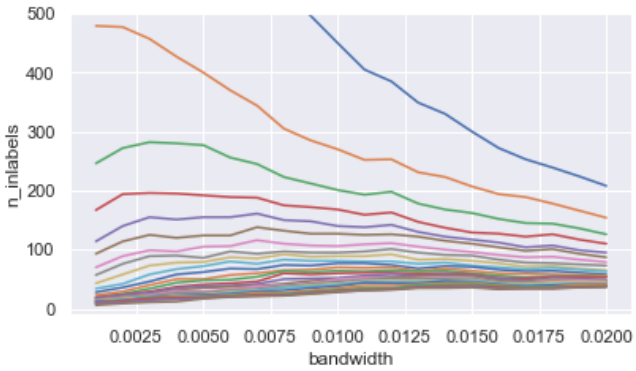



inertia
0.25
0.20
0.15
0.10
0.05
0.00
0.0025 0.0050 0.0075 0.0100 0.0125 0.0150 0.0175 0.0200
bandwidth


silhouette
1.0
0.9
0.8
0.7
0.6
0.0025 0.0050 0.0075 0.0100 0.0125 0.0150 0.0175 0.0200
bandwidth


bouldin
0.5
0.4
0.3
0.2
0.1
0.0025 0.0050 0.0075 0.0100 0.0125 0.0150 0.0175 0.0200
bandwidth


n_inlabels
500
400
300
200
100
0
0 5 10 15 20 25
min_samples


n_inlabels
500
400
300
200
100
0
0.0025 0.0050 0.0075 0.0100 0.0125 0.0150 0.0175 0.0200
bandwidth