WATER BAG CLUSTERS IN RIO DE JANEIRO - FINAL MODELS

Notebook Sections:

1. Utility functions
2. Data Cleaning
3. Final Cluster Model
4. Clusters' Numeric and Geometric Properties
5. Clusters' 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
```

```
C:\Users\luisr\AppData\Roaming\Python\Python38\site-packages\pandas\core\computation\expressions.py:21: UserWarning: Panda
s requires version '2.7.3' or newer of 'numexpr' (version '2.7.1' currently installed).
  from pandas.core.computation.check import NUMEXPR_INSTALLED
```

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 [ ]:
```
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()
```

---

0. Utility functions

Functions to format and correct street number text variable

In [4]:
```
from Modulos.text_formatter import text_transform_pipeline, get_not_number, drop_letters, drop_space, drop_chars, split_av
```

Unsupervised learning algorithms, evaluation metrics and preprocessing functions

In [5]:
```
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 [6]:
```
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 [7]:
```
from Modulos.cluster_tunning import (
    labels_size_stats,
    log_range,
    cluster_grid_search,
    evaluate_labels,
    min_samples_analysis,
    rotate_3d_plot
)
```

---

1. Data Cleaning

Format and correct street number variable

In [8]:
```
not_number = get_not_number(catalog['street_number'])
not_number_corrected =  text_transform_pipeline(not_number, [drop_letters, drop_space, drop_chars, split_avg])

data.loc[not_number.index, ['street_number']] = not_number_corrected
```

Data type conversion

In [9]:
```
float_cols = ['EVENTO_LATITUDE', 'EVENTO_LONGITUDE', 'search_lat', 'search_lng', 'street_number']
data[float_cols] = data[float_cols].astype(float)
```

---

4. Final Water Bag Coordinates Cluster Model

Scale algorithm input data

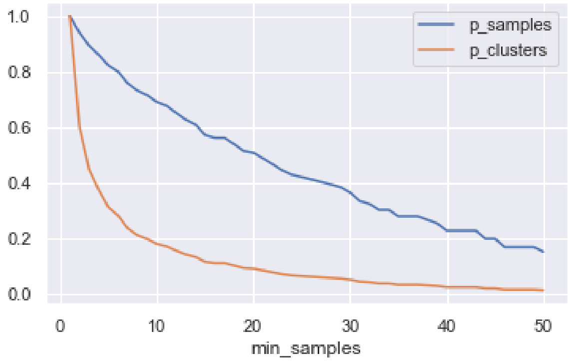
In [10]:
```
profile_cols = ['EVENTO_LONGITUDE', 'EVENTO_LATITUDE']
coords = pd.DataFrame(mms().fit_transform(data[profile_cols]), columns=profile_cols, index=data.index)
```

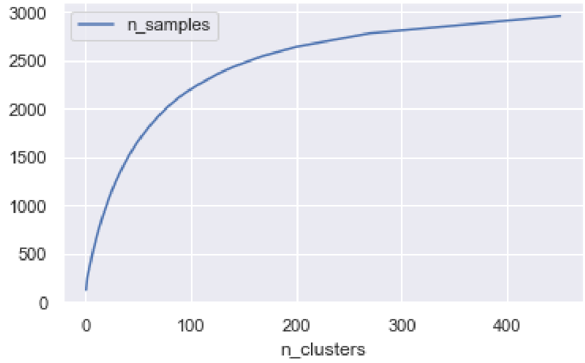
Fit model of selected hyperparameters

In [ ]:
```
bandwidth = 0.01 # 0.01 and 0.05 for macro and micro clusters

alg = meanshift = cluster.MeanShift(
    bandwidth=bandwidth, cluster_all=False,
    max_iter=1000, n_jobs=-1
)

alg.fit(coords)
```

Choose number of clusters/samples left

In [12]:
```
size_stats = labels_size_stats(alg.labels_, max_samples=None)

fig, ax = plt.subplots(1, 2, figsize=(13, 3.5))
size_stats[['p_samples', 'p_clusters']].head(50).plot(ax=ax[0])
size_stats.set_index('n_clusters')[['n_samples']].plot(ax=ax[1])
plt.show()
```





Filter cluster result:

1. Remove outliers
2. Remove clusters with less than 'min_samples'

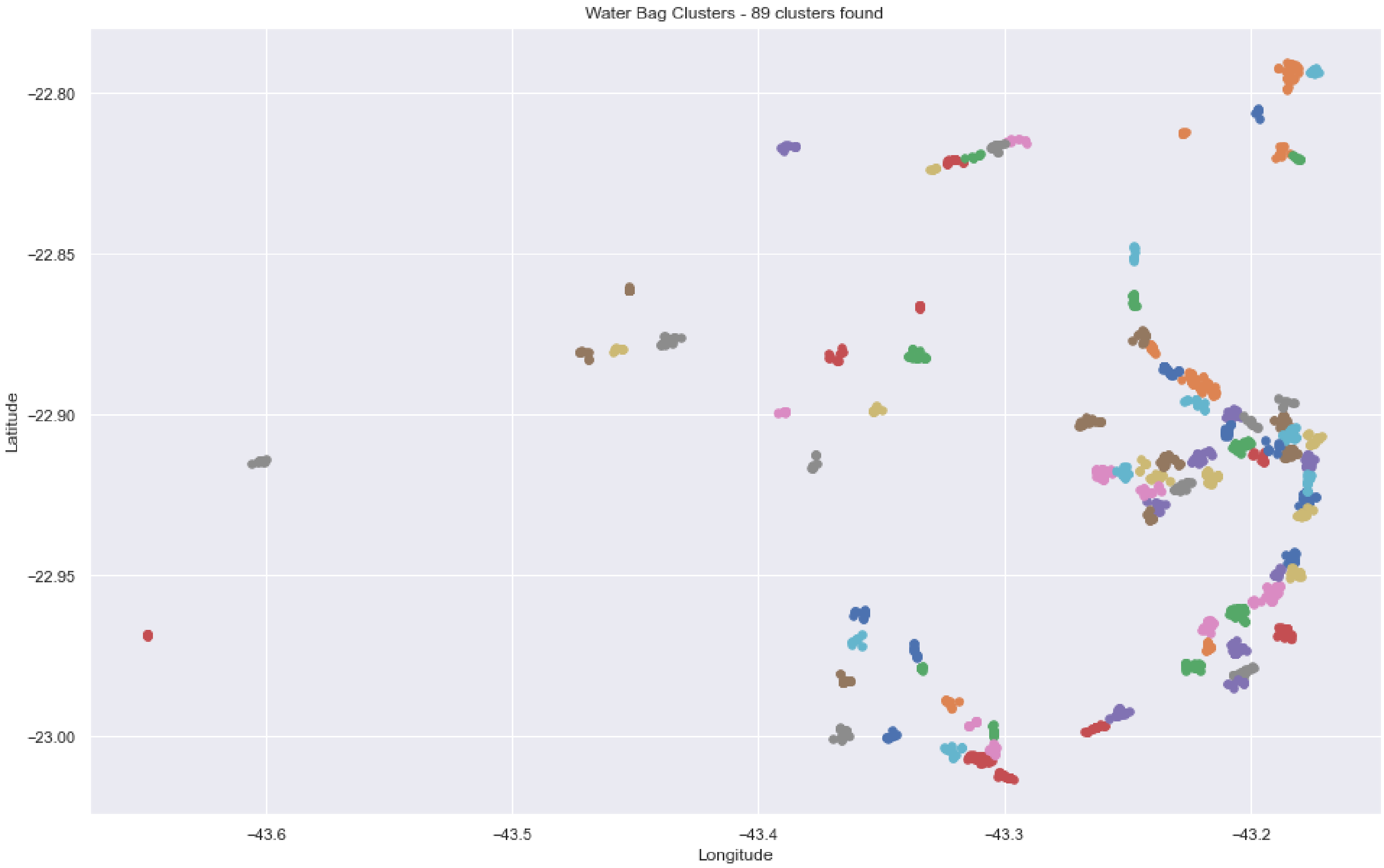
In [13]:
```
min_samples = 8

data['label'] = alg.labels_
in_data = data[data['label'] != -1]
top_data = filter_group_size(in_data, group_col='label', min_members=min_samples) # Excluing clusters with less then 'min_r

# Create new label column
outlabels = list(set(data['label']).difference(top_data['label']))
data['sublabel'] = data['label'].replace(outlabels, -1)

in_data = data[data['sublabel'] != -1]
top_data['sublabel'] = top_data['label']  # Since it already does not contain samples from clusters smallest than 'min_memb

print('Samples left:', len(top_data))
```

```
print('Clusters left:', len(top_data['sublabel'].unique())); print()
print('Samples left (%):', round(100 * len(top_data) / (data['label'] != -1).sum(), 1), '%')
print('Clusters left (%):', round(100 * len(top_data['sublabel'].unique()) / (len(data['label'].unique()) - 1), 1), '%')
```

```
Samples left: 2118
Clusters left: 89

Samples left (%): 71.5 %
Clusters left (%): 19.8 %
```

Scatter clusters on 2D plane

In [14]:
```
connect_coordinates_colored(
    top_data['EVENTO_LONGITUDE'], top_data['EVENTO_LATITUDE'],
    top_data['label'], top_data['street_number'], cmap=None,
    title='Water Bag Clusters - {} clusters found',
    figsize=(16, 10), connect=False
)
```



Include clusters' geometric propeties and address info

In [15]:
```
from Modulos.group_methods import groups_majority_class, group_majority_class_numeric_range
from Modulos.geometric_properties import clusters_geometry

clusters = data.set_index('EVENTO_ID')[['sublabel']]

# Join clusters' representative  neighborhood, route and street number range
clusters['main_neighborhood'] = groups_majority_class(data, group_col='sublabel', class_col='EVENTO_BAIRRO')
clusters['main_route'] = groups_majority_class(data, group_col='sublabel', class_col='route')
clusters['main_street_number_range'] = group_majority_class_numeric_range(data, group_col='sublabel', class_col='route', nu

# Join geometric properties
geometry = clusters_geometry(
    data['EVENTO_LATITUDE'], data['EVENTO_LONGITUDE'], clusters['sublabel'],
    include_box=True, include_center_radius=True
)
clusters = clusters.join(geometry)
```

Save and reload best cluster result

Cluster info:

1. Label
2. Incidents Count
3. Representative neighborhood, street and number range
4. Centroid
5. Box geometry

6. Circle geometry
7. Box and circle Incident Density

In [11]:
```
# clusters.to_csv('Dados/Clusters/clusters_bolsões_macro.csv', index=True)
clusters = pd.read_csv('Dados/Clusters/clusters_bolsões_micro.csv', index_col=0)

display(clusters.head(3), clusters.shape)
```

EVENTO_ID	sublabel	main_neighborhood	main_route	main_street_number_range	lat_centroid	lng_centroid	label_count	lat_min	lat_max
1258	9	Botafogo	Praia de Botafogo	360 - 314	-22.945530	-43.183139	28	-22.946042	-22.944774
1259	-1	Barra da Tijuca	Avenida Brasil	35025 - 14	-22.910743	-43.303404	1624	-23.031019	-22.763640
1260	-1	Barra da Tijuca	Avenida Brasil	35025 - 14	-22.910743	-43.303404	1624	-23.031019	-22.763640

(3140, 20)

Extract cluster dataset - Clusters as rows

In [10]:
```
# Extract geometry dataset of clusters as rows
areas = clusters.groupby('sublabel').first()

# Convert units
areas['radius'] = areas['radius'] * 1e-3                # m -> Km
areas['area_box'] = areas['area_box'] * 1e-6            # m2 -> Km2
areas['area_circle'] = areas['area_circle'] * 1e-6      # m2 -> Km2
areas['density_box'] = areas['density_box'] * 1e6       # /m2 -> /Km2
areas['density_circle'] = areas['density_circle'] * 1e6  # /m2 -> /Km2

# Format title for plotting tooltips
areas['title'] = (
    areas['main_route'] +
    ', ' +
    areas['main_street_number_range'] +
    '.  Incidents: ' +
    areas['label_count'].astype(str) +
    ',  Area: ' +
    (areas['area_box']).round(3).astype(str) +
    ' Km2,  Density: ' +
    (areas['density_box']).round(2).astype(str) +
    ' / 100 m2'
)
```

Save and reload clusters dataset

In [12]:
```
# areas.to_csv('Dados/Clusters/clusters_micro.csv', index=True)
areas = pd.read_csv('Dados/Clusters/clusters_micro.csv', index_col=0); display(areas.iloc[:5, :-10], areas.shape)
```

sublabel	main_neighborhood	main_route	main_street_number_range	lat_centroid	lng_centroid	label_count	lat_min	lat_max	lng_min
-1	Barra da Tijuca	Avenida Brasil	35025 - 14	-22.910743	-43.303404	1624	-23.031019	-22.763640	-43.692051
0	Barra da Tijuca	Avenida Armando Lombardi	3098 - 67	-23.006631	-43.310232	114	-23.007133	-23.006231	-43.312829
1	Catete	Rua do Catete	228 - 139	-22.926423	-43.176842	99	-22.927198	-22.925534	-43.178604
2	Copacabana	Rua Tonelero	236 - 9	-22.966793	-43.185999	43	-22.967739	-22.966181	-43.187500
3	Ipanema	Avenida Epitácio Pessoa	1910 - 1602	-22.979735	-43.202540	36	-22.980438	-22.979236	-43.204100

(80, 20)

Scatter clusters on terrain map

Terrain map with clusters surrounded by boxes or circles

In [12]:
```
data['sublabel'] = clusters.loc[data['EVENTO_ID']]['sublabel'].values
```

In [14]:
```
from Modulos.mapper import plot_markers, draw_circles, draw_rectangles
import folium

Map = folium.Map(
    location=[-22.9145, -43.2105], zoom_start=14,
    width='100%', height='100%', tiles='Stamen Terrain'
)

Map, LE = plot_markers(
    Map, data, radius=3,
    coord_cols=['EVENTO_LATITUDE', 'EVENTO_LONGITUDE'],
    group_col='sublabel', cmap='tab20',
    exclude=[], touch_coord=True, return_encoder=True
)

Map = draw_rectangles(
    Map, areas.drop(-1),
    loc=[['lat_min', 'lng_min'], ['lat_max', 'lng_max']],
    popup='main_neighborhood', tooltip='title',
    cmap='tab20', lut=len(areas), LE=LE,
    stroke=True, weight=3, fill=True,
    fill_color=None, fill_opacity=.3
)

# Map = draw_circles(
#     Map, areas,
#     loc=['lat_center', 'lng_center'], radius='radius',
#     popup='main_route', tooltip='main_route',
#     cmap='tab20', lut=len(areas), LE=LE,
#     stroke=True, weight=4, fill=True,
#     fill_color=None, fill_opacity=.3
# )

Map
```

Out[14]: Make this Notebook Trusted to load map: File -> Trust Notebook

Save map to html

In [50]:
```
Map.save('bolsoes_clusters_micro.html')
```

Extra: Convert to GeoJson data

In [49]:
```
import json

def save_json(obj, path):
```

```python
    if type(obj) is dict: obj = json.dumps(obj)
    with open(path, 'w') as file:
        file.write(obj)
    print('Done!')

def points_geojson(df, coords=['EVENTO_LONGITUDE', 'EVENTO_LATITUDE']):
    points_json = {
        "type": "FeatureCollection",
        "features": []
    }
    for row in df.iterrows():
        row = row[1]
        points_json['features'].append({
            'type': 'Feature',
            'geometry': {
                'type': 'Point',
                'coordinates': [row[coords[0]], row[coords[1]]],
            },
            'properties': row.drop(coords).to_dict()
        })
    return points_json

def polygon_geojson(df, coords=['lng_min', 'lng_max', 'lat_min', 'lat_max']):
    polygon_json = {
        "type": "FeatureCollection",
        "features": []
    }
    for row in df.iterrows():
        row = row[1]
        polygon_json['features'].append({
            'type': 'Feature',
            'geometry': {
                'type': 'Polygon',
                'coordinates': [[
                    [row[coords[0]], row[coords[2]]],
                    [row[coords[0]], row[coords[3]]],
                    [row[coords[1]], row[coords[3]]],
                    [row[coords[1]], row[coords[2]]],
                    [row[coords[0]], row[coords[2]]],
                ]],
            },
            'properties': row.drop(coords).to_dict()
        })
    return polygon_json
```

Points geojson

In [61]:

```python
points = clusters[['sublabel']].join(data.set_index('EVENTO_ID'), how='left').reset_index()

points_json = points_geojson(points, coords=['EVENTO_LONGITUDE', 'EVENTO_LATITUDE'])
save_json(points_json, 'Dados/Clusters/points_micro.geojson')
```

```
Done!
```

Polygon geojson

In [66]:

```python
polygons = areas.reset_index()

polygons_json = polygon_geojson(polygons, coords=['lng_min', 'lng_max', 'lat_min', 'lat_max'])
save_json(polygons_json, 'Dados/Clusters/polygons_micro.geojson')
```

```
Done!
```

In [ ]:

```python
areas
```

Out[ ]:

sublabel	main_neighborhood	main_route	main_street_number_range	lat_centroid	lng_centroid	label_count	lat_min	lat_max	lng_min
-1	Barra da Tijuca	Avenida Brasil	35025 - 14	-22.910743	-43.303404	1624	-23.031019	-22.763640	-43.692051
0	Barra da Tijuca	Avenida Armando Lombardi	3098 - 67	-23.006631	-43.310232	114	-23.007133	-23.006231	-43.312829
1	Catete	Rua do Catete	228 - 139	-22.926423	-43.176842	99	-22.927198	-22.925534	-43.178604
2	Copacabana	Rua Tonelero	236 - 9	-22.966793	-43.185999	43	-22.967739	-22.966181	-43.187500
3	Ipanema	Avenida Epitácio Pessoa	1910 - 1602	-22.979735	-43.202540	36	-22.980438	-22.979236	-43.204100
...	...	...	...	...	...	...	...	...	...
76	Bangu	Rua da Feira	540 - 359	-22.880275	-43.472239	10	-22.880398	-22.880150	-43.472600
77	Jardim Carioca	Rua Muiatuca	74 - 73	-22.805012	-43.196837	9	-22.805086	-22.804934	-43.197100
78	Lagoa	Avenida Epitácio Pessoa	3000 - 1015	-22.972562	-43.203594	9	-22.973107	-22.972293	-43.204600
81	Bangu	Rua Francisco Real	1365 - 974	-22.879638	-43.456768	9	-22.880320	-22.879291	-43.458700
82	Guaratiba	Estrada da Pedra	5726 - 5291	-22.968270	-43.647878	9	-22.968601	-22.968175	-43.647900

80 rows × 20 columns

---

5. Final Model Result Analysis

Number of clusters extracted

In [15]:

```
len(areas) - 1
```

Out[15]: 79

Number of events left in clusters

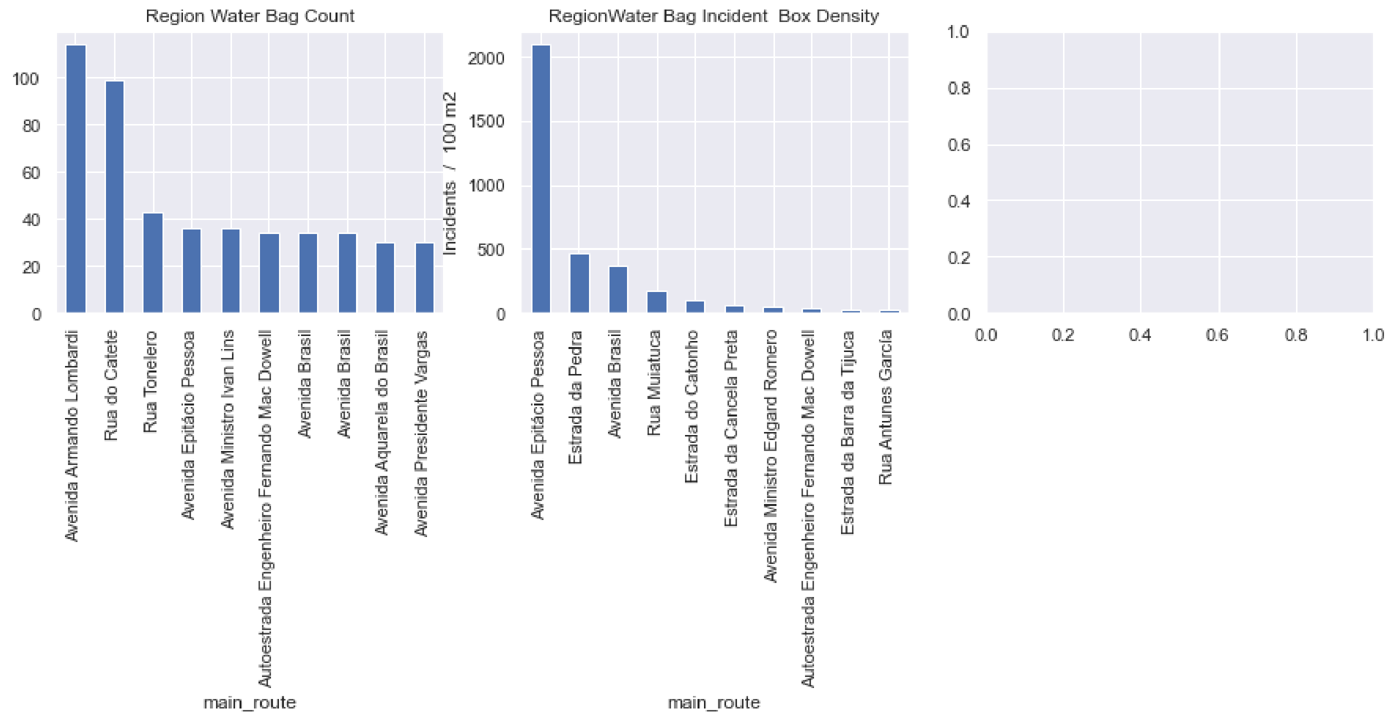
In [16]:
```
(clusters['sublabel'] != -1).mean()
```

Out[16]: 0.48280254777070064

Top regions by historical incident count and routes per cluster histogram

In [19]:
```
top_dense = areas.sort_values('density_box').iloc[-1].name # incident density outlier

fig, axes = plt.subplots(1, 3, figsize=(15, 3.3), tight_layout=True)

#### Top clusters by historical incident count
areas.drop(-1).set_index('main_route')['label_count'].nlargest(10).plot.bar(
    title='Region Water Bag Count', ax=axes[0]
)
#### Top clusters by historical incident density
ax = (areas.drop([-1, top_dense]).set_index('main_route')['density_box'].nlargest(10) * 1e-2).plot.bar(
    title='RegionWater Bag Incident  Box Density', ax=axes[1]
)
axes[1].set(ylabel='Incidents  /  100 m2')

# #### Routes per cluster distribution
# bins = np.linspace(0.5, 10.5, 11)
# xticks=np.linspace(1, 10, 10)
# top_data.groupby(['sublabel'])[['route']].nunique().sort_values('route', ascending=False).plot.hist(
#     bins=bins, xticks=xticks, ax=axes[2]
# )
# axes[2].set(title='Routes per cluster distribution - Histogram', ylabel='Clusters', xlabel='Route count')

plt.show()
```

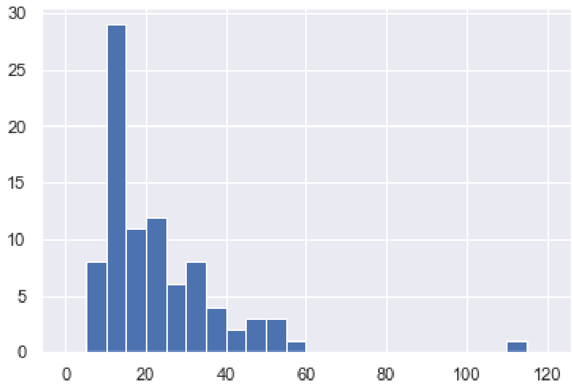
```
c:\Users\luisr\anaconda3\lib\site-packages\IPython\core\pylabtools.py:132: UserWarning: Tight layout not applied. The bott
om and top margins cannot be made large enough to accommodate all axes decorations.
  fig.canvas.print_figure(bytes_io, **kw)
```



Cluster size distribution

In [22]:
```
areas.drop(-1).set_index('main_route')['label_count'].hist(bins=np.arange(0, 121, 5))
```

Out[22]: <matplotlib.axes._subplots.AxesSubplot at 0x22c30458220>



Numeric variables statistical description

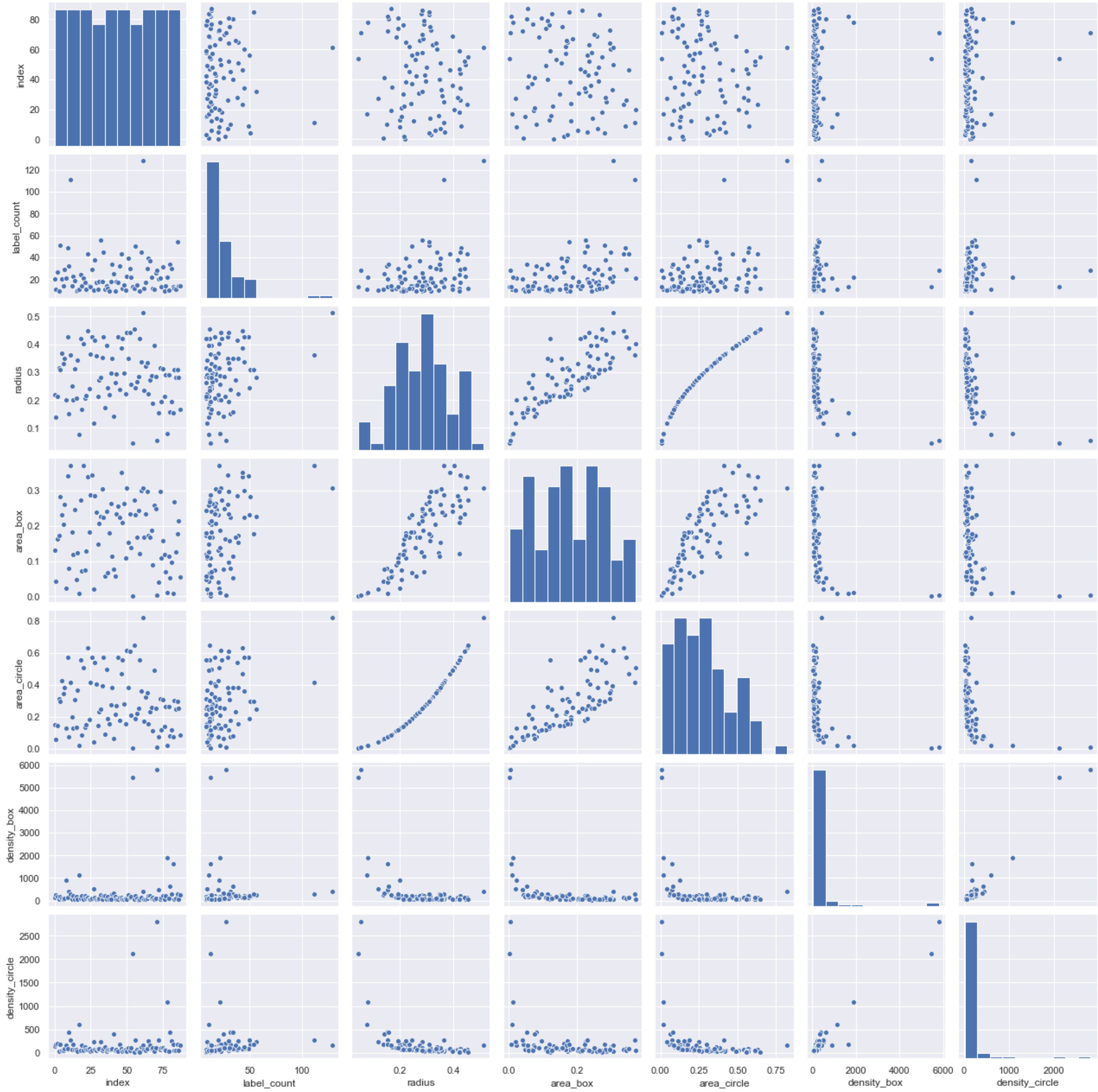
In [23]:
```
numeric_cols = ['label_count', 'radius', 'area_box', 'area_circle', 'density_box', 'density_circle']

areas[numeric_cols].describe().drop('count')
```

Out[23]:

	label_count	radius	area_box	area_circle	density_box	density_circle
mean	34.888889	0.575093	17.899093	25.605077	846.206795	231.850914
std	106.906811	2.812024	168.138421	240.272587	4967.732464	646.966595
min	9.000000	0.023583	0.000192	0.001747	0.640641	0.448304
25%	12.000000	0.212086	0.099617	0.141312	74.543291	49.545039
50%	18.000000	0.284044	0.178001	0.253466	124.976097	77.404289
75%	30.000000	0.351936	0.256449	0.389122	223.845875	165.437196
max	1022.000000	26.937931	1595.276593	2279.703384	46753.366995	5151.104120

Numeric variables distribution and relationship

In [24]:
```
formatted_areas = areas.drop([-1, top_dense])[numeric_cols].sample(frac=1).reset_index(drop=True).reset_index(drop=False)
ax = sns.pairplot(formatted_areas)
```



Numeric variables boxplots

In [25]:
```
fig, axes = plt.subplots(1, 6, figsize=(15, 4), tight_layout=True)
ax = areas.drop([-1, top_dense])[numeric_cols].plot.box(subplots=(3,3), ax=axes)
plt.show()
```