Reto -> Entrega 1 Limpieza, análisis, visualización y kmeans

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In [99]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

In [100…
```
df = pd.read_csv('../data/Datos_de_calidad_del_agua_2020/Datos_de_calidad_del_agua_de_s
df.head()
```

Out[100…

	CLAVE	SITIO	ORGANISMO_DE_CUENCA	ESTADO	MUNICIPIO	ACUIFER
0	DLAGU6	POZO SAN GIL	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	ASIENTOS	VALLE I CHICALO
1	DLAGU6516	POZO R013 CAÑADA HONDA	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	AGUASCALIENTES	VALLE I CHICALO
2	DLAGU7	POZO COSIO	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	COSIO	VALLE I AGUASCALIENT
3	DLAGU9	POZO EL SALITRILLO	LERMA SANTIAGO PACIFICO	AGUASCALIENTES	RINCON DE ROMOS	VALLE I AGUASCALIENT
4	DLBAJ107	RANCHO EL TECOLOTE	PENINSULA DE BAJA CALIFORNIA	BAJA CALIFORNIA SUR	LA PAZ	TODOS SANTC

5 rows × 57 columns

Limpiando el dataset

In [101…

```
columnas_remover = ['CLAVE', 'SITIO', 'ORGANISMO_DE_CUENCA', 'ESTADO', 'MUNICIPIO', 'AC
'SUBTIPO', 'PERIODO', 'SDT_mg/L', 'CD_TOT_mg/L', 'HG_TOT_mg/L', 'PB_TOT_mg/L',
'COLI_FEC_NMP/100_mL', 'AS_TOT_mg/L', 'CR_TOT_mg/L', 'MN_TOT_mg/L', 'FE_TOT_mg/L'
]
df.drop(columnas_remover, axis=1, inplace=True)
# ALC_mg/L      CONDUCT_mS/cm   SDT_M_mg/L      DUR_mg/L        N_NO3_mg/L
```

In [102…

```
df.head()
```

Out[102…

	LONGITUD	LATITUD	ALC_mg/L	CALIDAD_ALC	CONDUCT_mS/cm	CALIDAD_CONDUC	SDT_M_mg/L
0	-102.02210	22.20887	229.990	Alta	940.0	Permisible para riego	603.6
1	-102.20075	21.99958	231.990	Alta	608.0	Buena para riego	445.4
2	-102.28801	22.36685	204.920	Alta	532.0	Buena para riego	342
3	-102.29449	22.18435	327.000	Alta	686.0	Buena para riego	478.6
4	-110.24480	23.45138	309.885	Alta	1841.0	Permisible para riego	1179

5 rows × 40 columns

In [103…

```
# REPLACE VALUES FOR THESE COLUMNS
df = df[df['SDT_M_mg/L'] != '<25']
df = df[df['DUR_mg/L'] != '<20']
df['N_NO3_mg/L'].replace('<0.02', 0, inplace=True)
df['FLUORUROS_mg/L'].replace('<0.2', 0, inplace=True)
df.dropna(inplace=True)

df = df.astype({'SDT_M_mg/L':'float32', 'N_NO3_mg/L':'float32', 'DUR_mg/L':'float32', '
```

In [104…

```
numerics = ['int64', 'int32', 'int64', 'float16', 'float32', 'float64']
df_numeric = df.select_dtypes(include=numerics)
df_numeric.head()
```

Out[104…

	LONGITUD	LATITUD	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L
2	-102.288010	22.366850	204.920	532.0	342.000000	1.8045	120.719002
4	-110.244800	23.451380	309.885	1841.0	1179.000000	0.2343	476.987213
5	-110.220670	23.464930	224.475	570.3	554.799988	0.2756	201.878403
7	-109.907306	22.890500	350.760	2253.3	1160.199951	0.5607	269.171204
9	-110.054722	23.824722	332.605	1703.0	1017.799988	0.5088	559.021423

In [105…

```
df_numeric.isna().sum()
```

Out[105…

```
LONGITUD          0
LATITUD           0
ALC_mg/L          0
CONDUCT_mS/cm     0
SDT_M_mg/L        0
FLUORUROS_mg/L    0
DUR_mg/L          0
N_NO3_mg/L        0
dtype: int64
```

In [106…

```
df_numeric.describe()
```

Out[106…

	LONGITUD	LATITUD	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_
count	604.000000	604.000000	604.000000	604.000000	604.000000	604.000000	604.0
mean	-101.737853	23.332116	255.888642	1483.175662	1221.766357	1.221470	457.7
std	6.831866	3.733554	122.799179	1533.756739	3615.350830	1.587721	434.0
min	-116.664250	15.064110	26.640000	188.000000	139.399994	0.000000	21.9
25%	-104.916900	20.472502	182.730000	608.750000	432.400002	0.311025	149.1
50%	-102.268905	23.006460	231.077500	1132.000000	778.000000	0.635900	342.7
75%	-99.008530	25.521922	315.002500	1790.750000	1288.000000	1.659050	613.0
max	-86.868880	32.677713	1650.000000	18577.000000	82170.000000	15.424300	3810.6

In [107…

```
target = ['SEMAFORO']
features = [v for v in df.columns.values.tolist() if v not in target]
target_df = df[target]
features_df = df[features]
```

In [108…

```
not_numeric_cols = [key for key in dict(features_df.dtypes) if dict(features_df.dtypes)
new_numeric_df = pd.get_dummies(features_df, prefix=not_numeric_cols)
```

In [109…

```
final_df = new_numeric_df.copy()
final_df['SEMAFORO'] = target_df
final_df.to_csv('../data/data_subterraneos_clean.csv', encoding='ISO-8859-1', index=Fal
```

In [110…

```
final_df.dtypes
```

Out[110…

```
LONGITUD            float64
LATITUD             float64
ALC_mg/L            float64
CONDUCT_mS/cm       float64
SDT_M_mg/L          float32
                     ...
CUMPLE_CON_MN_NO      uint8
CUMPLE_CON_MN_SI      uint8
```

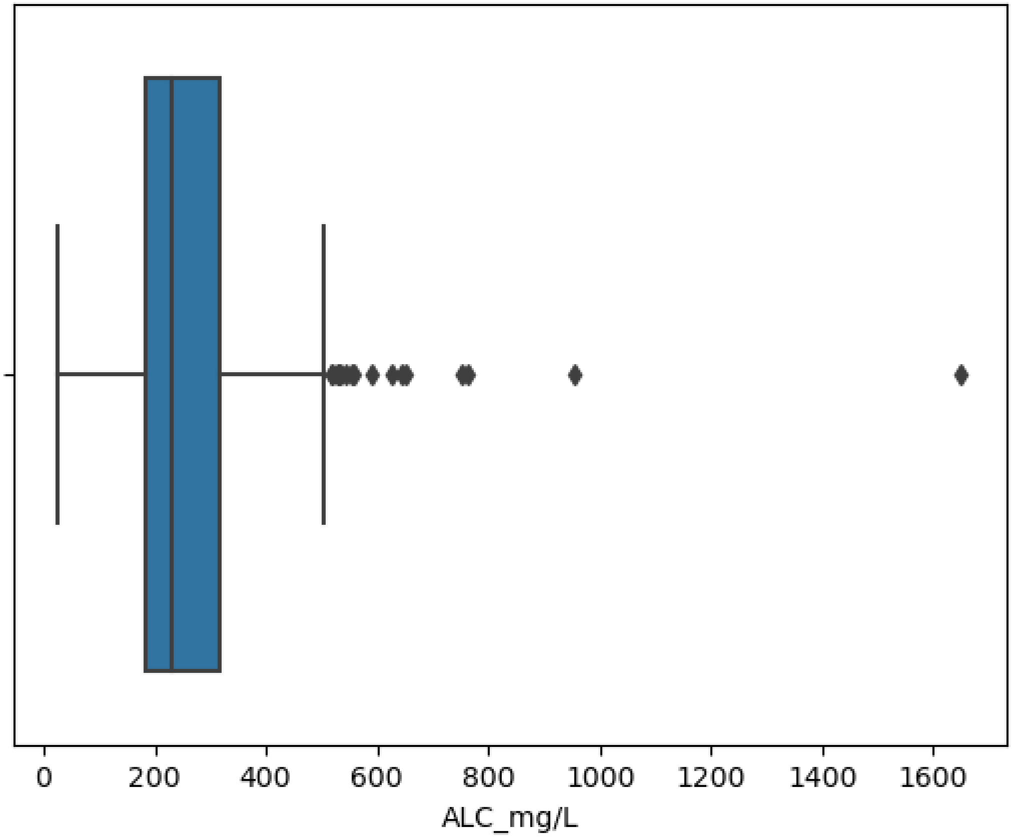
```
CUMPLE_CON_FE_NO      uint8
CUMPLE_CON_FE_SI      uint8
SEMAFORO             object
Length: 212, dtype: object
```

In [111…

```
sns.boxplot(x=final_df['ALC_mg/L'])
```

Out[111…

```
<AxesSubplot:xlabel='ALC_mg/L'>
```



In [112…

```
quantile_ALC_3 = final_df['ALC_mg/L'].quantile(0.75)
outliers = (final_df['ALC_mg/L'] > quantile_ALC_3).sum()
print(f'Number of outliers {outliers}')
```

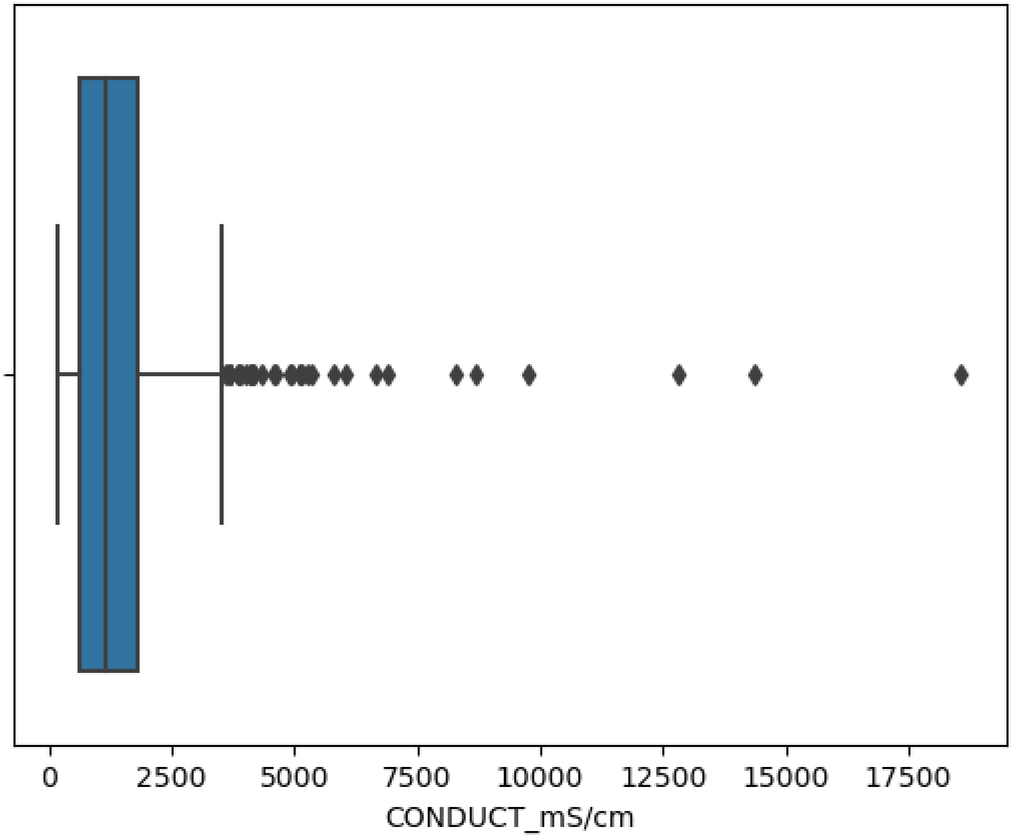
```
Number of outliers 151
```

In [113…

```
sns.boxplot(x=final_df['CONDUCT_mS/cm'])
```

Out[113…

```
<AxesSubplot:xlabel='CONDUCT_mS/cm'>
```



In [114…

```
quantile_CONDUCT_3 = final_df['CONDUCT_mS/cm'].quantile(0.75)
outliers = (final_df['CONDUCT_mS/cm'] > quantile_CONDUCT_3).sum()
print(f'Number of outliers {outliers}')
```

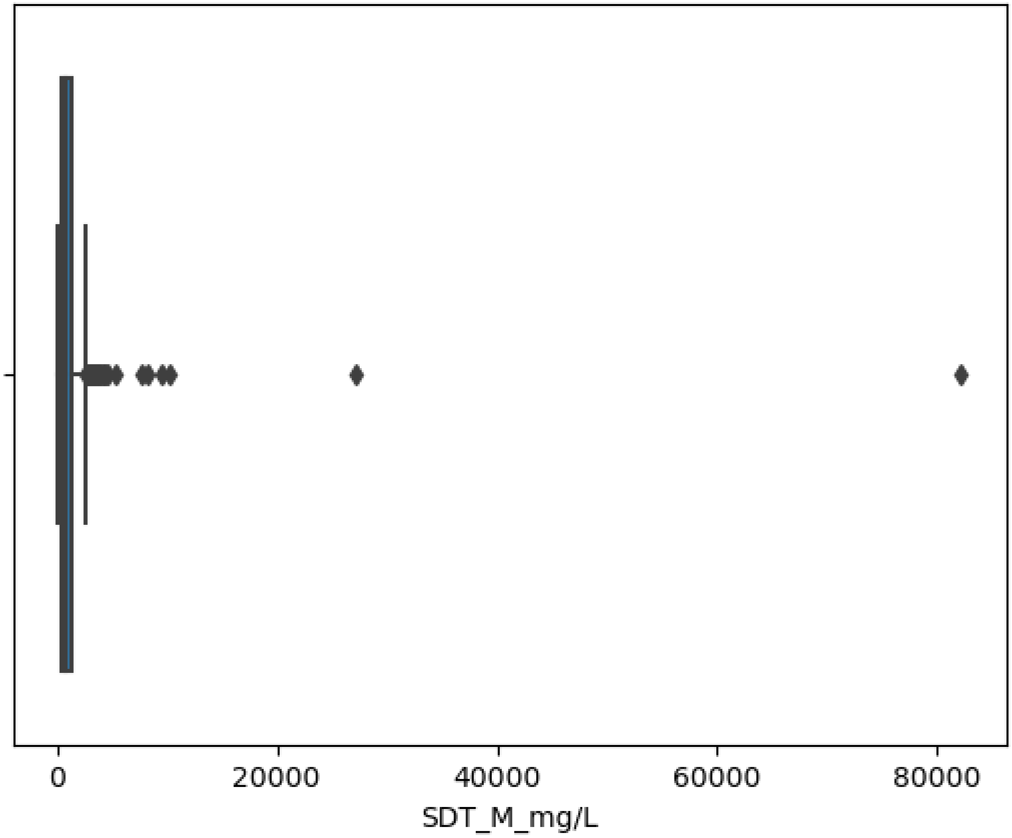
```
Number of outliers 151
```

In [115…

```
sns.boxplot(x=final_df['SDT_M_mg/L'])
```

Out[115…

```
<AxesSubplot:xlabel='SDT_M_mg/L'>
```

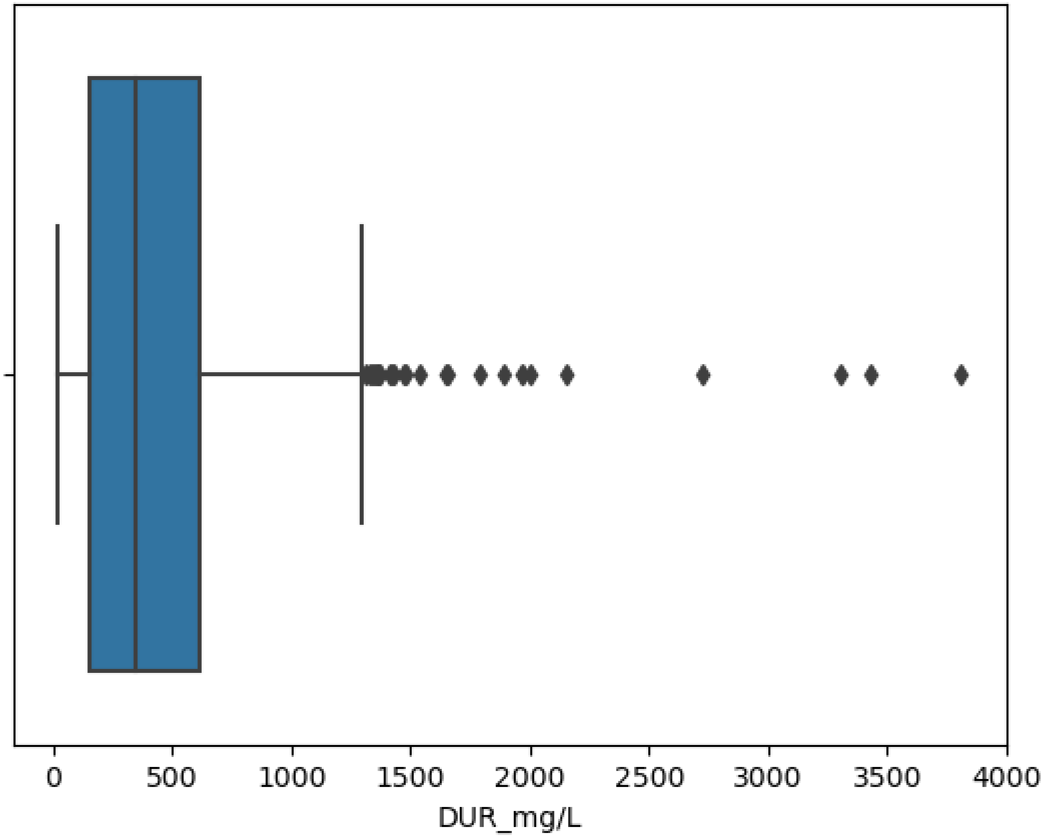


```
In [116…
quantile_SDT_M_mg_3 = final_df['SDT_M_mg/L'].quantile(0.75)
outliers = (final_df['SDT_M_mg/L'] > quantile_SDT_M_mg_3).sum()
print(f'Number of outliers {outliers}')
```

```
Number of outliers 150
```

```
In [117…
sns.boxplot(x=final_df['DUR_mg/L'])
```

```
Out[117…
<AxesSubplot:xlabel='DUR_mg/L'>
```



In [118…

```
quantile_DUR_mg_3 = final_df['DUR_mg/L'].quantile(0.75)
outliers = (final_df['DUR_mg/L'] > quantile_DUR_mg_3).sum()
print(f'Number of outliers {outliers}')
```

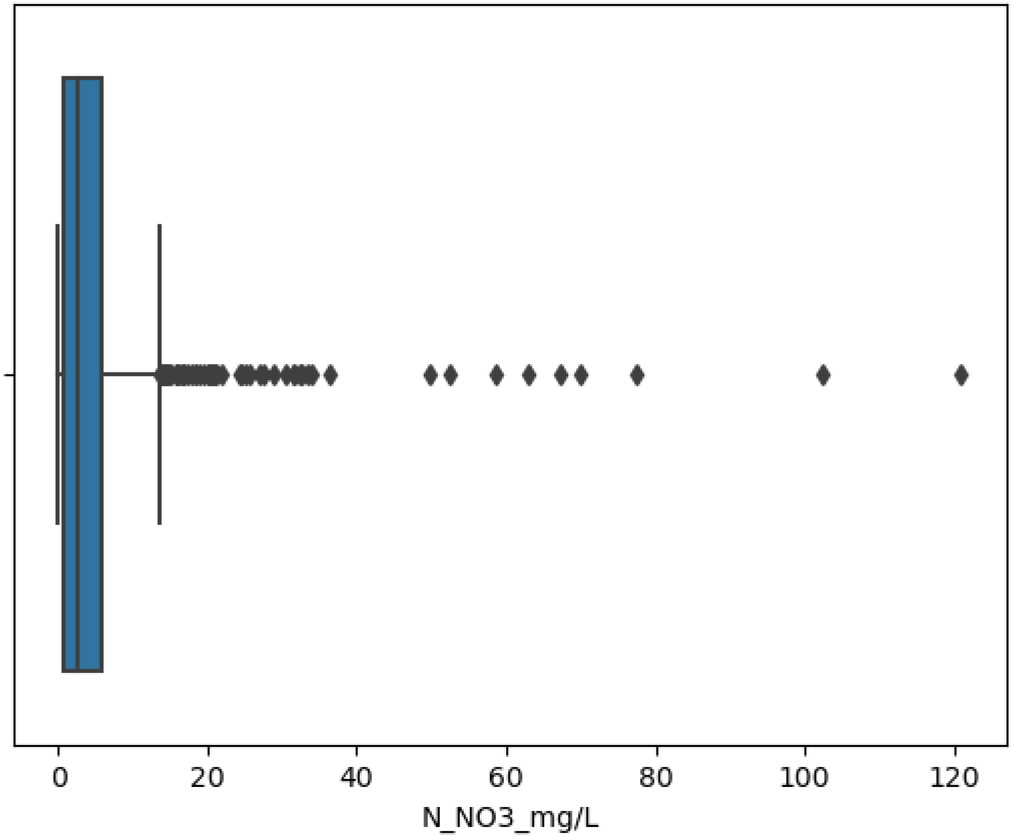
```
Number of outliers 151
```

In [119…

```
sns.boxplot(x=final_df['N_NO3_mg/L'])
```

Out[119…

```
<AxesSubplot:xlabel='N_NO3_mg/L'>
```



In [123…

```
quantile_N_NO3_mg_3 = final_df['N_NO3_mg/L'].quantile(0.75)
outliers = (final_df['N_NO3_mg/L'] > quantile_N_NO3_mg_3).sum()
print(f'Number of outliers {outliers}')
```

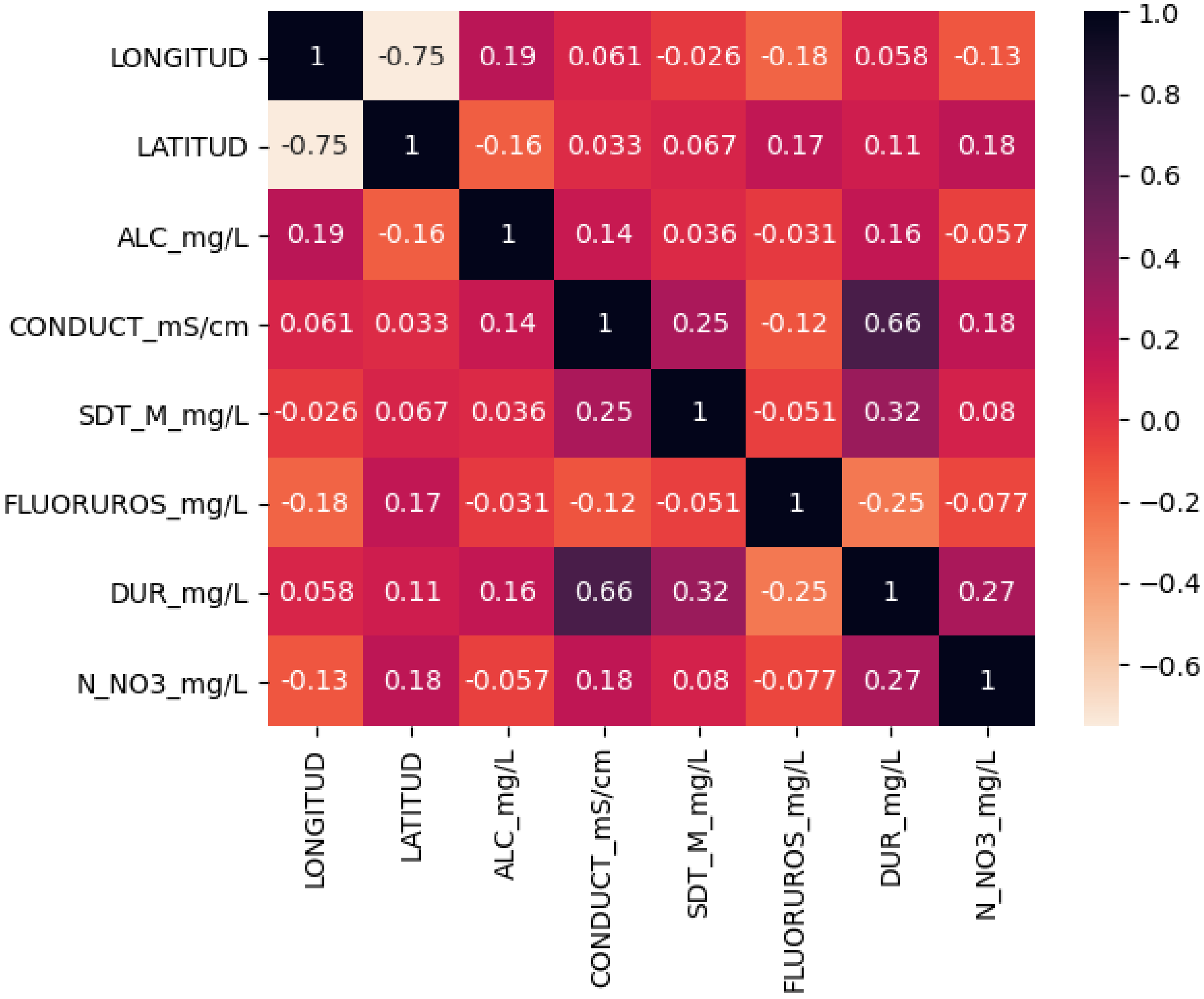
```
Number of outliers 151
```

In [122…

```
sns.heatmap(df_numeric.corr(), annot=True, cmap='rocket_r')
```

Out[122…

```
<AxesSubplot:>
```



Usando kmeans para determinar el numero de agrupamientos

In [127…

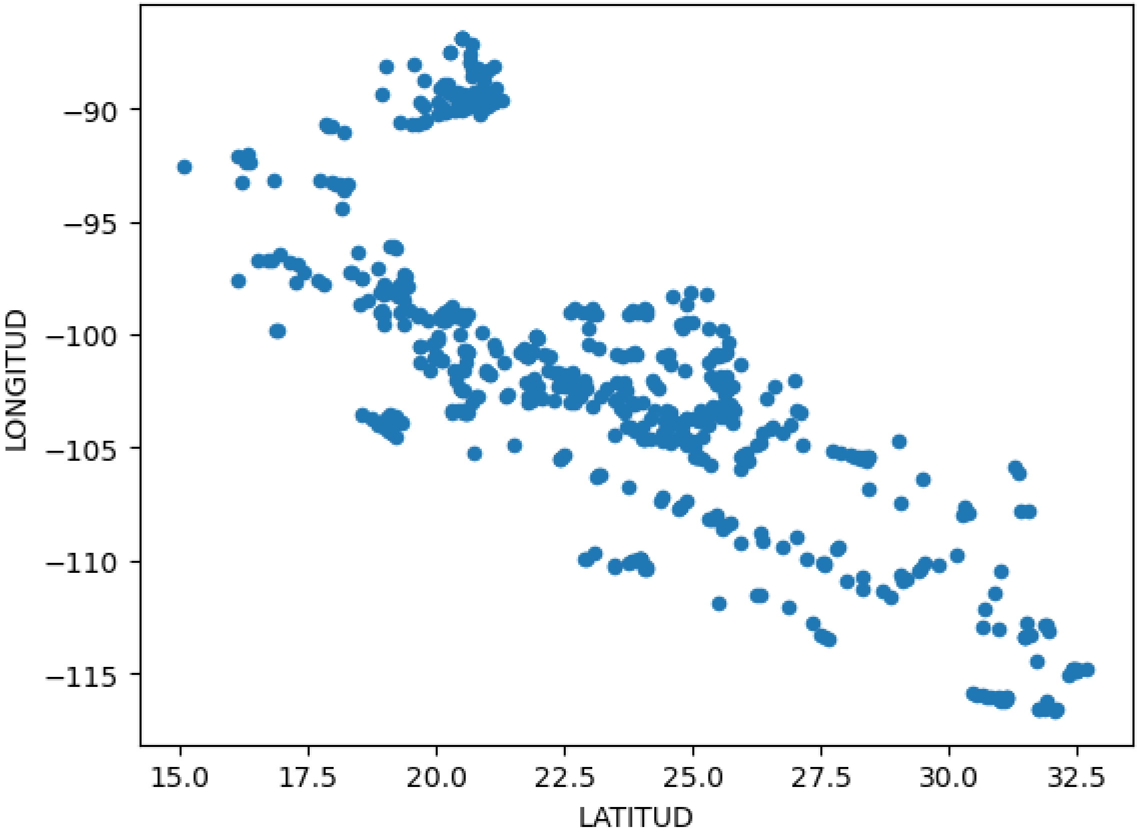
```
latlong=final_df[["LATITUD","LONGITUD"]]
```

In [128…

```
latlong.plot.scatter( "LATITUD","LONGITUD")
```

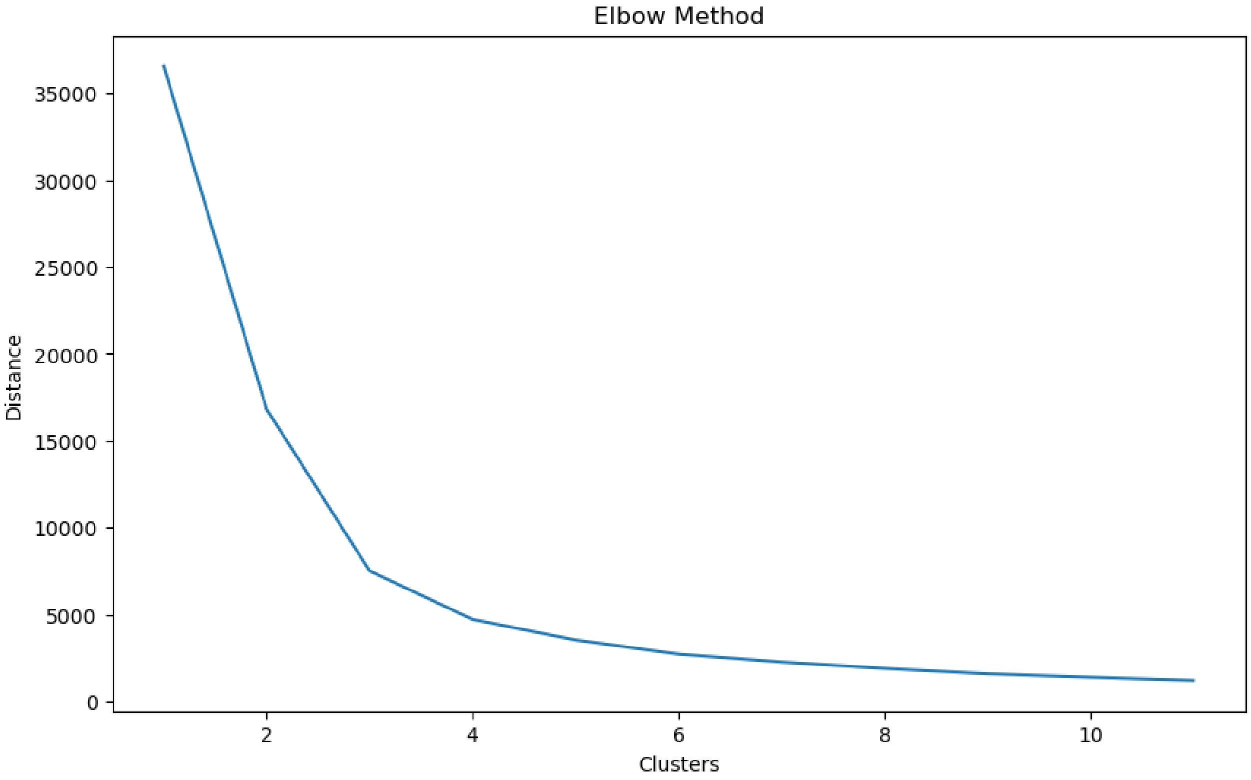
Out[128…

```
<AxesSubplot:xlabel='LATITUD', ylabel='LONGITUD'>
```



In [133…

```
from sklearn.cluster import KMeans
import geopandas as gpd
from shapely.geometry import Point
K = range(1,12)
distance=[]

for k in K:
    kmeans = KMeans(n_clusters=k, random_state=1, n_init=20).fit(latlong)
    distance.append(kmeans.inertia_)

plt.figure(figsize=(10, 6))
plt.plot(K, distance)
plt.title('Elbow Method')
plt.xlabel('Clusters')
plt.ylabel('Distance')
plt.show()

# NÚMERO OPTIMO ES 3 CLUSTERS
```



In [130…

```
kmeans = KMeans(n_clusters=3, random_state=1)
kmean_p = kmeans.fit_predict(latlong) # Nos dice a que cluster pertenece cada ubicacion
countTotal = np.bincount(kmean_p)
print(countTotal)
print(kmeans.cluster_centers_) # Latitud y longitud de los lugares optimos
```

```
[108 127 369]
[[  19.72207237  -90.44847336]
 [  28.33881983 -110.8363076 ]
 [  22.66553988 -101.91061549]]
```

In [42]:

```
map_colors = {0: 'red', 1: 'cyan', 2: 'green'}
kmeans_pred_colors = [map_colors[v] for v in kmean_p]
```

In [131…

```
# Obtener las ciudades de cada almacen
from geopy.geocoders import Nominatim
centers = kmeans.cluster_centers_
geolocator = Nominatim(user_agent="kmeans_app")
locations = []
for i in range(len(centers)):
  location = geolocator.reverse(str(centers[i][0]) + "," + str(centers[i][1]))
  locations.append(location.address)
  print(f'Location {i+1}: {location.address}')
```

```
Location 1: Mucuychakán, Municipio de Campeche, Campeche, México
Location 2: Las Cuatas, Guaymas, Sonora, México
Location 3: Viborillas, Salinas, San Luis Potosí, México
```

In [134…

```
sitios = pd.DataFrame()
sitios['LocationName'] = locations
sitios[['Latitude', 'Longitude']] = centers
```

```
sitios["Coordinates"] = list(zip(sitios.Longitude, sitios.Latitude))
sitios["Coordinates"] = sitios["Coordinates"].apply(Point)
```

In [135…

```
final_df["Coordinates"] = list(zip(final_df.LONGITUD, final_df.LATITUD))
final_df["Coordinates"] = final_df["Coordinates"].apply(Point)
final_df.head()
```

Out[135…

	LONGITUD	LATITUD	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L
2	-102.288010	22.366850	204.920	532.0	342.000000	1.8045	120.719002
4	-110.244800	23.451380	309.885	1841.0	1179.000000	0.2343	476.987213
5	-110.220670	23.464930	224.475	570.3	554.799988	0.2756	201.878403
7	-109.907306	22.890500	350.760	2253.3	1160.199951	0.5607	269.171204
9	-110.054722	23.824722	332.605	1703.0	1017.799988	0.5088	559.021423

5 rows × 213 columns

In [137…

```
gdf = gpd.GeoDataFrame(final_df, geometry="Coordinates")
gdf.head()
```

Out[137…

	LONGITUD	LATITUD	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L
2	-102.288010	22.366850	204.920	532.0	342.000000	1.8045	120.719002
4	-110.244800	23.451380	309.885	1841.0	1179.000000	0.2343	476.987213
5	-110.220670	23.464930	224.475	570.3	554.799988	0.2756	201.878403
7	-109.907306	22.890500	350.760	2253.3	1160.199951	0.5607	269.171204
9	-110.054722	23.824722	332.605	1703.0	1017.799988	0.5088	559.021423

5 rows × 213 columns

In [138…

```
#mapa

world = gpd.read_file(gpd.datasets.get_path("naturalearth_lowres"))
world = world.set_index("iso_a3")

world.head()
```

Out[138…

iso_a3	pop_est	continent	name	gdp_md_est	geometry
FJI	889953.0	Oceania	Fiji	5496	MULTIPOLYGON (((180.00000 -16.06713, 180.00000...
TZA	58005463.0	Africa	Tanzania	63177	POLYGON ((33.90371 -0.95000, 34.07262 -1.05982...
ESH	603253.0	Africa	W. Sahara	907	POLYGON ((-8.66559 27.65643, -8.66512 27.58948...
CAN	37589262.0	North America	Canada	1736425	MULTIPOLYGON (((-122.84000 49.00000, -122.9742...
USA	328239523.0	North America	United States of America	21433226	MULTIPOLYGON (((-122.84000 49.00000, -120.0000...

In [139…

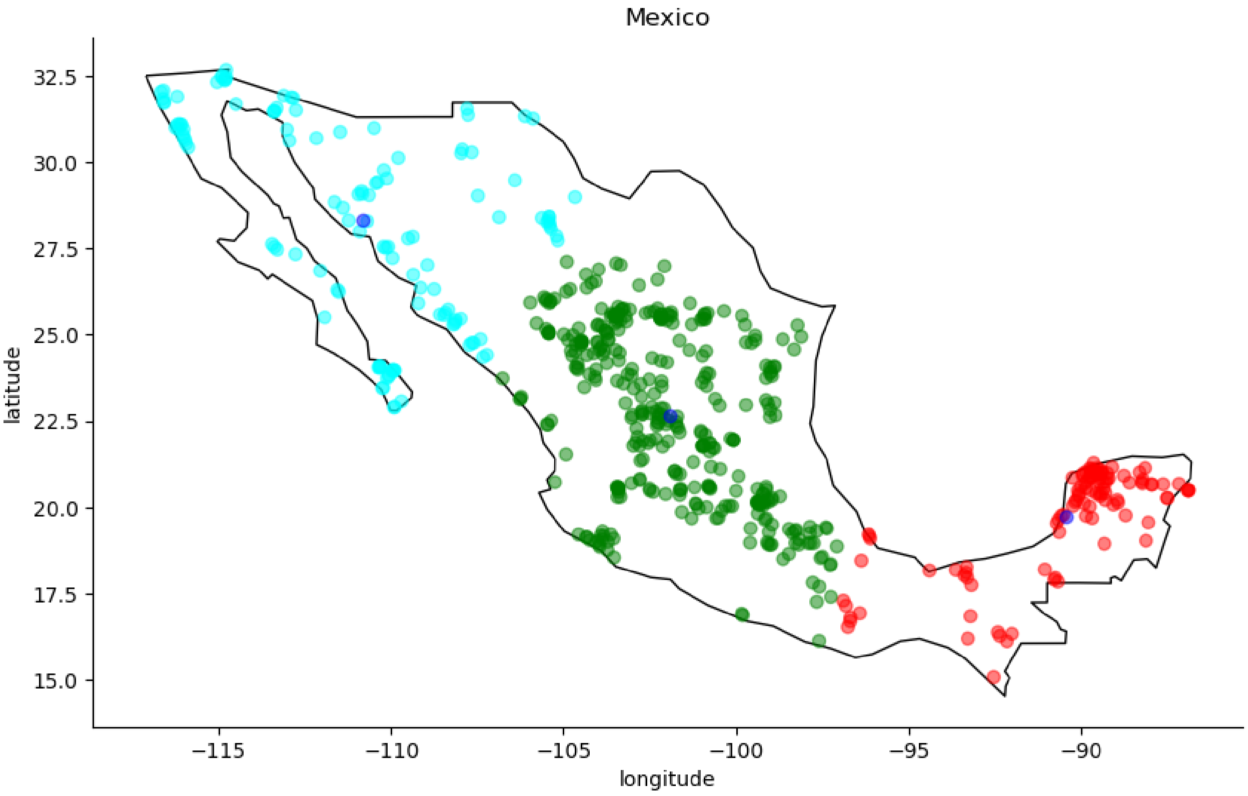
```
sitios_gpd = gpd.GeoDataFrame(sitios, geometry="Coordinates")
sitios_gpd.head()
```

Out[139…

	LocationName	Latitude	Longitude	Coordinates
0	Mucuychakán, Municipio de Campeche, Campeche, ...	19.722072	-90.448473	POINT (-90.44847 19.72207)
1	Las Cuatas, Guaymas, Sonora, México	28.338820	-110.836308	POINT (-110.83631 28.33882)
2	Viborillas, Salinas, San Luis Potosí, México	22.665540	-101.910615	POINT (-101.91062 22.66554)

In [43]:

```
# Step 3: Plot the cities onto the map
# We mostly use the code from before --- we still want the country borders plotted ---
# add a command to plot the cities
fig, gax = plt.subplots(figsize=(10,10))

# By only plotting rows in which the continent is 'South America' we only plot, well,
# South America.
world.query("name == 'Mexico'").plot(ax = gax, edgecolor='black', color='white')

# This plot the cities. It's the same syntax, but we are plotting from a different GeoD
# I want the cities as pale red dots.
gdf.plot(ax=gax, color=kmeans_pred_colors, alpha = 0.5)
sitios_gpd.plot(ax=gax, color='blue', alpha = 0.5)

gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('Mexico')

gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```


Mexico
32.5
30.0
27.5
25.0
22.5
20.0
17.5
15.0
latitude
−115
−110
−105
−100
−95
−90
longitude