###Maestría en Inteligencia Artificial Aplicada

###**Curso: Ciencia y Analítica de Datos**

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###**Objetivo:**

###Implementar conocimientos adquiridos a lo largo de curso en el desarrollo de un proyecto con datos reales.

```
#Carga de Librerias
import numpy as np
import matplotlib as plt
import pandas as pd
import seaborn as sns
%matplotlib inline
import matplotlib

from sklearn import metrics
from sklearn.metrics import r2_score

! pip install qeds fiona geopandas xgboost gensim folium pyLDAvis descartes
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting qeds
  Downloading qeds-0.7.0.tar.gz (24 kB)
Collecting fiona
  Downloading Fiona-1.8.22-cp37-cp37m-manylinux2014_x86_64.whl (16.7 MB)
ent already satisfied: xgboost in /usr/local/lib/python3.7/dist-packages (0.90)
Requirement already satisfied: gensim in /usr/local/lib/python3.7/dist-packages (3.6.0)
Requirement already satisfied: folium in
```

```
/usr/local/lib/python3.7/dist-packages (0.12.1.post1)
Collecting pyLDAvis
  Downloading pyLDAvis-3.3.1.tar.gz (1.7 MB)
ents to build wheel ... etadata ... ent already satisfied: descartes
in /usr/local/lib/python3.7/dist-packages (1.1.0)
Requirement already satisfied: pandas in
/usr/local/lib/python3.7/dist-packages (from qeds) (1.3.5)
Requirement already satisfied: requests in
/usr/local/lib/python3.7/dist-packages (from qeds) (2.23.0)
Collecting quandl
  Downloading Quandl-3.7.0-py2.py3-none-any.whl (26 kB)
Requirement already satisfied: scipy in /usr/local/lib/python3.7/dist-
packages (from qeds) (1.7.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.7/dist-
packages (from qeds) (1.21.6)
Collecting quantecon
  Downloading quantecon-0.5.3-py3-none-any.whl (179 kB)
ent already satisfied: matplotlib in /usr/local/lib/python3.7/dist-
packages (from qeds) (3.2.2)
Requirement already satisfied: pyarrow in
/usr/local/lib/python3.7/dist-packages (from qeds) (6.0.1)
Requirement already satisfied: openpyxl in
/usr/local/lib/python3.7/dist-packages (from qeds) (3.0.10)
Requirement already satisfied: plotly in
/usr/local/lib/python3.7/dist-packages (from qeds) (5.5.0)
Requirement already satisfied: pandas_datareader in
/usr/local/lib/python3.7/dist-packages (from qeds) (0.9.0)
Requirement already satisfied: scikit-learn in
/usr/local/lib/python3.7/dist-packages (from qeds) (1.0.2)
Requirement already satisfied: seaborn in
/usr/local/lib/python3.7/dist-packages (from qeds) (0.11.2)
Requirement already satisfied: statsmodels in
/usr/local/lib/python3.7/dist-packages (from qeds) (0.12.2)
Requirement already satisfied: attrs>=17 in
/usr/local/lib/python3.7/dist-packages (from fiona) (22.1.0)
Requirement already satisfied: six>=1.7 in
/usr/local/lib/python3.7/dist-packages (from fiona) (1.15.0)
Requirement already satisfied: certifi in
/usr/local/lib/python3.7/dist-packages (from fiona) (2022.9.24)
Collecting munch
  Downloading munch-2.5.0-py2.py3-none-any.whl (10 kB)
Requirement already satisfied: click>=4.0 in
/usr/local/lib/python3.7/dist-packages (from fiona) (7.1.2)
Collecting cligj>=0.5
  Downloading cligj-0.7.2-py3-none-any.whl (7.1 kB)
Requirement already satisfied: setuptools in
/usr/local/lib/python3.7/dist-packages (from fiona) (57.4.0)
Collecting click-plugins>=1.0
  Downloading click_plugins-1.1.1-py2.py3-none-any.whl (7.5 kB)
Collecting pyproj>=2.2.0
```

```
  Downloading pyproj-3.2.1-cp37-cp37m-manylinux2010_x86_64.whl (6.3
MB)
ent already satisfied: shapely>=1.6 in /usr/local/lib/python3.7/dist-
packages (from geopandas) (1.8.5.post1)
Requirement already satisfied: python-dateutil>=2.7.3 in
/usr/local/lib/python3.7/dist-packages (from pandas->qeds) (2.8.2)
Requirement already satisfied: pytz>=2017.3 in
/usr/local/lib/python3.7/dist-packages (from pandas->qeds) (2022.6)
Requirement already satisfied: smart-open>=1.2.1 in
/usr/local/lib/python3.7/dist-packages (from gensim) (5.2.1)
Requirement already satisfied: jinja2>=2.9 in
/usr/local/lib/python3.7/dist-packages (from folium) (2.11.3)
Requirement already satisfied: branca>=0.3.0 in
/usr/local/lib/python3.7/dist-packages (from folium) (0.6.0)
Requirement already satisfied: MarkupSafe>=0.23 in
/usr/local/lib/python3.7/dist-packages (from jinja2>=2.9->folium)
(2.0.1)
Requirement already satisfied: joblib in
/usr/local/lib/python3.7/dist-packages (from pyLDAvis) (1.2.0)
Collecting funcy
  Downloading funcy-1.17-py2.py3-none-any.whl (33 kB)
Collecting sklearn
  Downloading sklearn-0.0.post1.tar.gz (3.6 kB)
Requirement already satisfied: numexpr in
/usr/local/lib/python3.7/dist-packages (from pyLDAvis) (2.8.4)
Requirement already satisfied: future in
/usr/local/lib/python3.7/dist-packages (from pyLDAvis) (0.16.0)
Requirement already satisfied: cycler>=0.10 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->qeds)
(0.11.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!
=2.1.6,>=2.0.1 in /usr/local/lib/python3.7/dist-packages (from
matplotlib->qeds) (3.0.9)
Requirement already satisfied: kiwisolver>=1.0.1 in
/usr/local/lib/python3.7/dist-packages (from matplotlib->qeds) (1.4.4)
Requirement already satisfied: typing-extensions in
/usr/local/lib/python3.7/dist-packages (from kiwisolver>=1.0.1-
>matplotlib->qeds) (4.1.1)
Requirement already satisfied: et-xmlfile in
/usr/local/lib/python3.7/dist-packages (from openpyxl->qeds) (1.1.0)
Requirement already satisfied: lxml in /usr/local/lib/python3.7/dist-
packages (from pandas_datareader->qeds) (4.9.1)
Requirement already satisfied: idna<3,>=2.5 in
/usr/local/lib/python3.7/dist-packages (from requests->qeds) (2.10)
Requirement already satisfied: chardet<4,>=3.0.2 in
/usr/local/lib/python3.7/dist-packages (from requests->qeds) (3.0.4)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1
in /usr/local/lib/python3.7/dist-packages (from requests->qeds)
(1.24.3)
Requirement already satisfied: tenacity>=6.2.0 in
```

```
/usr/local/lib/python3.7/dist-packages (from plotly->qeds) (8.1.0)
Collecting inflection>=0.3.1
  Downloading inflection-0.5.1-py2.py3-none-any.whl (9.5 kB)
Requirement already satisfied: more-itertools in
/usr/local/lib/python3.7/dist-packages (from quandl->qeds) (9.0.0)
Requirement already satisfied: sympy in /usr/local/lib/python3.7/dist-
packages (from quantecon->qeds) (1.7.1)
Requirement already satisfied: numba in /usr/local/lib/python3.7/dist-
packages (from quantecon->qeds) (0.56.4)
Requirement already satisfied: llvmlite<0.40,>=0.39.0dev0 in
/usr/local/lib/python3.7/dist-packages (from numba->quantecon->qeds)
(0.39.1)
Requirement already satisfied: importlib-metadata in
/usr/local/lib/python3.7/dist-packages (from numba->quantecon->qeds)
(4.13.0)
Requirement already satisfied: zipp>=0.5 in
/usr/local/lib/python3.7/dist-packages (from importlib-metadata-
>numba->quantecon->qeds) (3.10.0)
Requirement already satisfied: threadpoolctl>=2.0.0 in
/usr/local/lib/python3.7/dist-packages (from scikit-learn->qeds)
(3.1.0)
Requirement already satisfied: patsy>=0.5 in
/usr/local/lib/python3.7/dist-packages (from statsmodels->qeds)
(0.5.3)
Requirement already satisfied: mpmath>=0.19 in
/usr/local/lib/python3.7/dist-packages (from sympy->quantecon->qeds)
(1.2.1)
Building wheels for collected packages: qeds, pyLDAvis, sklearn
  Building wheel for qeds (setup.py) ... e=qeds-0.7.0-py3-none-any.whl
size=27812
sha256=d3955ddd5ae4ab3e20e026278957bb1b6edd628e642193784752c455dc60f17
a
  Stored in directory:
/root/.cache/pip/wheels/fc/8c/52/0cc036b9730b75850b9845770780f8d05ed08
ff38a67cbaa29
  Building wheel for pyLDAvis (PEP 517) ... e=pyLDAvis-3.3.1-py2.py3-
none-any.whl size=136898
sha256=1f88ec95f52aeef4ac55fb1839a44336ba8ac63f1894dc90800e6d859790914
8
  Stored in directory:
/root/.cache/pip/wheels/c9/21/f6/17bcf2667e8a68532ba2fbf6d5c72fdf4c7f7
d9abfa4852d2f
  Building wheel for sklearn (setup.py) ... e=sklearn-0.0.post1-py3-
none-any.whl size=2344
sha256=6a1d7c65e48add8feab83561ae6ca6dcde2ad3563a7b0425b94af592e890fd6
b
  Stored in directory:
/root/.cache/pip/wheels/42/56/cc/4a8bf86613aafd5b7f1b310477667c1fca5c5
1c3ae4124a003
Successfully built qeds pyLDAvis sklearn
```

```
Installing collected packages: munch, inflection, cligj, click-plugins, sklearn, quantecon, quandl, pyproj, funcy, fiona, qeds, pyLDAvis, geopandas
Successfully installed click-plugins-1.1.1 cligj-0.7.2 fiona-1.8.22 funcy-1.17 geopandas-0.10.2 inflection-0.5.1 munch-2.5.0 pyLDAvis-3.3.1 pyproj-3.2.1 qeds-0.7.0 quandl-3.7.0 quantecon-0.5.3 sklearn-0.0.post1
```

#Parte 1

```
#Lectura de la Base de Datos de Aguas Subterraneas
df =
pd.read_csv('/content/sample_data/AguasSubterraneas_2020.csv',encoding
='cp1252')
df.sample(10)
```

```
           CLAVE                                              SITIO  \
273    DLEST6147                          SITIO No. 11 NORIA IMSS
289    DLGUA1036                                   RODEO DE AYALA
882    OCNOR6506                                            URES.
878    OCNOR6264                                          LA MORA
821    OCNOR4036                             EL REAL DEL CATORCE
192     DLDUR654                                   POZO PRESIDIOS
557    DLZAC2613  POZO 524 AGUA POTABLE RANCHO NUEVO (SUSTITUTO ...
870  OCNOR4224M1                                    POZO QUITOVAC
209     DLDUR691                              POZO 3 PEÑON BLANCO
498    DLSAN5384                           EL HUIZACHE CNA-11-248

            ORGANISMO_DE_CUENCA           ESTADO  \
273      LERMA SANTIAGO PACIFICO           MEXICO
289      LERMA SANTIAGO PACIFICO       GUANAJUATO
882                    NOROESTE           SONORA
878                    NOROESTE           SONORA
821                    NOROESTE           SONORA
192  CUENCAS CENTRALES DEL NORTE          DURANGO
557  CUENCAS CENTRALES DEL NORTE        ZACATECAS
870                    NOROESTE           SONORA
209  CUENCAS CENTRALES DEL NORTE          DURANGO
498  CUENCAS CENTRALES DEL NORTE  SAN LUIS POTOSI

                       MUNICIPIO                ACUIFERO SUBTIPO  \
273                 ZINACANTEPEC         VALLE DE TOLUCA   NORIA
289                      PENJAMO         PENJAMO-ABASOLO    POZO
882                         URES              RIO SONORA    POZO
878                    BANAMICHI              RIO SONORA    POZO
821                   HERMOSILLO     COSTA DE HERMOSILLO    POZO
192                  TEPEHUANES     TEPEHUANES-SANTIAGO    POZO
557                    ZACATECAS           BENITO JUAREZ    POZO
870  GENERAL PLUTARCO ELIAS CALLES  SONOYTA-PUERTO PEÑASCO    POZO
209                 PEÑON BLANCO            PEÑON BLANCO    POZO
498    SOLEDAD DE GRACIANO SANCHEZ         SAN LUIS POTOSI    POZO
```

```
       LONGITUD    LATITUD  PERIODO  ...  CUMPLE_CON_DUR CUMPLE_CON_CF  \
273  -99.733256  19.290975     2020  ...              SI            SI

289 -101.625050  20.485330     2020  ...              SI            SI

882 -110.382940  29.424050     2020  ...              SI            SI

878 -110.204800  29.977650     2020  ...              SI            SI

821 -111.055560  28.961570     2020  ...              SI            SI

192 -105.628800  25.282450     2020  ...              SI            SI

557 -102.736960  22.754910     2020  ...              SI            SI

870 -112.750556  31.515833     2020  ...              SI            SI

209 -104.027790  24.790060     2020  ...              SI            SI

498 -100.853056  22.236667     2020  ...              SI            SI


     CUMPLE_CON_NO3 CUMPLE_CON_AS  CUMPLE_CON_CD CUMPLE_CON_CR
CUMPLE_CON_HG  \
273              SI            SI             SI            SI
SI
289              SI            NO             SI            SI
SI
882              SI            SI             SI            SI
SI
878              SI            SI             SI            SI
SI
821              SI            SI             SI            SI
SI
192              SI            NO             SI            SI
SI
557              SI            NO             SI            SI
SI
870              SI            NO             SI            SI
SI
209              SI            NO             SI            SI
SI
498              SI            SI             SI            SI
SI

    CUMPLE_CON_PB CUMPLE_CON_MN CUMPLE_CON_FE
273            SI            SI            SI
```

```
289           SI           SI           SI
882           SI           SI           SI
878           SI           SI           SI
821           SI           SI           SI
192           SI           SI           SI
557           SI           SI           SI
870           SI           SI           SI
209           SI           SI           SI
498           SI           SI           SI

[10 rows x 57 columns]
```

```
#¿Que tipo de dato son las variables del conjunto de Datos?
df.dtypes
```

```
CLAVE                       object
SITIO                       object
ORGANISMO_DE_CUENCA         object
ESTADO                      object
MUNICIPIO                   object
ACUIFERO                    object
SUBTIPO                     object
LONGITUD                   float64
LATITUD                    float64
PERIODO                      int64
ALC_mg/L                   float64
CALIDAD_ALC                 object
CONDUCT_mS/cm              float64
CALIDAD_CONDUC              object
SDT_mg/L                   float64
SDT_M_mg/L                  object
CALIDAD_SDT_ra              object
CALIDAD_SDT_salin           object
FLUORUROS_mg/L              object
CALIDAD_FLUO                object
DUR_mg/L                    object
CALIDAD_DUR                 object
COLI_FEC_NMP/100_mL         object
CALIDAD_COLI_FEC            object
N_NO3_mg/L                  object
CALIDAD_N_NO3               object
AS_TOT_mg/L                 object
CALIDAD_AS                  object
CD_TOT_mg/L                 object
CALIDAD_CD                  object
CR_TOT_mg/L                 object
CALIDAD_CR                  object
HG_TOT_mg/L                 object
CALIDAD_HG                  object
PB_TOT_mg/L                 object
```

```
CALIDAD_PB                 object
MN_TOT_mg/L                object
CALIDAD_MN                 object
FE_TOT_mg/L                object
CALIDAD_FE                 object
SEMAFORO                   object
CONTAMINANTES              object
CUMPLE_CON_ALC             object
CUMPLE_CON_COND            object
CUMPLE_CON_SDT_ra          object
CUMPLE_CON_SDT_salin       object
CUMPLE_CON_FLUO            object
CUMPLE_CON_DUR             object
CUMPLE_CON_CF              object
CUMPLE_CON_NO3             object
CUMPLE_CON_AS              object
CUMPLE_CON_CD              object
CUMPLE_CON_CR              object
CUMPLE_CON_HG              object
CUMPLE_CON_PB              object
CUMPLE_CON_MN              object
CUMPLE_CON_FE              object
dtype: object
```

```
#¿Cuantas variables de cada tipo de dato tenemos en nuestro Dataset?
df.dtypes.value_counts()
```

```
object     51
float64     5
int64       1
dtype: int64
```

```
#Revisemos cual es la dimención de nuetro Dataset.
df.shape
```

```
(1068, 57)
```

###Este archivo contiene la calidad del agua de **1,068 sitios subterráneos** en México; calificando su calidad con base en cada uno de los Indicadores y sus respectivas escalas.

###Se incluyen las coordenadas geográficas y datos generales de ubicación de cada sitio.

```
#Confirmemos si en nuestros Dataset tenemos valore nulos/faltantes
df.isnull().any()
```

```
CLAVE                     False
SITIO                     False
ORGANISMO_DE_CUENCA       False
ESTADO                    False
MUNICIPIO                 False
ACUIFERO                  False
SUBTIPO                   False
```

```
LONGITUD                  False
LATITUD                   False
PERIODO                   False
ALC_mg/L                   True
CALIDAD_ALC                True
CONDUCT_mS/cm              True
CALIDAD_CONDUC             True
SDT_mg/L                   True
SDT_M_mg/L                 True
CALIDAD_SDT_ra             True
CALIDAD_SDT_salin          True
FLUORUROS_mg/L            False
CALIDAD_FLUO              False
DUR_mg/L                   True
CALIDAD_DUR                True
COLI_FEC_NMP/100_mL       False
CALIDAD_COLI_FEC          False
N_NO3_mg/L                 True
CALIDAD_N_NO3              True
AS_TOT_mg/L               False
CALIDAD_AS                False
CD_TOT_mg/L               False
CALIDAD_CD                False
CR_TOT_mg/L               False
CALIDAD_CR                False
HG_TOT_mg/L               False
CALIDAD_HG                False
PB_TOT_mg/L               False
CALIDAD_PB                False
MN_TOT_mg/L               False
CALIDAD_MN                False
FE_TOT_mg/L               False
CALIDAD_FE                False
SEMAFORO                  False
CONTAMINANTES              True
CUMPLE_CON_ALC            False
CUMPLE_CON_COND           False
CUMPLE_CON_SDT_ra         False
CUMPLE_CON_SDT_salin      False
CUMPLE_CON_FLUO           False
CUMPLE_CON_DUR            False
CUMPLE_CON_CF             False
CUMPLE_CON_NO3            False
CUMPLE_CON_AS             False
CUMPLE_CON_CD             False
CUMPLE_CON_CR             False
CUMPLE_CON_HG             False
CUMPLE_CON_PB             False
CUMPLE_CON_MN             False
```

```
CUMPLE_CON_FE            False
dtype: bool
```

```python
#Veamos cuantos valores nulos tenemos por variable
df.isnull().sum()
```

```
CLAVE                      0
SITIO                      0
ORGANISMO_DE_CUENCA        0
ESTADO                     0
MUNICIPIO                  0
ACUIFERO                   0
SUBTIPO                    0
LONGITUD                   0
LATITUD                    0
PERIODO                    0
ALC_mg/L                   4
CALIDAD_ALC                4
CONDUCT_mS/cm              6
CALIDAD_CONDUC             6
SDT_mg/L                1068
SDT_M_mg/L                 2
CALIDAD_SDT_ra             2
CALIDAD_SDT_salin          2
FLUORUROS_mg/L             0
CALIDAD_FLUO               0
DUR_mg/L                   1
CALIDAD_DUR                1
COLI_FEC_NMP/100_mL        0
CALIDAD_COLI_FEC           0
N_NO3_mg/L                 1
CALIDAD_N_NO3              1
AS_TOT_mg/L                0
CALIDAD_AS                 0
CD_TOT_mg/L                0
CALIDAD_CD                 0
CR_TOT_mg/L                0
CALIDAD_CR                 0
HG_TOT_mg/L                0
CALIDAD_HG                 0
PB_TOT_mg/L                0
CALIDAD_PB                 0
MN_TOT_mg/L                0
CALIDAD_MN                 0
FE_TOT_mg/L                0
CALIDAD_FE                 0
SEMAFORO                   0
CONTAMINANTES            434
CUMPLE_CON_ALC             0
CUMPLE_CON_COND            0
CUMPLE_CON_SDT_ra          0
```

```
CUMPLE_CON_SDT_salin       0
CUMPLE_CON_FLUO            0
CUMPLE_CON_DUR             0
CUMPLE_CON_CF              0
CUMPLE_CON_NO3             0
CUMPLE_CON_AS              0
CUMPLE_CON_CD              0
CUMPLE_CON_CR              0
CUMPLE_CON_HG              0
CUMPLE_CON_PB              0
CUMPLE_CON_MN              0
CUMPLE_CON_FE              0
dtype: int64
```

```python
#En total tendriamos 1532 datos nulos.
df.isnull().sum().sum()
```

```
1532
```

```python
#Mostramos las columnas para posteriormente revisar los diferentes
tipos de valores que se presentan en algunas de ellas.
df.columns
```

```
Index(['CLAVE', 'SITIO', 'ORGANISMO_DE_CUENCA', 'ESTADO', 'MUNICIPIO',
       'ACUIFERO', 'SUBTIPO', 'LONGITUD', 'LATITUD', 'PERIODO',
'ALC_mg/L',
       'CALIDAD_ALC', 'CONDUCT_mS/cm', 'CALIDAD_CONDUC', 'SDT_mg/L',
       'SDT_M_mg/L', 'CALIDAD_SDT_ra', 'CALIDAD_SDT_salin',
'FLUORUROS_mg/L',
       'CALIDAD_FLUO', 'DUR_mg/L', 'CALIDAD_DUR',
'COLI_FEC_NMP/100_mL',
       'CALIDAD_COLI_FEC', 'N_NO3_mg/L', 'CALIDAD_N_NO3',
'AS_TOT_mg/L',
       'CALIDAD_AS', 'CD_TOT_mg/L', 'CALIDAD_CD', 'CR_TOT_mg/L',
'CALIDAD_CR',
       'HG_TOT_mg/L', 'CALIDAD_HG', 'PB_TOT_mg/L', 'CALIDAD_PB',
'MN_TOT_mg/L',
       'CALIDAD_MN', 'FE_TOT_mg/L', 'CALIDAD_FE', 'SEMAFORO',
'CONTAMINANTES',
       'CUMPLE_CON_ALC', 'CUMPLE_CON_COND', 'CUMPLE_CON_SDT_ra',
       'CUMPLE_CON_SDT_salin', 'CUMPLE_CON_FLUO', 'CUMPLE_CON_DUR',
       'CUMPLE_CON_CF', 'CUMPLE_CON_NO3', 'CUMPLE_CON_AS',
'CUMPLE_CON_CD',
       'CUMPLE_CON_CR', 'CUMPLE_CON_HG', 'CUMPLE_CON_PB',
'CUMPLE_CON_MN',
       'CUMPLE_CON_FE'],
      dtype='object')
```

```python
df["PERIODO"].value_counts()
```

```
2020    1068
Name: PERIODO, dtype: int64
```

```
df["CONTAMINANTES"].value_counts()
```

```
FLUO,                                              78
DT,                                                65
FLUO,AS,                                           51
CF,                                                31
AS,                                                31
                                                   ..
ALC,CONDUC,SDT_ra,SDT_salin,DT,NO3,                 1
ALC,CONDUC,SDT_ra,SDT_salin,FLUO,DT,AS,MN,FE,       1
PB,MN,FE,                                           1
ALC,AS,FE,                                          1
ALC,DT,NO3,                                         1
Name: CONTAMINANTES, Length: 126, dtype: int64
```

###Observamos que nuestra variable **Valor de Alcalinidad Total en miligramos por litro(SDT_mg/L)** cuenta con **1068 valores nulos**, esto implica el 100% de las muestras por lo que se eliminara de nuestro Dataset.

###La variable **Contaminantes** cuenta con 434 valores nulos sin embargo esto es debido a que estas muestras(Sitios Subterranos) no presentan algun tipo de contaminación que se describa con esta variable, por lo que se mantiene en el Dataset.

###Las Variable **ALC_mg/L** presentan 4 Sitios Subterraneos sin valor, por consecuencía **CALIDAD_ALC** presenta los mismos datos nulos, la cantidad de datos nulos no es representativo para la muestra por lo que seran eliminados.

###Se presenta este mismo caso para las variables **CONDUCT_mS/cm**, **CALIDAD_CONDUC**, **CONDUCT_mS/cm**,**CALIDAD_CONDUC**,**SDT_M_mg/L** **CALIDAD_SDT_ra**,**CALIDAD_SDT_salin**, **DUR_mg/L**, **CALIDAD_DUR** que seran eliminadas sus muestras con valores nulos.

###La columna **"FECHA"** presenta el mismo valor para todas las muestras por lo que no sera relevante en nuestro analisis y sera eliminada.

```
#Agregaremos un valor a la Variable Contaminantes a aquellos valores
nulos que indican que no hay presencia de contaminantes
#para posteriormente eliminar los valores nulos del resto del Dataset.

df["CONTAMINANTES"].fillna("OK", inplace= True)

#Observamos que los valores nulos de la Columna "CONTAMINANTES" fueron
llenados con "OK" como indicación que no hay presencia de
Contaminantes.
df["CONTAMINANTES"].value_counts()
```

```
OK                                                 434
FLUO,                                               78
```

```
DT,                                                  65
FLUO,AS,                                             51
CF,                                                  31
                                                   ...
ALC,FLUO,AS,FE,                                       1
ALC,CONDUC,SDT_ra,SDT_salin,FLUO,DT,AS,MN,FE,         1
PB,MN,FE,                                             1
ALC,AS,FE,                                            1
ALC,DT,NO3,                                           1
Name: CONTAMINANTES, Length: 127, dtype: int64
```

```
#Eliminamos la columna "SDT_mg/L"
Clean_df= df.drop(["SDT_mg/L"],axis=1)

#Eliminamos las muestras con datos nulos.
Clean_df.dropna(inplace=True)

#Comprobamos que nuestro Dataset se encuentra libre de Datos nulos y
Variables que al momento no se consideran de relevancia para el
analisis.
Clean_df.isnull().sum()
```

```
CLAVE                   0
SITIO                   0
ORGANISMO_DE_CUENCA     0
ESTADO                  0
MUNICIPIO               0
ACUIFERO                0
SUBTIPO                 0
LONGITUD                0
LATITUD                 0
PERIODO                 0
ALC_mg/L                0
CALIDAD_ALC             0
CONDUCT_mS/cm           0
CALIDAD_CONDUC          0
SDT_M_mg/L              0
CALIDAD_SDT_ra          0
CALIDAD_SDT_salin       0
FLUORUROS_mg/L          0
CALIDAD_FLUO            0
DUR_mg/L                0
CALIDAD_DUR             0
COLI_FEC_NMP/100_mL     0
CALIDAD_COLI_FEC        0
N_NO3_mg/L              0
CALIDAD_N_NO3           0
AS_TOT_mg/L             0
CALIDAD_AS              0
CD_TOT_mg/L             0
CALIDAD_CD              0
```

```
CR_TOT_mg/L            0
CALIDAD_CR             0
HG_TOT_mg/L            0
CALIDAD_HG             0
PB_TOT_mg/L            0
CALIDAD_PB             0
MN_TOT_mg/L            0
CALIDAD_MN             0
FE_TOT_mg/L            0
CALIDAD_FE             0
SEMAFORO               0
CONTAMINANTES          0
CUMPLE_CON_ALC         0
CUMPLE_CON_COND        0
CUMPLE_CON_SDT_ra      0
CUMPLE_CON_SDT_salin   0
CUMPLE_CON_FLUO        0
CUMPLE_CON_DUR         0
CUMPLE_CON_CF          0
CUMPLE_CON_NO3         0
CUMPLE_CON_AS          0
CUMPLE_CON_CD          0
CUMPLE_CON_CR          0
CUMPLE_CON_HG          0
CUMPLE_CON_PB          0
CUMPLE_CON_MN          0
CUMPLE_CON_FE          0
dtype: int64
```

```
Clean_df.shape
```

```
(1054, 56)
```

###Ya con nuestro Dataset limpio continuaremos explorando

```
#Visualisemos la distribución de los sitios subterraneos por su ubicación(Estado)
gb = df.groupby('ESTADO').apply(len)
gb
```

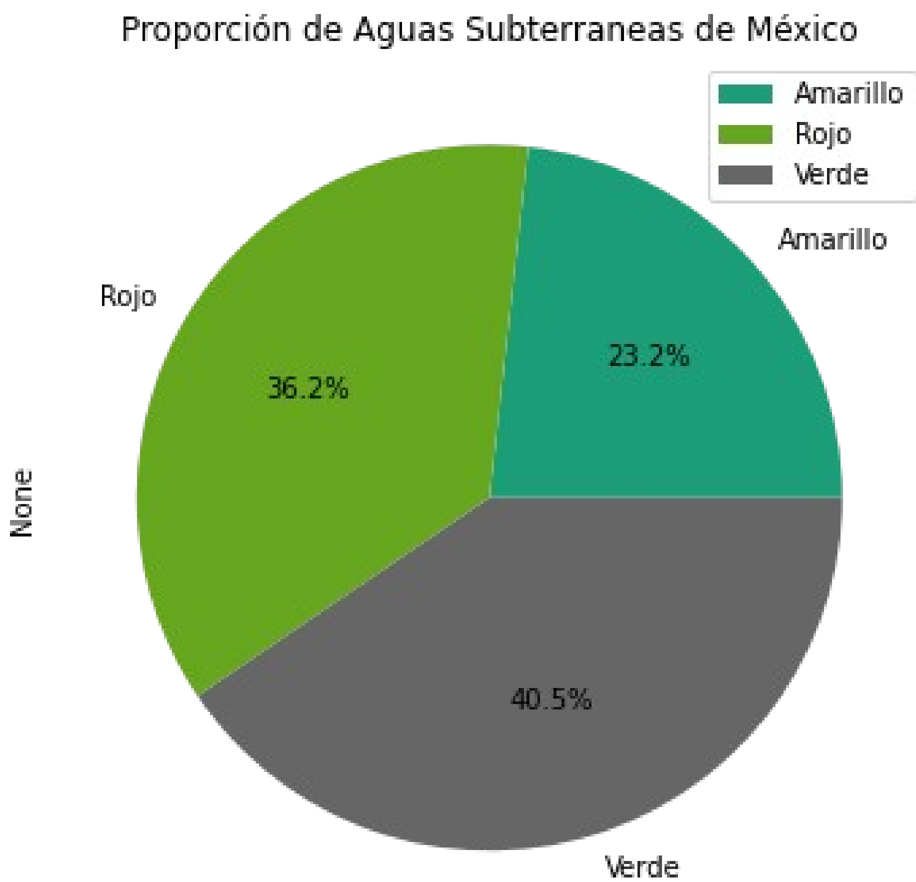
```
ESTADO
AGUASCALIENTES                  14
BAJA CALIFORNIA                 31
BAJA CALIFORNIA SUR             49
CAMPECHE                        25
CHIAPAS                         21
CHIHUAHUA                       35
COAHUILA DE ZARAGOZA            59
COLIMA                          26
DISTRITO FEDERAL                 2
DURANGO                        121
```

```
GUANAJUATO                            41
GUERRERO                               5
HIDALGO                               37
JALISCO                               33
MEXICO                                24
MICHOACAN DE OCAMPO                   27
MORELOS                               11
NAYARIT                                8
NUEVO LEON                            15
OAXACA                                20
PUEBLA                                23
QUERETARO ARTEAGA                      6
QUINTANA ROO                          15
SAN LUIS POTOSI                       47
SINALOA                               32
SONORA                               103
TABASCO                               13
TAMAULIPAS                            25
TLAXCALA                              24
VERACRUZ DE IGNACIO DE LA LLAVE       16
YUCATAN                               85
ZACATECAS                             75
dtype: int64
```

```
#Subtipo de cuerpo de agua donde se encuentra el sitio de muestreo
geb = df.groupby('SUBTIPO').apply(len)
geb
```

```
SUBTIPO
BOMBEO CENOTE       1
CENOTE              7
DESCARGA            1
MANANTIAL          12
NORIA               3
POZO             1039
POZO NORIA          4
Pozo                1
dtype: int64
```

```
#Veamos la proporción de nuestra variable "SEMAFORO" la cual nos
indica el nivel de contaminacion de acuerdo a los contaminantes
presentes
gsb = Clean_df.groupby('SEMAFORO').apply(len)
gsb.plot(kind='pie', title = 'Proporción de Aguas Subterraneas de
México',
cmap='Dark2', autopct="%.1f%%", figsize = (10,6), legend=True);
```




```
#Describamos nuestros datos numericos.
Clean_df.describe()
```

```
         LONGITUD      LATITUD  PERIODO     ALC_mg/L  CONDUCT_mS/cm
count  1054.000000  1054.000000   1054.0  1054.000000    1054.000000
mean   -101.848270    23.161796   2020.0   234.695266    1142.726471
std       6.697568     3.875005      0.0   111.147849    1248.990617
min    -116.664250    14.561150   2020.0    26.640000     110.000000
25%    -105.385170    20.224857   2020.0   164.257500     506.000000
50%    -102.170665    22.640705   2020.0   215.825000     820.000000
75%     -98.971268    25.508770   2020.0   292.930000    1328.000000
max     -86.864120    32.677713   2020.0  1650.000000   18577.000000
```

```
#Notamos que la función describe dejo fuera algunos otras variables
numericas por incluir el simbolo de desigualdad "<" como
'SDT_M_mg/L','DUR_mg/L', etc.
#Cambiemos este tipo de valor a numerico.

Clean_df['SDT_M_mg/L'] = Clean_df['SDT_M_mg/L'].str.replace('<', '')
Clean_df['SDT_M_mg/L'] = pd.to_numeric(Clean_df['SDT_M_mg/L'])
```

```
Clean_df['FLUORUROS_mg/L'] =
Clean_df['FLUORUROS_mg/L'].str.replace('<', '')
Clean_df['FLUORUROS_mg/L'] = pd.to_numeric(Clean_df['FLUORUROS_mg/L'])

Clean_df['DUR_mg/L'] = Clean_df['DUR_mg/L'].str.replace('<', '')
Clean_df['DUR_mg/L'] = pd.to_numeric(Clean_df['DUR_mg/L'])

Clean_df['COLI_FEC_NMP/100_mL'] =
Clean_df['COLI_FEC_NMP/100_mL'].str.replace('<', '')
Clean_df['COLI_FEC_NMP/100_mL'] =
pd.to_numeric(Clean_df['COLI_FEC_NMP/100_mL'])

Clean_df['N_NO3_mg/L'] = Clean_df['N_NO3_mg/L'].str.replace('<', '')
Clean_df['N_NO3_mg/L'] = pd.to_numeric(Clean_df['N_NO3_mg/L'])

Clean_df['AS_TOT_mg/L'] = Clean_df['AS_TOT_mg/L'].str.replace('<', '')
Clean_df['AS_TOT_mg/L'] = pd.to_numeric(Clean_df['AS_TOT_mg/L'])

Clean_df['CD_TOT_mg/L'] = Clean_df['CD_TOT_mg/L'].str.replace('<', '')
Clean_df['CD_TOT_mg/L'] = pd.to_numeric(Clean_df['CD_TOT_mg/L'])

Clean_df['CR_TOT_mg/L'] = Clean_df['CR_TOT_mg/L'].str.replace('<', '')
Clean_df['CR_TOT_mg/L'] = pd.to_numeric(Clean_df['CR_TOT_mg/L'])

Clean_df['HG_TOT_mg/L'] = Clean_df['HG_TOT_mg/L'].str.replace('<', '')
Clean_df['HG_TOT_mg/L'] = pd.to_numeric(Clean_df['HG_TOT_mg/L'])

Clean_df['PB_TOT_mg/L'] = Clean_df['PB_TOT_mg/L'].str.replace('<', '')
Clean_df['PB_TOT_mg/L'] = pd.to_numeric(Clean_df['PB_TOT_mg/L'])

Clean_df['MN_TOT_mg/L'] = Clean_df['MN_TOT_mg/L'].str.replace('<', '')
Clean_df['MN_TOT_mg/L'] = pd.to_numeric(Clean_df['MN_TOT_mg/L'])

Clean_df['FE_TOT_mg/L'] = Clean_df['FE_TOT_mg/L'].str.replace('<', '')
Clean_df['FE_TOT_mg/L'] = pd.to_numeric(Clean_df['FE_TOT_mg/L'])



#Describamos nuevamente nuestros datos numericos.
Clean_df.describe()
```

```
          LONGITUD      LATITUD  PERIODO     ALC_mg/L
CONDUCT_mS/cm  \
count  1054.000000  1054.000000   1054.0  1054.000000    1054.000000

mean   -101.848270    23.161796   2020.0   234.695266    1142.726471

std       6.697568     3.875005      0.0   111.147849    1248.990617
```

min	-116.664250	14.561150	2020.0	26.640000	110.000000
25%	-105.385170	20.224857	2020.0	164.257500	506.000000
50%	-102.170665	22.640705	2020.0	215.825000	820.000000
75%	-98.971268	25.508770	2020.0	292.930000	1328.000000
max	-86.864120	32.677713	2020.0	1650.000000	18577.000000

\	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L	COLI_FEC_NMP/100_mL
count	1054.000000	1054.000000	1054.000000	1054.000000
mean	896.945797	1.078547	349.893584	359.734156
std	2765.757924	1.931204	360.960153	2065.705773
min	101.200000	0.200000	20.000000	1.100000
25%	338.050000	0.269475	121.512000	1.100000
50%	551.400000	0.506950	245.994450	1.100000
75%	915.600000	1.142400	455.617200	10.750000
max	82170.000000	34.803300	3810.692200	24196.000000

\	N_NO3_mg/L	AS_TOT_mg/L	CD_TOT_mg/L	CR_TOT_mg/L	HG_TOT_mg/L
count	1054.000000	1054.000000	1054.00000	1054.000000	1054.000000
mean	4.321651	0.019504	0.00303	0.013353	0.000557
std	8.378332	0.035051	0.00090	0.155412	0.000470
min	0.020000	0.010000	0.00300	0.005000	0.000500
25%	0.651667	0.010000	0.00300	0.005000	0.000500
50%	2.082916	0.010000	0.00300	0.005000	0.000500
75%	5.190385	0.010000	0.00300	0.005000	0.000500
max	121.007813	0.452200	0.03211	5.003200	0.014150

```
       PB_TOT_mg/L  MN_TOT_mg/L  FE_TOT_mg/L
count  1054.000000  1054.000000  1054.000000
mean      0.005285     0.072960     0.412234
std       0.003276     0.378856     5.574307
min       0.005000     0.001500     0.025000
25%       0.005000     0.001500     0.025000
50%       0.005000     0.001500     0.046900
75%       0.005000     0.009830     0.172275
max       0.080900     8.982000   178.615000
```

```python
#Dejemos fuera las variables de "LONGITUD", "LATITUD" y "PERIODO" para seguir explorando nuestros datos
df_explore =
Clean_df[["ALC_mg/L","CONDUCT_mS/cm","SDT_M_mg/L","FLUORUROS_mg/L","DUR_mg/L","COLI_FEC_NMP/100_mL","N_NO3_mg/L","AS_TOT_mg/L","CD_TOT_mg/L","CR_TOT_mg/L","HG_TOT_mg/L",
                 "PB_TOT_mg/L","MN_TOT_mg/L","FE_TOT_mg/L"]].copy()

#Media de nuestros datos númericos
df_explore.mean()
```

```
ALC_mg/L                234.695266
CONDUCT_mS/cm          1142.726471
SDT_M_mg/L              896.945797
FLUORUROS_mg/L            1.078547
DUR_mg/L                349.893584
COLI_FEC_NMP/100_mL     359.734156
N_NO3_mg/L                4.321651
AS_TOT_mg/L               0.019504
CD_TOT_mg/L               0.003030
CR_TOT_mg/L               0.013353
HG_TOT_mg/L               0.000557
PB_TOT_mg/L               0.005285
MN_TOT_mg/L               0.072960
FE_TOT_mg/L               0.412234
dtype: float64
```

```python
#Mediana de nuestros datos númericos
df_explore.median()
```

```
ALC_mg/L               215.825000
CONDUCT_mS/cm          820.000000
SDT_M_mg/L             551.400000
FLUORUROS_mg/L           0.506950
DUR_mg/L               245.994450
COLI_FEC_NMP/100_mL      1.100000
N_NO3_mg/L               2.082916
AS_TOT_mg/L              0.010000
CD_TOT_mg/L              0.003000
CR_TOT_mg/L              0.005000
```

```
HG_TOT_mg/L             0.000500
PB_TOT_mg/L             0.005000
MN_TOT_mg/L             0.001500
FE_TOT_mg/L             0.046900
dtype: float64
```

```python
#Valores maximos de nuestros datos númericos
df_explore.max()
```

```
ALC_mg/L                 1650.000000
CONDUCT_mS/cm           18577.000000
SDT_M_mg/L              82170.000000
FLUORUROS_mg/L             34.803300
DUR_mg/L                 3810.692200
COLI_FEC_NMP/100_mL     24196.000000
N_NO3_mg/L                121.007813
AS_TOT_mg/L                 0.452200
CD_TOT_mg/L                 0.032110
CR_TOT_mg/L                 5.003200
HG_TOT_mg/L                 0.014150
PB_TOT_mg/L                 0.080900
MN_TOT_mg/L                 8.982000
FE_TOT_mg/L               178.615000
dtype: float64
```

```python
#Valores minimos de nuestros datos númericos
df_explore.min()
```

```
ALC_mg/L                 26.6400
CONDUCT_mS/cm           110.0000
SDT_M_mg/L              101.2000
FLUORUROS_mg/L            0.2000
DUR_mg/L                 20.0000
COLI_FEC_NMP/100_mL       1.1000
N_NO3_mg/L                0.0200
AS_TOT_mg/L               0.0100
CD_TOT_mg/L               0.0030
CR_TOT_mg/L               0.0050
HG_TOT_mg/L               0.0005
PB_TOT_mg/L               0.0050
MN_TOT_mg/L               0.0015
FE_TOT_mg/L               0.0250
dtype: float64
```

```python
#Valores desviación estandar de nuestros datos númericos
df_explore.std()
```

```
ALC_mg/L                 111.147849
CONDUCT_mS/cm           1248.990617
SDT_M_mg/L              2765.757924
FLUORUROS_mg/L             1.931204
```

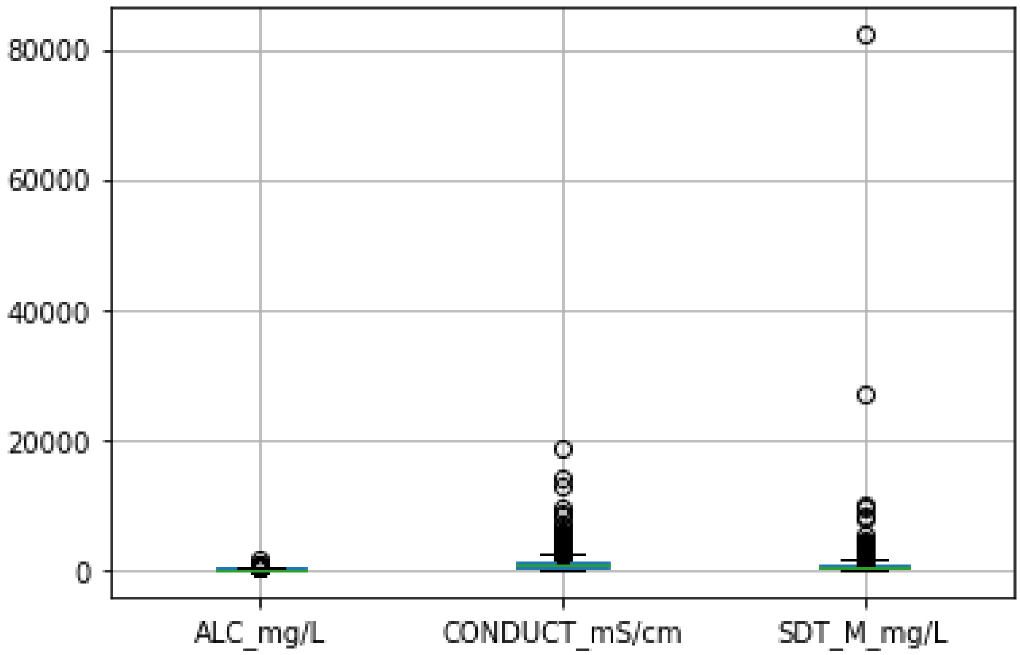
```
DUR_mg/L                 360.960153
COLI_FEC_NMP/100_mL     2065.705773
N_NO3_mg/L                 8.378332
AS_TOT_mg/L                0.035051
CD_TOT_mg/L                0.000900
CR_TOT_mg/L                0.155412
HG_TOT_mg/L                0.000470
PB_TOT_mg/L                0.003276
MN_TOT_mg/L                0.378856
FE_TOT_mg/L                5.574307
dtype: float64
```

```
#Media de nuestros datos númericos
df_explore.var()
```

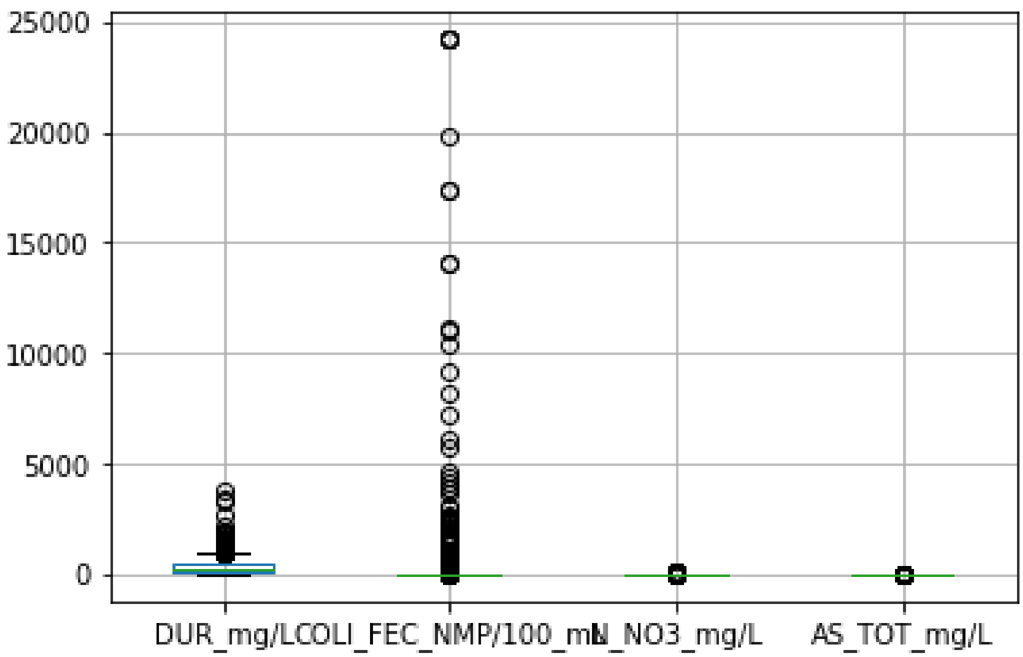
```
ALC_mg/L                1.235384e+04
CONDUCT_mS/cm           1.559978e+06
SDT_M_mg/L              7.649417e+06
FLUORUROS_mg/L          3.729549e+00
DUR_mg/L                1.302922e+05
COLI_FEC_NMP/100_mL     4.267140e+06
N_NO3_mg/L              7.019645e+01
AS_TOT_mg/L             1.228557e-03
CD_TOT_mg/L             8.102546e-07
CR_TOT_mg/L             2.415279e-02
HG_TOT_mg/L             2.206552e-07
PB_TOT_mg/L             1.073068e-05
MN_TOT_mg/L             1.435322e-01
FE_TOT_mg/L             3.107290e+01
dtype: float64
```

```
#Explemos nuestros datos a traves de Boxplot
b_plot = df_explore.boxplot(column =
["ALC_mg/L","CONDUCT_mS/cm","SDT_M_mg/L",])
b_plot.plot()
#plot.show()
```

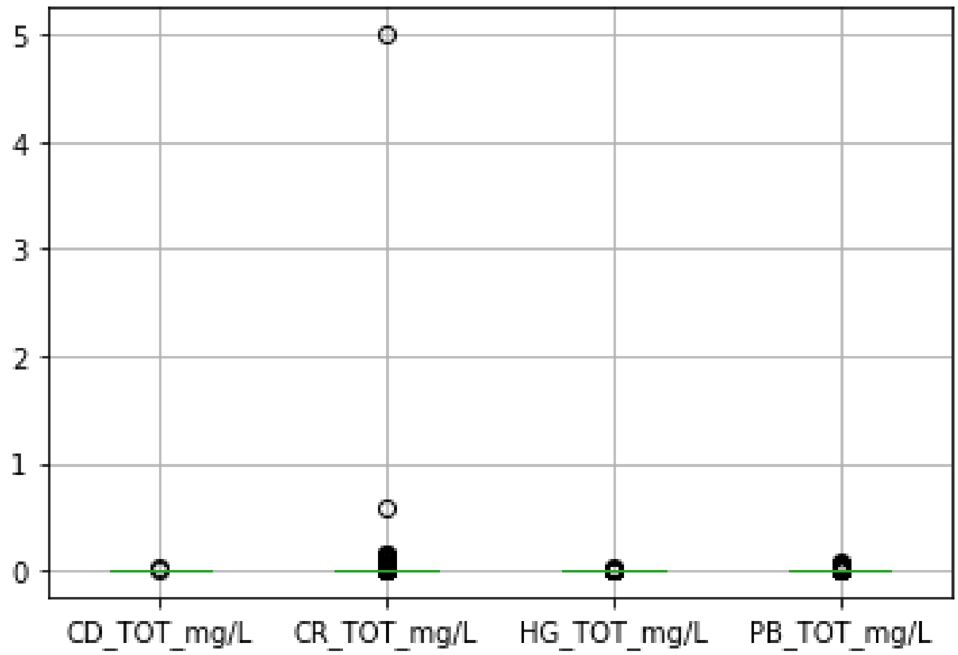
```
[]
```



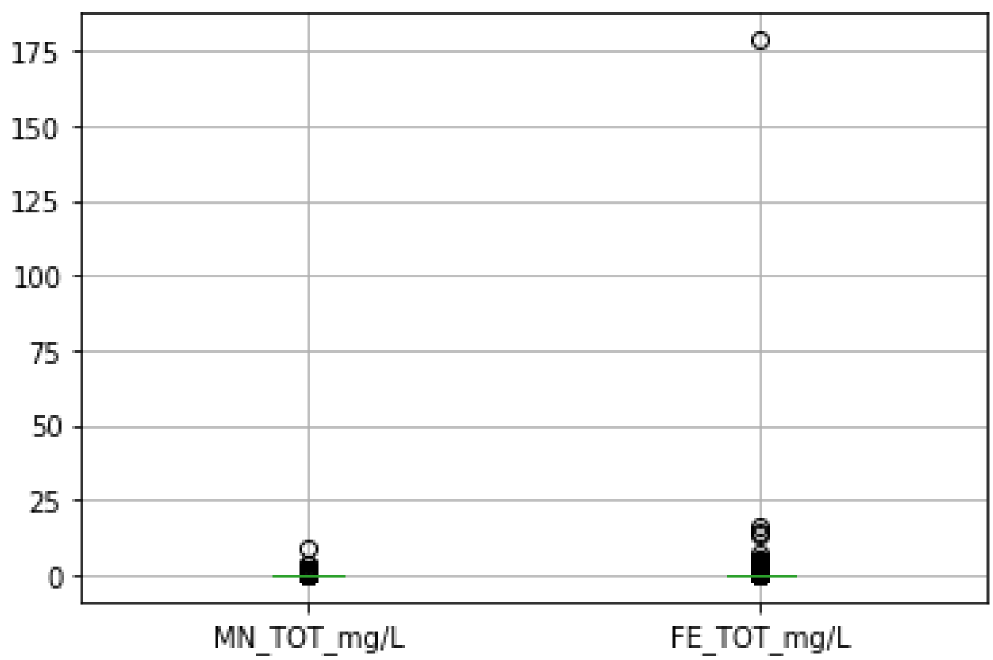

```
boxplot =
df_explore.boxplot(column=["DUR_mg/L","COLI_FEC_NMP/100_mL","N_NO3_mg/
L","AS_TOT_mg/L"])
```




```
boxplot =
df_explore.boxplot(column=["CD_TOT_mg/L","CR_TOT_mg/L","HG_TOT_mg/
L","PB_TOT_mg/L"])
```

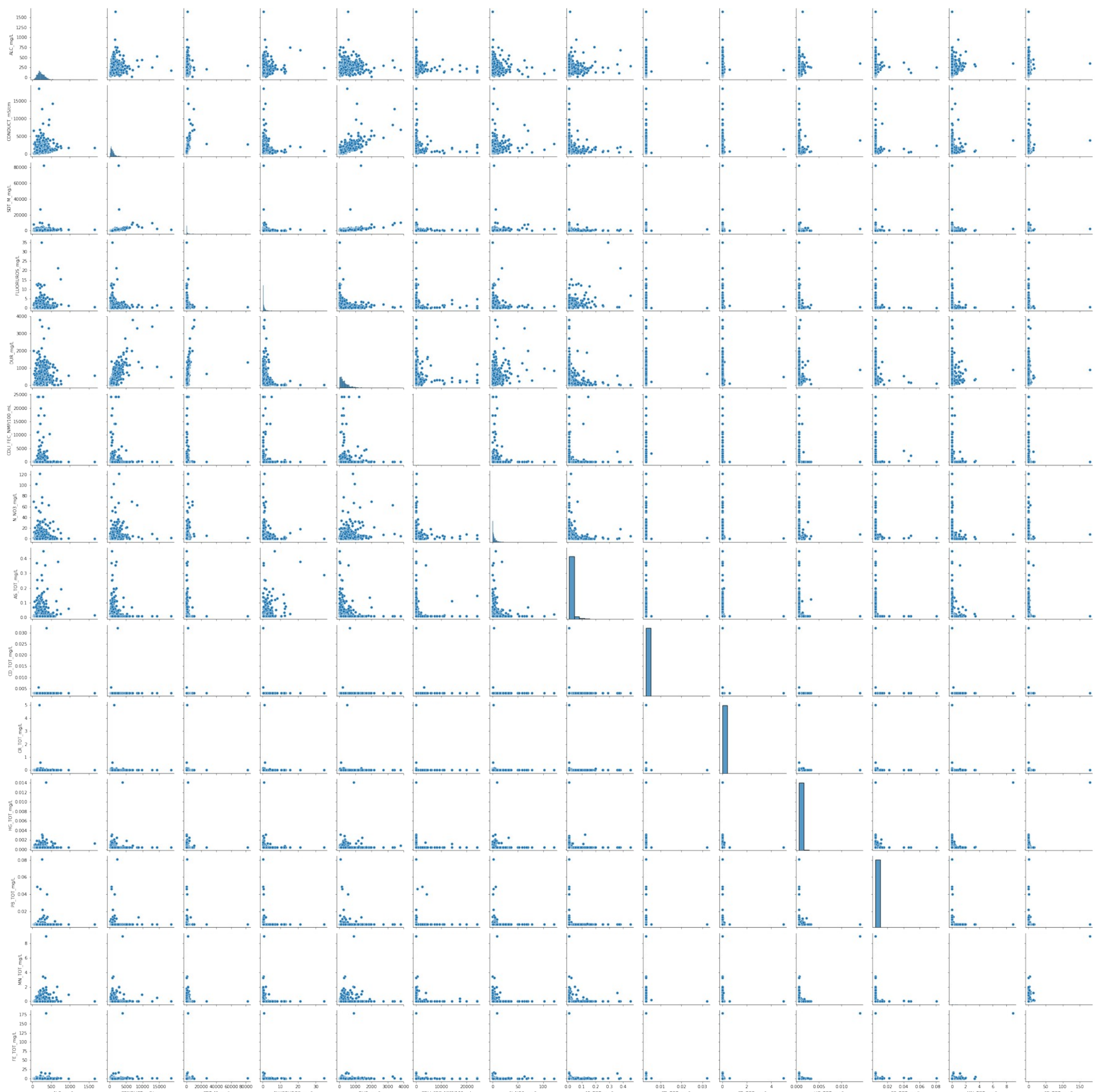



```
boxplot = df_explore.boxplot(column=["MN_TOT_mg/L","FE_TOT_mg/L"])
```

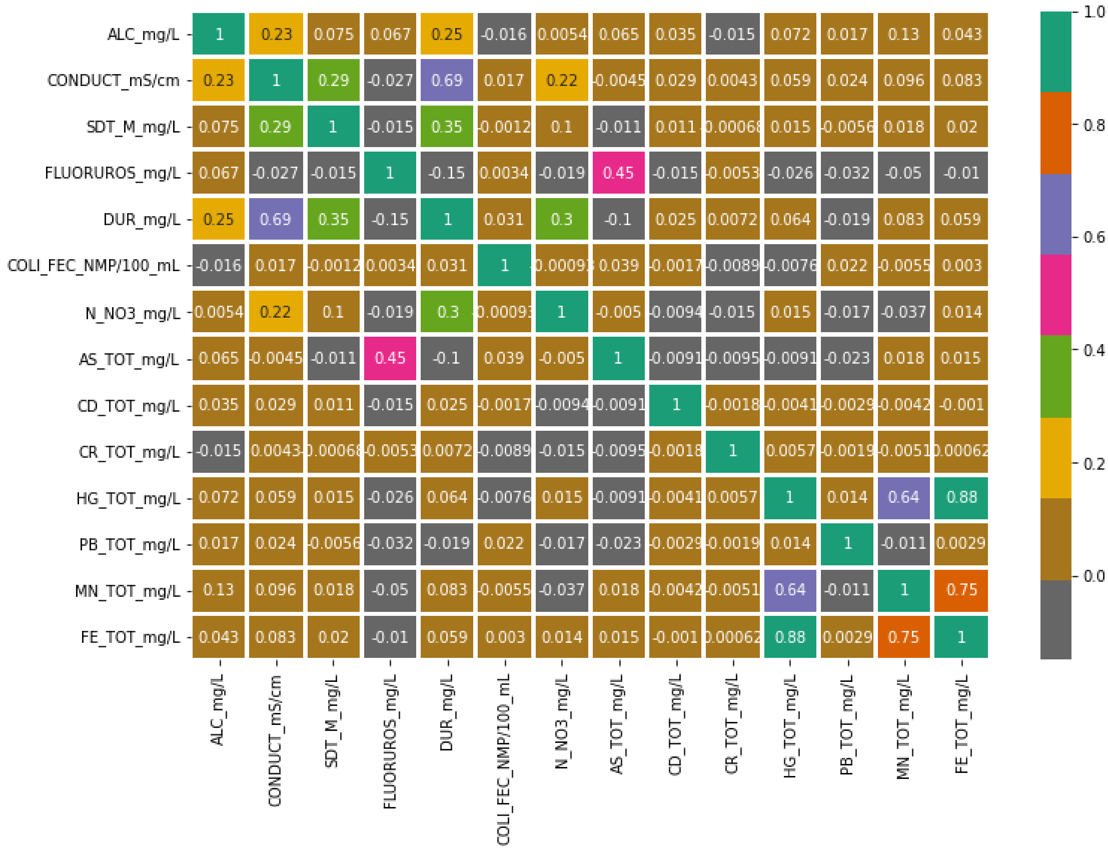



```
#Graficas de dispersión de las diferentes variables, estas
#nos permiten identificar visualmente la correlación de las
#variables o la dispersión.

sns.pairplot(df_explore)
```

```
<seaborn.axisgrid.PairGrid at 0x7ff6fc5b8a10>
```



```
#Mapa de correlaciones nos permite identificar
#que variables se encuentran correlacionadas.
import matplotlib.pyplot as plt
plt.figure(figsize=(12,8))
sns.heatmap(df_explore.corr(), annot=True, cmap='Dark2_r', linewidths
= 2)
plt.show()
```




```
#Llamado a librerias para el graficado de las
#coordenadas de las localidades de las aguas subterraneas
import geopandas
from geopy.geocoders import Nominatim
import geopandas as gpd
from shapely.geometry import Point
import qeds
qeds.themes.mpl_style();
```

```
#Latitudes y Longitudes
latlong =Clean_df[["LATITUD","LONGITUD"]]
latlong["Coordinates"] = list(zip(latlong.LONGITUD, latlong.LATITUD))
latlong["Coordinates"] = latlong["Coordinates"].apply(Point)
latlong.head()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing
imports until
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:4:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  after removing the cwd from sys.path.
```

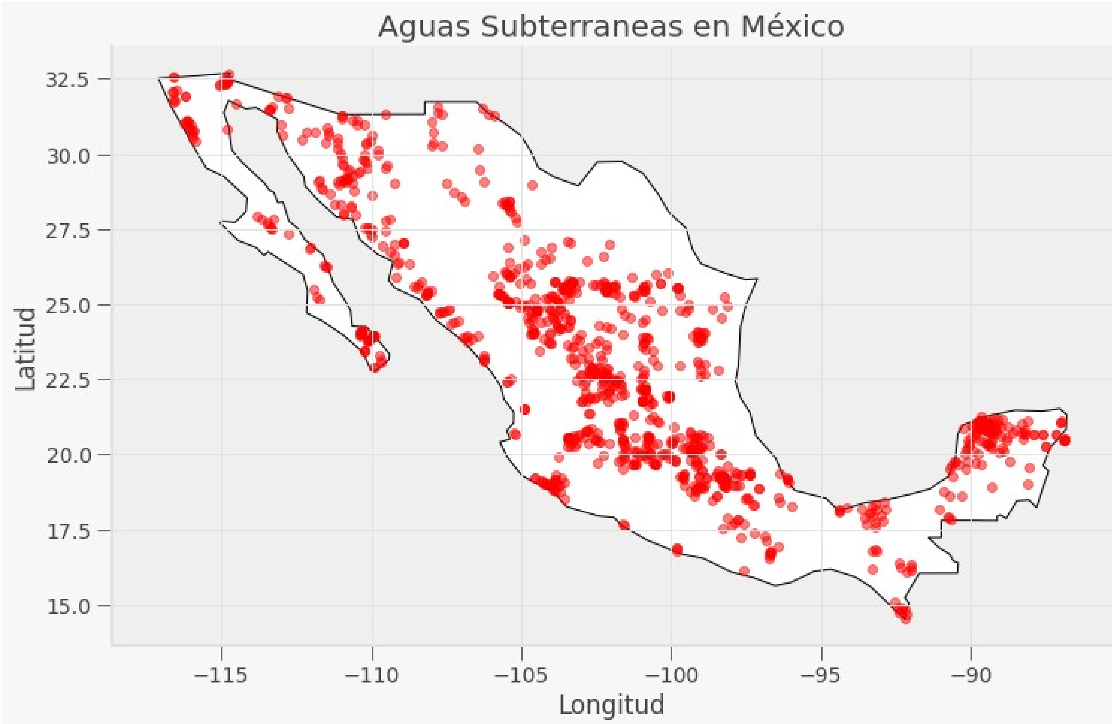
	LATITUD	LONGITUD	Coordinates
0	22.20887	-102.02210	POINT (-102.0221 22.20887)
1	21.99958	-102.20075	POINT (-102.20075 21.99958)
2	22.36685	-102.28801	POINT (-102.28801 22.36685)
3	22.18435	-102.29449	POINT (-102.29449 22.18435)
4	23.45138	-110.24480	POINT (-110.2448 23.45138)

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

	LATITUD	LONGITUD	Coordinates
0	22.20887	-102.02210	POINT (-102.02210 22.20887)
1	21.99958	-102.20075	POINT (-102.20075 21.99958)
2	22.36685	-102.28801	POINT (-102.28801 22.36685)
3	22.18435	-102.29449	POINT (-102.29449 22.18435)
4	23.45138	-110.24480	POINT (-110.24480 23.45138)

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

```
import matplotlib.pyplot as plt
fig, gax = plt.subplots(figsize=(12,12))

world.query("name == 'Mexico'").plot(ax=gax,
edgecolor='black',color='white')

gdf.plot(ax=gax, color='red', alpha = 0.5)
gax.set_xlabel('Longitud')
gax.set_ylabel('Latitud')
gax.set_title('Aguas Subterraneas en México')
gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)
plt.show()
```



#*Realizar un análisis para encontrar si existe una relación entre la calidad de agua y su ubicación geográfica a través de K-means.

```
! pip install haversine
```

```
Looking in indexes: https://pypi.org/simple, https://us-python.pkg.dev/colab-wheels/public/simple/
Collecting haversine
  Downloading haversine-2.7.0-py2.py3-none-any.whl (6.9 kB)
Installing collected packages: haversine
Successfully installed haversine-2.7.0
```

```
#Librerias para el análisis de K-MEANS
import scipy.spatial
from haversine import haversine
from sklearn.cluster import KMeans
```

```
#Revisión de los datos de latitud y longitud
latlong =Clean_df[["LATITUD","LONGITUD"]]
latlong.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1054 entries, 0 to 1067
Data columns (total 2 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   LATITUD   1054 non-null   float64
 1   LONGITUD  1054 non-null   float64
```

```
dtypes: float64(2)
memory usage: 24.7 KB
```

```
#Ajuste del modelo
kmeans = KMeans(n_clusters=3)
kmeans.fit(latlong)
```

```
KMeans(n_clusters=3)
```

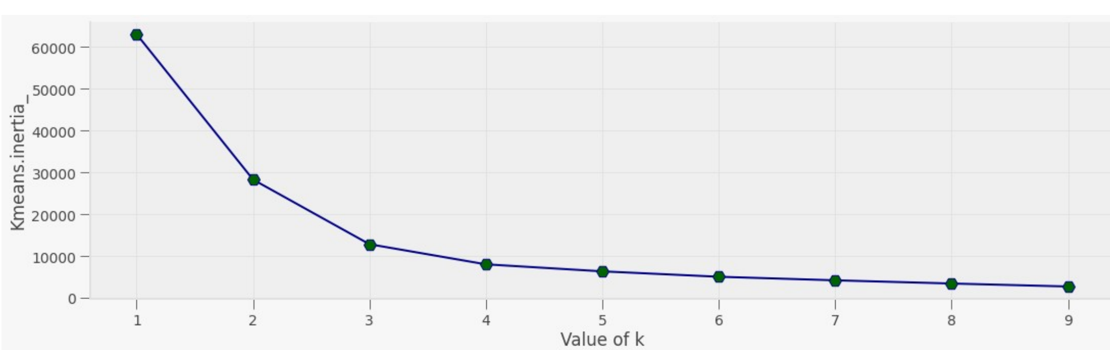
```
#Centro obtenidos por el análisis de K-MEANS
centers = kmeans.cluster_centers_
print("'kmeans' model intances is trained and the cluster centroids
are stored in 'centers'")
centers
```

```
'kmeans' model intances is trained and the cluster centroids are
stored in 'centers'
```

```
array([[  22.27162356, -101.71558109],
       [  28.42037512, -110.74089614],
       [  19.47516461,  -90.69843377]])
```

```
#Método de Codo, para obtener el valor de K-MEANS "Optimo"
sum_square = {}
for k in range(1, 10):
 kmeans = KMeans(n_clusters=k).fit(latlong)
 sum_square[k] = kmeans.inertia_

fig,ax = plt.subplots(figsize=(18,5))
ax.plot(list(sum_square.keys()),
list(sum_square.values()),ls='-',marker='H', color='DarkBlue', lw=2,
markersize=12,markerfacecolor = 'DarkGreen')
ax.set_xlabel("Value of k")
ax.set_ylabel("Kmeans.inertia_")
```

```
Text(0, 0.5, 'Kmeans.inertia_')
```




```
#Las coordenadas se encuentran etiquetadas a un determinado "Cluster"
#esto como resultado del análisis
clustering = KMeans(n_clusters = 3, max_iter= 10000)
clustering.fit(latlong)
```

```
Optimal_centers =  pd.DataFrame(clustering.cluster_centers_)
print("Los centroides se encuentran en las siguientes coordenadas:\n",
clustering.cluster_centers_)
latlong["Cluster"] = clustering.labels_
latlong
```

```
Los centroides se encuentran en las siguientes coordenadas:
 [[  28.42037512 -110.74089614]
 [  19.47516461  -90.69843377]
 [  22.27162356 -101.71558109]]

/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:7:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  import sys

       LATITUD   LONGITUD  Cluster
0     22.20887 -102.02210        2
1     21.99958 -102.20075        2
2     22.36685 -102.28801        2
3     22.18435 -102.29449        2
4     23.45138 -110.24480        0
...        ...        ...      ...
1063  24.76036  -99.54191        2
1064  24.78280  -99.70099        2
1065  25.55197  -99.82249        2
1066  24.80118 -100.32683        2
1067  25.09380 -100.73302        2

[1054 rows x 3 columns]
```

```
Optimal_centers
```

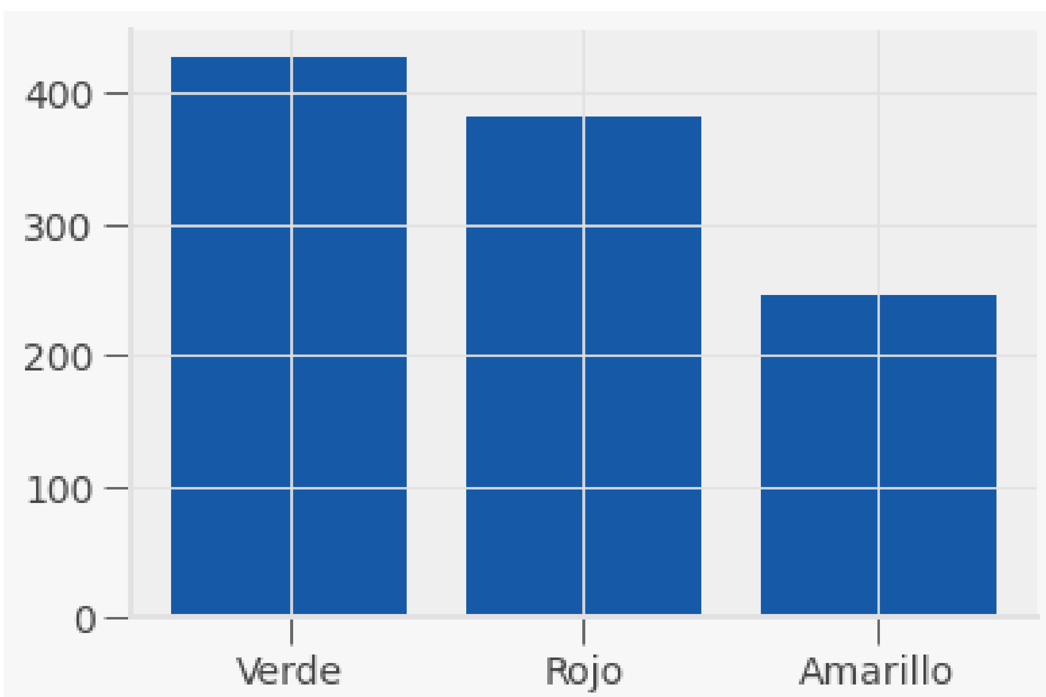
```
           0           1
0  28.420375 -110.740896
1  19.475165  -90.698434
2  22.271624 -101.715581
```

```
latlong["SEMAFORO"] = Clean_df['SEMAFORO']
latlong
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:1:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead
```

```
See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.

       LATITUD   LONGITUD  Cluster SEMAFORO
0     22.20887 -102.02210        2    Verde
1     21.99958 -102.20075        2    Verde
2     22.36685 -102.28801        2     Rojo
3     22.18435 -102.29449        2    Verde
4     23.45138 -110.24480        0     Rojo
...        ...        ...      ...      ...
1063  24.76036  -99.54191        2     Rojo
1064  24.78280  -99.70099        2     Rojo
1065  25.55197  -99.82249        2     Rojo
1066  24.80118 -100.32683        2    Verde
1067  25.09380 -100.73302        2    Verde

[1054 rows x 4 columns]
```

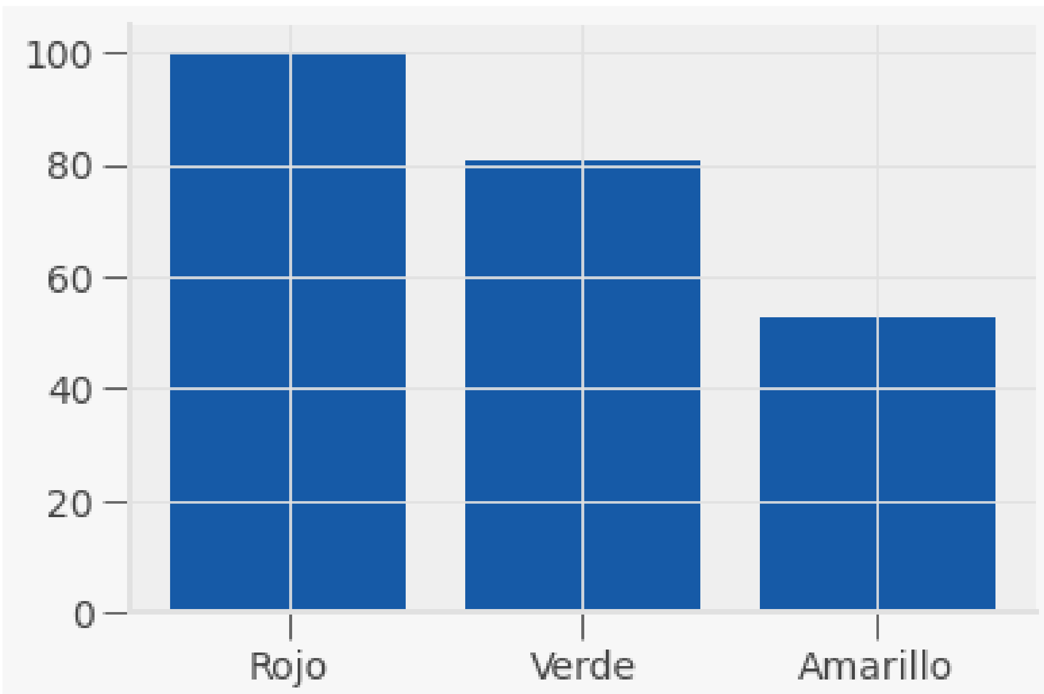
```
#Relación de la calidad del agua y su ubicación geográfica
x_values = latlong['SEMAFORO'].unique()
y_values = latlong['SEMAFORO'].value_counts().tolist()
plt.bar(x_values, y_values)
plt.show()
plt.close('all')
y_values
```



```
[427, 382, 245]
```

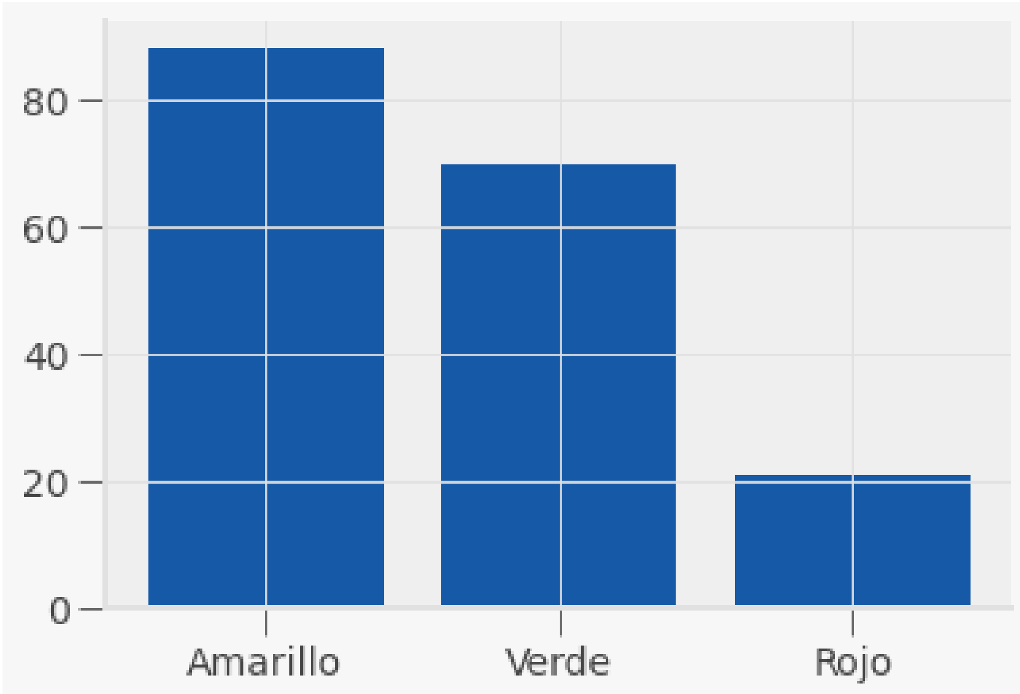
```
rslt_df_clt_0 = latlong[latlong['Cluster'] == 0]
rslt_df_clt_1 = latlong[latlong['Cluster'] == 1]
rslt_df_clt_2 = latlong[latlong['Cluster'] == 2]
```

```
#Esta grafica de barras muestra el semafaro del "Cluster #0"
x_values = rslt_df_clt_0['SEMAFORO'].unique()
y_values = rslt_df_clt_0['SEMAFORO'].value_counts().tolist()
plt.bar(x_values, y_values)
plt.show()
plt.close('all')
y_values
```



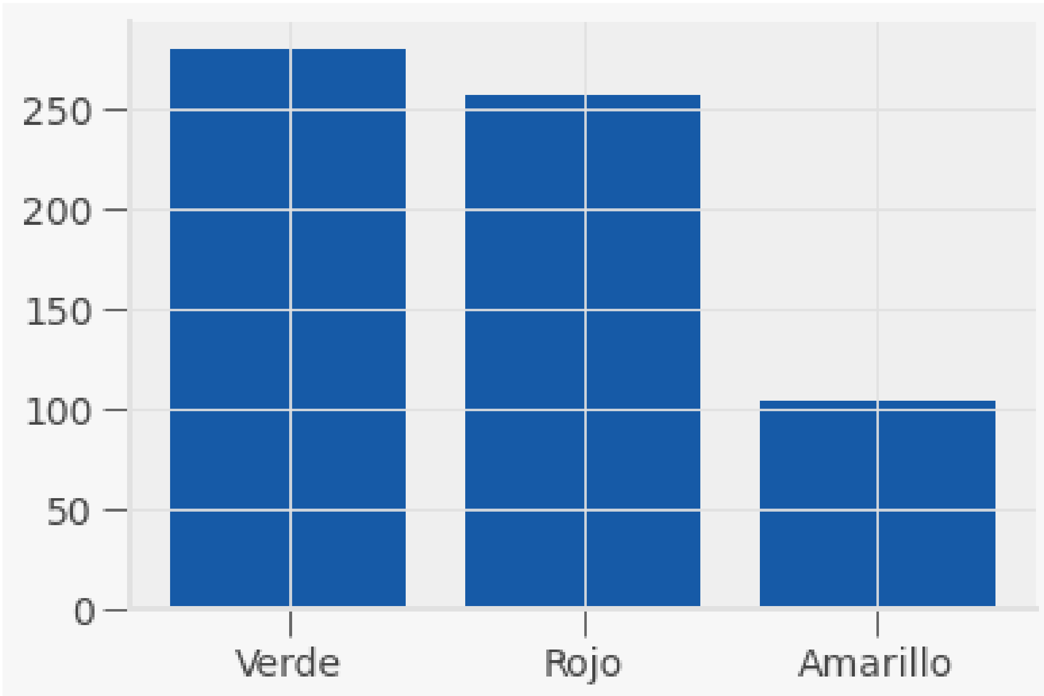

```
[100, 81, 53]
```

```
#Esta grafica de barras muestra el semafaro del "Cluster #1"
x_values = rslt_df_clt_1['SEMAFORO'].unique()
y_values = rslt_df_clt_1['SEMAFORO'].value_counts().tolist()
plt.bar(x_values, y_values)
plt.show()
plt.close('all')
y_values
```




```
[88, 70, 21]
```

```
#Esta grafica de barras muestra el semafaro del "Cluster #2"
x_values = rslt_df_clt_2['SEMAFORO'].unique()
y_values = rslt_df_clt_2['SEMAFORO'].value_counts().tolist()
plt.bar(x_values, y_values)
plt.show()
plt.close('all')
y_values
```




```
[280, 257, 104]
```

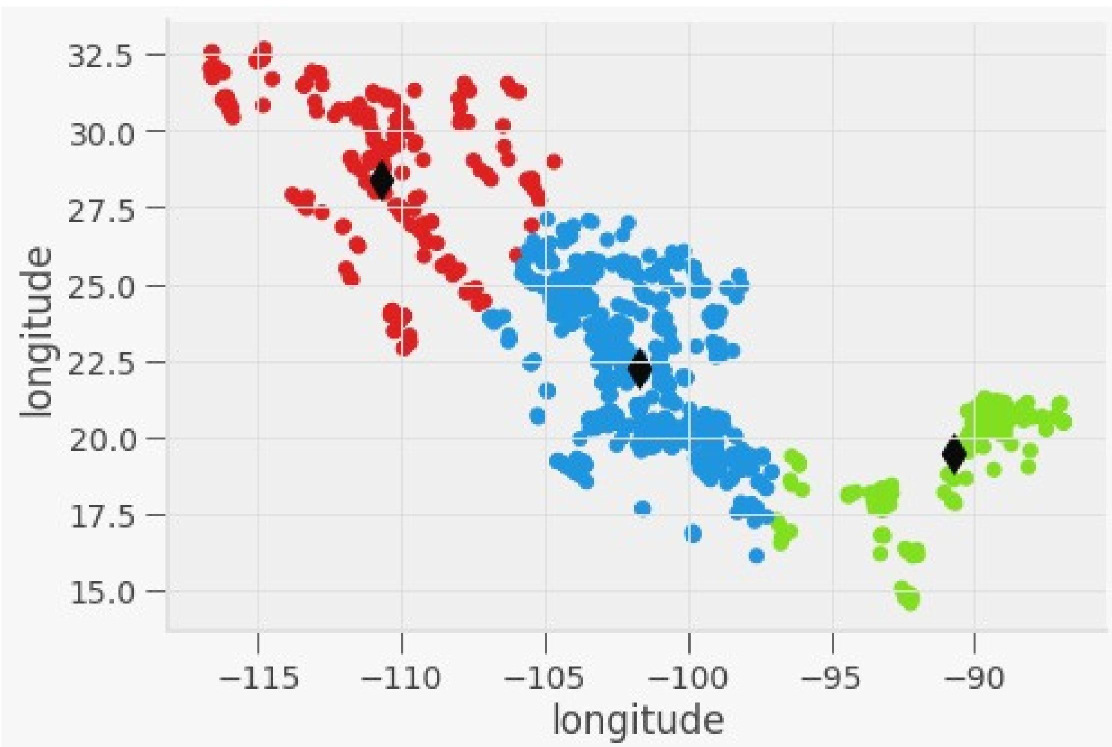
```
latlong.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1054 entries, 0 to 1067
Data columns (total 4 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   LATITUD   1054 non-null   float64
 1   LONGITUD  1054 non-null   float64
 2   Cluster   1054 non-null   int32  
 3   SEMAFORO  1054 non-null   object 
dtypes: float64(2), int32(1), object(1)
memory usage: 37.1+ KB
```

```
#Grafica de dispersion que muestra las diferentes "Cluster" y su
respectivo "Centro".
colors = ["#DF2020", "#81DF20", "#2095DF"]
latlong["colormap"] = latlong.Cluster.map({0:colors[0], 1:colors[1],
2:colors[2]})

Lat = pd.DataFrame(latlong["LATITUD"])
Long = pd.DataFrame(latlong["LONGITUD"])
Clus = pd.DataFrame(latlong["colormap"])



plt.scatter(latlong.LONGITUD, latlong.LATITUD, c=latlong.colormap)
plt.scatter(Optimal_centers[1], Optimal_centers[0], marker = "d",
```

```
s=150, color= "#0A0A0A")
plt.gcf().set_size_inches((7.5,5))

plt.xlabel("longitude")
plt.ylabel("longitude")
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:3:
SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation:
https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#
returning-a-view-versus-a-copy
  This is separate from the ipykernel package so we can avoid doing
imports until
```




```
#Ubicación gregrafica de los "Centros de Cada Cluster"
geolocator = Nominatim(user_agent="geoapiExercises")
location_1 = geolocator.reverse(" 22.271624, -101.715581")
print(location_1)
location_2 = geolocator.reverse(" 19.475165, -90.698434")
print(location_2)
location_3 = geolocator.reverse("28.420375, -110.740896")
print(location_3)
```

```
Pinos, Zacatecas, México
Ciudad del Sol, Champotón, Campeche, México
Guaymas, Sonora, México
```

#Parte 2

```
#Preparación de los datos para el entrenamiento de los algoritmos de
"Arbol de Decisión" y "Bosque Aleatorio"
df_train_test =
Clean_df[["ALC_mg/L","CONDUCT_mS/cm","SDT_M_mg/L","FLUORUROS_mg/L","DU
R_mg/L","COLI_FEC_NMP/100_mL","N_NO3_mg/L","AS_TOT_mg/L","CD_TOT_mg/
L","CR_TOT_mg/L","HG_TOT_mg/L",

"PB_TOT_mg/L","MN_TOT_mg/L","FE_TOT_mg/L","SEMAFORO"]].copy()
df_train_test
```

```
      ALC_mg/L  CONDUCT_mS/cm  SDT_M_mg/L  FLUORUROS_mg/L  DUR_mg/L  \
0      229.990          940.0    603.6000          0.9766  213.7320
1      231.990          608.0    445.4000          0.9298  185.0514
2      204.920          532.0    342.0000          1.8045  120.7190
3      327.000          686.0    478.6000          1.1229  199.8790
4      309.885         1841.0   1179.0000          0.2343  476.9872
...        ...            ...         ...             ...       ...
1063   231.045         2350.0   1545.8000          0.2000  752.0960
1064   256.000          529.0    297.0000          0.2000  273.0000
1065   330.690         2600.0   1873.0000          0.7574  660.2126
1066   193.140          873.0    690.6667          0.7108  406.3680
1067   263.070          817.0    495.0000          0.4002  362.5440

      COLI_FEC_NMP/100_mL  N_NO3_mg/L  AS_TOT_mg/L  CD_TOT_mg/L
CR_TOT_mg/L  \
0                     1.1    4.184656       0.0161        0.003
0.005
1                     1.1    5.750110       0.0134        0.003
0.005
2                     1.1    1.449803       0.0370        0.003
0.005
3                     1.1    1.258597       0.0154        0.003
0.005
4                   291.0   15.672251       0.0100        0.003
0.005
...                   ...         ...          ...          ...
...
1063                  1.1   14.615488       0.0100        0.003
0.005
1064                  1.1   77.392000       0.0100        0.003
0.005
1065                620.0   36.477104       0.0100        0.003
0.005
1066                  1.1    0.020000       0.0100        0.003
0.005
```

```
1067                  1.1    0.811876       0.0100        0.003
0.005

      HG_TOT_mg/L  PB_TOT_mg/L  MN_TOT_mg/L  FE_TOT_mg/L SEMAFORO
0          0.0005        0.005      0.00150      0.08910    Verde
1          0.0005        0.005      0.00150      0.02500    Verde
2          0.0005        0.005      0.00150      0.02500     Rojo
3          0.0005        0.005      0.00150      0.02500    Verde
4          0.0005        0.005      0.00150      0.02500     Rojo
...           ...          ...          ...          ...      ...
1063       0.0005        0.005      0.00150      0.02500     Rojo
1064       0.0005        0.005      0.00709      0.07578     Rojo
1065       0.0005        0.005      0.02420      0.21290     Rojo
1066       0.0005        0.005      0.01200      0.17860    Verde
1067       0.0005        0.005      0.00150      0.02500    Verde

[1054 rows x 15 columns]

#Datos Preparados para el entrenamiento de los
#modelos de Arbol de Decisión y Bosque Aleatorio
from sklearn import preprocessing
label_encoder = preprocessing.LabelEncoder()

#Codificación de los "Targets"
df_train_test['SEMAFORO']=
label_encoder.fit_transform(df_train_test['SEMAFORO'])
df_train_test

      ALC_mg/L  CONDUCT_mS/cm  SDT_M_mg/L  FLUORUROS_mg/L  DUR_mg/L  \
0      229.990          940.0    603.6000          0.9766  213.7320
1      231.990          608.0    445.4000          0.9298  185.0514
2      204.920          532.0    342.0000          1.8045  120.7190
3      327.000          686.0    478.6000          1.1229  199.8790
4      309.885         1841.0   1179.0000          0.2343  476.9872
...        ...            ...         ...             ...       ...
1063   231.045         2350.0   1545.8000          0.2000  752.0960
1064   256.000          529.0    297.0000          0.2000  273.0000
1065   330.690         2600.0   1873.0000          0.7574  660.2126
1066   193.140          873.0    690.6667          0.7108  406.3680
1067   263.070          817.0    495.0000          0.4002  362.5440

      COLI_FEC_NMP/100_mL  N_NO3_mg/L  AS_TOT_mg/L  CD_TOT_mg/L
CR_TOT_mg/L  \
0                     1.1    4.184656       0.0161        0.003
0.005
1                     1.1    5.750110       0.0134        0.003
0.005
2                     1.1    1.449803       0.0370        0.003
0.005
3                     1.1    1.258597       0.0154        0.003
```

```
0.005
4                    291.0   15.672251       0.0100        0.003
0.005
...                    ...         ...          ...          ...
...
1063                   1.1   14.615488       0.0100        0.003
0.005
1064                   1.1   77.392000       0.0100        0.003
0.005
1065                 620.0   36.477104       0.0100        0.003
0.005
1066                   1.1    0.020000       0.0100        0.003
0.005
1067                   1.1    0.811876       0.0100        0.003
0.005

      HG_TOT_mg/L  PB_TOT_mg/L  MN_TOT_mg/L  FE_TOT_mg/L  SEMAFORO
0          0.0005        0.005      0.00150      0.08910         2
1          0.0005        0.005      0.00150      0.02500         2
2          0.0005        0.005      0.00150      0.02500         1
3          0.0005        0.005      0.00150      0.02500         2
4          0.0005        0.005      0.00150      0.02500         1
...           ...          ...          ...          ...       ...
1063       0.0005        0.005      0.00150      0.02500         1
1064       0.0005        0.005      0.00709      0.07578         1
1065       0.0005        0.005      0.02420      0.21290         1
1066       0.0005        0.005      0.01200      0.17860         2
1067       0.0005        0.005      0.00150      0.02500         2

[1054 rows x 15 columns]
```

```
#Variables a utilizar para el entrenamiento y variable de salida
X =
df_train_test[["ALC_mg/L","CONDUCT_mS/cm","SDT_M_mg/L","FLUORUROS_mg/
L","DUR_mg/L","COLI_FEC_NMP/100_mL","N_NO3_mg/L","AS_TOT_mg/
L","CD_TOT_mg/L","CR_TOT_mg/L","HG_TOT_mg/L",
                 "PB_TOT_mg/L","MN_TOT_mg/L","FE_TOT_mg/L"]]

y = df_train_test[["SEMAFORO"]]

print(X.shape)
print(y.shape)
```

```
(1054, 14)
(1054, 1)
```

```
#Division de los datos en entrenamiento y prueba
from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split(X, y,
```

```
random_state=0, train_size = .80)

print(X_train.shape)
print(y_train.shape)
print(X_test.shape)
print(y_test.shape)
```

```
(843, 14)
(843, 1)
(211, 14)
(211, 1)
```

```
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
import seaborn as sns

# Crea el Arbol de Decisión
mdl_dt = DecisionTreeClassifier()

# Entrena el Clasificador de Arbol de Decisión
clf = mdl_dt.fit(X_train,y_train)

#Realiza Predicciones con los Datos de Prueba
y_pred = mdl_dt.predict(X_test)

#Metricas del Modelo de Arboles de Decision
target_names = ['clase 0', 'clase 1', 'clase 2']
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred,
target_names=target_names))
```

```
Accuracy: 0.985781990521327
              precision    recall  f1-score   support

     clase 0       0.97      0.97      0.97        40
     clase 1       0.99      0.97      0.98        73
     clase 2       0.99      1.00      0.99        98

    accuracy                           0.99       211
   macro avg       0.98      0.98      0.98       211
weighted avg       0.99      0.99      0.99       211
```

```
#Matriz de Confusion del Modelo de Arboles de Decision
cf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff6d597fc90>
```


```python
#Import Random Forest Model
from sklearn.ensemble import RandomForestClassifier

#Crea el Bosque Aleatorio
mdl_rf=RandomForestClassifier(n_estimators=100)

#Entrena el Clasificador de Bosque Aleatorio
mdl_rf.fit(X_train,y_train)

#Realiza Predicciones con los Datos de Prueba
y_pred=mdl_rf.predict(X_test)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:8:
DataConversionWarning: A column-vector y was passed when a 1d array
was expected. Please change the shape of y to (n_samples,), for
example using ravel().
```

```python
#Metricas del Modelo de Bosques Aleatorios
target_names = ['clase 0', 'clase 1', 'clase 2']
print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
print(classification_report(y_test, y_pred,
target_names=target_names))
```

```
Accuracy: 0.9715639810426541
              precision    recall  f1-score   support

     clase 0       0.95      0.97      0.96        40
     clase 1       0.97      0.96      0.97        73
```

```
     clase 2       0.98      0.98      0.98        98

    accuracy                           0.97       211
   macro avg       0.97      0.97      0.97       211
weighted avg       0.97      0.97      0.97       211
```

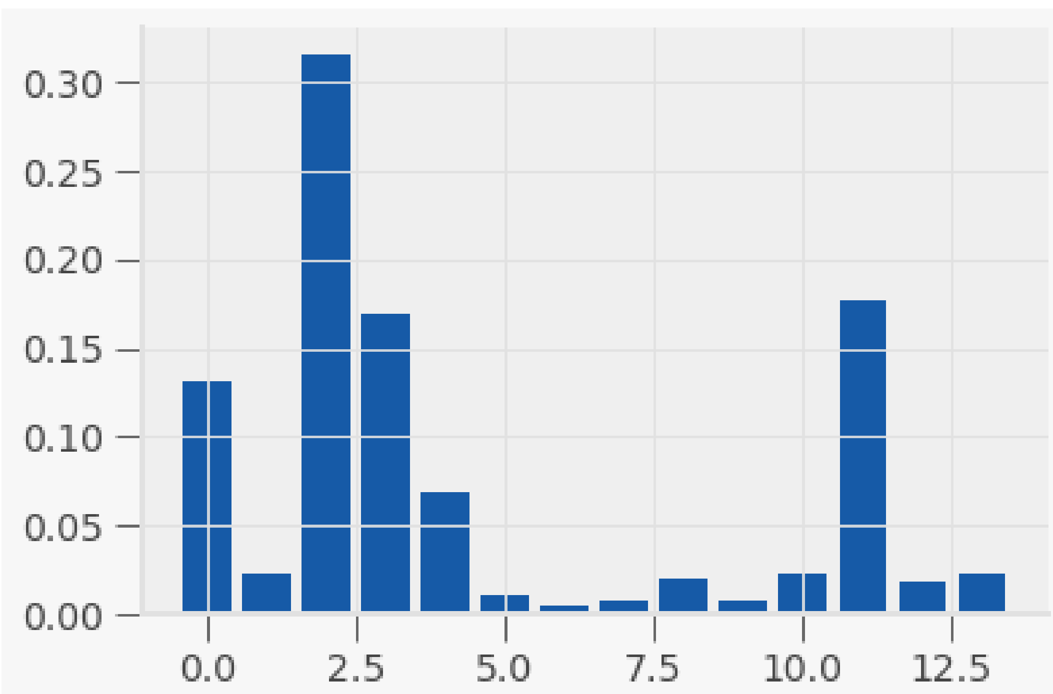
```
#Matriz de Confusion del Modelo de Bosque Aleatorios
cf_matrix = confusion_matrix(y_test, y_pred)
sns.heatmap(cf_matrix/np.sum(cf_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff6d59b7410>
```


```
#Analisis de Caracteristicas de Importancia
from sklearn.datasets import make_classification
from sklearn.tree import DecisionTreeClassifier
from matplotlib import pyplot
# Conjunto de Datos
X, y = make_classification(n_samples=1000, n_features=14,
n_informative=5, n_redundant=5, random_state=1)
# Definición del modelo
model = DecisionTreeClassifier()
# Entrenamiento del modelo
model.fit(X, y)
# Importancia de las caracteristicas
importance = model.feature_importances_
# Resumen de las caracteristicas de importancia
for i,v in enumerate(importance):
```

```
    print('Feature: %0d, Score: %.5f' % (i,v))
# Graficado de las caracteristicas en una grafica de barras
pyplot.bar([x for x in range(len(importance))], importance)
pyplot.show()
```

```
Feature: 0, Score: 0.13077
Feature: 1, Score: 0.02305
Feature: 2, Score: 0.31446
Feature: 3, Score: 0.16901
Feature: 4, Score: 0.06828
Feature: 5, Score: 0.01115
Feature: 6, Score: 0.00512
Feature: 7, Score: 0.00857
Feature: 8, Score: 0.01987
Feature: 9, Score: 0.00812
Feature: 10, Score: 0.02312
Feature: 11, Score: 0.17730
Feature: 12, Score: 0.01812
Feature: 13, Score: 0.02306
```



Ciencia y analítica de datos

Profesora: Dra. María de la Paz Rico Fernández

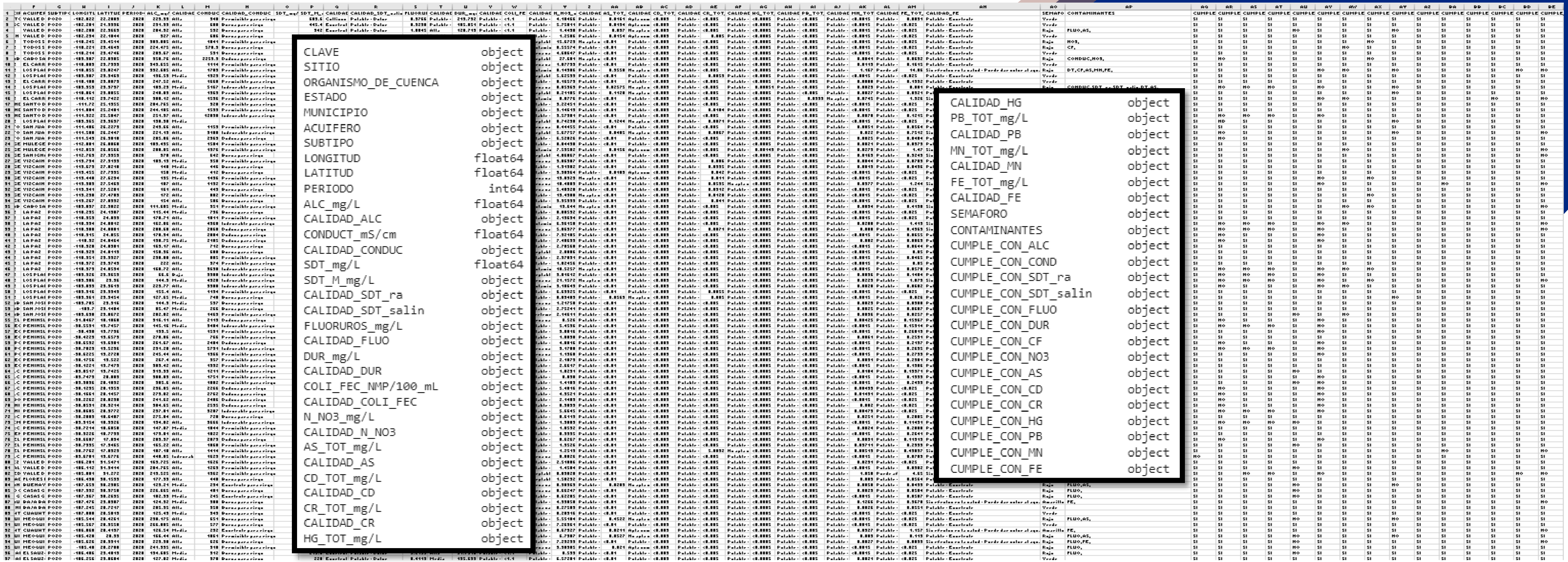
Francisco Javier Ramírez Arias: A01316379

Jesús Ángel Rincón Ruiz: A01793960

Tecnológico de Monterrey

▪ Datos

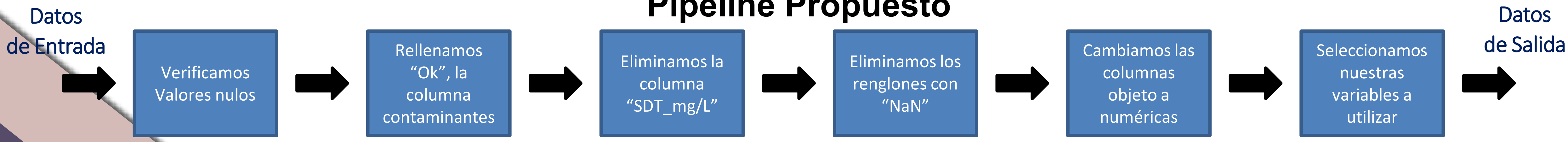
Tamaño de los datos: 1068 muestras, 57 variables



```
CLAVE                  object
SITIO                  object
ORGANISMO_DE_CUENCA    object
ESTADO                 object
MUNICIPIO              object
ACUIFERO               object
SUBTIPO                object
LONGITUD              float64
LATITUD               float64
PERIODO                 int64
ALC_mg/L              float64
CALIDAD_ALC            object
CONDUCT_mS/cm         float64
CALIDAD_CONDUC         object
SDT_mg/L              float64
SDT_M_mg/L             object
CALIDAD_SDT_ra         object
CALIDAD_SDT_salin      object
FLUORUROS_mg/L         object
CALIDAD_FLUO           object
DUR_mg/L               object
CALIDAD_DUR            object
COLI_FEC_NMP/100_mL    object
CALIDAD_COLI_FEC       object
N_NO3_mg/L             object
CALIDAD_N_NO3          object
AS_TOT_mg/L            object
CALIDAD_AS             object
CD_TOT_mg/L            object
CALIDAD_CD             object
CR_TOT_mg/L            object
CALIDAD_CR             object
HG_TOT_mg/L            object
```

```
CALIDAD_HG             object
PB_TOT_mg/L            object
CALIDAD_PB             object
MN_TOT_mg/L            object
CALIDAD_MN             object
FE_TOT_mg/L            object
CALIDAD_FE             object
SEMAFORO               object
CONTAMINANTES          object
CUMPLE_CON_ALC         object
CUMPLE_CON_COND        object
CUMPLE_CON_SDT_ra      object
CUMPLE_CON_SDT_salin   object
CUMPLE_CON_FLUO        object
CUMPLE_CON_DUR         object
CUMPLE_CON_CF          object
CUMPLE_CON_NO3         object
CUMPLE_CON_AS          object
CUMPLE_CON_CD          object
CUMPLE_CON_CR          object
CUMPLE_CON_HG          object
CUMPLE_CON_PB          object
CUMPLE_CON_MN          object
CUMPLE_CON_FE          object
```

Pipeline Propuesto

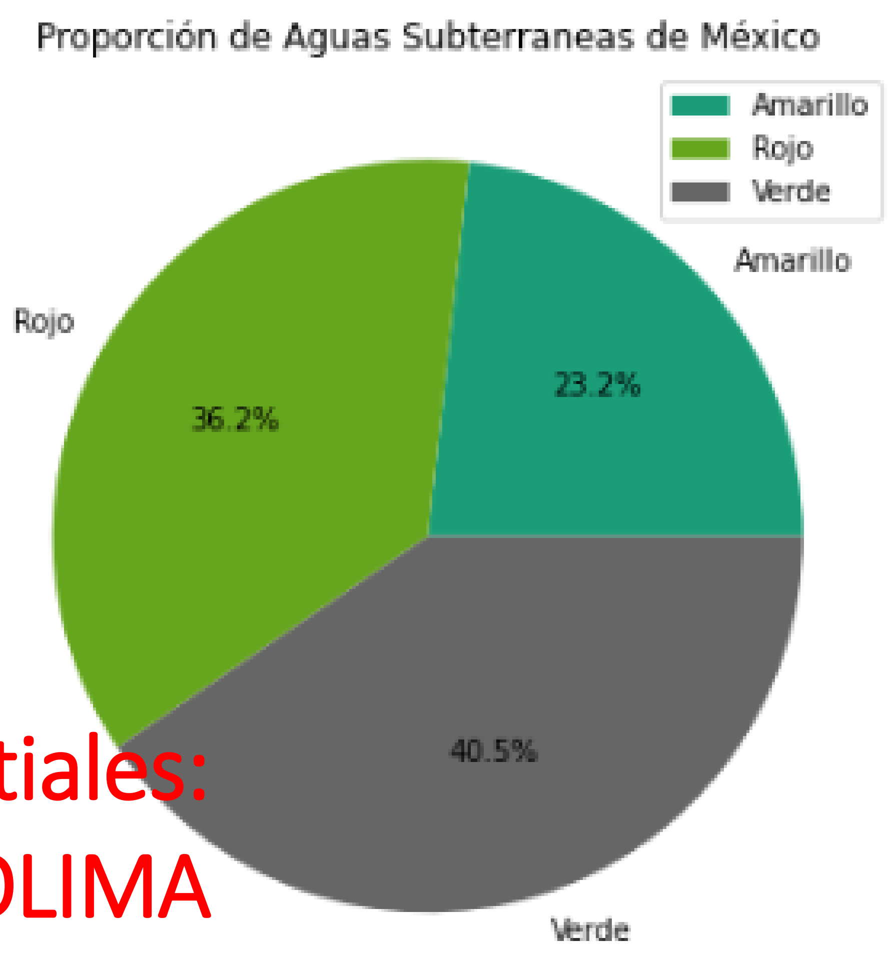


Tamaño de los datos: 1054 muestras, 15 variables

Proporción de Aguas Subterráneas

```
ESTADO
AGUASCALIENTES                     14
BAJA CALIFORNIA                    31
BAJA CALIFORNIA SUR                49
CAMPECHE                           25
CHIAPAS                            21
CHIHUAHUA                          35
COAHUILA DE ZARAGOZA               59
COLIMA                             26
DISTRITO FEDERAL                    2
DURANGO                           121
GUANAJUATO                         41
GUERRERO                            5
HIDALGO                            37
JALISCO                            33
MEXICO                             24
MICHOACAN DE OCAMPO                27
MORELOS                            11
NAYARIT                             8
NUEVO LEON                         15
OAXACA                             20
PUEBLA                             23
QUERETARO ARTEAGA                   6
QUINTANA ROO                       15
SAN LUIS POTOSI                    47
SINALOA                            32
SONORA                            103
TABASCO                            13
TAMAULIPAS                         25
TLAXCALA                           24
VERACRUZ DE IGNACIO DE LA LLAVE    16
YUCATAN                            85
ZACATECAS                          75
```

```
SUBTIPO
BOMBEO CENOTE       1
CENOTE              7
DESCARGA            1
MANANTIAL          12
NORIA               3
POZO             1039
POZO NORIA          4
Pozo                1
dtype: int64
```



Manantiales:
50% COLIMA
41.66% HIDALGO

Descripción de nuestro datos (variables utilizadas)

	LONGITUD	LATITUD	PERIODO	ALC_mg/L	CONDUCT_mS/cm	SDT_M_mg/L	FLUORUROS_mg/L	DUR_mg/L
count	1054.000000	1054.000000	1054.0	1054.000000	1054.000000	1054.000000	1054.000000	1054.000000
mean	-101.848270	23.161796	2020.0	234.695266	1142.726471	896.945797	1.078547	349.893584
std	6.697568	3.875005	0.0	111.147849	1248.990617	2765.757924	1.931204	360.960153
min	-116.664250	14.561150	2020.0	26.640000	110.000000	101.200000	0.200000	20.000000
25%	-105.385170	20.224857	2020.0	164.257500	506.000000	338.050000	0.269475	121.512000
50%	-102.170665	22.640705	2020.0	215.825000	820.000000	551.400000	0.506950	245.994450
75%	-98.971268	25.508770	2020.0	292.930000	1328.000000	915.600000	1.142400	[illegible]
max	-86.864120	32.677713	2020.0	1650.000000	18577.000000	82170.000000	34.803300	3810.692200

	COLI_FEC_NMP/100_mL	N_NO3_mg/L	AS_TOT_mg/L	CD_TOT_mg/L	CR_TOT_mg/L	HG_TOT_mg/L	PB_TOT_mg/L	MN_TOT_mg/L	FE_TOT_mg/L
count	1054.000000	1054.000000	1054.000000	1054.00000	1054.000000	1054.000000	1054.000000	1054.000000	1054.000000
mean	359.734156	4.321651	0.019504	0.00303	0.013353	0.000557	0.005285	0.072960	0.412234
std	2065.705773	8.378332	0.035051	0.00090	0.155412	0.000470	0.003276	0.378856	5.574307
min	1.100000	0.020000	0.010000	0.00300	0.005000	0.000500	0.005000	0.001500	0.025000
25%	1.100000	0.651667	0.010000	0.00300	0.005000	0.000500	0.005000	0.001500	0.025000
50%	1.100000	2.082916	0.010000	0.00300	0.005000	0.000500	0.005000	0.001500	0.046900
75%	[illegible]	[illegible]	0.010000	0.00300	0.005000	0.000500	0.005000	0.009830	0.172275
max	24196.000000	121.007813	0.452200	0.03211	5.003200	0.014150	0.080900	8.982000	178.615000

Posibles Outliers

Promedio

ALC_mg/L	234.695266
CONDUCT_mS/cm	1142.726471
SDT_M_mg/L	896.945797
FLUORUROS_mg/L	1.078547
DUR_mg/L	349.893584
COLI_FEC_NMP/100_mL	359.734156
N_NO3_mg/L	4.321651
AS_TOT_mg/L	0.019504
CD_TOT_mg/L	0.003030
CR_TOT_mg/L	0.013353
HG_TOT_mg/L	0.000557
PB_TOT_mg/L	0.005285
MN_TOT_mg/L	0.072960
FE_TOT_mg/L	0.412234

Mediana

ALC_mg/L	215.825000
CONDUCT_mS/cm	820.000000
SDT_M_mg/L	551.400000
FLUORUROS_mg/L	0.506950
DUR_mg/L	245.994450
COLI_FEC_NMP/100_mL	1.100000
N_NO3_mg/L	2.082916
AS_TOT_mg/L	0.010000
CD_TOT_mg/L	0.003000
CR_TOT_mg/L	0.005000
HG_TOT_mg/L	0.000500
PB_TOT_mg/L	0.005000
MN_TOT_mg/L	0.001500
FE_TOT_mg/L	0.046900

Máximo

ALC_mg/L	1650.000000
CONDUCT_mS/cm	18577.000000
SDT_M_mg/L	82170.000000
FLUORUROS_mg/L	34.803300
DUR_mg/L	3810.692200
COLI_FEC_NMP/100_mL	24196.000000
N_NO3_mg/L	121.007813
AS_TOT_mg/L	0.452200
CD_TOT_mg/L	0.032110
CR_TOT_mg/L	5.003200
HG_TOT_mg/L	0.014150
PB_TOT_mg/L	0.080900
MN_TOT_mg/L	8.982000
FE_TOT_mg/L	178.615000

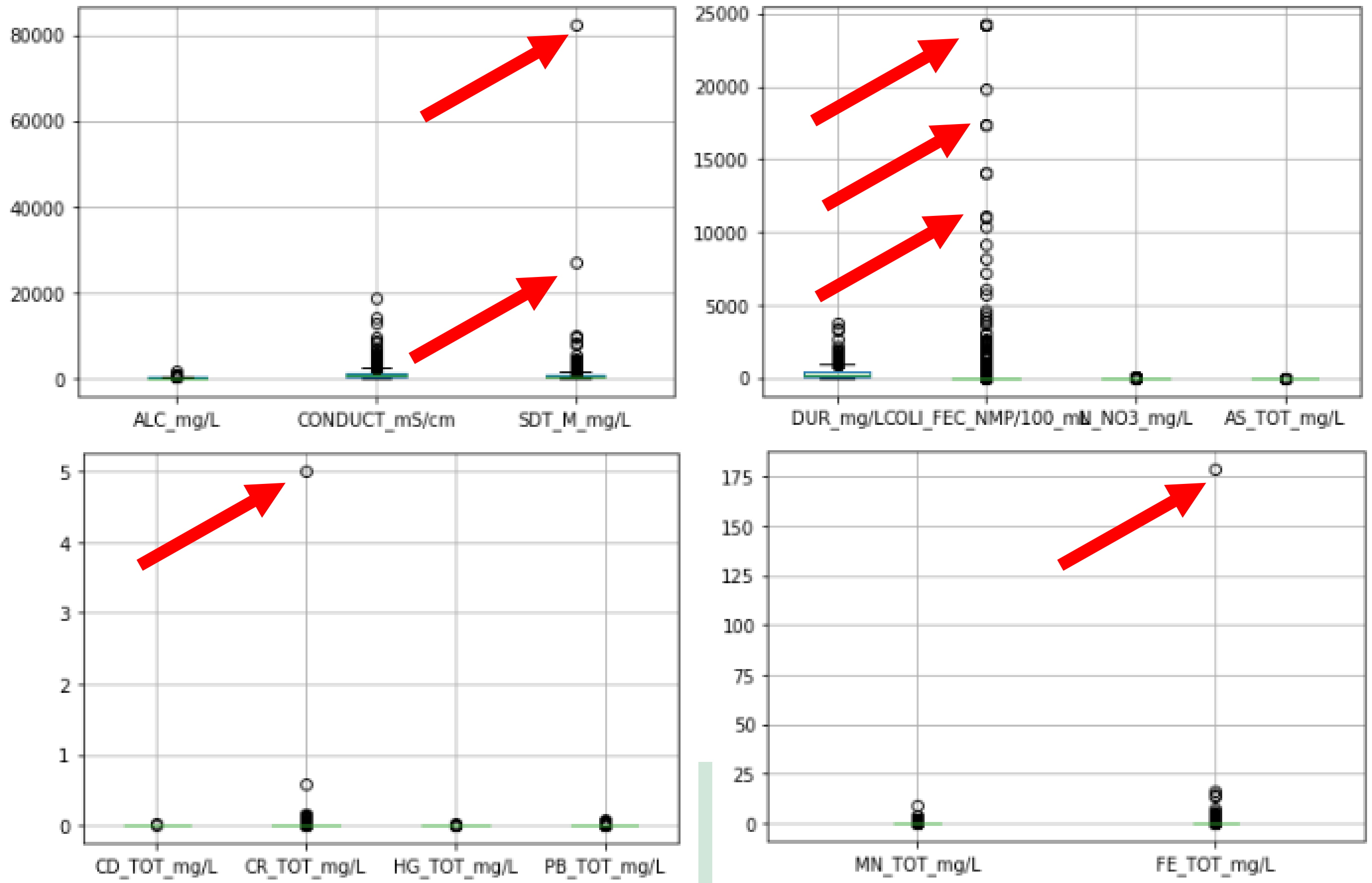
Mínimo

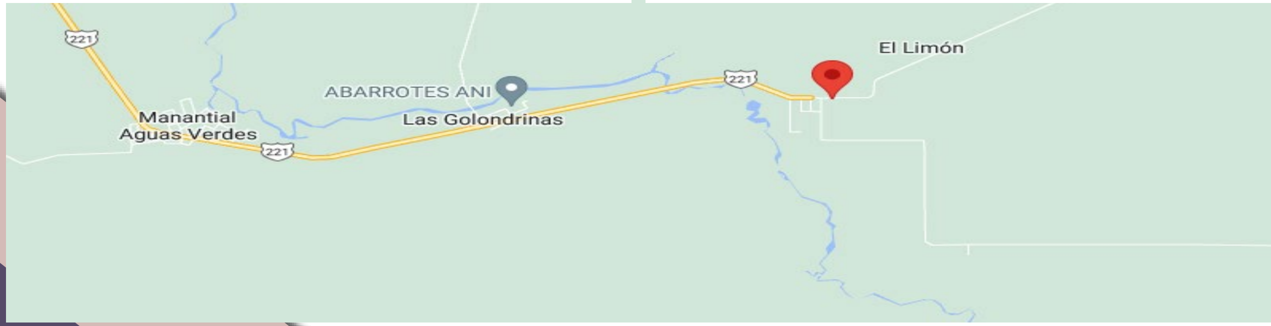
ALC_mg/L	26.6400
CONDUCT_mS/cm	110.0000
SDT_M_mg/L	101.2000
FLUORUROS_mg/L	0.2000
DUR_mg/L	20.0000
COLI_FEC_NMP/100_mL	1.1000
N_NO3_mg/L	0.0200
AS_TOT_mg/L	0.0100
CD_TOT_mg/L	0.0030
CR_TOT_mg/L	0.0050
HG_TOT_mg/L	0.0005
PB_TOT_mg/L	0.0050
MN_TOT_mg/L	0.0015
FE_TOT_mg/L	0.0250

Desviación estándar

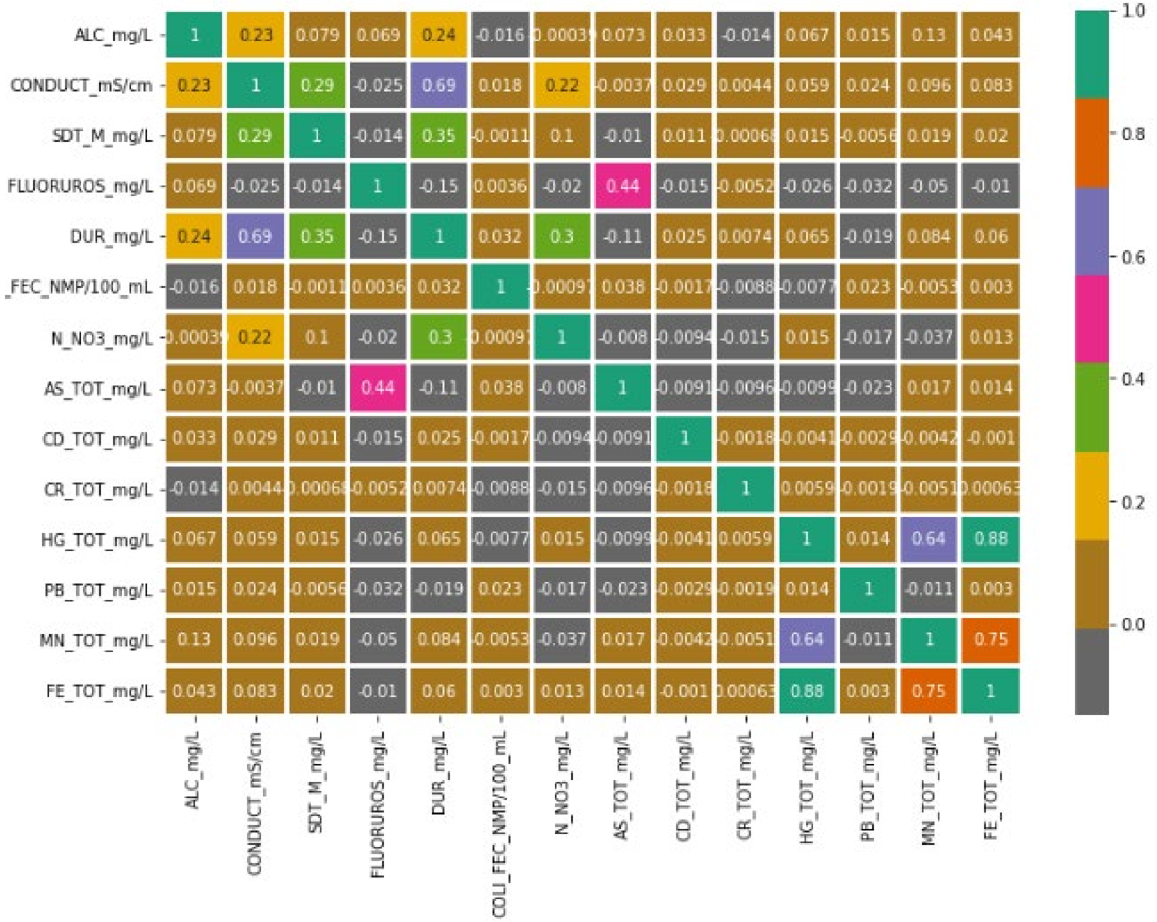
ALC_mg/L	111.147849
CONDUCT_mS/cm	1248.990617
SDT_M_mg/L	2765.757924
FLUORUROS_mg/L	1.931204
DUR_mg/L	360.960153
COLI_FEC_NMP/100_mL	2065.705773
N_NO3_mg/L	8.378332
AS_TOT_mg/L	0.035051
CD_TOT_mg/L	0.000900
CR_TOT_mg/L	0.155412
HG_TOT_mg/L	0.000470
PB_TOT_mg/L	0.003276
MN_TOT_mg/L	0.378856
FE_TOT_mg/L	5.574307

Outliers

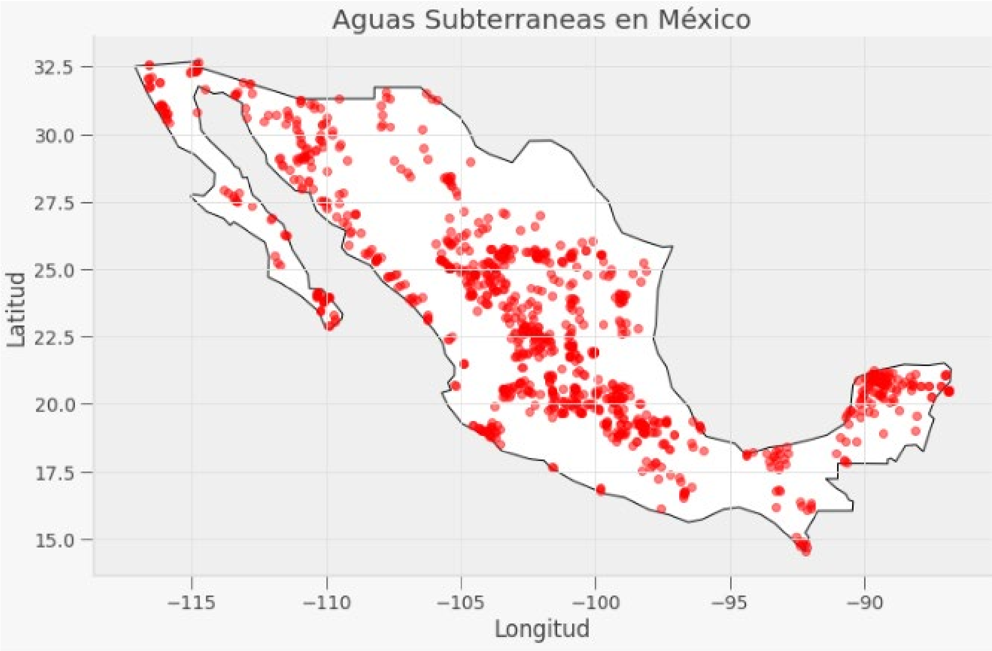


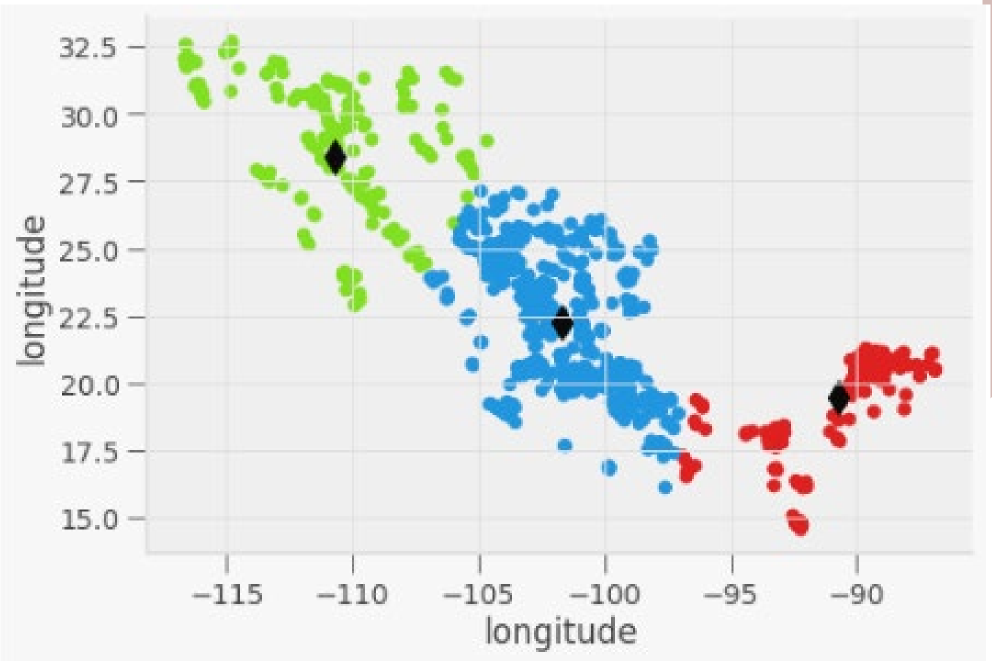


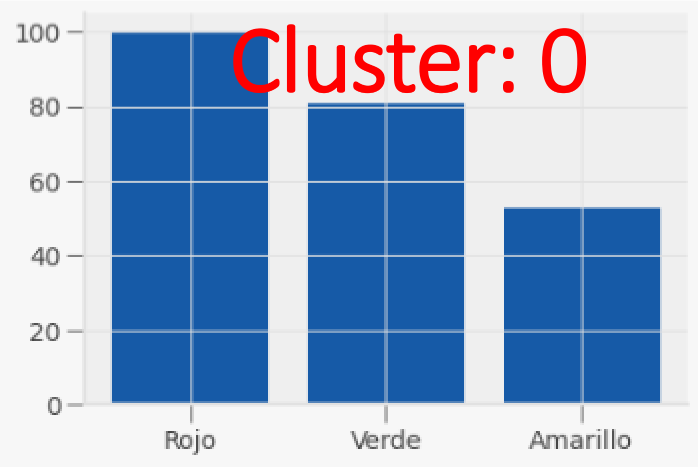
Correlaciones



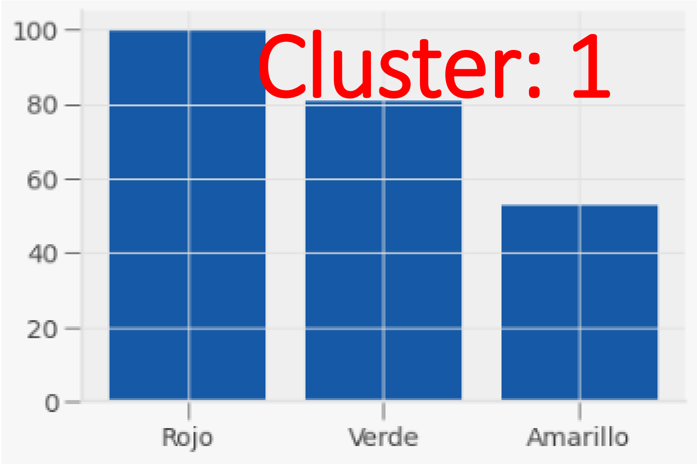
K-MEANS: Análisis



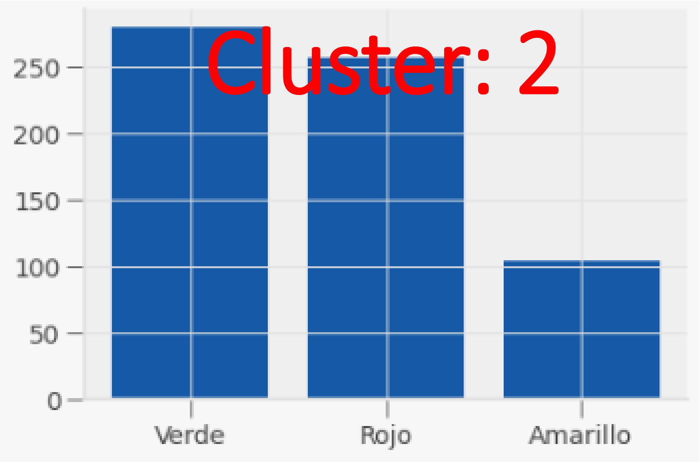




[100, 81, 53]



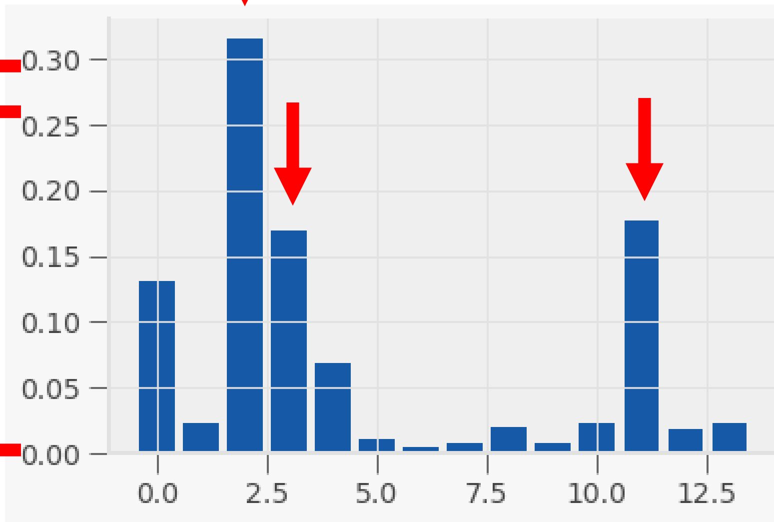
[100, 81, 53]

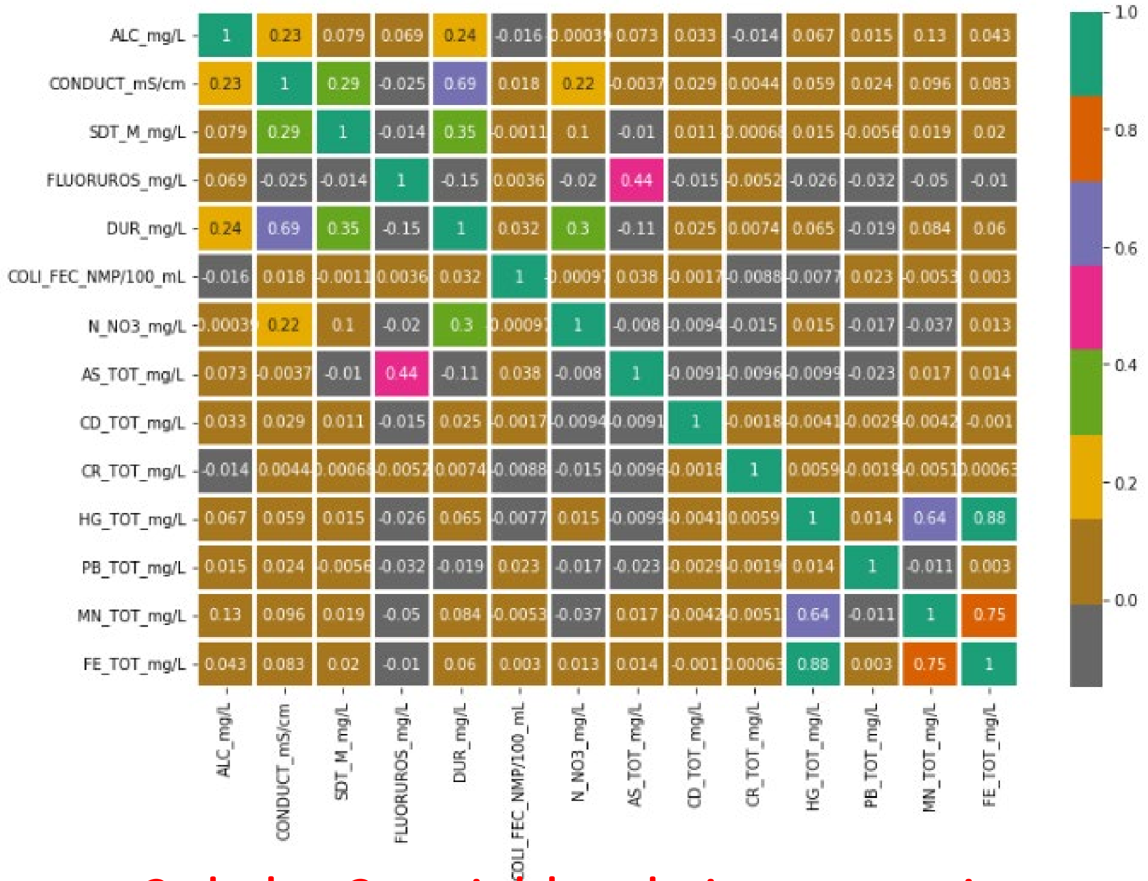


[280, 257, 104]

▪ Análisis de Características de Importancia

```
Feature: 0, Score: 0.13077
Feature: 1, Score: 0.02305
Feature: 2, Score: 0.31446
Feature: 3, Score: 0.16901
Feature: 4, Score: 0.06828
Feature: 5, Score: 0.01115
Feature: 6, Score: 0.00512
Feature: 7, Score: 0.00857
Feature: 8, Score: 0.01987
Feature: 9, Score: 0.00812
Feature: 10, Score: 0.02312
Feature: 11, Score: 0.17730
Feature: 12, Score: 0.01812
Feature: 13, Score: 0.02306
```





Variables de Importancia:

- SDT_M_mg/L
- FLUORUROS_mg/L
- PB_TOT_mg/L

2 de las 3 variables de importancia seleccionadas se encuentran en la grafica de correlación: SDT_M_mg/L, FLUORUROS_mg/L

Entrenamiento de los Clasificadores y Métricas

```
# Crea el Arbol de Decisión
mdl_dt = DecisionTreeClassifier()

# Entrena el Clasificador de Arbol de Decisión
clf = mdl_dt.fit(X_train,y_train)

#Realiza Predicciones con los Datos de Prueba
y_pred = mdl_dt.predict(X_test)
```

```
#Crea el Bosque Aleatorio
mdl_rf=RandomForestClassifier(n_estimators=100)

#Entrena el Clasificador de Bosque Aleatorio
mdl_rf.fit(X_train,y_train)

#Realiza Predicciones con los Datos de Prueba
y_pred=mdl_rf.predict(X_test)
```

Métricas del Árbol de Decisión

Accuracy: 0.985781990521327

	precision	recall	f1-score	support
clase 0	0.97	0.97	0.97	40
clase 1	0.99	0.97	0.98	73
clase 2	0.99	1.00	0.99	98
accuracy			0.99	211
macro avg	0.98	0.98	0.98	211
weighted avg	0.99	0.99	0.99	211

Este modelo presenta mejores métricas

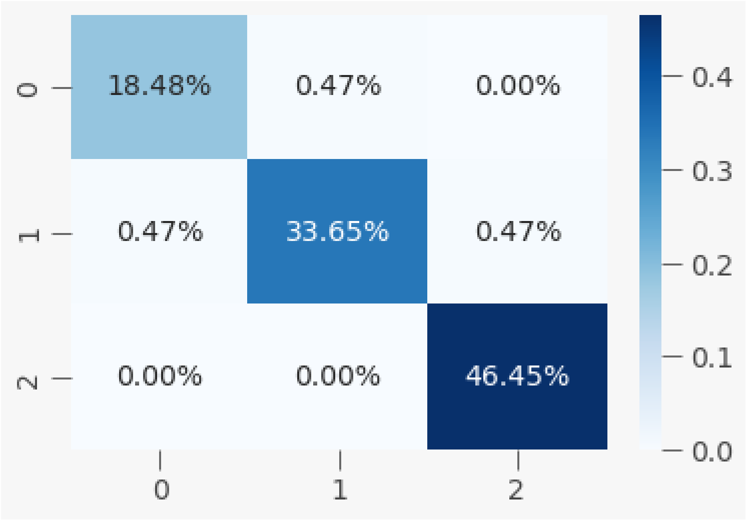
Métricas del Bosque Aleatorio

Accuracy: 0.9715639810426541

	precision	recall	f1-score	support
clase 0	0.95	0.97	0.96	40
clase 1	0.97	0.96	0.97	73
clase 2	0.98	0.98	0.98	98
accuracy			0.97	211
macro avg	0.97	0.97	0.97	211
weighted avg	0.97	0.97	0.97	211

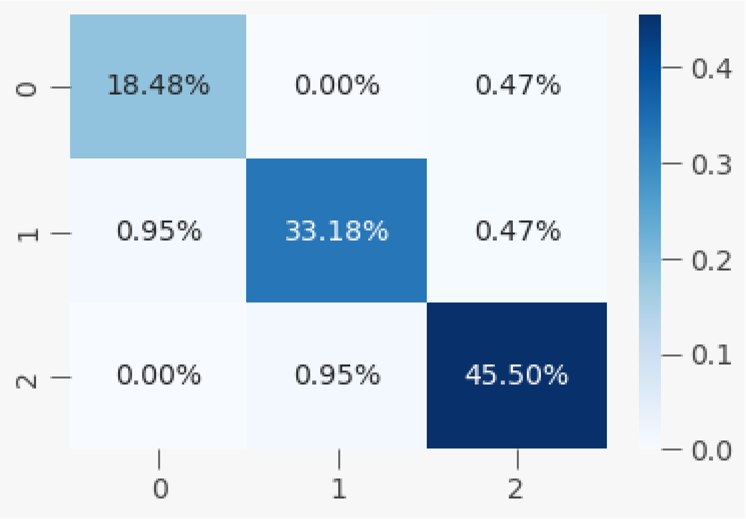
Matriz de Confusión

Árbol de Decisión



El modelo no tiene dificultad con la clase rojo, presenta mayor dificultad en clasificar la clase amarillo, y menos al clasificar la clase verde .

Bosque Aleatorio



El modelo tiene cierta dificultad al clasificar la clase rojo y verde. Mientras en la clase amarillo presenta una dificultad mayor.

Conclusiones

- Aproximadamente 40% de las aguas subterráneas son adecuadas para consumo, mientras que el 60% no son adecuadas, debido a que encuentra presente algún contaminante.
- HG_TOT_mg/L, MN_TOT_mg/L y FE_TOT_mg/L son las variables que presentan las correlaciones con mayor índice, en la grafica de correlación.
- Existe una correlación entre la calidad de agua y su ubicación geográfica como lo muestra K-MMEANS.
- Las variables SDT_M_mg/L, FLUORUROS_mg/L, del análisis de importancia se encuentran presentes en la grafica de correlaciones.
- El modelo de Árbol de Decisión presenta una exactitud del 99%, mientras que el modelo de Bosque Aleatorio presenta una exactitud de 97%.
- El modelo de Árbol de Decisión se confunde menos con las diferentes clases en comparación con el Bosque Aleatorio, como se aprecia en las matrices de confusión.