SCRIPT PREDICCION PARTE 2

June 8, 2023

[1]:
```
import pandas as pd
import numpy as np
import math
import warnings
warnings.filterwarnings("ignore")
```

[2]:
```
df = pd.read_pickle('df.pkl')
df
```

[2]:
```
      CAMPAÑA  ID_FINCA  ID_ZONA  ID_ESTACION     ALTITUD  VARIEDAD  MODO  \
0          14     76953      515            4  660.000000        26     2
1          14     84318      515            4  660.000000        26     2
2          14     85579      340            4  520.000000        32     2
3          14     69671      340            4  520.000000        32     2
4          14     14001      852           14  659.097938        81     1
…         …        …        …          …           …       …     …
9596       22     37461      239            6  700.000000        52     2
9597       22     58769      239            6  700.000000        32     2
9598       22     58769      239            6  700.000000        59     2
9599       22     88928      239            6  700.000000        40     2
9600       22     88928      239            6  700.000000        52     2

      TIPO  COLOR  SUPERFICIE  PRODUCCION
0        0      1    4.902003     22215.0
1        0      1    4.633973     22215.0
2        0      1    4.995608     20978.0
3        0      1    7.126296     40722.0
4        0      1    4.354864     14126.0
…      …     …          …           …
9596     0      1    3.680000         NaN
9597     0      1    4.250000         NaN
9598     0      1    4.070000         NaN
9599     0      1    4.572700         NaN
9600     0      1    1.609900         NaN

[9601 rows x 11 columns]
```

La estrategia que vamos a desarrollar va a ser codificar la variable ID_ESTACION por la media para cada estacion de la variable meteorológica que más correlación tenga con la variable PRODUCCION

[3]:
```
#Definimos una funcion para meter las variables meteorológicas de interés
def metervariables(df):
    meses=['enero', 'febrero', 'marzo', 'abril', 'mayo', 'junio']
    for m in range(len(meses)):
        precip_col = f"precip_{meses[m]}"
        df[precip_col] = np.nan

    # Rellenamos los valores de precip_mes en función de CAMPAÑA y ID_ESTACION
    for c in range(16, 23):
        for e in range(20):
            for m in range(6):
                precip_mes = globals()[f"precip_mes_{c}"][e][m]
                mes_index = meses[m]
                precip_col = f"precip_{mes_index}"
                df.loc[(df['CAMPAÑA'] == c) & (df['ID_ESTACION'] == e),␣
↪precip_col] = precip_mes

    for m in range(len(meses)):
        windspeed_col = f"windspeed_{meses[m]}"
        df[windspeed_col] = np.nan

    # Rellenamos los valores de windspeed_mes en función de CAMPAÑA y␣
↪ID_ESTACION
    for c in range(16, 23):
        for e in range(20):
            for m in range(6):
                windspeed_mes = globals()[f"windspeed_mes_{c}"][e][m]
                mes_index = meses[m]
                windspeed_col = f"windspeed_{mes_index}"
                df.loc[(df['CAMPAÑA'] == c) & (df['ID_ESTACION'] == e),␣
↪windspeed_col] = windspeed_mes

    # Rellenamos los valores de temp_mes en función de CAMPAÑA y ID_ESTACION
    for m in range(len(meses)):
        temp_col = f"t_mes_{meses[m]}"
        df[temp_col] = np.nan
    for c in range(16, 23):
        for e in range(20):
            for m in range(6):
                temp_mes = globals()[f"t_mes_{c}"][e][m]
                mes_index = meses[m]
                temp_col = f"t_mes_{mes_index}"
                df.loc[(df['CAMPAÑA'] == c) & (df['ID_ESTACION'] == e),␣
↪temp_col] = temp_mes
    for m in range(len(meses)):
```

```
        rhum_col = f"rhum_mes_{meses[m]}"
        df[rhum_col] = np.nan
    for c in range(16, 23):
        for e in range(20):
            for m in range(6):
                rhum_mes = globals()[f"rhum_mes_{c}"][e][m]
                mes_index = meses[m]
                rhum_col = f"rhum_mes_{mes_index}"
                df.loc[(df['CAMPAÑA'] == c) & (df['ID_ESTACION'] == e),␣
↪rhum_col] = rhum_mes
    return df
```

[4]:

```
#Importamos las variables
import pickle

with open('rhum_mes_16.pkl', 'rb') as file:
    rhum_mes_16 = pickle.load(file)

with open('rhum_mes_17.pkl', 'rb') as file:
    rhum_mes_17 = pickle.load(file)

with open('rhum_mes_18.pkl', 'rb') as file:
    rhum_mes_18 = pickle.load(file)

with open('rhum_mes_19.pkl', 'rb') as file:
    rhum_mes_19 = pickle.load(file)

with open('rhum_mes_20.pkl', 'rb') as file:
    rhum_mes_20 = pickle.load(file)

with open('rhum_mes_21.pkl', 'rb') as file:
    rhum_mes_21 = pickle.load(file)

with open('rhum_mes_22.pkl', 'rb') as file:
    rhum_mes_22 = pickle.load(file)

with open('windspeed_mes_16.pkl', 'rb') as file:
    windspeed_mes_16 = pickle.load(file)

with open('windspeed_mes_17.pkl', 'rb') as file:
    windspeed_mes_17 = pickle.load(file)

with open('windspeed_mes_18.pkl', 'rb') as file:
    windspeed_mes_18 = pickle.load(file)

with open('windspeed_mes_19.pkl', 'rb') as file:
    windspeed_mes_19 = pickle.load(file)
```

```
with open('windspeed_mes_20.pkl', 'rb') as file:
    windspeed_mes_20 = pickle.load(file)

with open('windspeed_mes_21.pkl', 'rb') as file:
    windspeed_mes_21 = pickle.load(file)

with open('windspeed_mes_22.pkl', 'rb') as file:
    windspeed_mes_22 = pickle.load(file)

with open('t_mes_15.pkl', 'rb') as file:
    t_mes_15 = pickle.load(file)

with open('t_mes_16.pkl', 'rb') as file:
    t_mes_16 = pickle.load(file)

with open('t_mes_17.pkl', 'rb') as file:
    t_mes_17 = pickle.load(file)

with open('t_mes_18.pkl', 'rb') as file:
    t_mes_18 = pickle.load(file)

with open('t_mes_19.pkl', 'rb') as file:
    t_mes_19 = pickle.load(file)

with open('t_mes_20.pkl', 'rb') as file:
    t_mes_20 = pickle.load(file)

with open('t_mes_21.pkl', 'rb') as file:
    t_mes_21 = pickle.load(file)

with open('t_mes_22.pkl', 'rb') as file:
    t_mes_22 = pickle.load(file)

with open('precip_mes_16.pkl', 'rb') as file:
    precip_mes_16 = pickle.load(file)

with open('precip_mes_17.pkl', 'rb') as file:
    precip_mes_17 = pickle.load(file)

with open('precip_mes_18.pkl', 'rb') as file:
    precip_mes_18 = pickle.load(file)

with open('precip_mes_19.pkl', 'rb') as file:
    precip_mes_19 = pickle.load(file)

with open('precip_mes_20.pkl', 'rb') as file:
```

```
    precip_mes_20 = pickle.load(file)

with open('precip_mes_21.pkl', 'rb') as file:
    precip_mes_21 = pickle.load(file)

with open('precip_mes_22.pkl', 'rb') as file:
    precip_mes_22 = pickle.load(file)
```

[5]:
```
#Creamos un dataframe df2 donde metemos las variables meteorológicas
df2=metervariables(df)
df = pd.read_pickle('df.pkl')
```

[6]:
```
#Estación 4
#Para la estación 4, no hay informacion para muchas de las variables␣
↪meteorológicas
df2[df2['ID_ESTACION']==4]
```

[6]:
```
   CAMPAÑA  ID_FINCA  ID_ZONA  ID_ESTACION  ALTITUD  VARIEDAD  MODO  TIPO  \
0       14     76953      515            4    660.0        26     2     0
1       14     84318      515            4    660.0        26     2     0
2       14     85579      340            4    520.0        32     2     0
3       14     69671      340            4    520.0        32     2     0

   COLOR  SUPERFICIE  …  t_mes_marzo  t_mes_abril  t_mes_mayo  t_mes_junio  \
0      1    4.902003  …          NaN          NaN         NaN          NaN
1      1    4.633973  …          NaN          NaN         NaN          NaN
2      1    4.995608  …          NaN          NaN         NaN          NaN
3      1    7.126296  …          NaN          NaN         NaN          NaN

   rhum_mes_enero  rhum_mes_febrero  rhum_mes_marzo  rhum_mes_abril  \
0             NaN               NaN             NaN             NaN
1             NaN               NaN             NaN             NaN
2             NaN               NaN             NaN             NaN
3             NaN               NaN             NaN             NaN

   rhum_mes_mayo  rhum_mes_junio
0            NaN             NaN
1            NaN             NaN
2            NaN             NaN
3            NaN             NaN

[4 rows x 35 columns]
```

[7]:
```
#Como son solo 4 observaciones decidimos eliminarlas
df = df.drop(df[df['ID_ESTACION'] == 4].index)
df2 = df2.drop(df2[df2['ID_ESTACION'] == 4].index)
```

```
[8]: #Definimos una función que calcule la media de las varaibles meteorológicas␣
 ↪para cada ID_ESTACION en los meses enero-junio
def calcular_variable_media(df,columnas_meses):
    # Filtrar el DataFrame para mantener solo las columnas de los meses de␣
 ↪enero a junio y la columna 'ID_ESTACION'
    df_filt = df[columnas_meses + ['ID_ESTACION']].copy()

    # Calcular la temperatura media para cada valor de ID_ESTACION
    df_media_temperaturas = df_filt.groupby('ID_ESTACION')[columnas_meses].
 ↪mean()
    df_media_temperaturas = df_media_temperaturas.reset_index()

    return df_media_temperaturas
```

Aplicamos la funcion anterior y vamos metiendo los resultados obtenidos en nuestro dataframe:

```
[9]: df_media=calcular_variable_media(df2, columnas_meses = ['windspeed_enero',␣
 ↪'windspeed_febrero', 'windspeed_marzo', 'windspeed_abril', 'windspeed_mayo',␣
 ↪'windspeed_junio'])
```

```
[10]: encoded_id_estacion=df_media.groupby('ID_ESTACION').mean().mean(axis=1).
 ↪reset_index(name='windspeed_media')
encoded_id_estacion
```

[10]:

	ID_ESTACION	windspeed_media
0	0	8.055134
1	1	13.853971
2	2	10.309313
3	3	12.022968
4	5	10.712688
5	6	11.664805
6	7	11.258397
7	8	12.295432
8	9	10.534987
9	10	10.132563
10	11	10.211159
11	12	11.647173
12	13	12.026949
13	14	12.172118
14	15	11.849458
15	16	10.843103
16	17	12.523165
17	18	10.417981
18	19	10.871163

```
[11]: df['windspeed_media'] = df['ID_ESTACION'].map(encoded_id_estacion.
 ↪set_index('ID_ESTACION')['windspeed_media'])
```

[12]:
```
df_media_temperaturas=calcular_variable_media(df2, columnas_meses =␣
↪['t_mes_enero', 't_mes_febrero', 't_mes_marzo', 't_mes_abril', 't_mes_mayo',␣
↪'t_mes_junio'])
```

[13]:
```
encoded_id_estacion=df_media_temperaturas.groupby('ID_ESTACION').mean().
↪mean(axis=1).reset_index(name='tmedia')
encoded_id_estacion
```

[13]:

	ID_ESTACION	tmedia
0	0	14.287836
1	1	11.802972
2	2	13.947971
3	3	12.972376
4	5	12.963303
5	6	12.589099
6	7	13.316537
7	8	12.737542
8	9	13.657491
9	10	14.182774
10	11	13.752891
11	12	13.713871
12	13	13.119273
13	14	12.094942
14	15	12.587852
15	16	12.946614
16	17	12.394114
17	18	12.946488
18	19	13.676968

[14]:
```
df['t_media'] = df['ID_ESTACION'].map(encoded_id_estacion.
↪set_index('ID_ESTACION')['tmedia'])
```

[15]:
```
df_media=calcular_variable_media(df2, columnas_meses = ['rhum_mes_enero',␣
↪'rhum_mes_febrero', 'rhum_mes_marzo', 'rhum_mes_abril', 'rhum_mes_mayo',␣
↪'rhum_mes_junio'])
```

[16]:
```
encoded_id_estacion=df_media.groupby('ID_ESTACION').mean().mean(axis=1).
↪reset_index(name='rhum_media')
encoded_id_estacion
```

[16]:

	ID_ESTACION	rhum_media
0	0	68.650047
1	1	65.857631
2	2	64.302105
3	3	66.280790
4	5	66.633674
5	6	66.438743

```
6             7   65.982460
7             8   66.031945
8             9   65.956254
9            10   65.434847
10           11   64.647435
11           12   65.781480
12           13   65.082082
13           14   66.492972
14           15   66.012340
15           16   66.640886
16           17   67.463580
17           18   66.513244
18           19   66.100459
```

[17]:
```
df['rhum_media'] = df['ID_ESTACION'].map(encoded_id_estacion.
 ↪set_index('ID_ESTACION')['rhum_media'])
```

[18]:
```
df_media=calcular_variable_media(df2, columnas_meses = ['precip_enero',␣
 ↪'precip_febrero', 'precip_marzo', 'precip_abril', 'precip_mayo',␣
 ↪'precip_junio'])
```

[19]:
```
encoded_id_estacion=df_media.groupby('ID_ESTACION').mean().mean(axis=1).
 ↪reset_index(name='precip_media')
encoded_id_estacion
```

[19]:
```
    ID_ESTACION  precip_media
0             0     65.166667
1             1     55.575000
2             2     39.023481
3             3     40.346064
4             5     41.422958
5             6     55.656785
6             7     39.262180
7             8     38.912033
8             9     40.980680
9            10     49.085008
10           11     40.451190
11           12     40.099020
12           13     39.370690
13           14     40.389625
14           15     38.996225
15           16     41.668350
16           17     35.540517
17           18     44.177987
18           19     39.823795
```

[20]:
```
df['precip_media'] = df['ID_ESTACION'].map(encoded_id_estacion.
↪set_index('ID_ESTACION')['precip_media'])
```

Una variable que no incluimos en nuestros modelos anteriores y que podría ser relevante es el índice de radiación ultravioleta. Acudimos a la base de datos de Meteo para obtener información sobre esta variable.

[21]:
```
meteo = pd.read_csv('DATOS_METEO.txt', delimiter='|')
```

[22]:
```
# Creamos columnas separadas para el año, mes, día y hora
meteo['validTimeUtc'] = pd.to_datetime(meteo['validTimeUtc'])

meteo['año'] = meteo['validTimeUtc'].dt.year
meteo['mes'] = meteo['validTimeUtc'].dt.month
meteo['dia'] = meteo['validTimeUtc'].dt.day
meteo['hora'] = meteo['validTimeUtc'].dt.hour

meteo
```

[22]:
```
                validTimeUtc  precip1Hour  precip6Hour  precip24Hour  \
0        2015-06-29 16:20:00          0.0          0.0           0.0
1        2015-06-29 17:20:00          0.0          0.0           0.0
2        2015-06-29 18:20:00          0.0          0.0           0.0
3        2015-06-29 19:20:00          0.0          0.0           0.0
4        2015-06-29 20:20:00          0.0          0.0           0.0
…                      …           …           …            …
1223655 2022-06-30 19:20:00          0.0          0.0           0.0
1223656 2022-06-30 20:20:00          0.0          0.0           0.0
1223657 2022-06-30 21:20:00          0.0          0.0           0.0
1223658 2022-06-30 22:20:00          0.0          0.0           0.0
1223659 2022-06-30 23:20:00          0.0          0.0           0.0

         precip2Day  precip3Day  precip7Day  precipMtd  precipYtd  \
0               NaN         NaN         NaN        NaN        NaN
1               NaN         NaN         NaN        NaN        NaN
2               NaN         NaN         NaN        NaN        NaN
3               NaN         NaN         NaN        NaN        NaN
4               NaN         NaN         NaN        NaN        NaN
…             …           …           …          …          …
1223655         0.0         0.0         2.0        9.0      238.0
1223656         0.0         0.0         2.0        9.0      238.0
1223657         0.0         0.0         2.0        9.0      238.0
1223658         0.0         0.0         2.0        9.0      238.0
1223659         0.0         0.0         2.0        9.0      238.0

         pressureChange  …  uvIndex  visibility  windDirection  windGust  \
0                  -1.4  …      2.0       16.09            NaN       NaN
1                  -1.0  …      1.0       16.09            NaN       NaN
```

```
2                  -0.3  …      0.0       16.09           NaN        NaN
3                   0.3  …      0.0       16.09           NaN        NaN
4                   0.9  …      0.0       16.09           NaN        NaN
…                    …  …     …        …            …        …
1223655             2.7  …      0.0       13.55         110.0        NaN
1223656             3.7  …      0.0       13.59          80.0        NaN
1223657             3.8  …      0.0       13.85          80.0        NaN
1223658             3.1  …      0.0       13.17          50.0        NaN
1223659             2.0  …      0.0        9.51          50.0        NaN

         windSpeed  ID_ESTACION   año  mes  dia  hora
0             18.7           13  2015    6   29    16
1             18.0           13  2015    6   29    17
2             16.6           13  2015    6   29    18
3             15.1           13  2015    6   29    19
4             10.1           13  2015    6   29    20
…              …          …   …   …   …   …
1223655       10.8            8  2022    6   30    19
1223656        9.0            8  2022    6   30    20
1223657        7.9            8  2022    6   30    21
1223658        8.3            8  2022    6   30    22
1223659       10.4            8  2022    6   30    23

[1223660 rows x 37 columns]
```

[23]:
```python
encoded_id_estacion = meteo[meteo['mes'].isin([1,2,3,4,5,6])].
 ↪groupby(['ID_ESTACION'])[['uvIndex']].mean()
encoded_id_estacion
```

[23]:
```
              uvIndex
ID_ESTACION
0            1.361512
1            1.370795
2            1.391665
3            1.365001
4            1.380275
5            1.365692
6            1.353117
7            1.368457
8            1.366779
9            1.359866
10           1.362236
11           1.384423
12           1.361512
13           1.375568
14           1.366548
15           1.369807
```

```
16          1.371914
17          1.370828
18          1.364046
19          1.365956
```

[24]:

```
#Mergeamos
df= df.merge(
    encoded_id_estacion,
    left_on='ID_ESTACION',
    right_index=True).sort_index()
df
```

[24]:

```
      CAMPAÑA  ID_FINCA  ID_ZONA  ID_ESTACION     ALTITUD  VARIEDAD  MODO  \
4          14     14001      852           14  659.097938        81     1
5          14     17059      852           14  659.097938        81     1
6          14     87611      602           14  659.097938        81     1
7          14     12257      215           14  659.097938        17     1
8          14     97286      142           14  659.097938        17     1
…         …         …        …            …           …  …
9596       22     37461      239            6  700.000000        52     2
9597       22     58769      239            6  700.000000        32     2
9598       22     58769      239            6  700.000000        59     2
9599       22     88928      239            6  700.000000        40     2
9600       22     88928      239            6  700.000000        52     2

      TIPO  COLOR  SUPERFICIE  PRODUCCION  windspeed_media    t_media  \
4        0      1    4.354864     14126.0        12.172118  12.094942
5        0      1    2.773533      6054.0        12.172118  12.094942
6        0      1    5.377166     12900.0        12.172118  12.094942
7        0      1    2.148042      5450.0        12.172118  12.094942
8        0      1    5.390867     30720.0        12.172118  12.094942
…     …     …           …         …              …         …
9596     0      1    3.680000         NaN        11.664805  12.589099
9597     0      1    4.250000         NaN        11.664805  12.589099
9598     0      1    4.070000         NaN        11.664805  12.589099
9599     0      1    4.572700         NaN        11.664805  12.589099
9600     0      1    1.609900         NaN        11.664805  12.589099

      rhum_media  precip_media   uvIndex
4      66.492972     40.389625  1.366548
5      66.492972     40.389625  1.366548
6      66.492972     40.389625  1.366548
7      66.492972     40.389625  1.366548
8      66.492972     40.389625  1.366548
…            …            …        …
9596   66.438743     55.656785  1.353117
9597   66.438743     55.656785  1.353117
```

```
9598   66.438743     55.656785  1.353117
9599   66.438743     55.656785  1.353117
9600   66.438743     55.656785  1.353117

[9597 rows x 16 columns]
```

Ahora vamos a ver variable meteorológica está más correlacionada con la Produccion.

[25]:
```
correlations = df.corr()['PRODUCCION'].drop('PRODUCCION')
sorted_correlations = correlations.abs().sort_values(ascending=False)
sorted_correlations
```

[25]:
```
SUPERFICIE         0.758146
MODO               0.270606
precip_media       0.181404
ALTITUD            0.146438
windspeed_media    0.131001
uvIndex            0.130138
t_media            0.117513
rhum_media         0.088291
ID_ESTACION        0.079442
ID_FINCA           0.042188
COLOR              0.041029
VARIEDAD           0.035179
TIPO               0.032299
ID_ZONA            0.032092
CAMPAÑA            0.027473
Name: PRODUCCION, dtype: float64
```

Vamos a usar F-test y mutual information para captar relaciones no lineales

[26]:
```
from sklearn.feature_selection import f_regression, mutual_info_regression
import warnings
import matplotlib.pyplot as plt
warnings.filterwarnings("ignore")
```

[27]:
```
# convertimos el DataFrame al formato necesario para scikit-learn
datos=df[df['CAMPAÑA'] != 22]
datos=datos.
 ↪drop(['CAMPAÑA','ID_FINCA','ID_ZONA','ID_ESTACION','ALTITUD','VARIEDAD','MODO','TIPO','COLO
datos
```

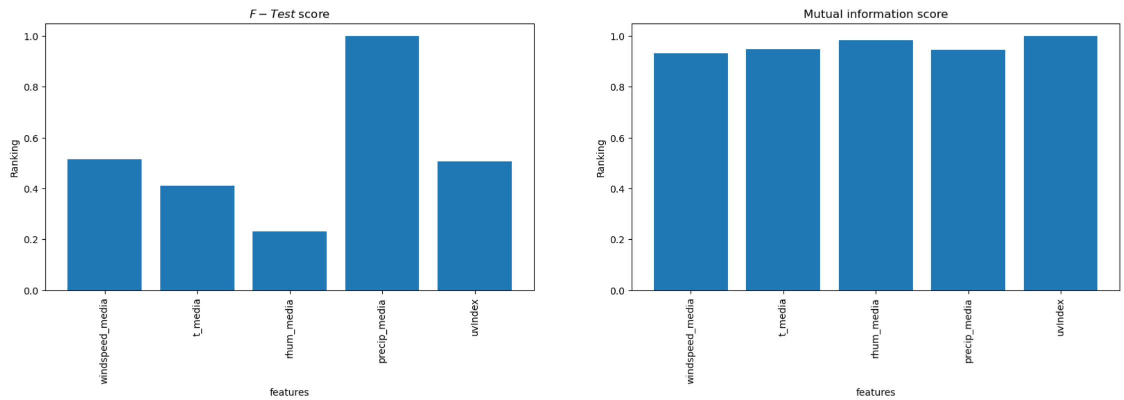
[27]:
```
      PRODUCCION  windspeed_media    t_media  rhum_media  precip_media  \
4        14126.0        12.172118  12.094942   66.492972     40.389625
5         6054.0        12.172118  12.094942   66.492972     40.389625
6        12900.0        12.172118  12.094942   66.492972     40.389625
7         5450.0        12.172118  12.094942   66.492972     40.389625
8        30720.0        12.172118  12.094942   66.492972     40.389625
```

```
…       …            …         …          …            …
8521    28160.1      11.664805  12.589099  66.438743    55.656785
8522    41310.0      11.664805  12.589099  66.438743    55.656785
8523    45420.0      11.664805  12.589099  66.438743    55.656785
8524    56140.0      11.664805  12.589099  66.438743    55.656785
8525    13869.9      11.664805  12.589099  66.438743    55.656785

       uvIndex
4     1.366548
5     1.366548
6     1.366548
7     1.366548
8     1.366548
…          …
8521  1.353117
8522  1.353117
8523  1.353117
8524  1.353117
8525  1.353117

[8522 rows x 6 columns]
```

[28]:
```
data = datos.values
```

[29]:
```
y = data[:,0:1]      #  Produccion
X = data[:,1:]       # el resto de variables meteorológicas

feature_names = datos.columns[1:]



# do calculations
f_test, _ = f_regression(X, y)
f_test /= np.max(f_test)

mi = mutual_info_regression(X, y)
mi /= np.max(mi)

# do some plotting
plt.figure(figsize=(20, 5))

plt.subplot(1,2,1)
plt.bar(range(X.shape[1]),f_test,  align="center")
plt.xticks(range(X.shape[1]),feature_names, rotation = 90)
plt.xlabel('features')
plt.ylabel('Ranking')
plt.title('$F-Test$ score')
```

```python
plt.subplot(1,2,2)
plt.bar(range(X.shape[1]),mi, align="center")
plt.xticks(range(X.shape[1]),feature_names, rotation = 90)
plt.xlabel('features')
plt.ylabel('Ranking')
plt.title('Mutual information score')

plt.show()
```



[30]:
```python
#Vamos a utilizar para codificar ID_ESTACION la variable precip_media
```

[31]:
```python
df=df.
↪drop(['t_media','rhum_media','uvIndex','ID_ESTACION','windspeed_media'],axis=1)
```

[32]:
```python
df
```

[32]:
```
      CAMPAÑA  ID_FINCA  ID_ZONA     ALTITUD  VARIEDAD  MODO  TIPO  COLOR  \
4          14     14001      852  659.097938        81     1     0      1
5          14     17059      852  659.097938        81     1     0      1
6          14     87611      602  659.097938        81     1     0      1
7          14     12257      215  659.097938        17     1     0      1
8          14     97286      142  659.097938        17     1     0      1
…         …        …       …          …         …    …    …     …
9596       22     37461      239  700.000000        52     2     0      1
9597       22     58769      239  700.000000        32     2     0      1
9598       22     58769      239  700.000000        59     2     0      1
9599       22     88928      239  700.000000        40     2     0      1
9600       22     88928      239  700.000000        52     2     0      1

      SUPERFICIE  PRODUCCION  precip_media
4       4.354864     14126.0     40.389625
5       2.773533      6054.0     40.389625
6       5.377166     12900.0     40.389625
```

```
7       2.148042      5450.0     40.389625
8       5.390867     30720.0     40.389625
…          …         …           …
9596    3.680000         NaN     55.656785
9597    4.250000         NaN     55.656785
9598    4.070000         NaN     55.656785
9599    4.572700         NaN     55.656785
9600    1.609900         NaN     55.656785

[9597 rows x 11 columns]
```

0.1 Estudio de Outliers

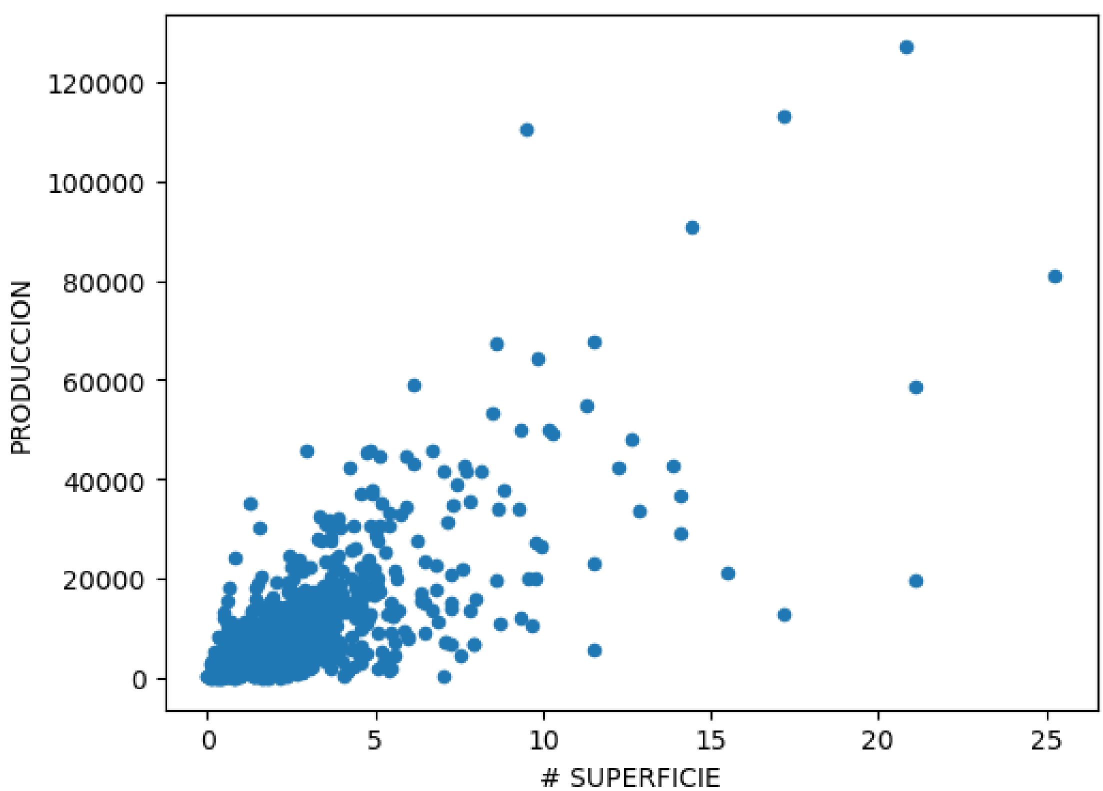
[33]:
```
import matplotlib.pyplot as plt
import seaborn as sns
```

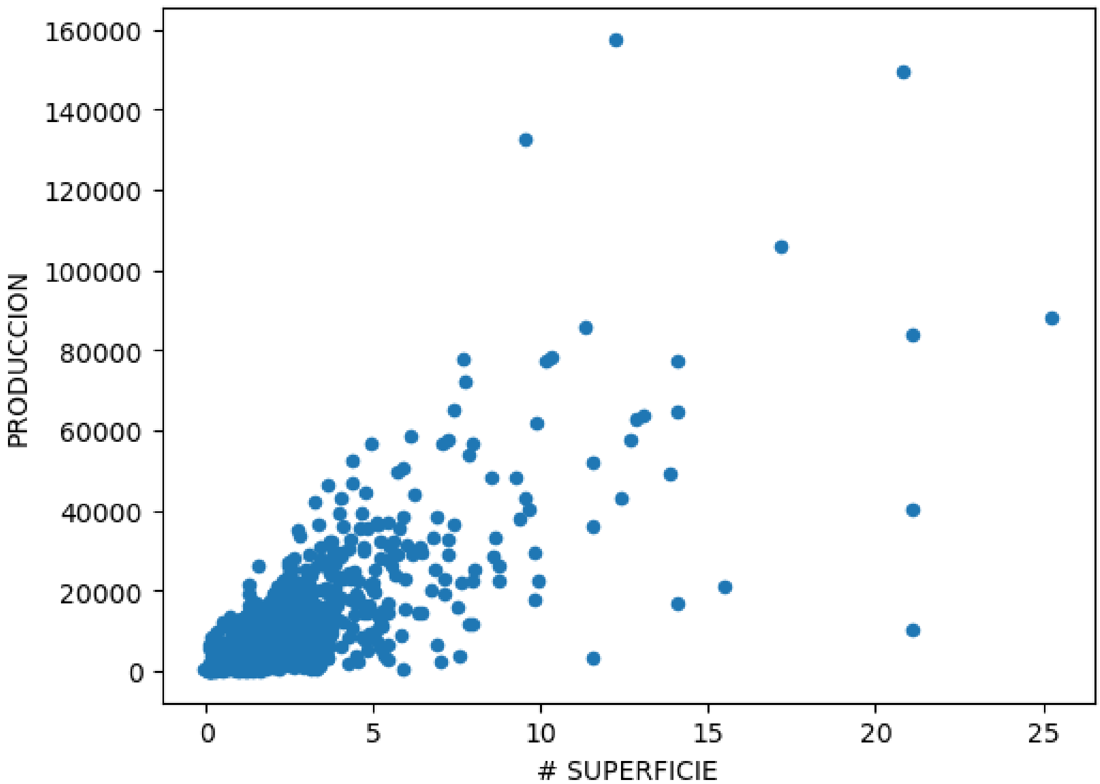
[34]:
```
df14=df[df['CAMPAÑA']==14]
df15=df[df['CAMPAÑA']==15]
df16=df[df['CAMPAÑA']==16]
df17=df[df['CAMPAÑA']==17]
df18=df[df['CAMPAÑA']==18]
df19=df[df['CAMPAÑA']==19]
df20=df[df['CAMPAÑA']==20]
df21=df[df['CAMPAÑA']==21]
```

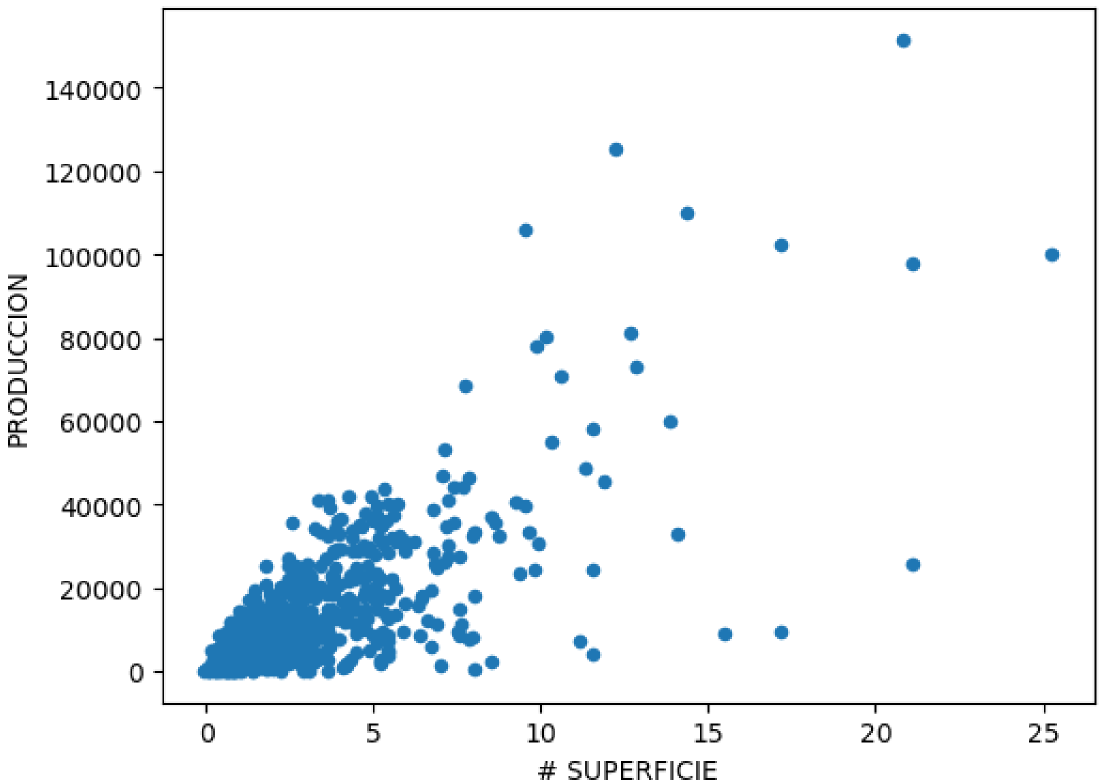
La metodología para el estudio de posibles outliers será la siguiente: - Dibujamos scatterplots para las variables que mayor correlación presentan con la variable a predecir (PRODUCCIÓN) en los distintos años. - Vemos si las observaciones que pueden ser consideradas outliers se mantienen todos los años o solo en años concretos. - Si se mantienen los mismos patrones todos los años, no las imputamos. - En caso contrario, las imputamos.

[35]:
```
#Grafico x=SUPERFICIE
df14.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()

df15.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()

df16.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()

df17.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
```

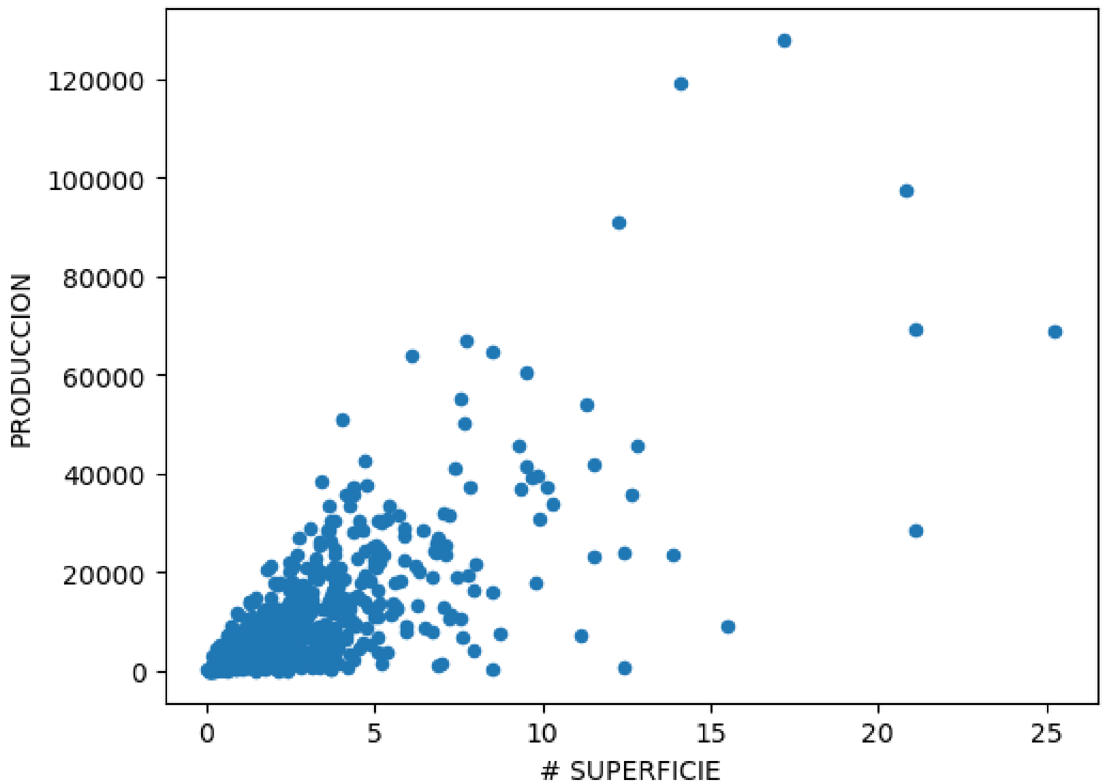
```
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()

df18.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()

df19.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()

df20.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()

df21.plot(kind = 'scatter',x='SUPERFICIE',y = 'PRODUCCION')
plt.xlabel('# SUPERFICIE')
plt.ylabel('PRODUCCION')
plt.show()
```



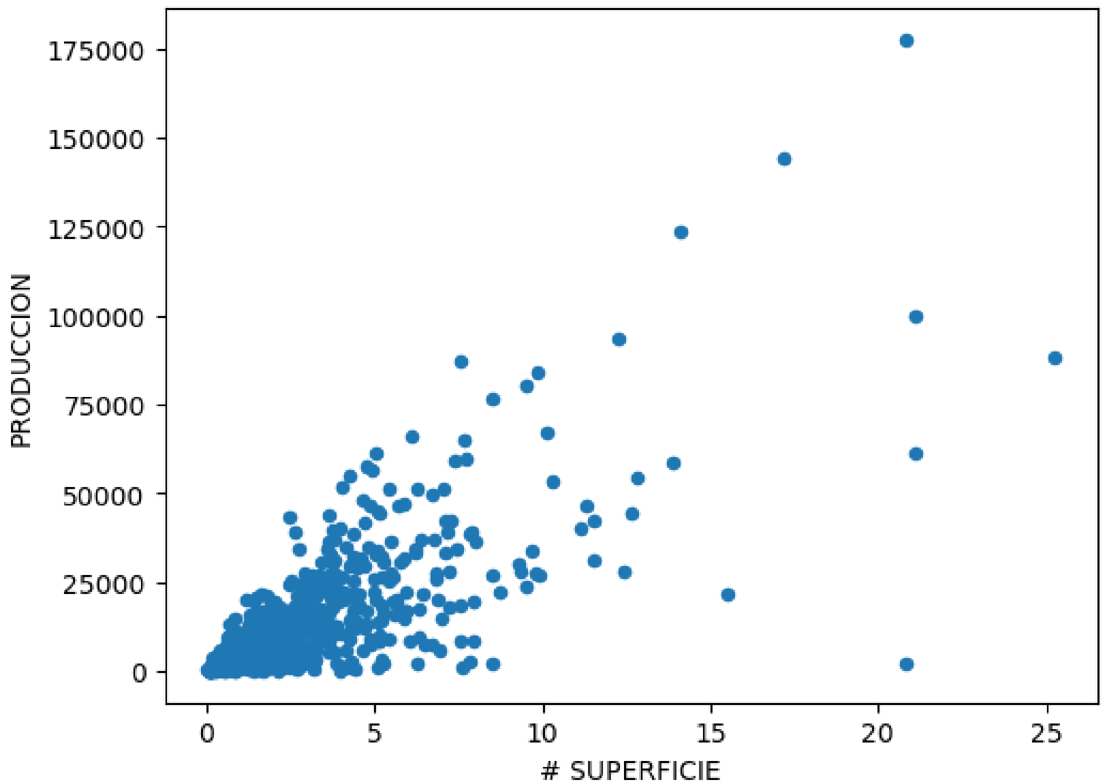

160000
140000
120000
100000
80000
60000
40000
20000
0
PRODUCCION
0
5
10
15
20
25
SUPERFICIE

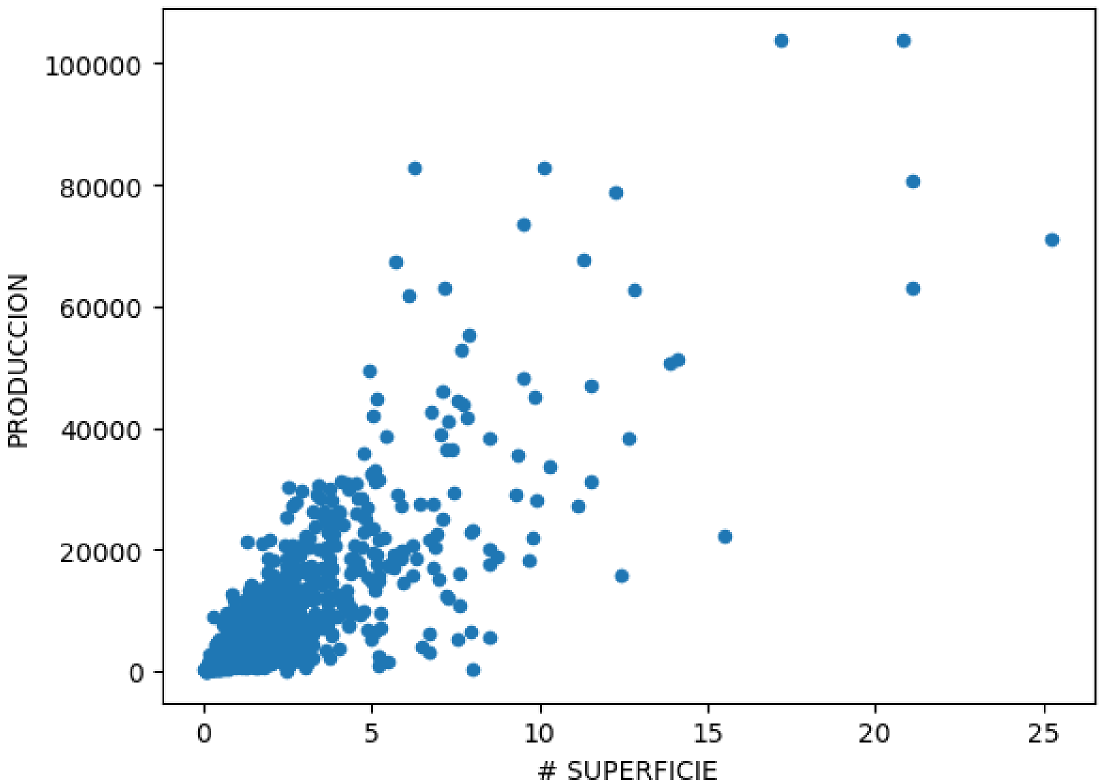


140000
120000
100000
80000
60000
40000
20000
0
PRODUCCION
0
5
10
15
20
25
SUPERFICIE

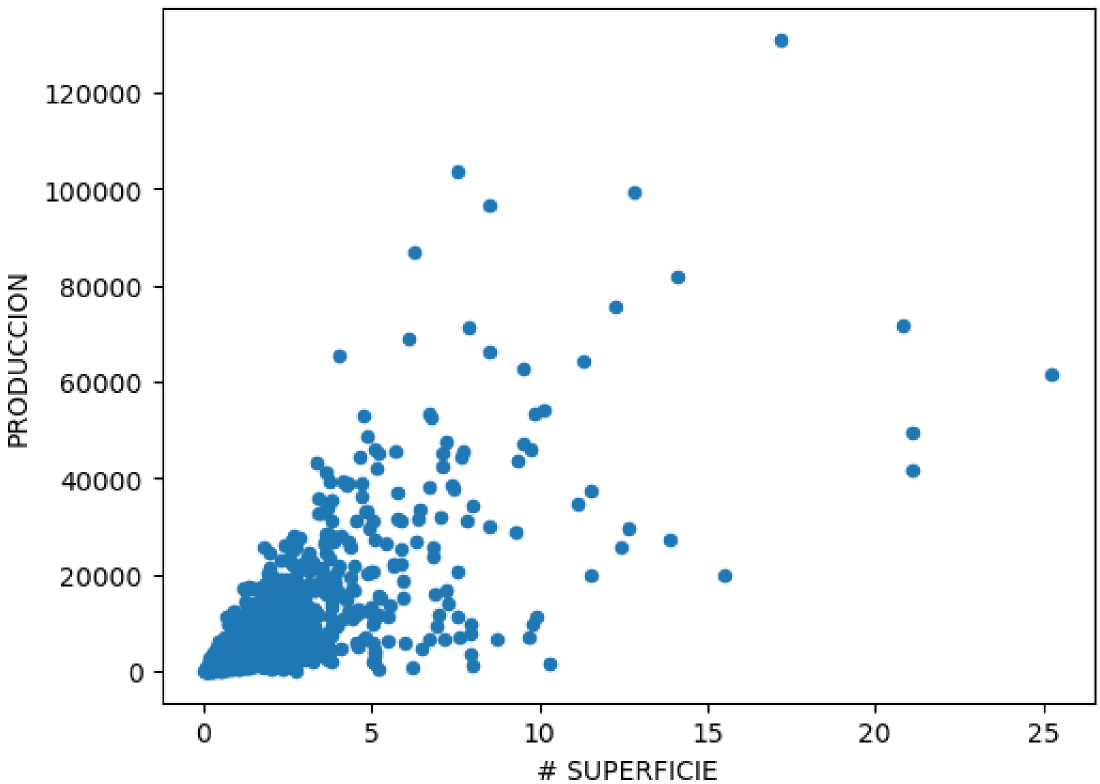


120000
100000
80000
60000
40000
20000
0
PRODUCCION
0
5
10
15
20
25
SUPERFICIE

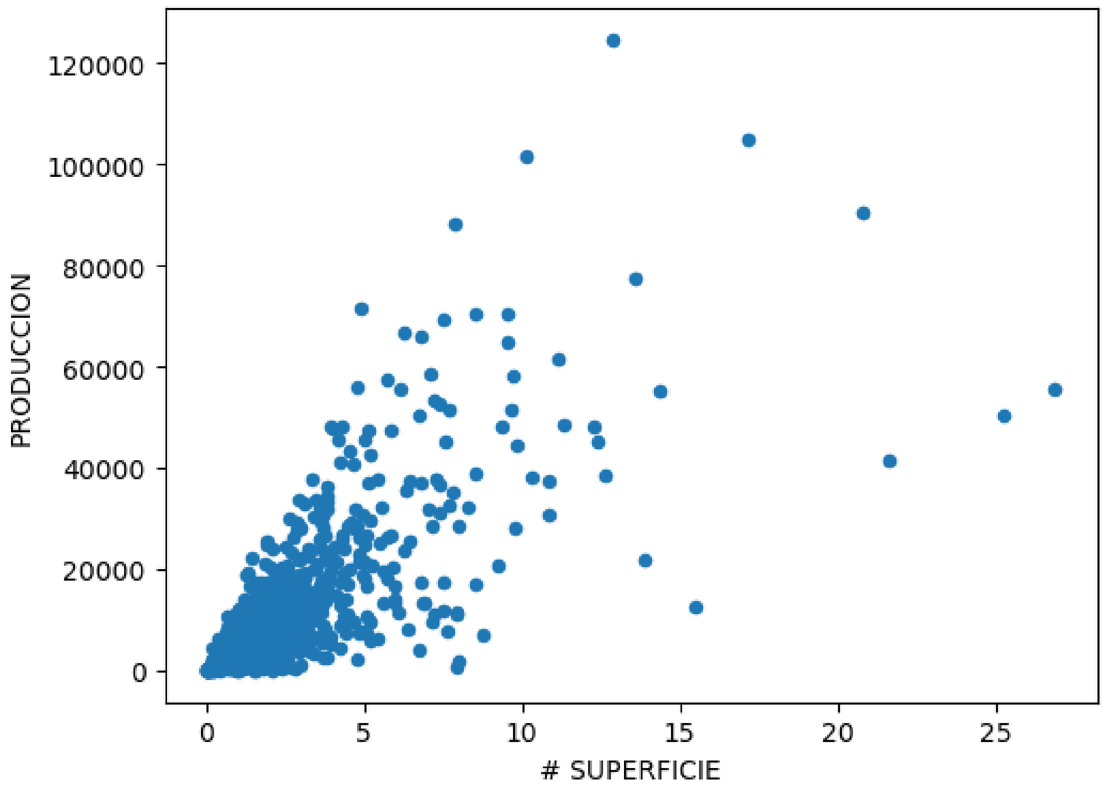

175000
150000
125000
100000
75000
50000
25000
0
PRODUCCION
0
5
10
15
20
25
SUPERFICIE



100000
80000
60000
40000
20000
0
PRODUCCION
0
5
10
15
20
25
SUPERFICIE



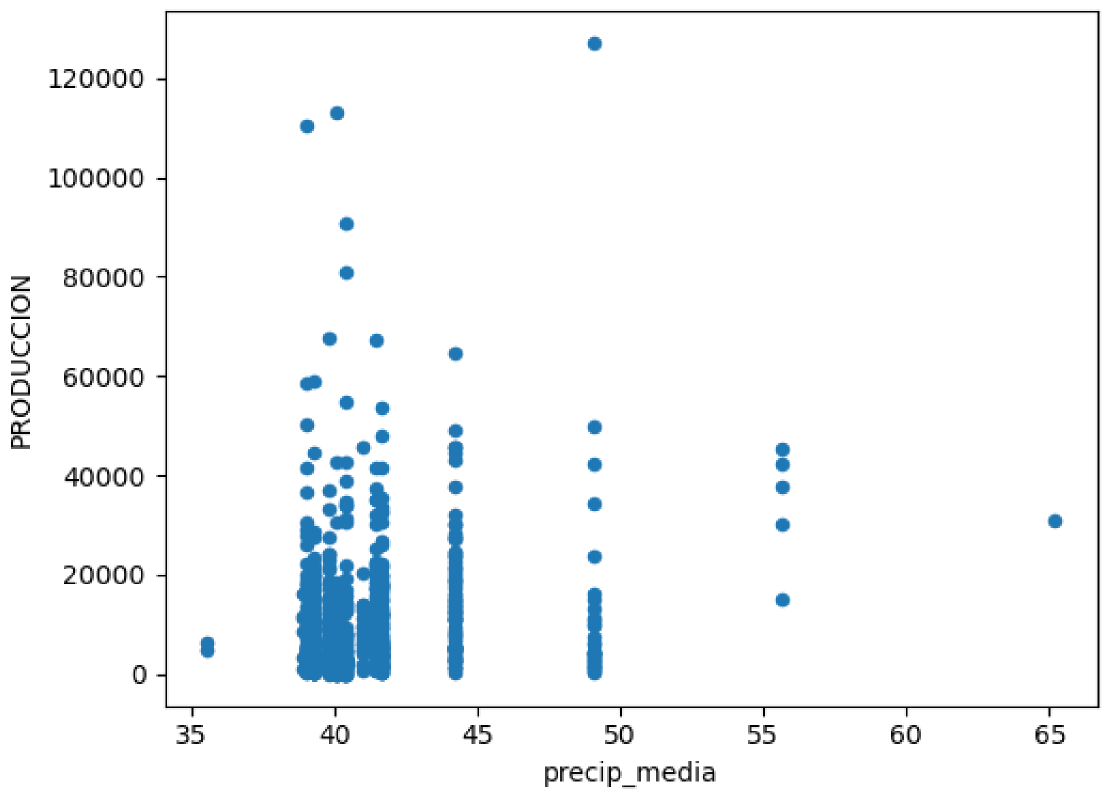
120000
100000
80000
60000
40000
20000
0
PRODUCCION
0
5
10
15
20
25
SUPERFICIE

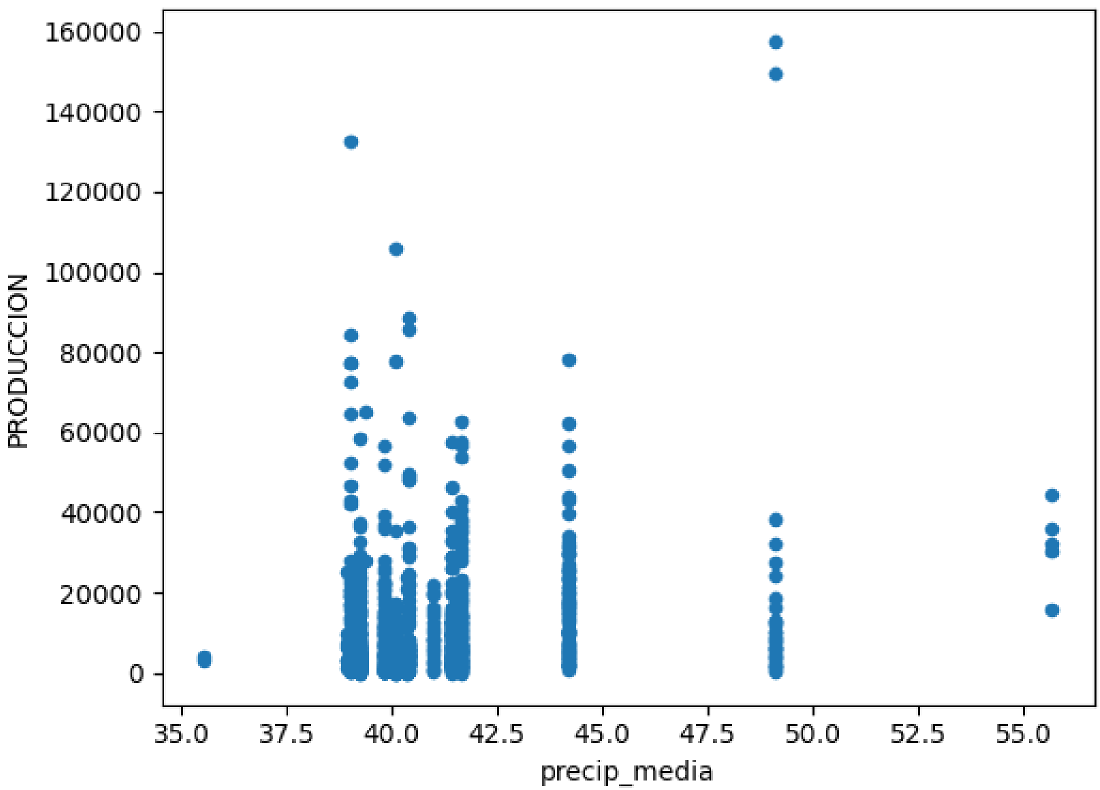


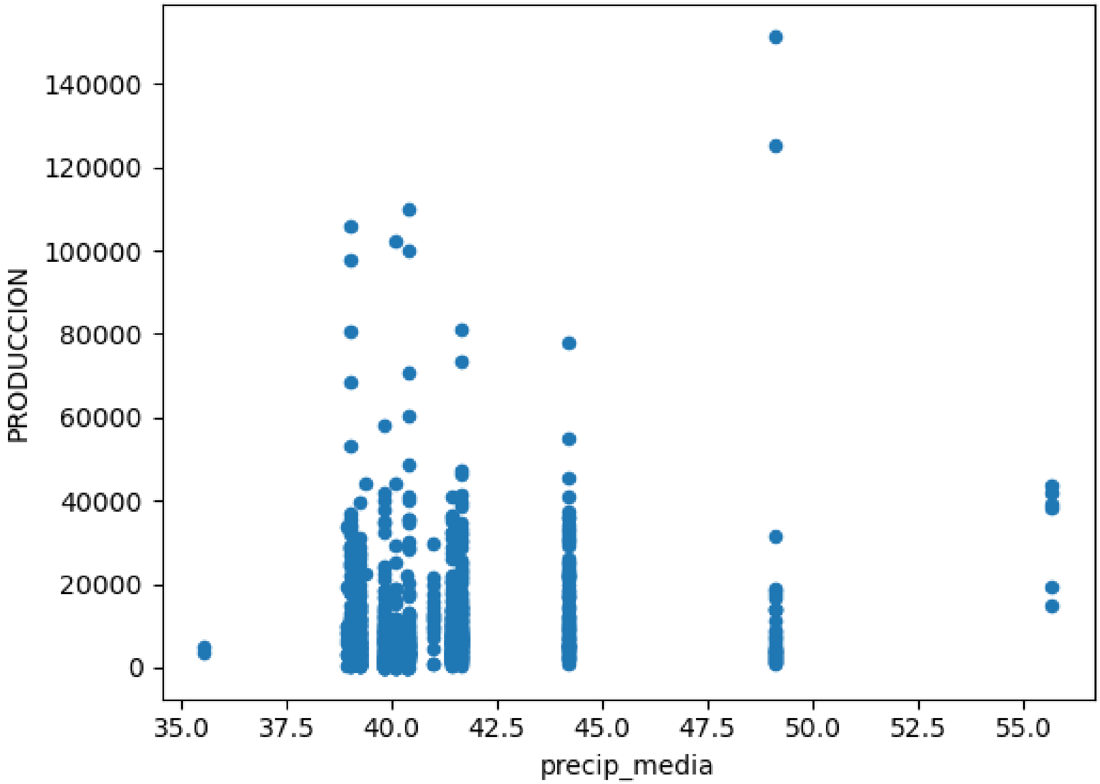
[36]:

```
# Gráfico para x=precip_media
df14.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()

df15.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()

df16.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()

df17.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()
```

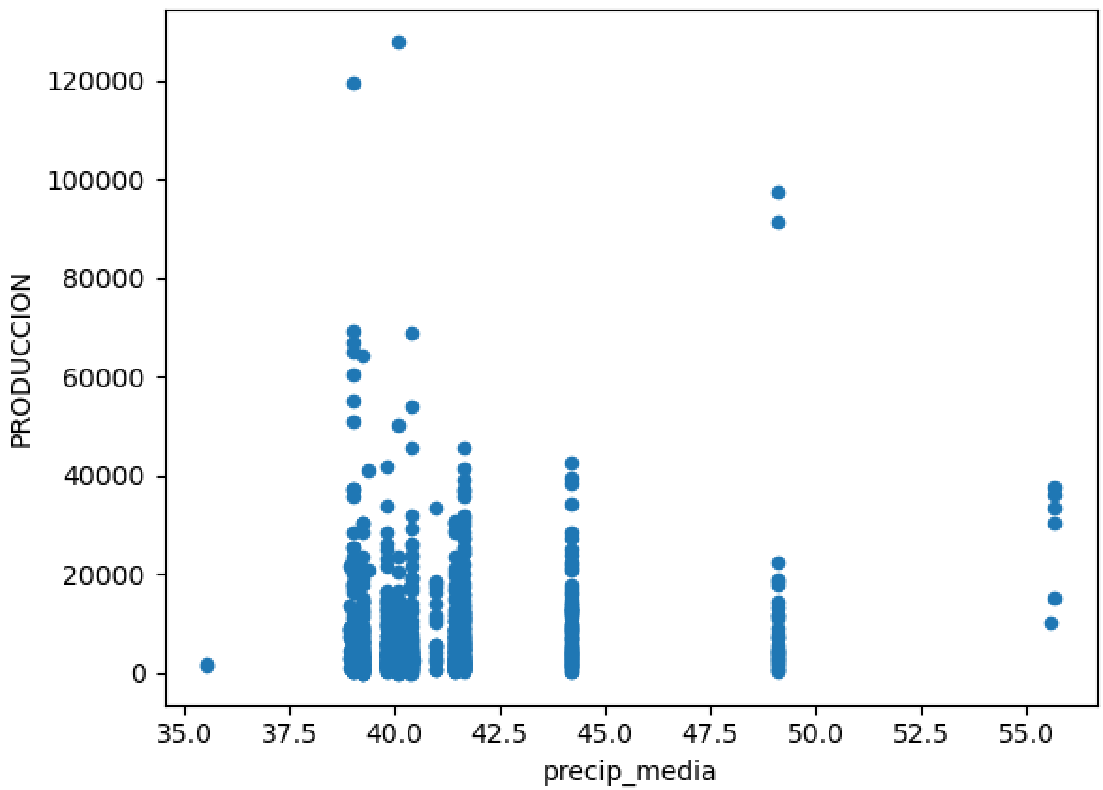
```
df18.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()

df19.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()

df20.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()

df21.plot(kind='scatter', x='precip_media', y='PRODUCCION')
plt.xlabel('precip_media')
plt.ylabel('PRODUCCION')
plt.show()
```

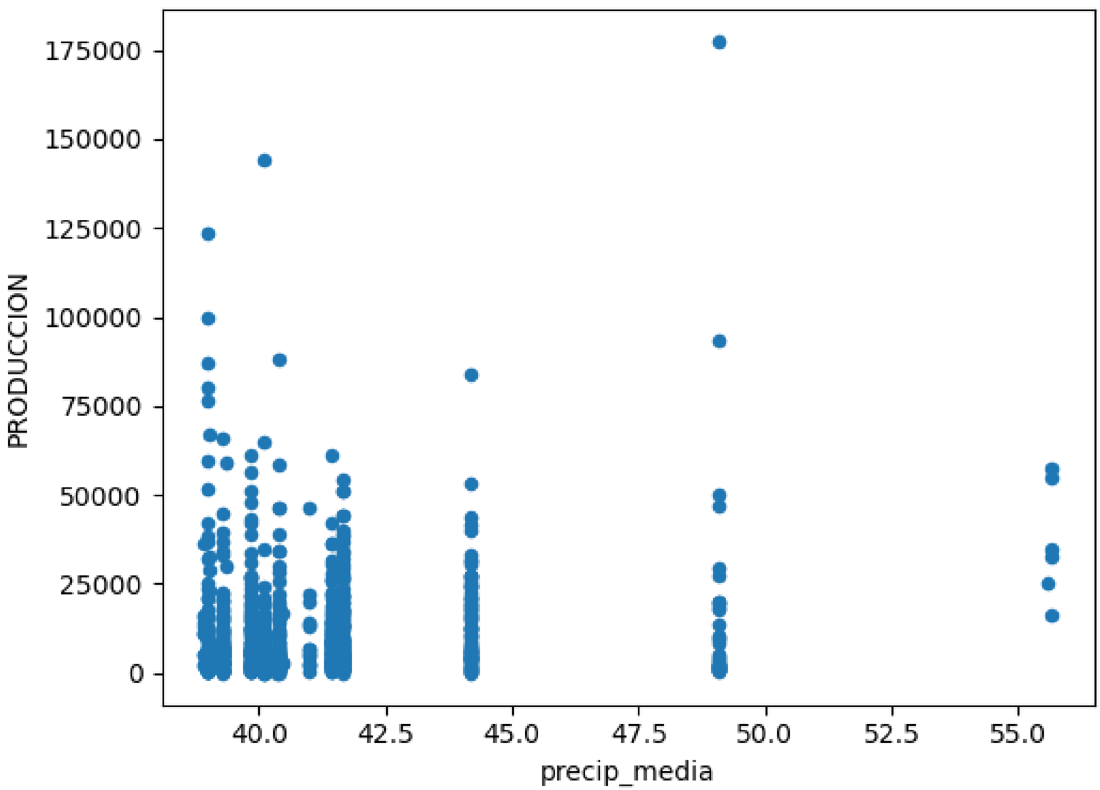



160000
140000
120000
100000
80000
60000
40000
20000
0
PRODUCCION
35.0
37.5
40.0
42.5
45.0
47.5
50.0
52.5
55.0
precip_media

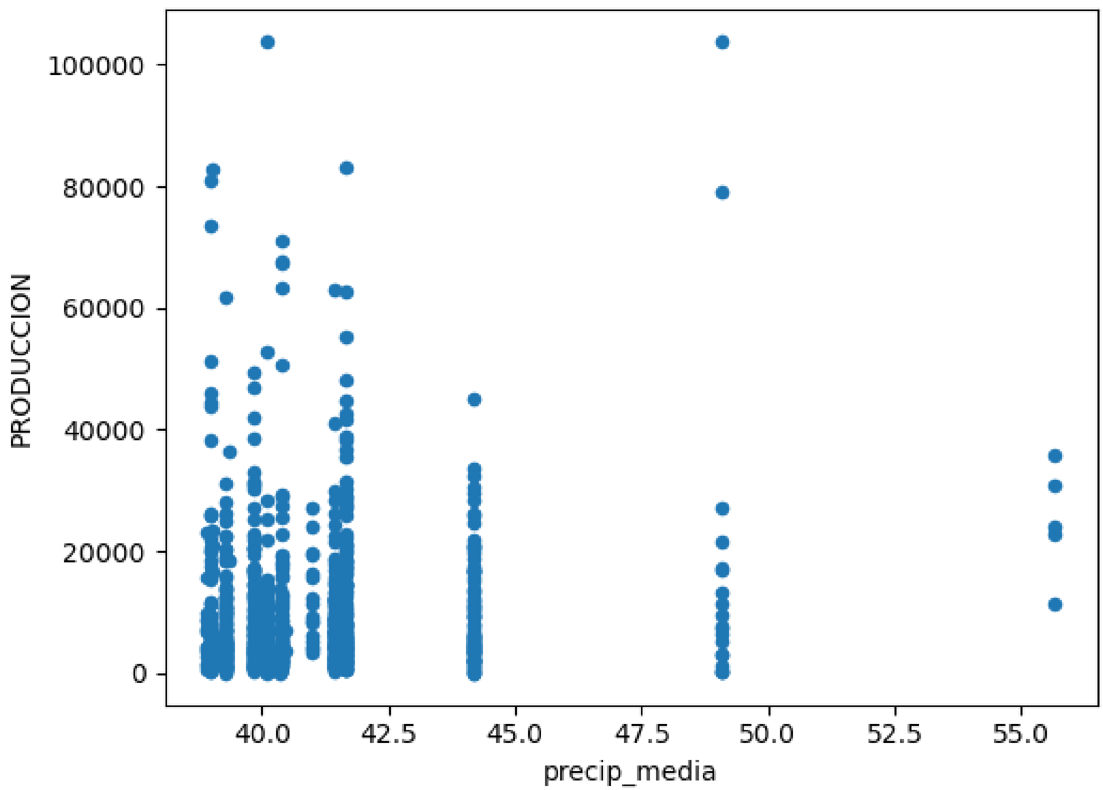


140000
120000
100000
80000
60000
40000
20000
0
PRODUCCION
35.0
37.5
40.0
42.5
45.0
47.5
50.0
52.5
55.0
precip_media

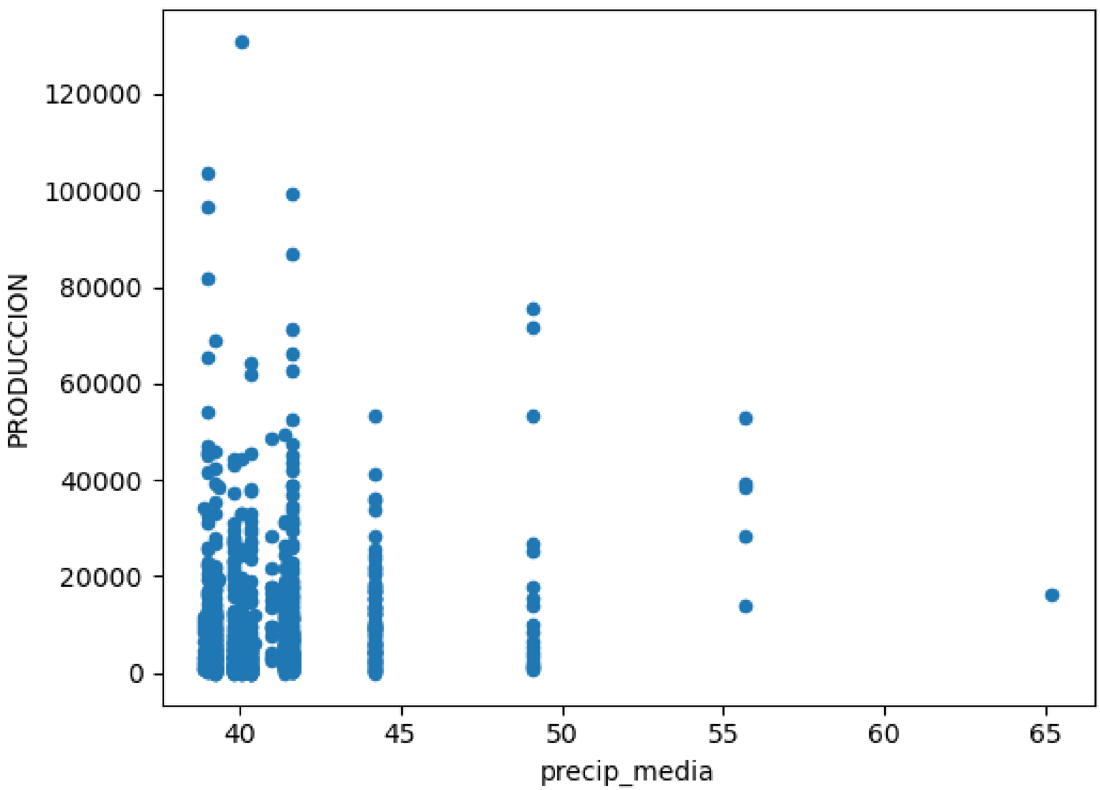

PRODUCCION
0
20000
40000
60000
80000
100000
120000
35.0
37.5
40.0
42.5
45.0
47.5
50.0
52.5
55.0
precip_media

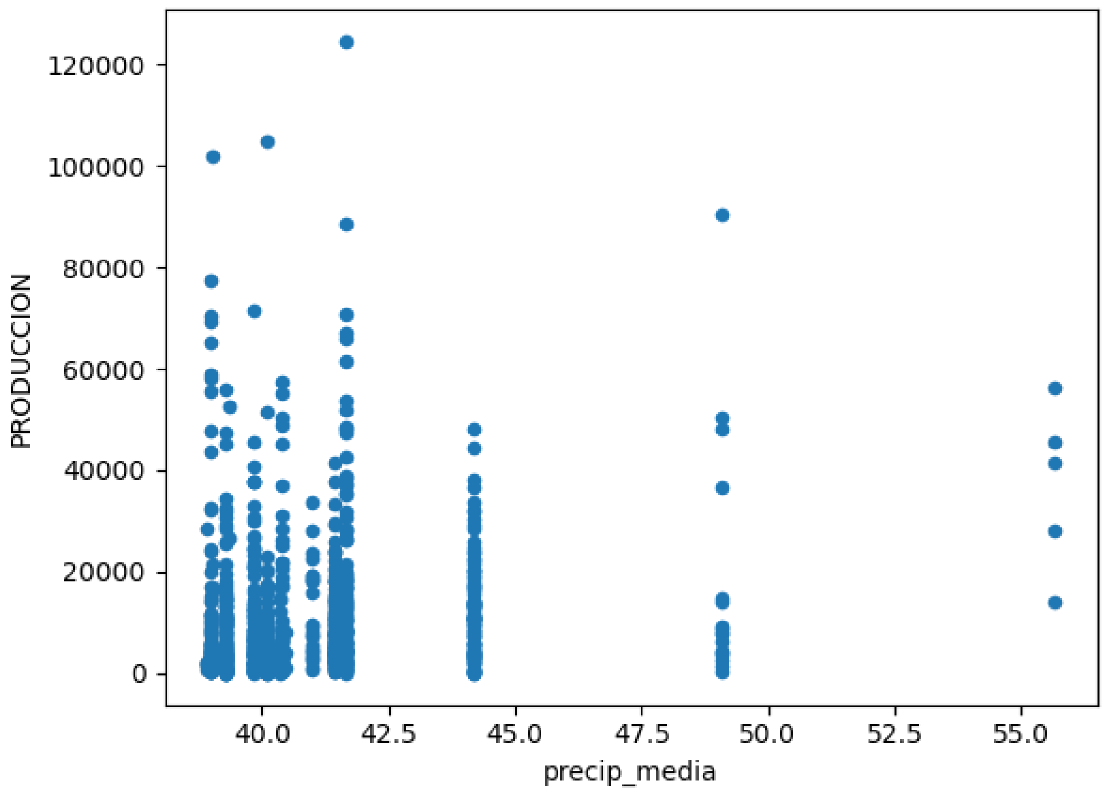


175000
150000
125000
100000
75000
50000
25000
0
PRODUCCION
40.0
42.5
45.0
47.5
50.0
52.5
55.0
precip_media



100000
80000
60000
40000
20000
0
PRODUCCION
40.0
42.5
45.0
47.5
50.0
52.5
55.0
precip_media

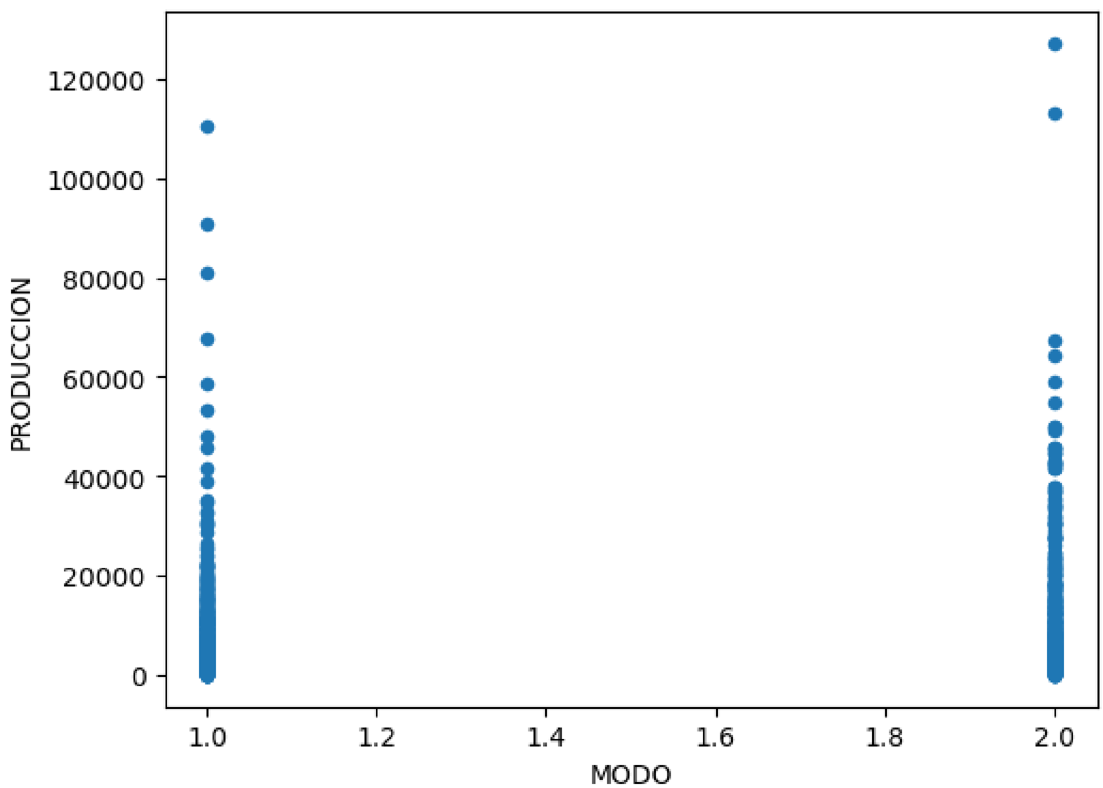

120000
100000
80000
60000
40000
20000
0
PRODUCCION
40
45
50
55
60
65
precip_media

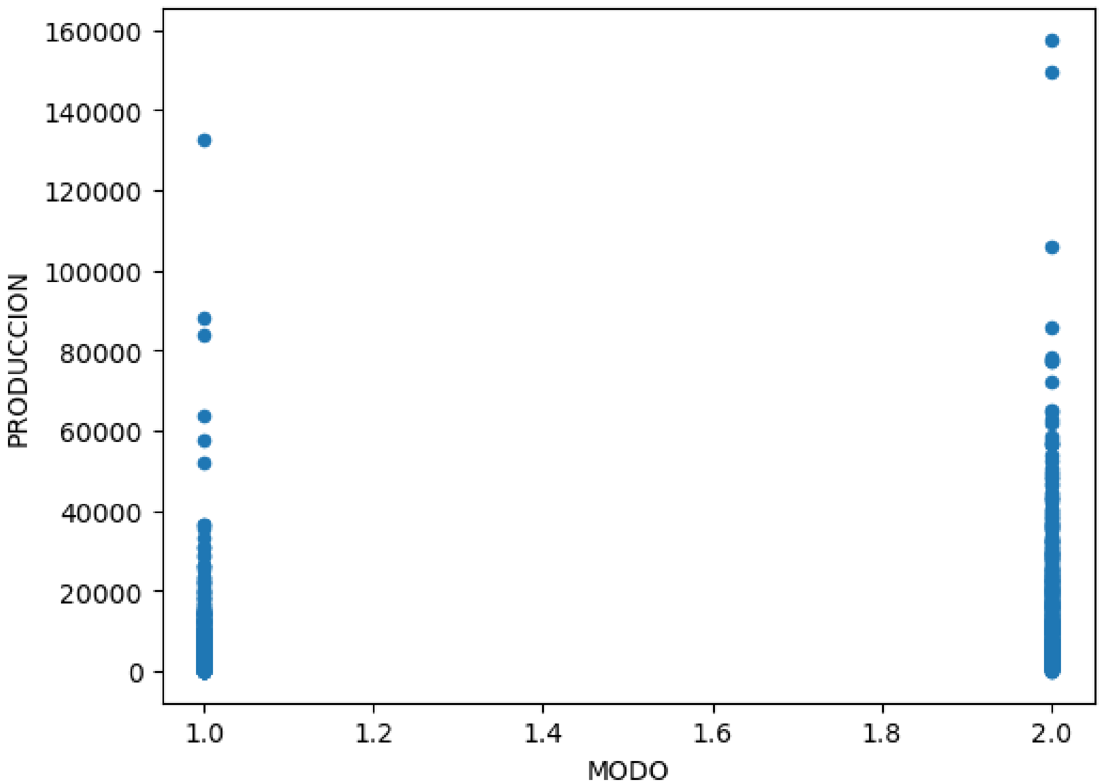


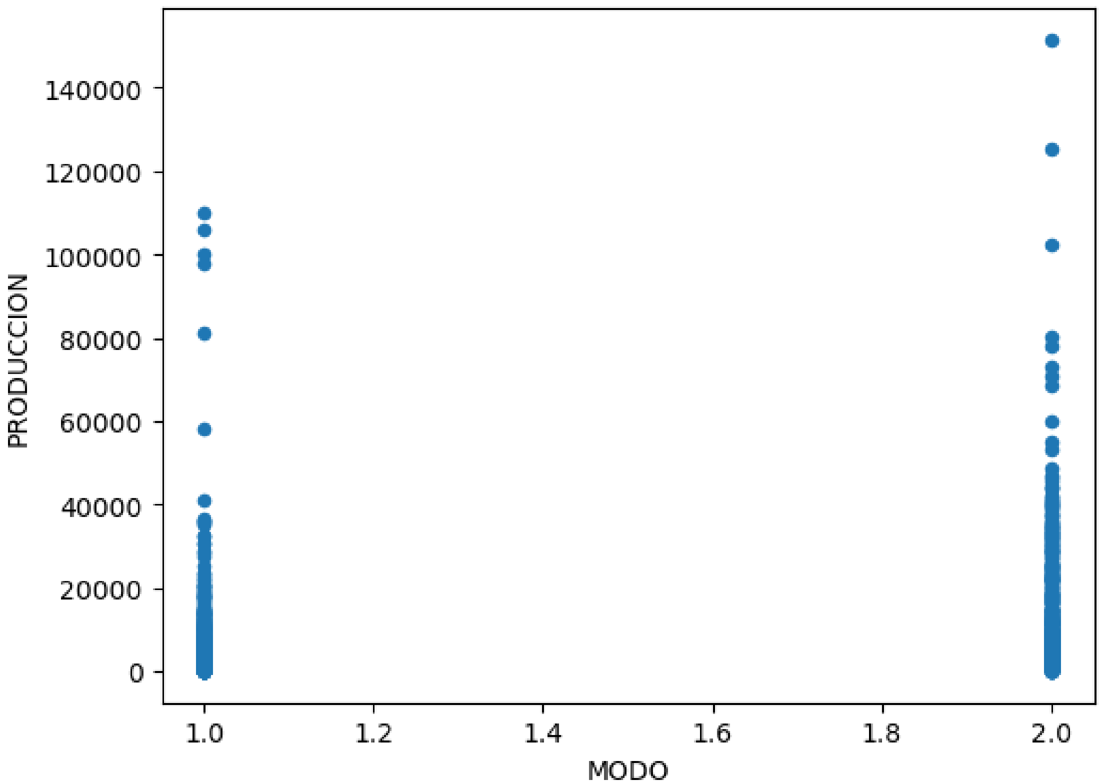
[37]:

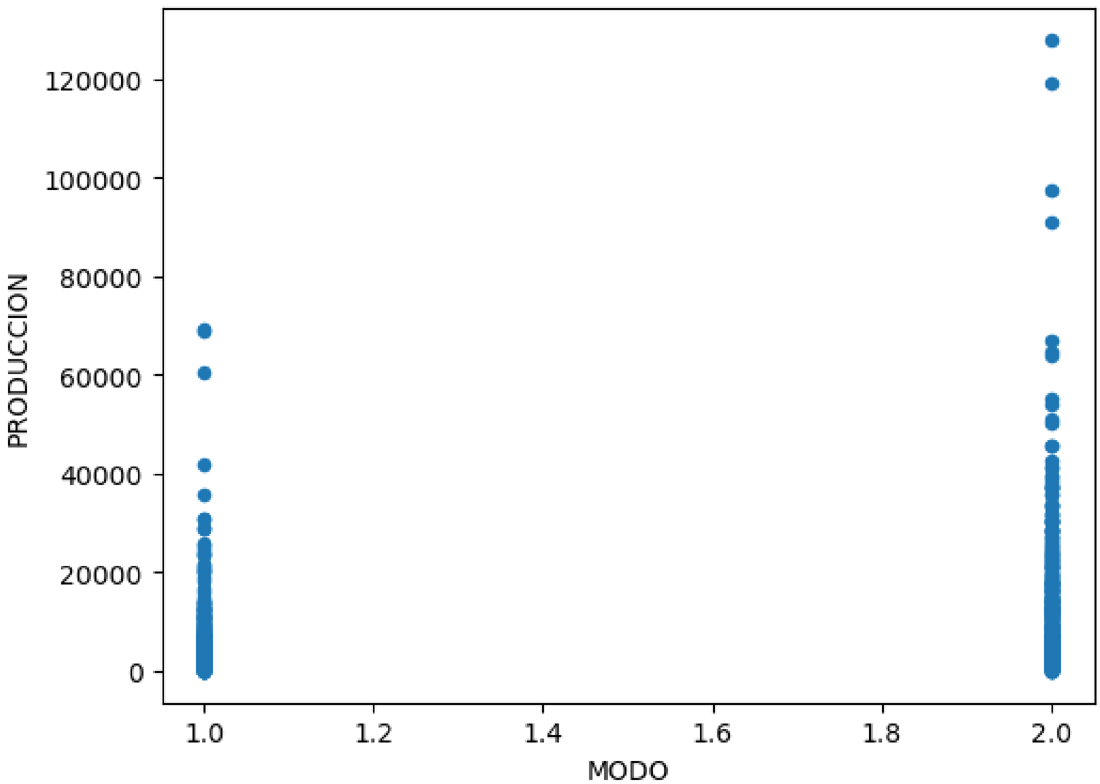
```
df14.plot(kind='scatter', x='MODO', y='PRODUCCION')
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()

df15.plot(kind='scatter', x='MODO', y='PRODUCCION')
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()

df16.plot(kind='scatter', x='MODO', y='PRODUCCION')
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()

df17.plot(kind='scatter', x='MODO', y='PRODUCCION')
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()

df18.plot(kind='scatter', x='MODO', y='PRODUCCION')
```

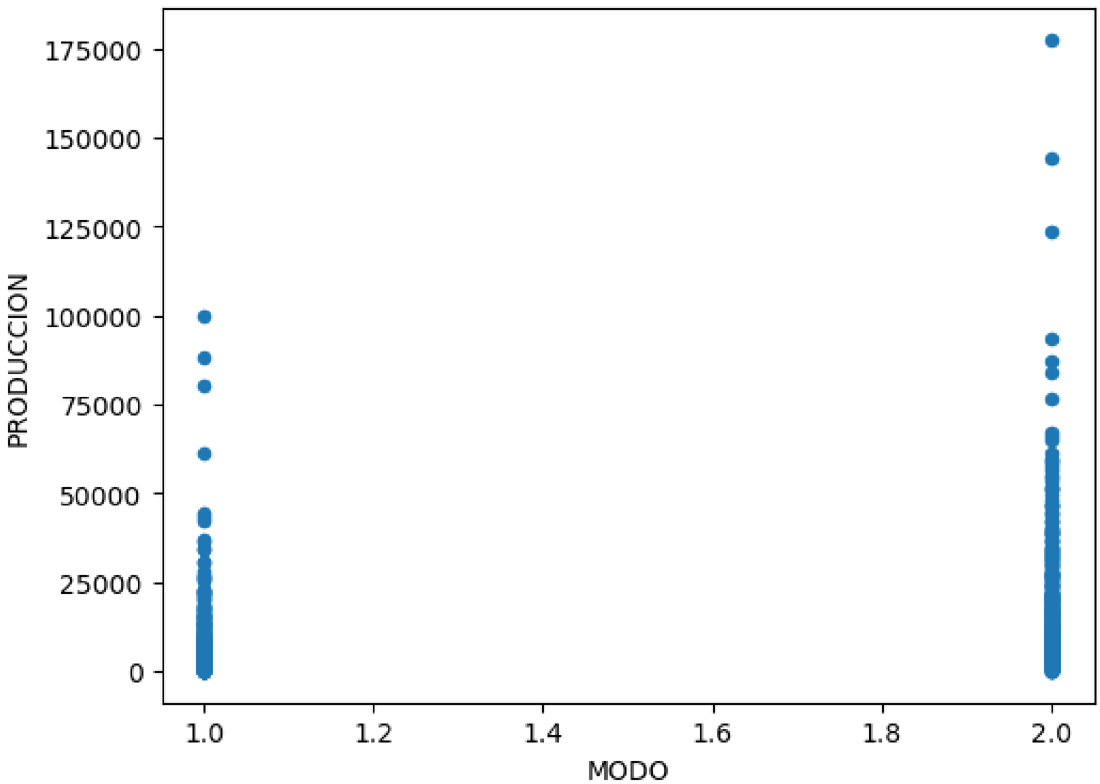
```
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()

df19.plot(kind='scatter', x='MODO', y='PRODUCCION')
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()

df20.plot(kind='scatter', x='MODO', y='PRODUCCION')
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()

df21.plot(kind='scatter', x='MODO', y='PRODUCCION')
plt.xlabel('MODO')
plt.ylabel('PRODUCCION')
plt.show()
```

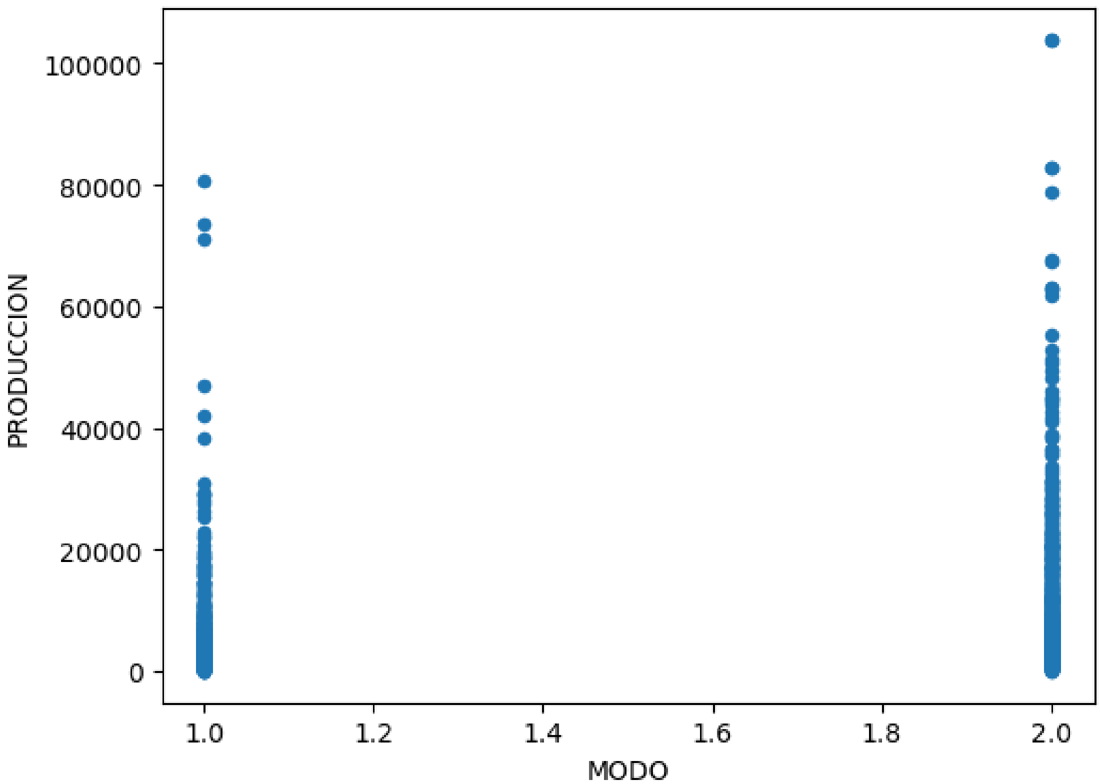



160000
140000
120000
100000
80000
60000
40000
20000
0
PRODUCCION
1.0
1.2
1.4
1.6
1.8
2.0
MODO

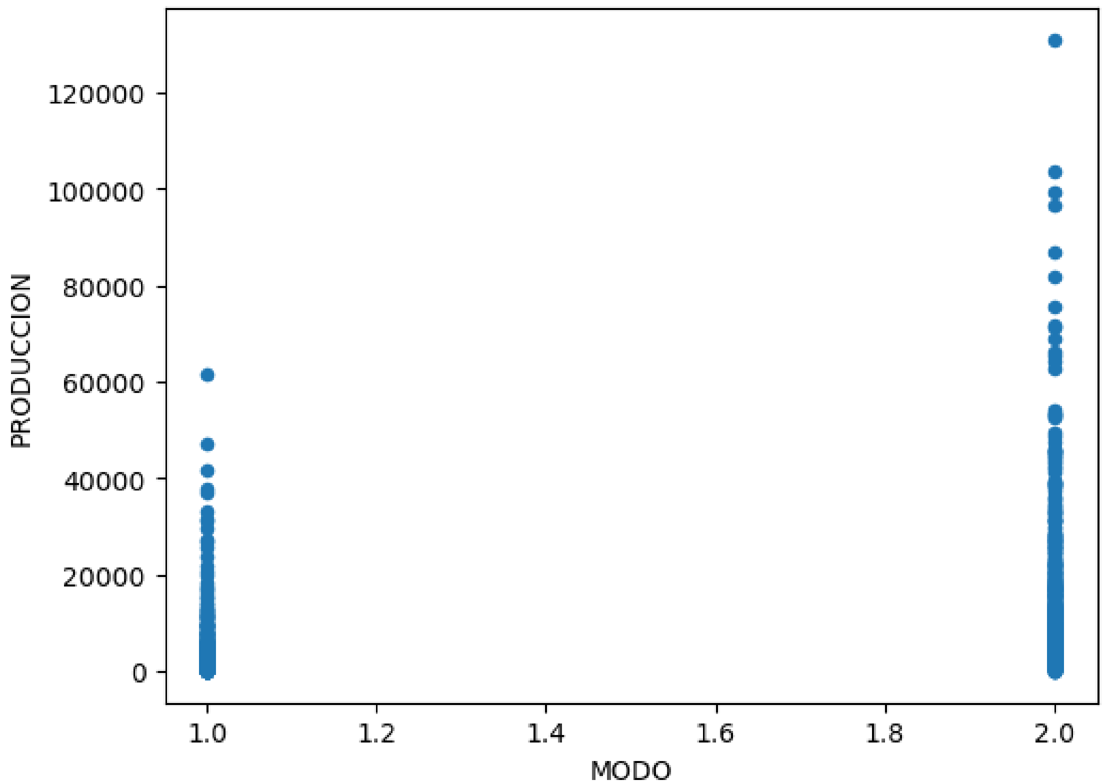

140000
120000
100000
80000
60000
40000
20000
0
PRODUCCION
1.0
1.2
1.4
1.6
1.8
2.0
MODO


PRODUCCION
120000
100000
80000
60000
40000
20000
0
1.0
1.2
1.4
1.6
1.8
2.0
MODO

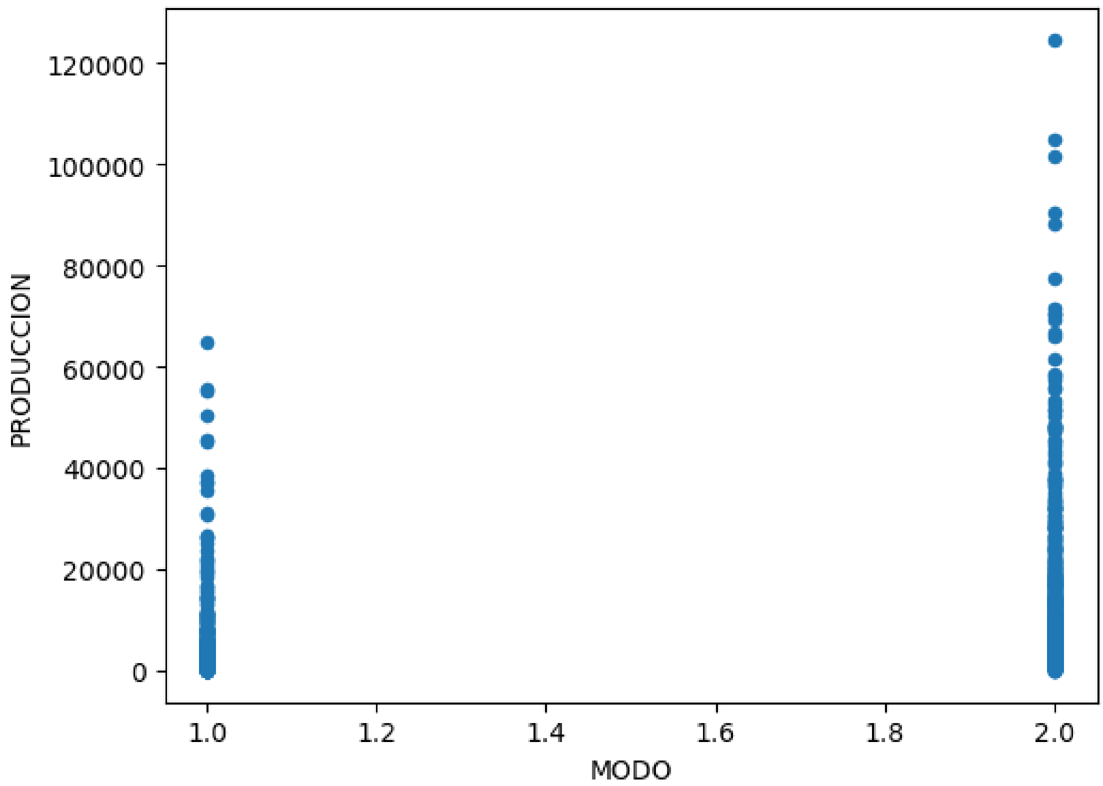

175000
150000
125000
100000
75000
50000
25000
0
PRODUCCION
1.0
1.2
1.4
1.6
1.8
2.0
MODO



100000
80000
60000
40000
20000
0
PRODUCCION
1.0
1.2
1.4
1.6
1.8
2.0
MODO

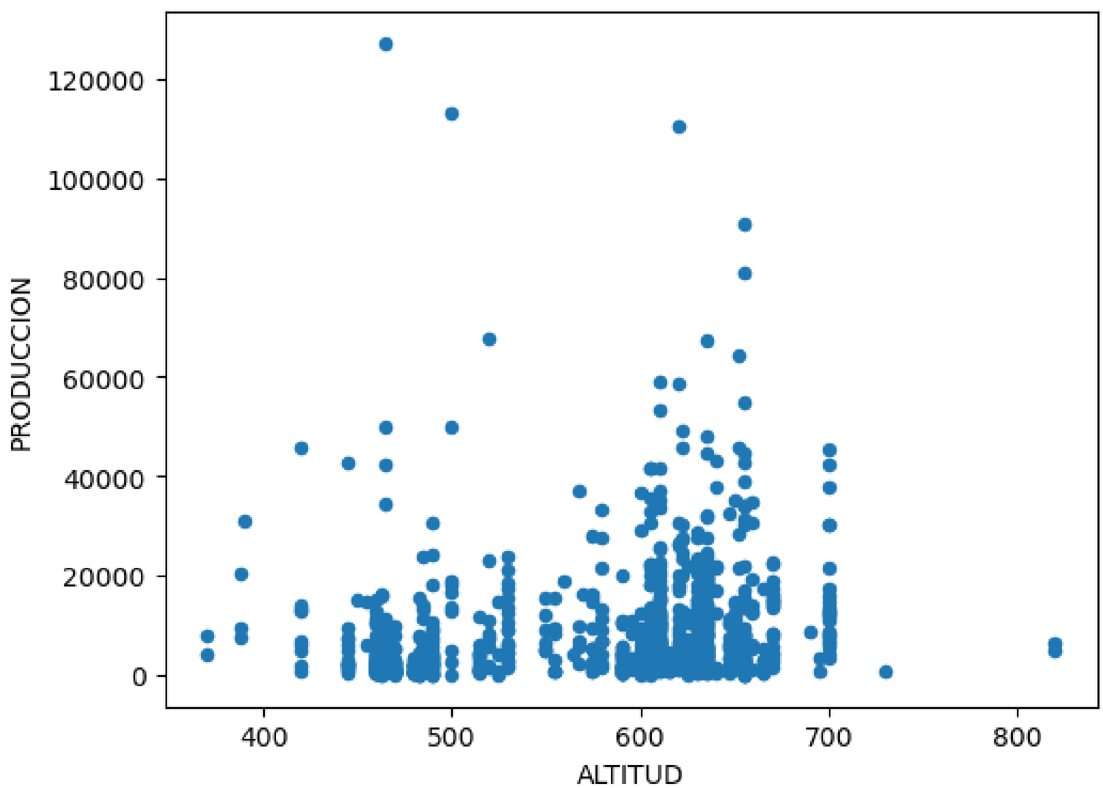


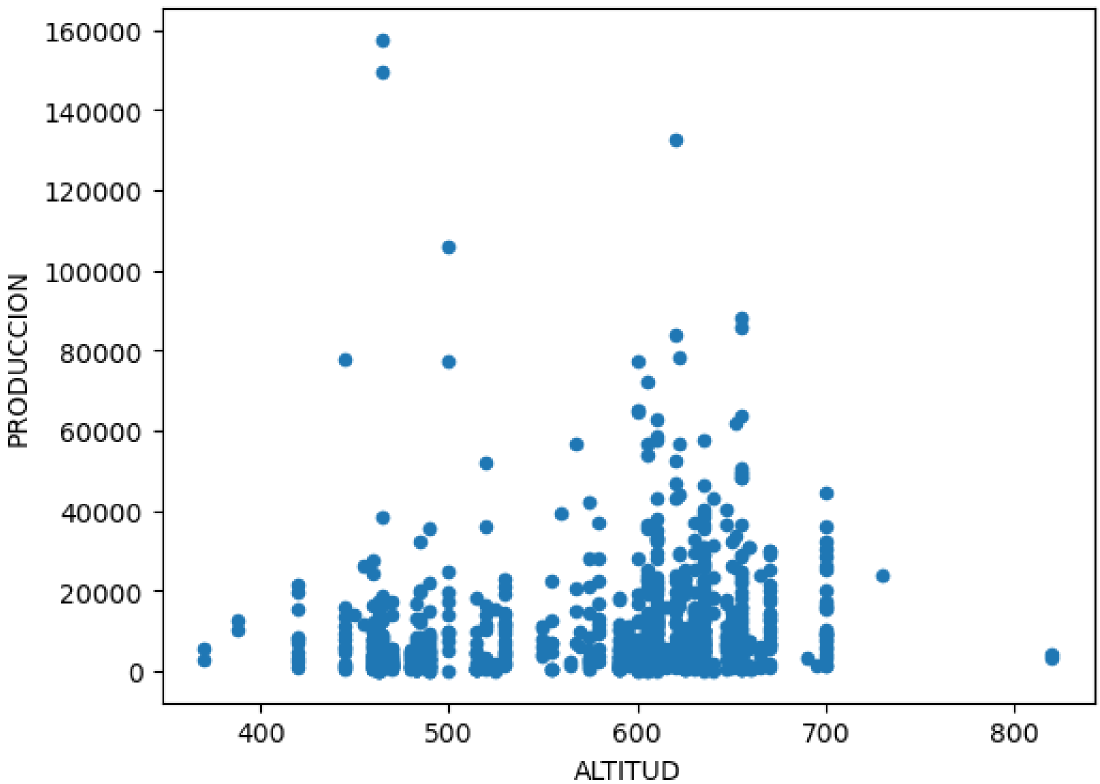
120000
100000
80000
60000
40000
20000
0
PRODUCCION
1.0
1.2
1.4
1.6
1.8
2.0
MODO



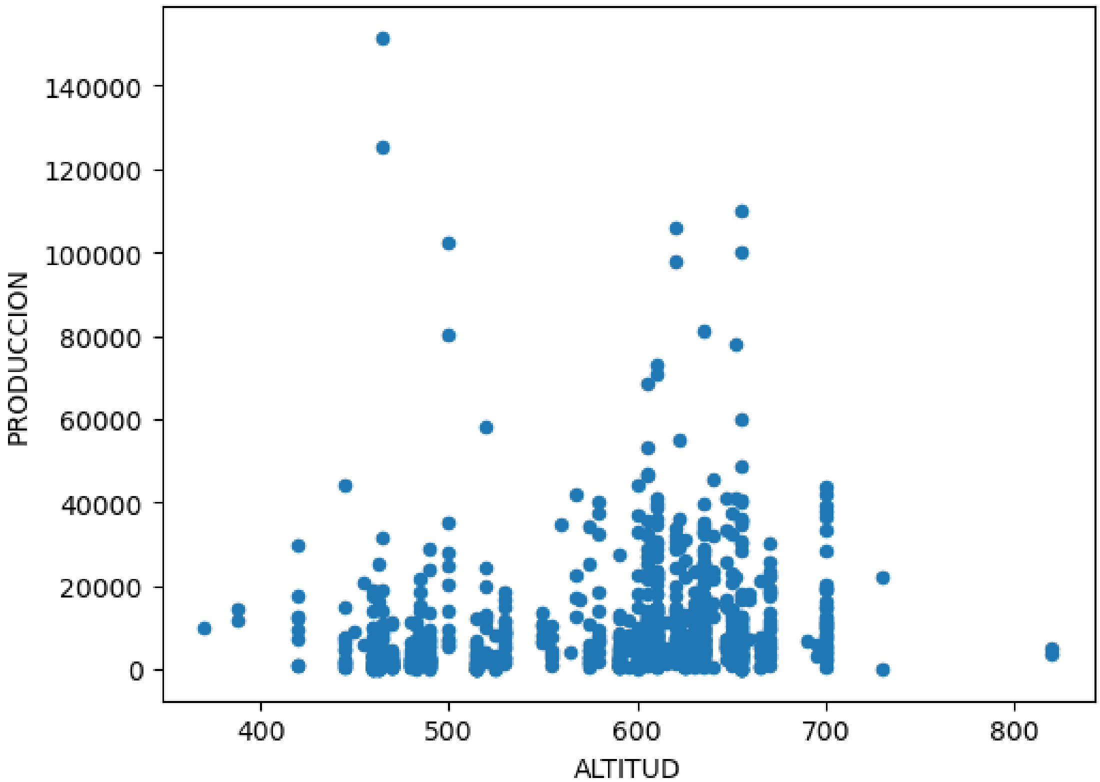
[38]:
```
df14.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()

df15.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()

df16.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()

df17.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()

df18.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
```

```
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()

df19.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()

df20.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()

df21.plot(kind='scatter', x='ALTITUD', y='PRODUCCION')
plt.xlabel('ALTITUD')
plt.ylabel('PRODUCCION')
plt.show()
```

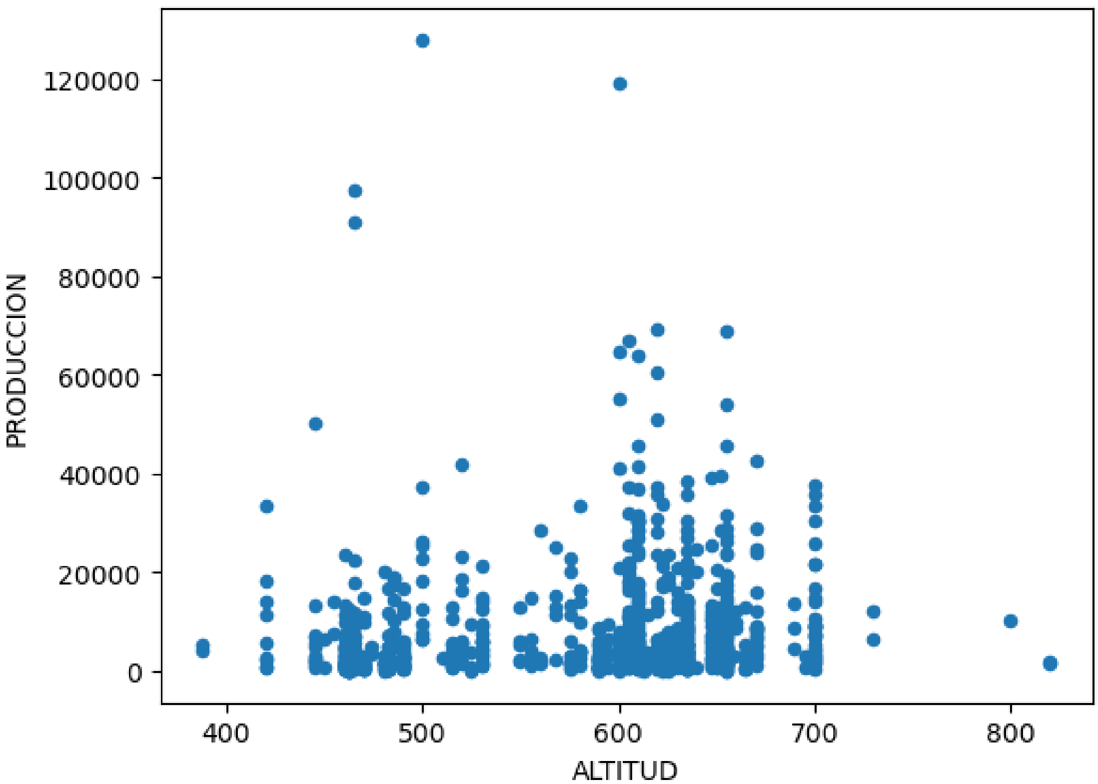


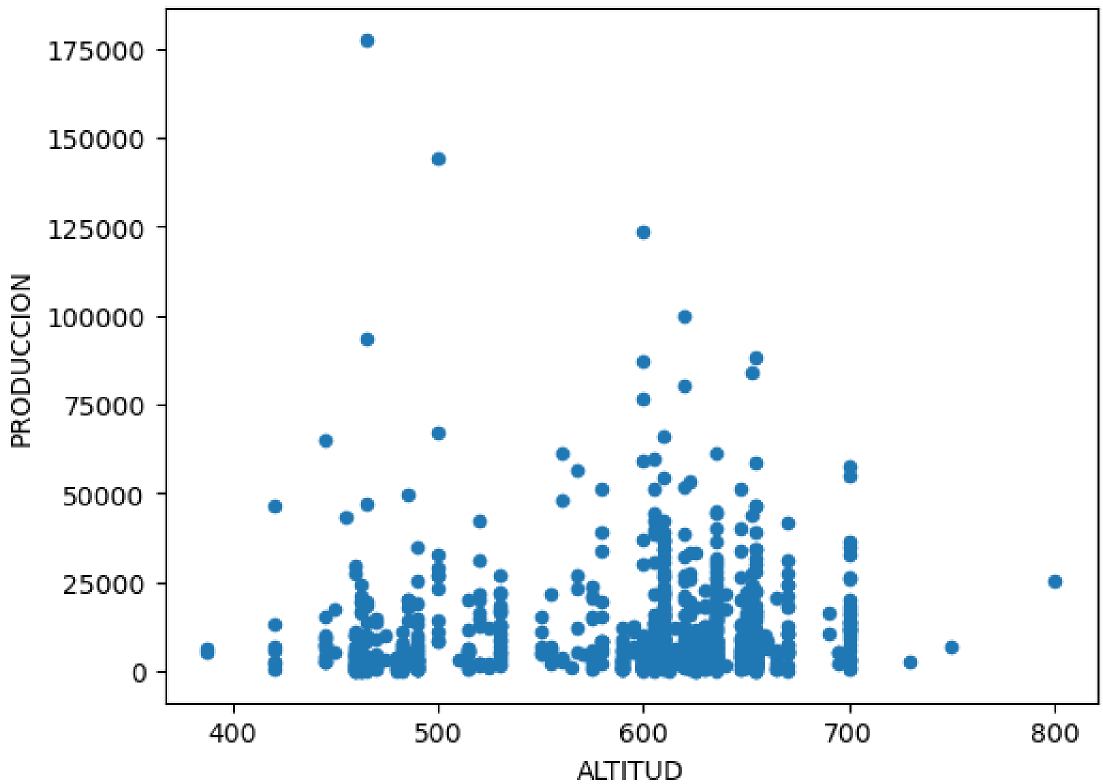


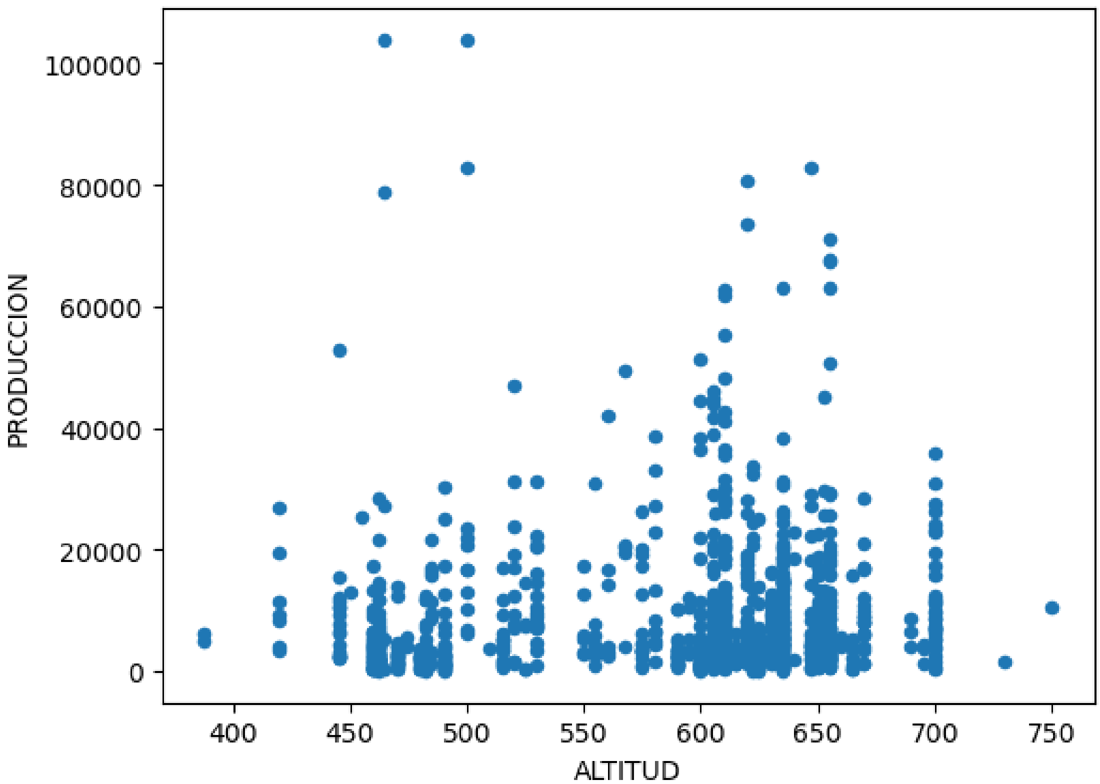
160000
140000
120000
100000
80000
60000
40000
20000
0
PRODUCCION
400
500
600
700
800
ALTITUD



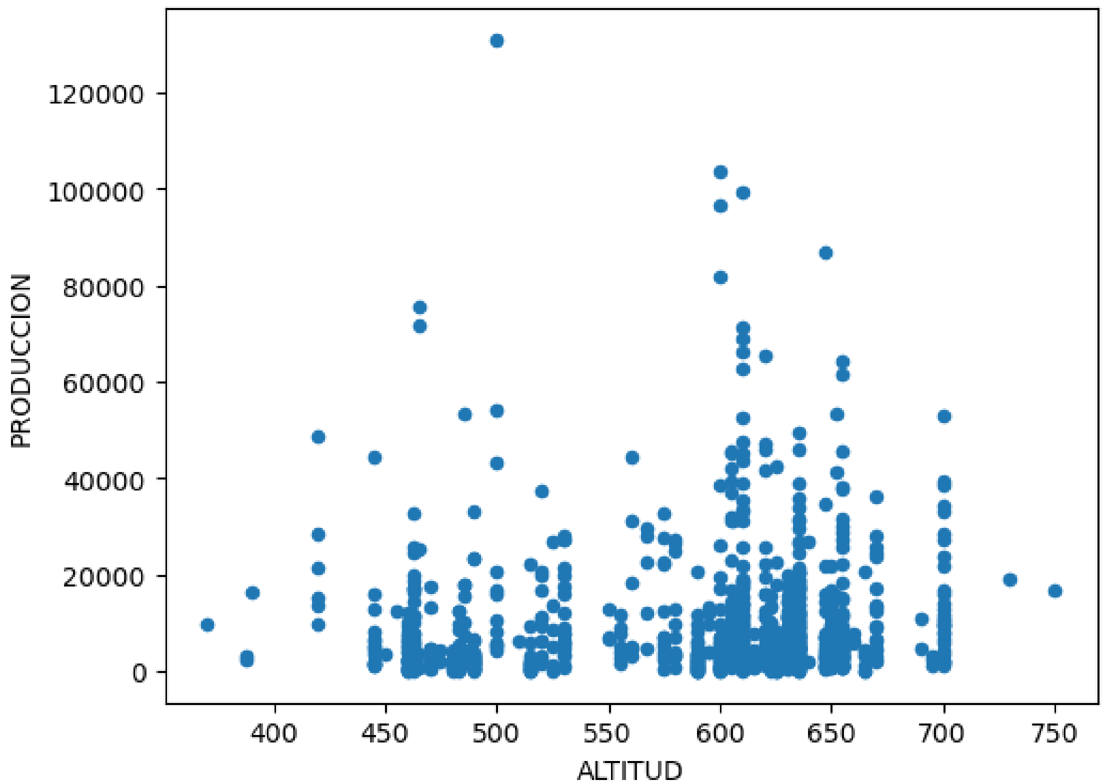
PRODUCCION
ALTITUD
0
20000
40000
60000
80000
100000
120000
140000
400
500
600
700
800


120000
100000
80000
60000
40000
20000
0
PRODUCCION
400
500
600
700
800
ALTITUD

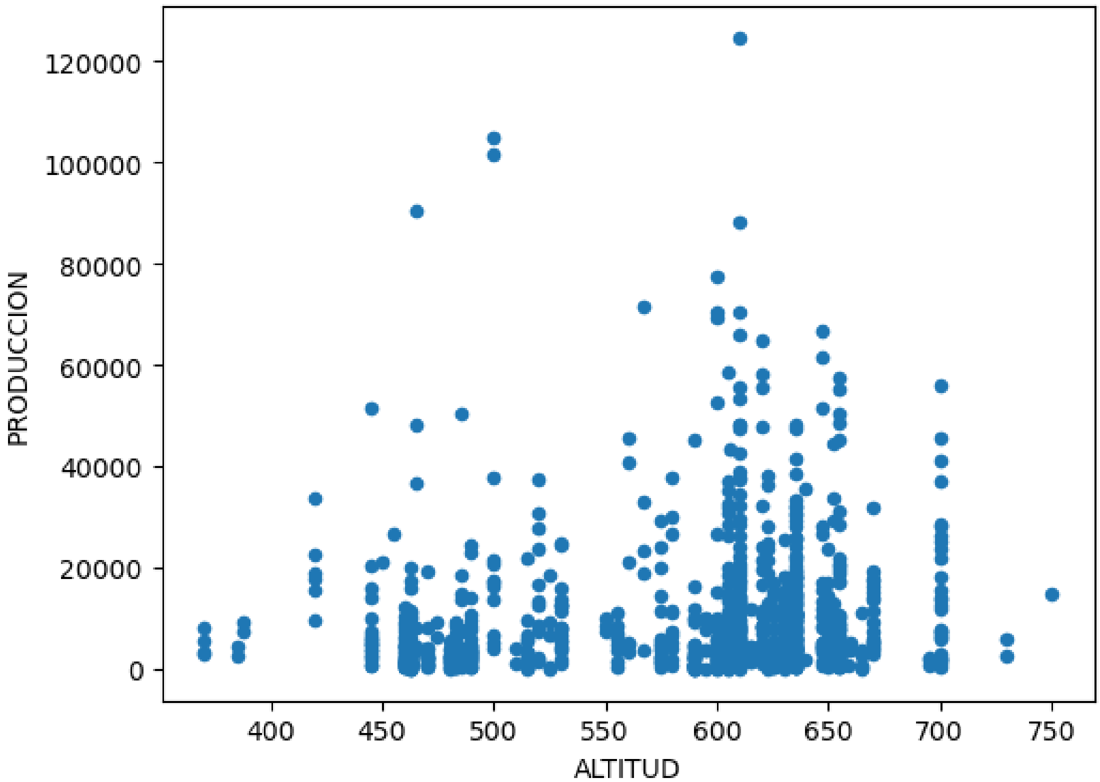

175000
150000
125000
100000
75000
50000
25000
0
PRODUCCION
400
500
600
700
800
ALTITUD



100000
80000
60000
40000
20000
0
PRODUCCION
400
450
500
550
600
650
700
750
ALTITUD



PRODUCCION
120000
100000
80000
60000
40000
20000
0
400
450
500
550
600
650
700
750
ALTITUD



Como los patrones de las observaciones son similares para todos los años para las variables más correlacionadas con PRODUCCIÓN, decidimos no imputar ninguna observación

0.2 MODELOS

[39]:
```
#Creamos un diccionario para ir guardando los resultados
results_test = {
    'XGboost': {'RMSE': None, 'MAE': None, 'R2': None},
    'GradientBoost': {'RMSE': None, 'MAE': None, 'R2': None},
    'Red Neuronal': {'RMSE': None, 'MAE': None, 'R2':None},
    'Bagging': {'RMSE': None, 'MAE': None, 'R2': None}
}
results_train = {
    'XGboost': {'RMSE': None, 'MAE': None, 'R2': None},
    'GradientBoots': {'RMSE': None, 'MAE': None, 'R2': None},
    'Bagging': {'RMSE': None, 'MAE': None, 'R2': None},
    'Red Neuronal': {'RMSE': None, 'MAE': None, 'R2':None}
}
```

[40]:
```
from sklearn.model_selection import train_test_split
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.metrics import mean_squared_error, mean_absolute_error
```

```
from sklearn.metrics import r2_score
```

0.3 Conjunto de Entrenamiento

[41]:
```
#Conjunto de datos de entrenamiento
df1421=df[df['CAMPAÑA'] != 22]
```

[42]:
```
#Train y evaluación
X = df1421.drop('PRODUCCION', axis=1).values
y = df1421['PRODUCCION'].values.reshape(-1, 1)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)
```

0.4 Gradient Boosting

[43]:
```
# Creamos el modelo de Gradient Boosting
gbr = GradientBoostingRegressor(n_estimators=100, learning_rate=0.15,␣
↪max_depth=6, random_state=42)

# Ajustamos el modelo con los datos de entrenamiento
gbr.fit(X_train, y_train)

y_pred_test=gbr.predict(X_test)
```

[44]:
```
# Vemos como ha sido el entrenamiento
y_pred_train=gbr.predict(X_train)
rmse_train = mean_squared_error(y_train, y_pred_train, squared=False)
mae_train = mean_absolute_error(y_train, y_pred_train)
r2 = r2_score(y_train, y_pred_train)
print(f'RMSE en train: {rmse_train:.5f}')
print(f'MAE en train: {mae_train:.5f}')
print("R2 score:", r2)

#Las guardo en el diccionario
results_train['GradientBoots']['RMSE'] = rmse_train
results_train['GradientBoots']['MAE'] = mae_train
results_train['GradientBoots']['R2'] = r2



# En test
rmse = mean_squared_error(y_test, y_pred_test, squared=False)
print('RMSE:', rmse)
mae=mean_absolute_error(y_test, y_pred_test)
print('MAE:', mae)
r2 = r2_score(y_test, y_pred_test)
print("R2 score:", r2)
```

```python
#Las guardo en el diccionario
results_test['GradientBoost']['RMSE'] = rmse
results_test['GradientBoost']['MAE'] = mae
results_test['GradientBoost']['R2'] = r2
```

```
RMSE en train: 3261.51790
MAE en train: 2138.47911
R2 score: 0.9412560407833545
RMSE: 5282.798720503473
MAE: 3021.8006237884983
R2 score: 0.8202239812225536
```

0.5 XGBOOST

[45]:
```python
import xgboost as xgb
```

[46]:
```python
# Defino los hiperparámetros
params = {'objective': 'reg:squarederror',
          'max_depth': 6,
          'learning_rate': 0.1,
          'subsample': 0.5,
          'colsample_bytree': 0.5,
          'n_estimators': 100}

# Entreno el modelo
model = xgb.XGBRegressor(**params)
model.fit(X_train, y_train)

# Realizamos predicciones en el conjunto de prueba
y_pred_test = model.predict(X_test)
```

[47]:
```python
# Vemos como ha sido el entrenamiento
y_pred_train=model.predict(X_train)
rmse_train = mean_squared_error(y_train, y_pred_train, squared=False)
mae_train = mean_absolute_error(y_train, y_pred_train)
r2 = r2_score(y_train, y_pred_train)
print(f'RMSE en train: {rmse_train:.5f}')
print(f'MAE en train: {mae_train:.5f}')
print("R2 score:", r2)

#Las guardo en el diccionario
results_train['XGboost']['RMSE'] = rmse_train
results_train['XGboost']['MAE'] = mae_train
results_train['XGboost']['R2'] = r2

# En test
rmse = mean_squared_error(y_test, y_pred_test, squared=False)
```

```
print('RMSE:', rmse)
mae=mean_absolute_error(y_test, y_pred_test)
print('MAE:', mae)
r2 = r2_score(y_test, y_pred_test)
print("R2 score:", r2)

#Las guardo en el diccionario
results_test['XGboost']['RMSE'] = rmse
results_test['XGboost']['MAE'] = mae
results_test['XGboost']['R2'] = r2
```

```
RMSE en train: 4733.25977
MAE en train: 2848.65287
R2 score: 0.8762787323801671
RMSE: 5928.3168595662255
MAE: 3397.416068268864
R2 score: 0.7736052004736758
```

0.6 Bagging

[48]:
```
from sklearn.ensemble import BaggingRegressor
from sklearn.tree import DecisionTreeRegressor
```

[49]:
```
# Creo modelo base de árbol de decisión
base_model = DecisionTreeRegressor()

# Creo modelo de Bagging con 100 estimadores
bagging_model = BaggingRegressor(base_estimator=base_model, n_estimators=100,␣
 ↪random_state=42)

# Entreno modelo con datos de entrenamiento
bagging_model.fit(X_train, y_train)

# Hago predicciones en conjunto de test
y_pred_test = bagging_model.predict(X_test)

# Vemos como ha sido el entrenamiento
y_pred_train=bagging_model.predict(X_train)
rmse_train = mean_squared_error(y_train, y_pred_train, squared=False)
mae_train = mean_absolute_error(y_train, y_pred_train)
r2 = r2_score(y_train, y_pred_train)
print(f'RMSE en train: {rmse_train:.5f}')
print(f'MAE en train: {mae_train:.5f}')
print("R2 score:", r2)

#Las guardo en el diccionario
results_train['Bagging']['RMSE'] = rmse_train
```

```
results_train['Bagging']['MAE'] = mae_train
results_train['Bagging']['R2'] = r2

# En test
rmse = mean_squared_error(y_test, y_pred_test, squared=False)
print('RMSE:', rmse)
mae=mean_absolute_error(y_test, y_pred_test)
print('MAE:', mae)
r2 = r2_score(y_test, y_pred_test)
print("R2 score:", r2)


#Las guardo en el diccionario
results_test['Bagging']['RMSE'] = rmse
results_test['Bagging']['MAE'] = mae
results_test['Bagging']['R2'] = r2
```

```
RMSE en train: 2191.69715
MAE en train: 1124.53874
R2 score: 0.9734732058033906
RMSE: 5310.449504090665
MAE: 2874.3143787170675
R2 score: 0.8183371188555317
```

0.7 Red Neuronal

[50]:
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense
from tensorflow.keras.metrics import RootMeanSquaredError
from tensorflow.keras.metrics import MeanAbsoluteError

# Definir la arquitectura de la red neuronal
model = Sequential()
model.add(Dense(64, activation='relu', input_shape=(X_train.shape[1],)))
model.add(Dense(64, activation='relu'))
model.add(Dense(1))

mae = MeanAbsoluteError()
rmse = RootMeanSquaredError()

# Compilar el modelo
model.compile(optimizer='adam', loss='mean_squared_error', metrics=[mae, rmse])

# Entrenar el modelo
model.fit(X_train, y_train, epochs=10, batch_size=32, validation_data=(X_test,␣
  ↪y_test))
```

```python
# Evaluar el modelo en el conjunto de entrenamiento
loss, mae, rmse = model.evaluate(X_train, y_train)
r2 = 1 - (rmse**2 / tf.math.reduce_variance(y_train))
print("Pérdida en el conjunto de prueba:", loss)
print("RMSE en el conjunto de prueba", rmse)
print("MAE en el conjunto de prueba:", mae)
print("R2 en el conjunto de prueba:", r2)
```

```
Epoch 1/10
214/214 [==============================] - 1s 2ms/step - loss: 204351648.0000 -
mean_absolute_error: 8463.8867 - root_mean_squared_error: 14295.1621 - val_loss:
166434384.0000 - val_mean_absolute_error: 7473.3296 -
val_root_mean_squared_error: 12900.9453
Epoch 2/10
214/214 [==============================] - 0s 1ms/step - loss: 189596016.0000 -
mean_absolute_error: 8087.9746 - root_mean_squared_error: 13769.3867 - val_loss:
157651744.0000 - val_mean_absolute_error: 7893.4106 -
val_root_mean_squared_error: 12555.9443
Epoch 3/10
214/214 [==============================] - 0s 1ms/step - loss: 184540800.0000 -
mean_absolute_error: 8196.5605 - root_mean_squared_error: 13584.5791 - val_loss:
155993008.0000 - val_mean_absolute_error: 7151.0796 -
val_root_mean_squared_error: 12489.7158
Epoch 4/10
214/214 [==============================] - 0s 1ms/step - loss: 181883776.0000 -
mean_absolute_error: 8180.3018 - root_mean_squared_error: 13486.4297 - val_loss:
154250208.0000 - val_mean_absolute_error: 7666.9731 -
val_root_mean_squared_error: 12419.7510
Epoch 5/10
214/214 [==============================] - 0s 1ms/step - loss: 181336768.0000 -
mean_absolute_error: 8203.1885 - root_mean_squared_error: 13466.1338 - val_loss:
156571600.0000 - val_mean_absolute_error: 8258.9648 -
val_root_mean_squared_error: 12512.8574
Epoch 6/10
214/214 [==============================] - 0s 1ms/step - loss: 179982320.0000 -
mean_absolute_error: 8213.5850 - root_mean_squared_error: 13415.7490 - val_loss:
153430944.0000 - val_mean_absolute_error: 7567.6997 -
val_root_mean_squared_error: 12386.7246
Epoch 7/10
214/214 [==============================] - 0s 1ms/step - loss: 179978672.0000 -
mean_absolute_error: 8248.8291 - root_mean_squared_error: 13415.6133 - val_loss:
153227456.0000 - val_mean_absolute_error: 7639.2065 -
val_root_mean_squared_error: 12378.5078
Epoch 8/10
214/214 [==============================] - 0s 1ms/step - loss: 179719888.0000 -
mean_absolute_error: 8252.9473 - root_mean_squared_error: 13405.9648 - val_loss:
160659728.0000 - val_mean_absolute_error: 6931.7920 -
```

```
val_root_mean_squared_error: 12675.1621
Epoch 9/10
214/214 [==============================] - 0s 1ms/step - loss: 180225152.0000 -
mean_absolute_error: 8188.8667 - root_mean_squared_error: 13424.7959 - val_loss:
152798464.0000 - val_mean_absolute_error: 7528.9785 -
val_root_mean_squared_error: 12361.1680
Epoch 10/10
214/214 [==============================] - 0s 1ms/step - loss: 178962368.0000 -
mean_absolute_error: 8178.6772 - root_mean_squared_error: 13377.6816 - val_loss:
154488128.0000 - val_mean_absolute_error: 7181.6348 -
val_root_mean_squared_error: 12429.3252
214/214 [==============================] - 0s 777us/step - loss: 181237472.0000
- mean_absolute_error: 7613.6636 - root_mean_squared_error: 13462.4463
Pérdida en el conjunto de prueba: 181237472.0
RMSE en el conjunto de prueba 13462.4462890625
MAE en el conjunto de prueba: 7613.66357421875
R2 en el conjunto de prueba: tf.Tensor(-0.0008561169972987059, shape=(),
dtype=float64)
```

[51]:

```
#Las guardo en el diccionario
results_train['Red Neuronal']['RMSE'] = rmse
results_train['Red Neuronal']['MAE'] = mae
results_train['Red Neuronal']['R2'] = r2
```

[52]:

```
# Evaluar el modelo en el conjunto de prueba
loss, mae, rmse = model.evaluate(X_test, y_test)
r2 = 1 - (rmse**2 / tf.math.reduce_variance(y_test))
print("Pérdida en el conjunto de prueba:", loss)
print("RMSE en el conjunto de prueba", rmse)
print("MAE en el conjunto de prueba:", mae)
print("R2 en el conjunto de prueba:", r2)
```

```
54/54 [==============================] - 0s 866us/step - loss: 154488128.0000 -
mean_absolute_error: 7181.6348 - root_mean_squared_error: 12429.3252
Pérdida en el conjunto de prueba: 154488128.0
RMSE en el conjunto de prueba 12429.3251953125
MAE en el conjunto de prueba: 7181.634765625
R2 en el conjunto de prueba: tf.Tensor(0.004826661757593609, shape=(),
dtype=float64)
```

[53]:

```
#Las guardo en el diccionario
results_test['Red Neuronal']['RMSE'] = rmse
results_test['Red Neuronal']['MAE'] = mae
results_test['Red Neuronal']['R2'] = r2
```

[54]:

```
results_test
```

[54]:
```
{'XGboost': {'RMSE': 5928.3168595662255,
  'MAE': 3397.416068268864,
  'R2': 0.7736052004736758},
 'GradientBoost': {'RMSE': 5282.798720503473,
  'MAE': 3021.8006237884983,
  'R2': 0.8202239812225536},
 'Red Neuronal': {'RMSE': 12429.3251953125,
  'MAE': 7181.634765625,
  'R2': <tf.Tensor: shape=(), dtype=float64, numpy=0.004826661757593609>},
 'Bagging': {'RMSE': 5310.449504090665,
  'MAE': 2874.3143787170675,
  'R2': 0.8183371188555317}}
```

[55]:
```
results_train
```

[55]:
```
{'XGboost': {'RMSE': 4733.259772344792,
  'MAE': 2848.6528656022,
  'R2': 0.8762787323801671},
 'GradientBoots': {'RMSE': 3261.517901237745,
  'MAE': 2138.47911297073,
  'R2': 0.9412560407833545},
 'Bagging': {'RMSE': 2191.697154089147,
  'MAE': 1124.5387358931494,
  'R2': 0.9734732058033906},
 'Red Neuronal': {'RMSE': 13462.4462890625,
  'MAE': 7613.66357421875,
  'R2': <tf.Tensor: shape=(), dtype=float64, numpy=-0.0008561169972987059>}}
```

0.8 PREDICCION

En base a los modelos que hemos entrenado, podemos ahora predecir la producción para la campaña 22. Consideramos que el modelo de Gradient Boosting es el más adecuado, por lo que lo emplearemos para dar una prediccción.

[56]:
```
# Seleccionamos las filas del dataset correspondientes a la campaña 22 y␣
↪generamos con ellas
# un dataframe
df22=df[df['CAMPAÑA']==22]
X = df22.drop('PRODUCCION', axis=1).values
```

[57]:
```
# Generamos las predicciones
predicciones = gbr.predict(X)
```

[58]:
```
# Las añadimos al dataframe
df22['PRODUCCION']=predicciones
```

[59]:
```
# Vemos el resultado
df22
```

[59]:

```
      CAMPAÑA  ID_FINCA  ID_ZONA  ALTITUD  VARIEDAD  MODO  TIPO  COLOR  \
8526       22     48626      302    600.0        32     2     0      1
8527       22     47921      302    600.0        32     2     0      1
8528       22      5696      919    655.0        59     1     0      1
8529       22     98814      919    655.0        32     2     0      1
8530       22     98814      919    655.0        40     2     0      1
…         …         …        …        …         …     …     …      …
9596       22     37461      239    700.0        52     2     0      1
9597       22     58769      239    700.0        32     2     0      1
9598       22     58769      239    700.0        59     2     0      1
9599       22     88928      239    700.0        40     2     0      1
9600       22     88928      239    700.0        52     2     0      1

      SUPERFICIE    PRODUCCION  precip_media
8526      3.7503  21421.294747     39.370690
8527      7.3735  52235.319116     39.370690
8528      7.6200   4596.699651     40.389625
8529      3.3267  10427.578708     40.389625
8530      2.7724   9210.768702     40.389625
…            …             …           …
9596      3.6800  27953.833890     55.656785
9597      4.2500  38946.035967     55.656785
9598      4.0700  40267.601216     55.656785
9599      4.5727  39914.968326     55.656785
9600      1.6099  11721.321435     55.656785

[1075 rows x 11 columns]
```