

Dengue Case Prediction using Machine Learning



```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')

df = pd.read_csv('dengue_data.csv')

df.head()

  serial      tempmax      tempmin       temp  feelslikemax  feelslikemin
\0      0    34.053151    24.478082   28.709863    39.757808    25.317808
1      1    34.086179    25.694309   29.464228    41.338211    28.140650
2      2    34.573984    25.417886   29.526829    40.464228    26.560163
3      3    33.020325    25.080488   28.727642    37.878049    26.193496
4      4    30.660976    24.230894   26.774797    36.586992    24.263415

  feelslike      dew  humidity      precip ...
sealevelpressure \
0  32.306301  22.971233  73.508219    2.921726 ...          1007.911781
1  34.423577  23.484553  72.066667    3.783415 ...          1003.533333
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2 33.085366 22.580488 69.424390 3.065854 ... 1005.731707
3 31.772358 21.752033 69.297561 6.025203 ... 1003.359350
4 28.943902 24.214634 86.652033 23.336585 ... 1009.995935

    cloudcover visibility solarradiation solarenergy uvindex
conditions \
0 50.747945 3.789863 208.097808 17.973699 7.232877
2.558904
1 48.313821 2.884553 222.926016 19.246341 7.504065
1.658537
2 55.621138 4.242276 229.413008 19.802439 7.829268
1.910569
3 50.208130 2.991057 225.421951 19.480488 7.593496
1.300813
4 45.542276 3.886992 176.598374 15.261789 6.186992
0.967480

    stations cases labels
0 1.197260 4925 normal
1 0.991870 5077 normal
2 1.170732 7579 normal
3 0.146341 13706 normal
4 3.951220 82 normal

[5 rows x 26 columns]

df.tail()

    serial tempmax tempmin temp feelslikemax feelslikemin
feelslike \
597 597 32.3 24.4 28.5 35.9 24.4
31.2
598 598 32.7 26.4 29.3 36.3 26.4
32.5
599 599 33.0 26.3 29.8 40.5 26.3
34.5
600 600 35.1 26.8 30.6 42.9 29.1
35.1
601 601 34.0 26.3 30.2 38.1 26.3
33.1

    dew humidity precip ... sealevelpressure cloudcover
visibility \
597 23.3 75.0 0.0 ... 1008.9 50.4
3.1
598 22.6 68.5 0.0 ... 1010.4 50.5

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3.1
599 23.9      71.1     0.0 ...          1010.8        30.5
3.1
600 23.3      65.9     0.0 ...          1009.7        32.7
3.3
601 21.5      60.4     0.0 ...          1008.7        46.5
3.9

   solarradiation  solarenergy  uvindex  conditions  stations  cases
labels
597           252.5       21.9      9.0        1.0        1.0    6729
normal
598           242.7       20.9      8.0        1.0        1.0   10541
normal
599           195.3       16.9      8.0        1.0        1.0    6396
normal
600           187.6       16.0      7.0        1.0        1.0   10883
normal
601           136.2       11.7      5.0        1.0        1.0    7311
normal

[5 rows x 26 columns]

df.shape
(602, 26)

df.columns
Index(['serial', 'tempmax', 'tempmin', 'temp', 'feelslikemax',
'feelslikemin',
       'feelslike', 'dew', 'humidity', 'precip', 'precipprob',
'precipcover',
       'snow', 'snowdepth', 'windspeed', 'winddir',
'sealevelpressure',
       'cloudcover', 'visibility', 'solarradiation', 'solarenergy',
'uvindex',
       'conditions', 'stations', 'cases', 'labels'],
      dtype='object')

df = df.drop('serial', axis = 1)

df.duplicated().sum()
0

df.isnull().sum()

tempmax          0
tempmin          0
temp             0

```

```
feelslikemax      0
feelslikemin      0
feelslike         0
dew               0
humidity          0
precip            0
precipprob        0
precipcover       0
snow              0
snowdepth         0
windspeed         0
winddir           0
sealevelpressure  0
cloudcover        0
visibility        0
solarradiation    0
solarenergy       0
uvindex           0
conditions        0
stations          0
cases             0
labels            0
dtype: int64
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 602 entries, 0 to 601
Data columns (total 25 columns):
 #   Column           Non-Null Count  Dtype  
 --- 
 0   tempmax          602 non-null    float64
 1   tempmin          602 non-null    float64
 2   temp              602 non-null    float64
 3   feelslikemax     602 non-null    float64
 4   feelslikemin     602 non-null    float64
 5   feelslike         602 non-null    float64
 6   dew               602 non-null    float64
 7   humidity          602 non-null    float64
 8   precip            602 non-null    float64
 9   precipprob        602 non-null    float64
 10  precipcover       602 non-null    float64
 11  snow              602 non-null    int64  
 12  snowdepth         602 non-null    int64  
 13  windspeed         602 non-null    float64
 14  winddir           602 non-null    float64
 15  sealevelpressure  602 non-null    float64
 16  cloudcover        602 non-null    float64
 17  visibility        602 non-null    float64
 18  solarradiation    602 non-null    float64
```

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19 solarenergy      602 non-null    float64
20 uvindex         602 non-null    float64
21 conditions       602 non-null    float64
22 stations         602 non-null    float64
23 cases            602 non-null    int64
24 labels           602 non-null    object
dtypes: float64(21), int64(3), object(1)
memory usage: 117.7+ KB

df.describe()

      tempmax      tempmin       temp  feelslikemax  feelslikemin
\count  602.000000  602.000000  602.000000  602.000000  602.000000
mean   31.918079  24.588318  27.813181  38.476069  25.613154
std    2.737215   2.727919  2.412416  4.776400  4.178797
min   25.000000  12.740000  18.820000  25.000000  12.360000
25%  30.025000  23.200000  26.500000  35.600000  23.200000
50%  31.700000  25.000000  27.900000  38.400000  25.000000
75%  33.600000  26.500000  29.448171  41.900000  26.600000
max  41.200000  29.400000  33.300000  49.600000  37.900000

      feelslike        dew      humidity      precip  precipprob ...
\count  602.000000  602.000000  602.000000  602.000000  602.000000 ...
mean   31.485111  23.984349  81.254786  13.120862  69.625588 ...
std    4.672951   2.668014  9.406354  28.463365  45.539264 ...
min   18.626667   4.480000  40.833333  0.000000  0.000000 ...
25%  28.100000  23.300000  75.800000  0.000000  0.000000 ...
50%  31.500000  24.529268  82.800000  3.000000  100.000000 ...
75%  34.875000  25.475000  88.175000  12.589000  100.000000 ...
max  42.900000  28.100000  99.300000  302.000000  100.000000 ...

      winddir  sealevelpressure  cloudcover  visibility
solarradiation \

```

count	602.000000	602.000000	602.000000	602.000000
	602.000000			
mean	191.498693	1004.690531	59.701192	3.632620
	199.802695			
std	81.604668	41.364967	20.832639	1.890352
	54.128192			
min	0.500000	0.000000	0.000000	0.800000
	57.900000			
25%	134.425000	1002.025000	47.400000	2.523780
	160.350000			
50%	207.300000	1007.000000	63.700000	3.200000
	205.750000			
75%	252.375000	1010.185772	73.200000	4.300000
	238.800610			
max	359.200000	1020.000000	97.900000	24.033333
	318.500000			

	solarenergy	uvindex	conditions	stations	cases
count	602.000000	602.000000	602.000000	602.000000	602.000000
mean	17.251785	6.877674	1.827725	0.859734	8502.342193
std	4.676051	1.763928	1.237389	0.973575	6780.749627
min	5.000000	2.000000	0.000000	0.000000	52.000000
25%	13.900000	6.000000	1.000000	0.000000	3017.750000
50%	17.750000	7.000000	2.000000	1.000000	7490.000000
75%	20.600610	8.000000	3.000000	1.000000	12702.500000
max	27.700000	10.000000	4.000000	5.000000	24983.000000

[8 rows x 24 columns]

df.unique()

tempmax	118
tempmin	126
temp	125
feelslikemax	192
feelslikemin	157
feelslike	202
dew	123
humidity	295
precip	207
precipprob	17
precipcover	35
snow	1
snowdepth	1
windspeed	165
winddir	539
sealevelpressure	221
cloudcover	408
visibility	77
solarradiation	523

```
solarenergy      196
uvindex          24
conditions        20
stations          17
cases             578
labels            1
dtype: int64

object_columns = df.select_dtypes(include=['object']).columns
print("Object type columns:")
print(object_columns)

numerical_columns = df.select_dtypes(include=['int64',
                                             'float64']).columns
print("\nNumerical type columns:")
print(numerical_columns)

Object type columns:
Index(['labels'], dtype='object')

Numerical type columns:
Index(['tempmax', 'tempmin', 'temp', 'feelslikemax', 'feelslikemin',
       'feelslike', 'dew', 'humidity', 'precip', 'precipprob',
       'precipcover',
       'snow', 'snowdepth', 'windspeed', 'winddir',
       'sealevelpressure',
       'cloudcover', 'visibility', 'solarradiation', 'solarenergy',
       'uvindex',
       'conditions', 'stations', 'cases'],
      dtype='object')

def classify_features(df):
    categorical_features = []
    non_categorical_features = []
    discrete_features = []
    continuous_features = []

    for column in df.columns:
        if df[column].dtype == 'object':
            if df[column].nunique() < 20:
                categorical_features.append(column)
            else:
                non_categorical_features.append(column)
        elif df[column].dtype in ['int64', 'float64']:
            if df[column].nunique() < 10:
                discrete_features.append(column)
            else:
                continuous_features.append(column)
```

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    return categorical_features, non_categorical_features,
discrete_features, continuous_features

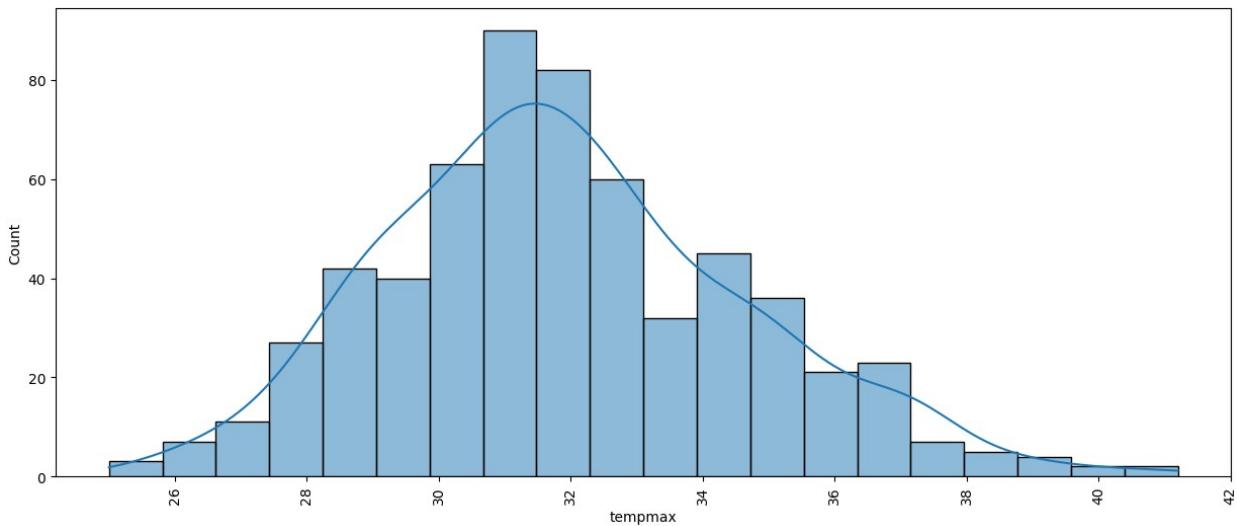
categorical, non_categorical, discrete, continuous =
classify_features(df)

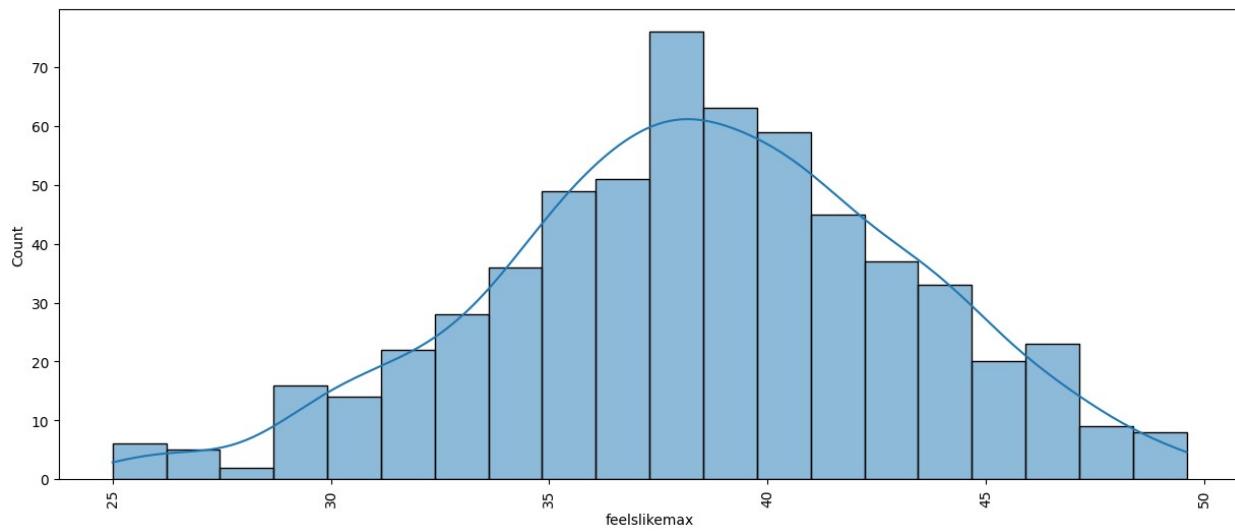
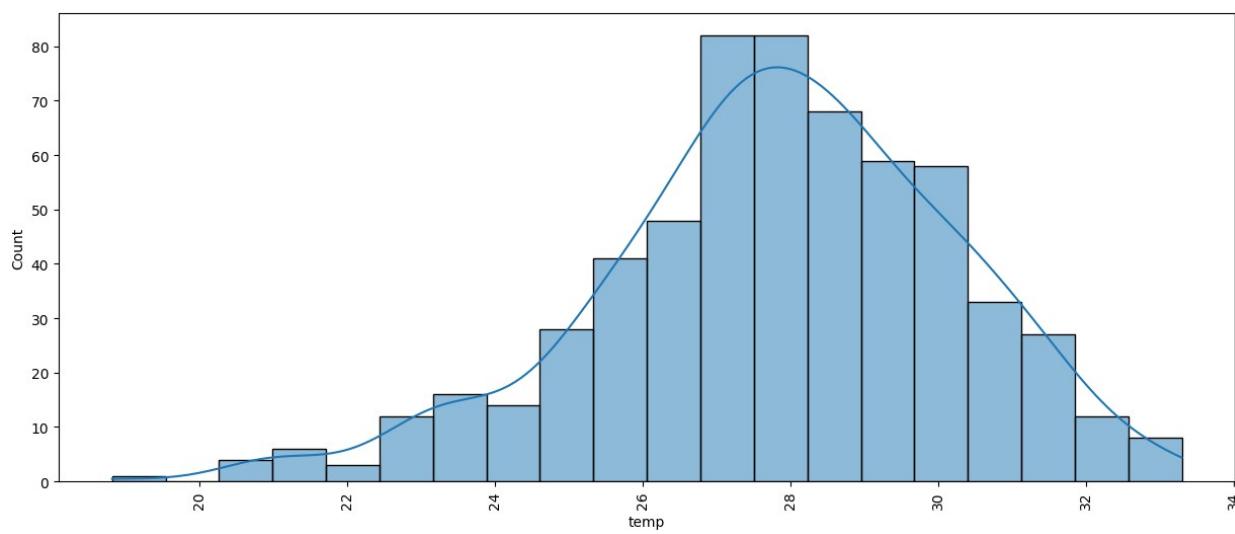
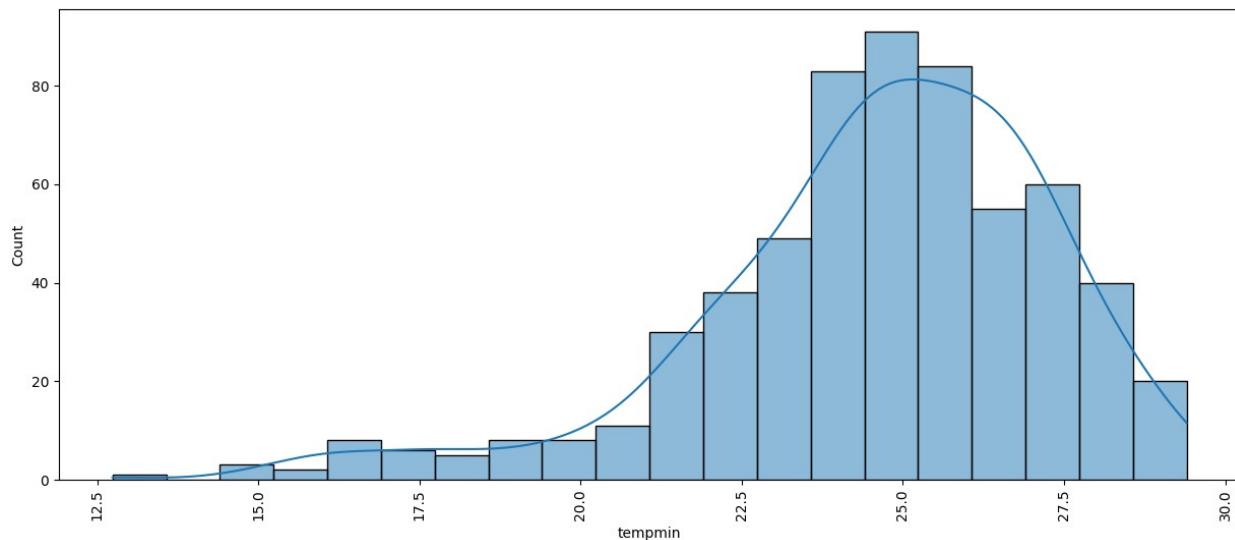
print("Categorical Features:", categorical)
print("Non-Categorical Features:", non_categorical)
print("Discrete Features:", discrete)
print("Continuous Features:", continuous)

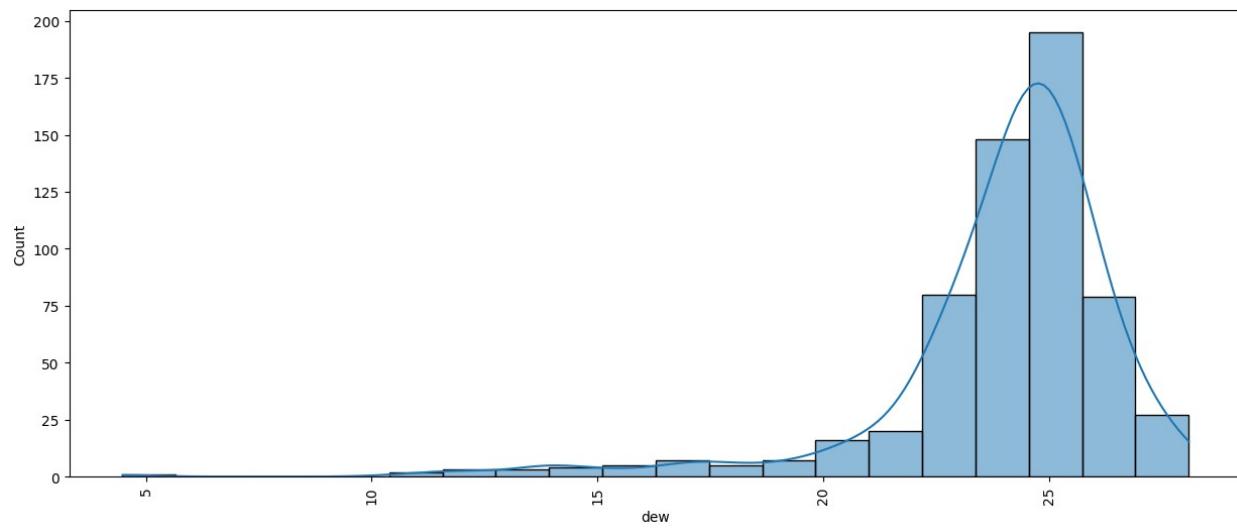
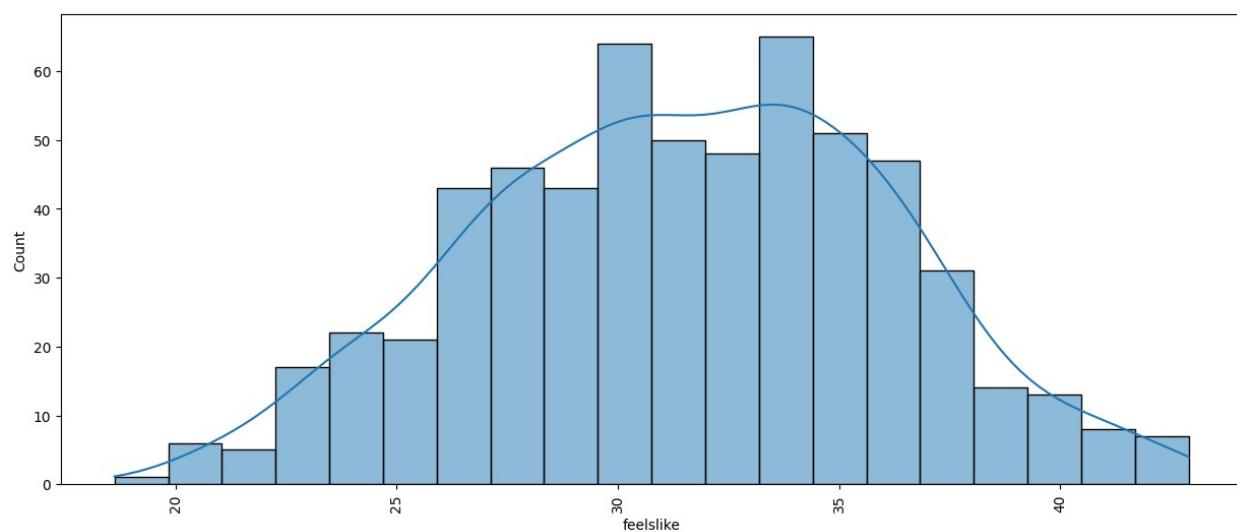
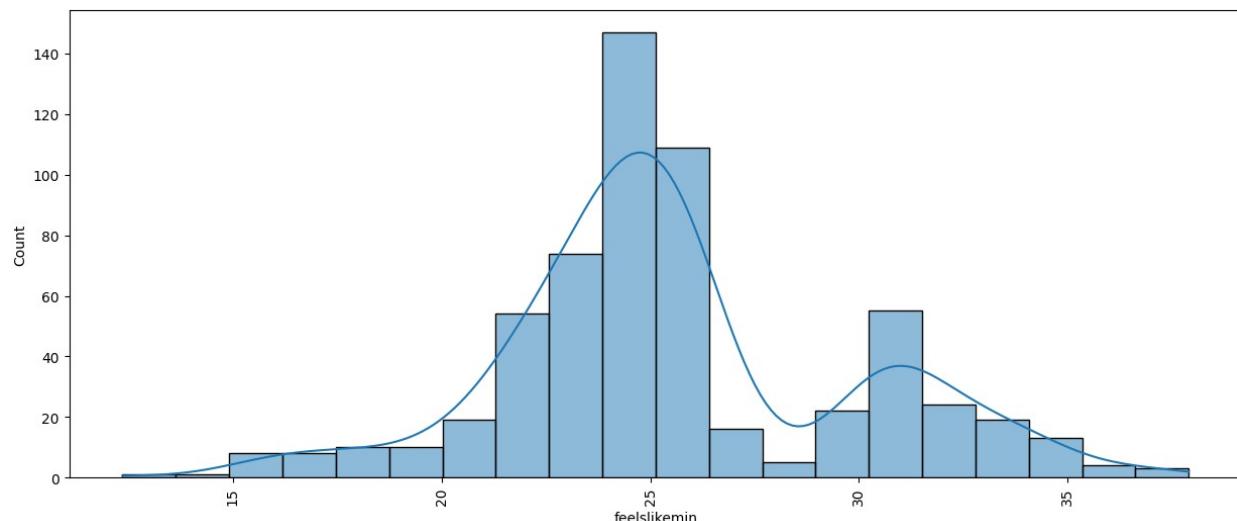
Categorical Features: ['labels']
Non-Categorical Features: []
Discrete Features: ['snow', 'snowdepth']
Continuous Features: ['tempmax', 'tempmin', 'temp', 'feelslikemax',
'feelslikemin', 'feelslike', 'dew', 'humidity', 'precip',
'precipprob', 'precipcover', 'windspeed', 'winddir',
'sealevelpressure', 'cloudcover', 'visibility', 'solarradiation',
'solarenergy', 'uvindex', 'conditions', 'stations', 'cases']

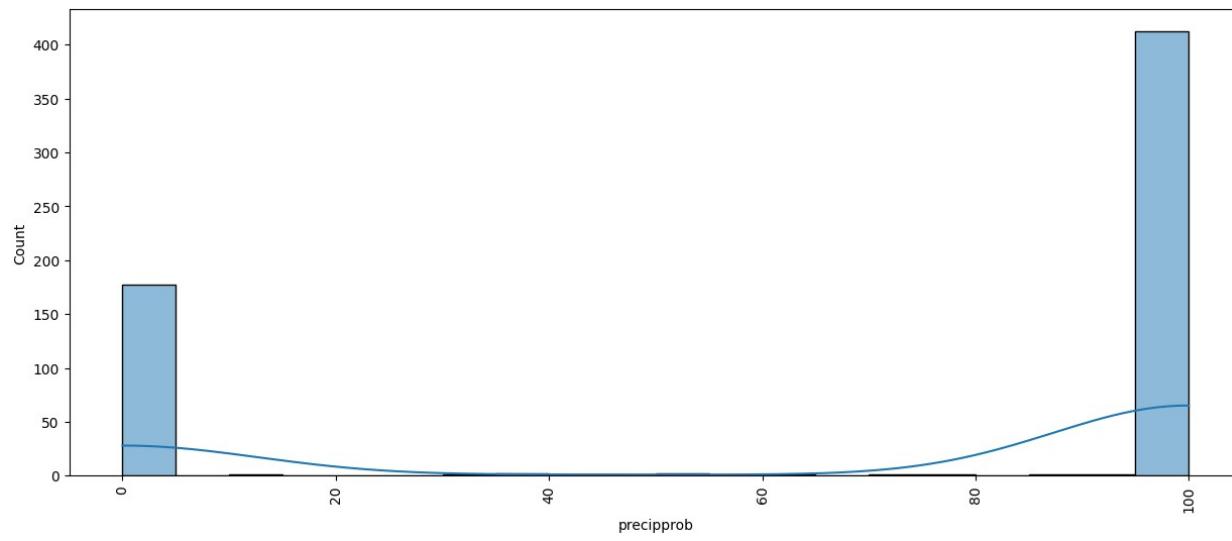
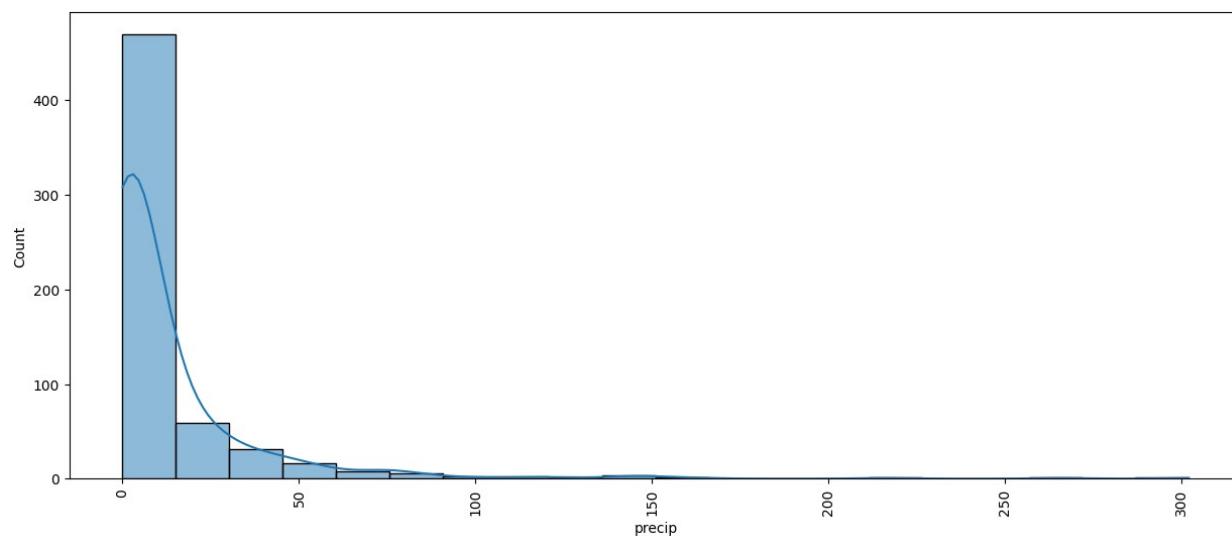
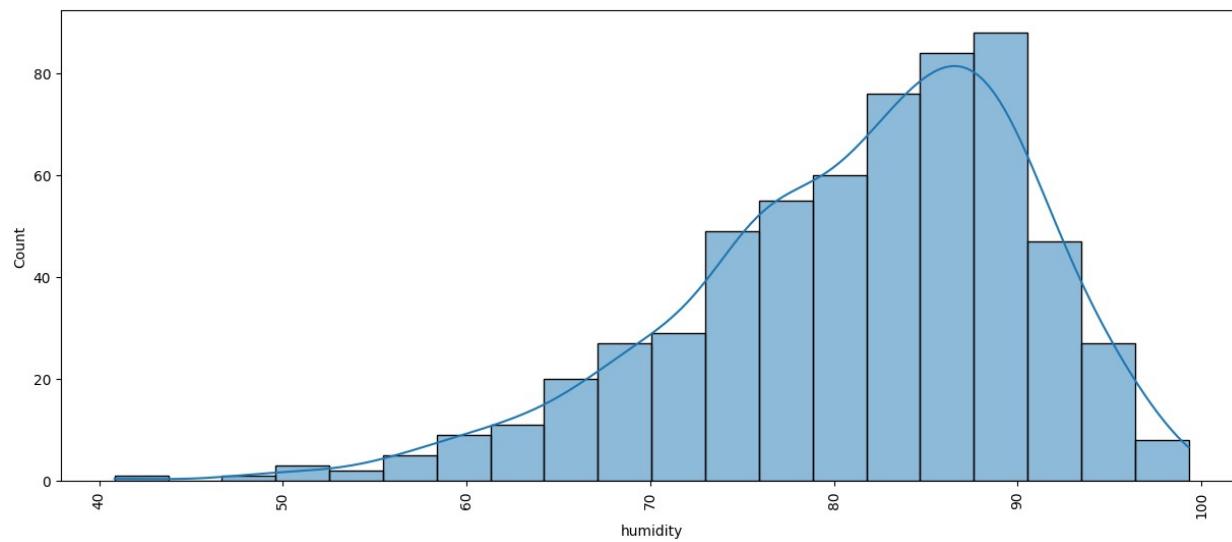
for i in continuous:
    plt.figure(figsize=(15,6))
    sns.histplot(df[i], bins = 20, kde = True, palette='hls')
    plt.xticks(rotation = 90)
    plt.show()

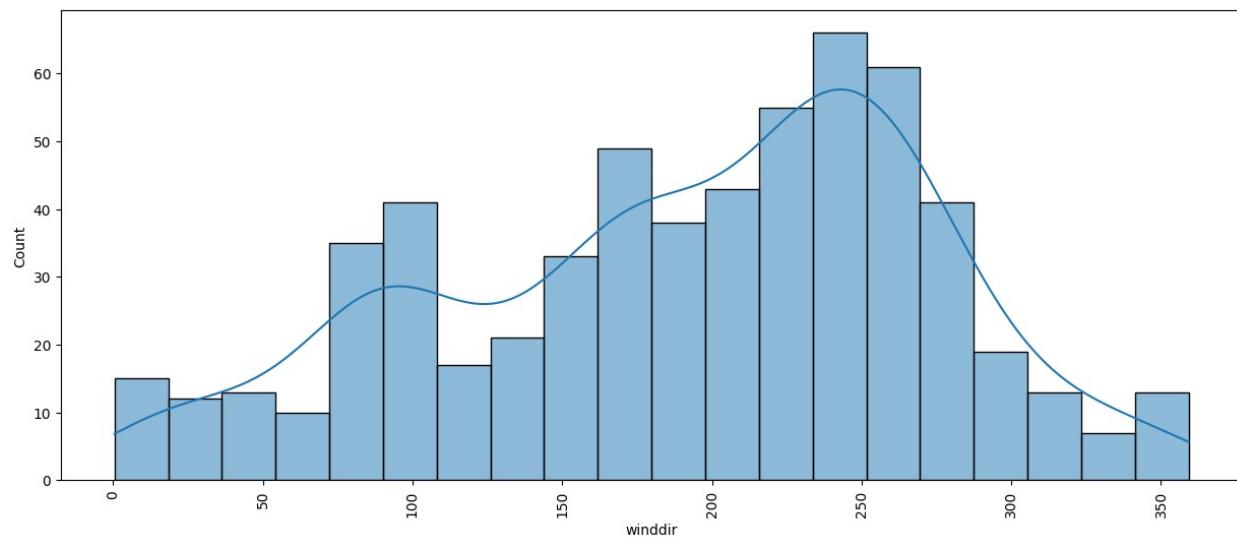
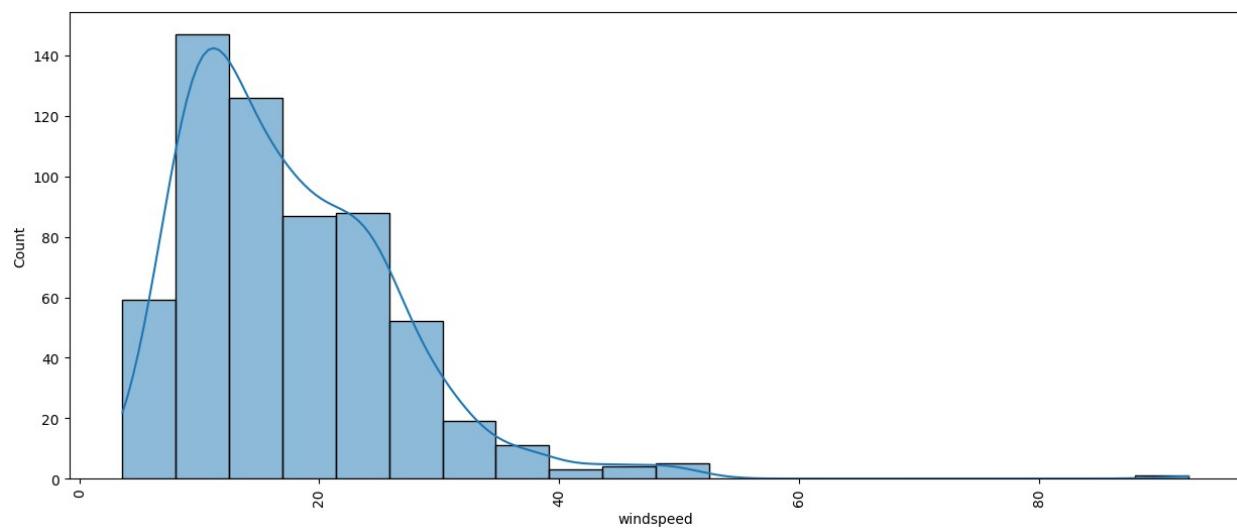
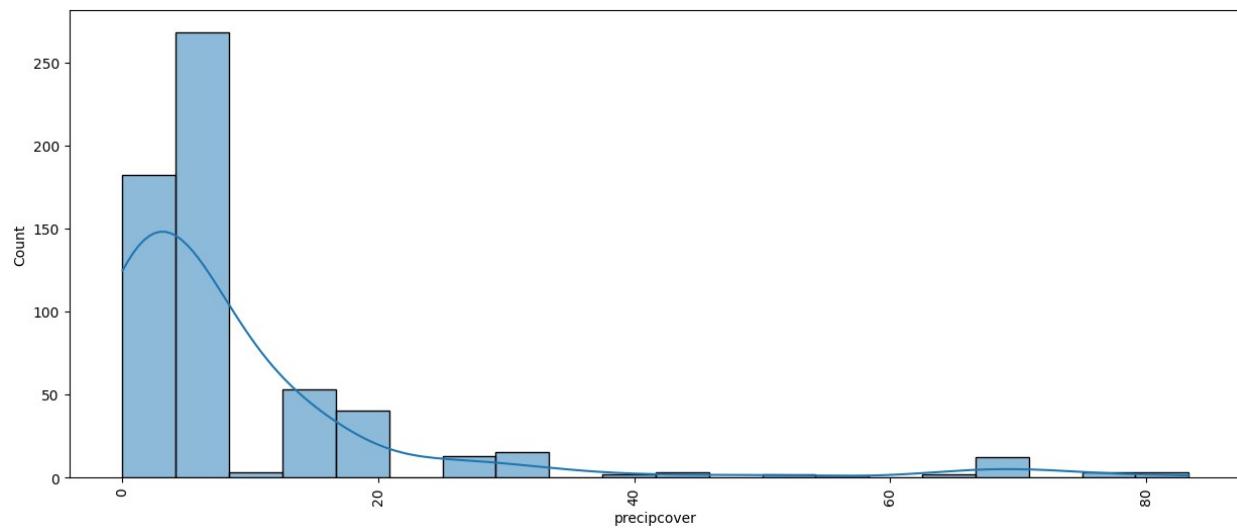
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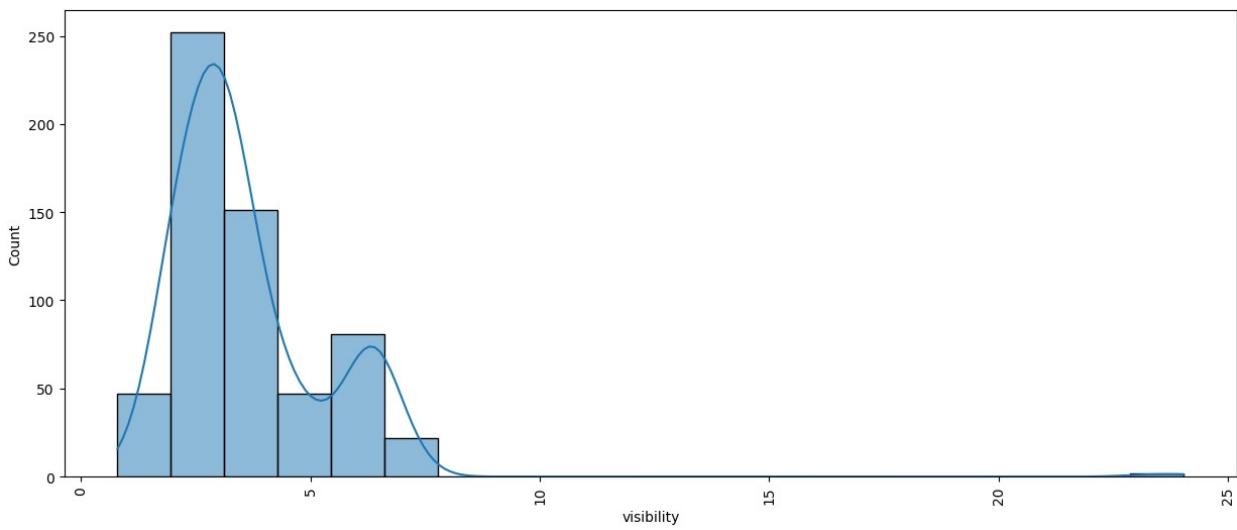
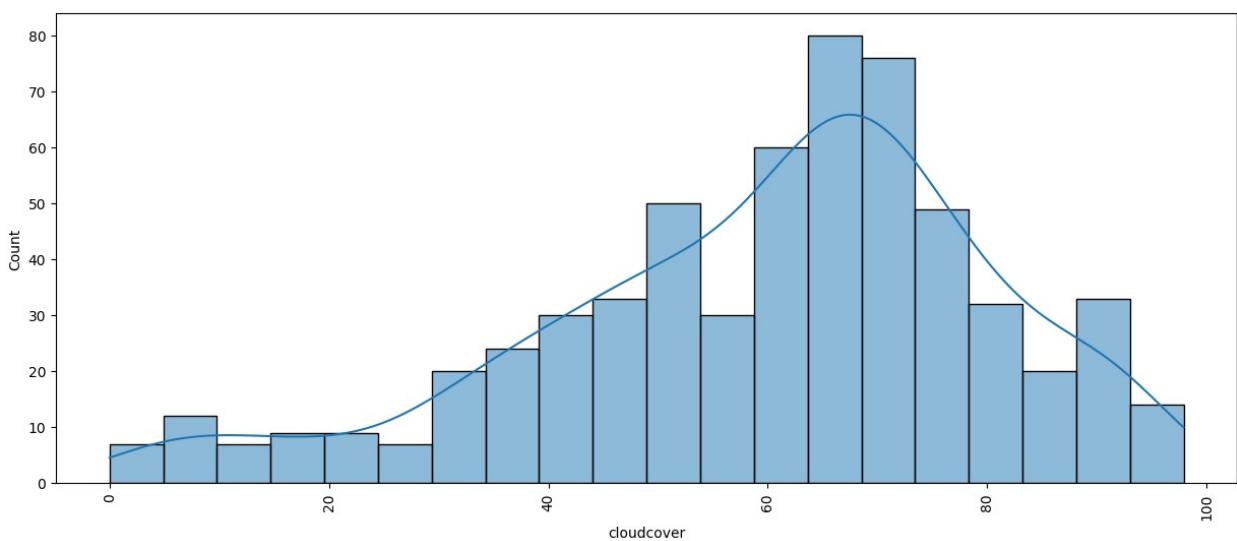
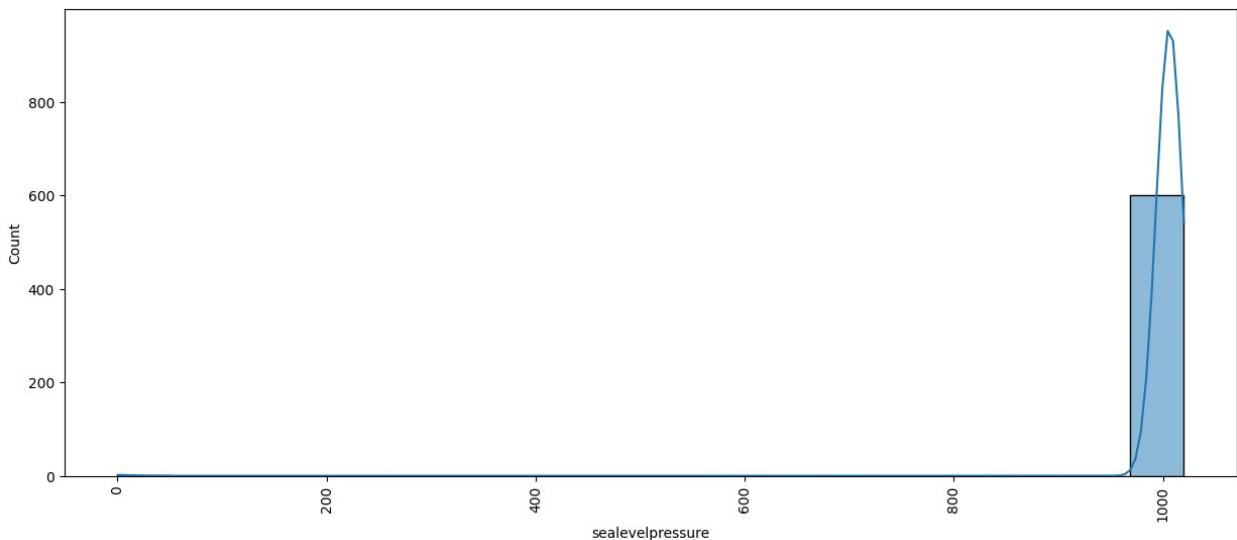


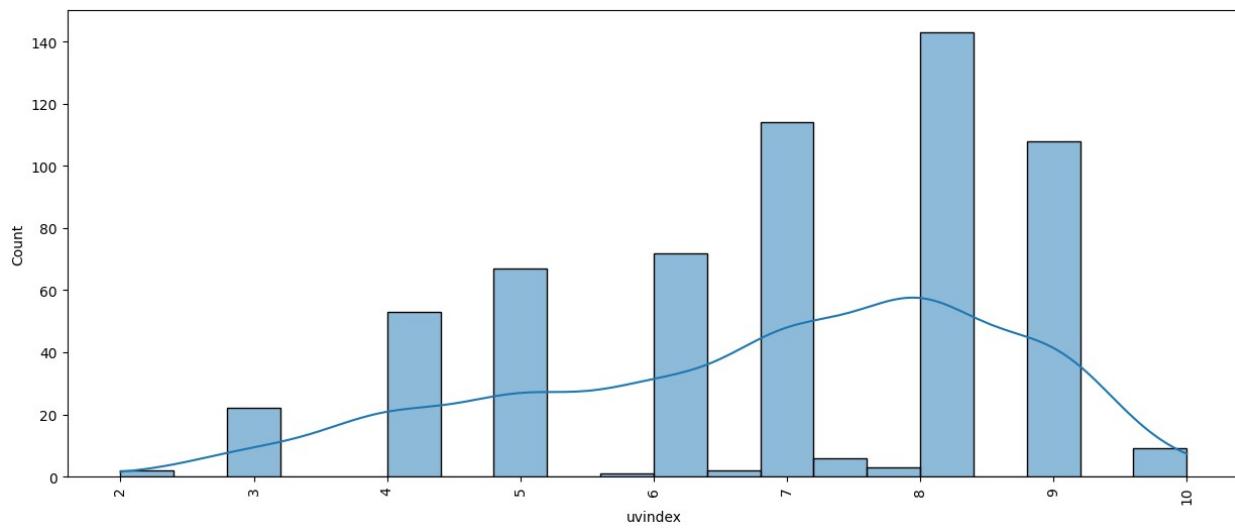
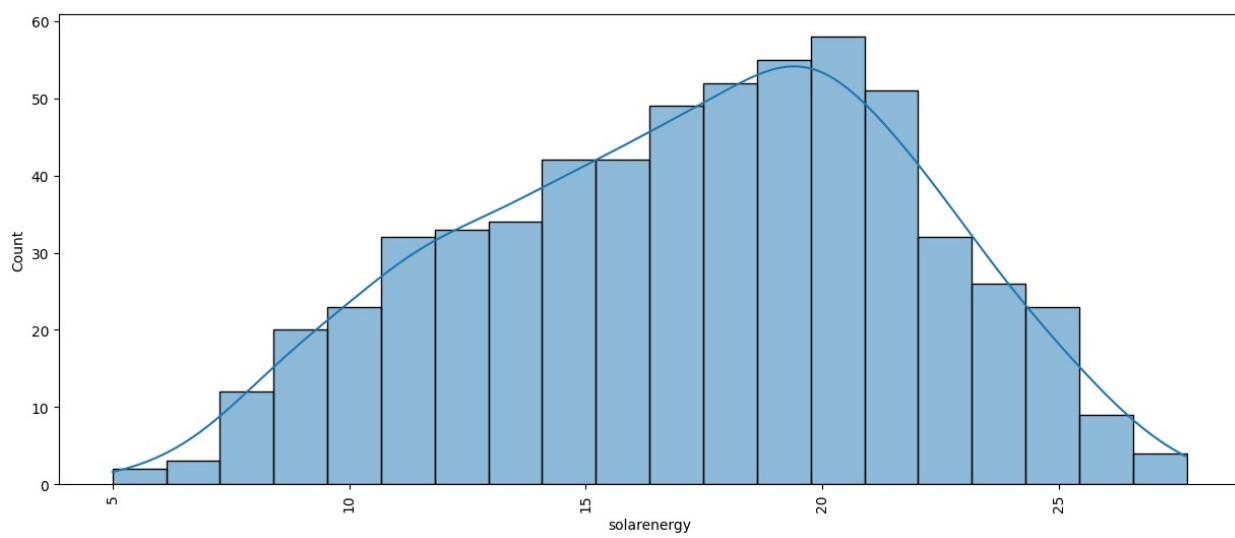
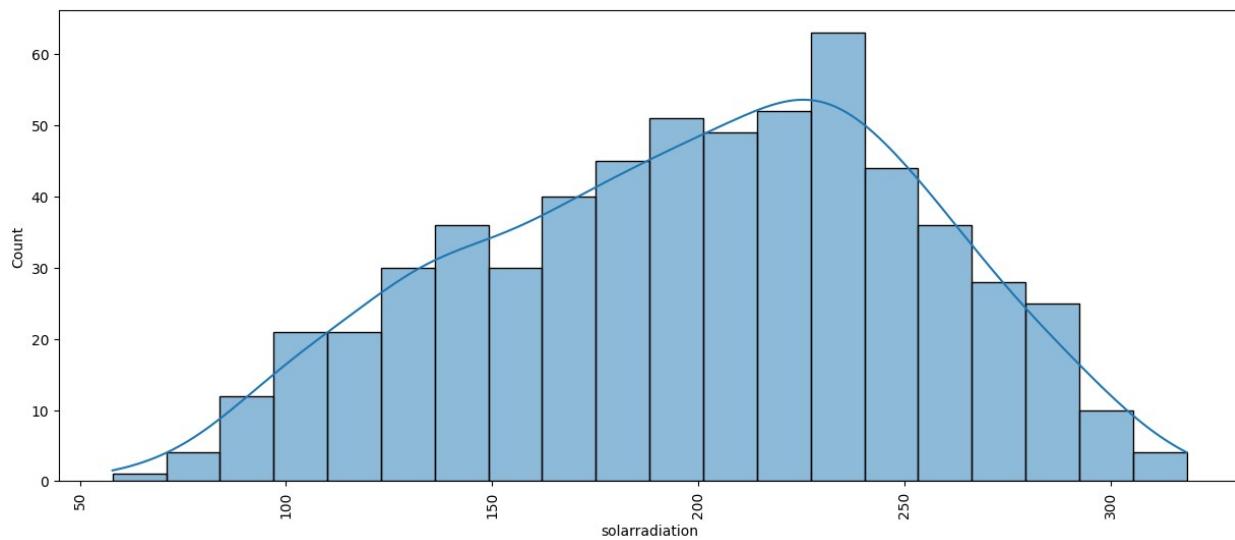


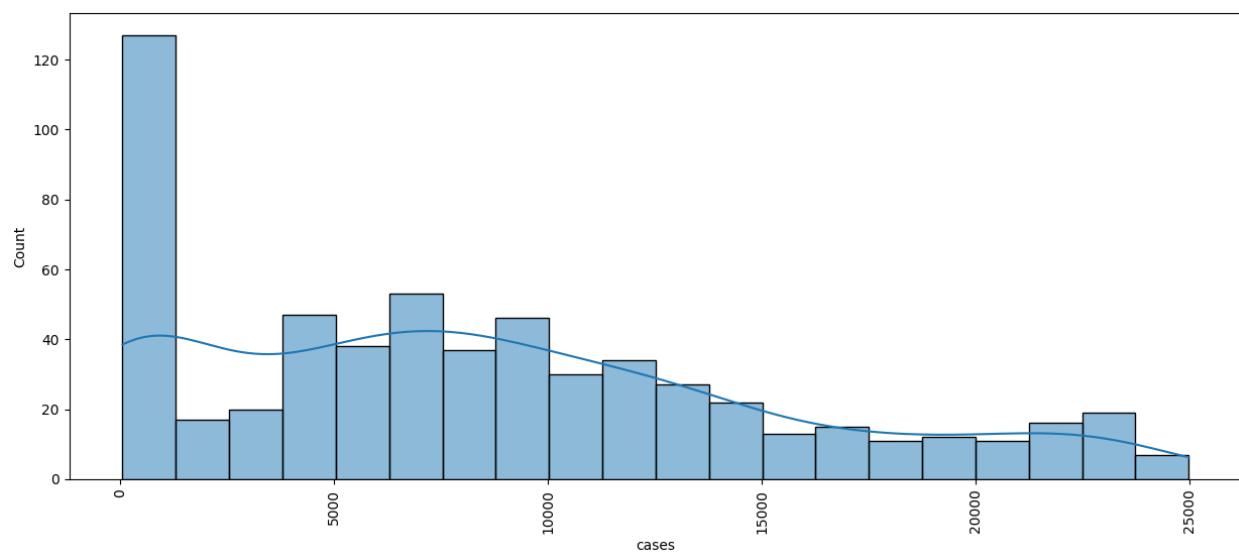
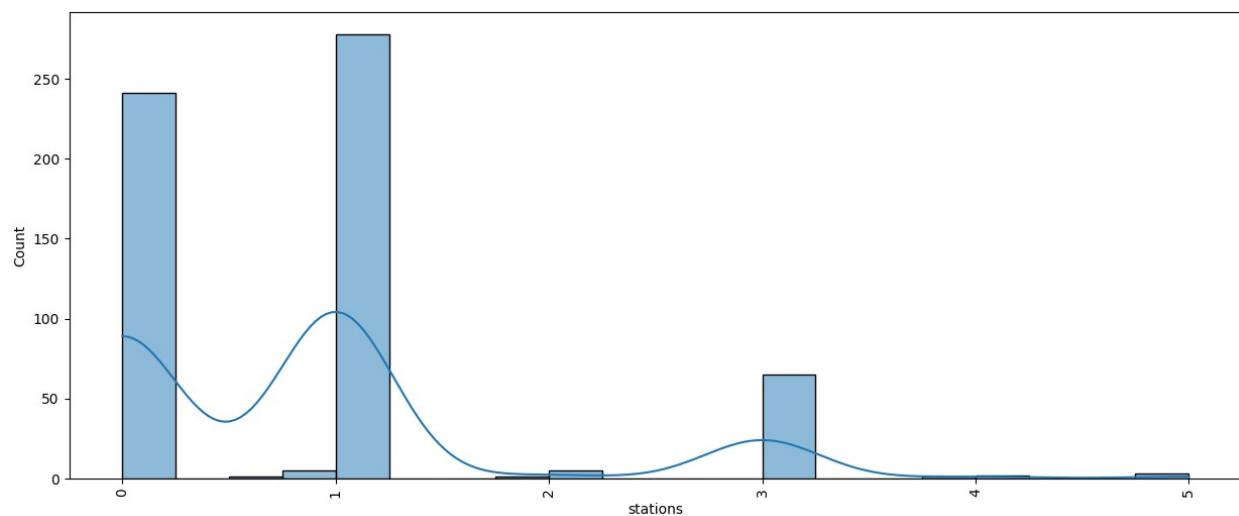
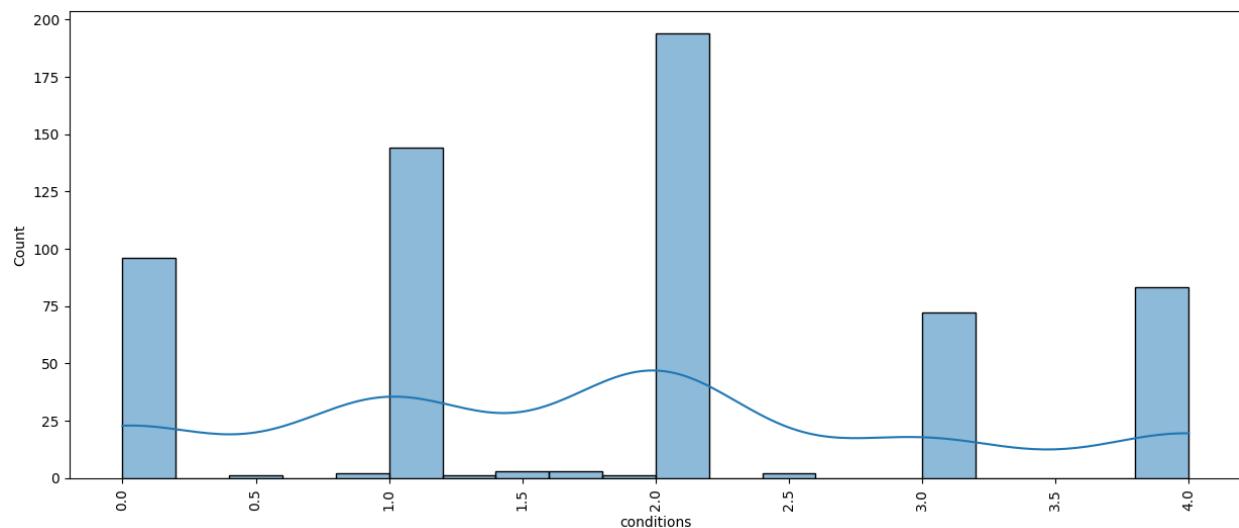




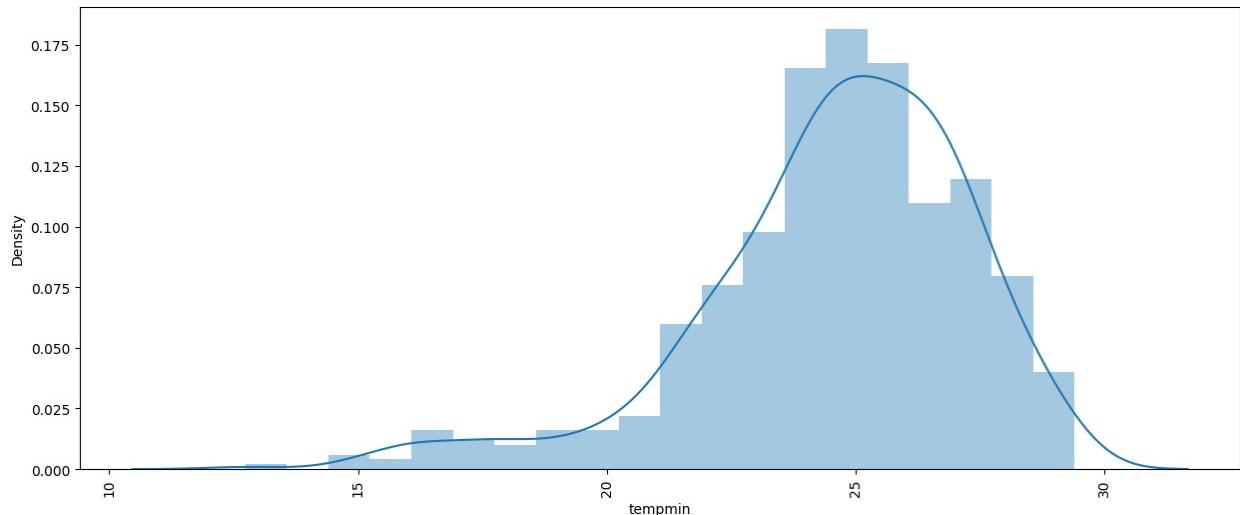
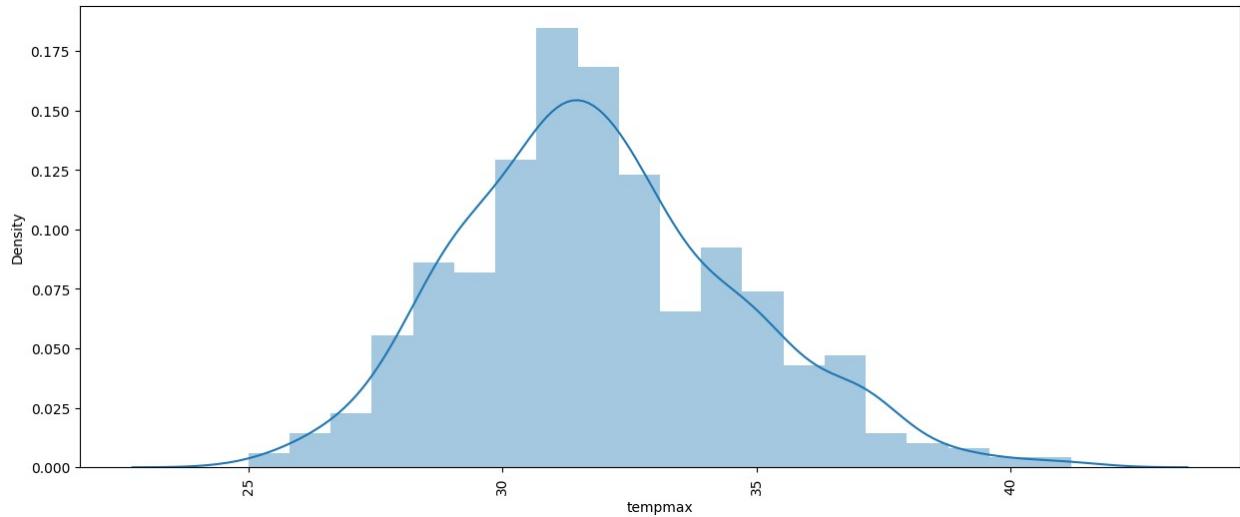


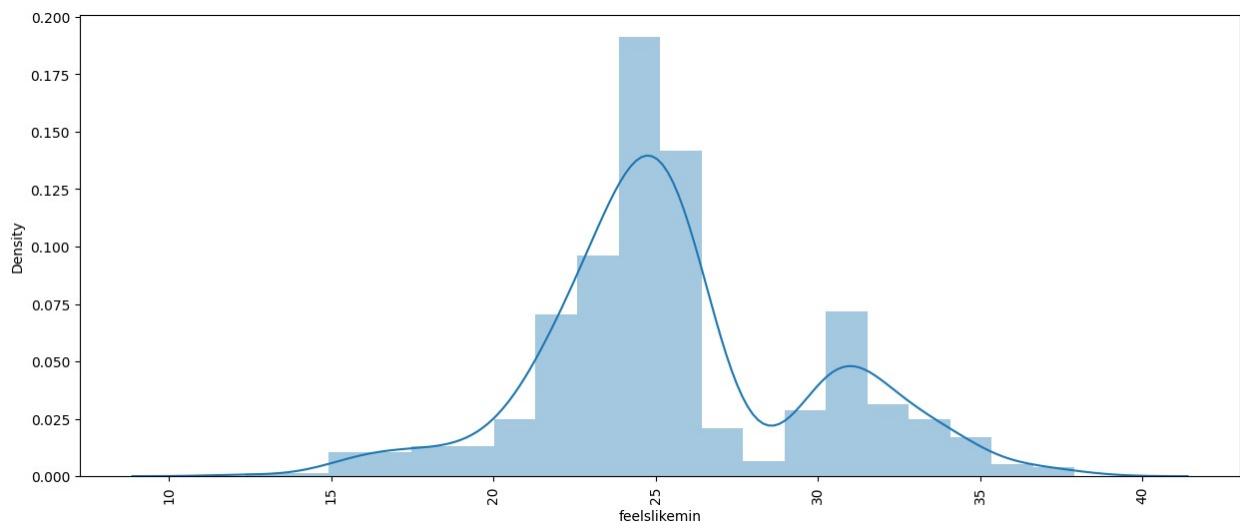
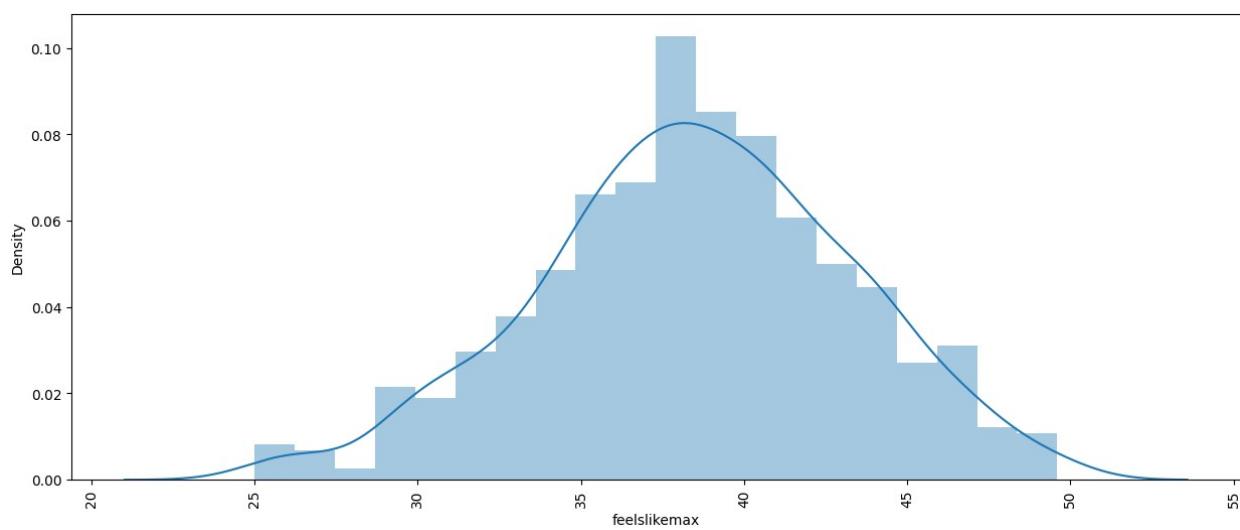
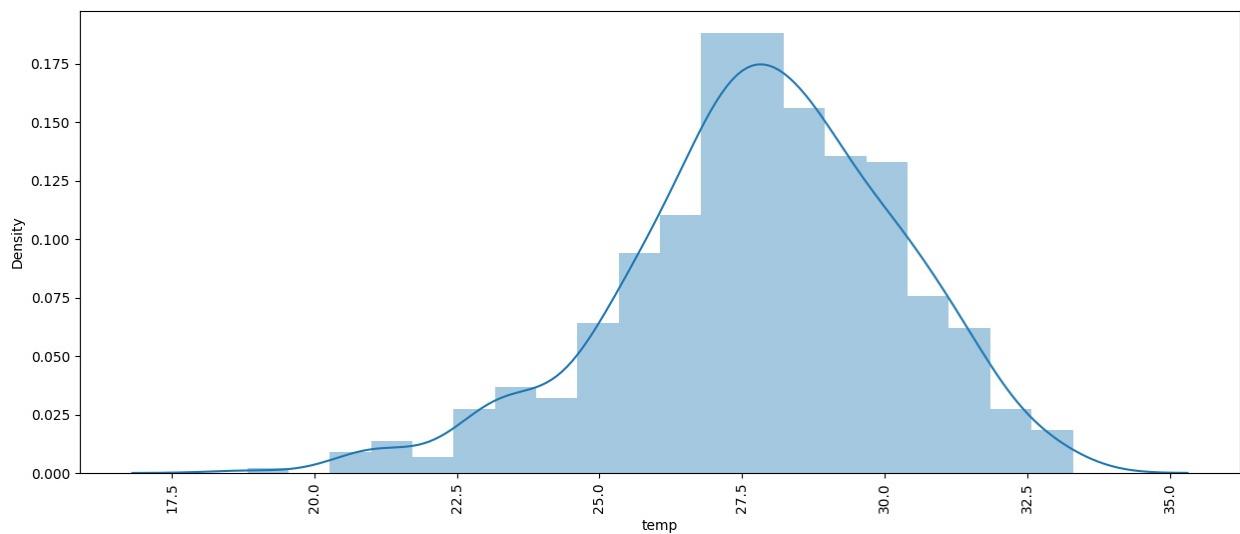


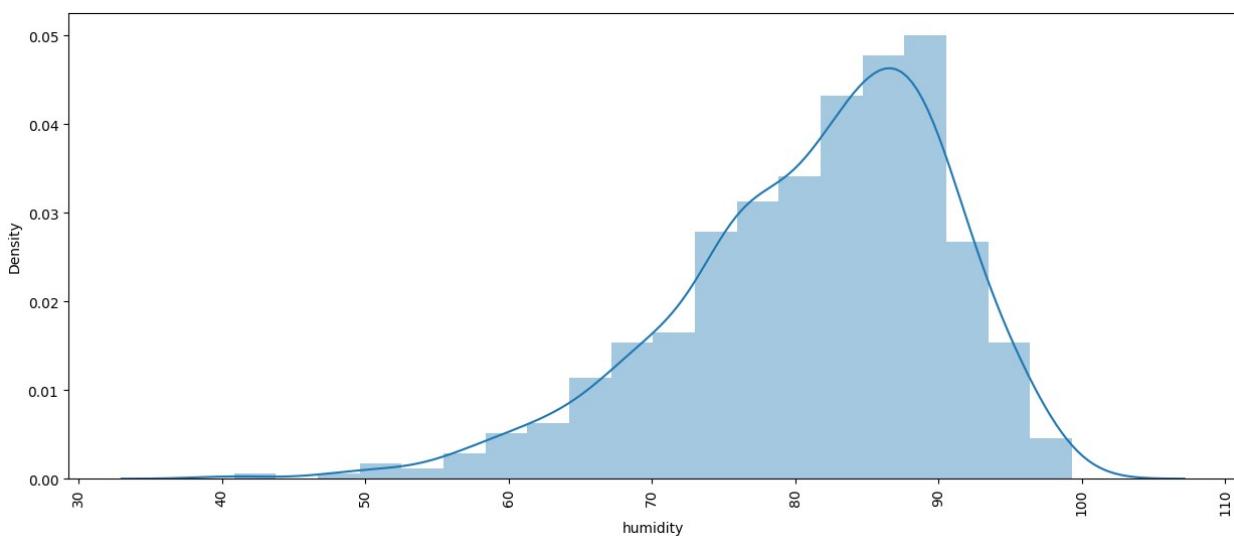
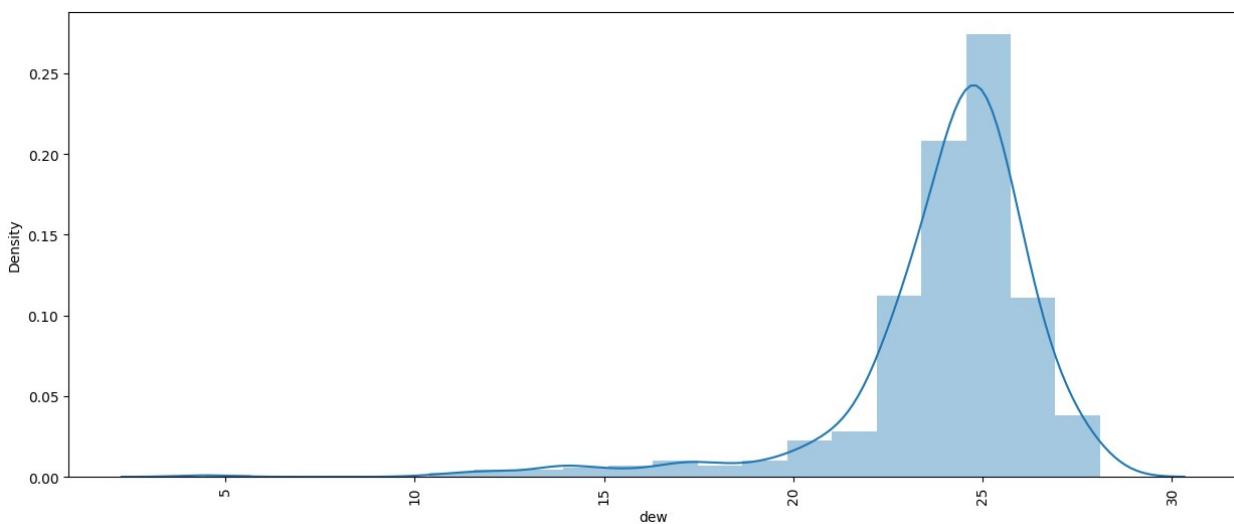
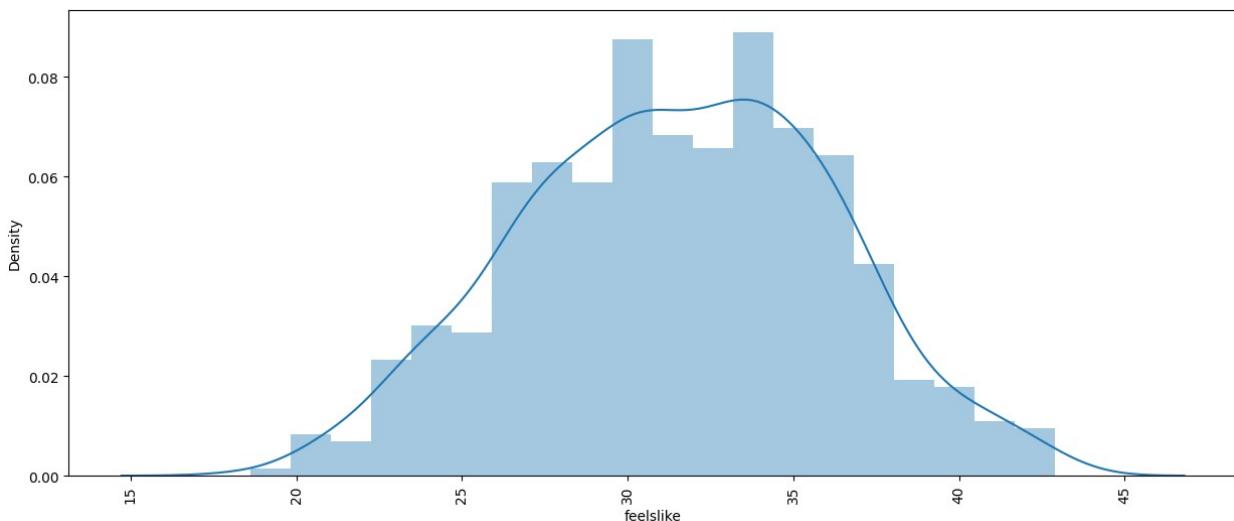


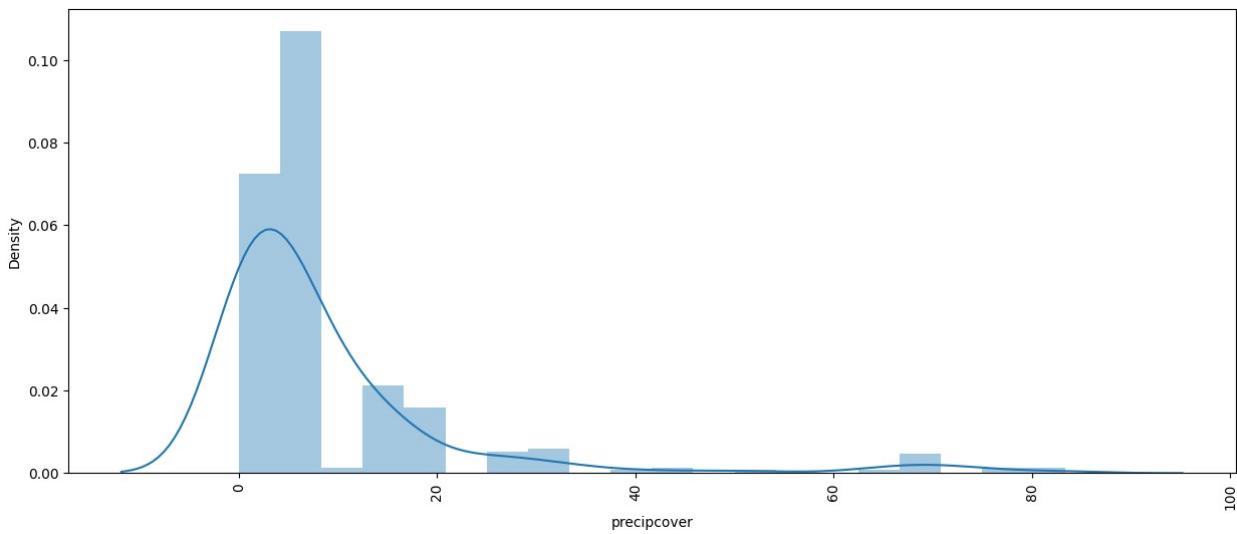
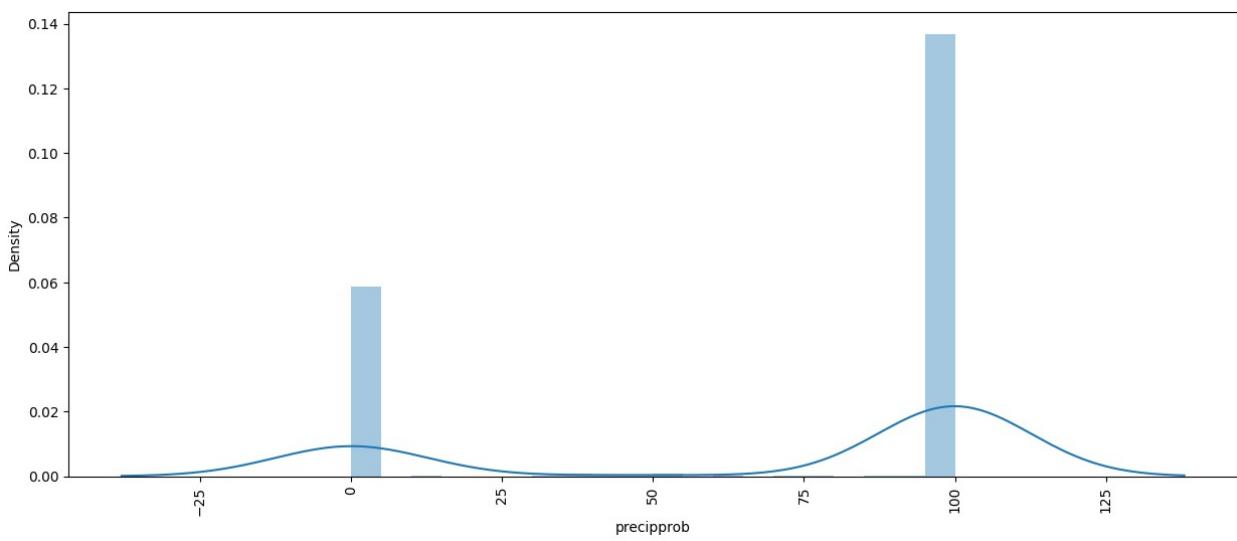
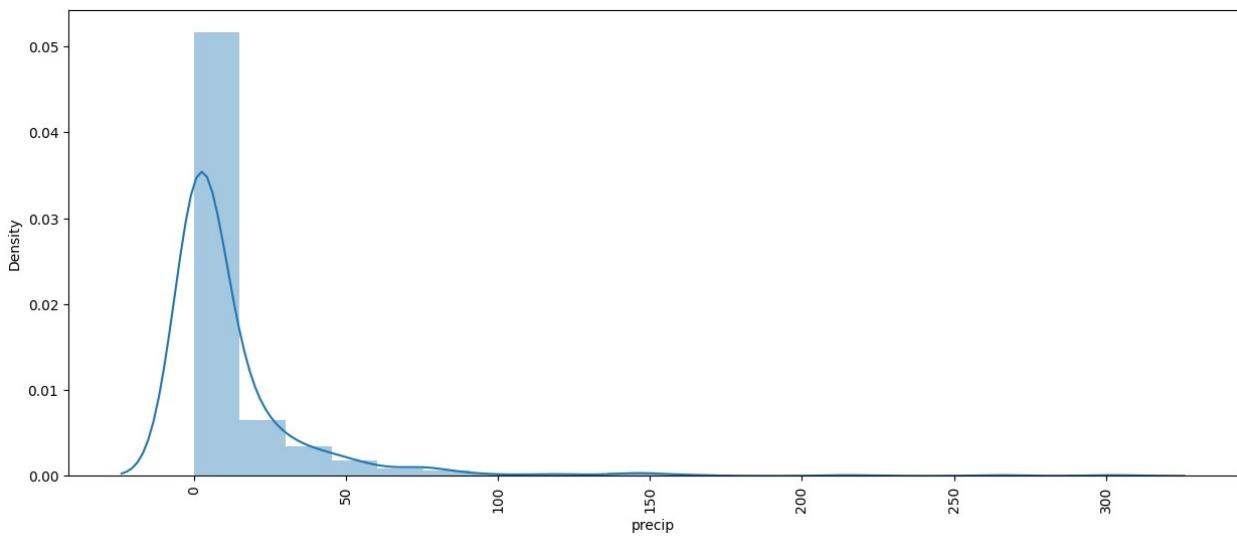


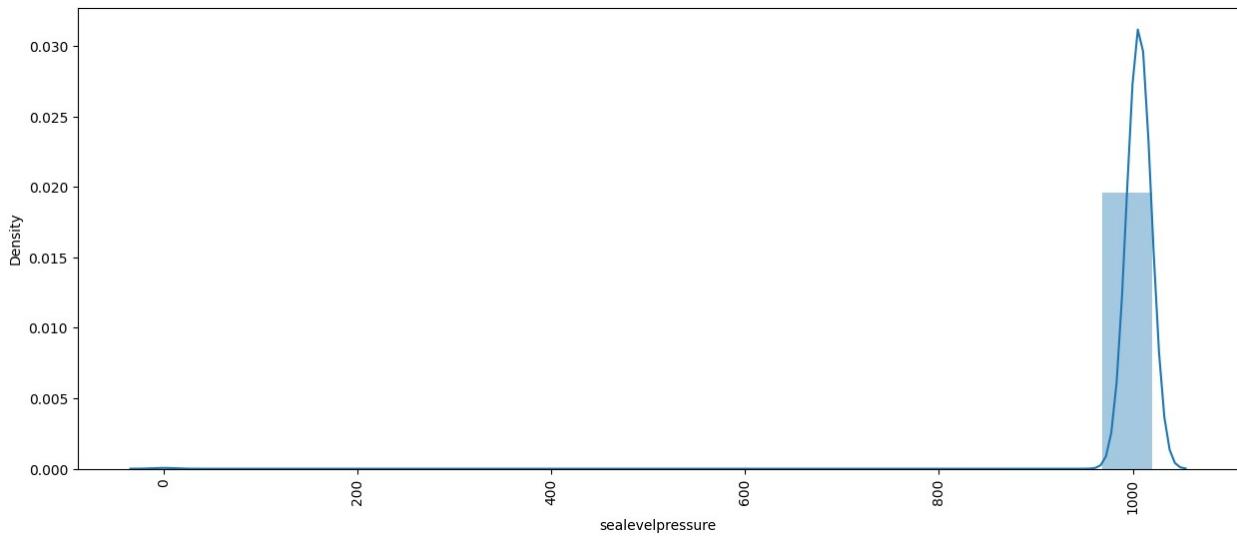
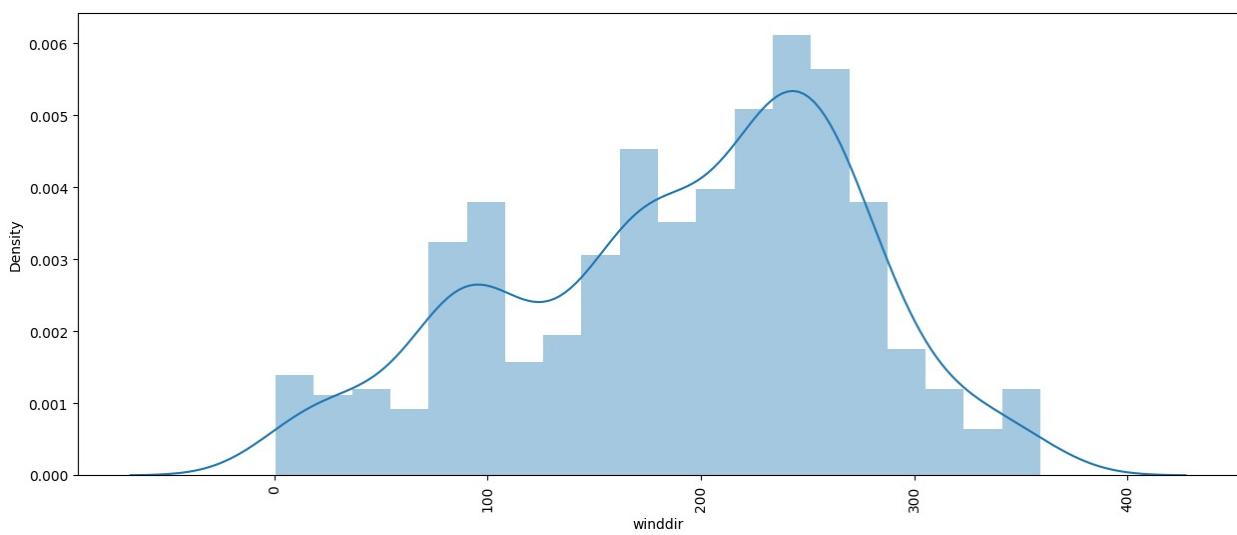
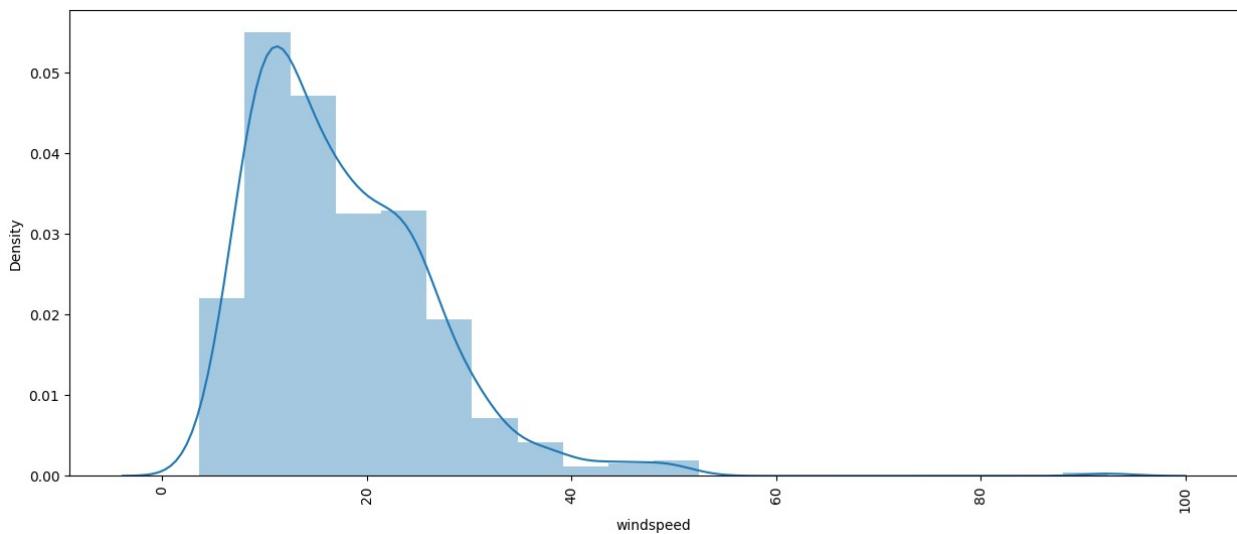
```
for i in continuous:  
    plt.figure(figsize=(15,6))  
    sns.distplot(df[i], bins = 20, kde = True)  
    plt.xticks(rotation = 90)  
    plt.show()
```

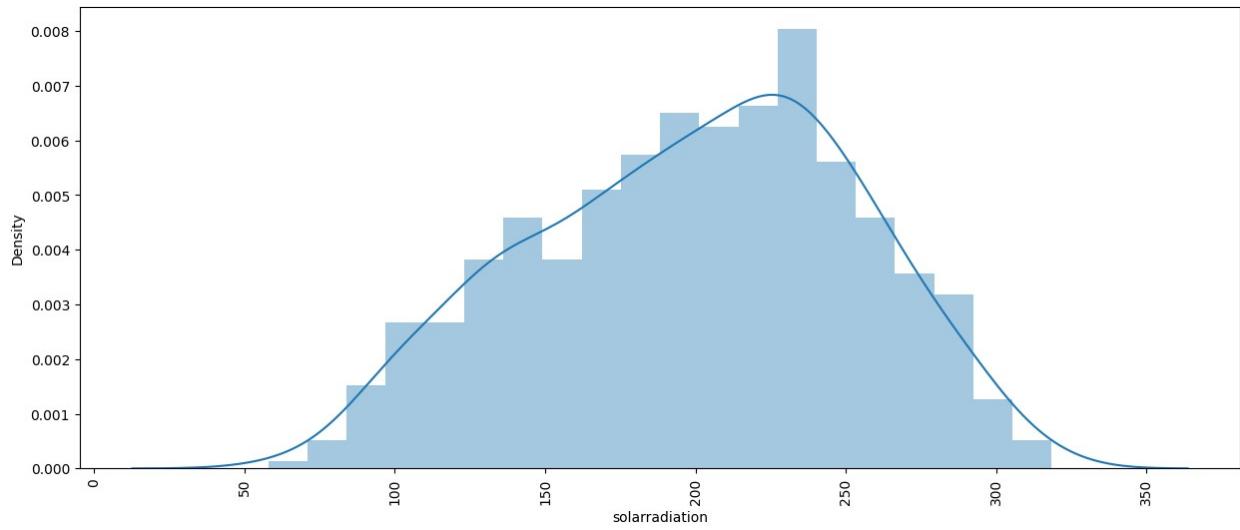
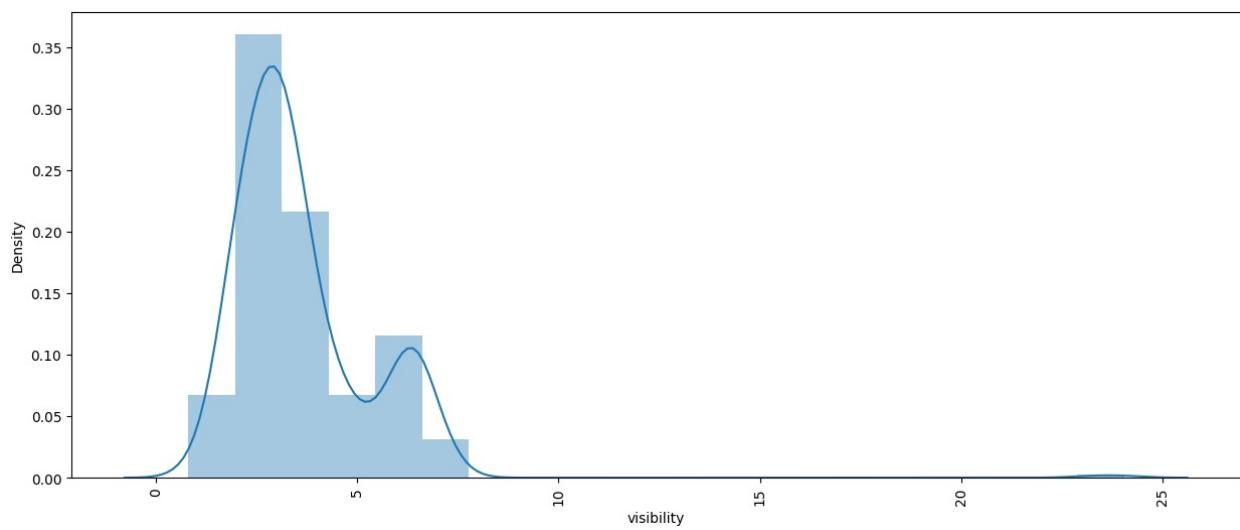
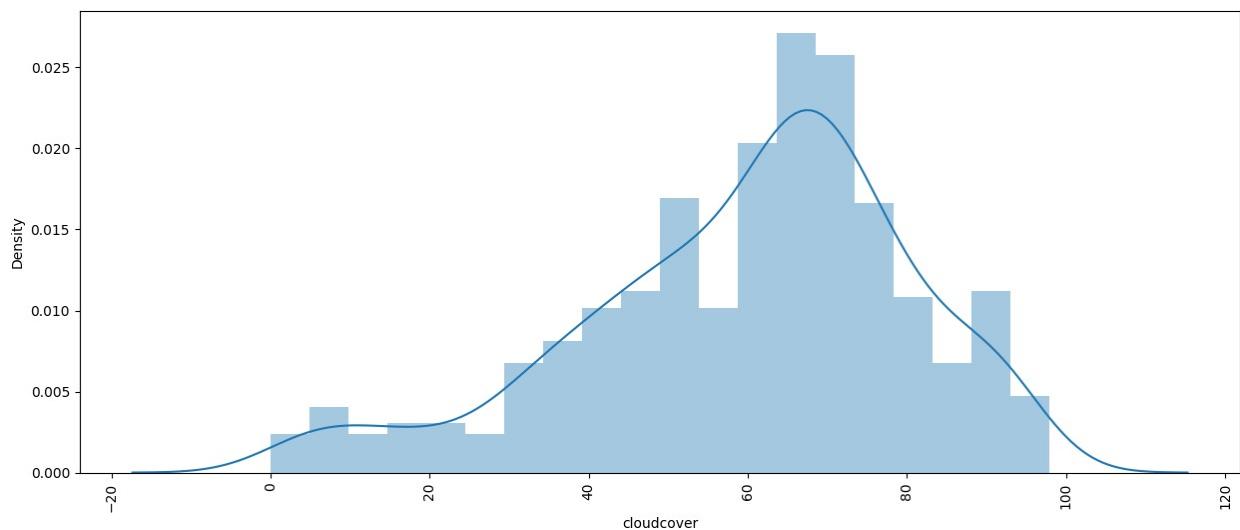


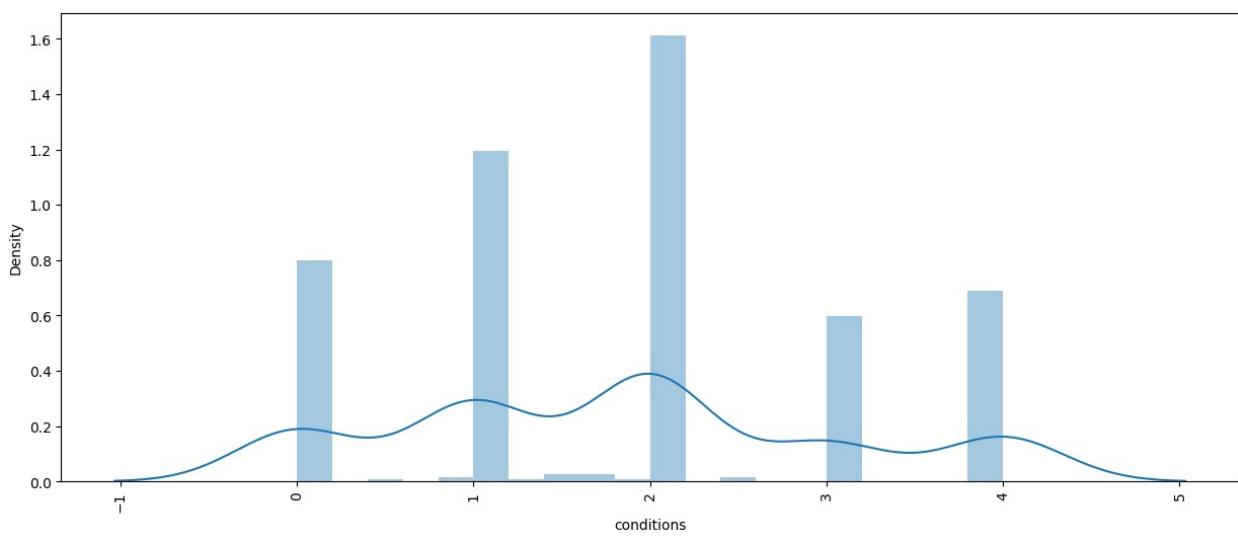
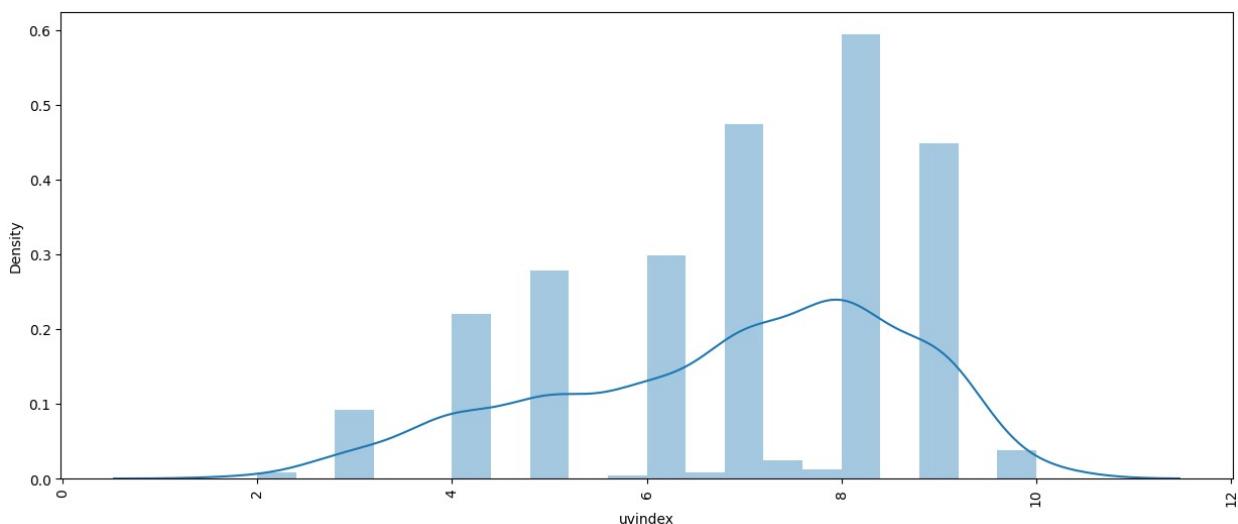
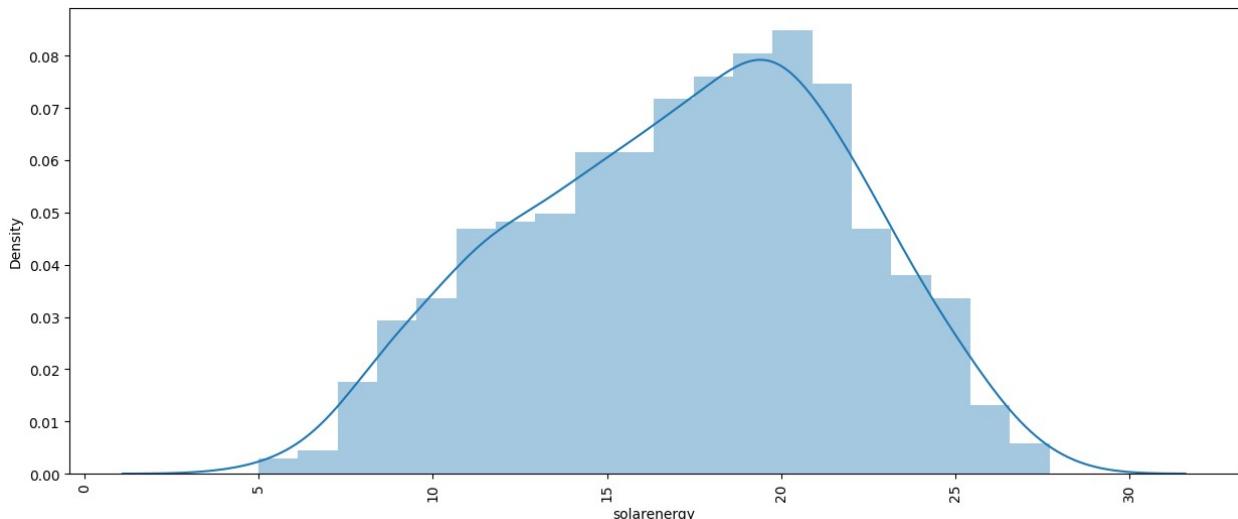


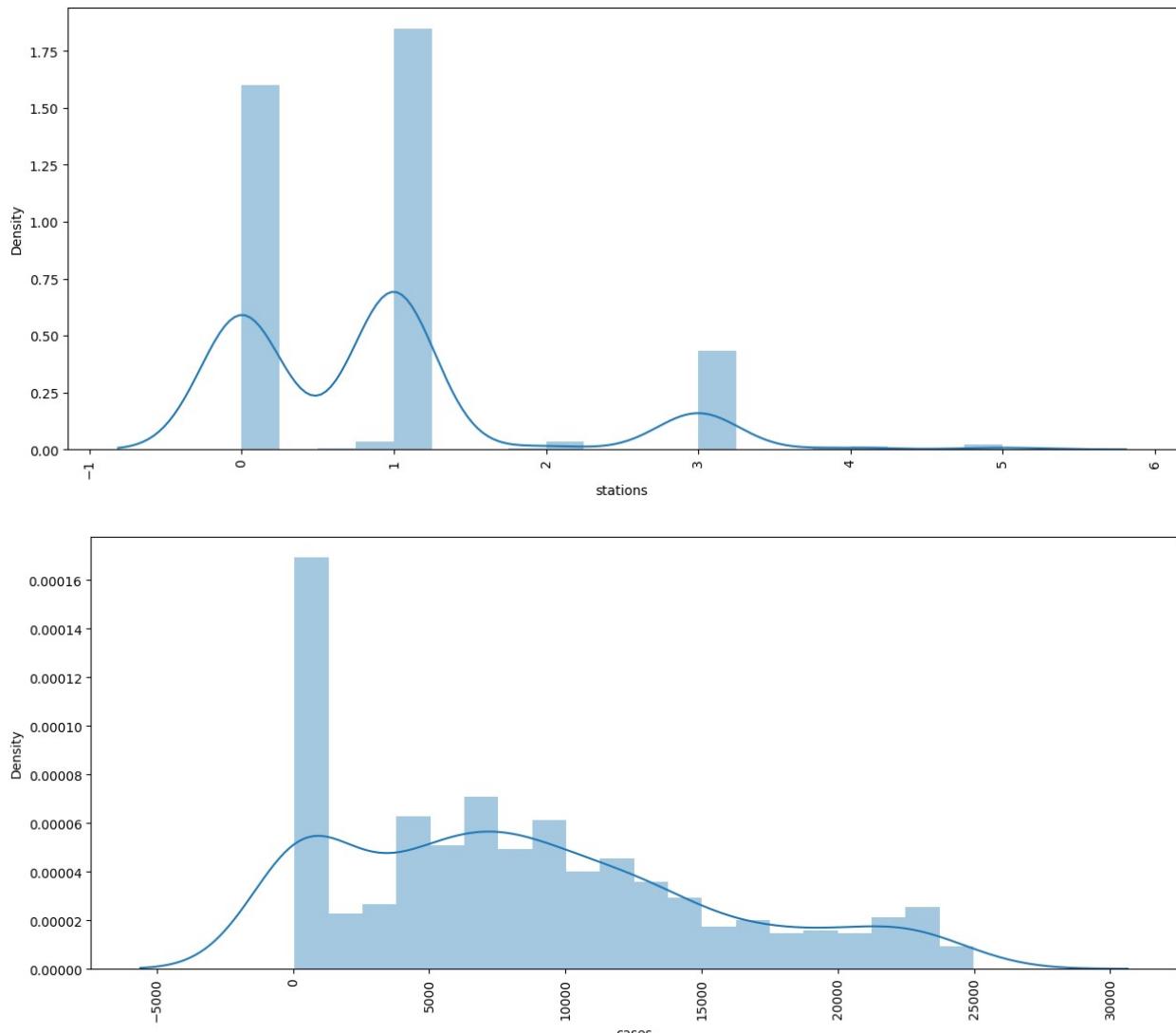




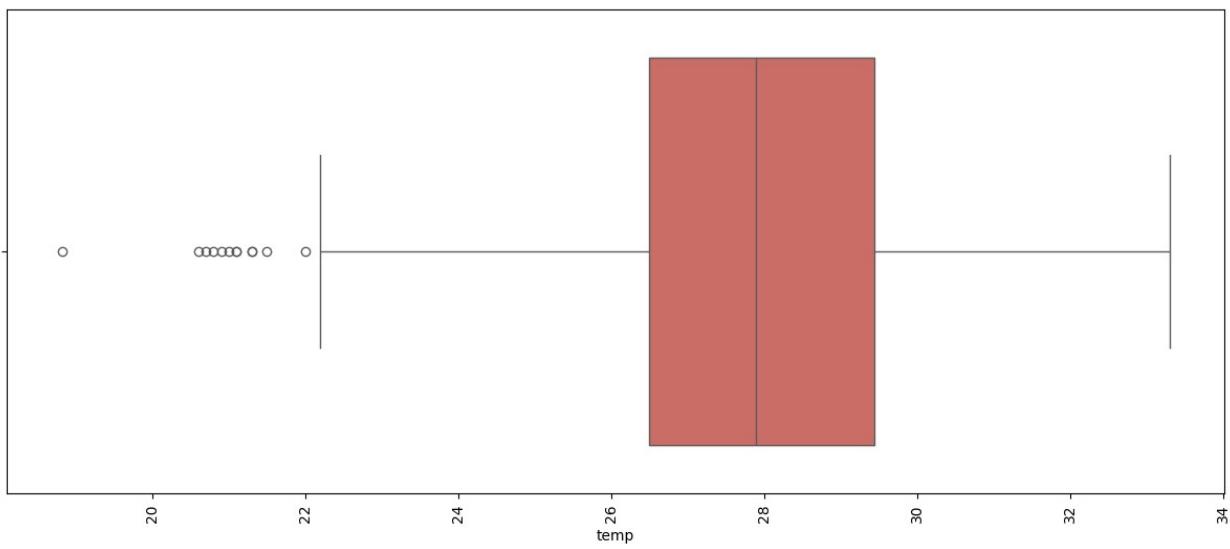
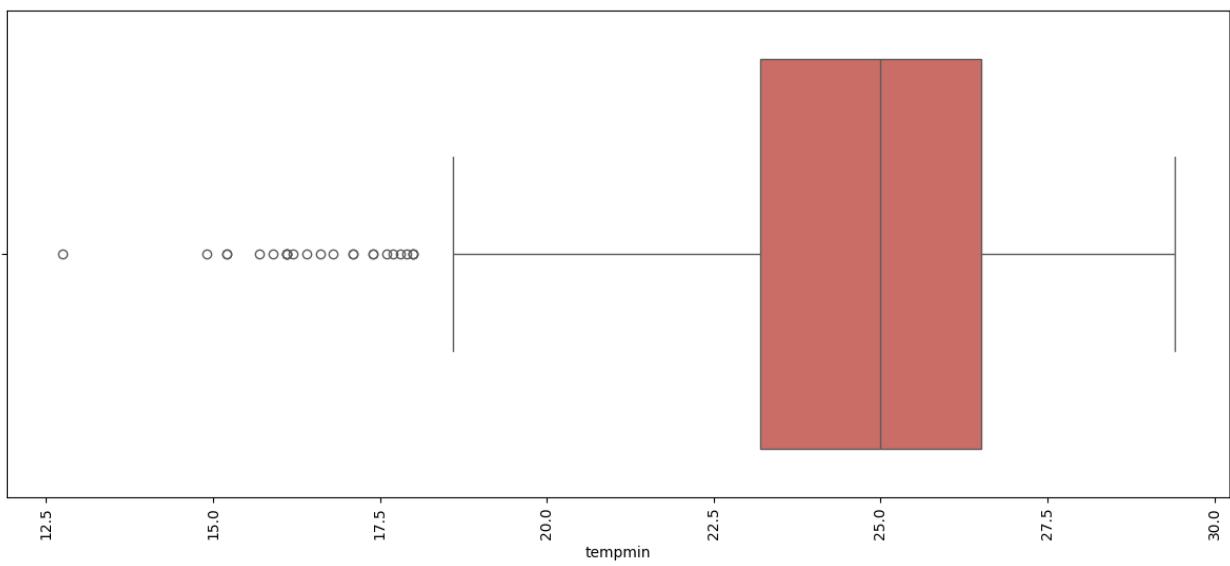
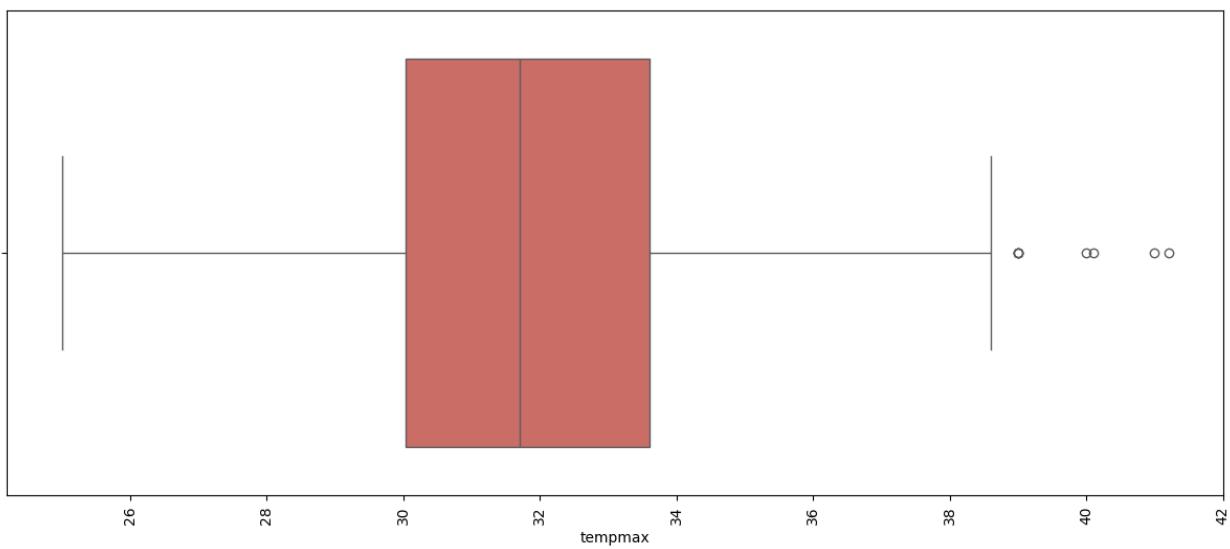


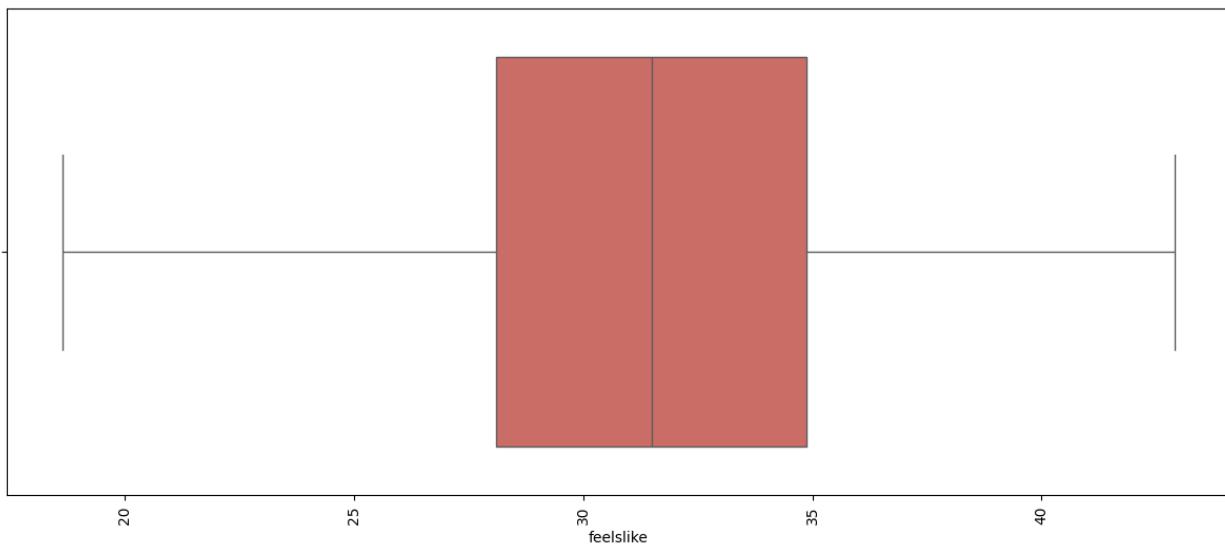
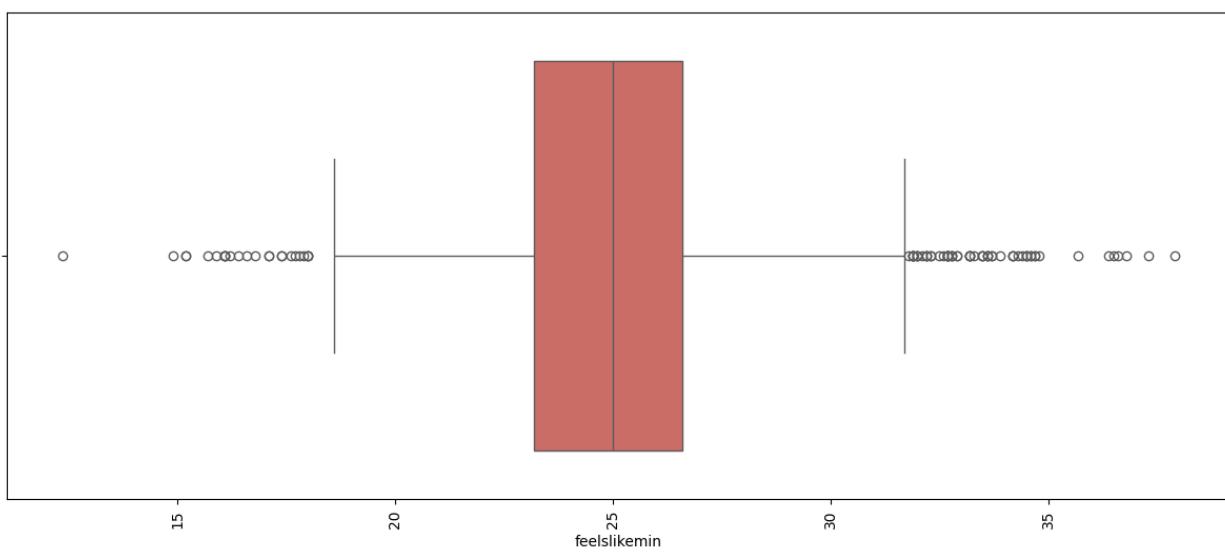
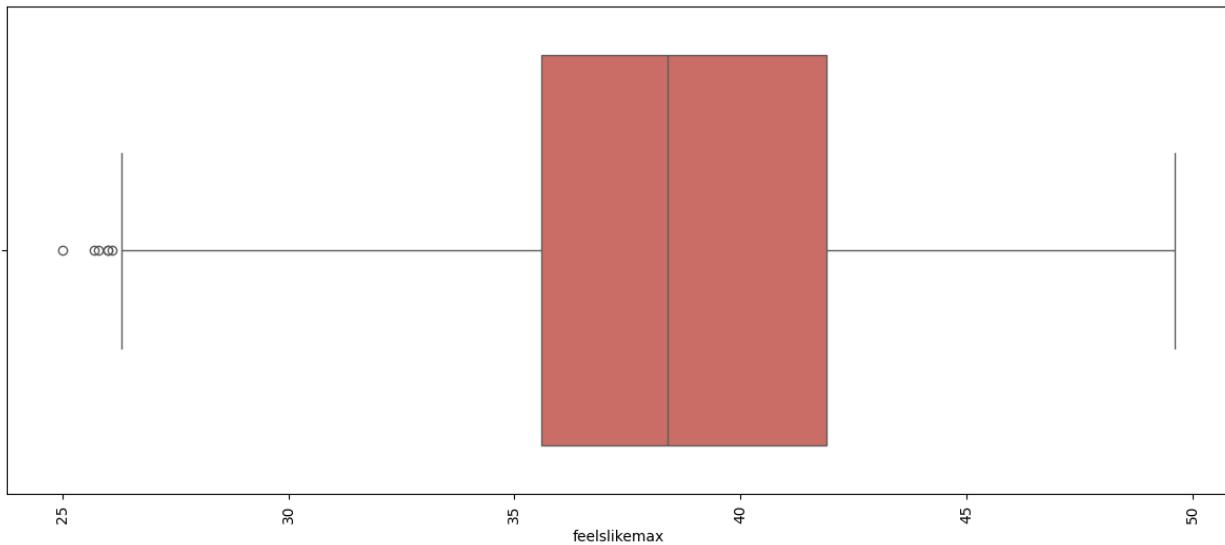


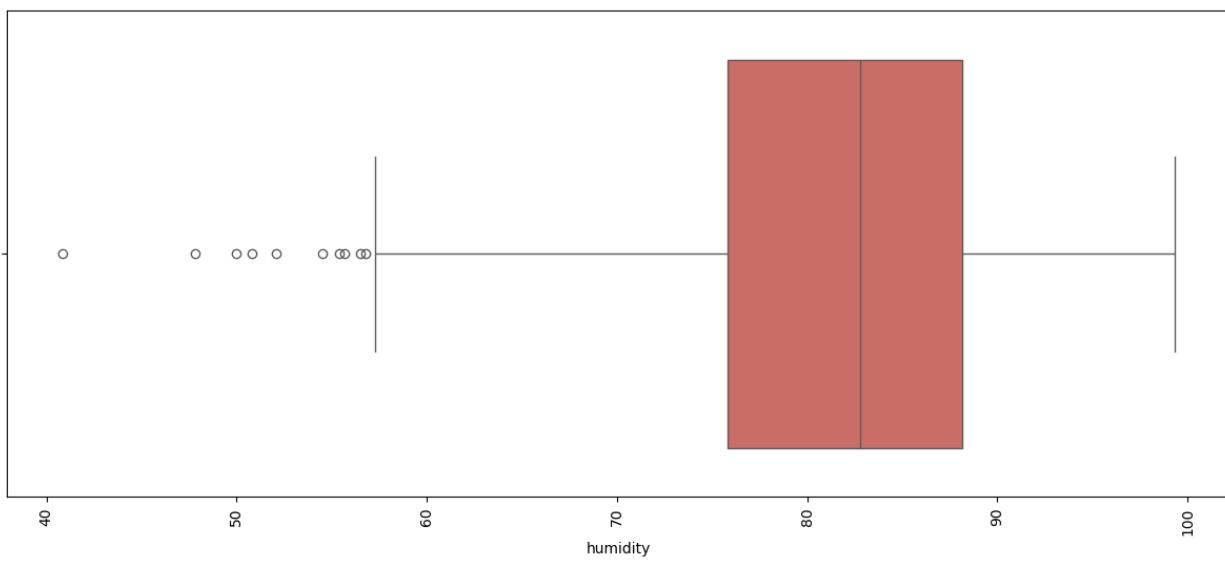
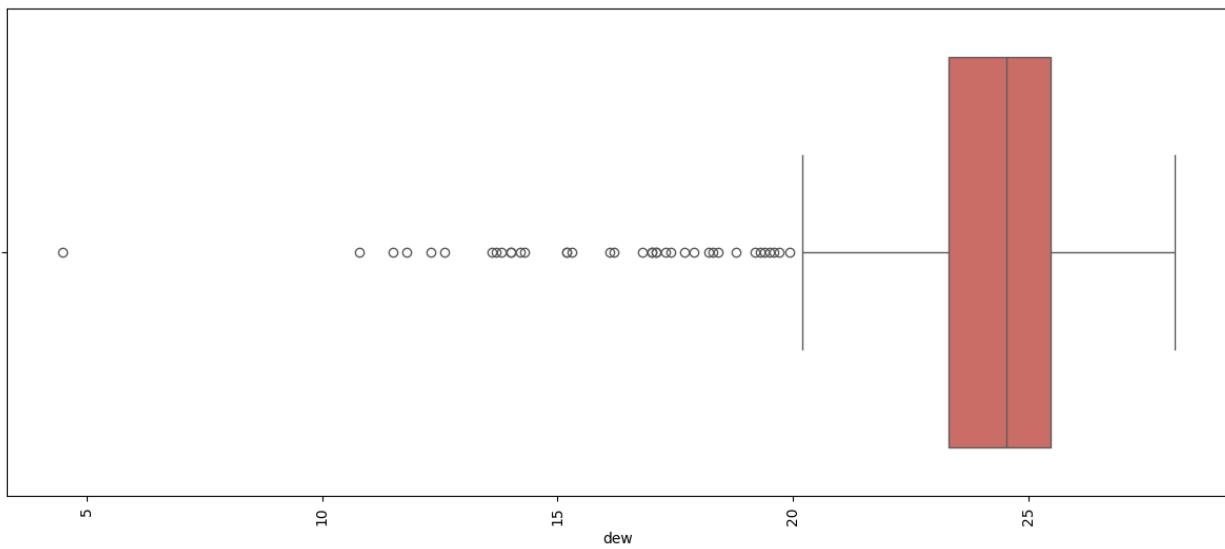


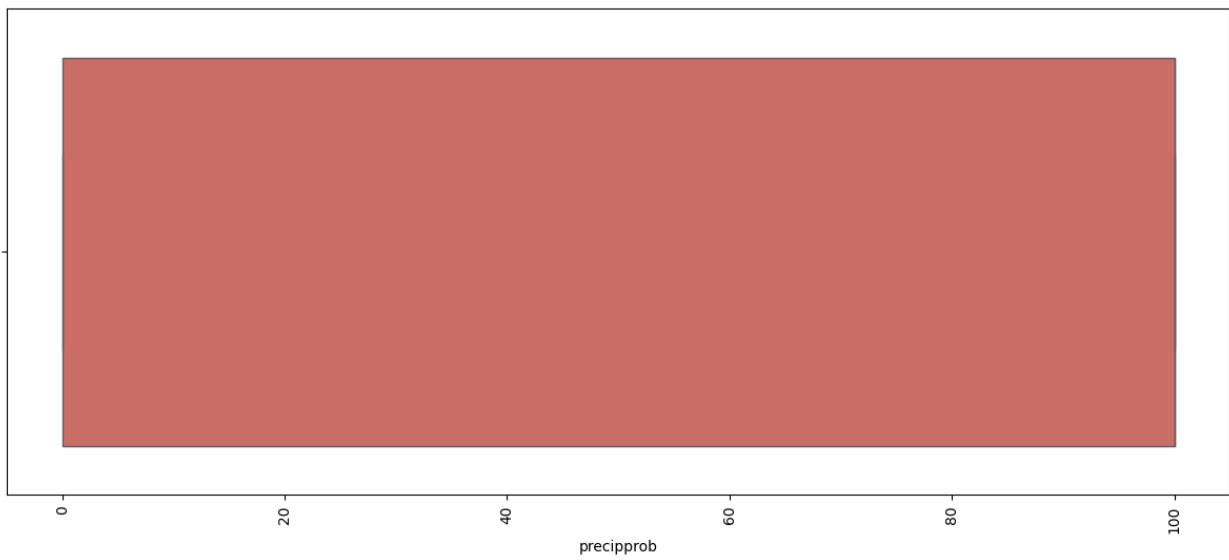
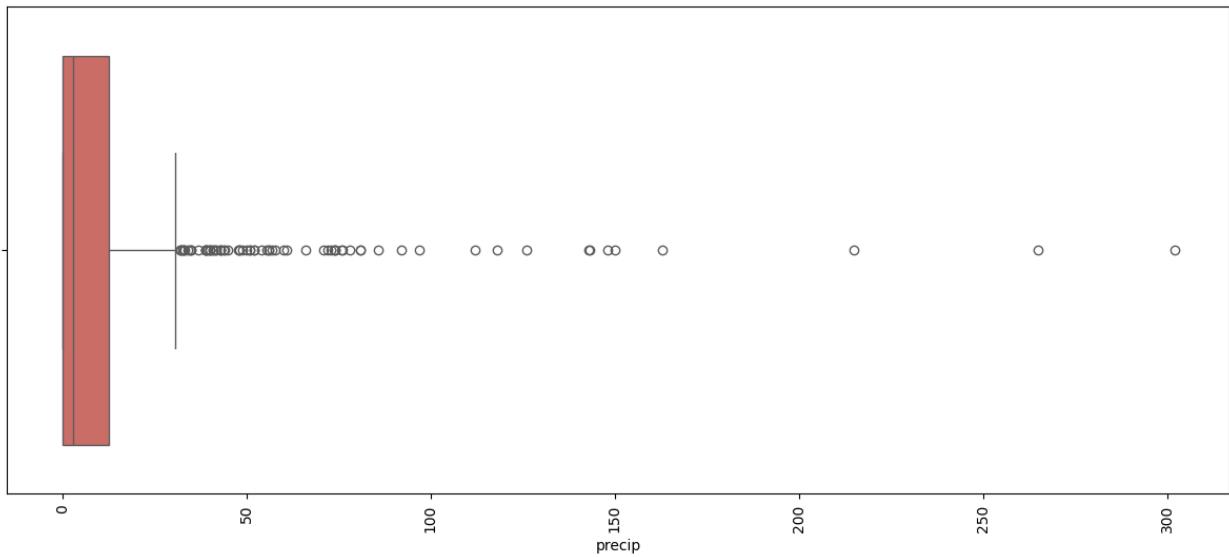


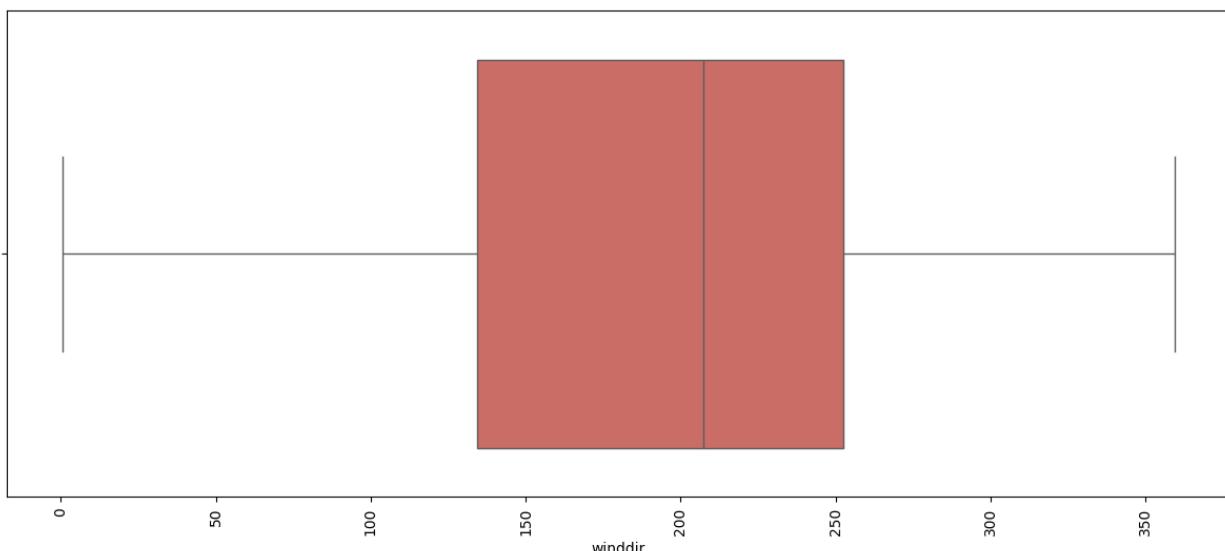
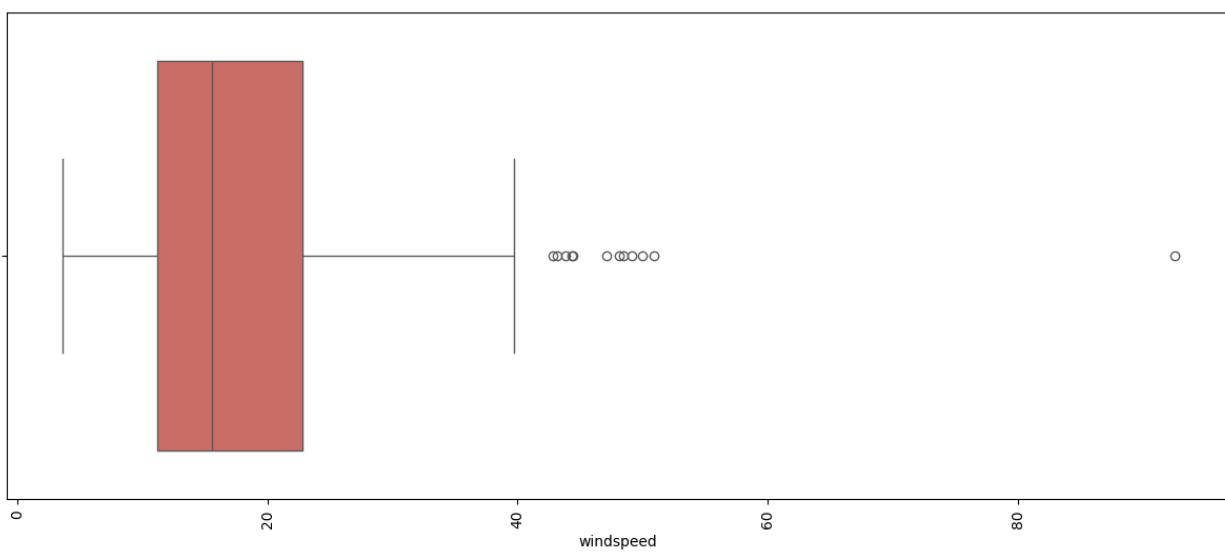
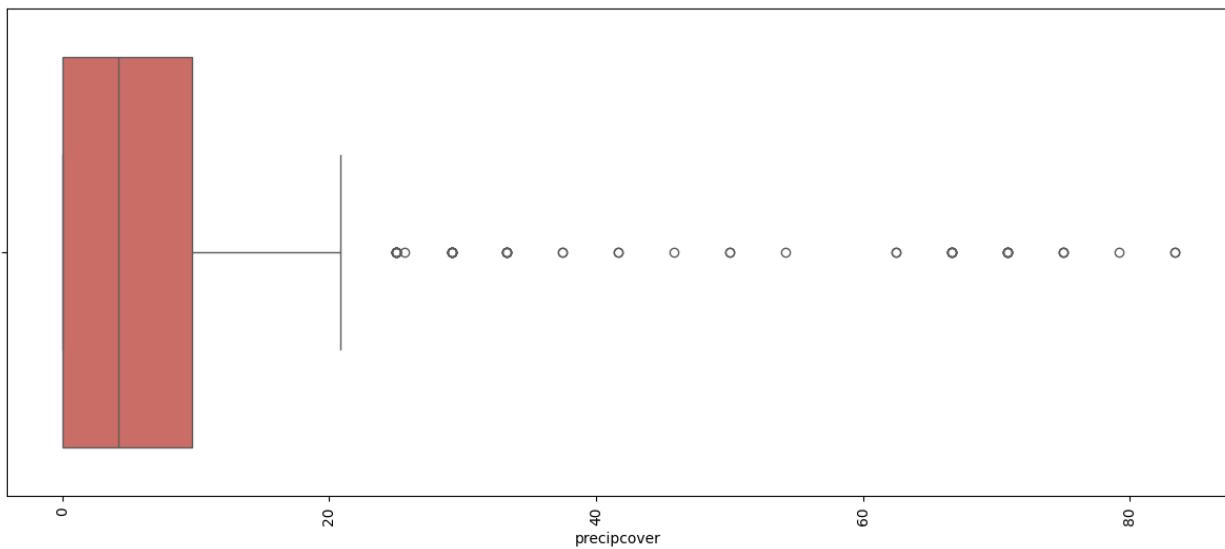
```
for i in continuous:  
    plt.figure(figsize=(15, 6))  
    sns.boxplot(x=i, data=df, palette='hls')  
    plt.xticks(rotation=90)  
    plt.show()
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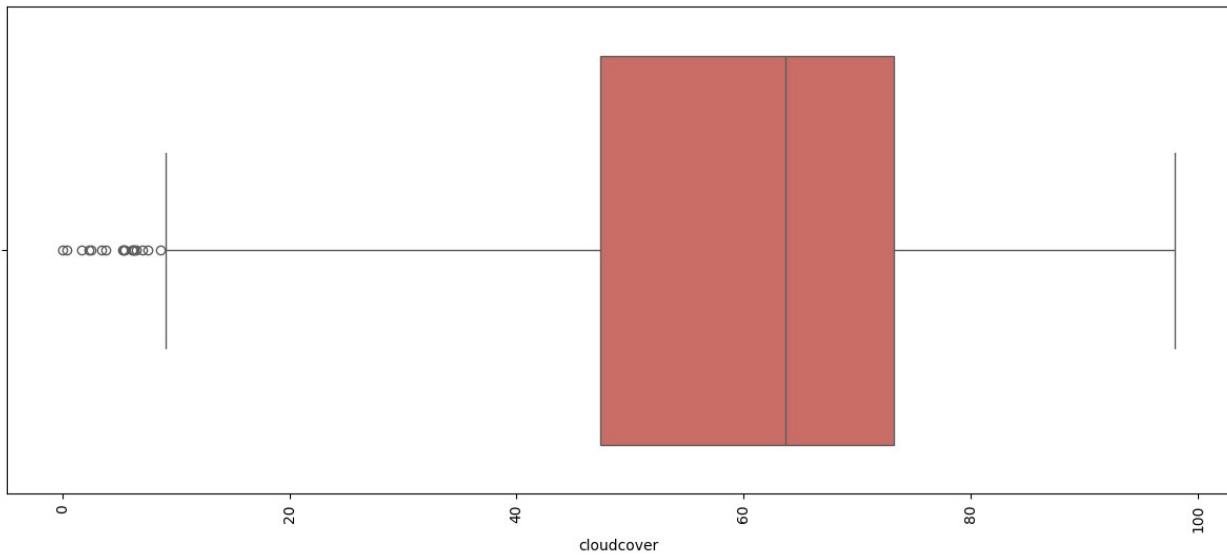
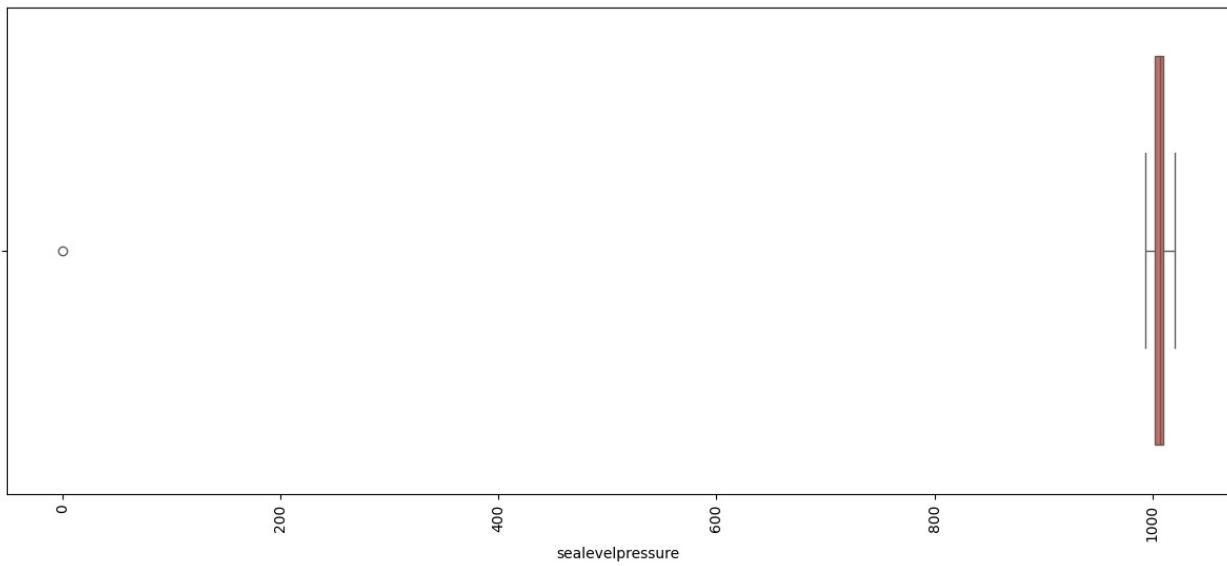


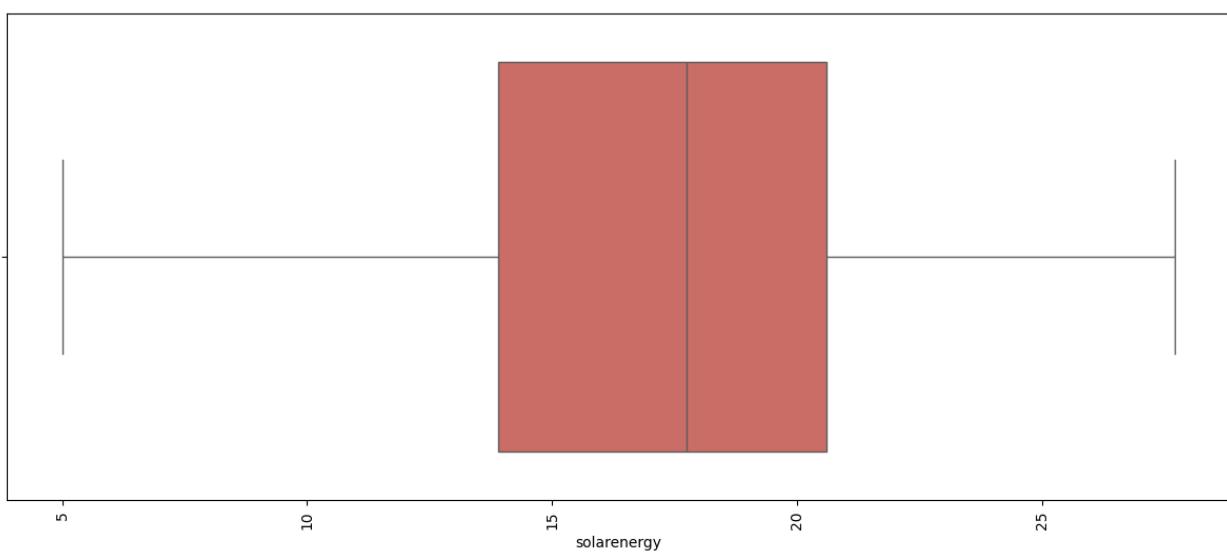
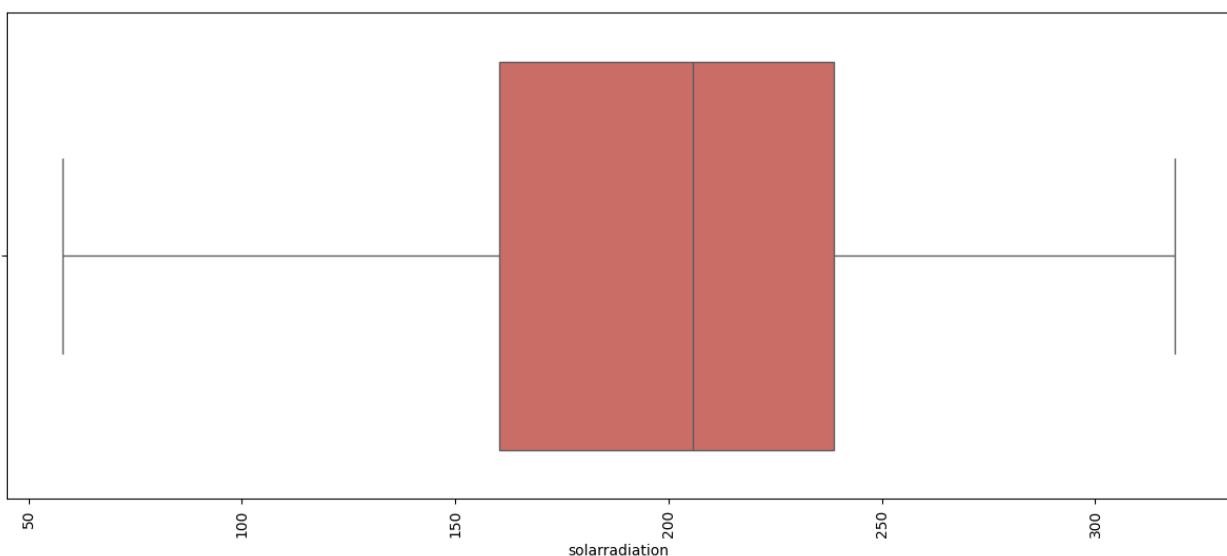
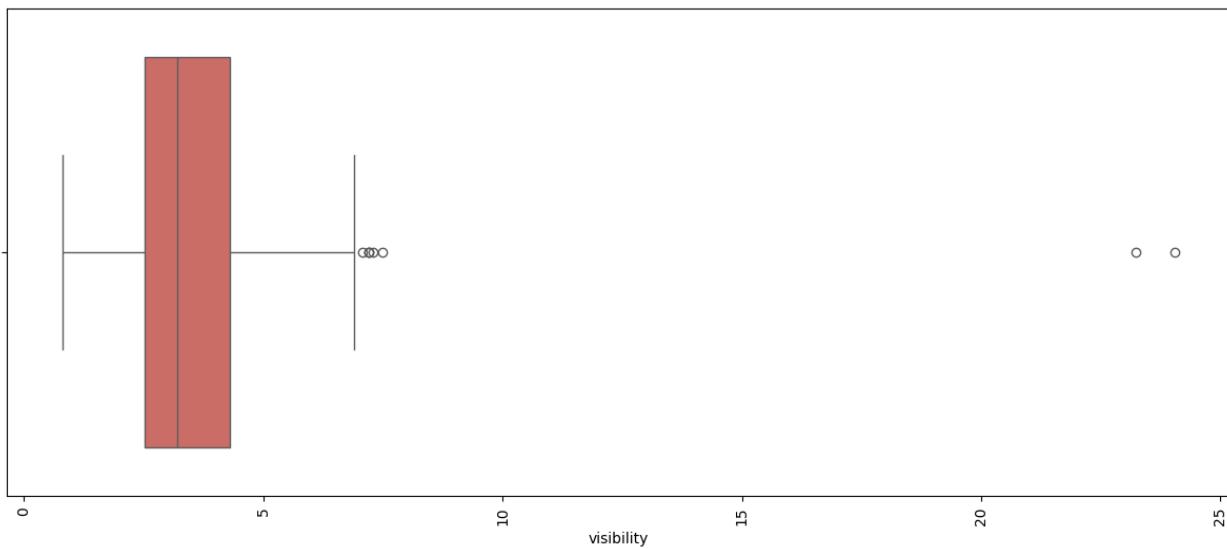


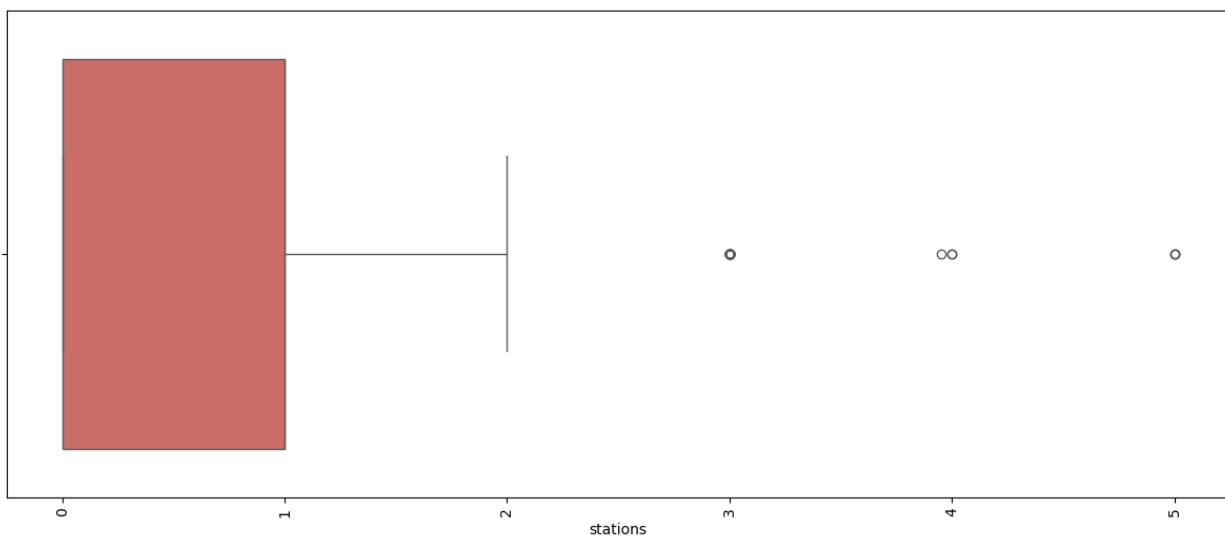
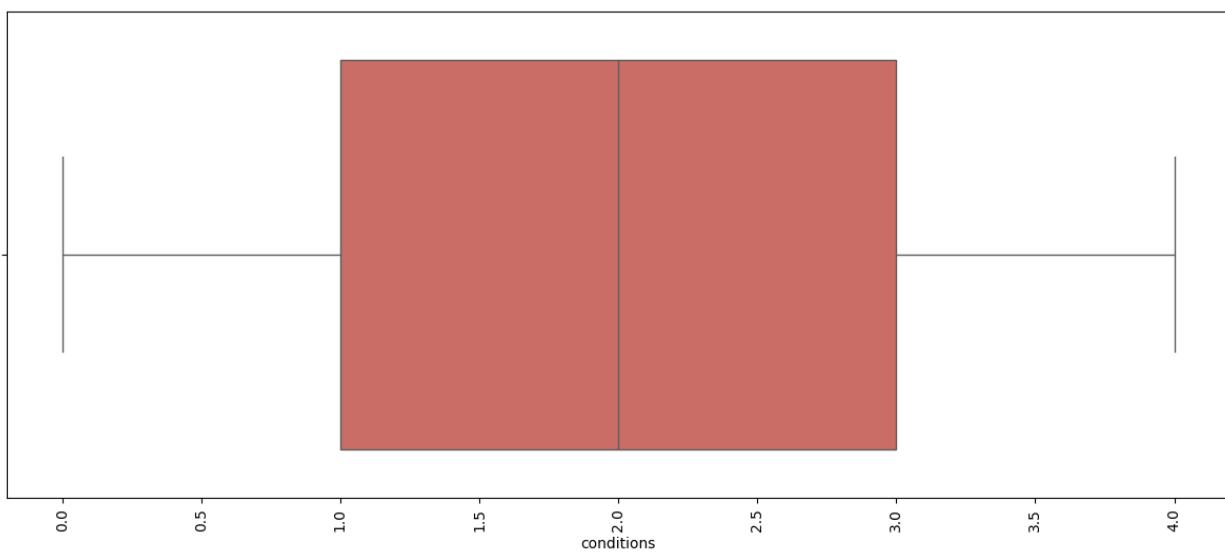
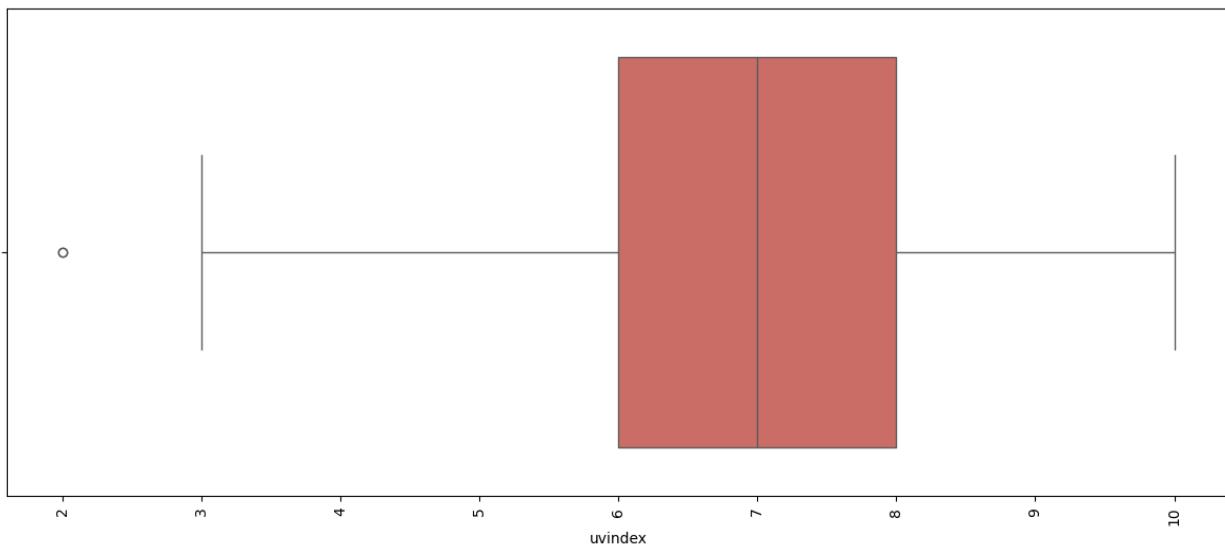


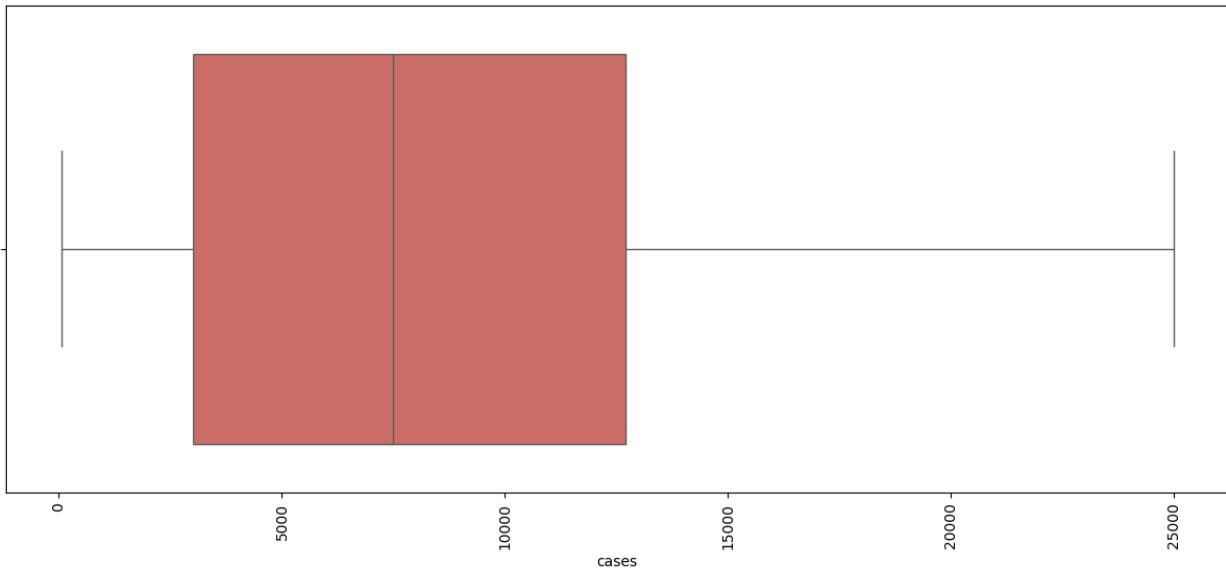




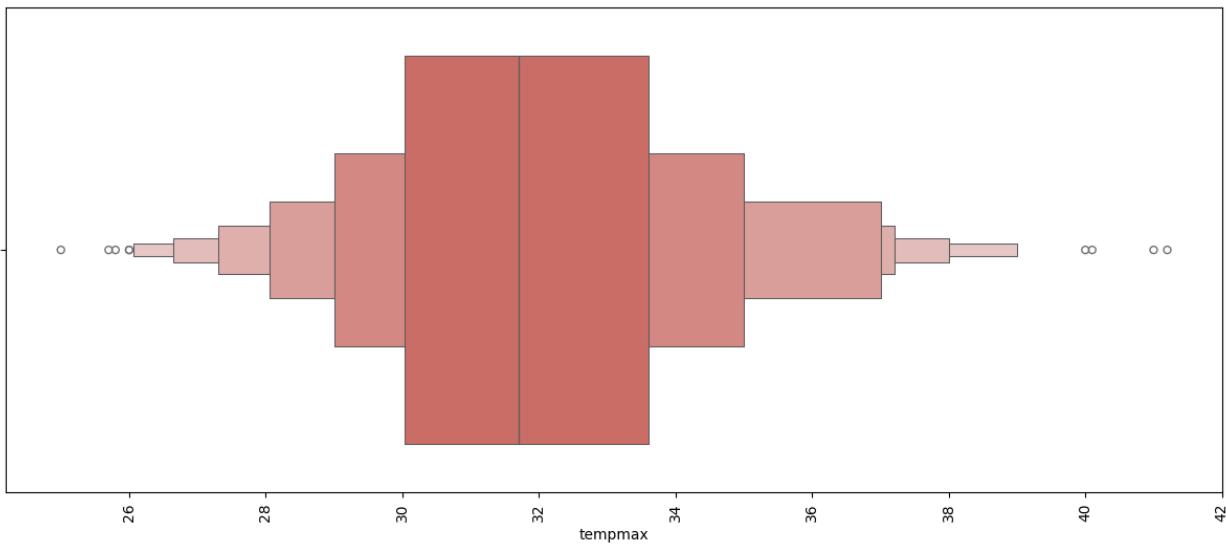


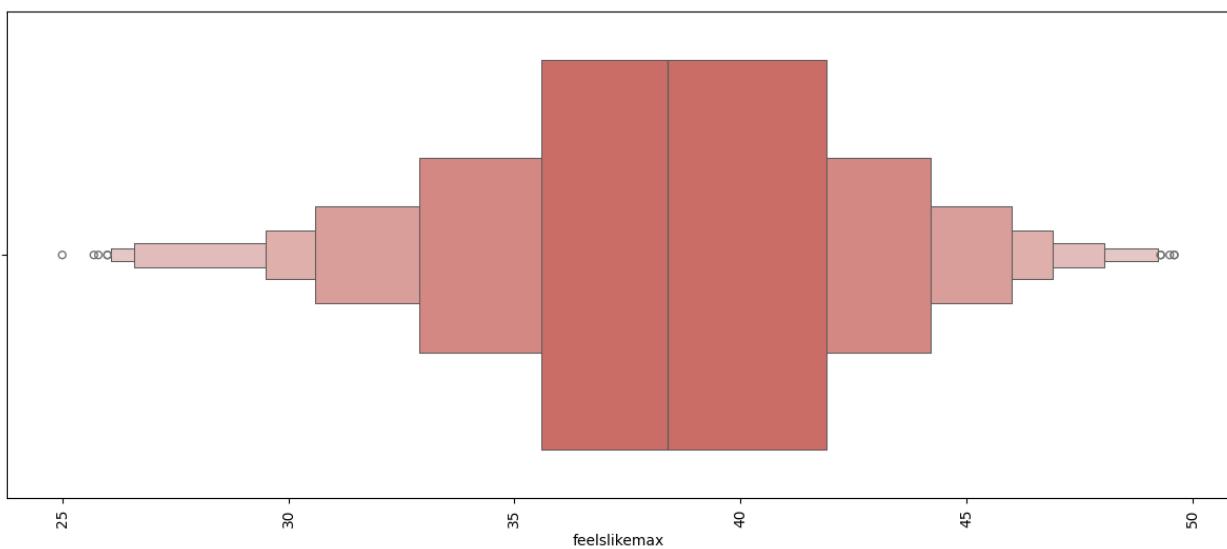
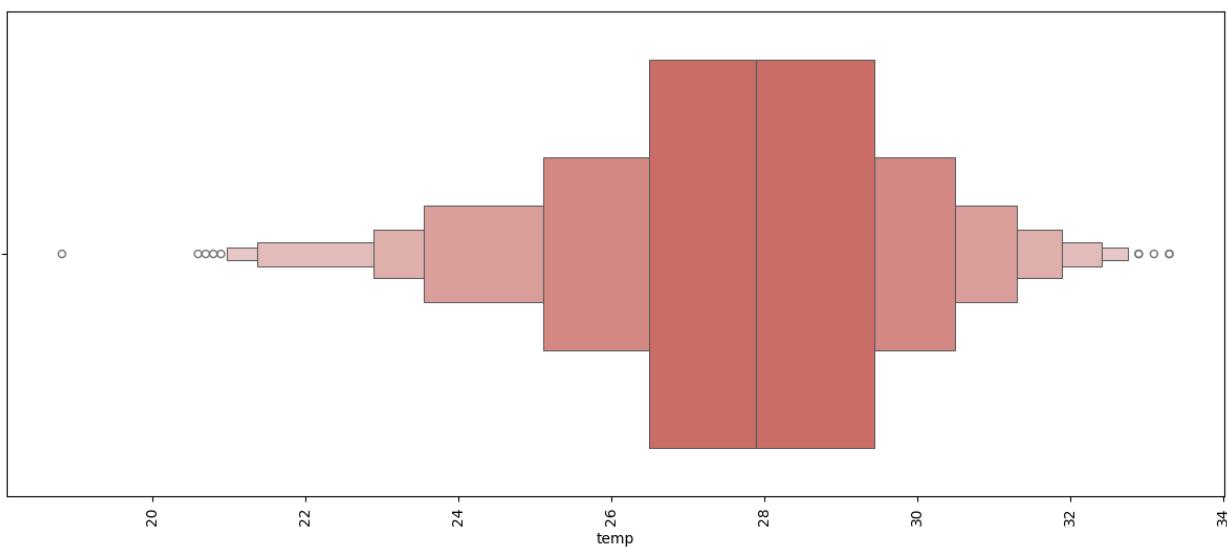
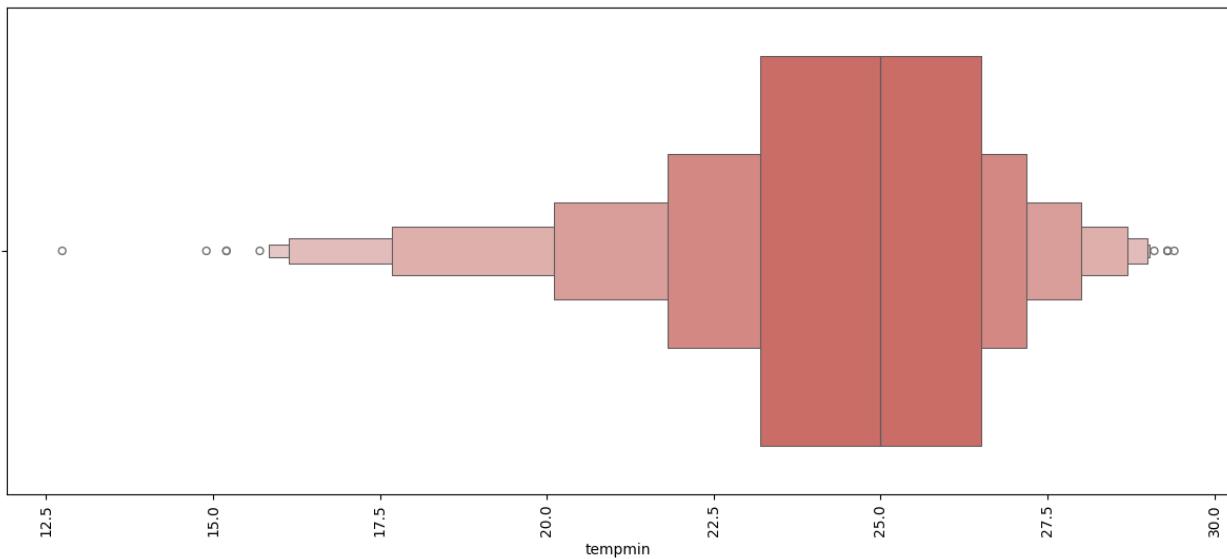


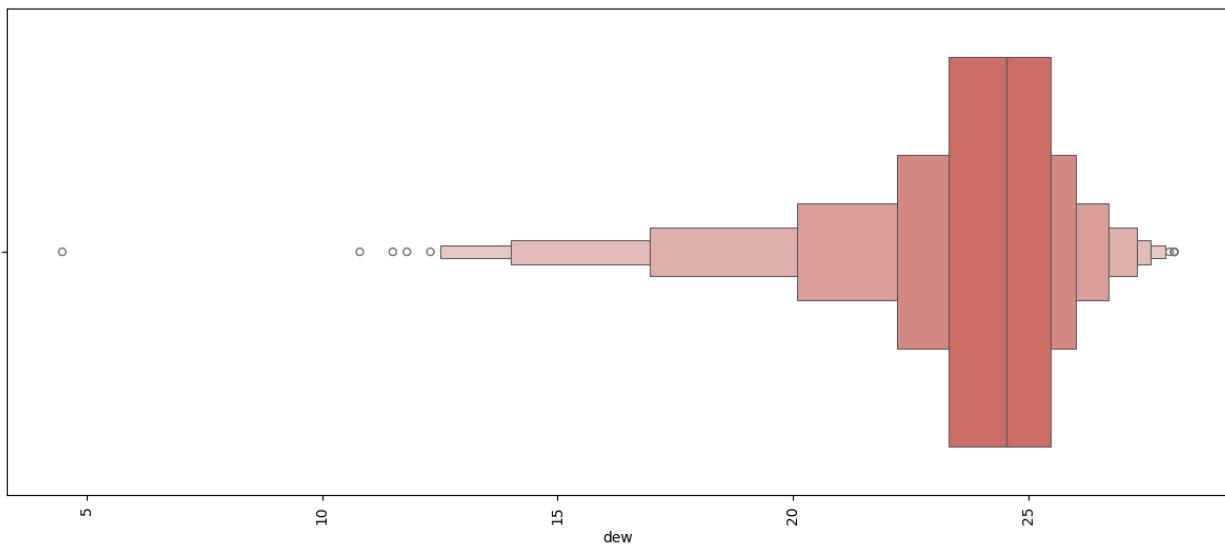
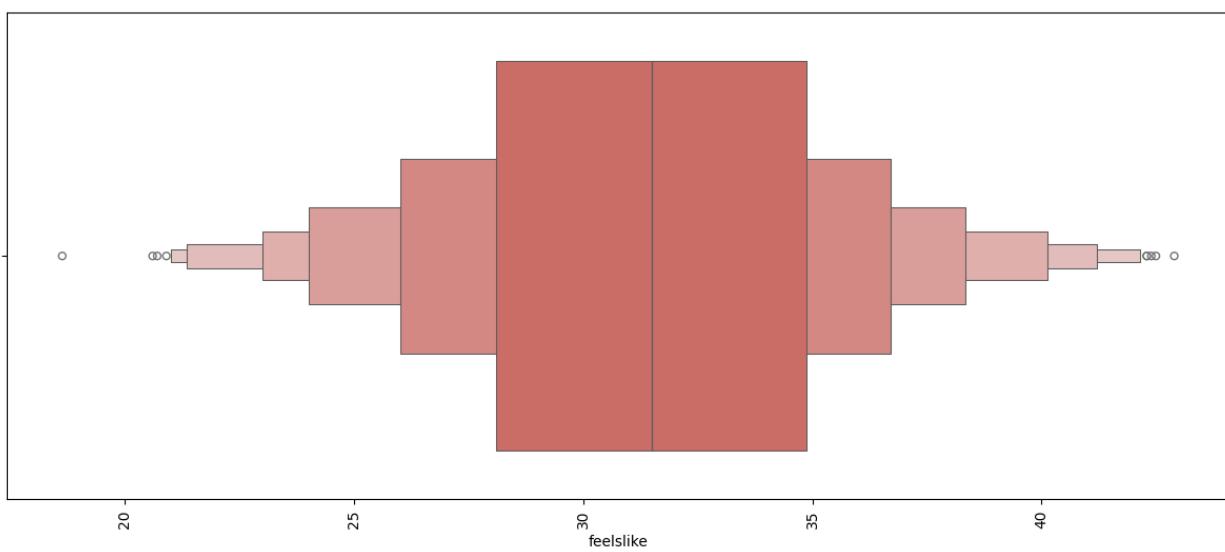
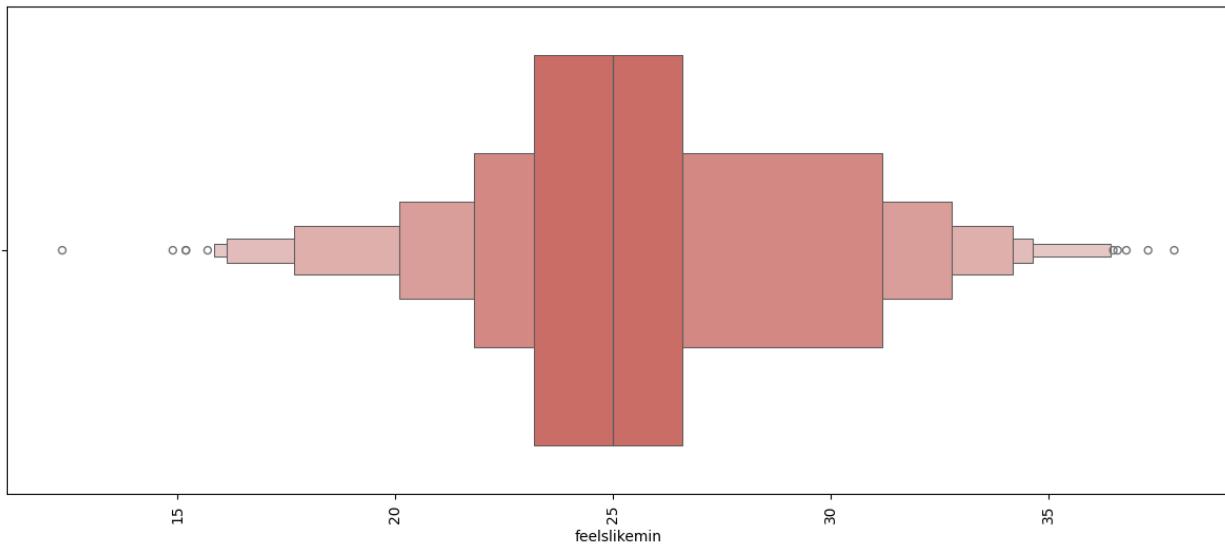


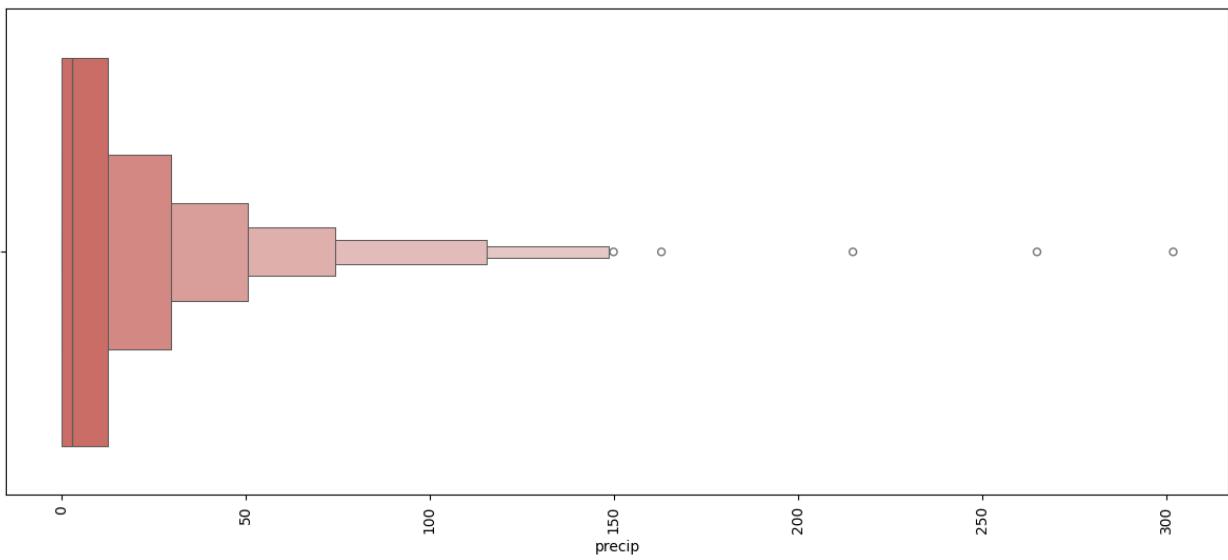
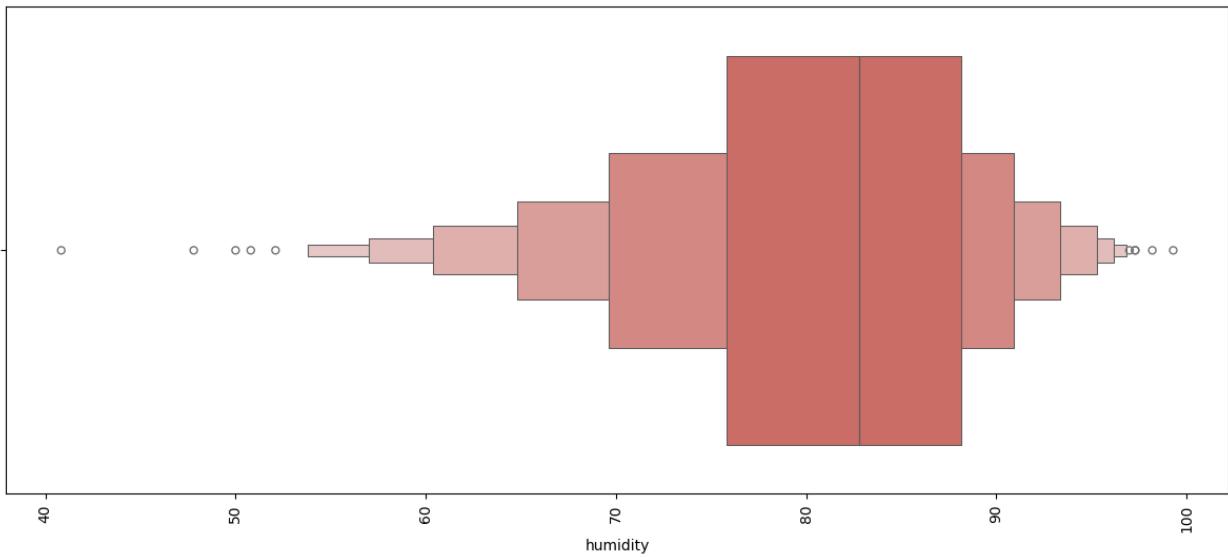


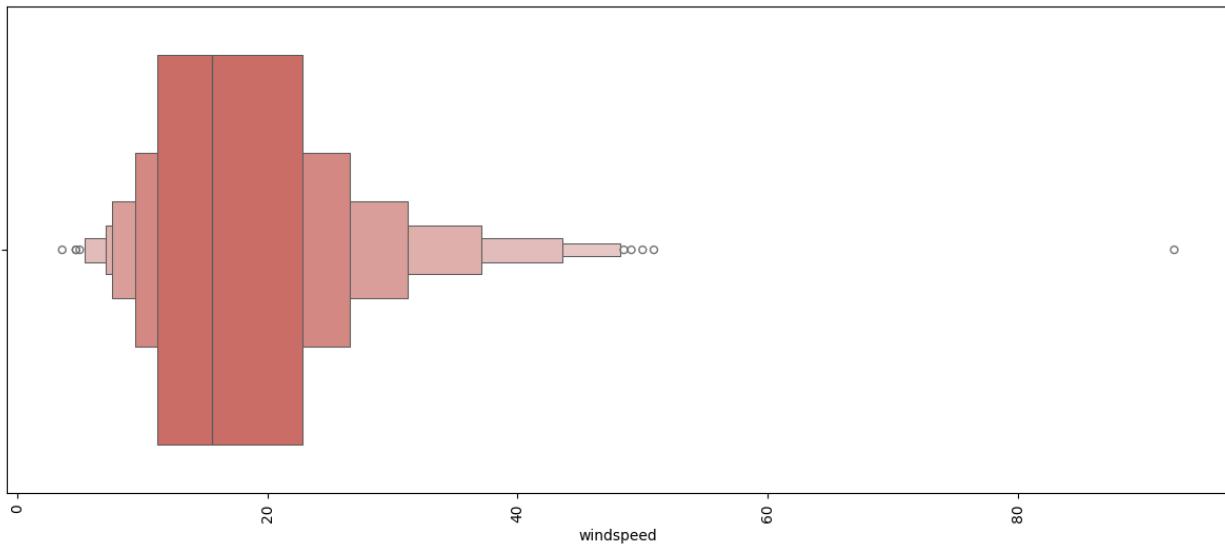
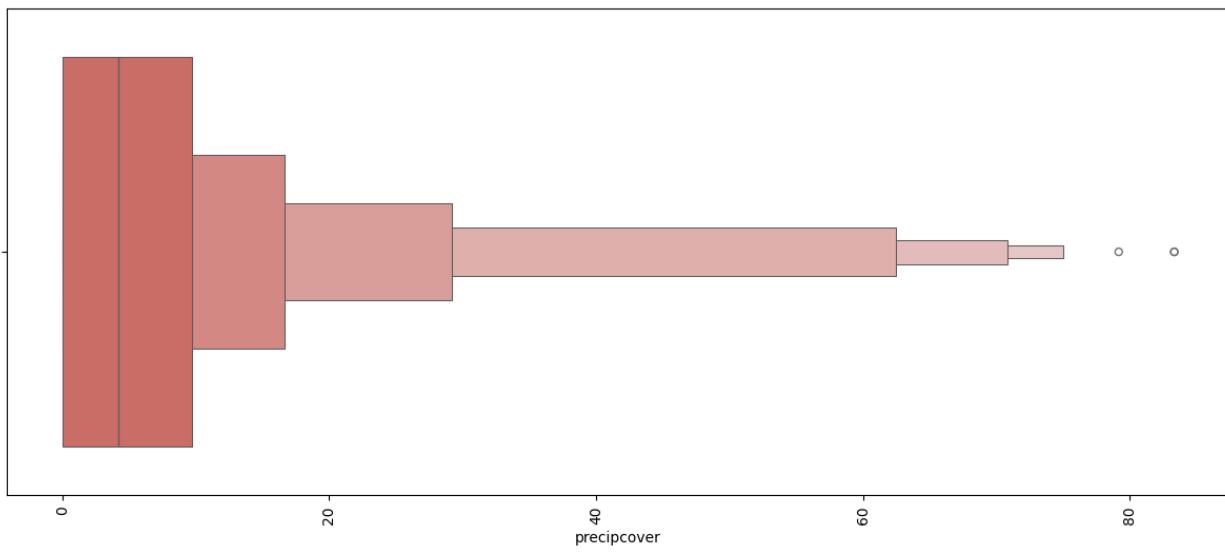
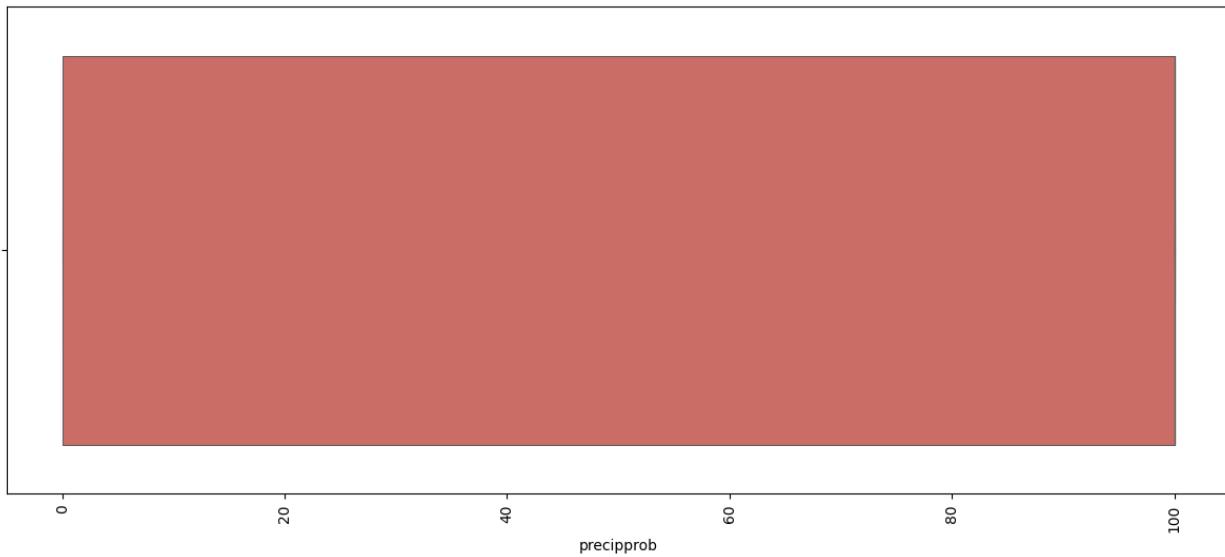
```
for i in continuous:  
    plt.figure(figsize=(15, 6))  
    sns.boxenplot(x=i, data=df, palette='hls')  
    plt.xticks(rotation=90)  
    plt.show()
```

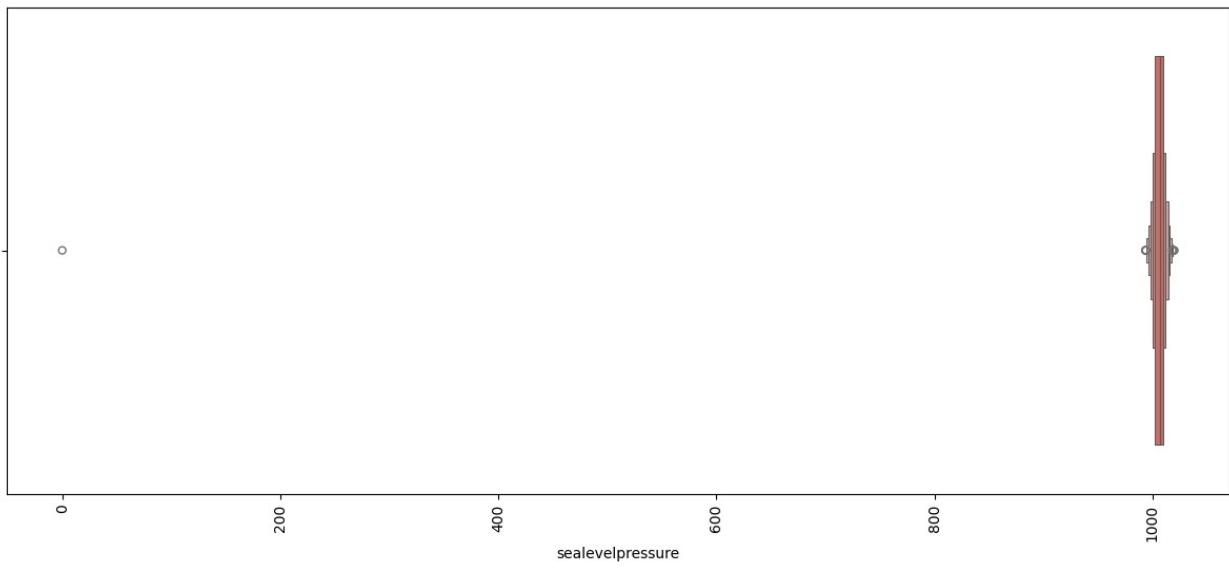
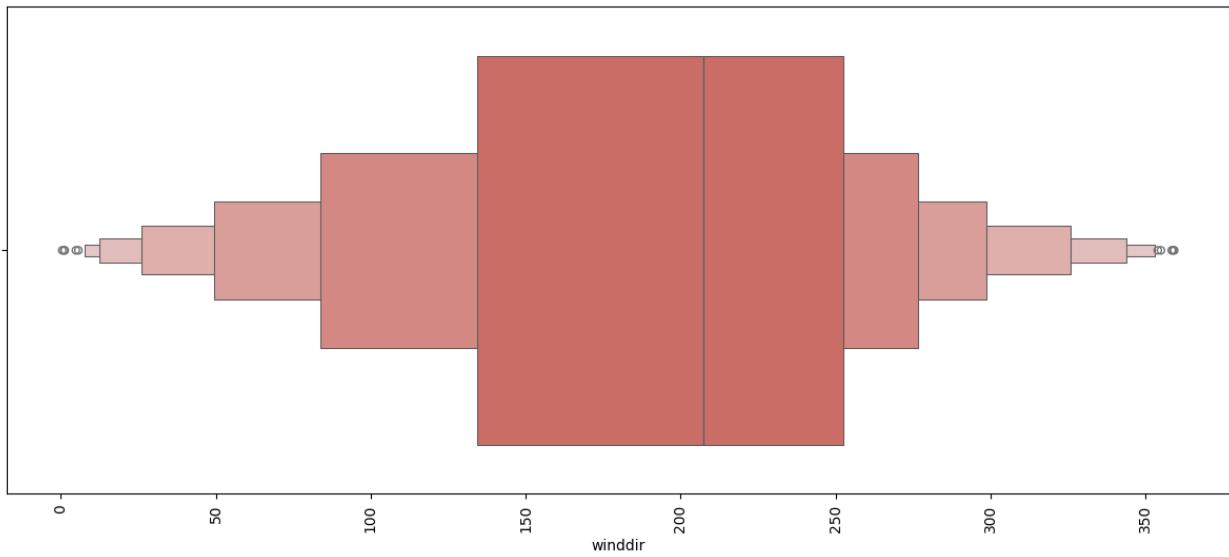


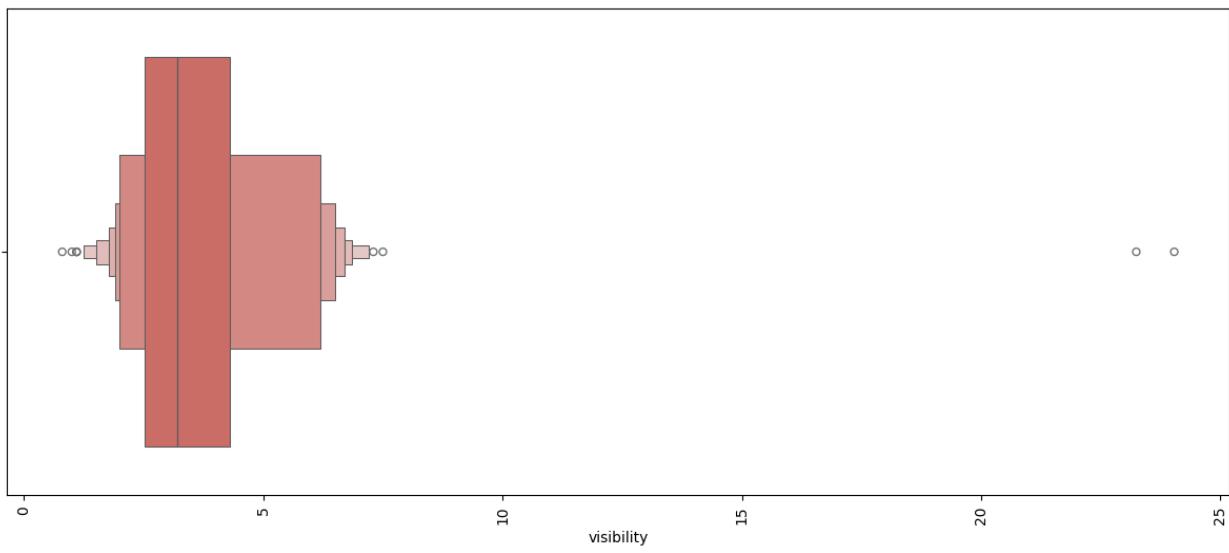
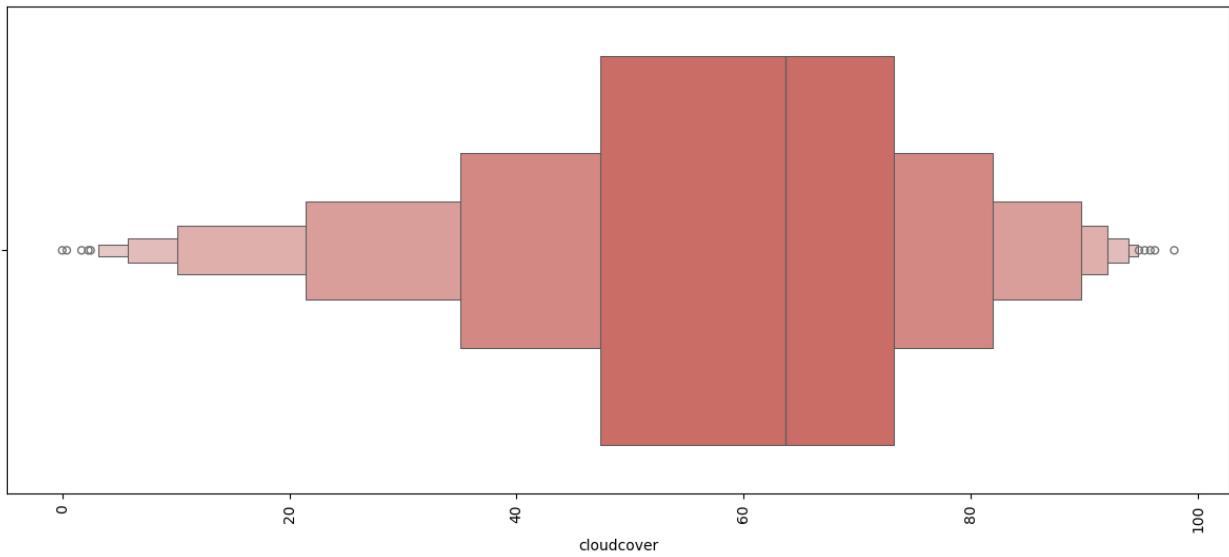


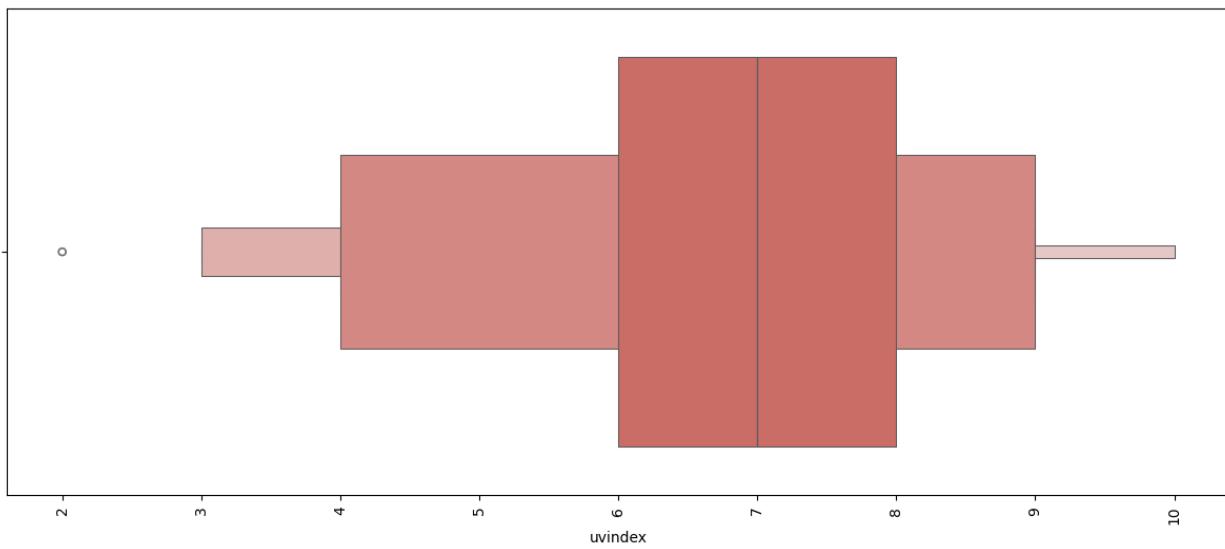
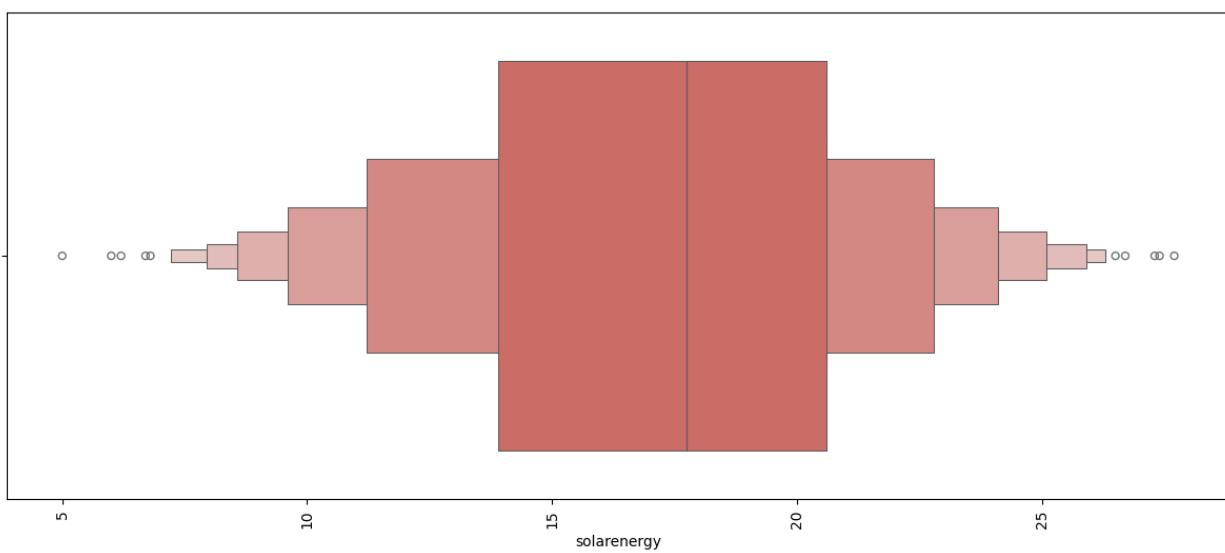
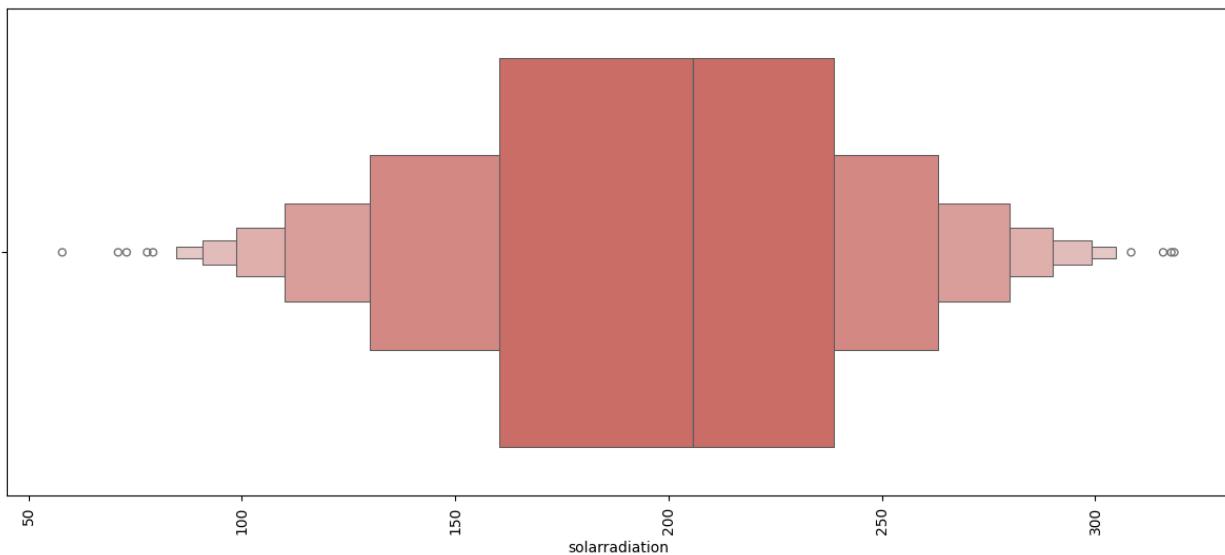


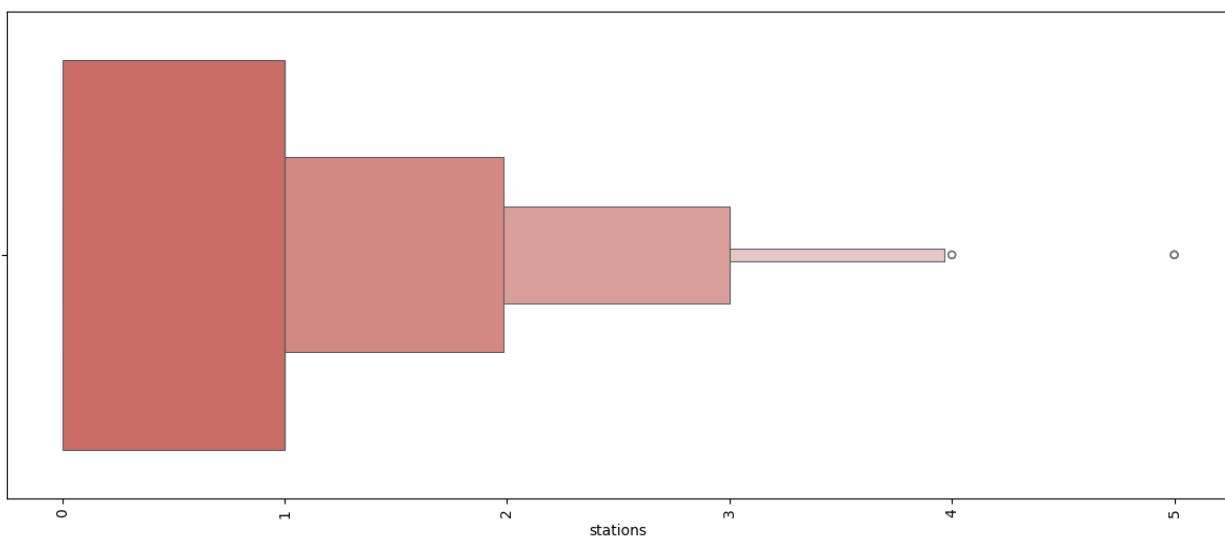
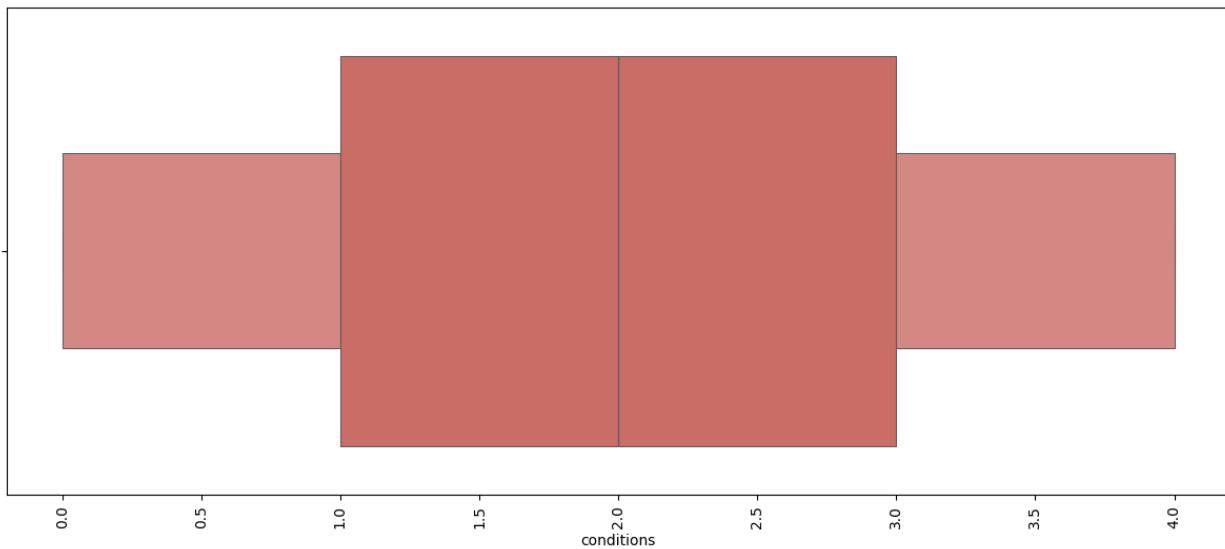


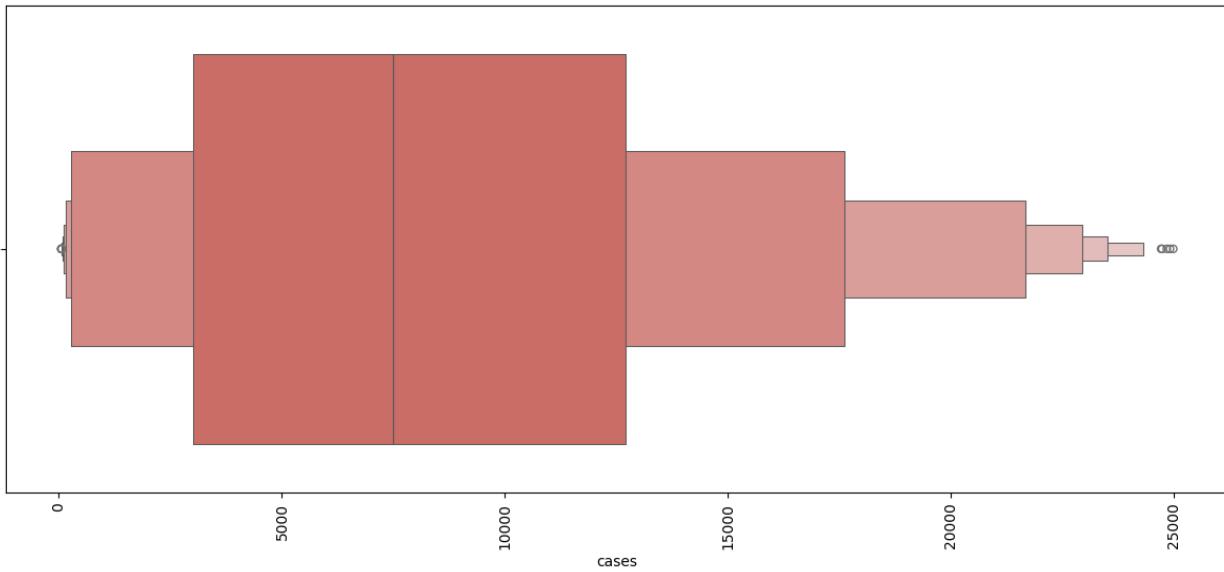




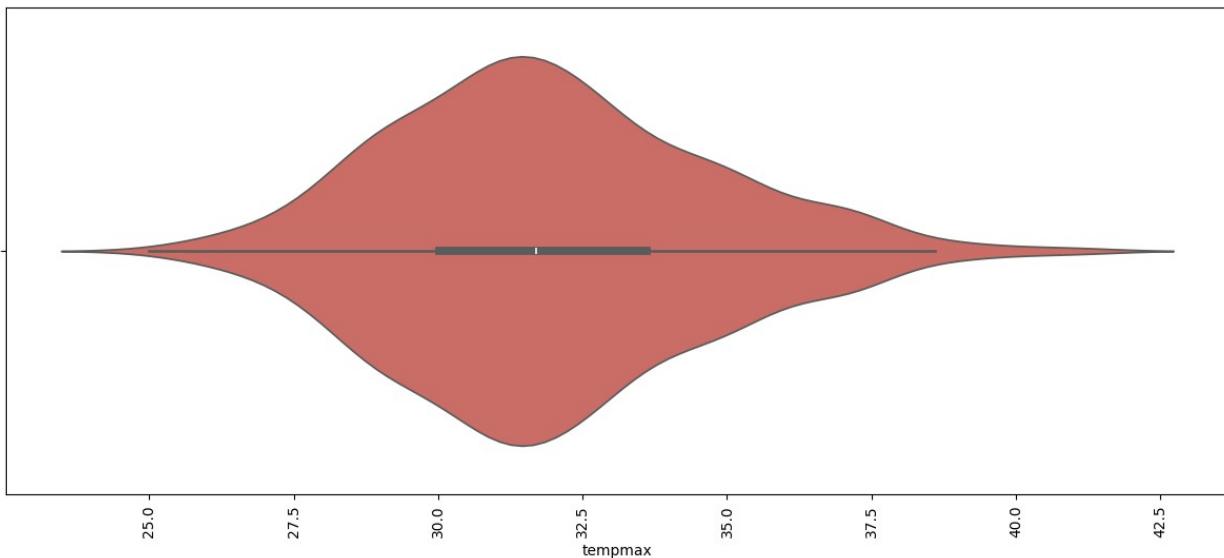


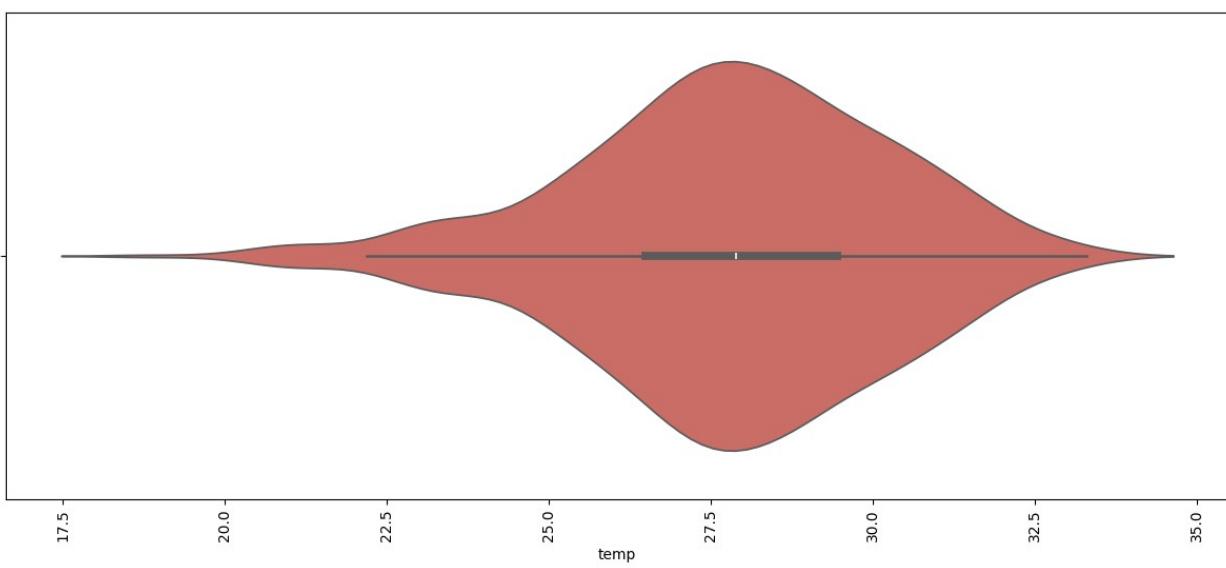
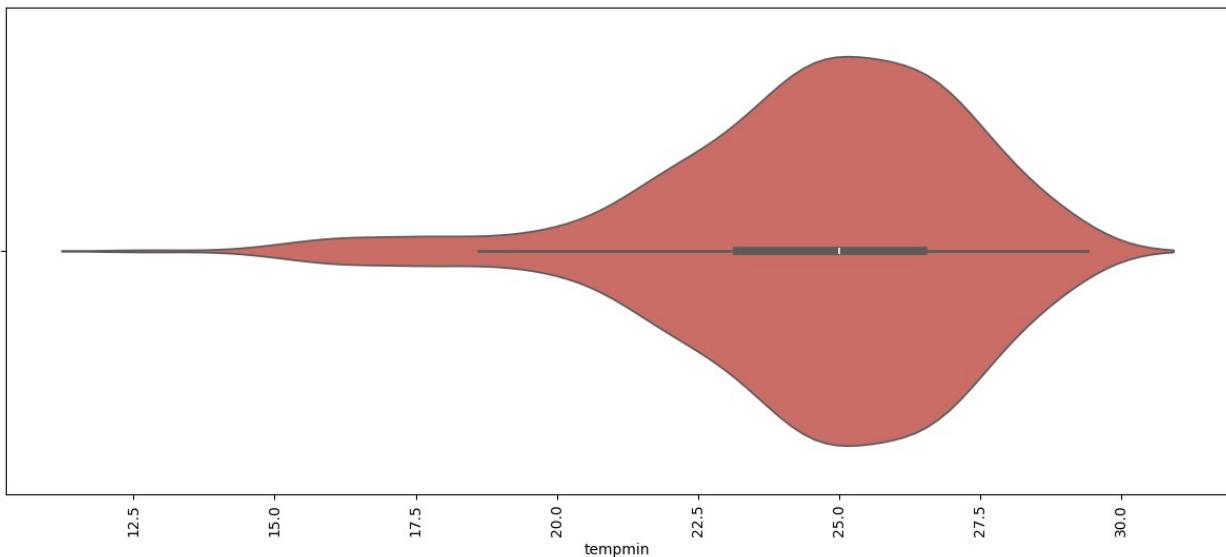


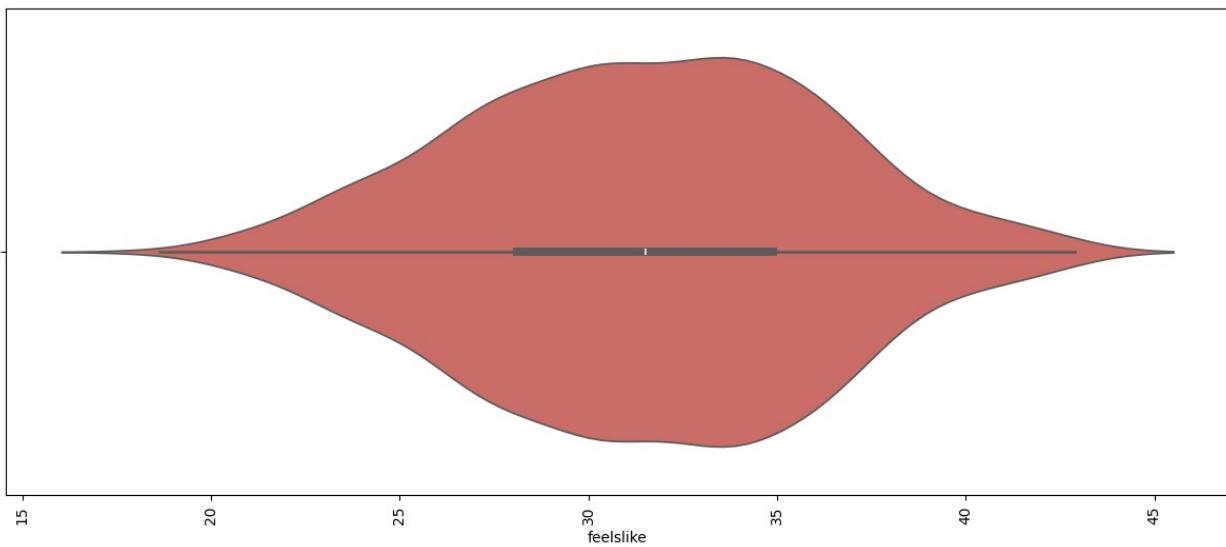
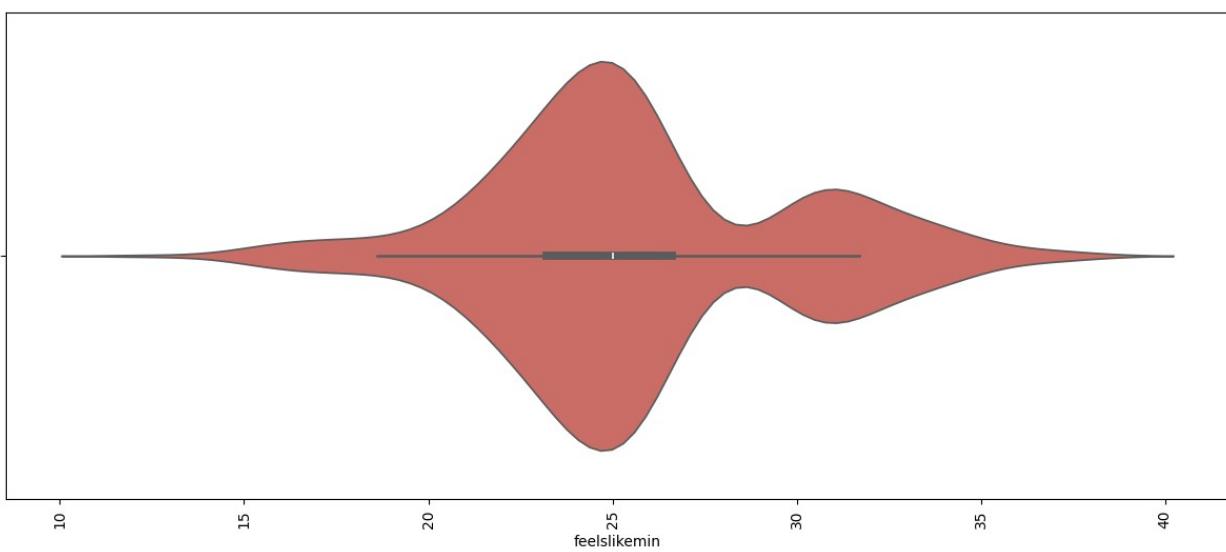
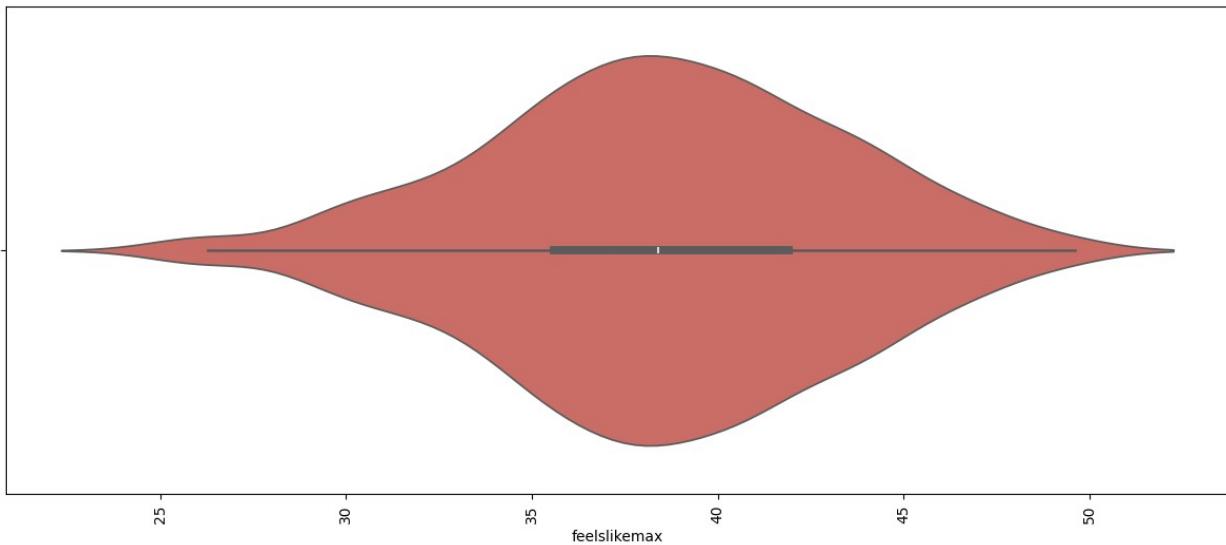


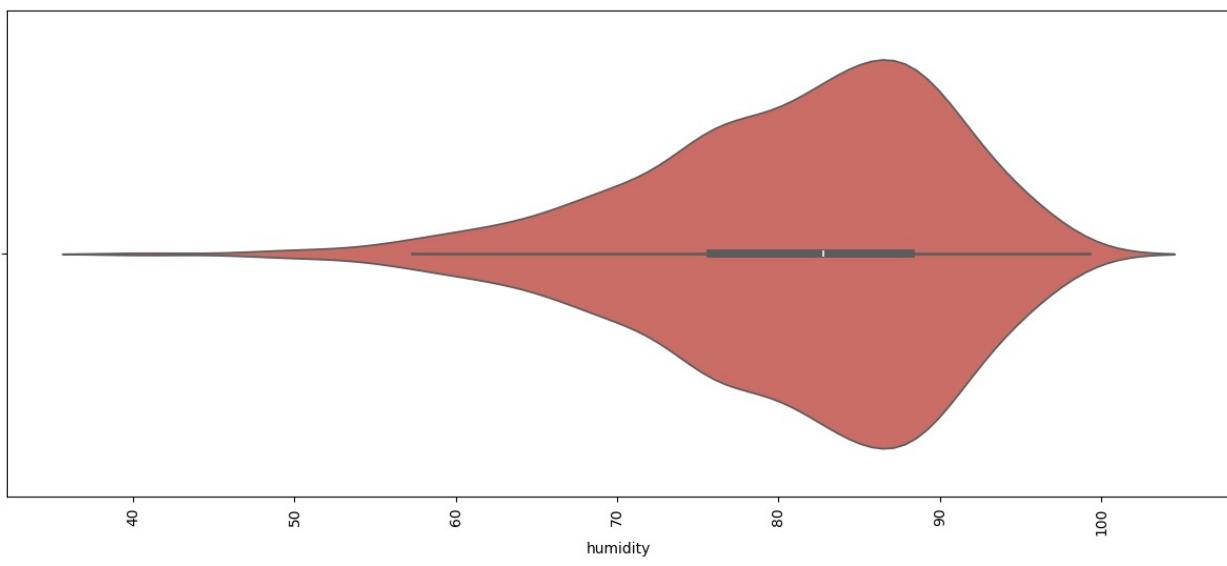
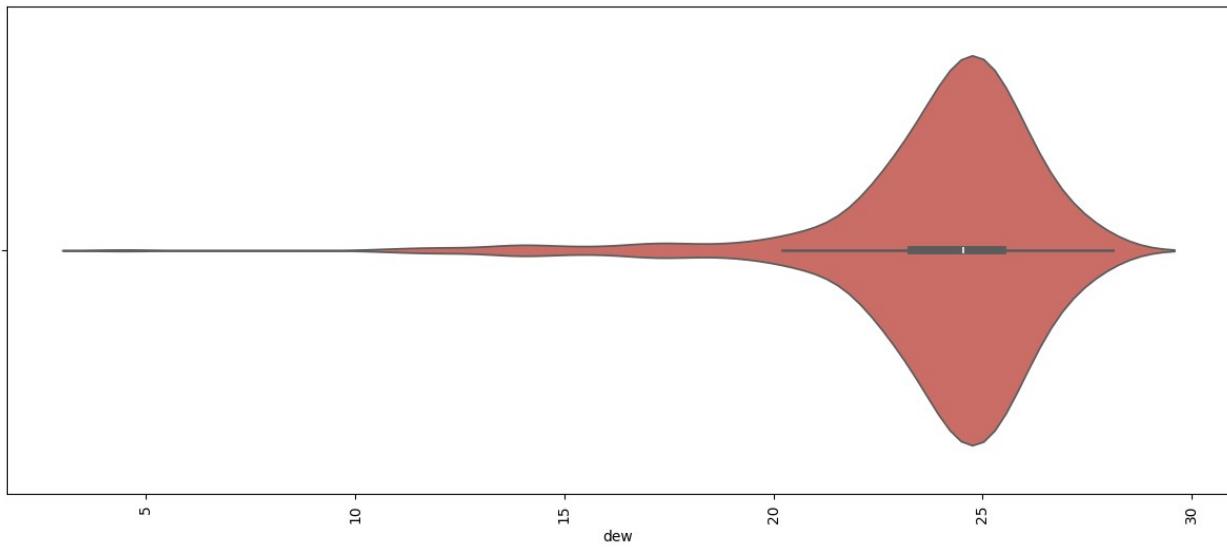


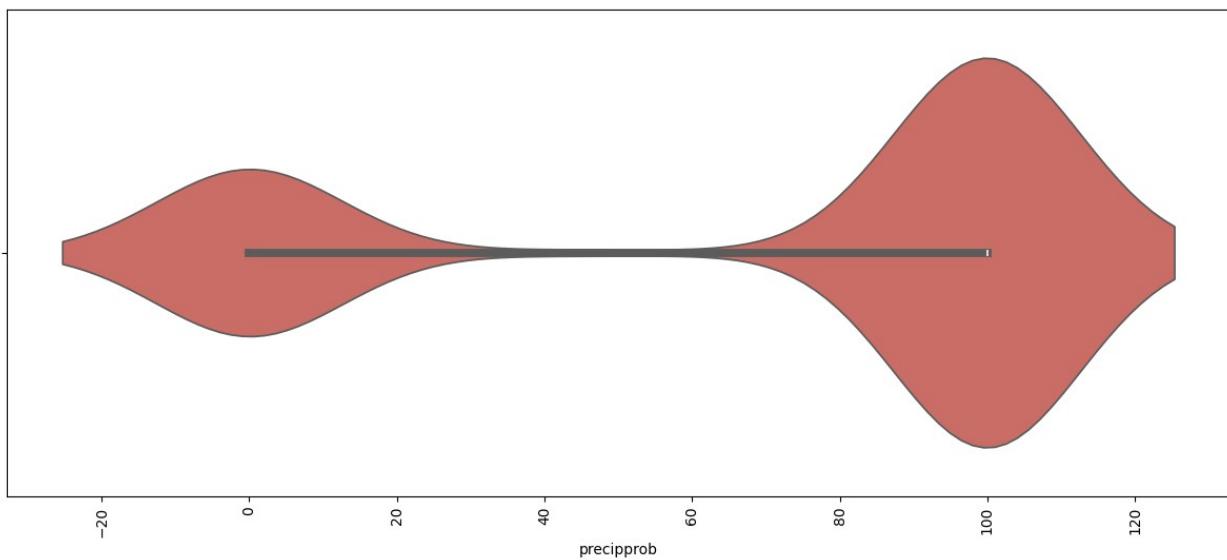
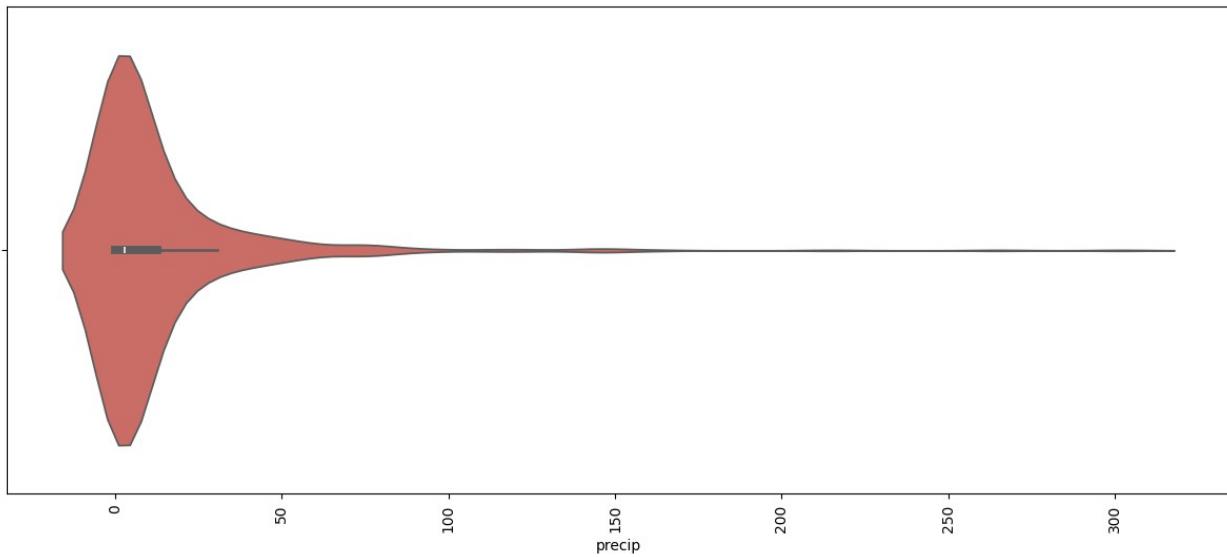
```
for i in continuous:  
    plt.figure(figsize=(15, 6))  
    sns.violinplot(x=i, data=df, palette='hls')  
    plt.xticks(rotation=90)  
    plt.show()
```

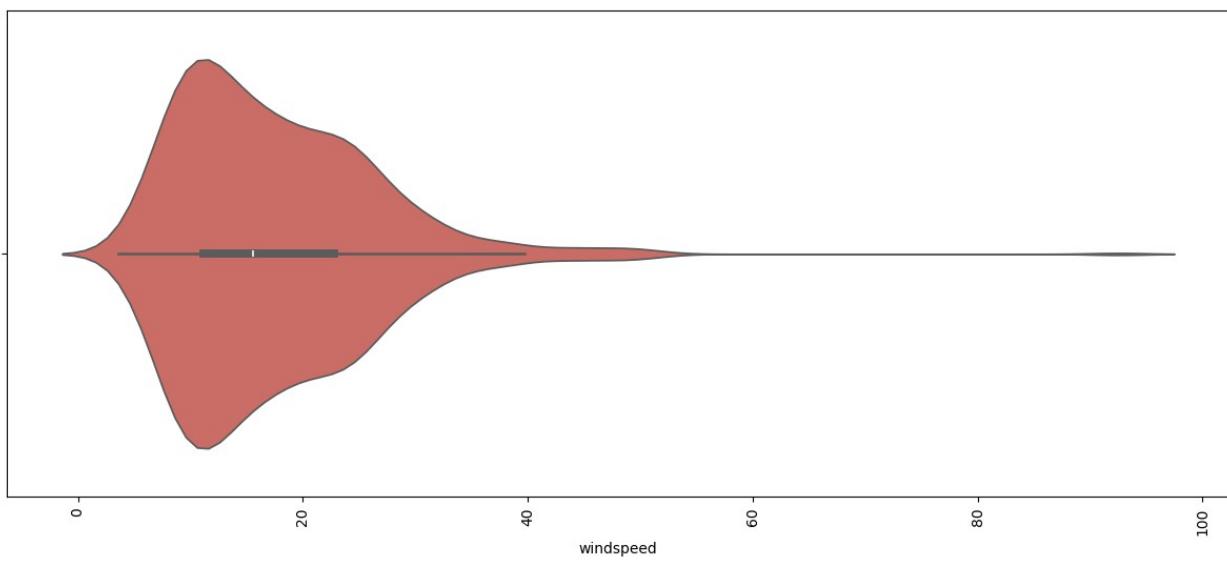
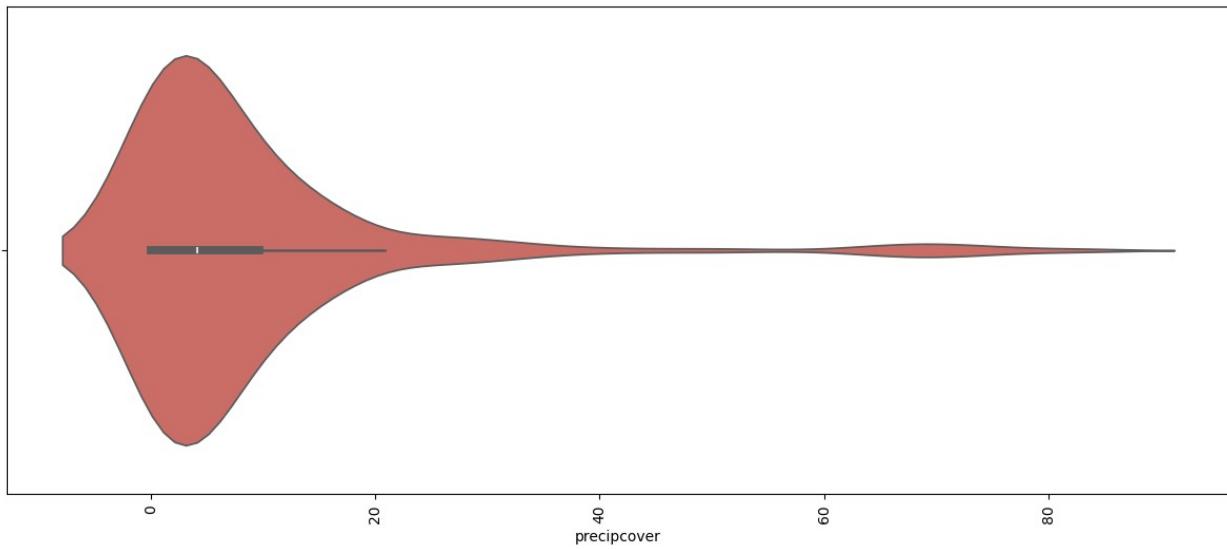


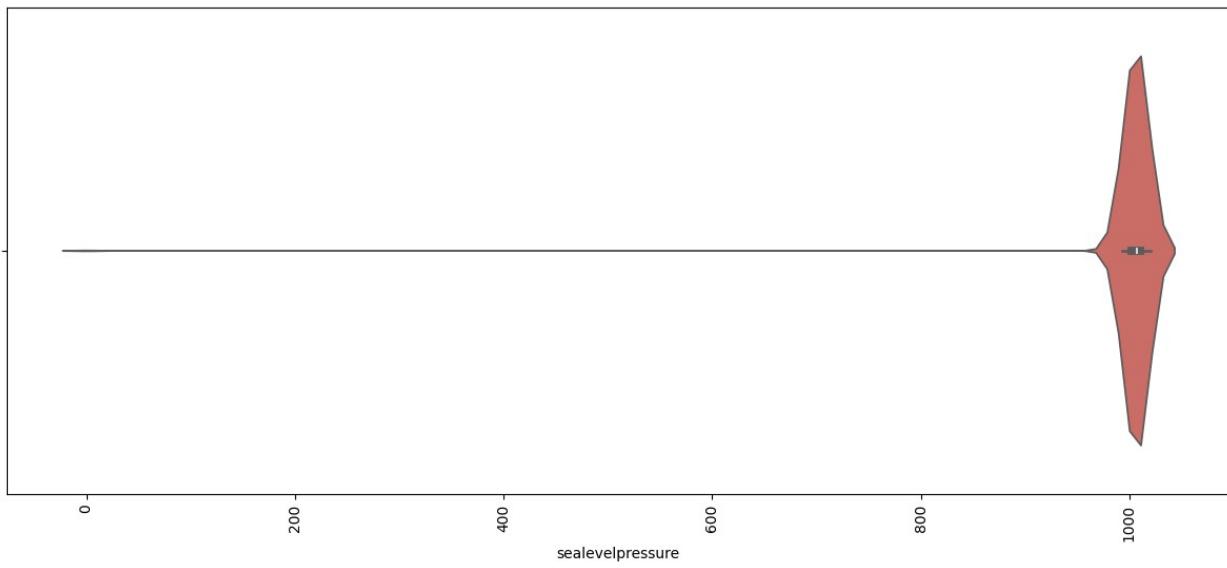
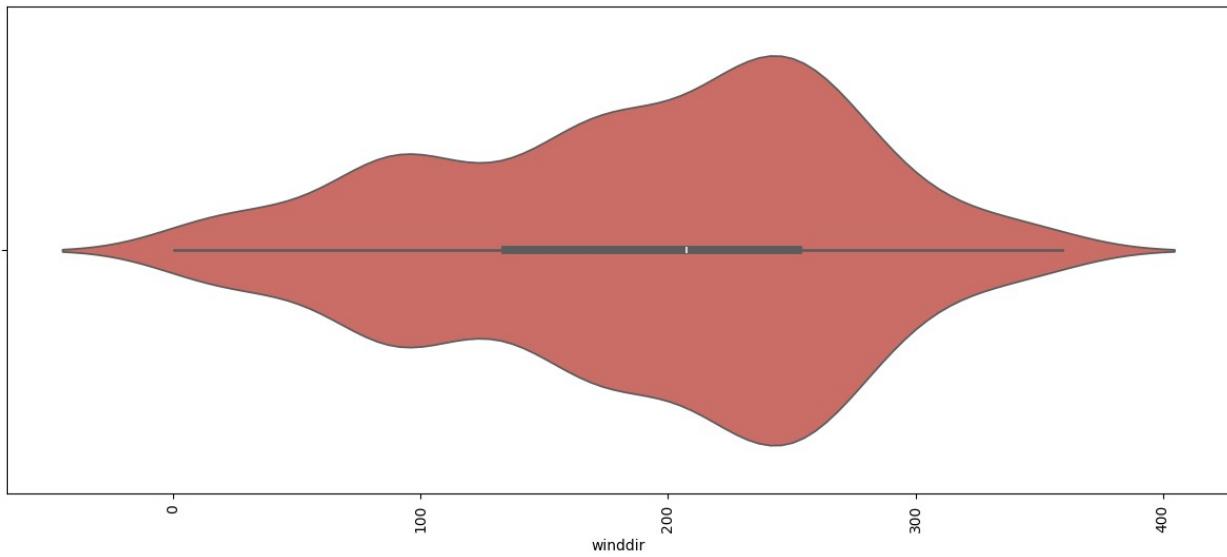


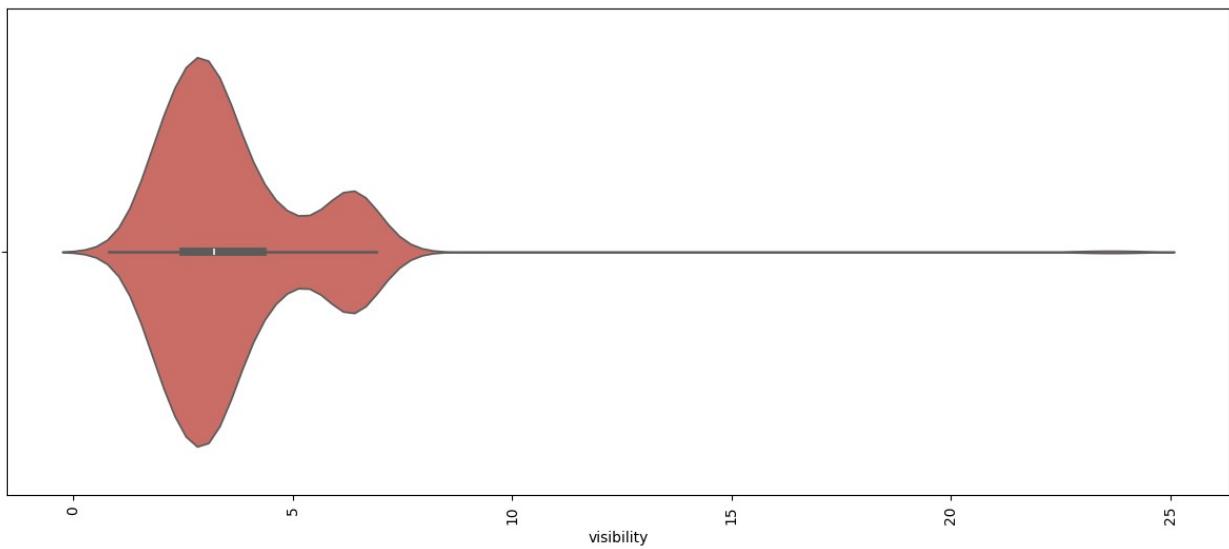
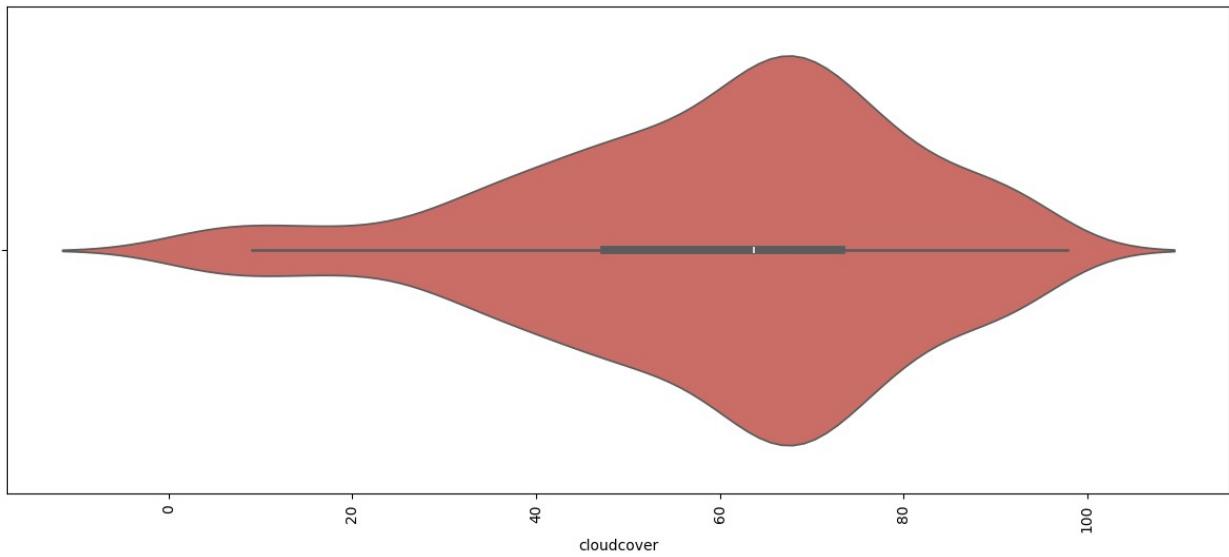


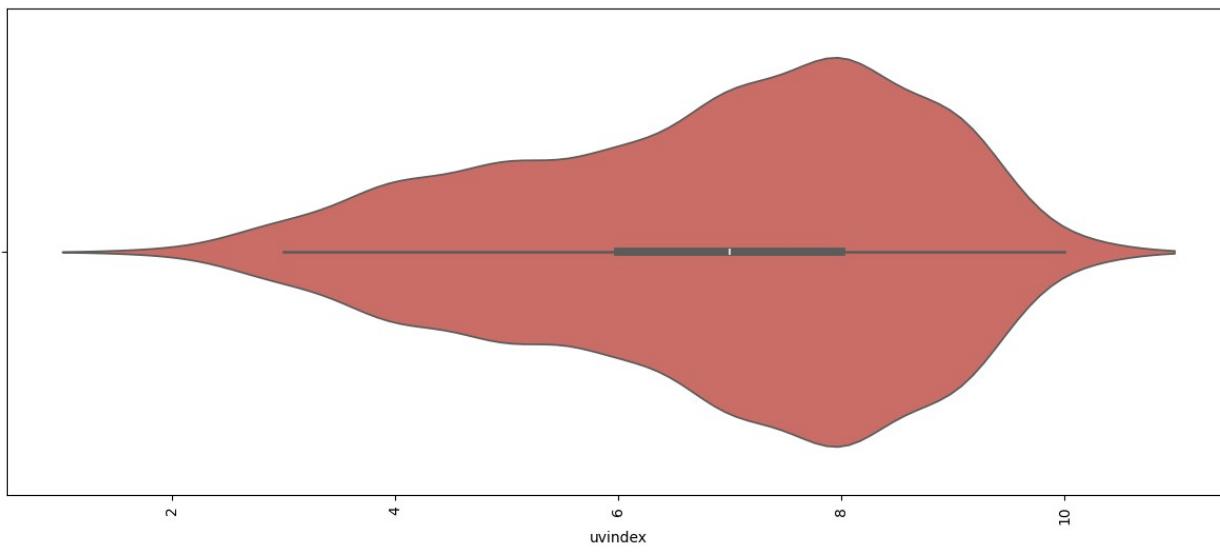
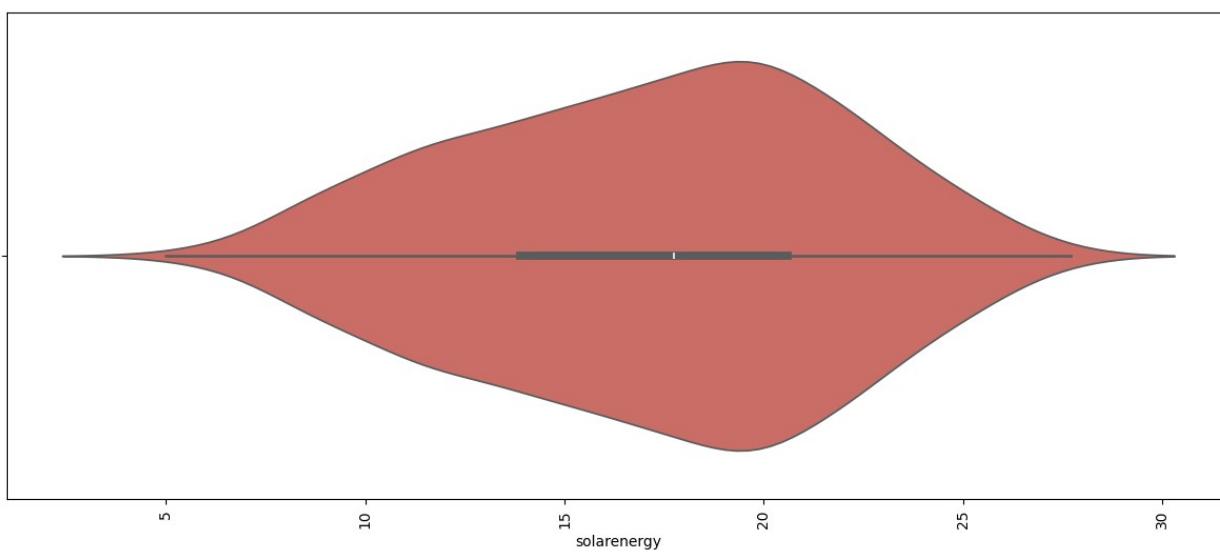
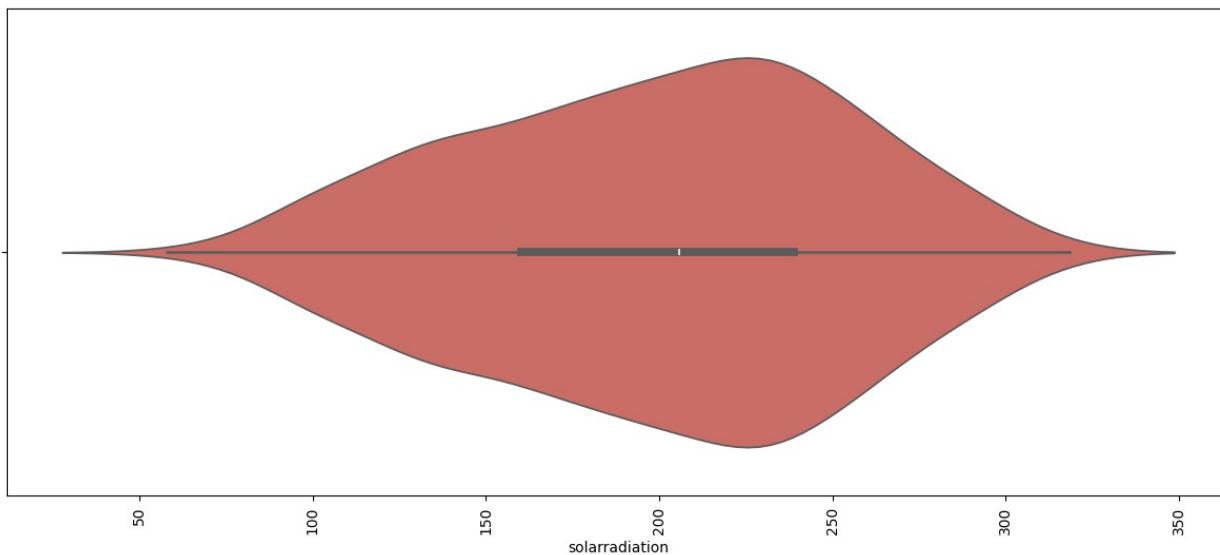


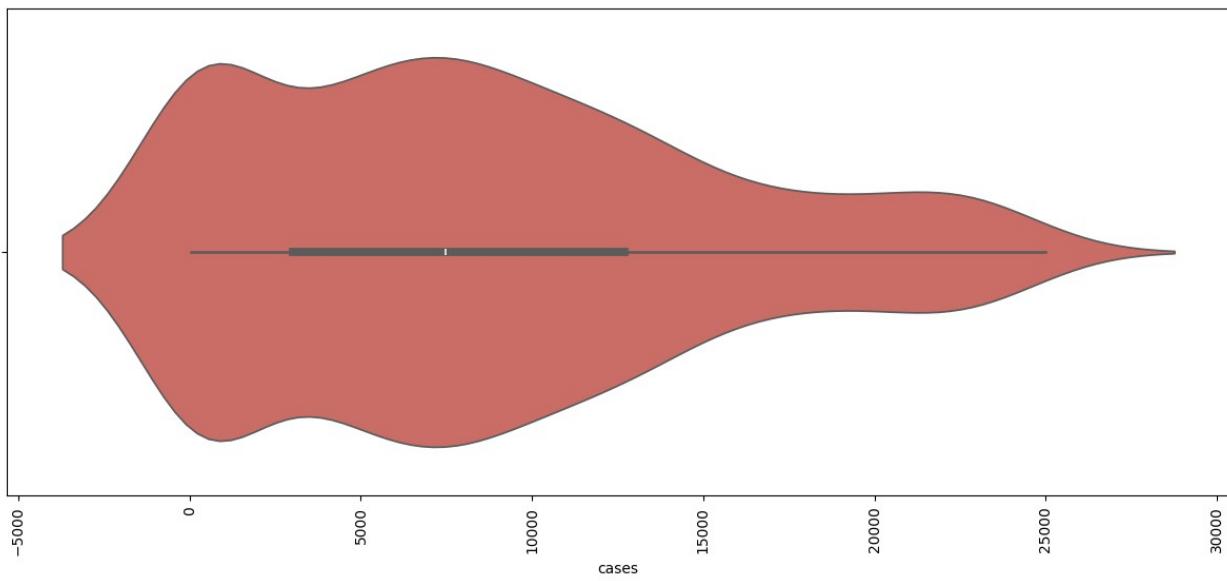
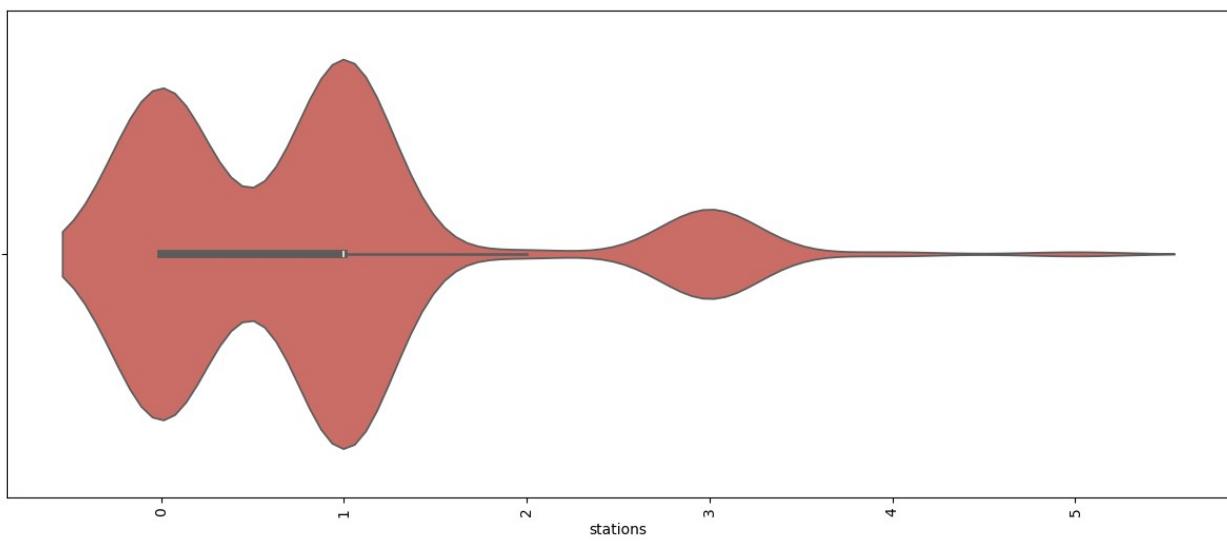
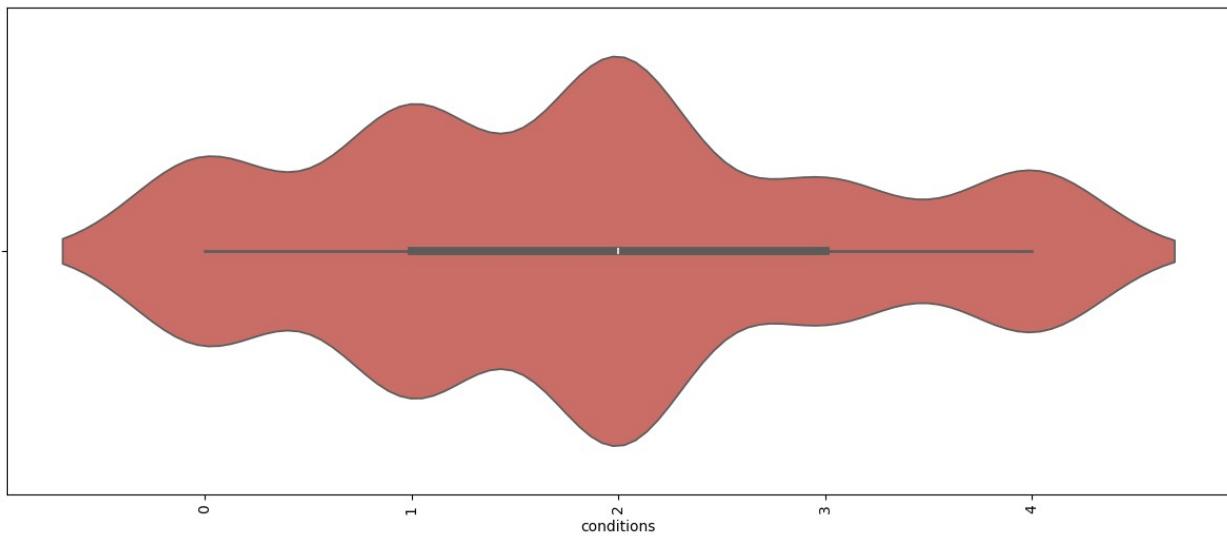








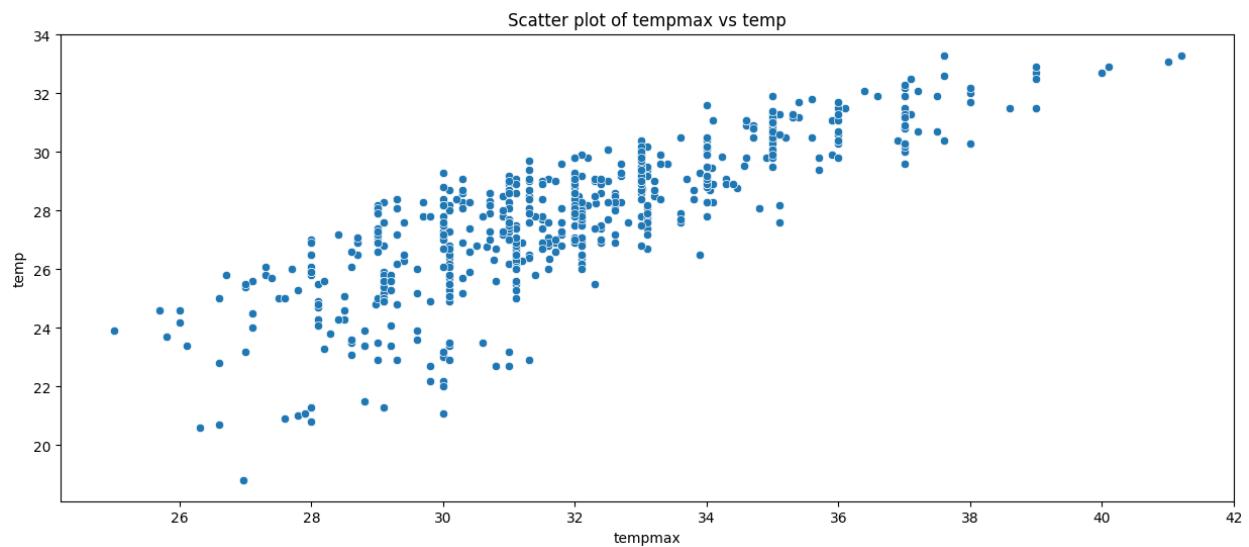
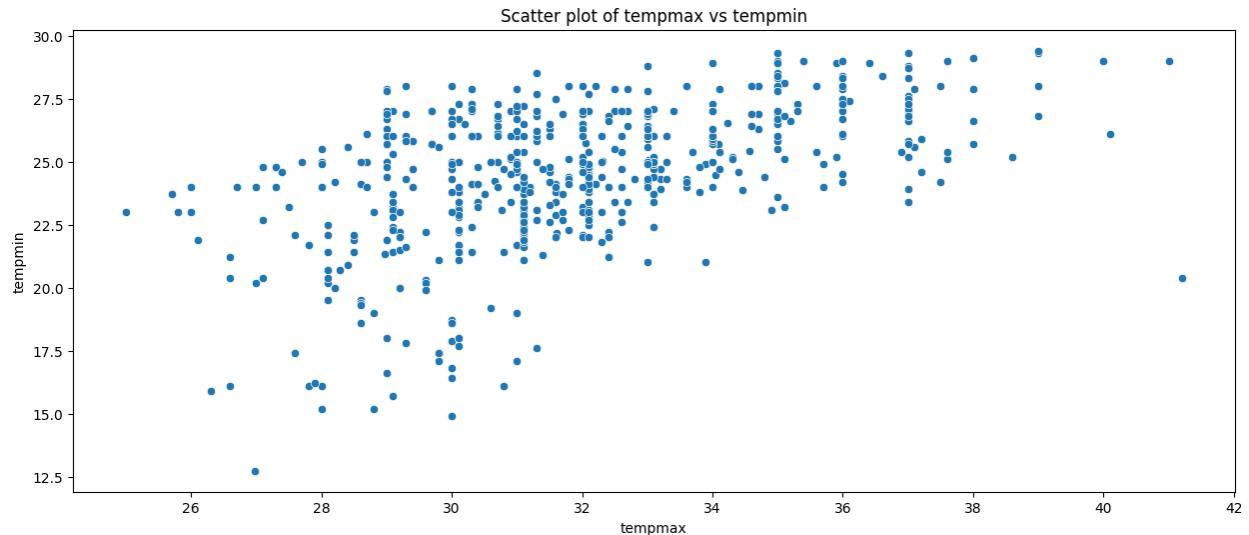




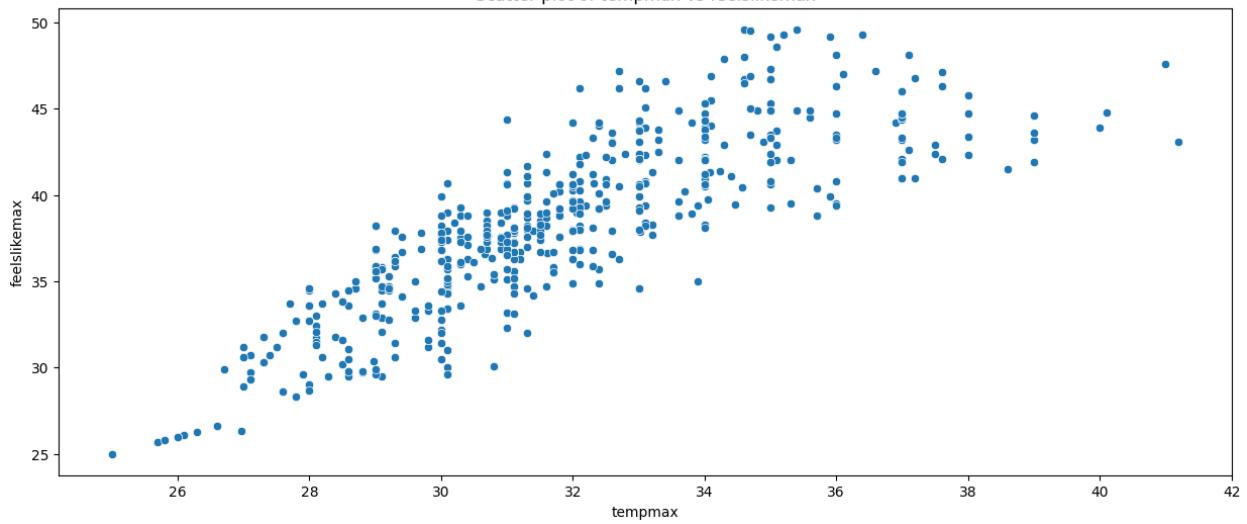
```

for i in range(len(continuous)):
    for j in range(i + 1, len(continuous)):
        plt.figure(figsize=(15, 6))
        sns.scatterplot(x=continuous[i], y=continuous[j], data=df,
                        palette='hls')
        plt.title(f'Scatter plot of {continuous[i]} vs
{continuous[j]}')
        plt.show()

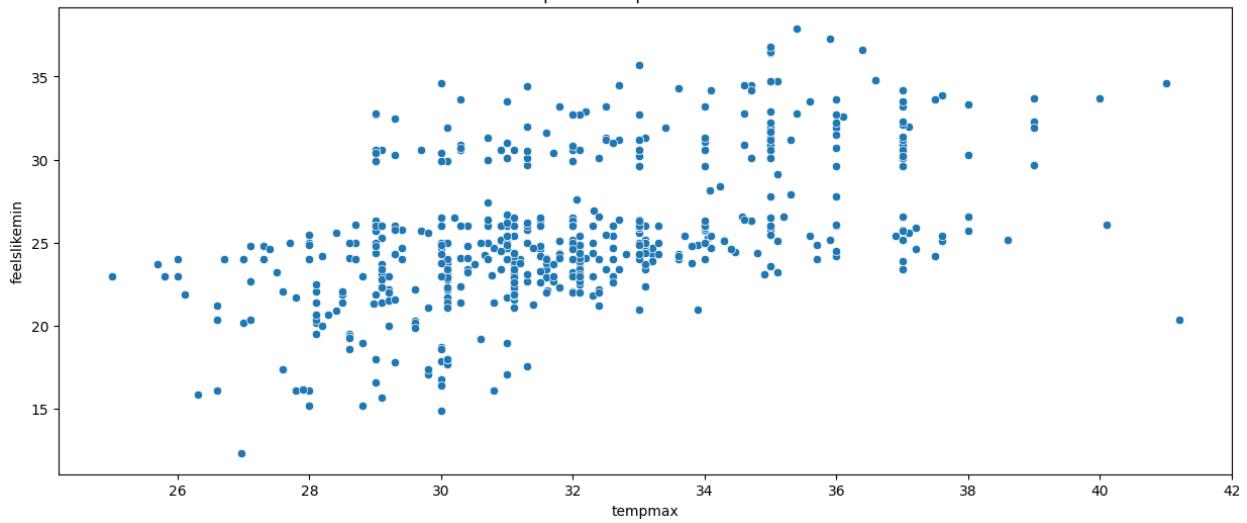
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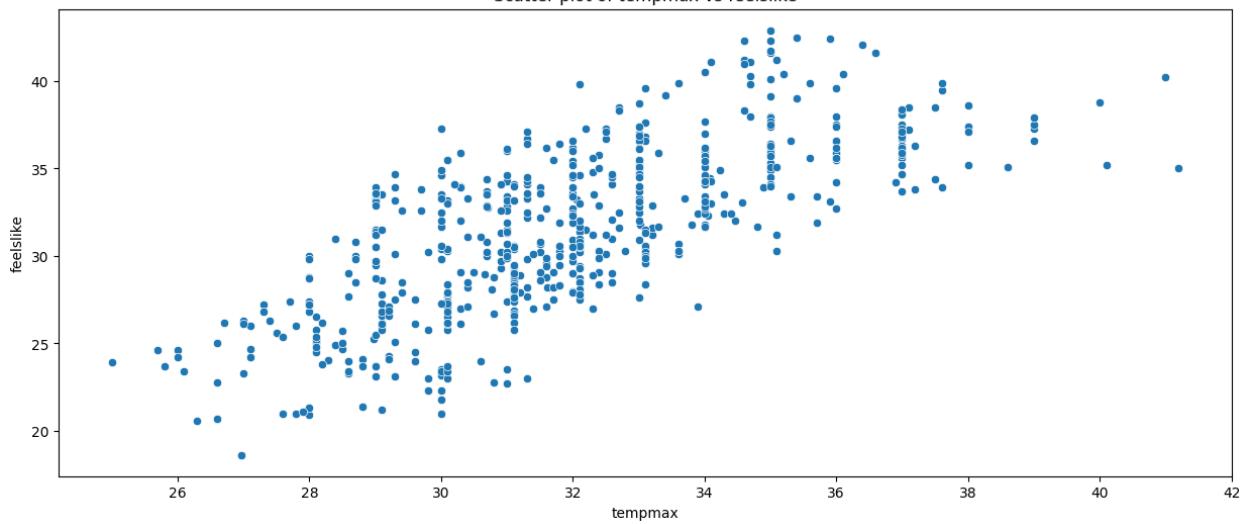
Scatter plot of tempmax vs feelslikemax



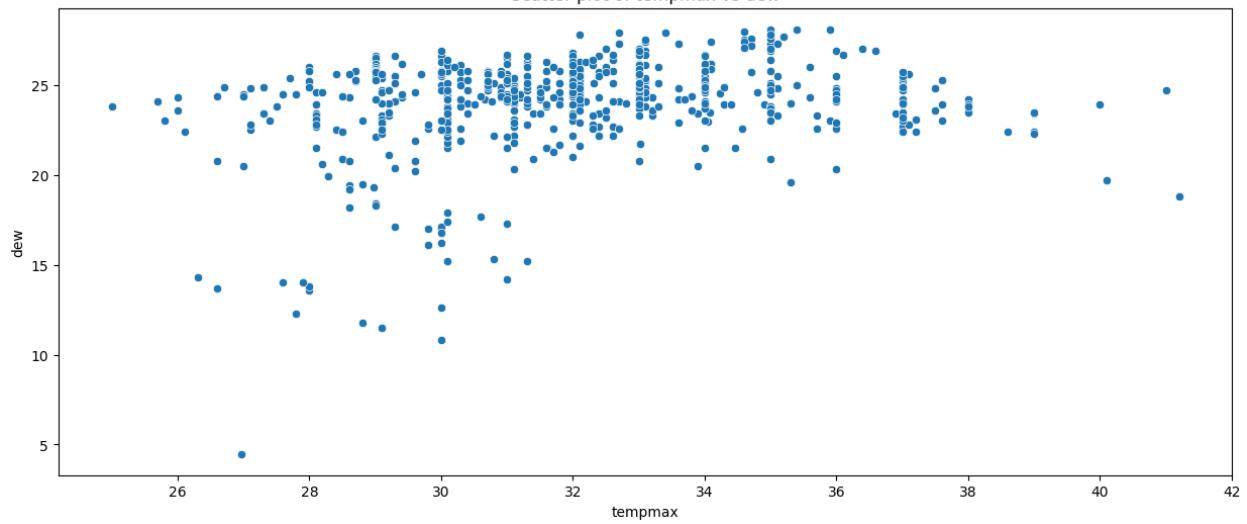
Scatter plot of tempmax vs feelslikemin



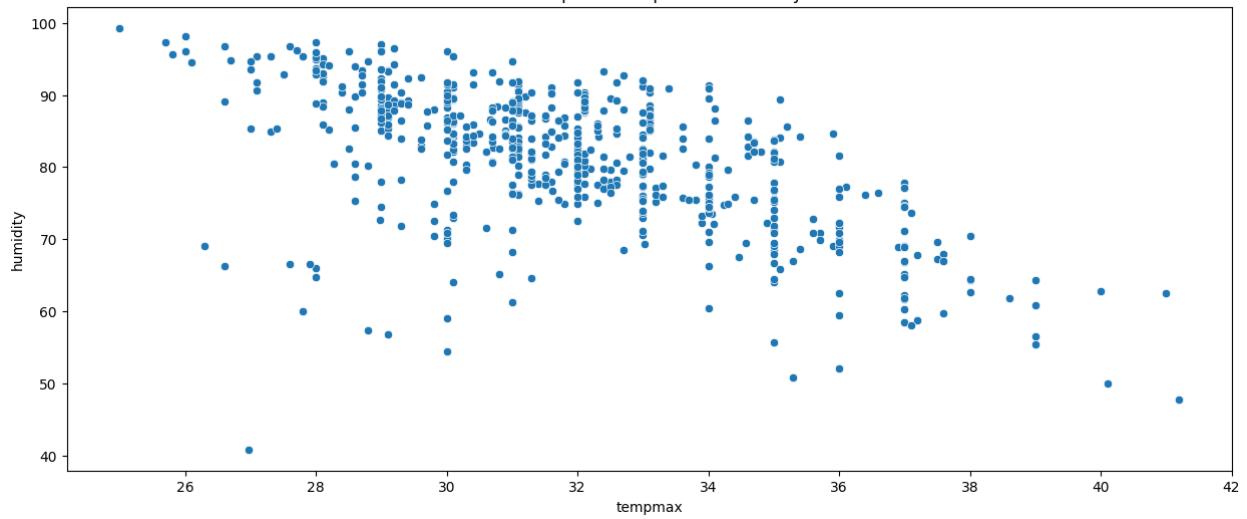
Scatter plot of tempmax vs feelslike



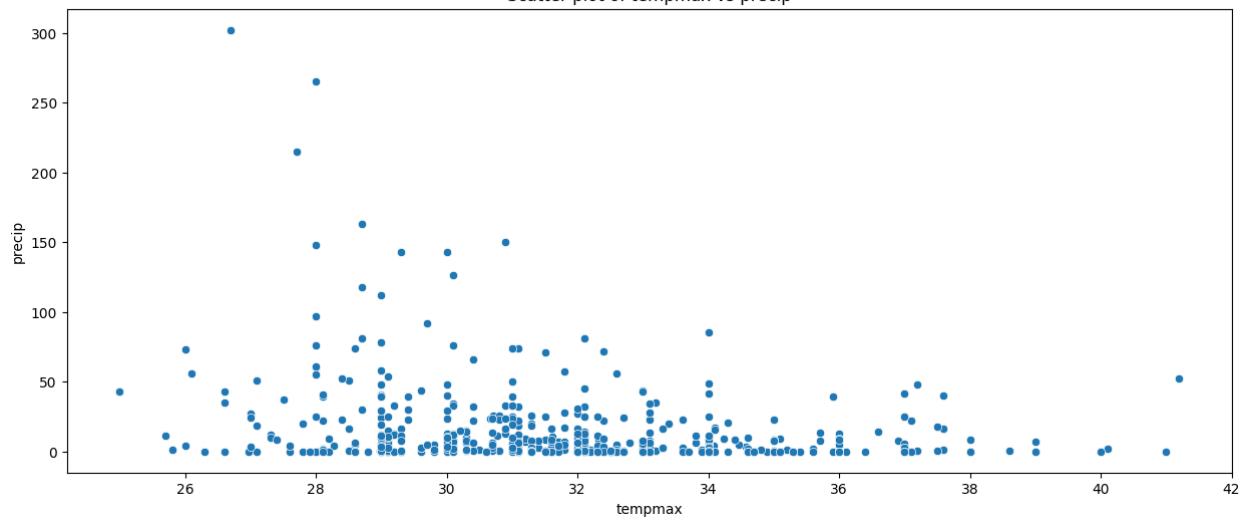
Scatter plot of tempmax vs dew

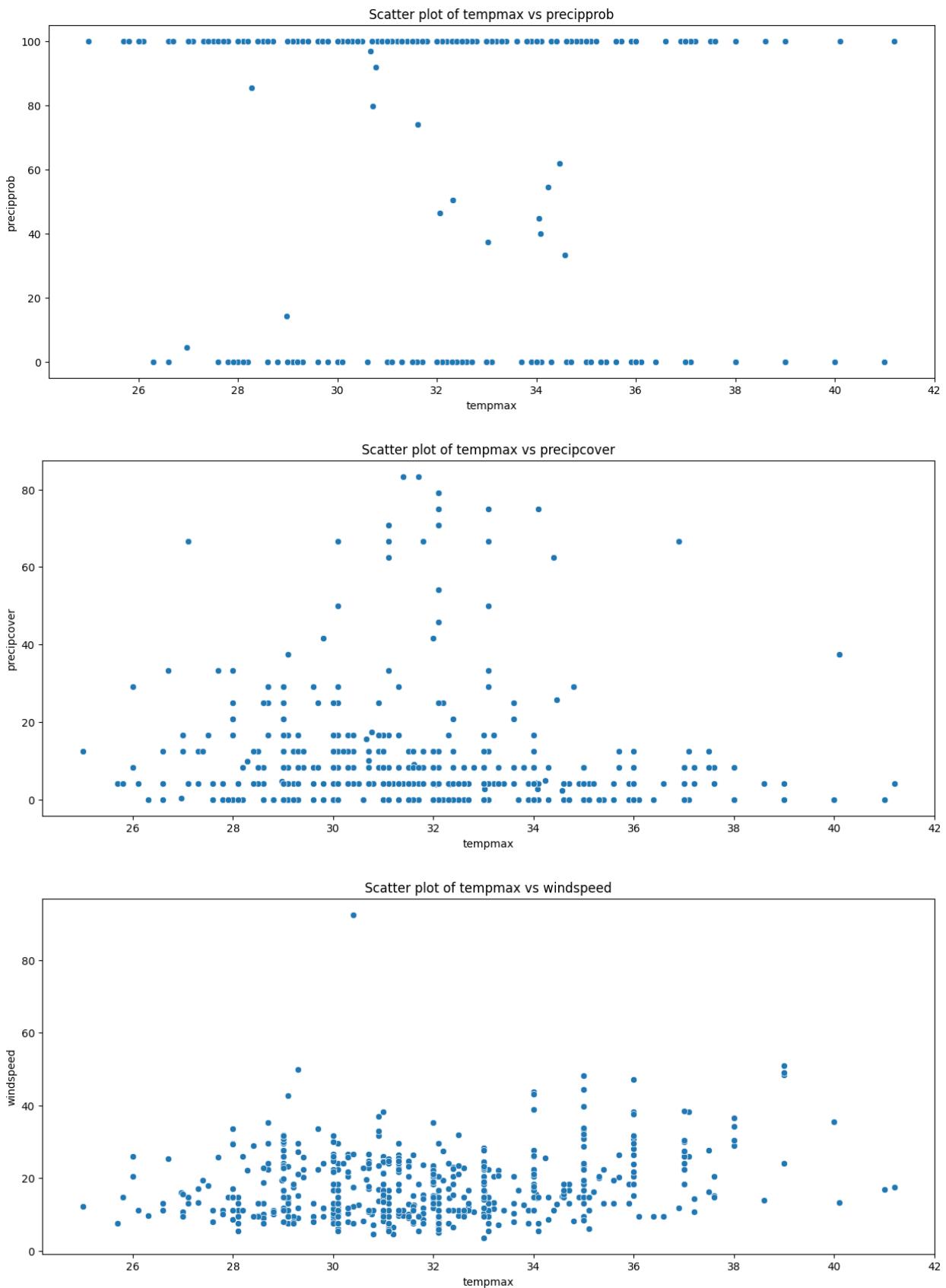


Scatter plot of tempmax vs humidity

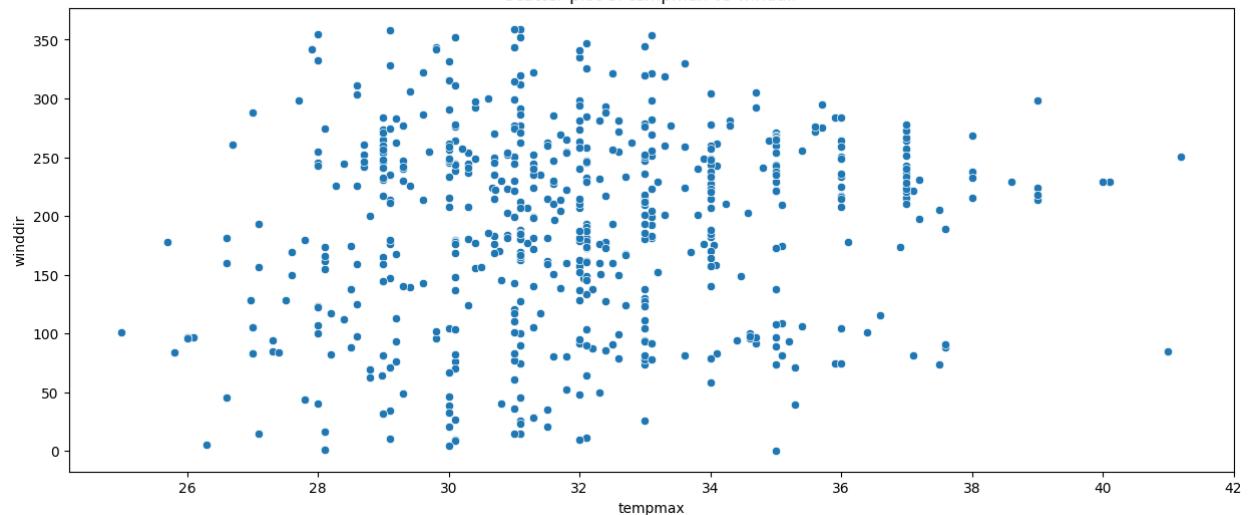


Scatter plot of tempmax vs precip

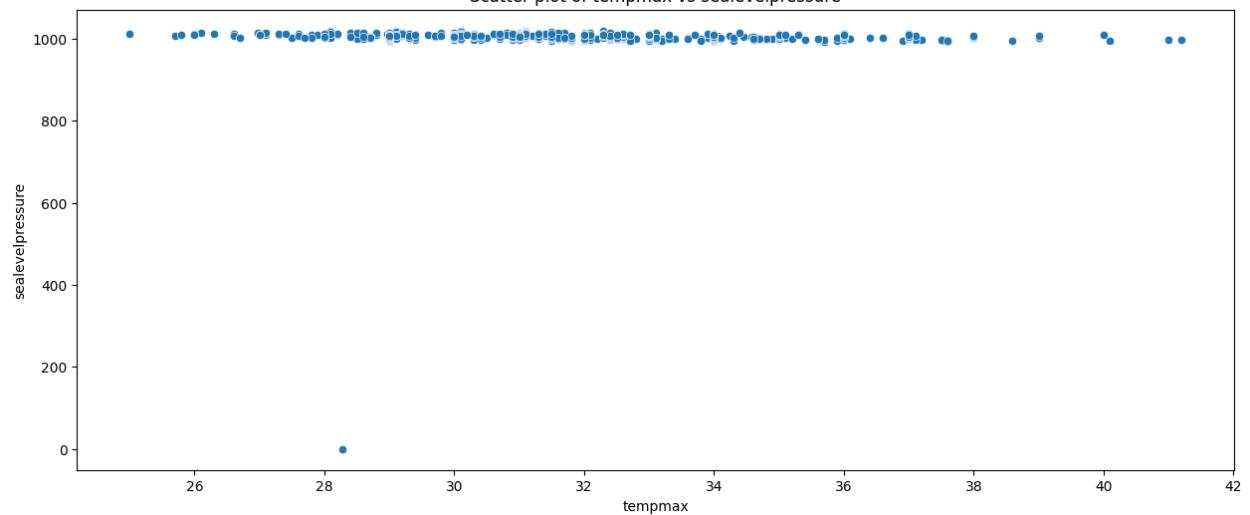




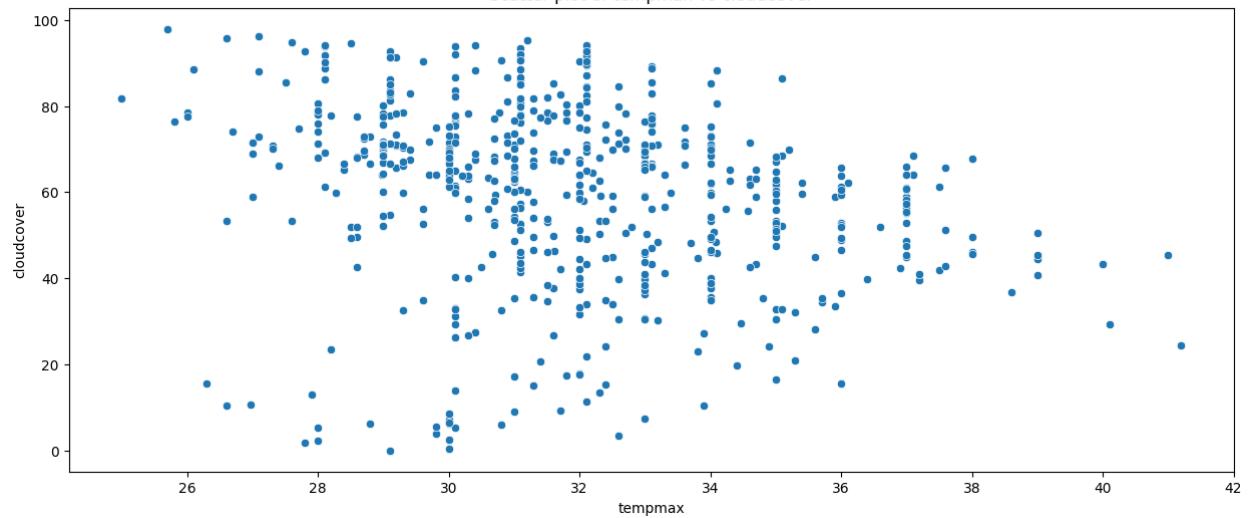
Scatter plot of tempmax vs winddir



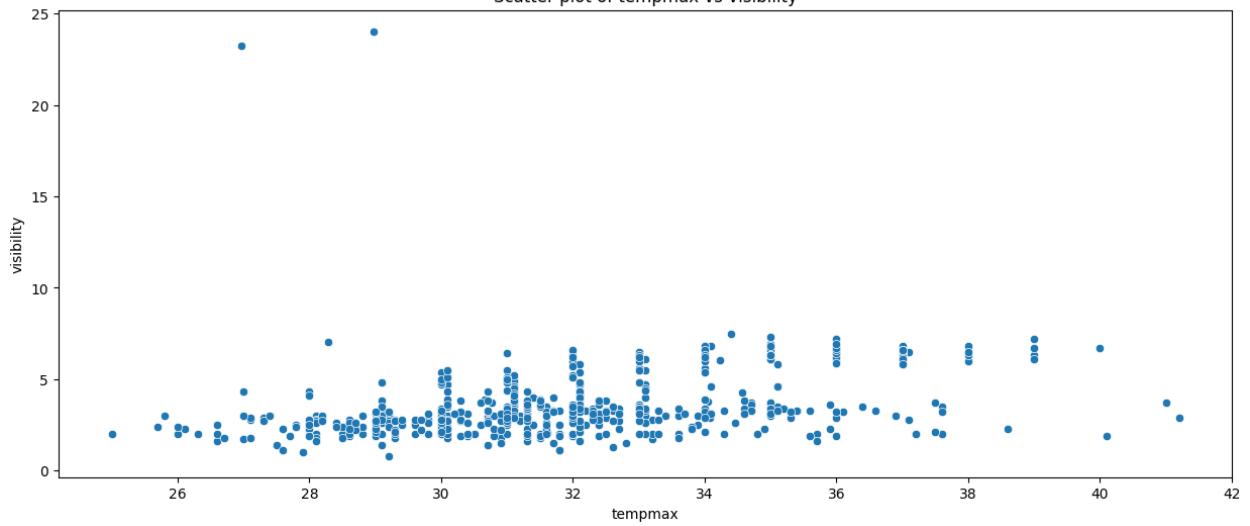
Scatter plot of tempmax vs sealevelpressure



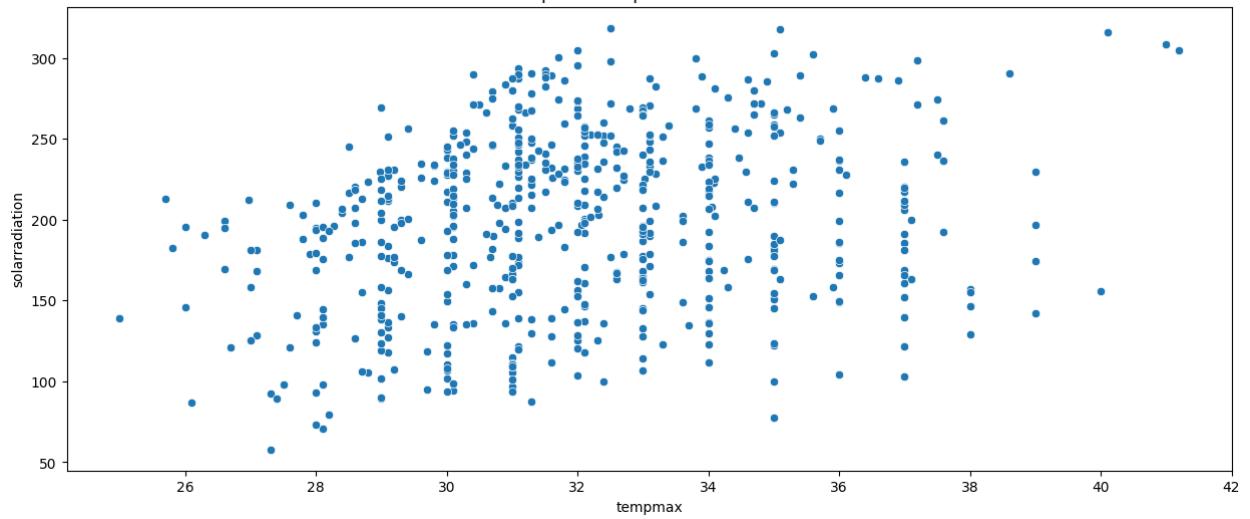
Scatter plot of tempmax vs cloudcover



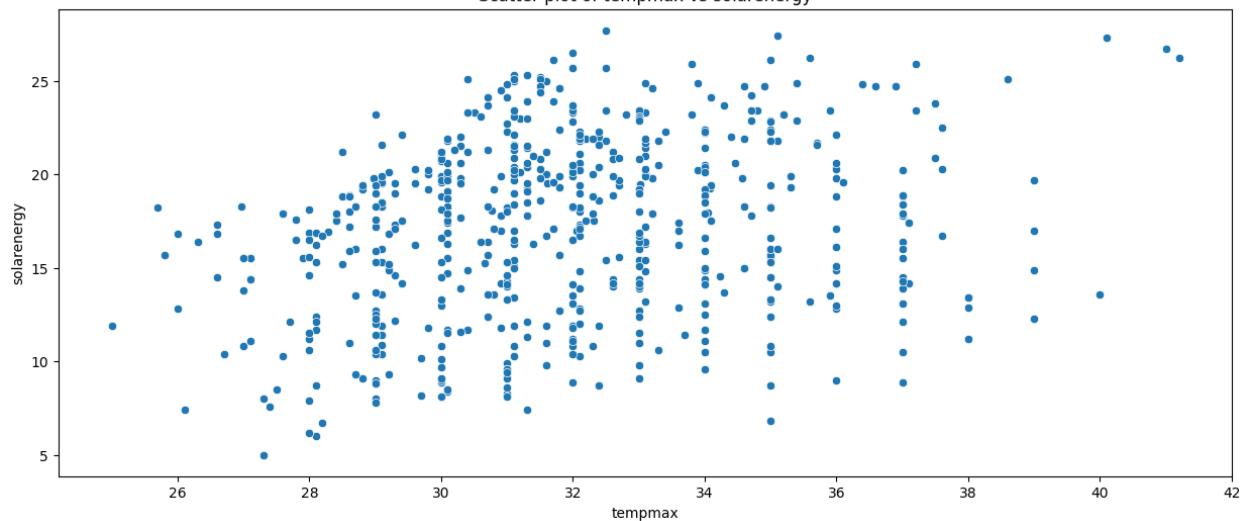
Scatter plot of tempmax vs visibility

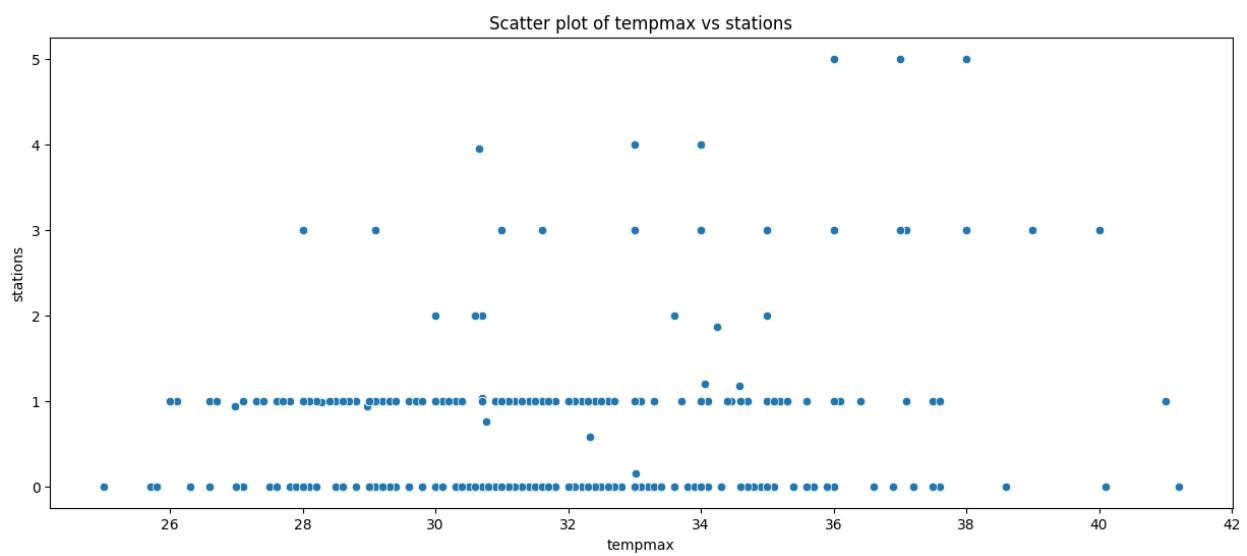
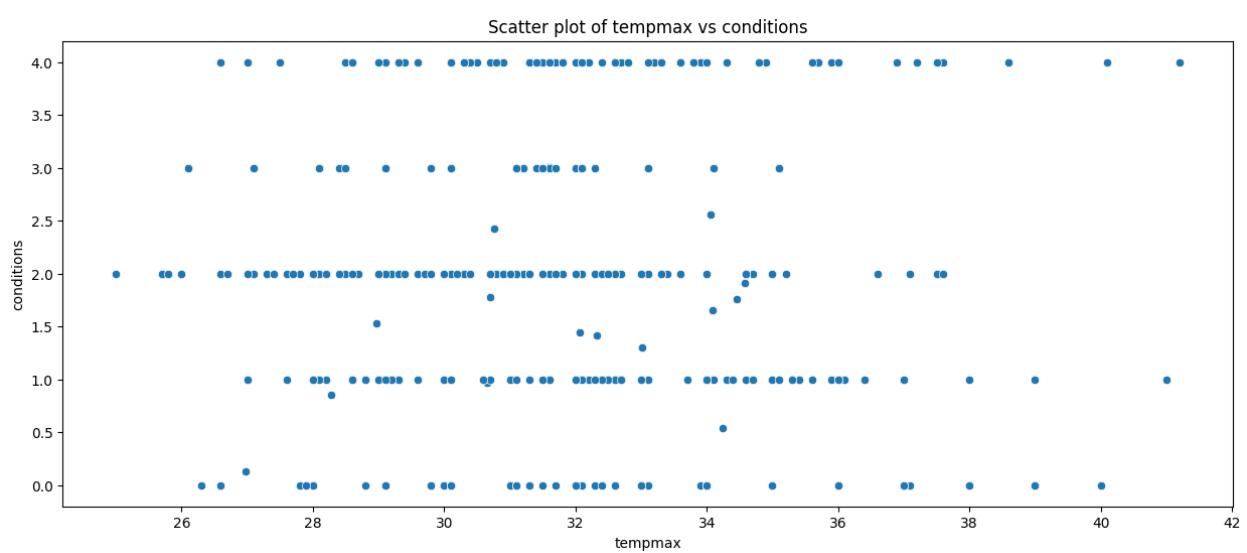
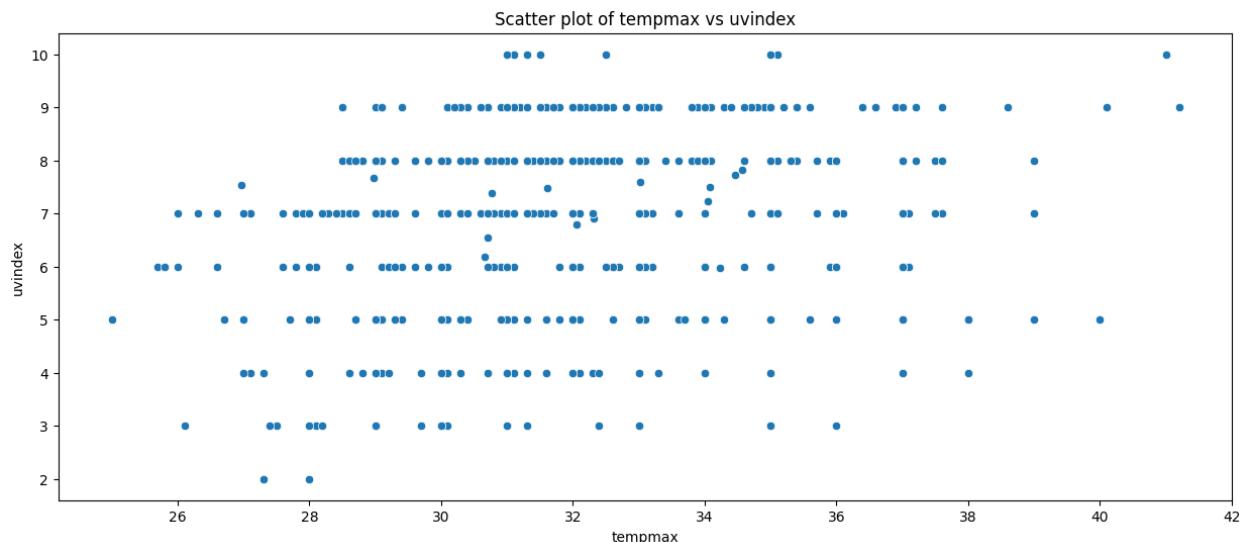


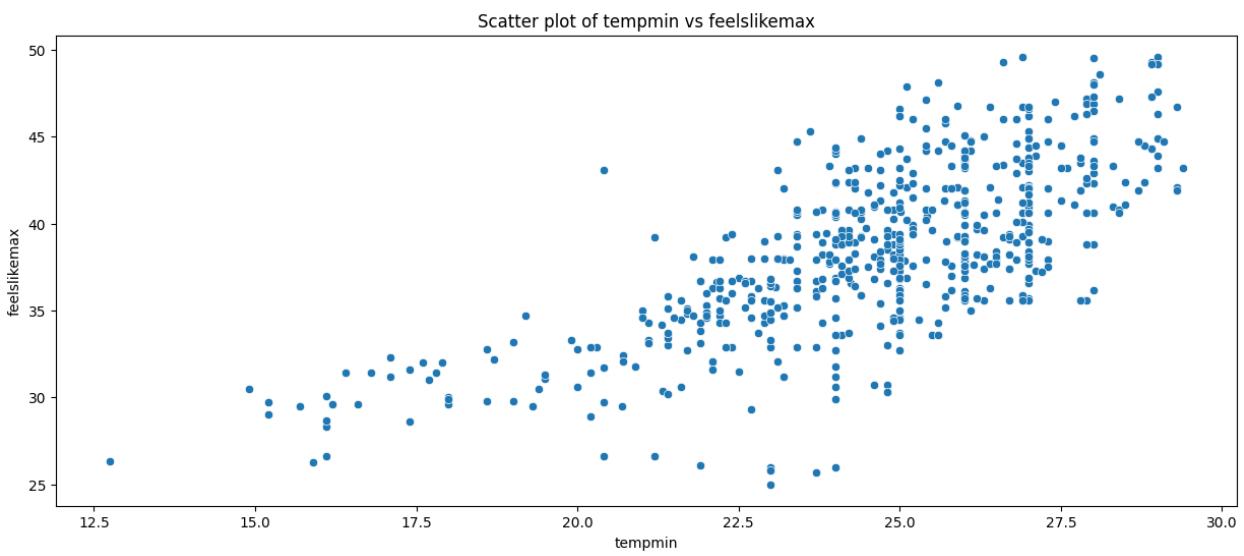
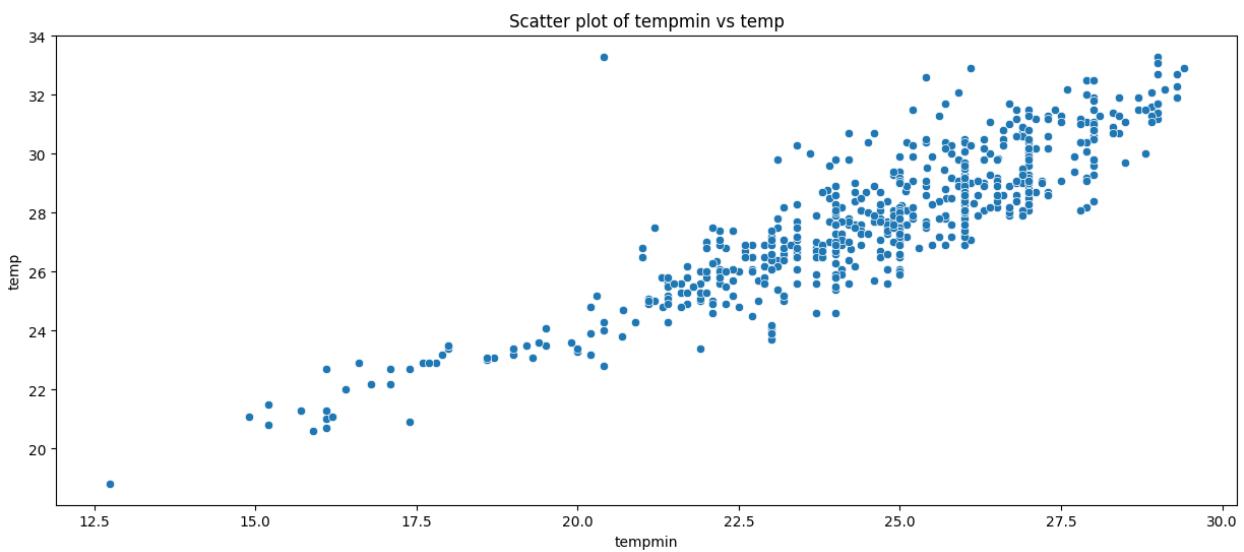
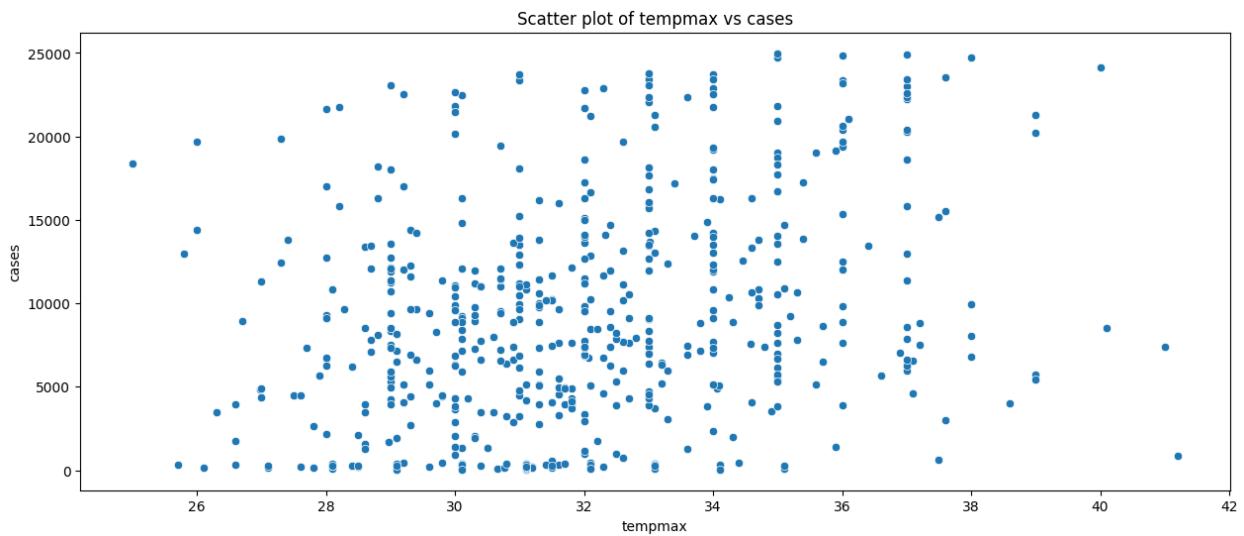
Scatter plot of tempmax vs solarradiation



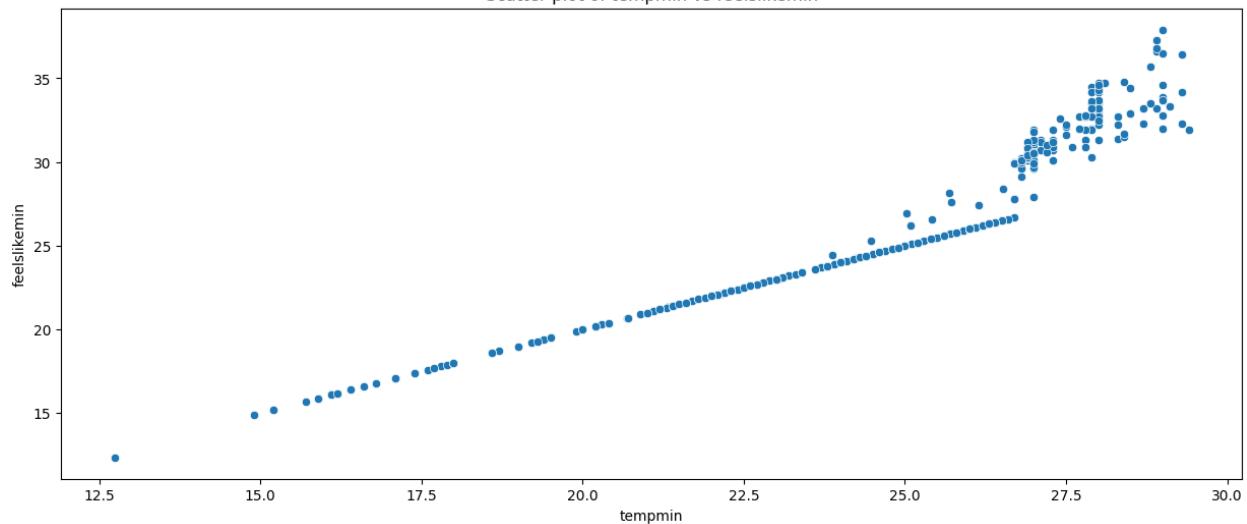
Scatter plot of tempmax vs solarenergy



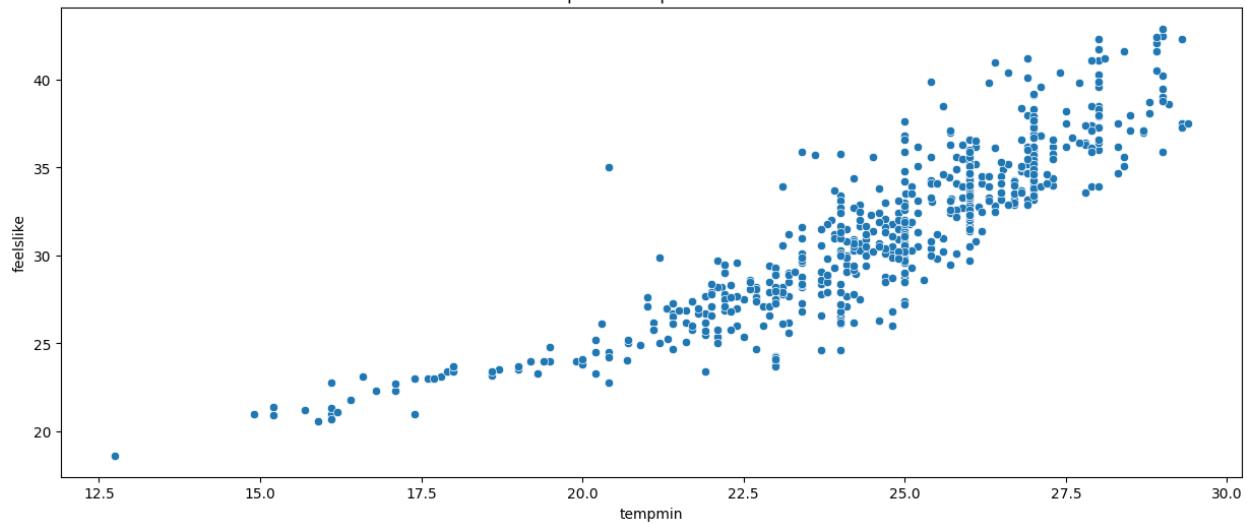




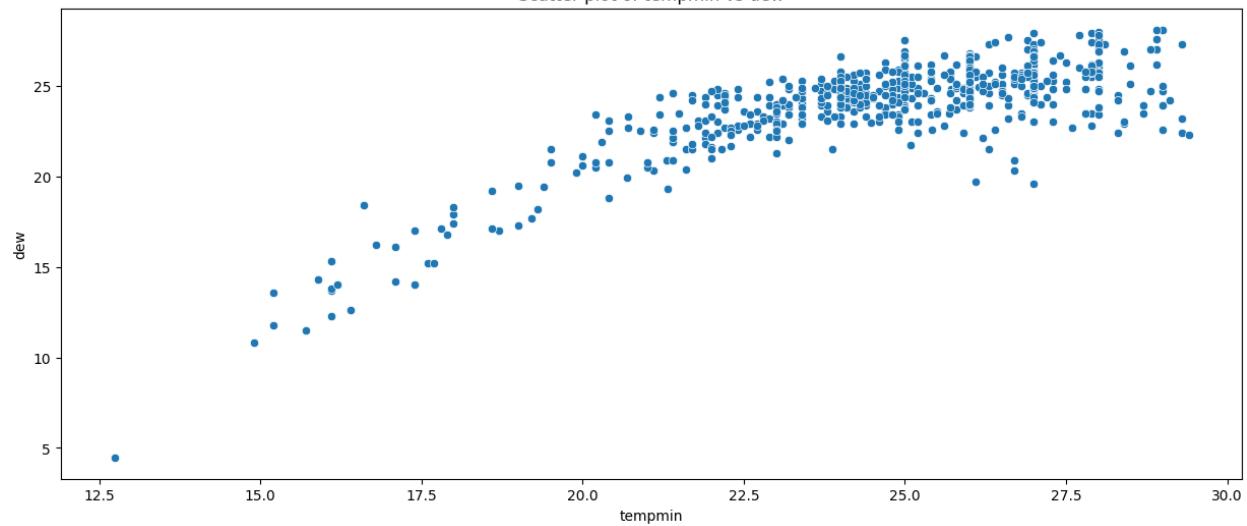
Scatter plot of tempmin vs feelslikemin



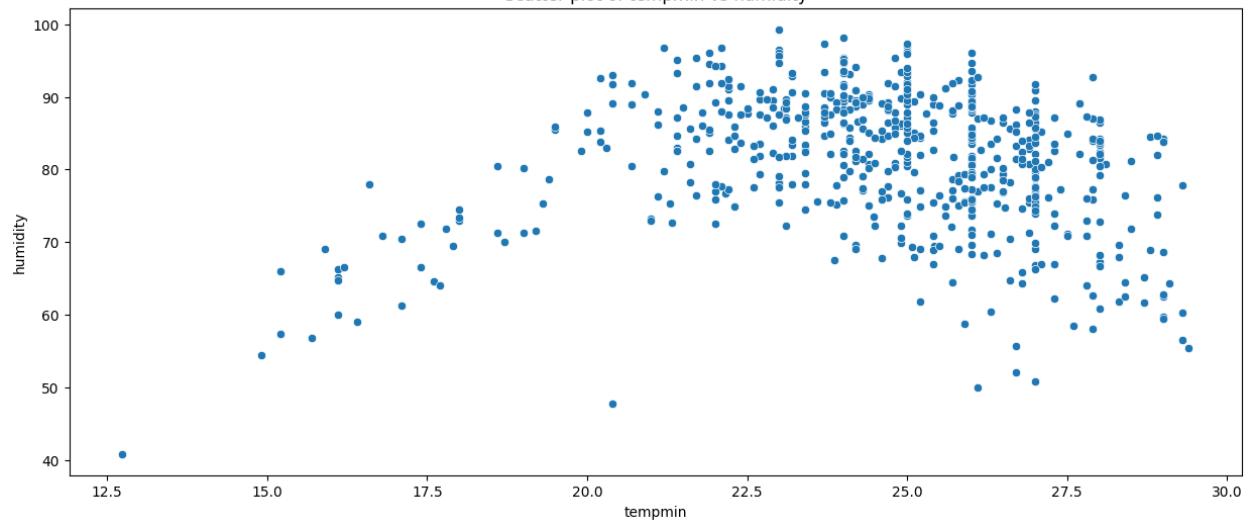
Scatter plot of tempmin vs feelslike



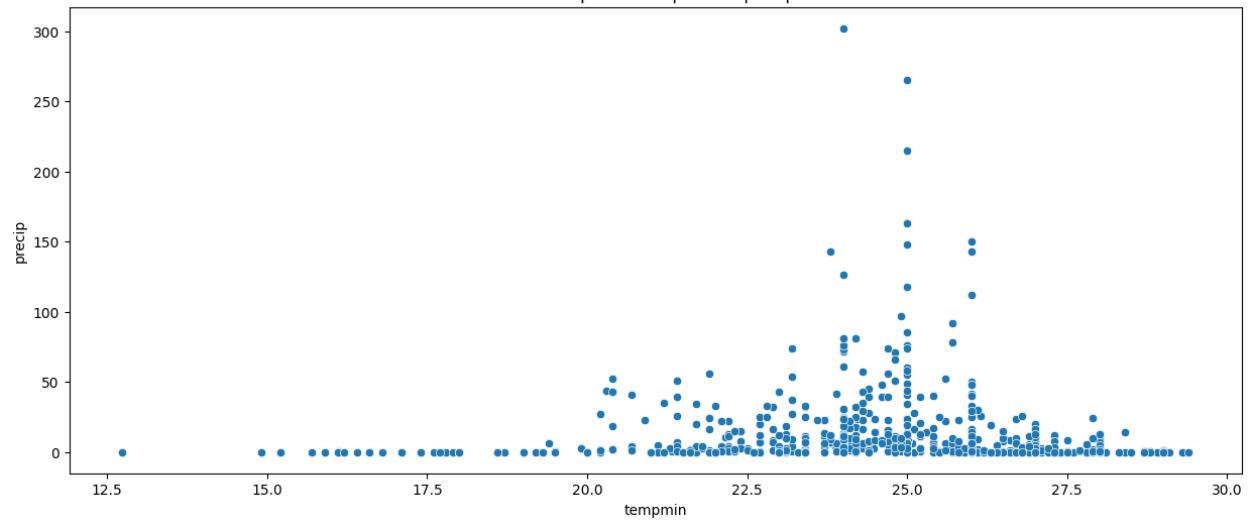
Scatter plot of tempmin vs dew



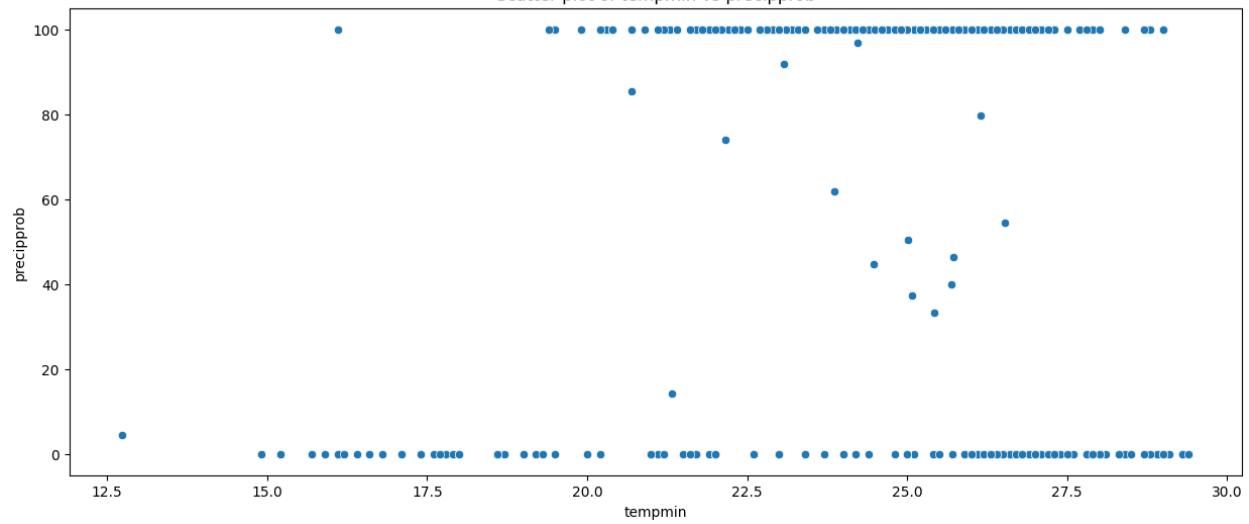
Scatter plot of tempmin vs humidity



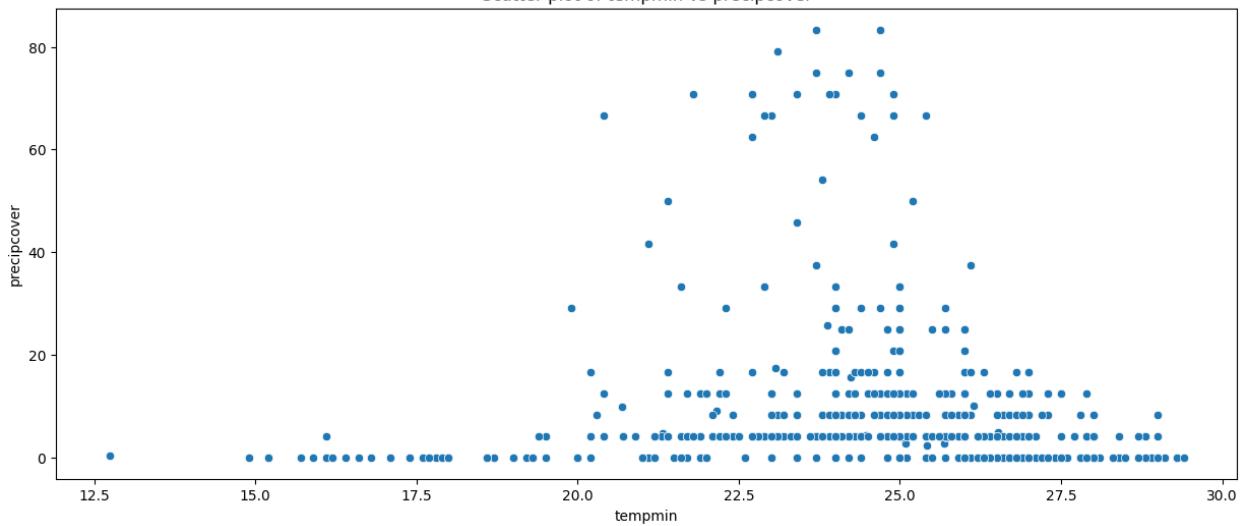
Scatter plot of tempmin vs precip



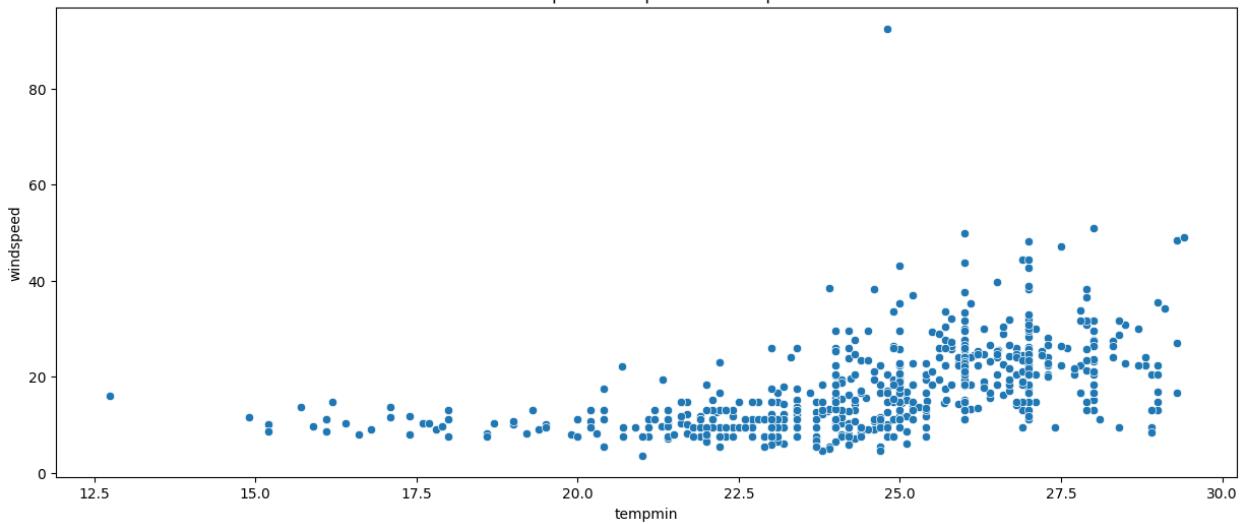
Scatter plot of tempmin vs precipprob



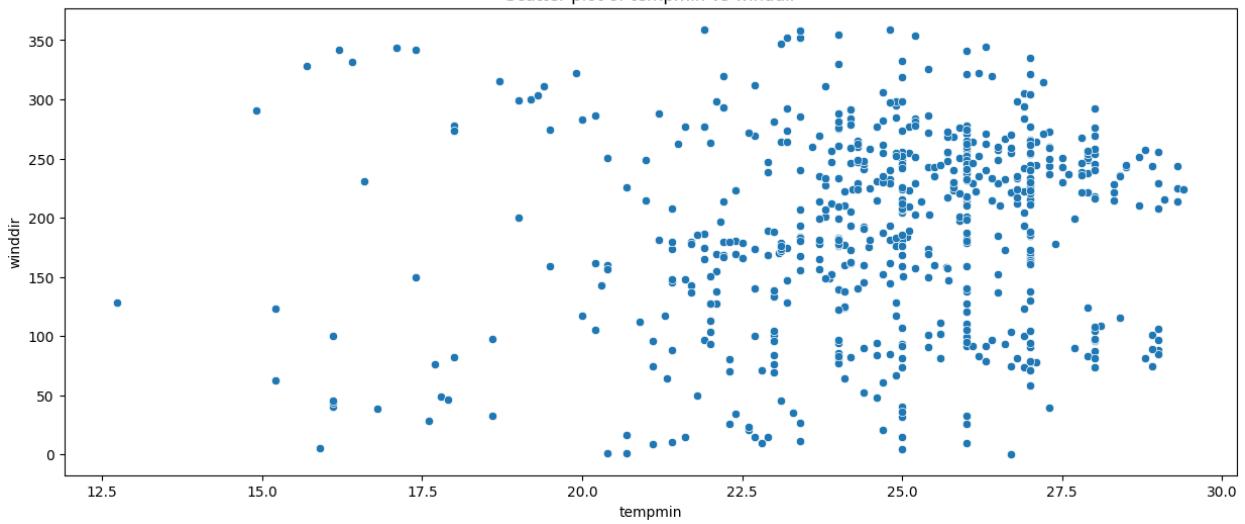
Scatter plot of tempmin vs precipcover

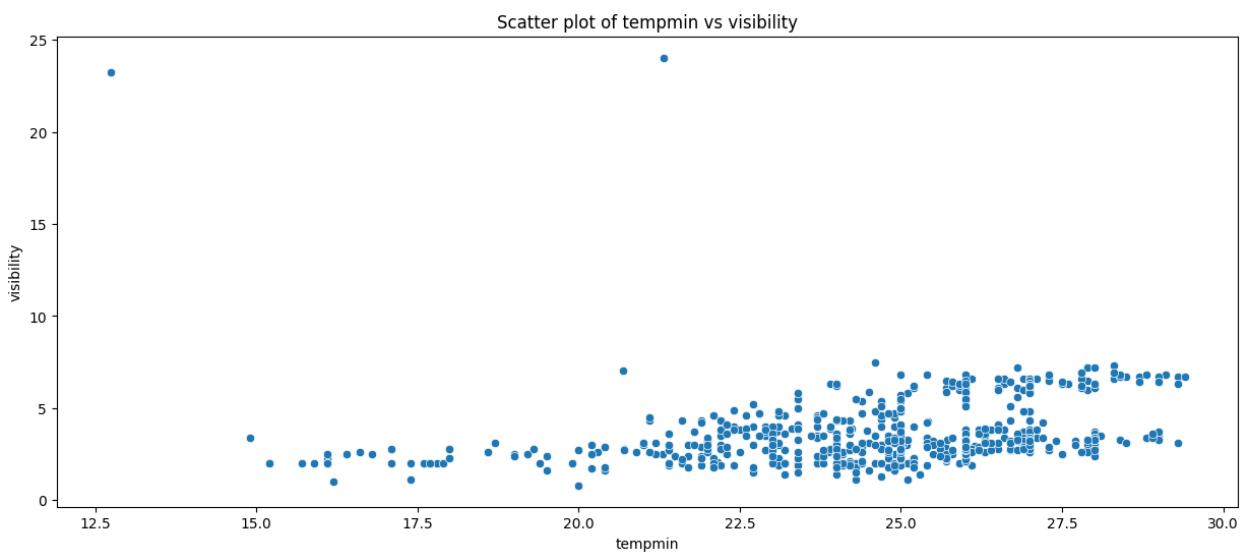
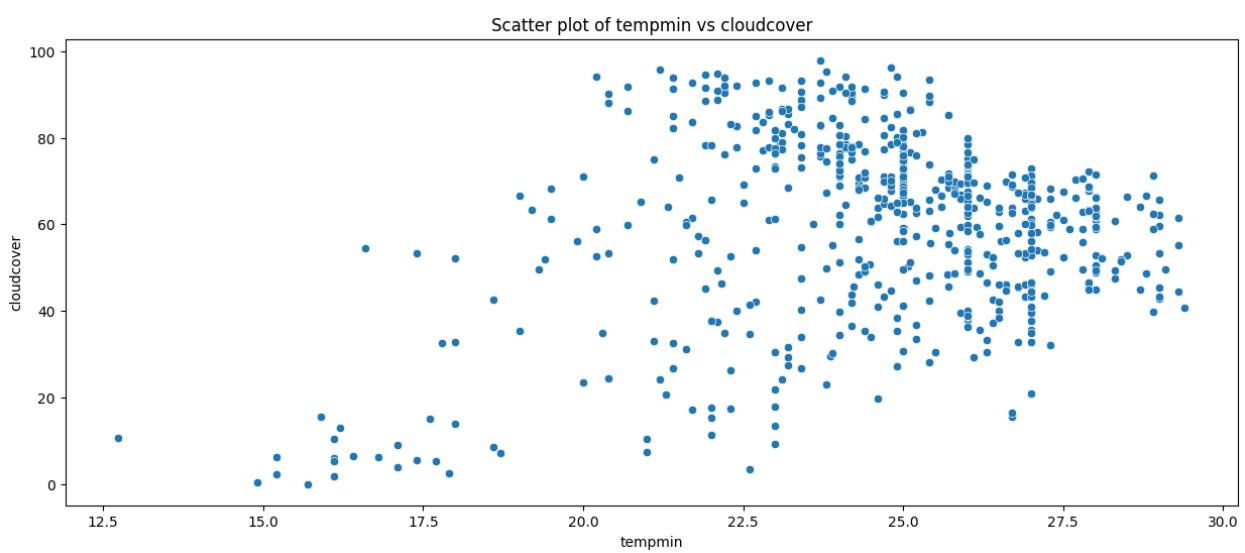
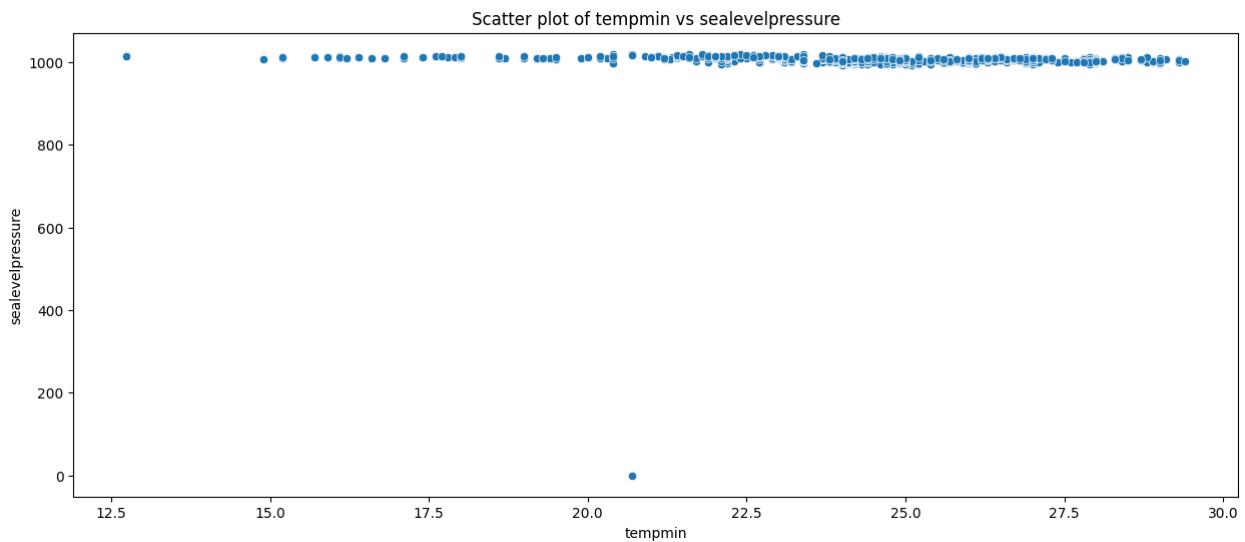


Scatter plot of tempmin vs windspeed

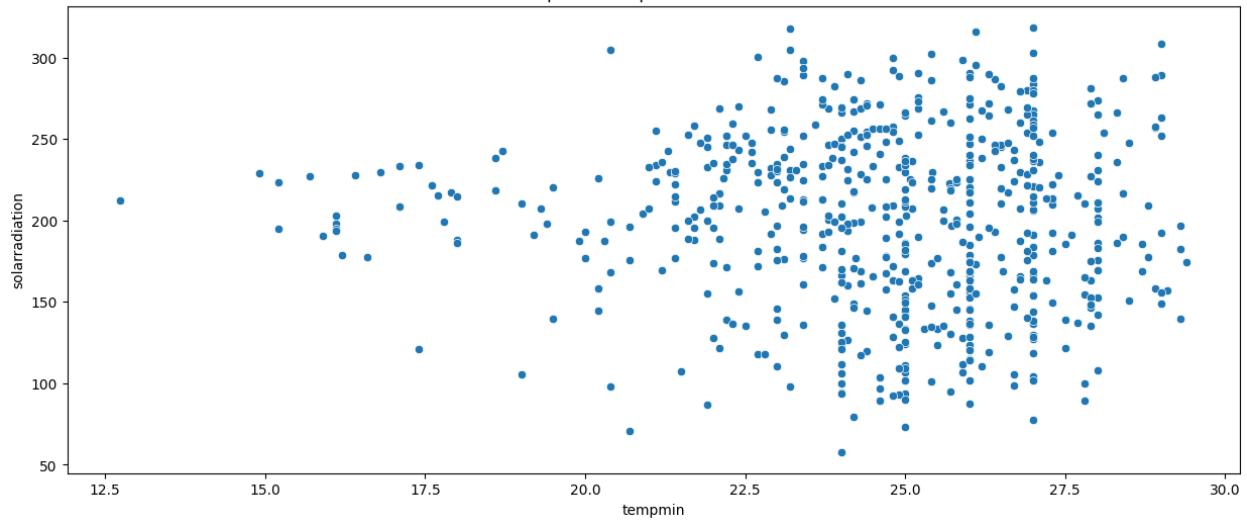


Scatter plot of tempmin vs winddir

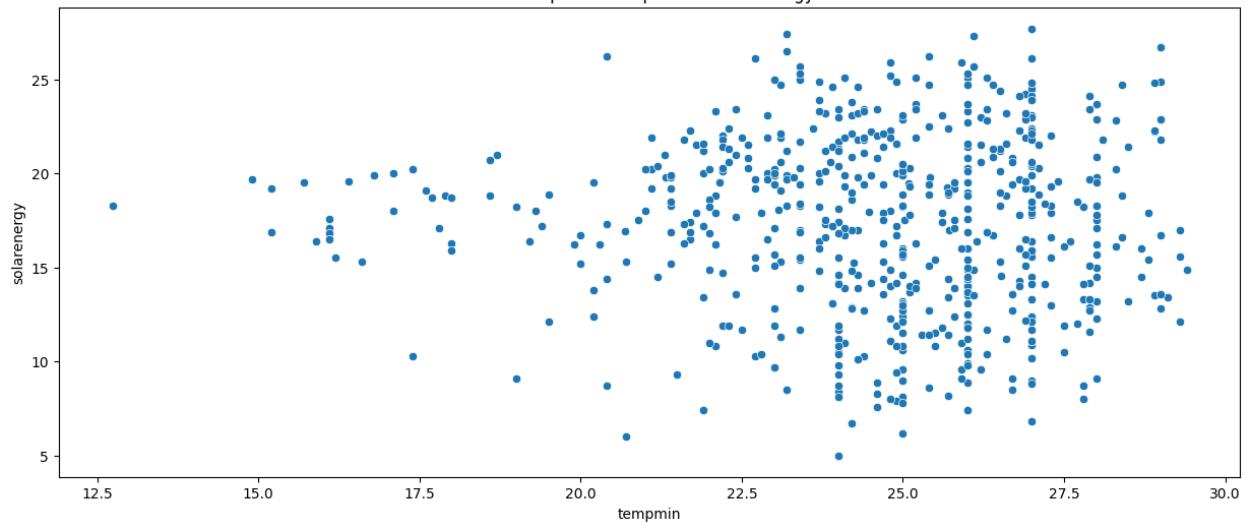




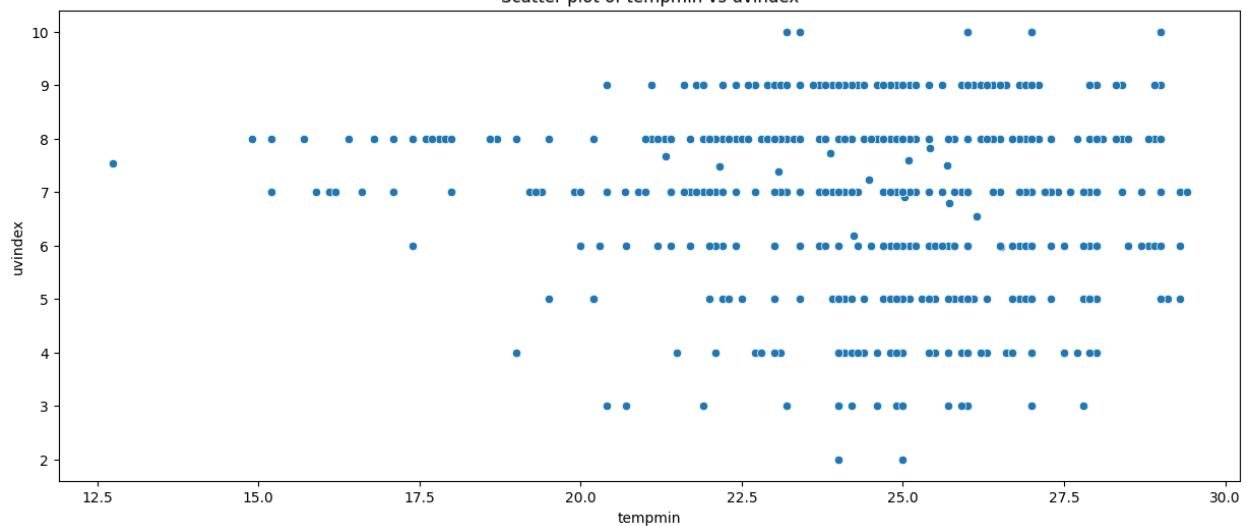
Scatter plot of tempmin vs solarradiation

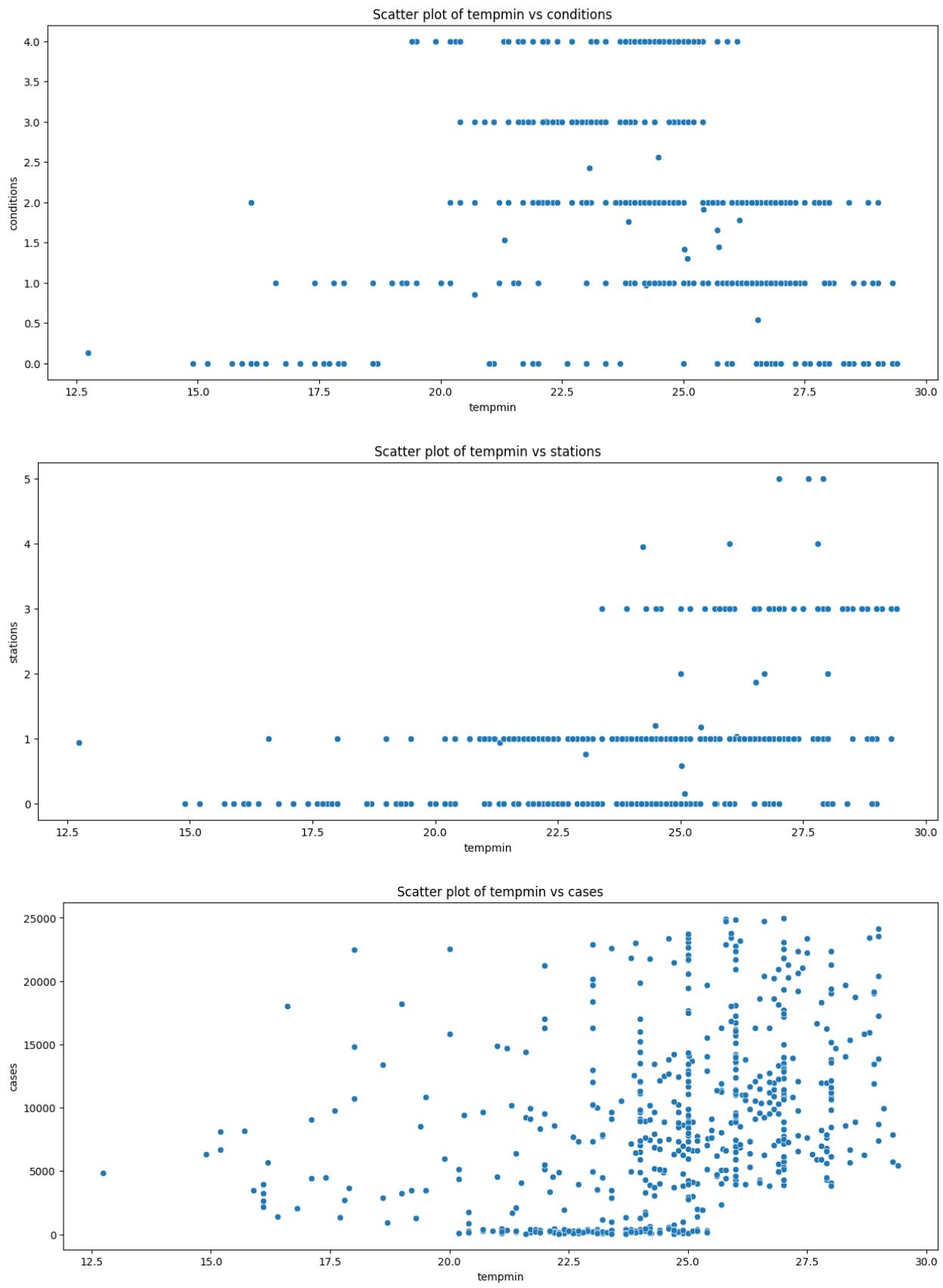


Scatter plot of tempmin vs solarenergy

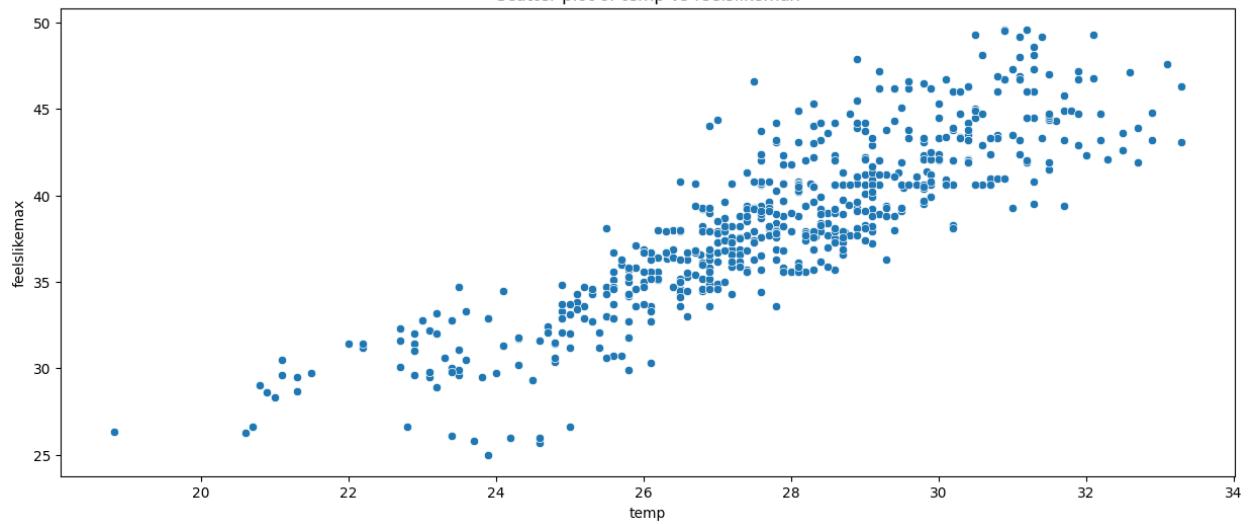


Scatter plot of tempmin vs uvindex

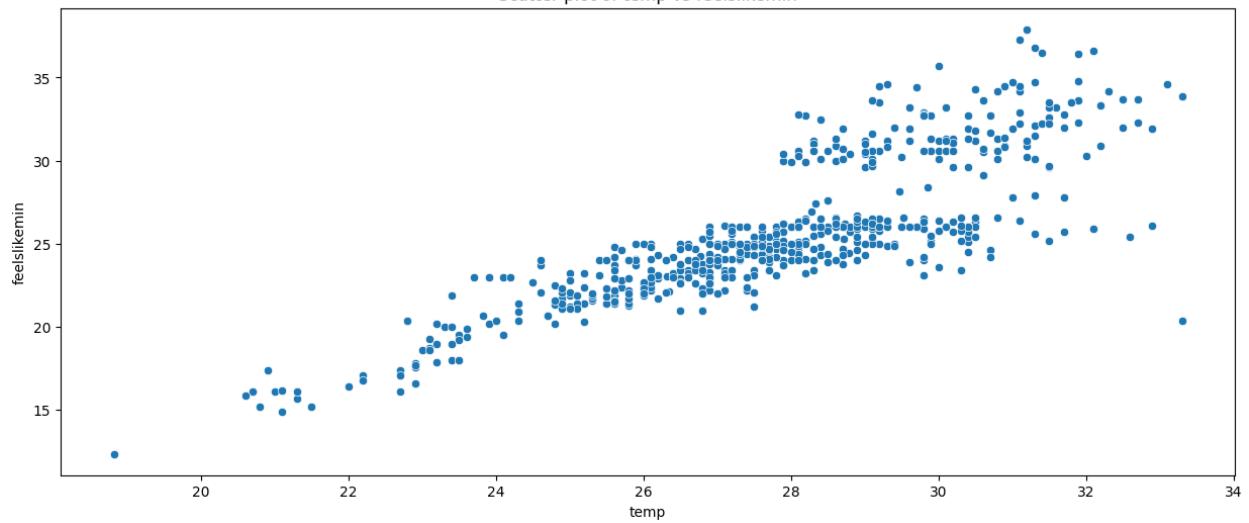




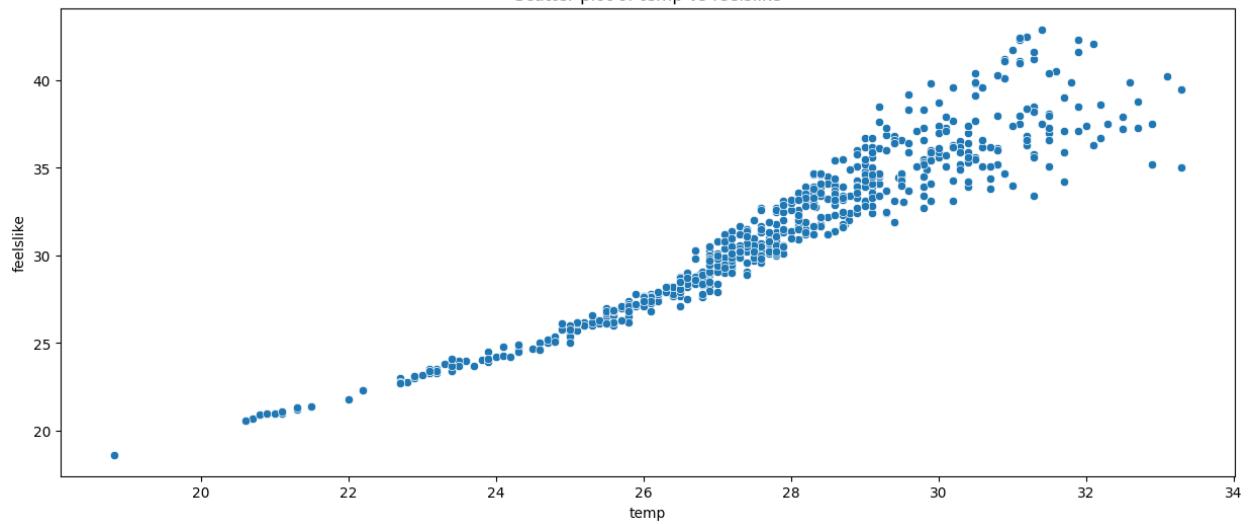
Scatter plot of temp vs feelslikemax



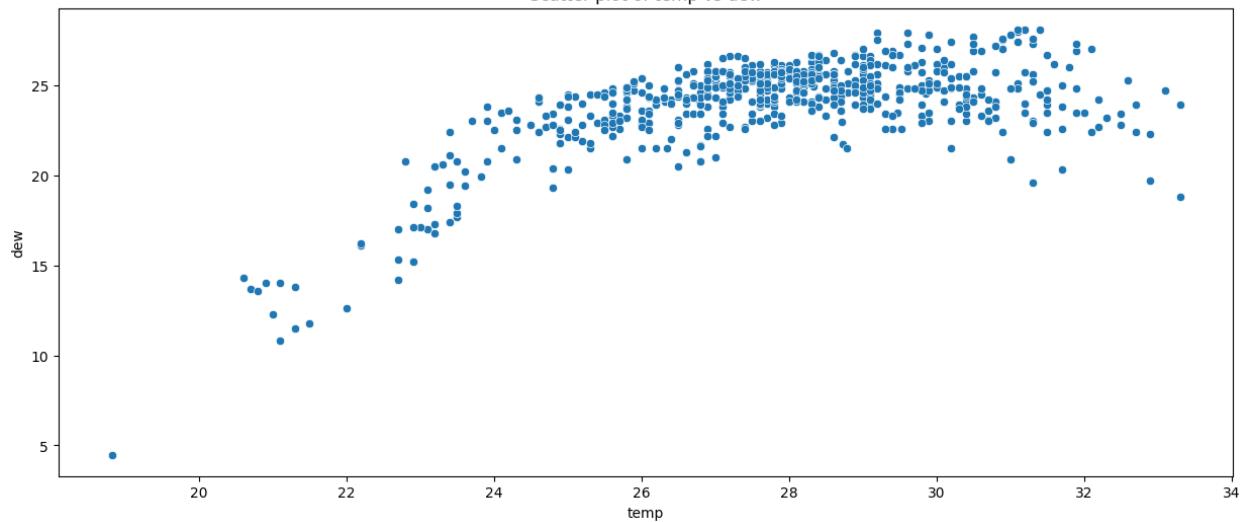
Scatter plot of temp vs feelslikemin



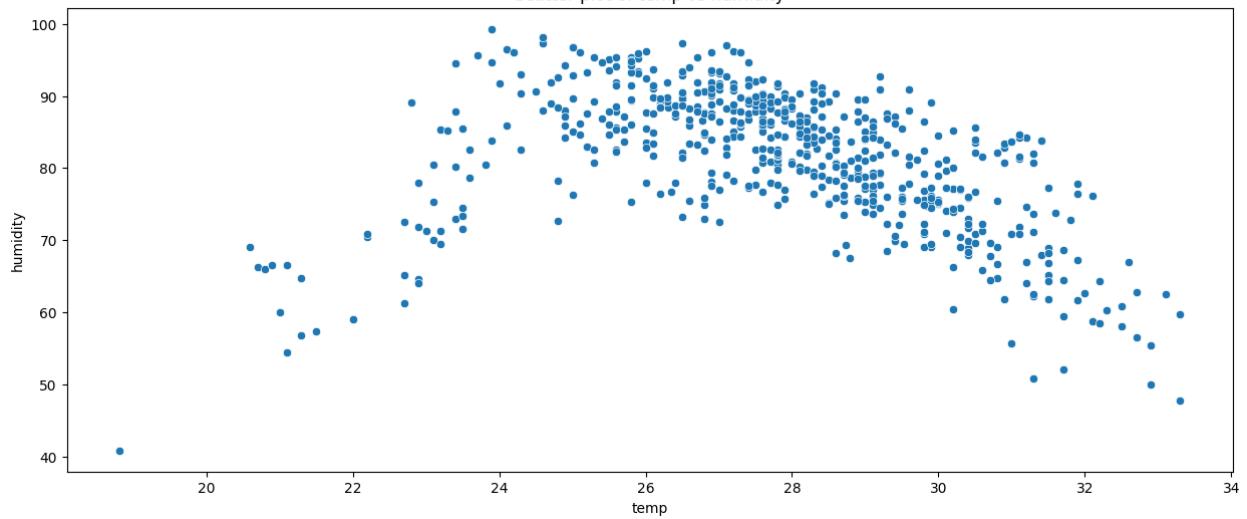
Scatter plot of temp vs feelslike



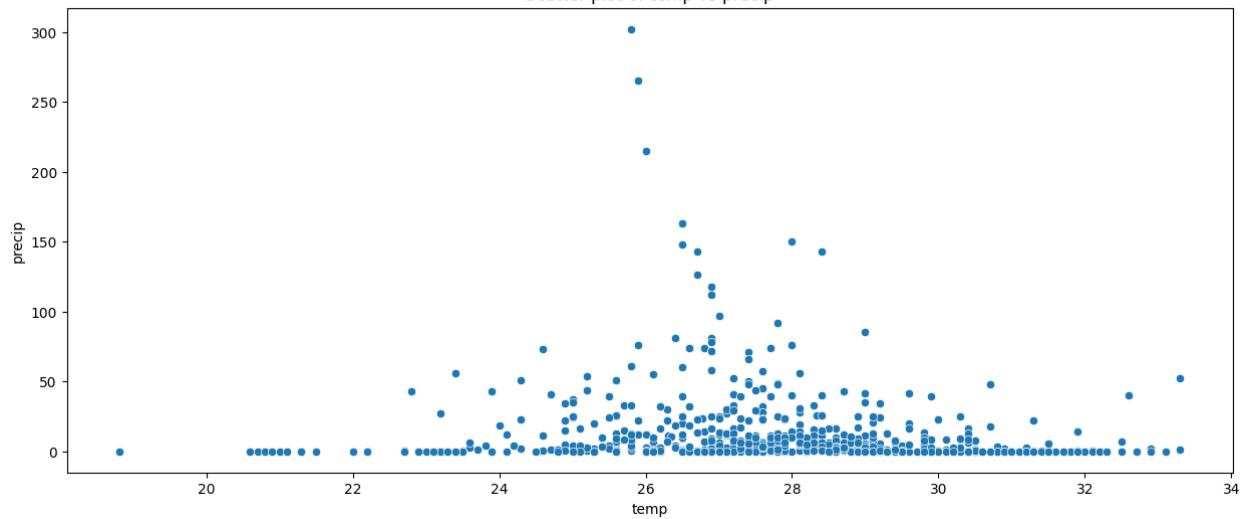
Scatter plot of temp vs dew

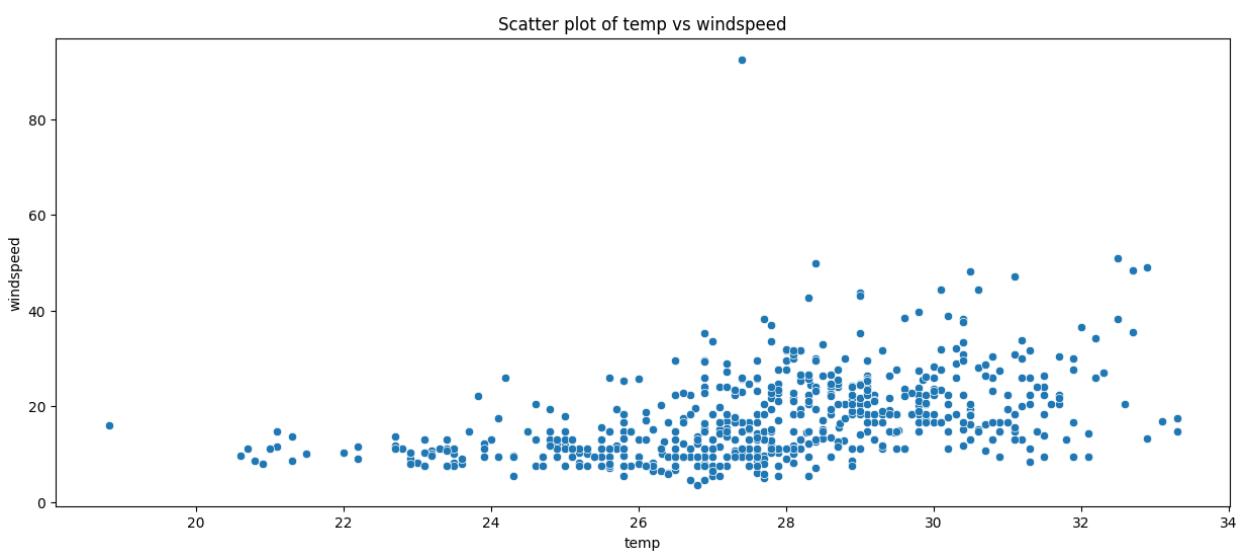
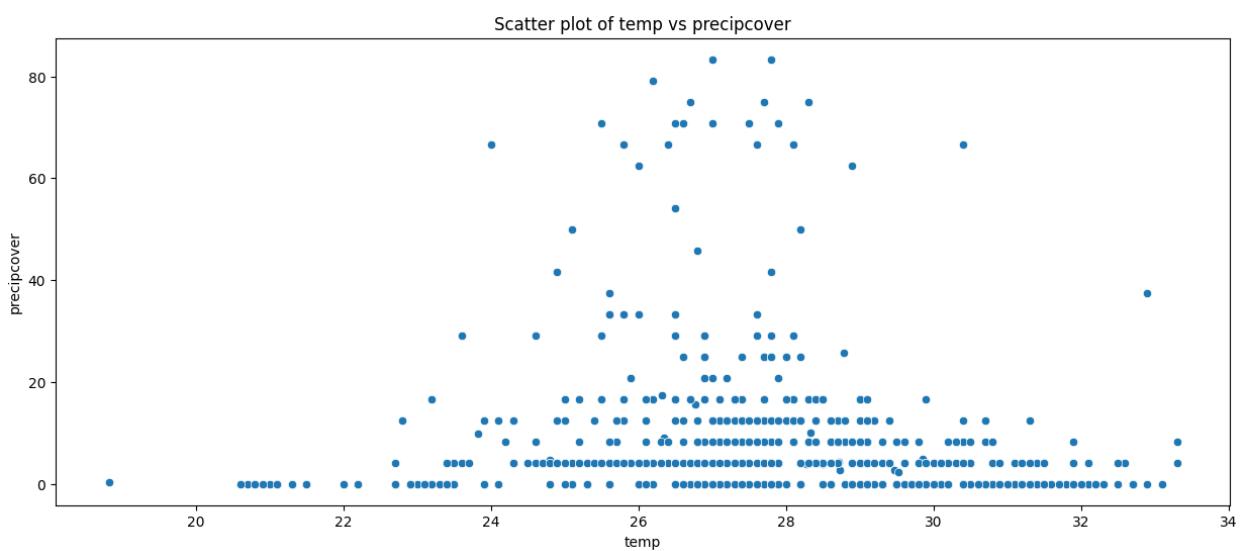
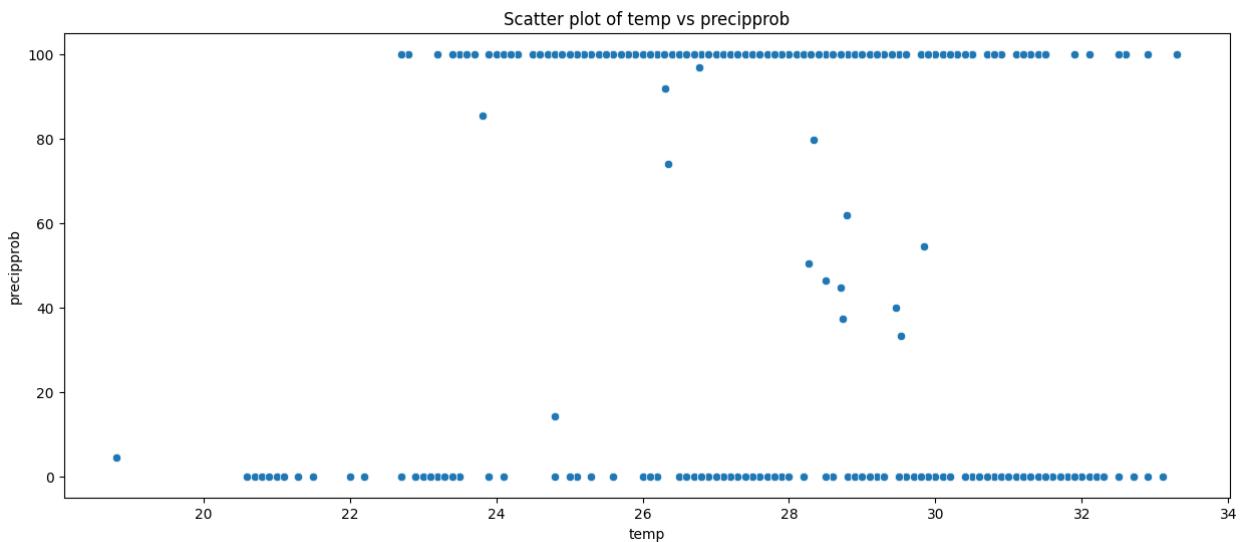


Scatter plot of temp vs humidity

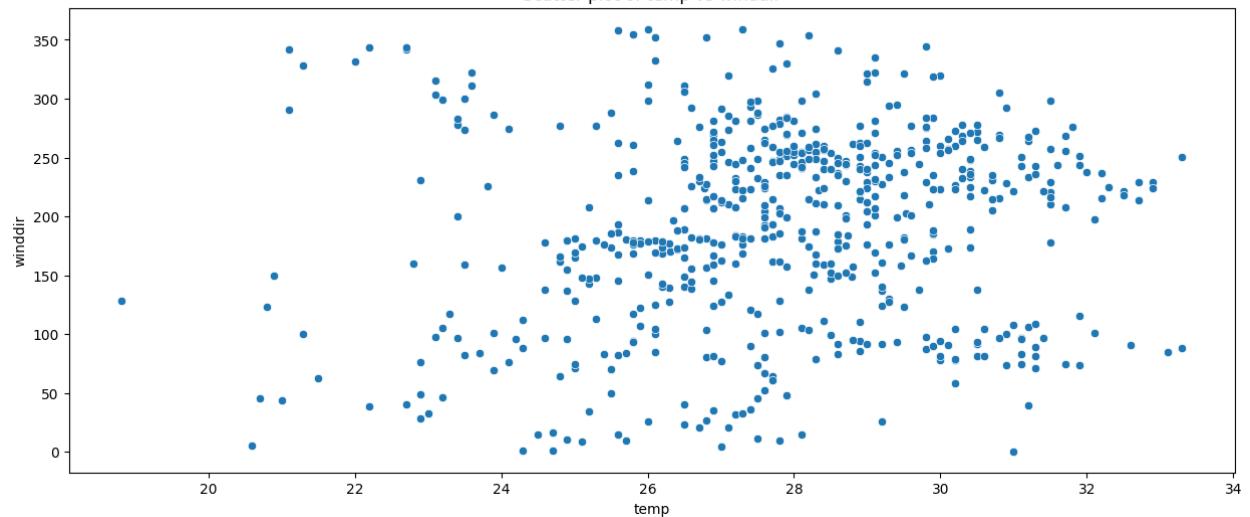


Scatter plot of temp vs precip

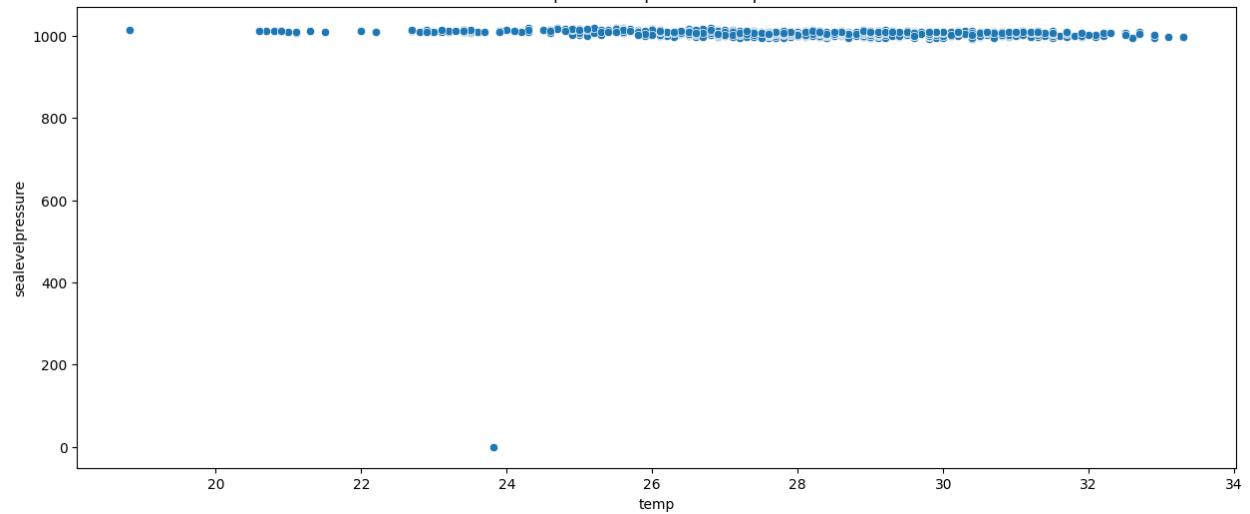




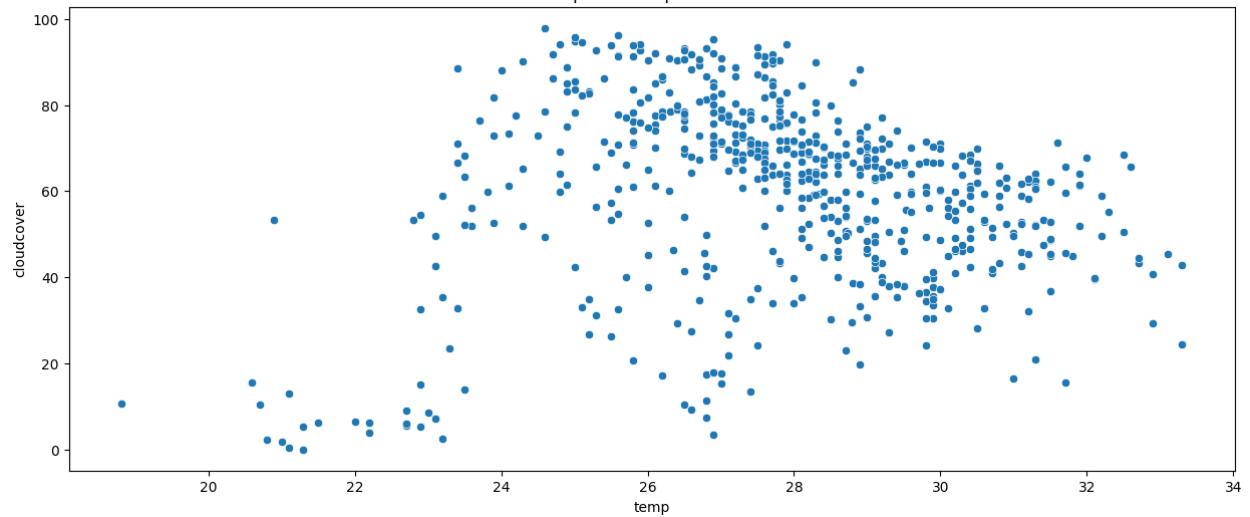
Scatter plot of temp vs winddir

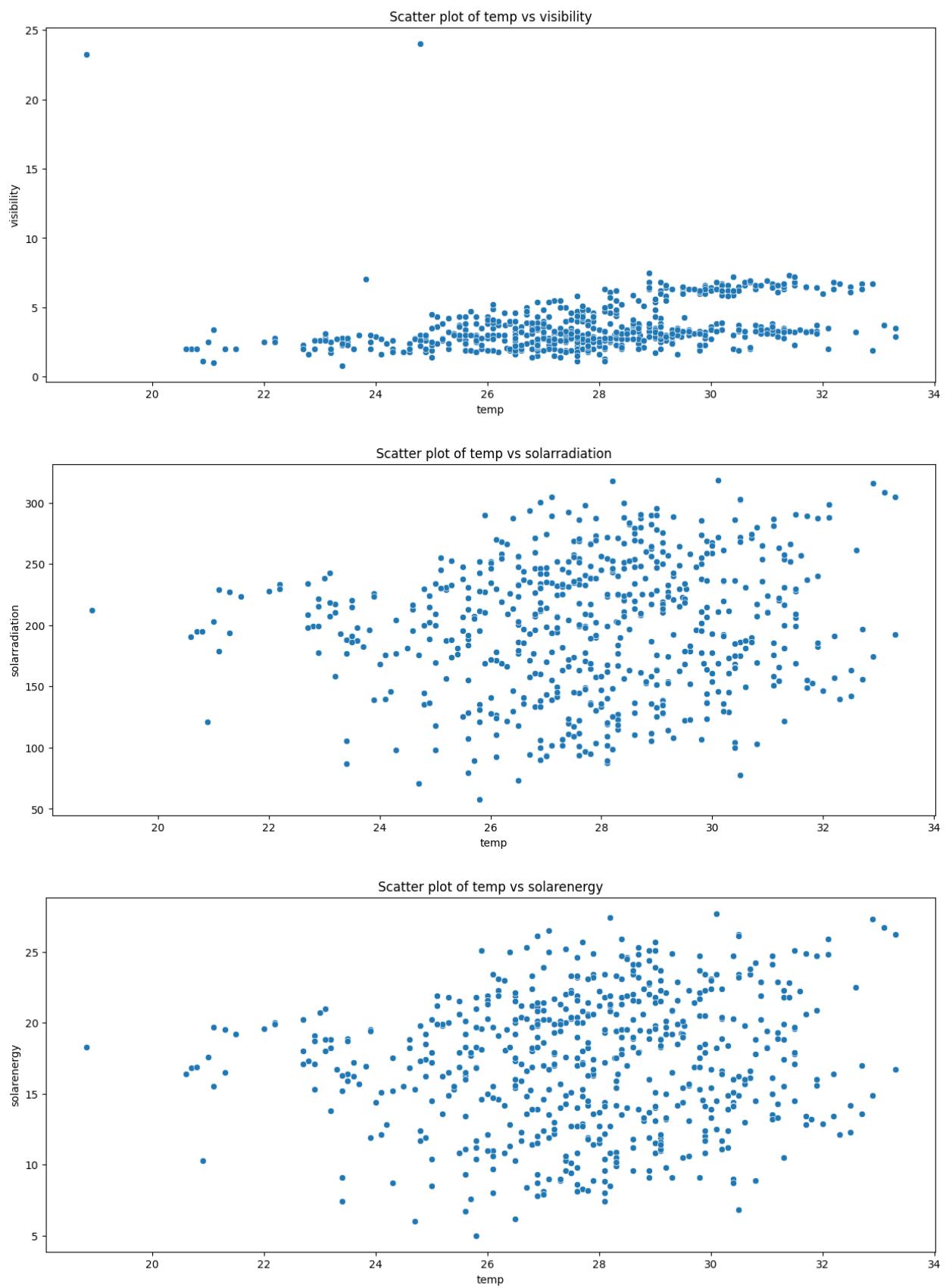


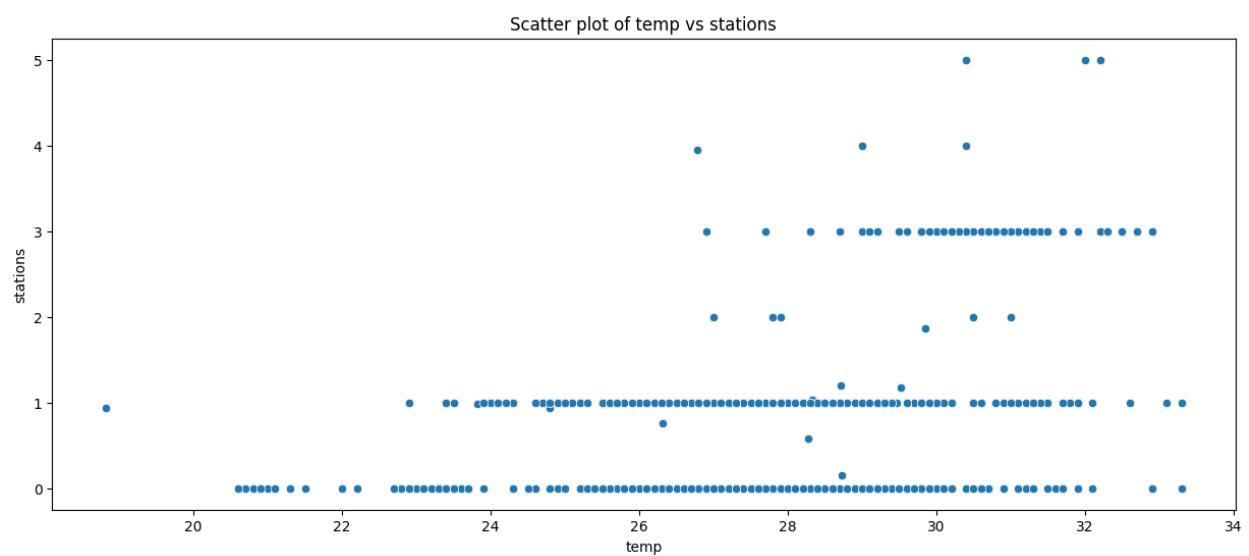
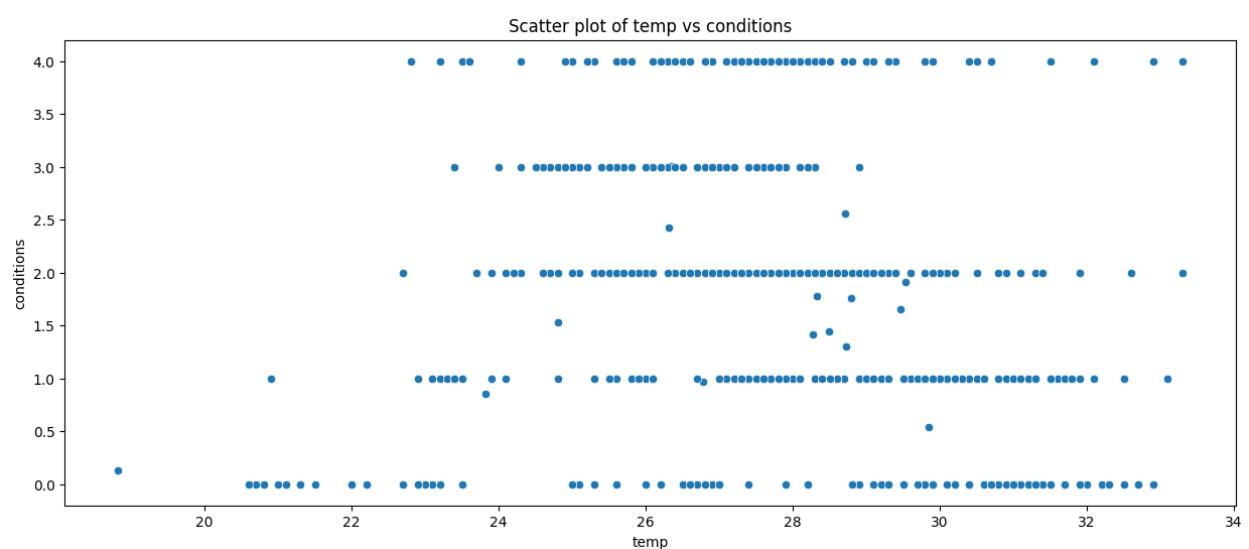
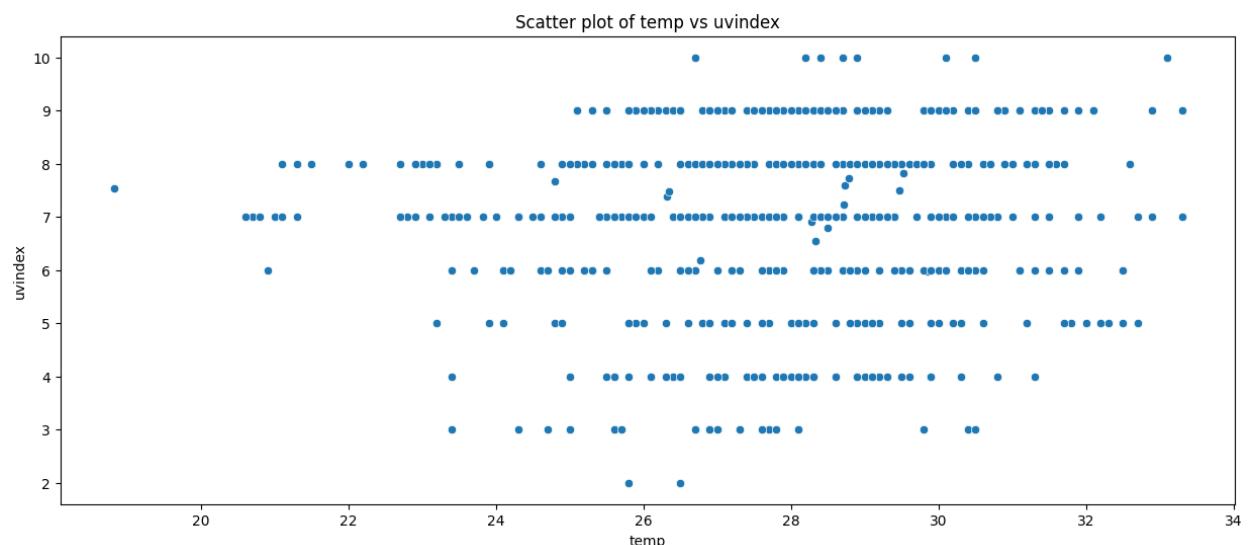
Scatter plot of temp vs sealevelpressure



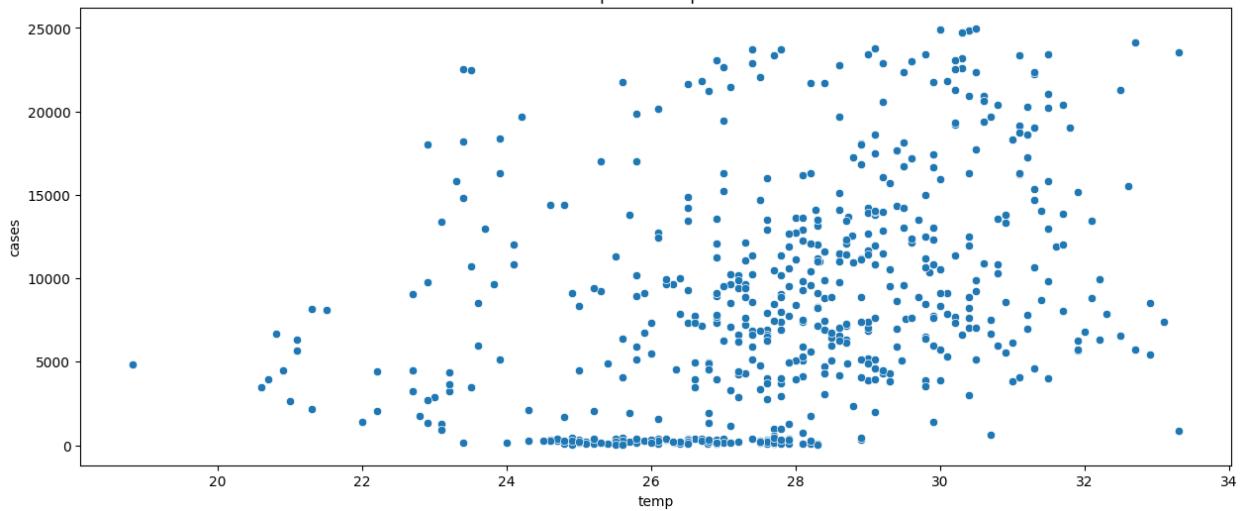
Scatter plot of temp vs cloudcover



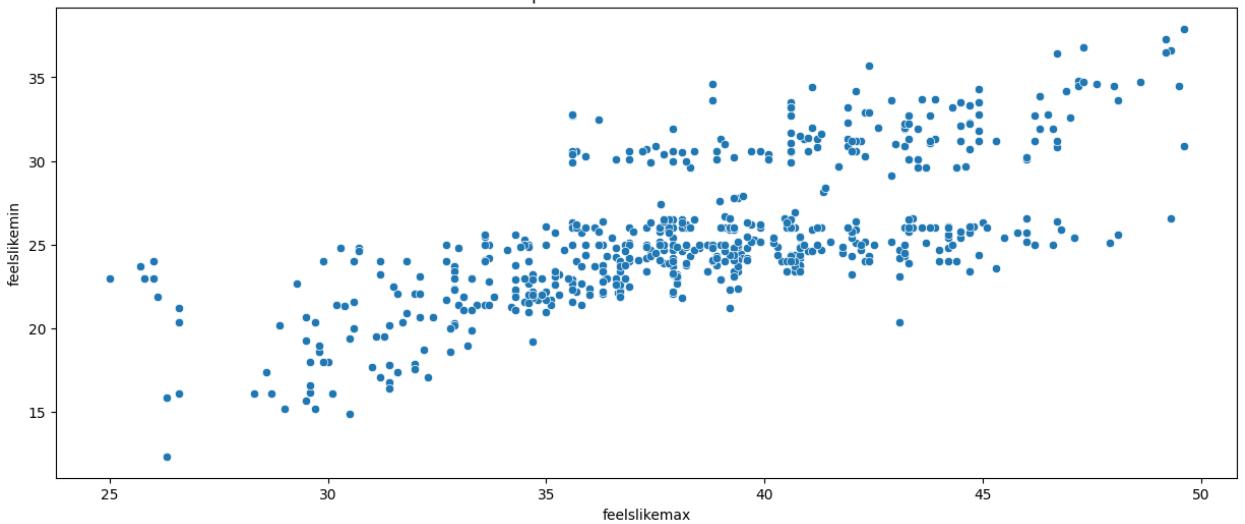




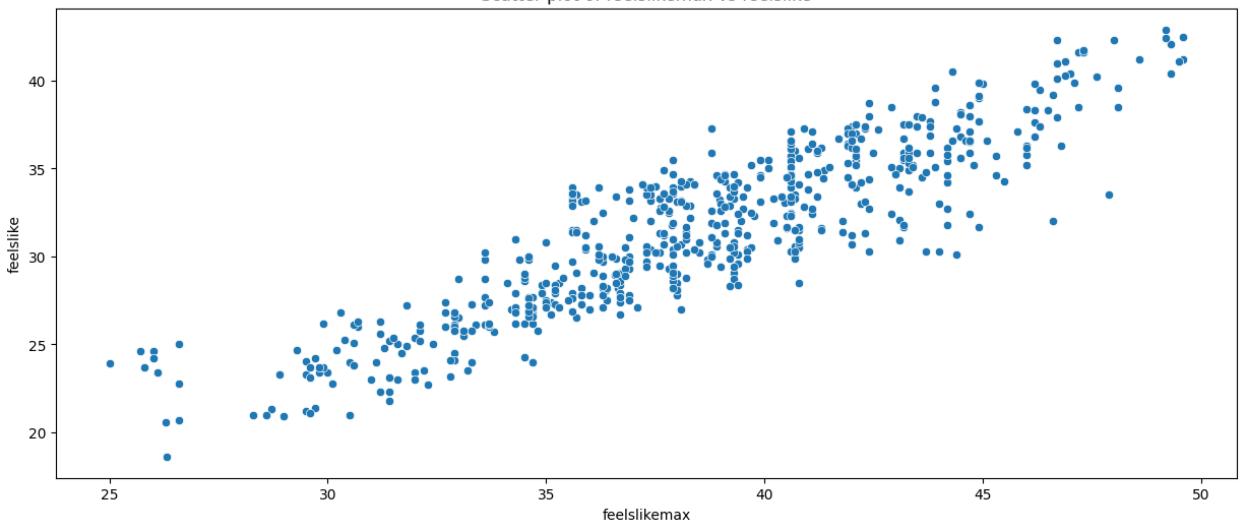
Scatter plot of temp vs cases



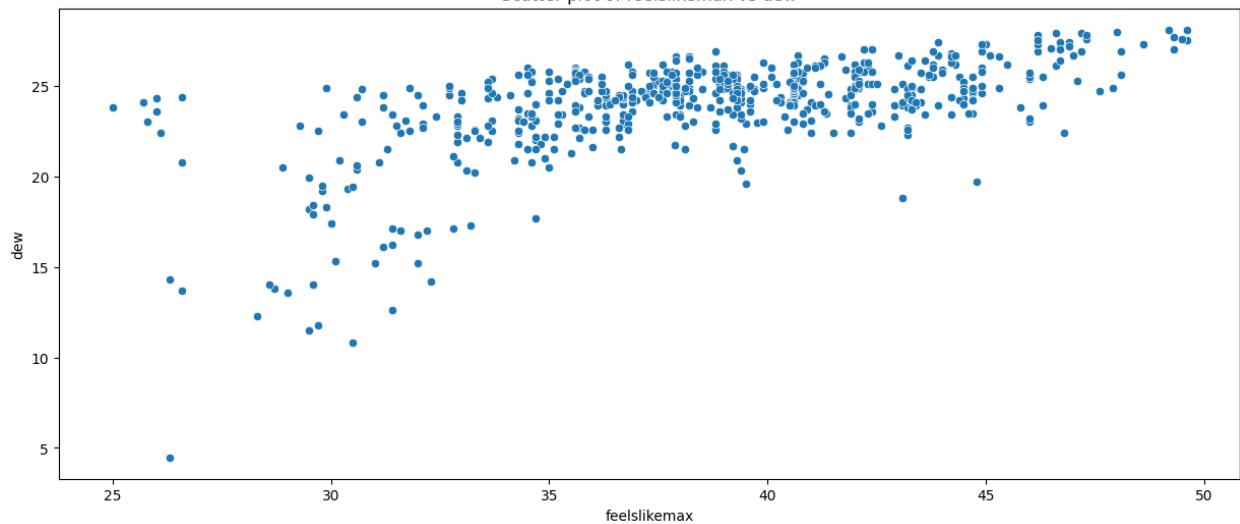
Scatter plot of feelslikemax vs feelslikemin



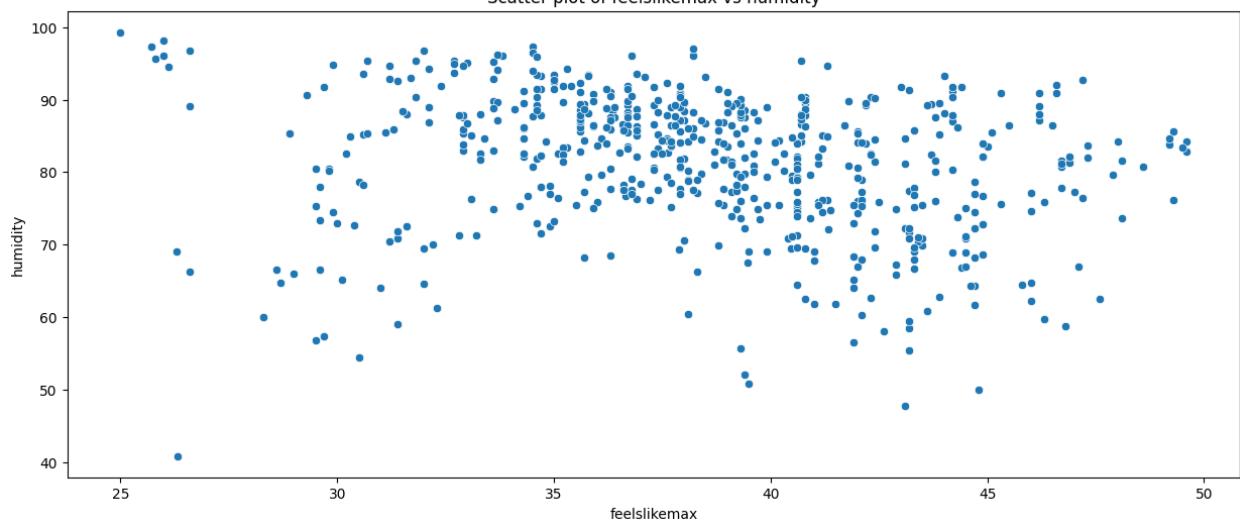
Scatter plot of feelslikemax vs feelslike



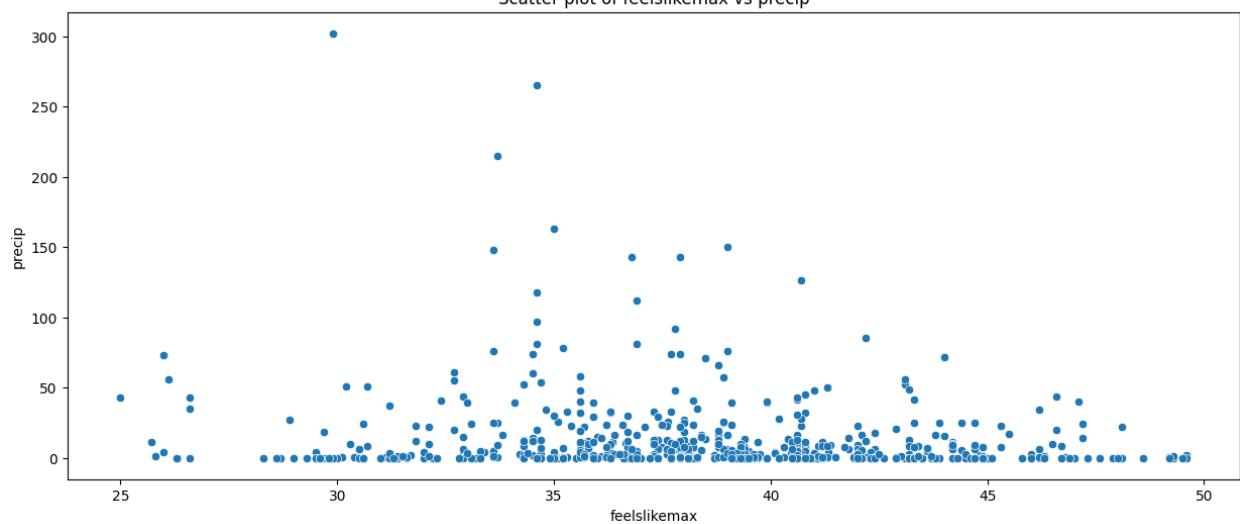
Scatter plot of feelslikemax vs dew



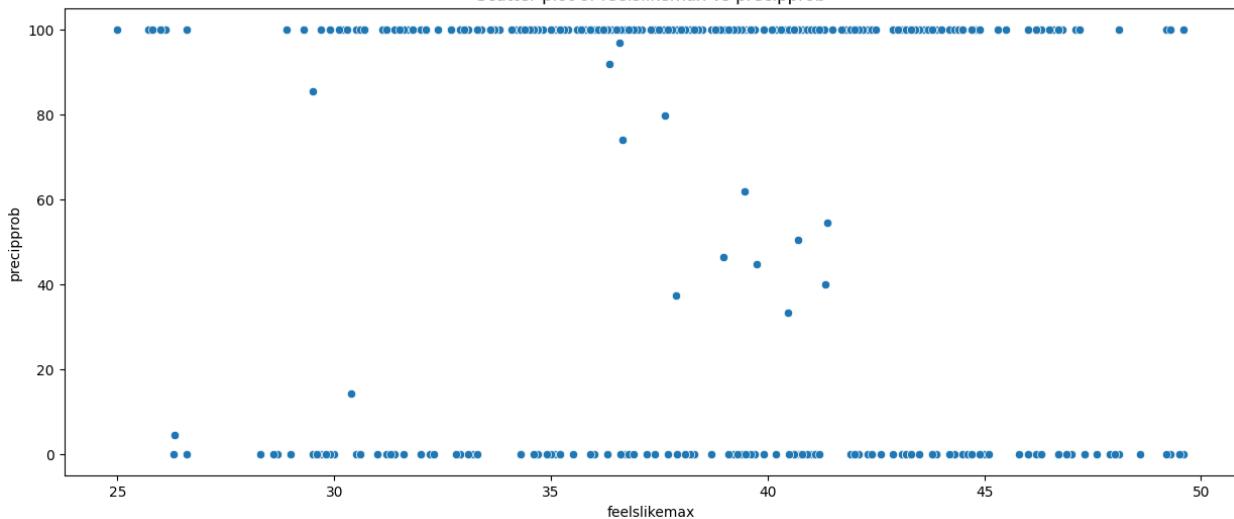
Scatter plot of feelslikemax vs humidity



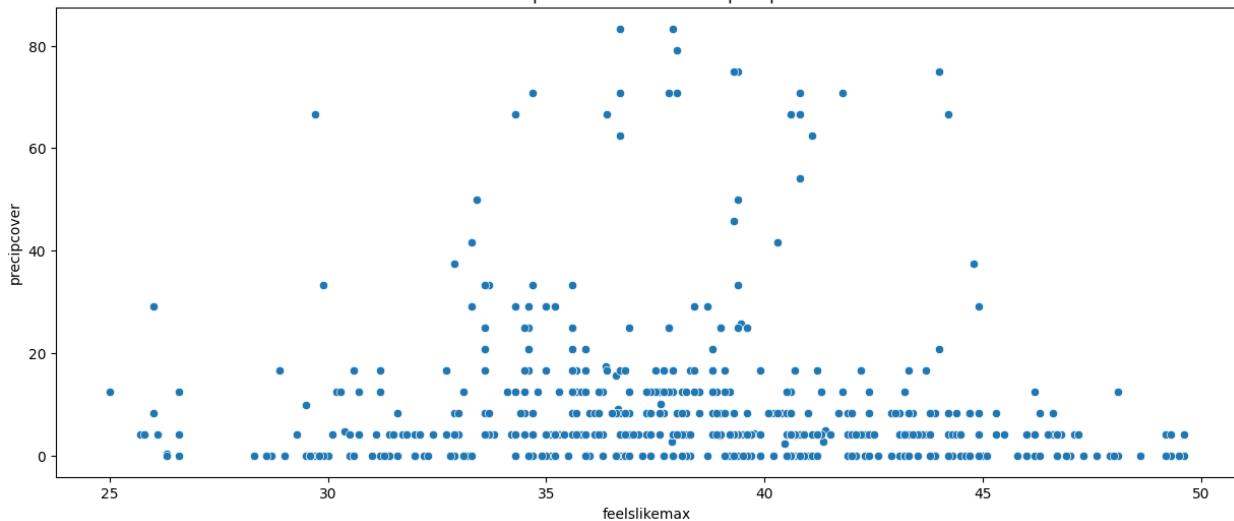
Scatter plot of feelslikemax vs precip



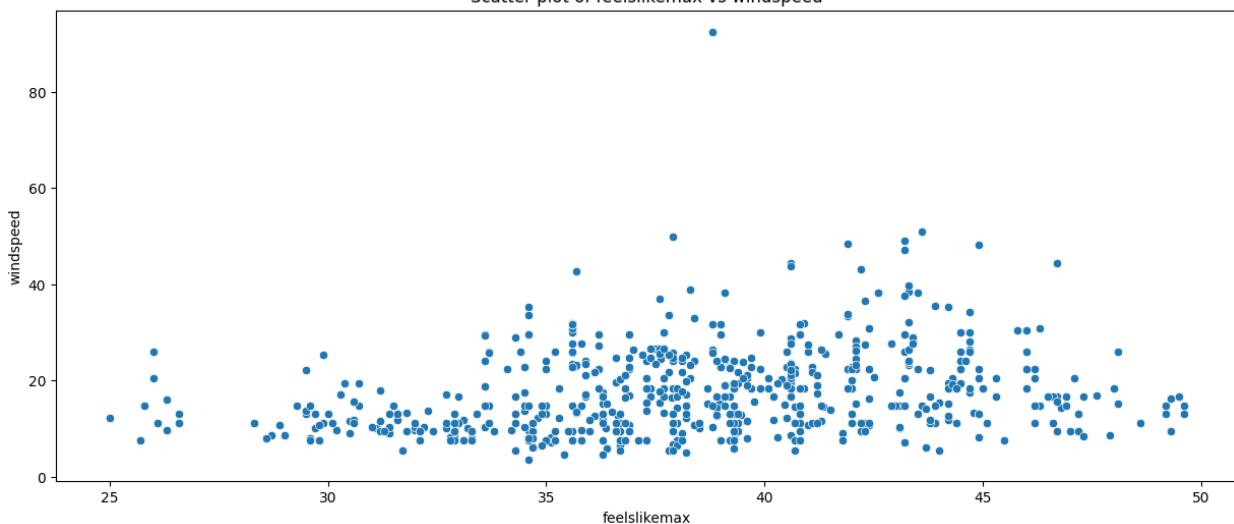
Scatter plot of feelslikemax vs precipprob



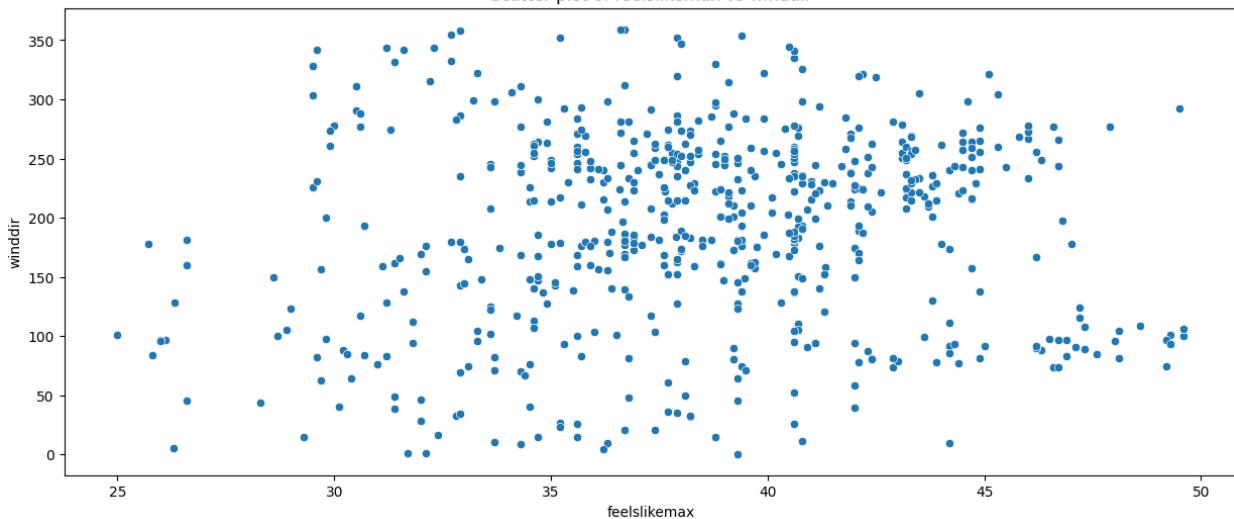
Scatter plot of feelslikemax vs precipcover



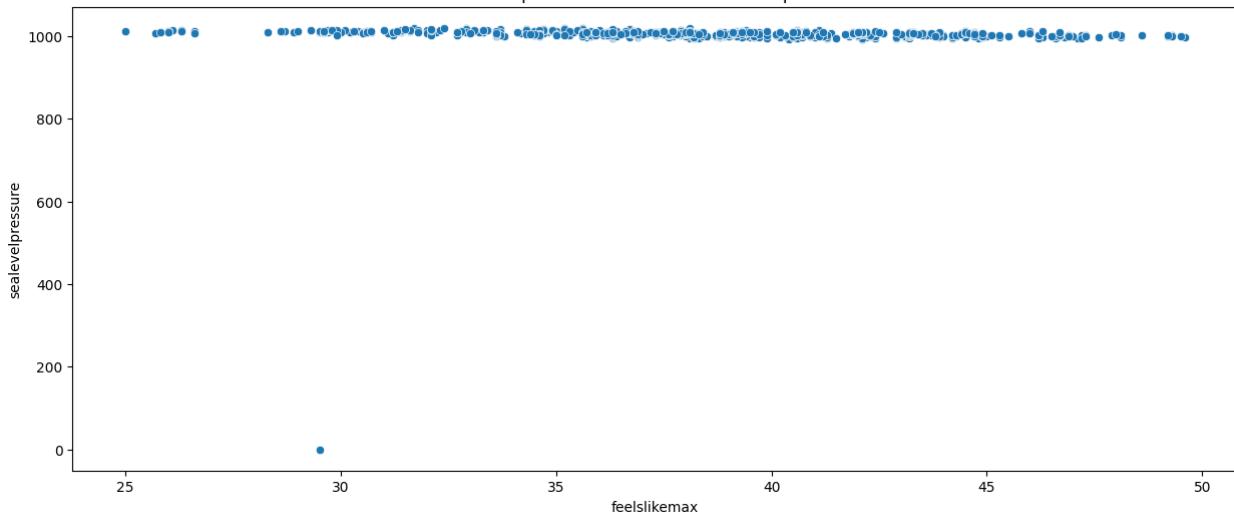
Scatter plot of feelslikemax vs windspeed



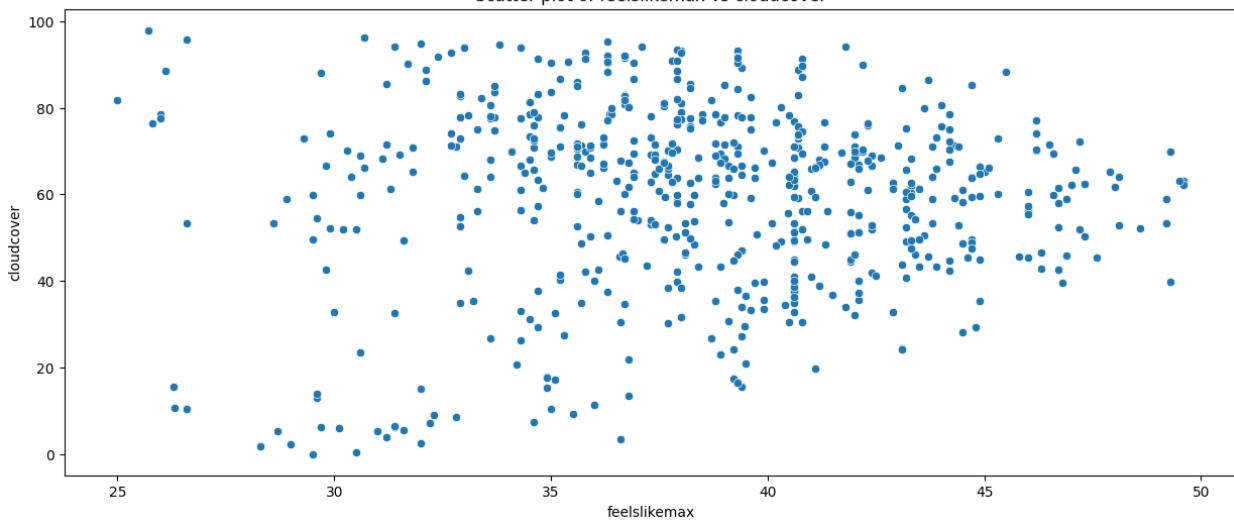
Scatter plot of feelslikemax vs winddir



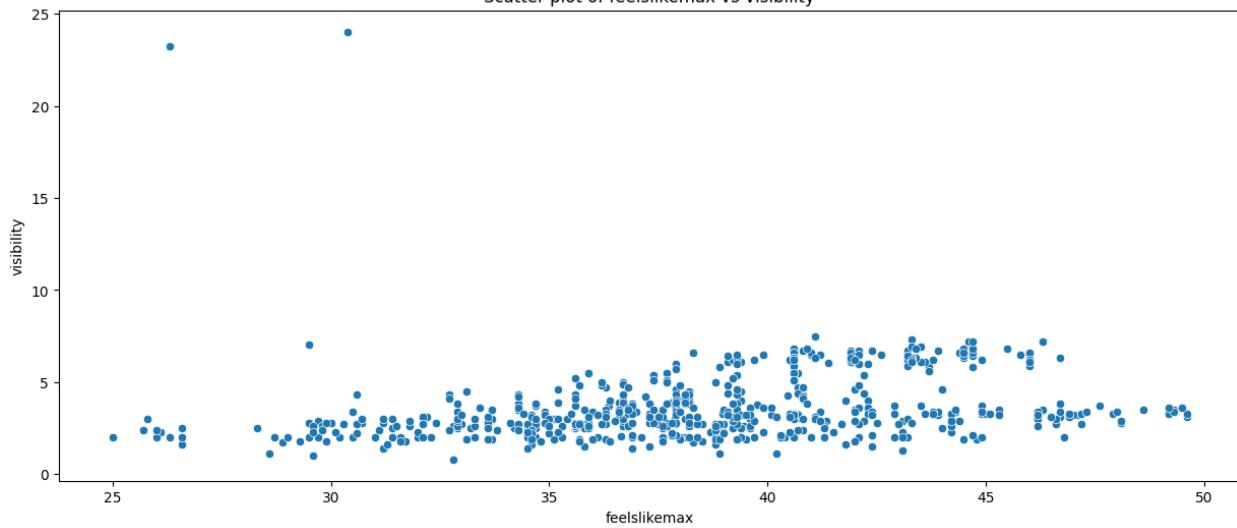
Scatter plot of feelslikemax vs sealevelpressure



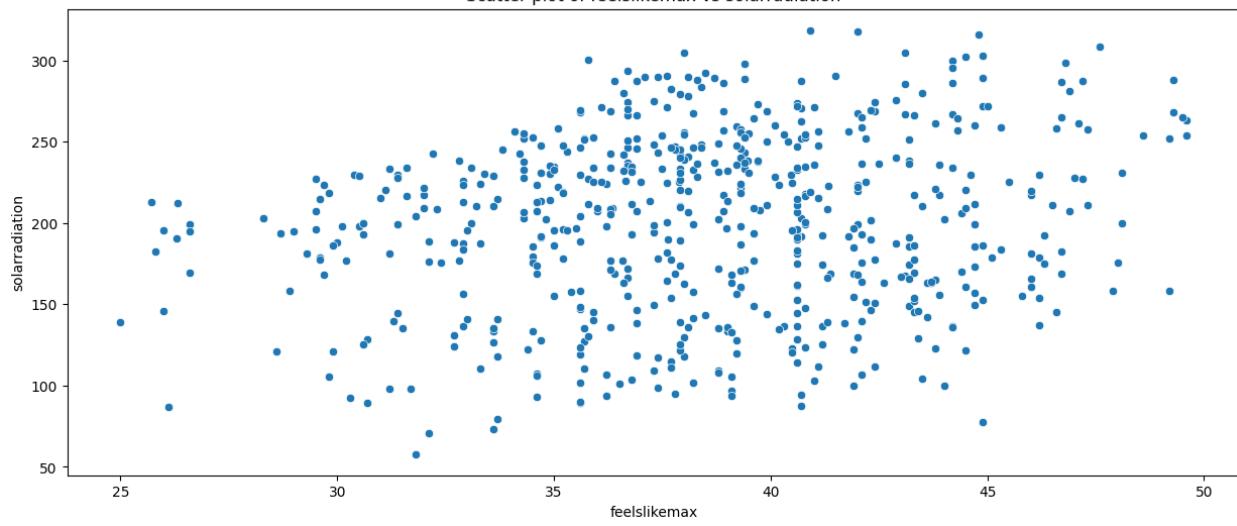
Scatter plot of feelslikemax vs cloudcover



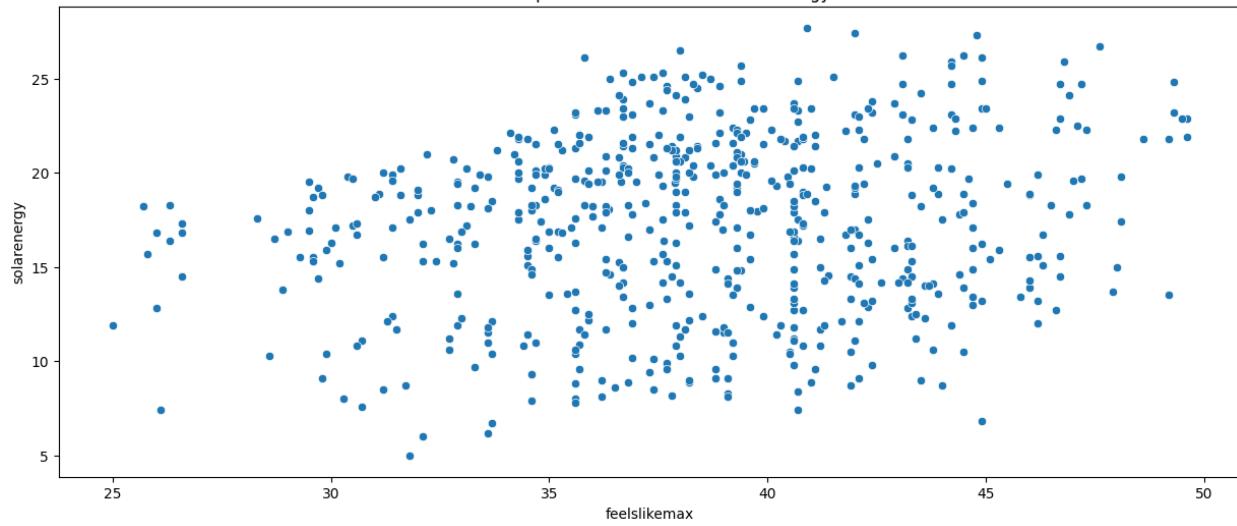
Scatter plot of feelslikemax vs visibility

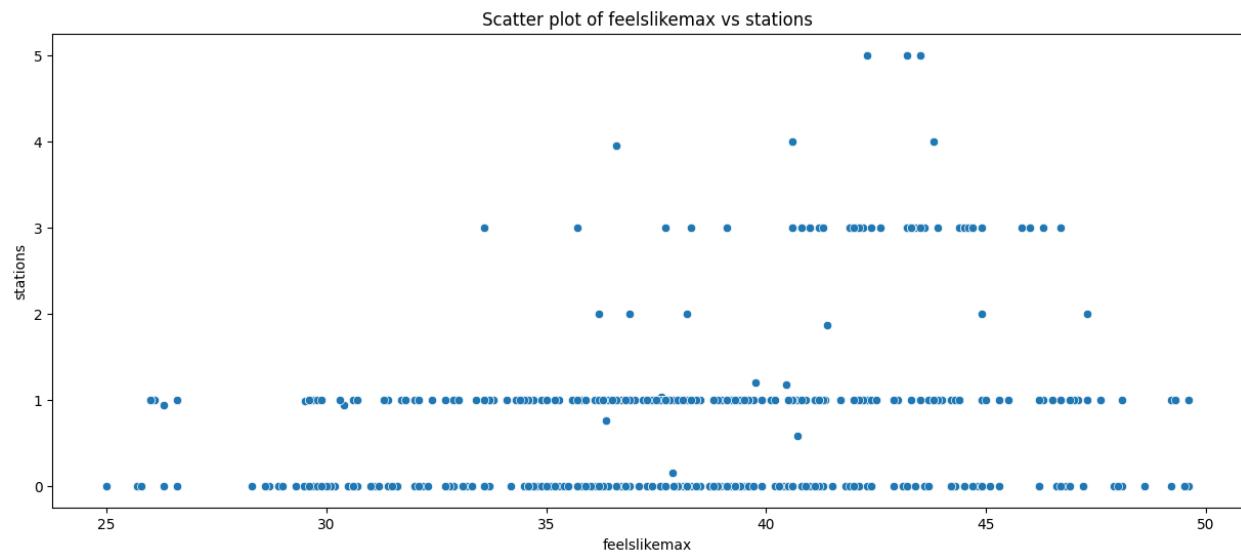
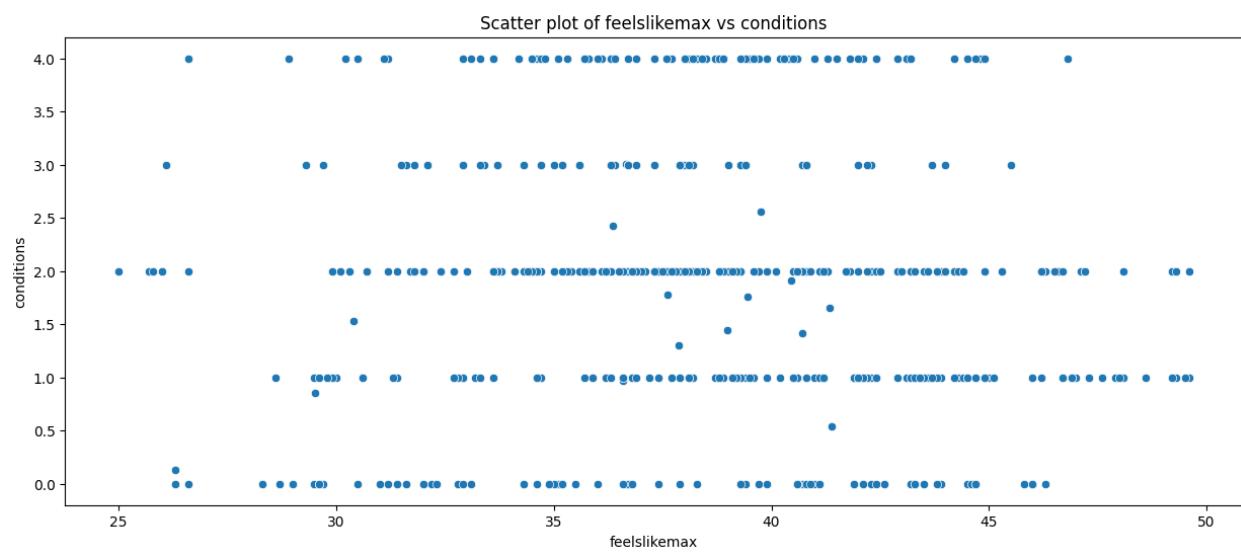
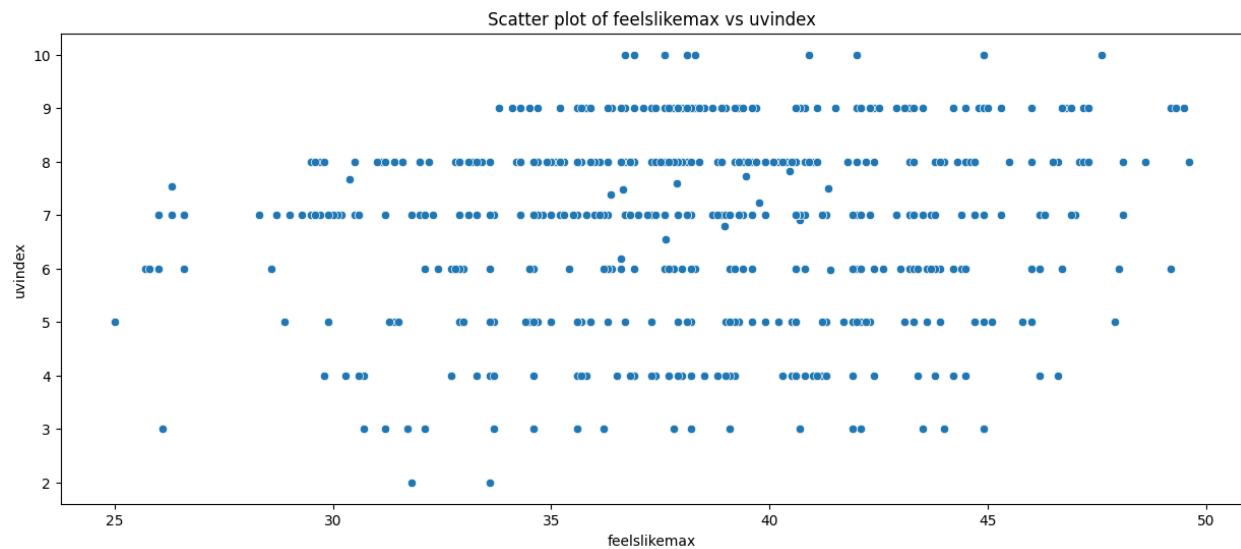


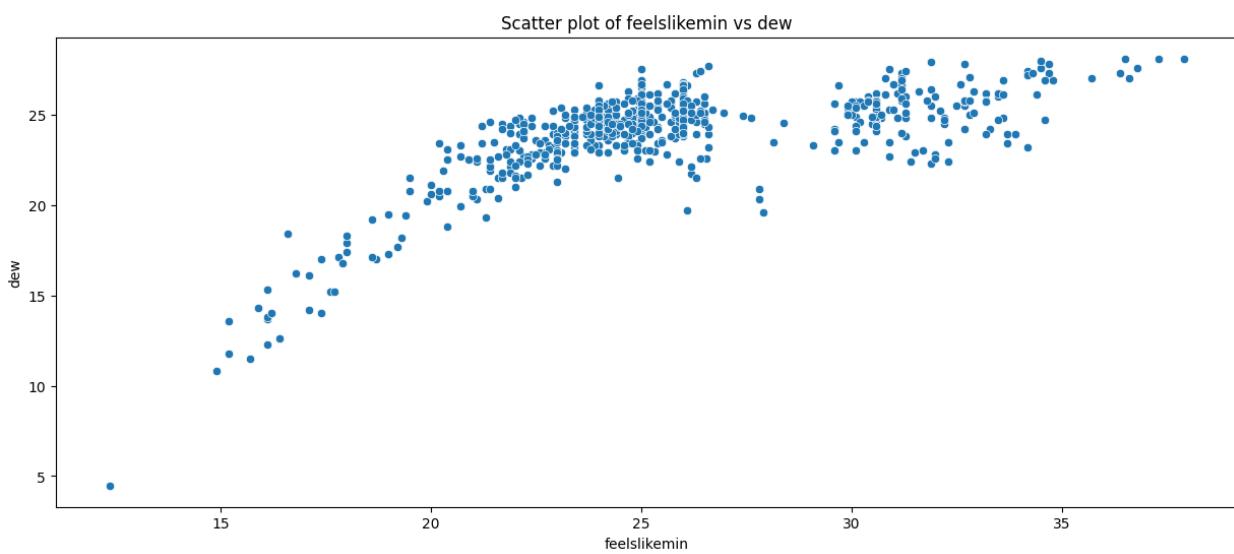
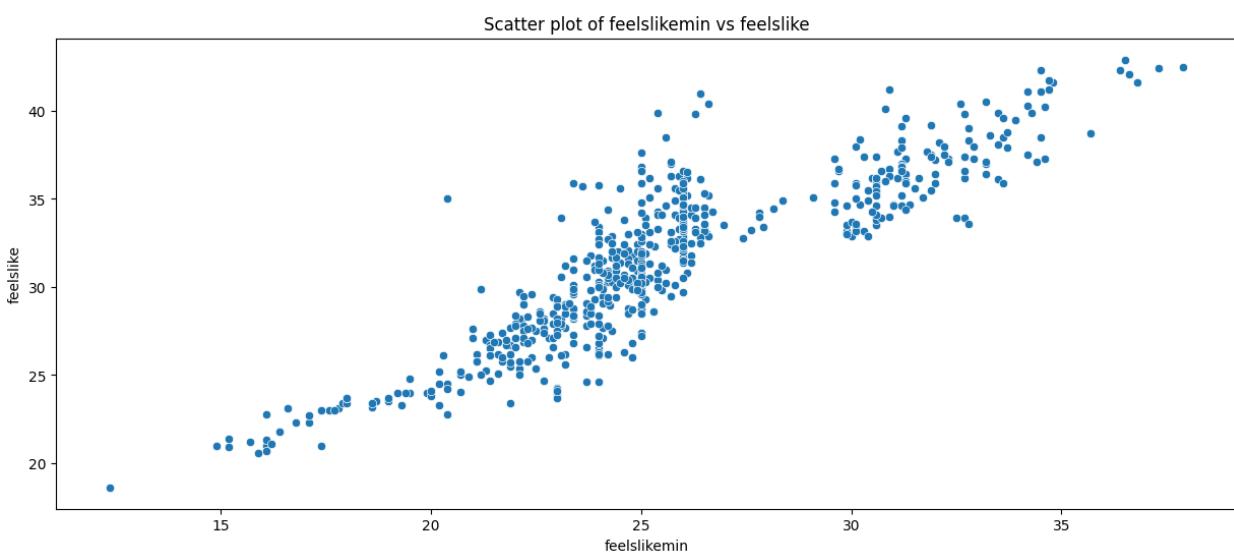
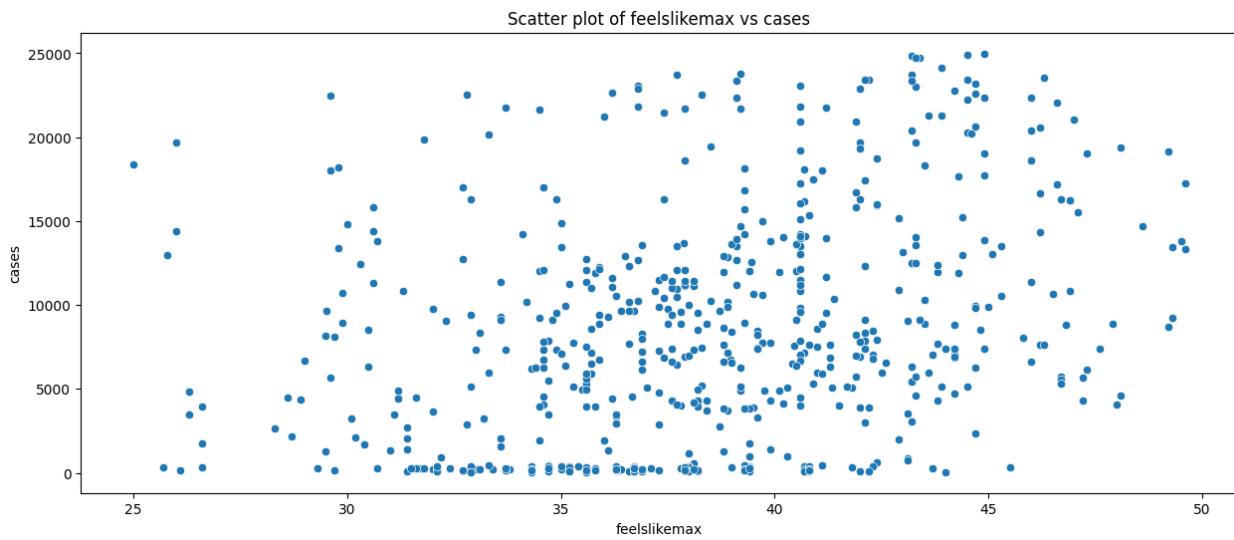
Scatter plot of feelslikemax vs solarradiation



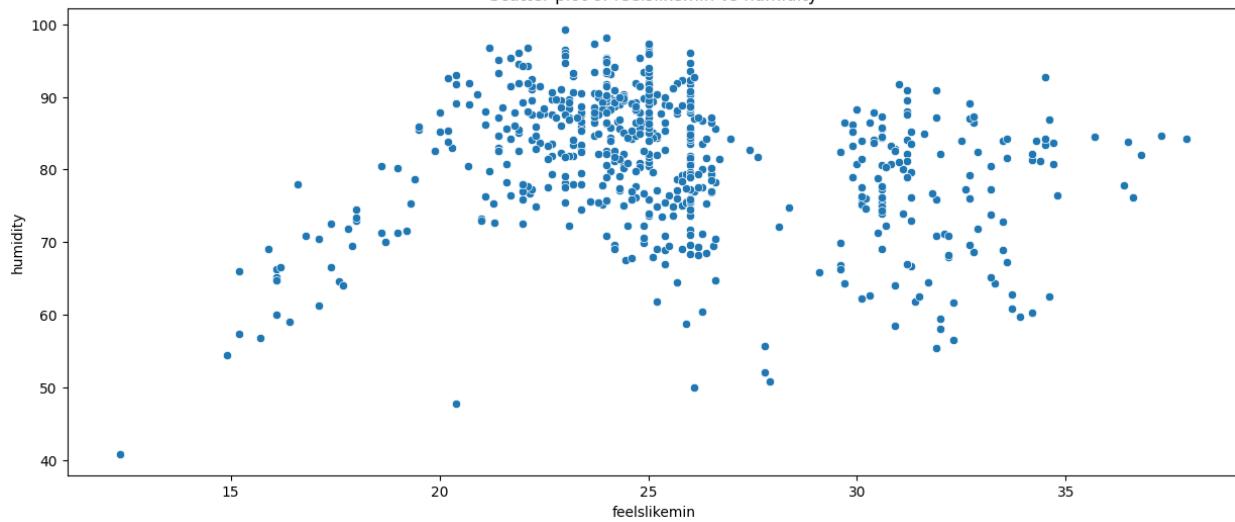
Scatter plot of feelslikemax vs solarenergy



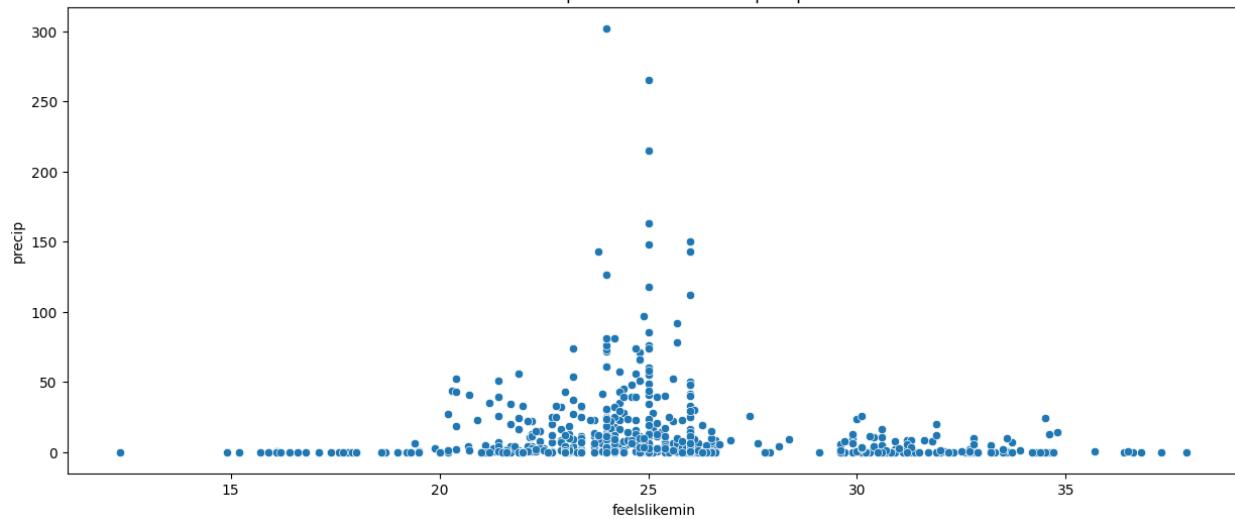




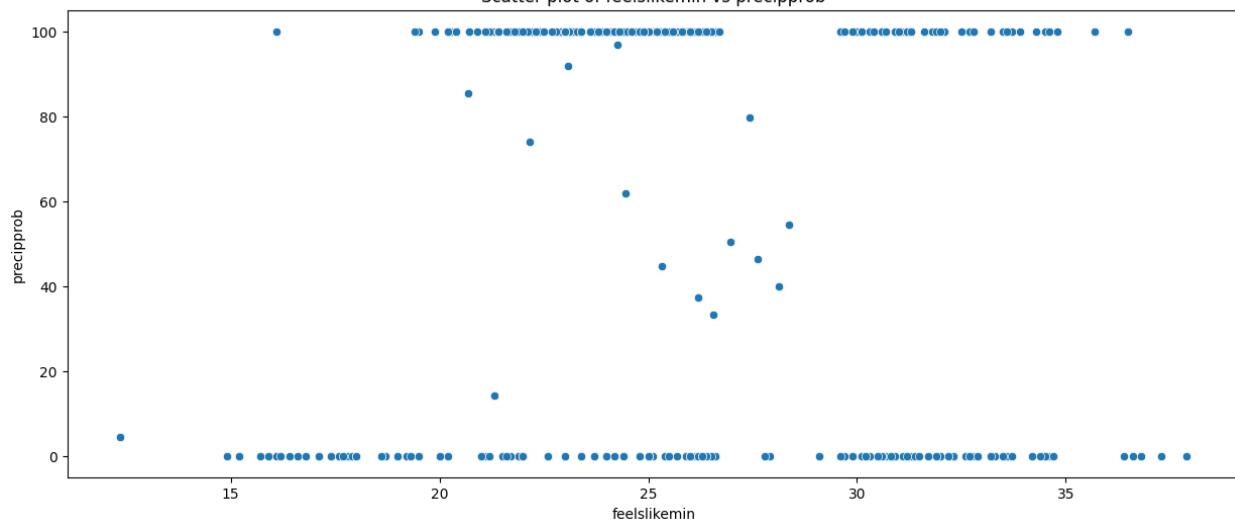
Scatter plot of feelslikemin vs humidity



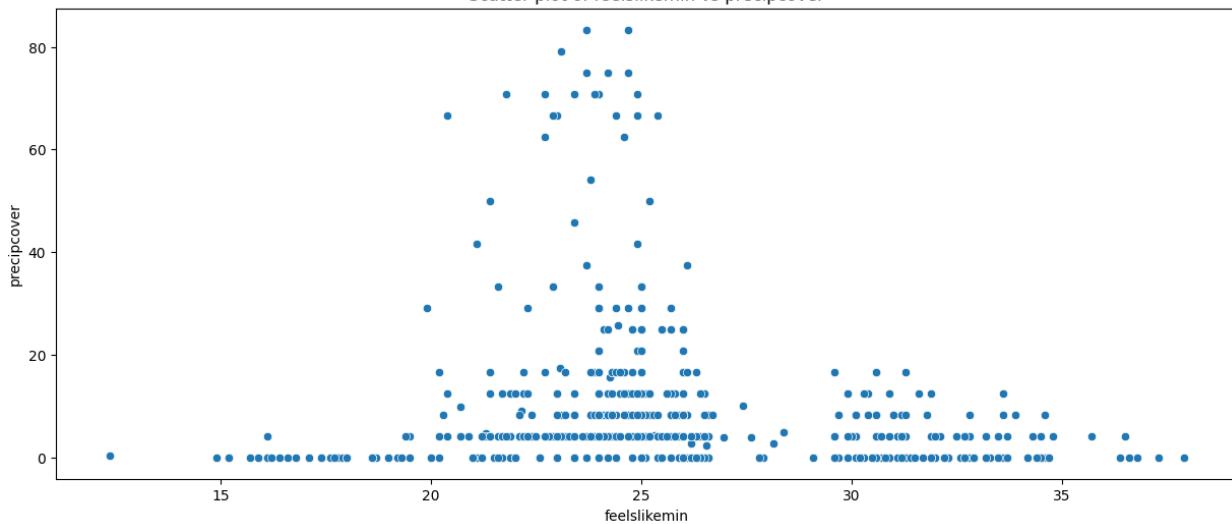
Scatter plot of feelslikemin vs precip



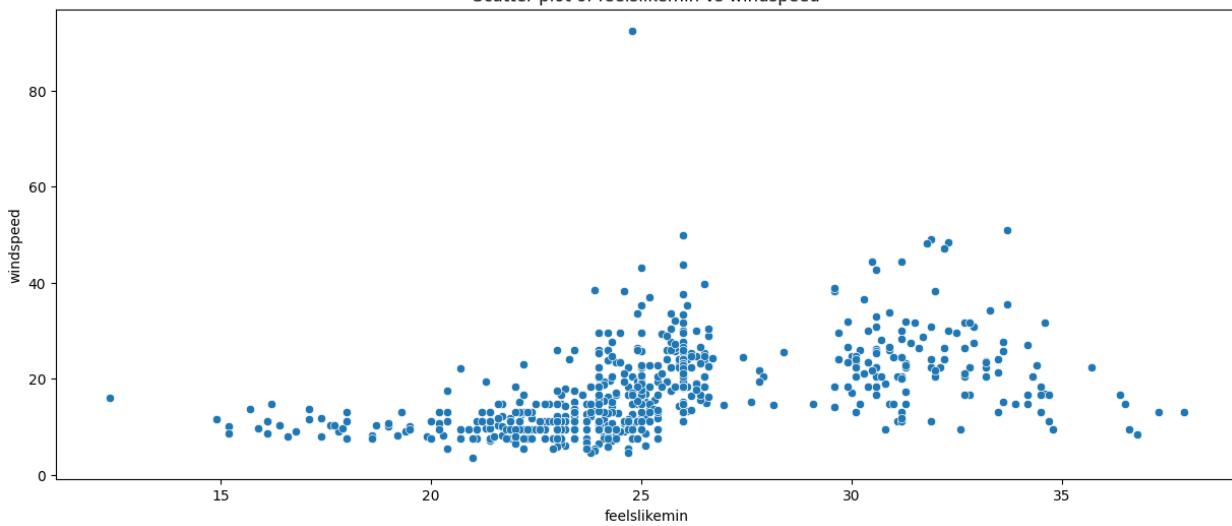
Scatter plot of feelslikemin vs precipprob



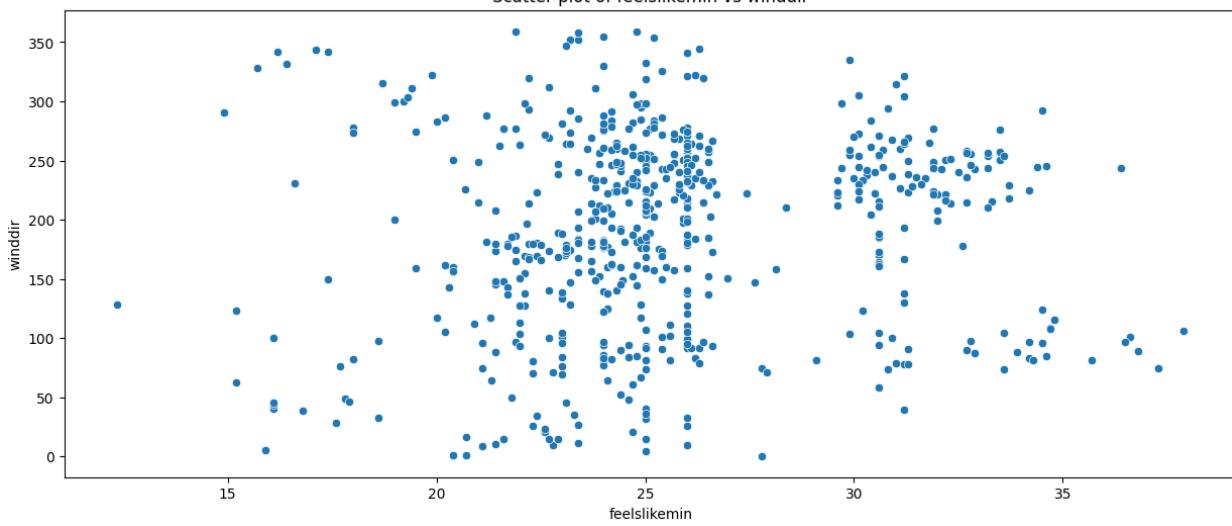
Scatter plot of feelslikemin vs precipcover

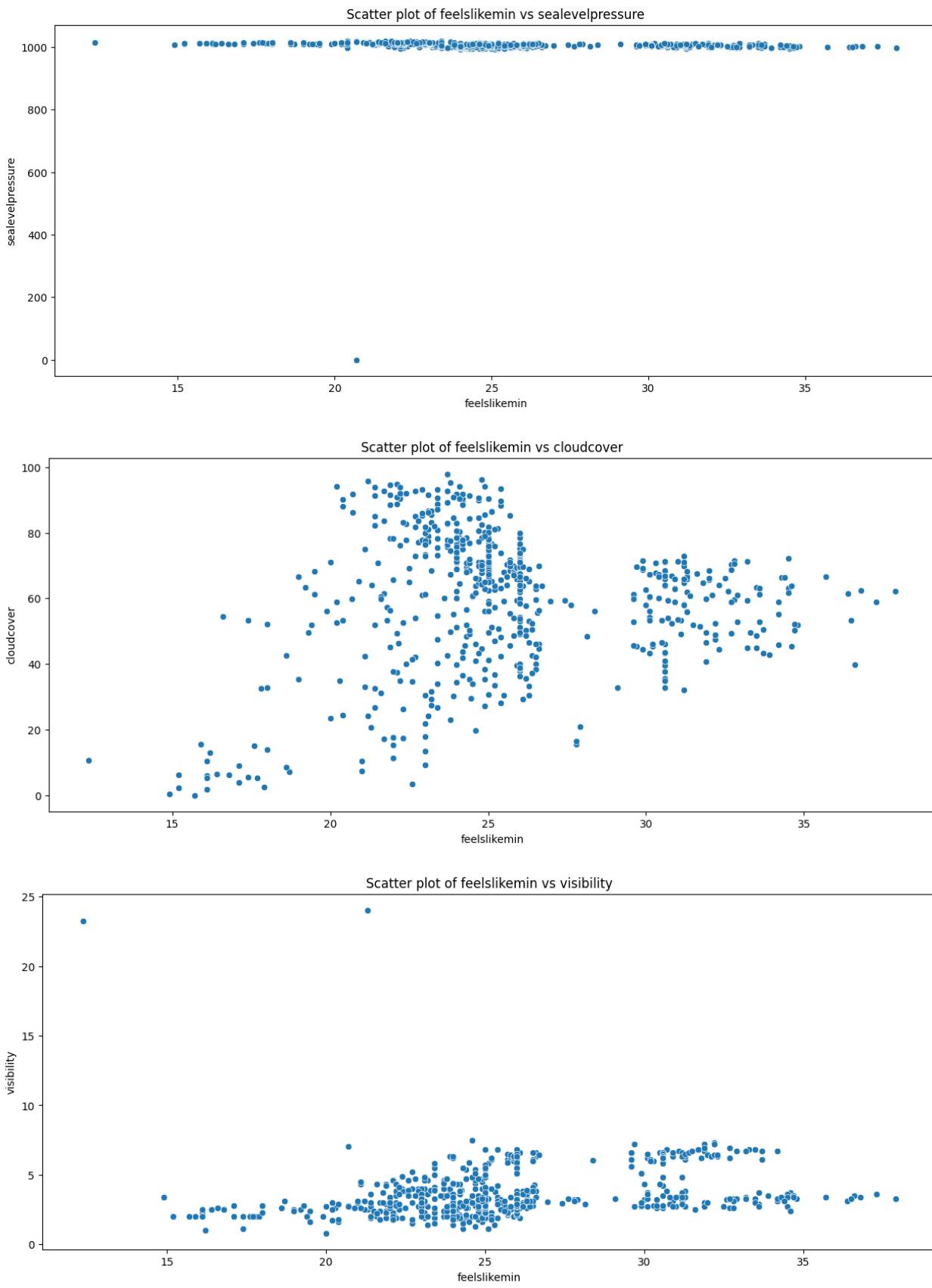


Scatter plot of feelslikemin vs windspeed

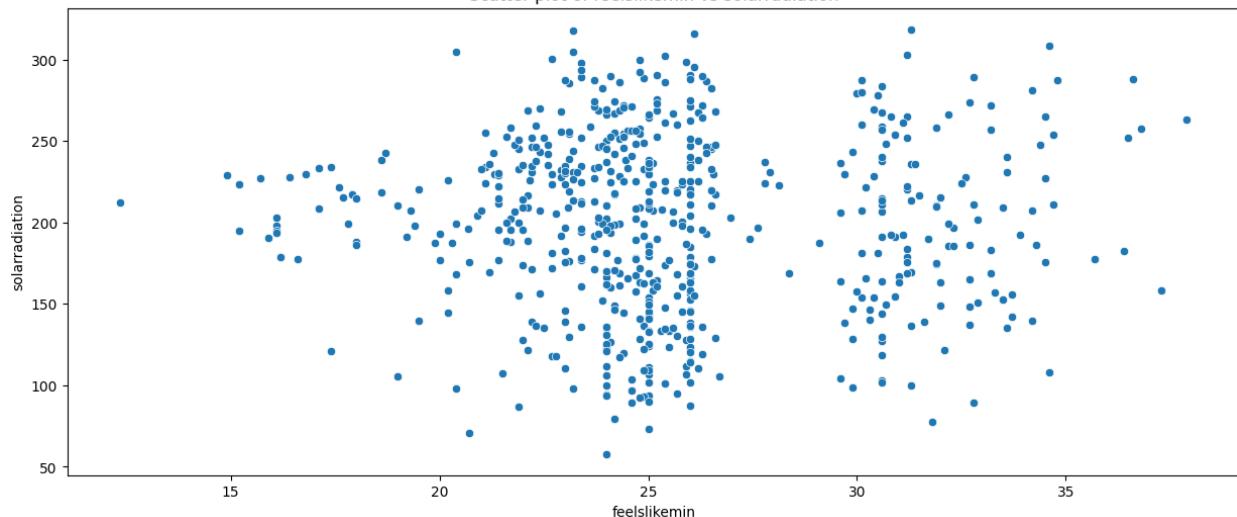


Scatter plot of feelslikemin vs winddir

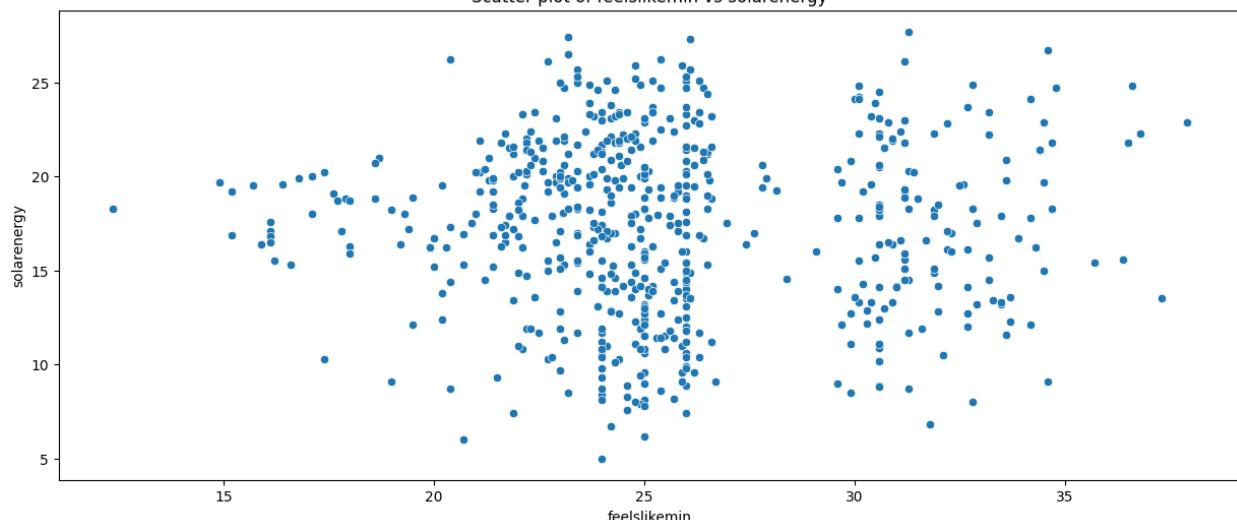




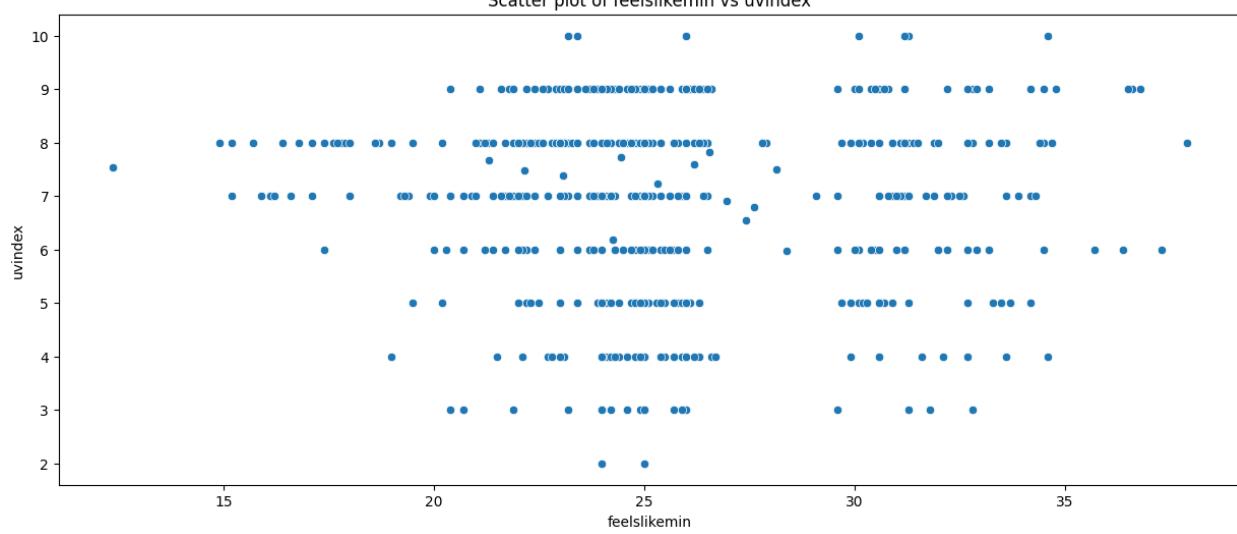
Scatter plot of feelslikemin vs solarradiation

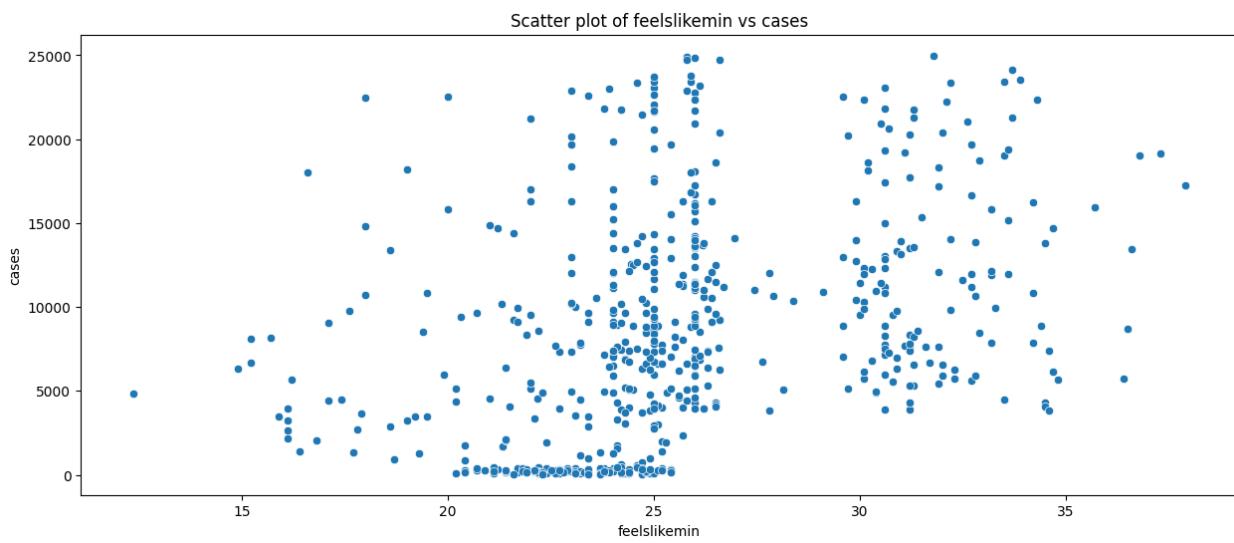
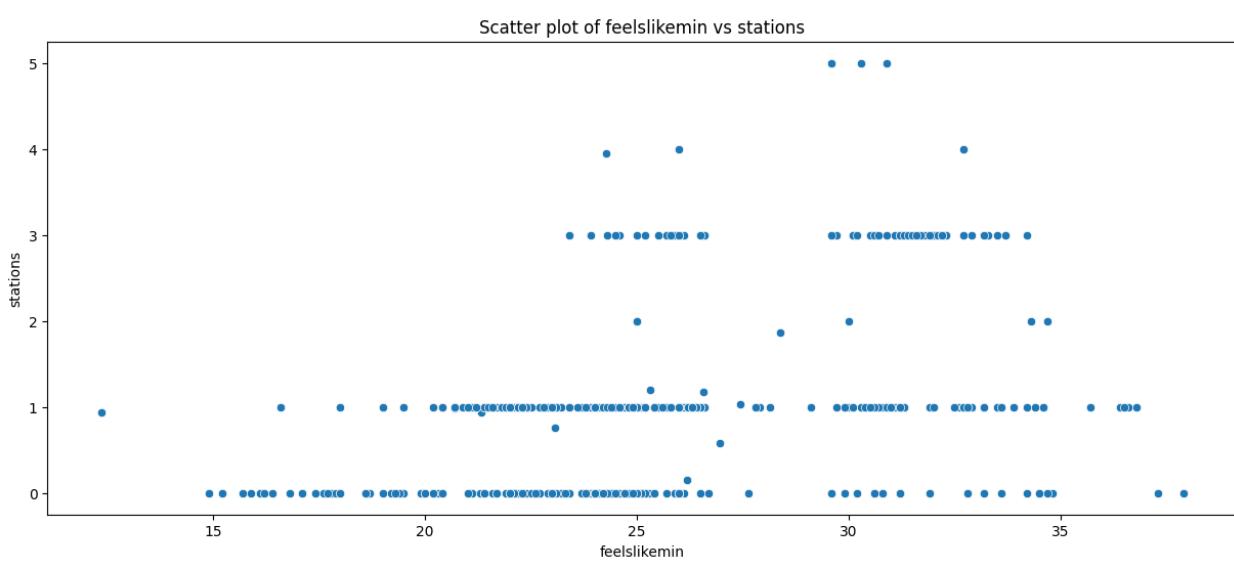
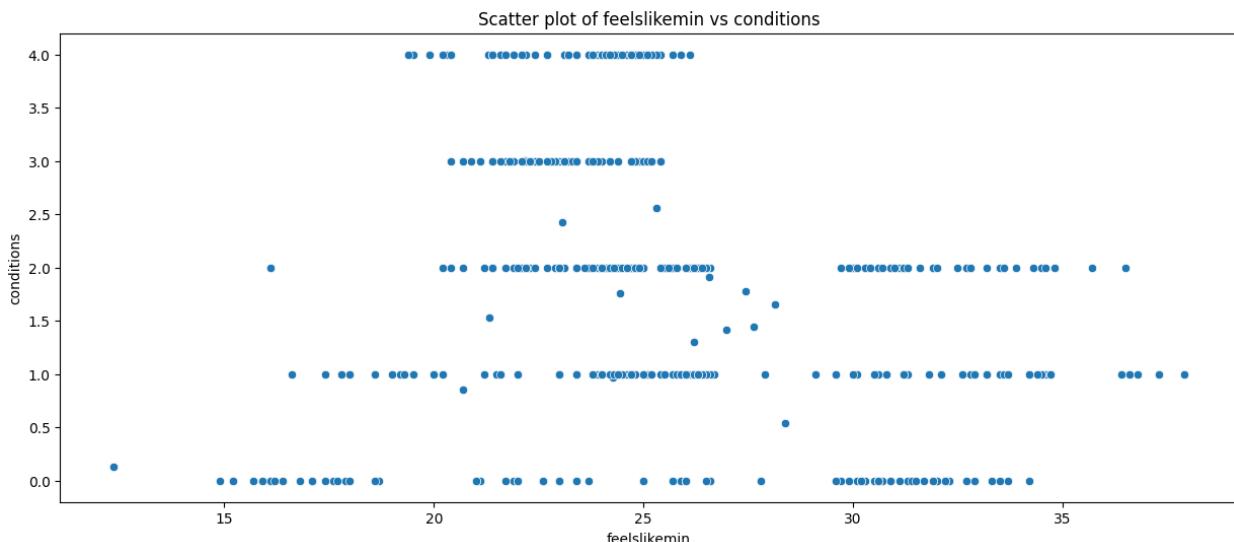


Scatter plot of feelslikemin vs solarenergy

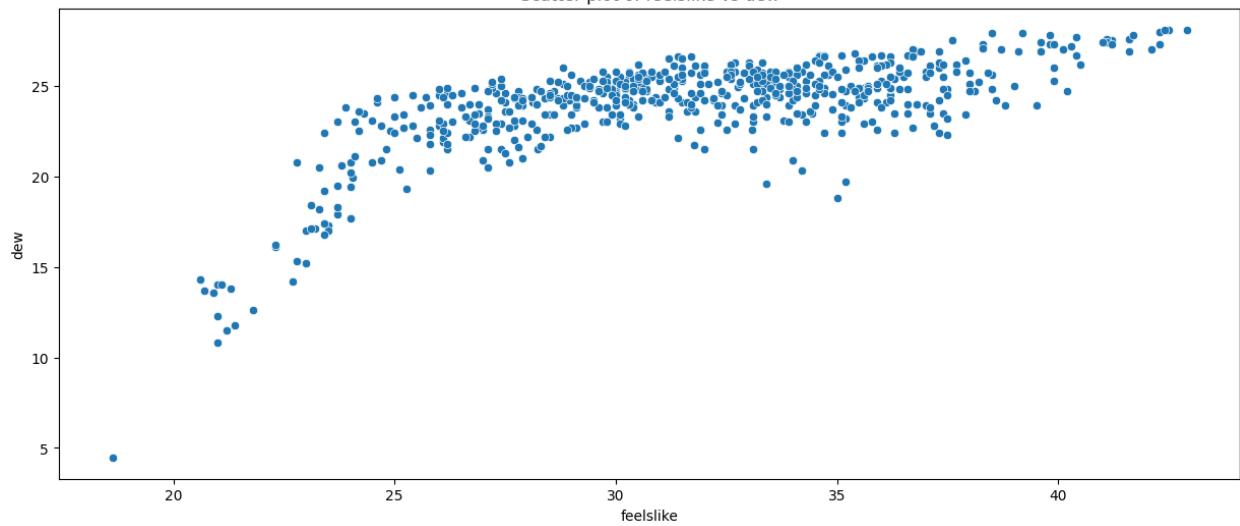


Scatter plot of feelslikemin vs uvindex

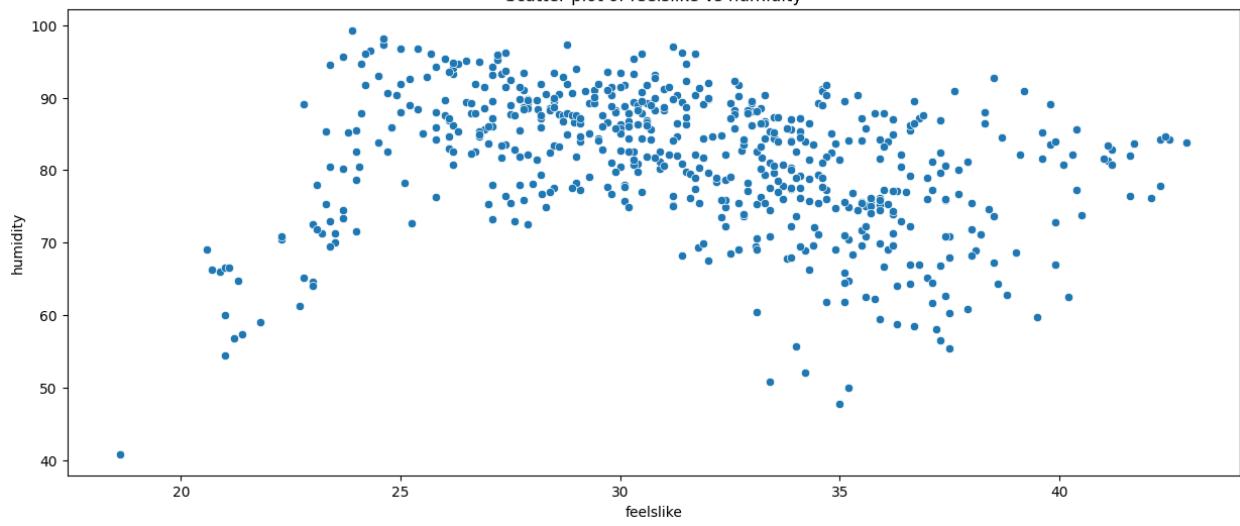




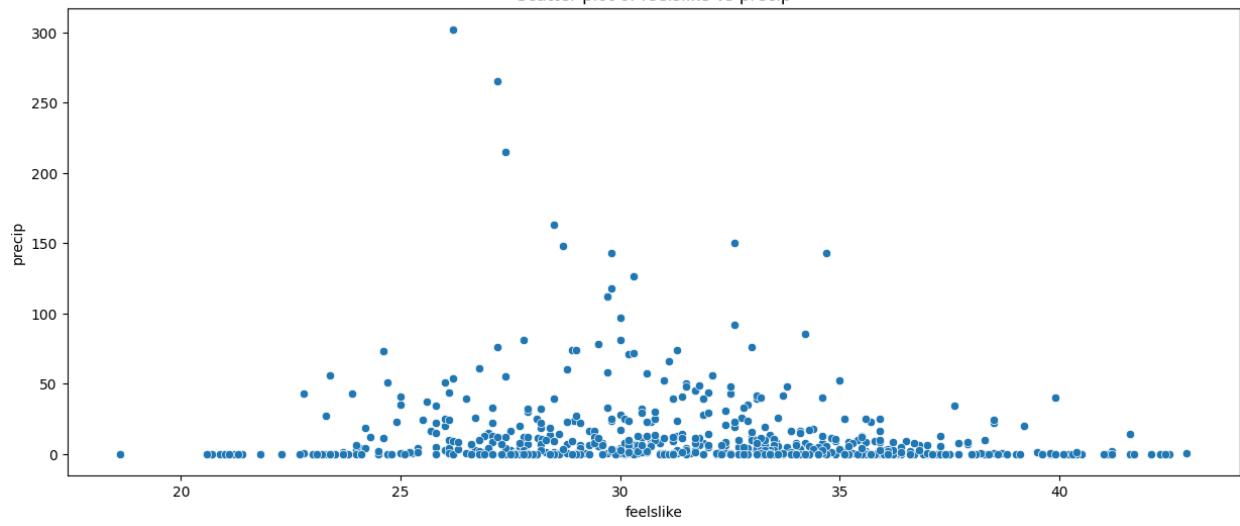
Scatter plot of feelslike vs dew



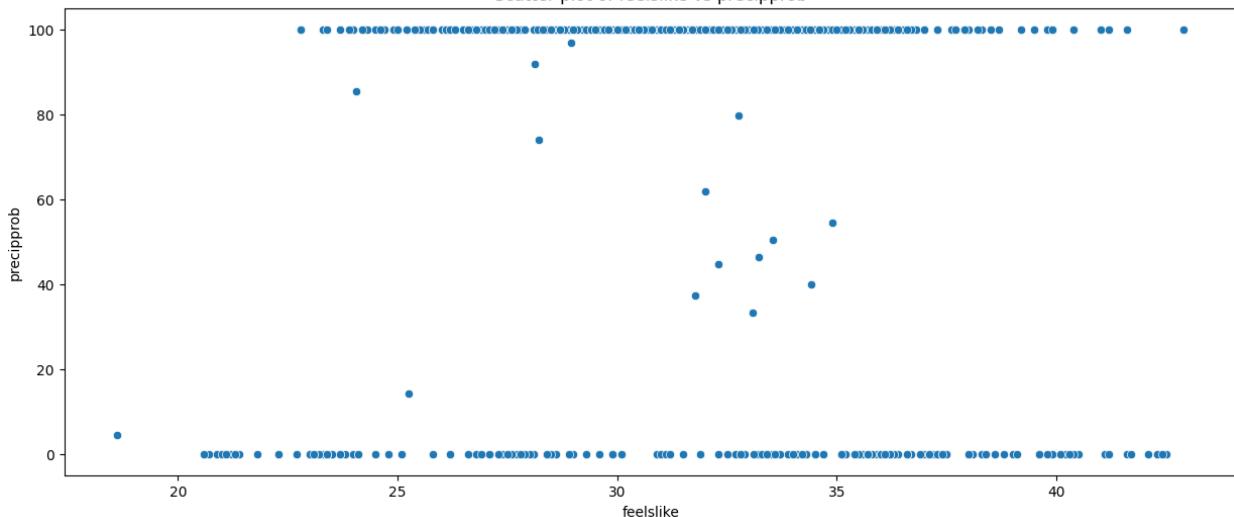
Scatter plot of feelslike vs humidity



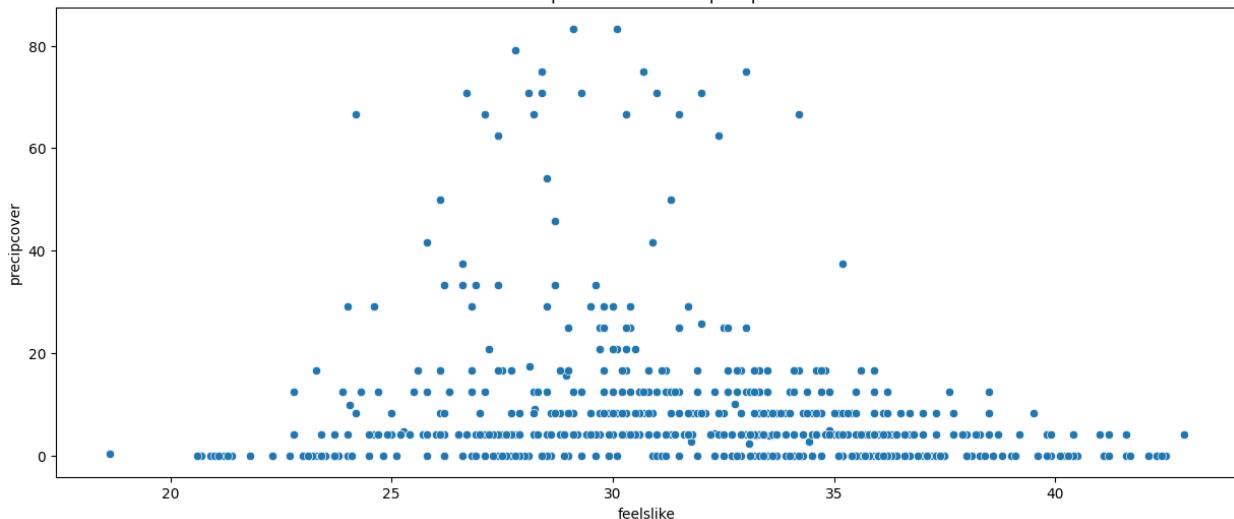
Scatter plot of feelslike vs precip



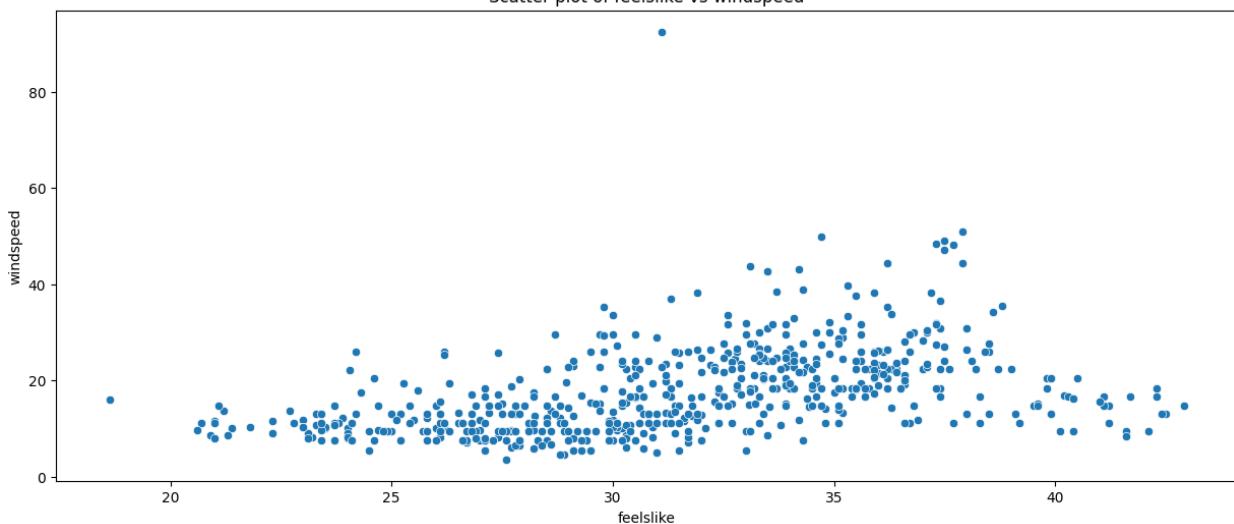
Scatter plot of feelslike vs precipprob



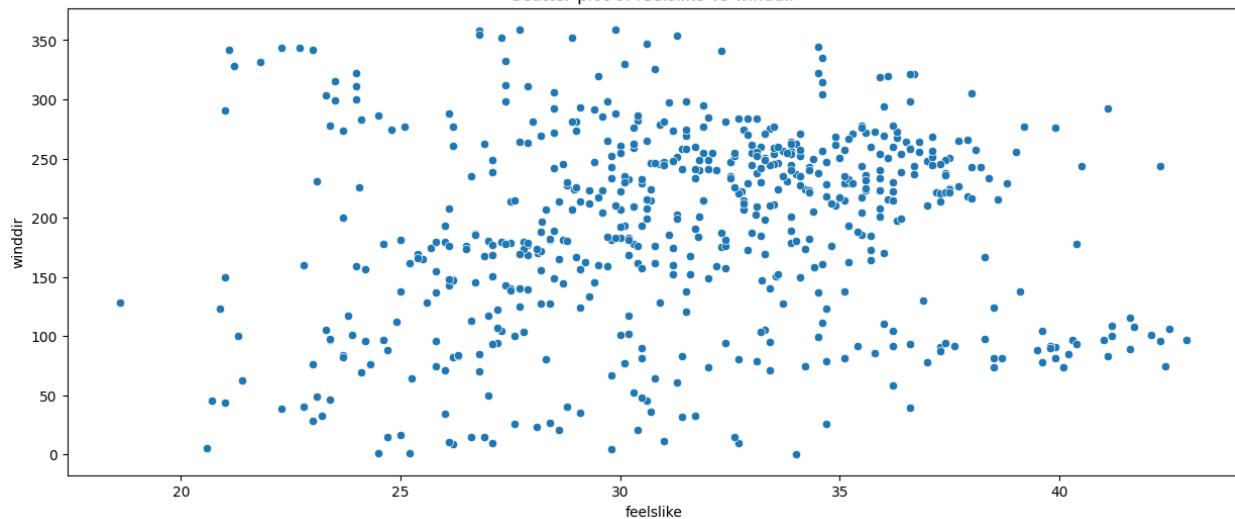
Scatter plot of feelslike vs precipcover



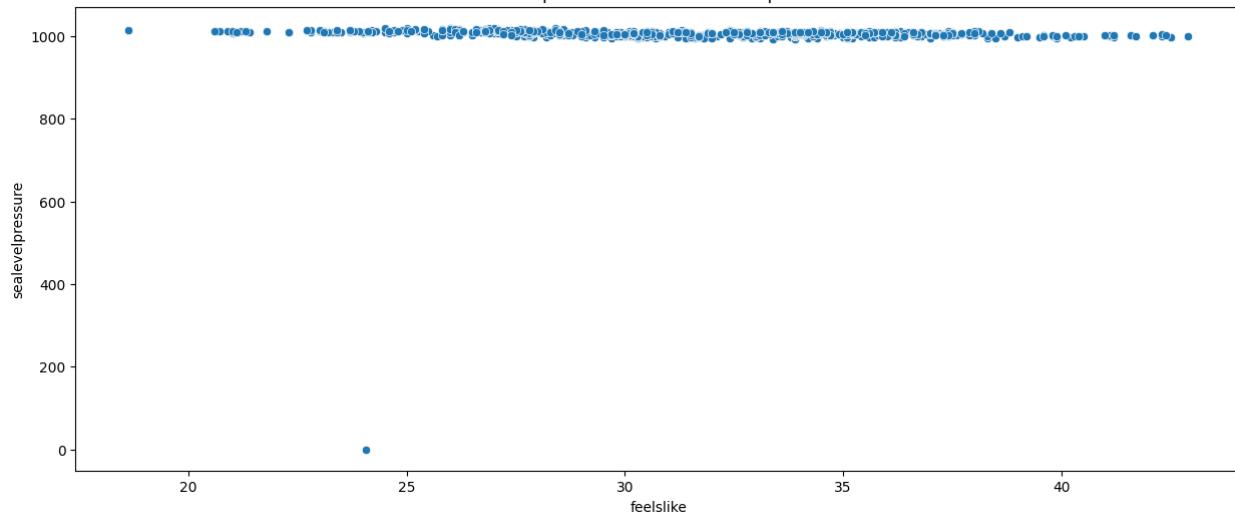
Scatter plot of feelslike vs windspeed



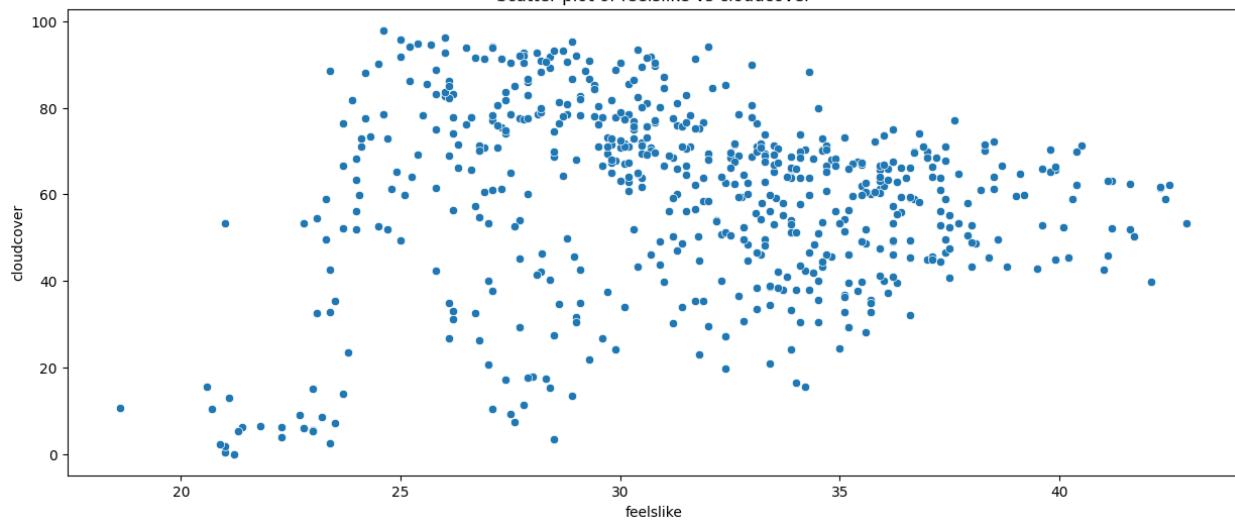
Scatter plot of feelslike vs winddir



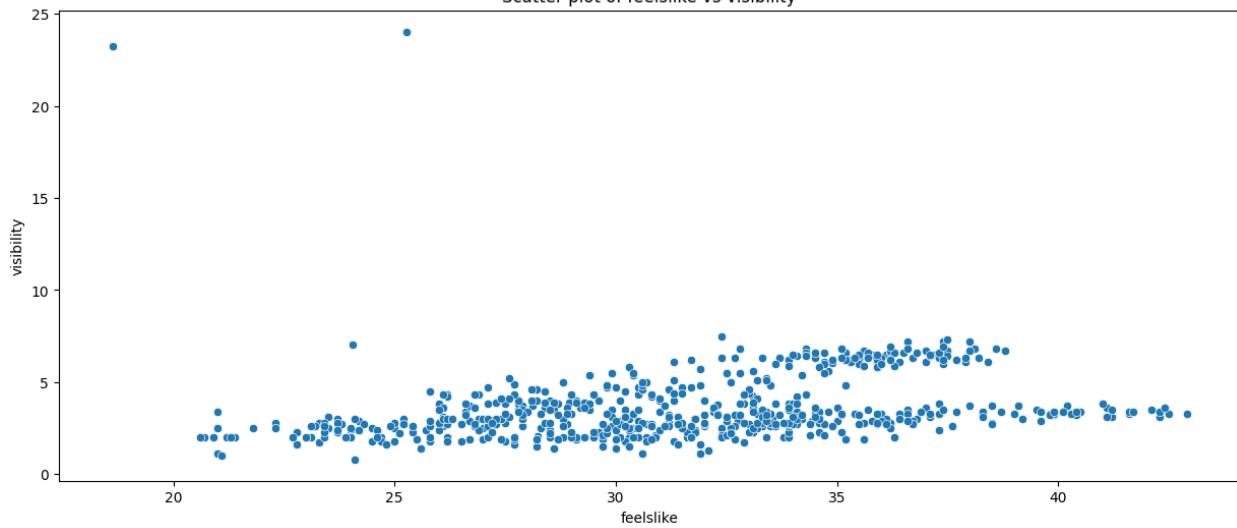
Scatter plot of feelslike vs sealevelpressure



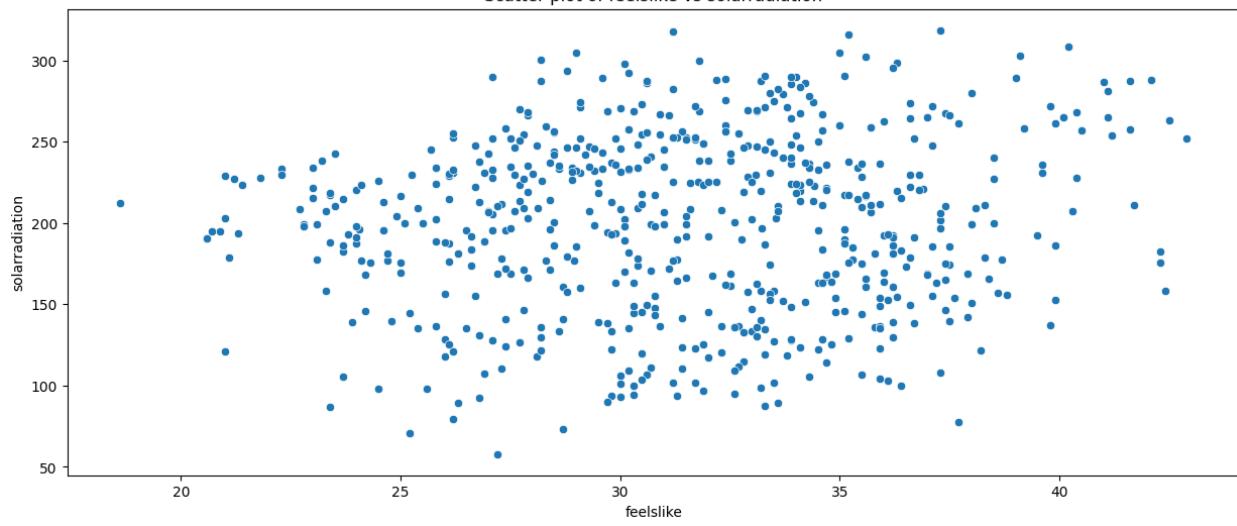
Scatter plot of feelslike vs cloudcover



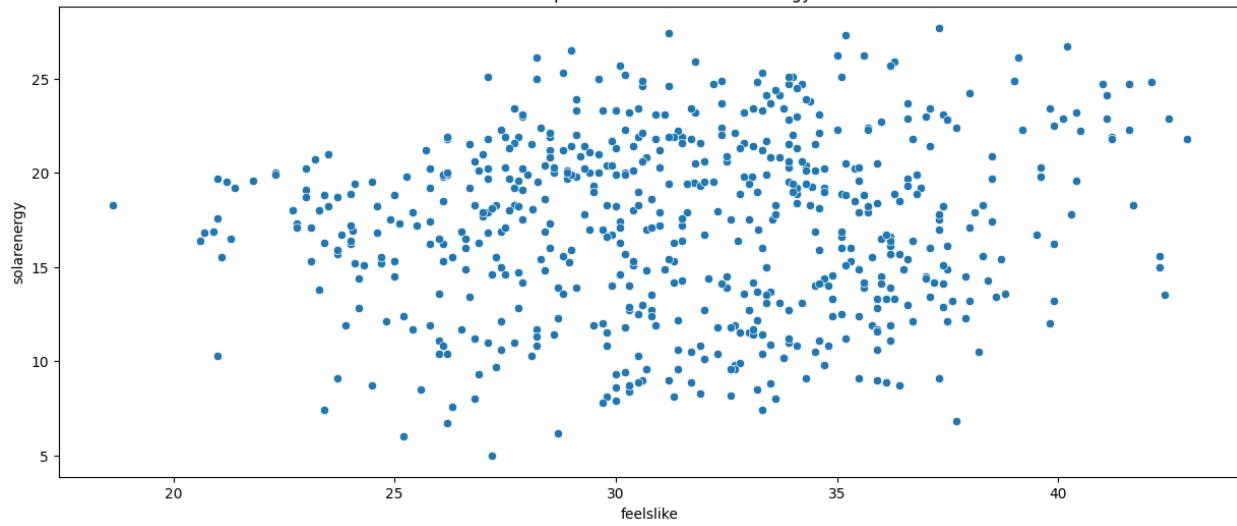
Scatter plot of feelslike vs visibility

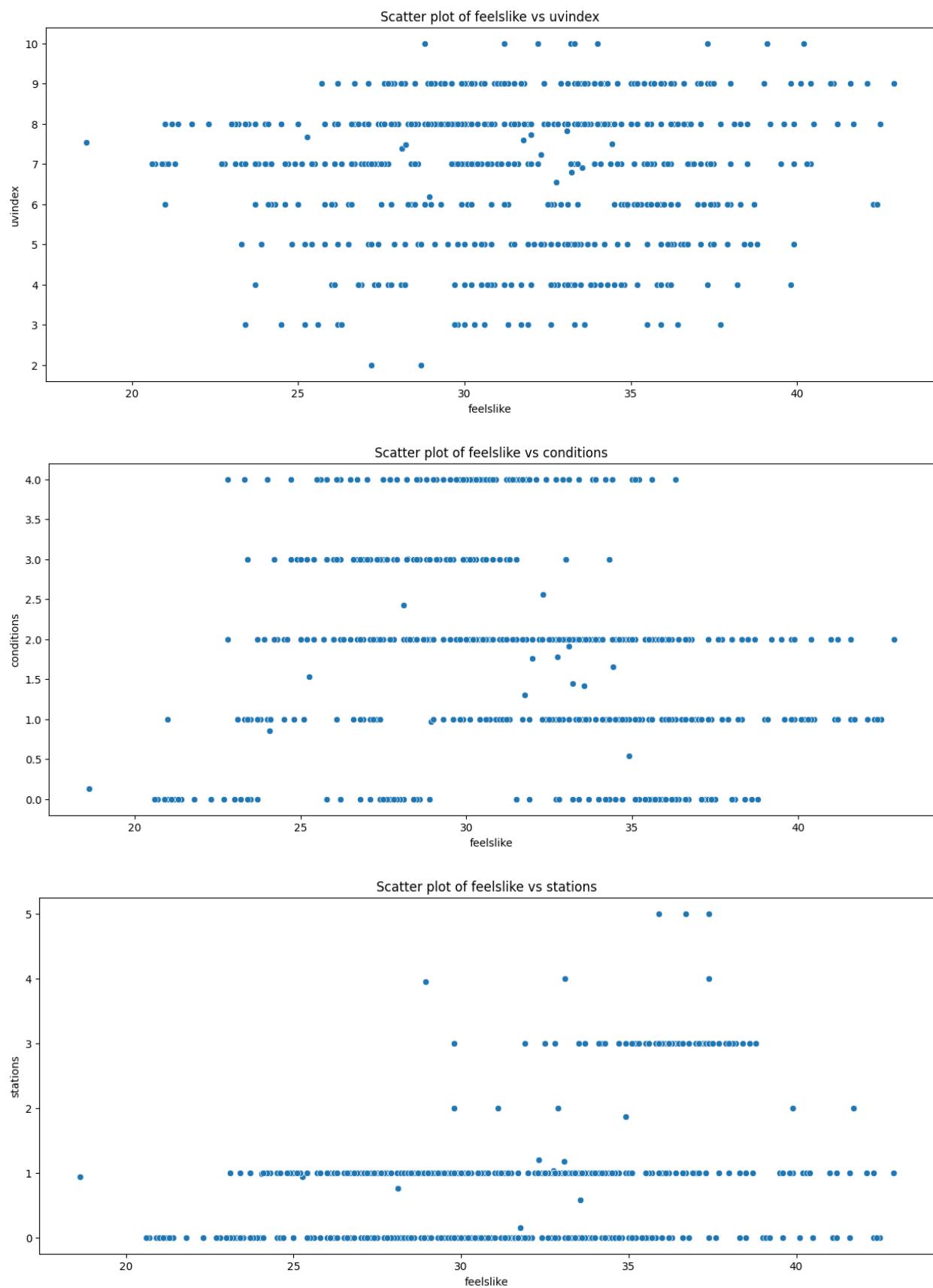


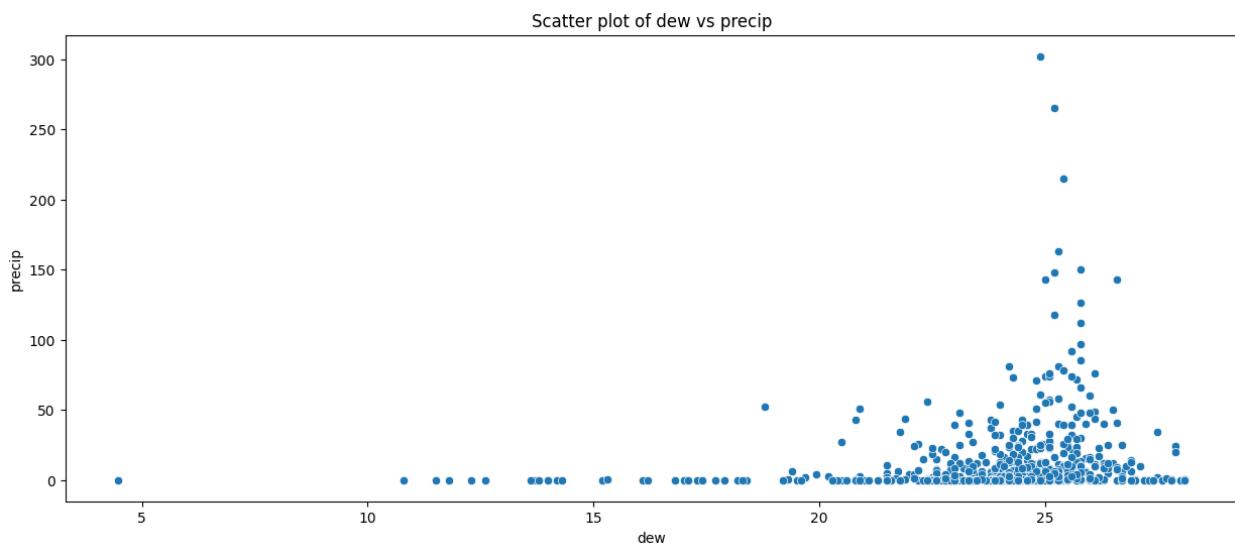
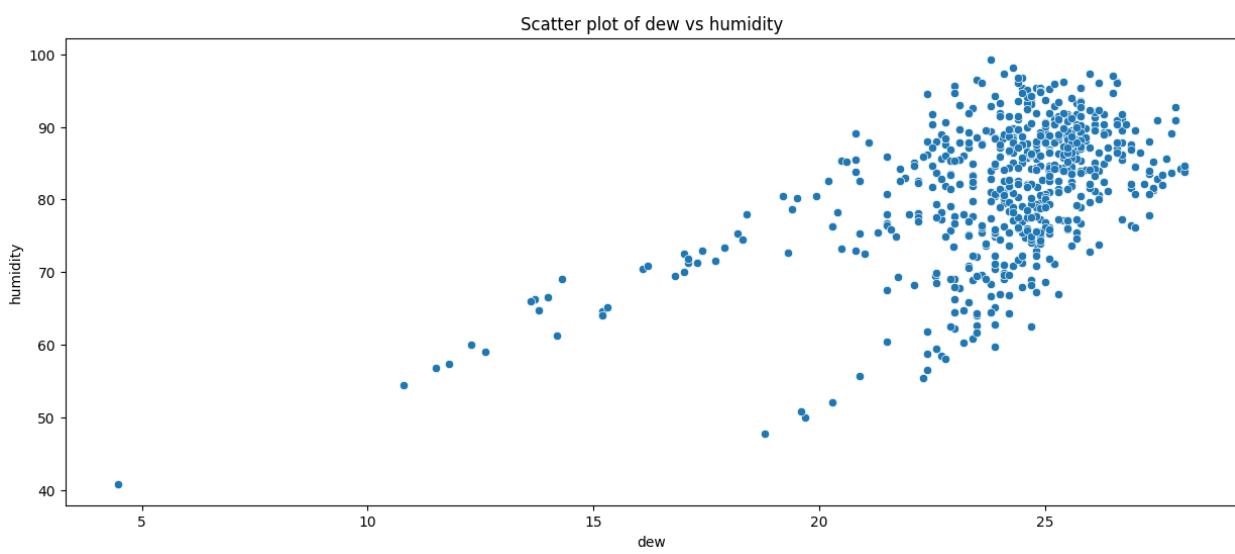
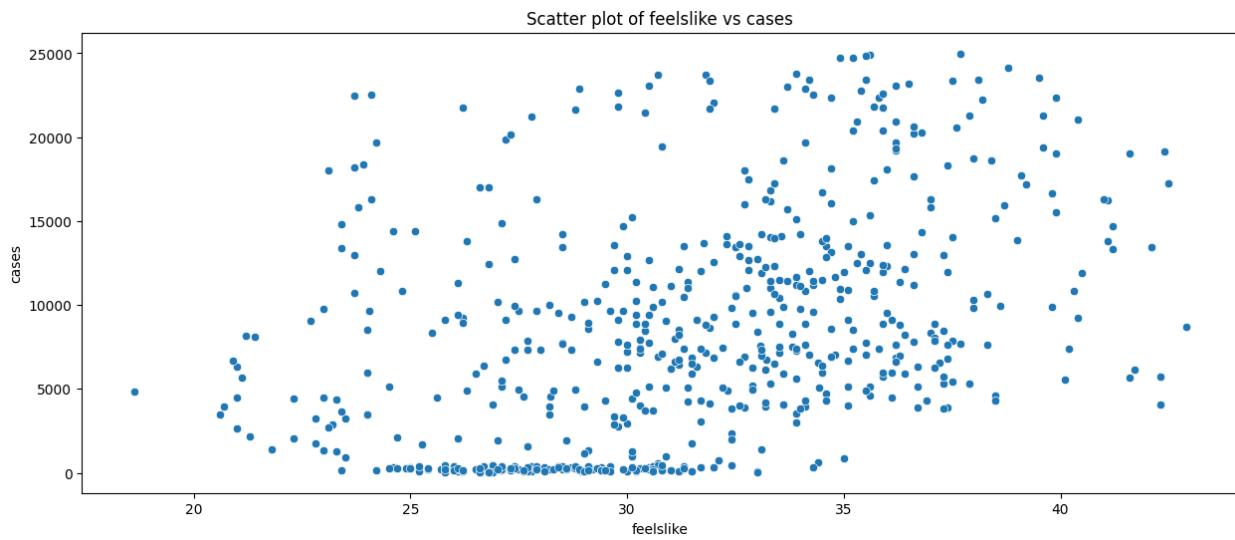
Scatter plot of feelslike vs solarradiation

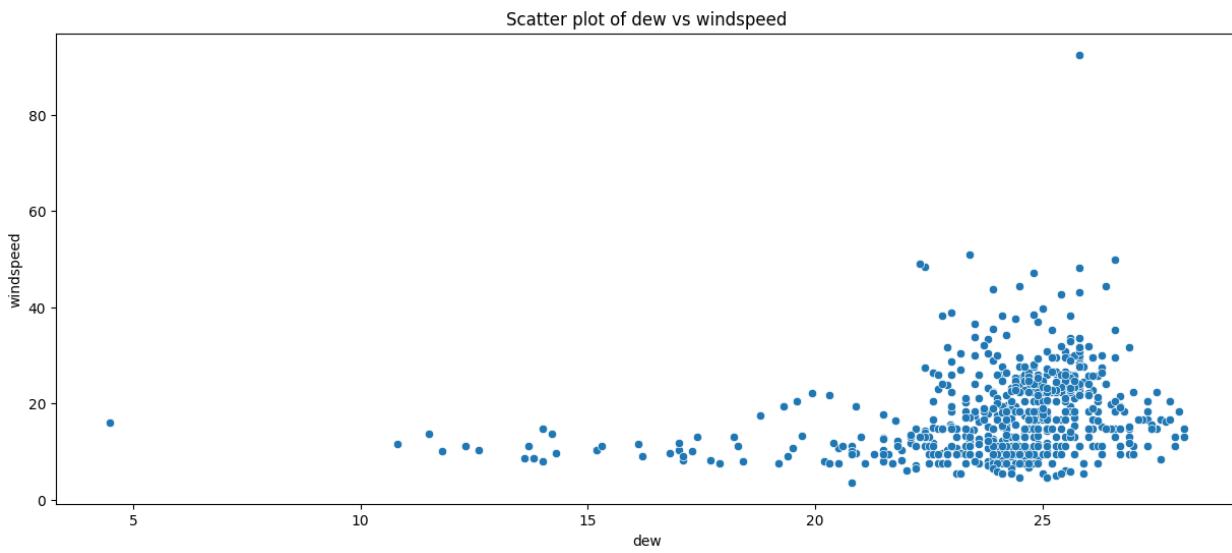
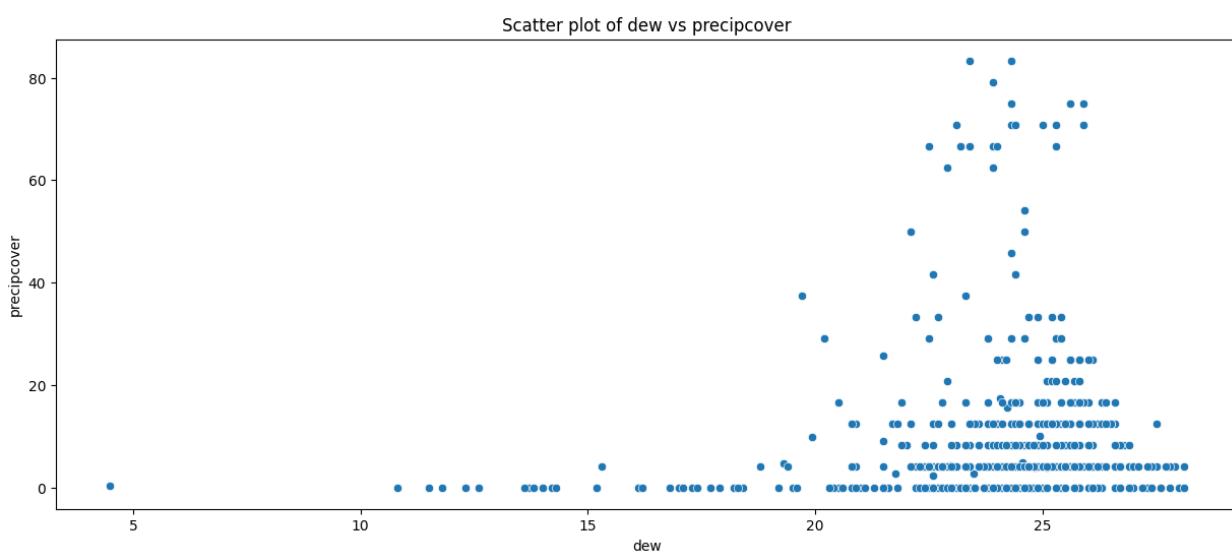
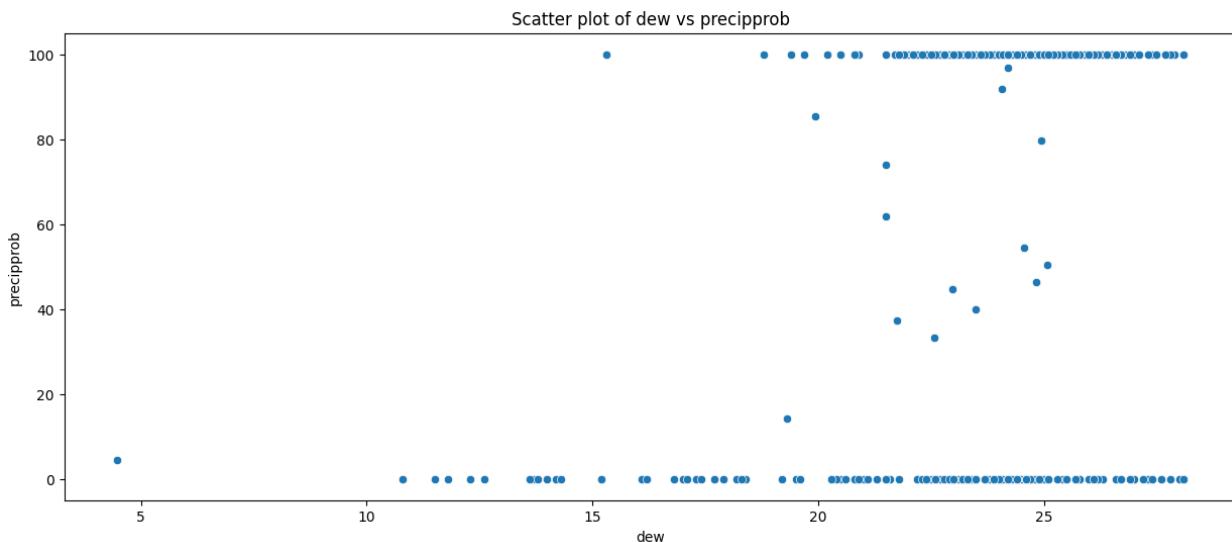


Scatter plot of feelslike vs solarenergy

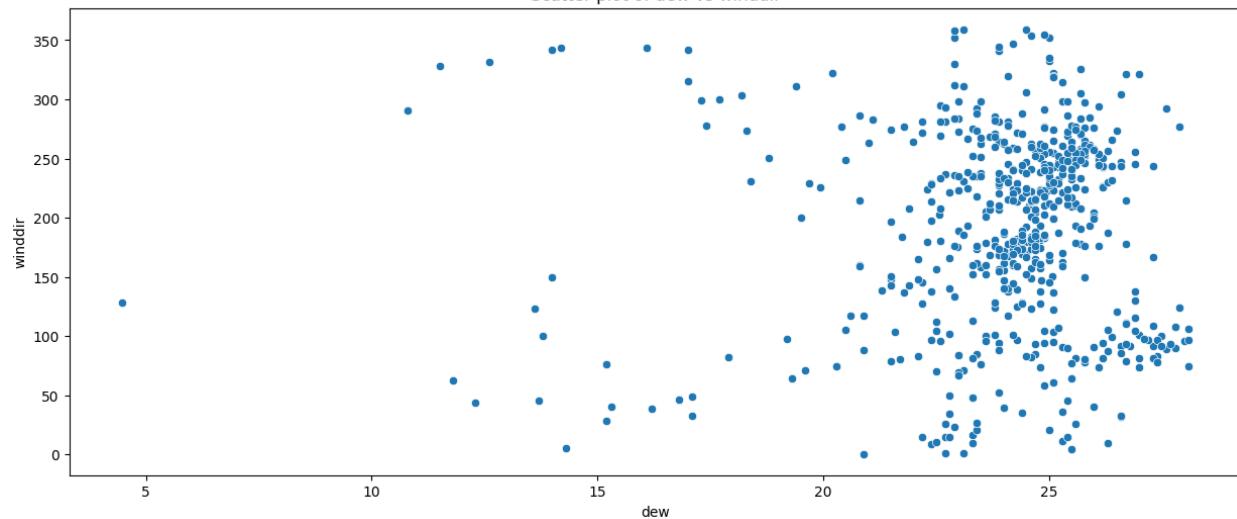




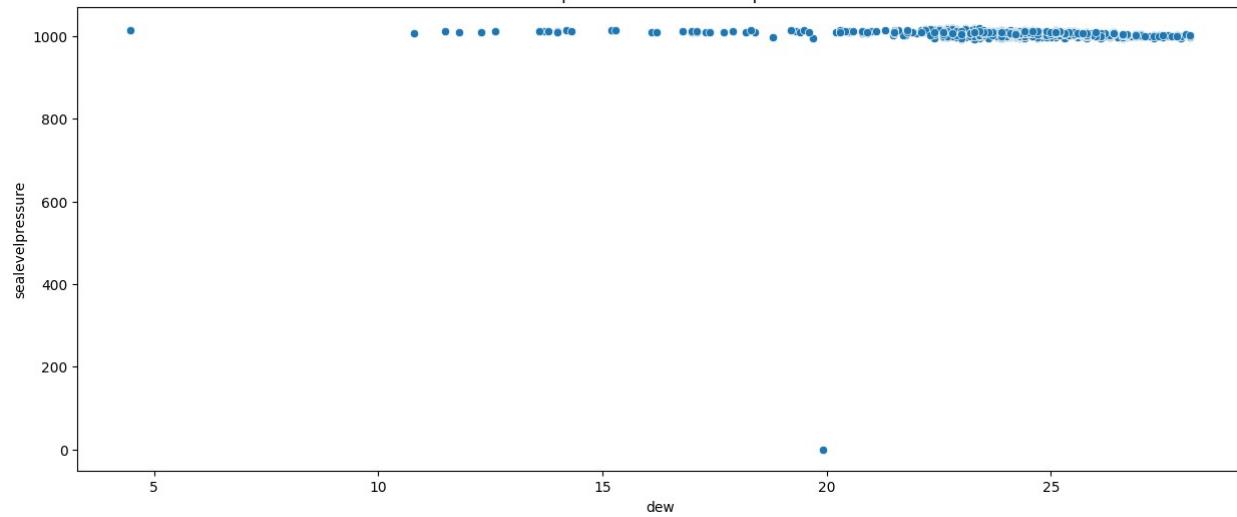




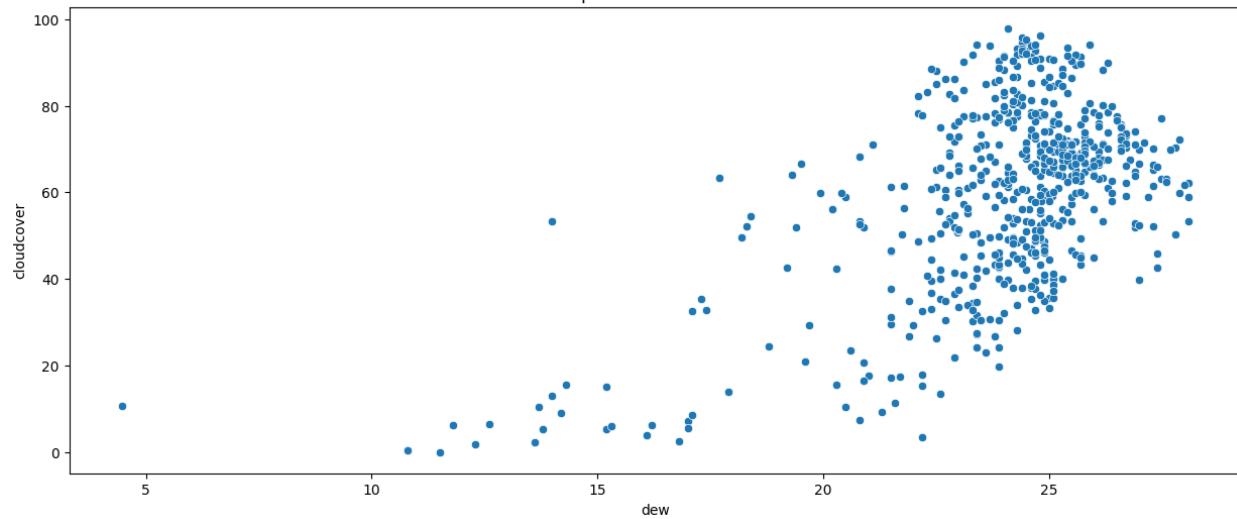
Scatter plot of dew vs winddir

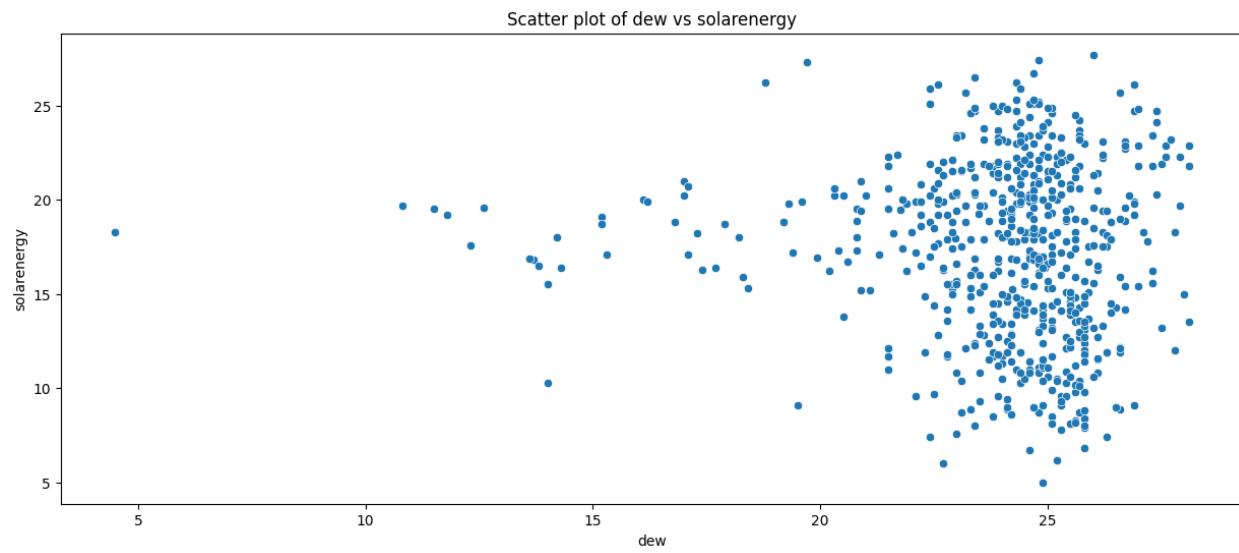
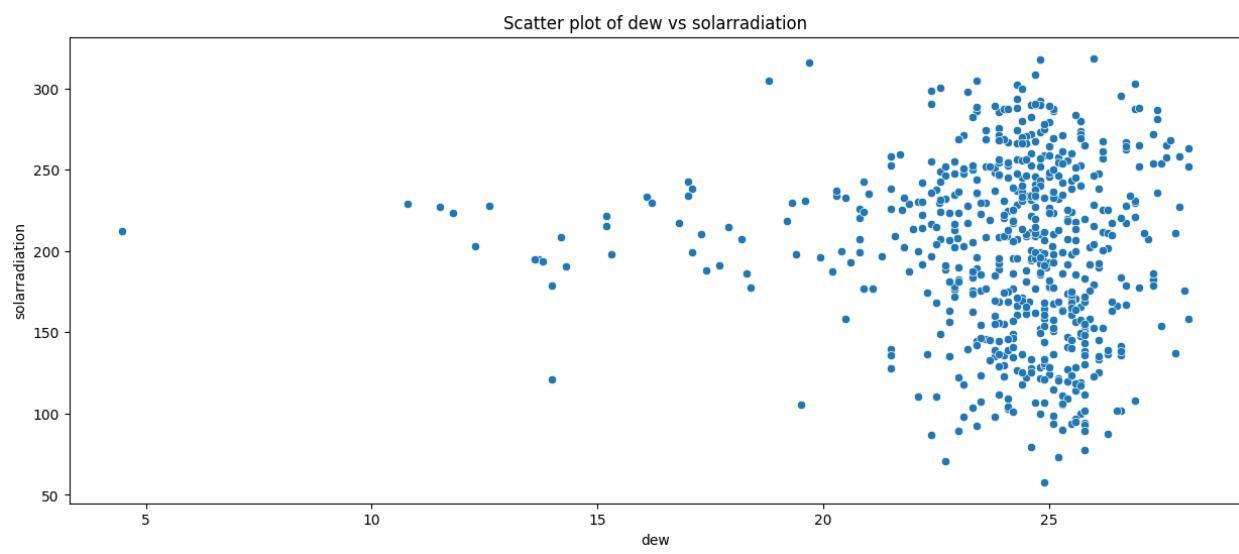
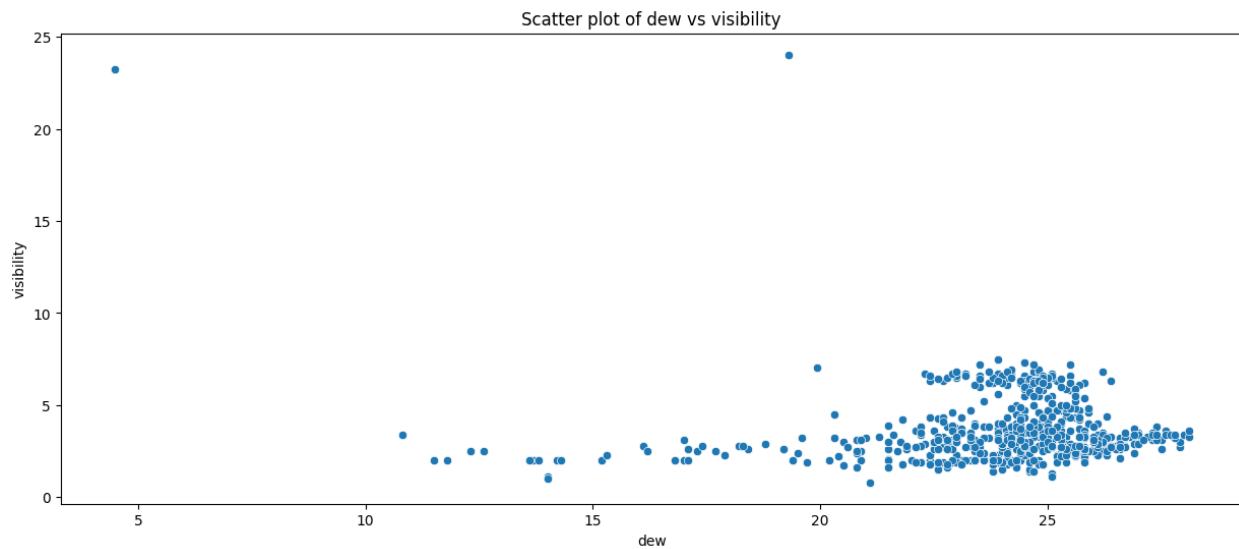


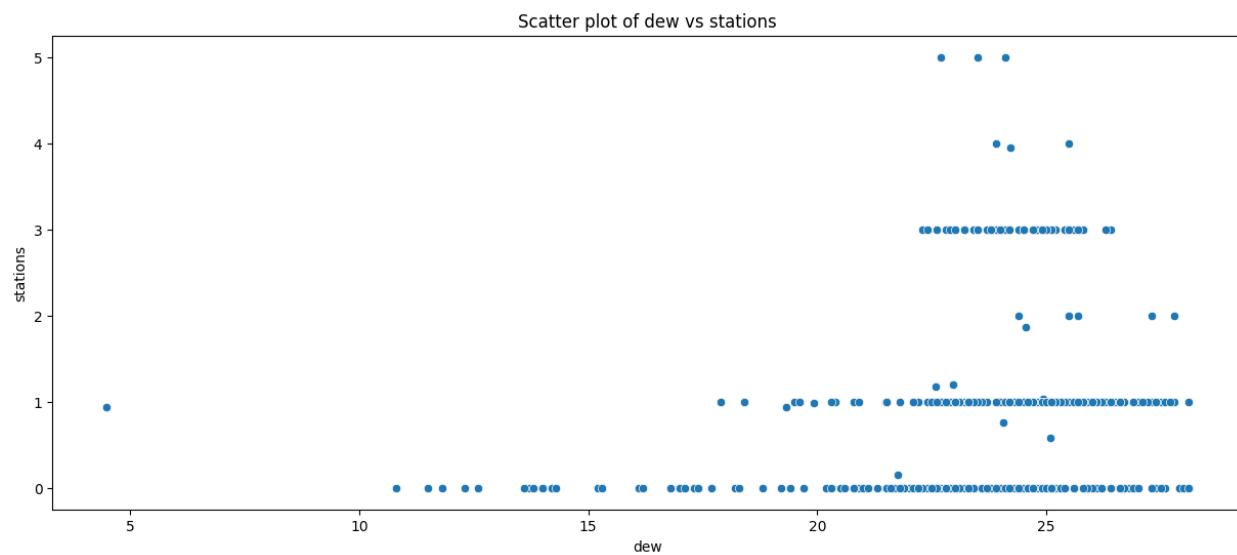
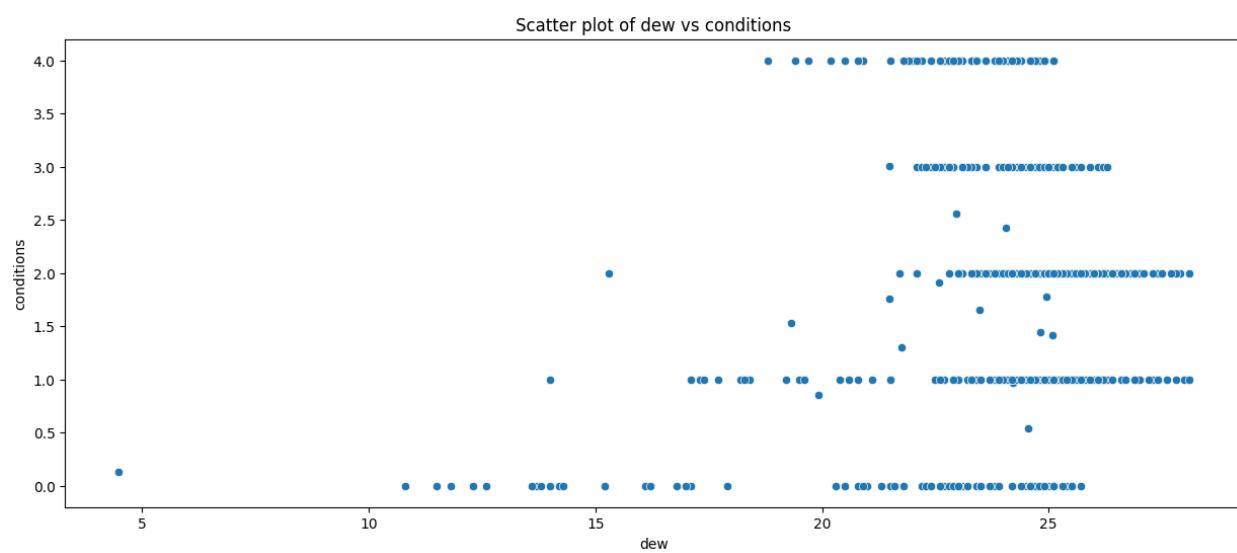
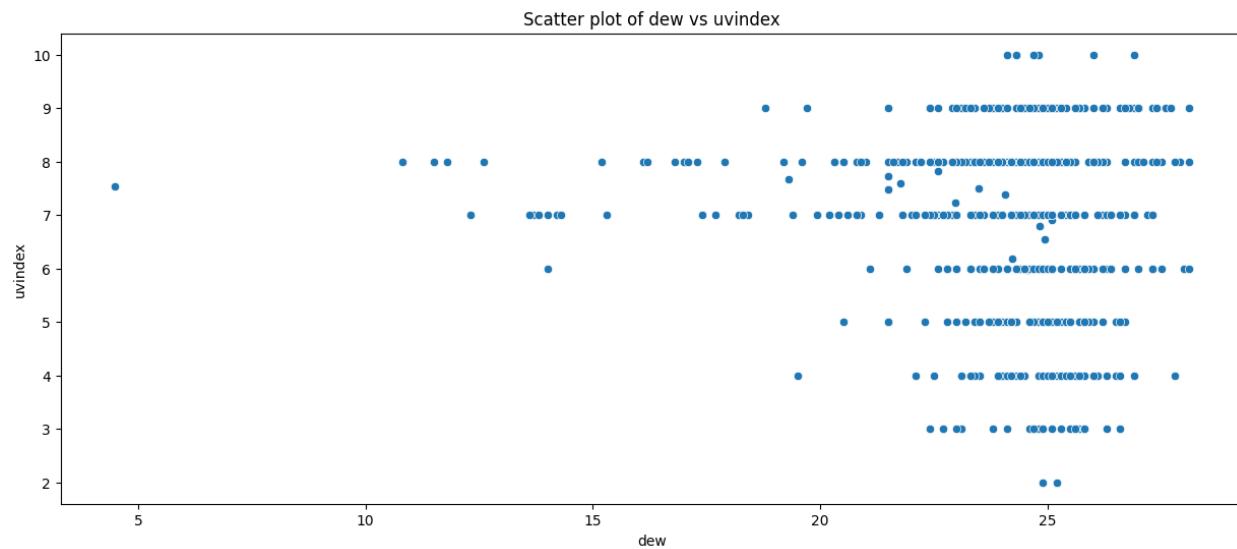
Scatter plot of dew vs sealevelpressure

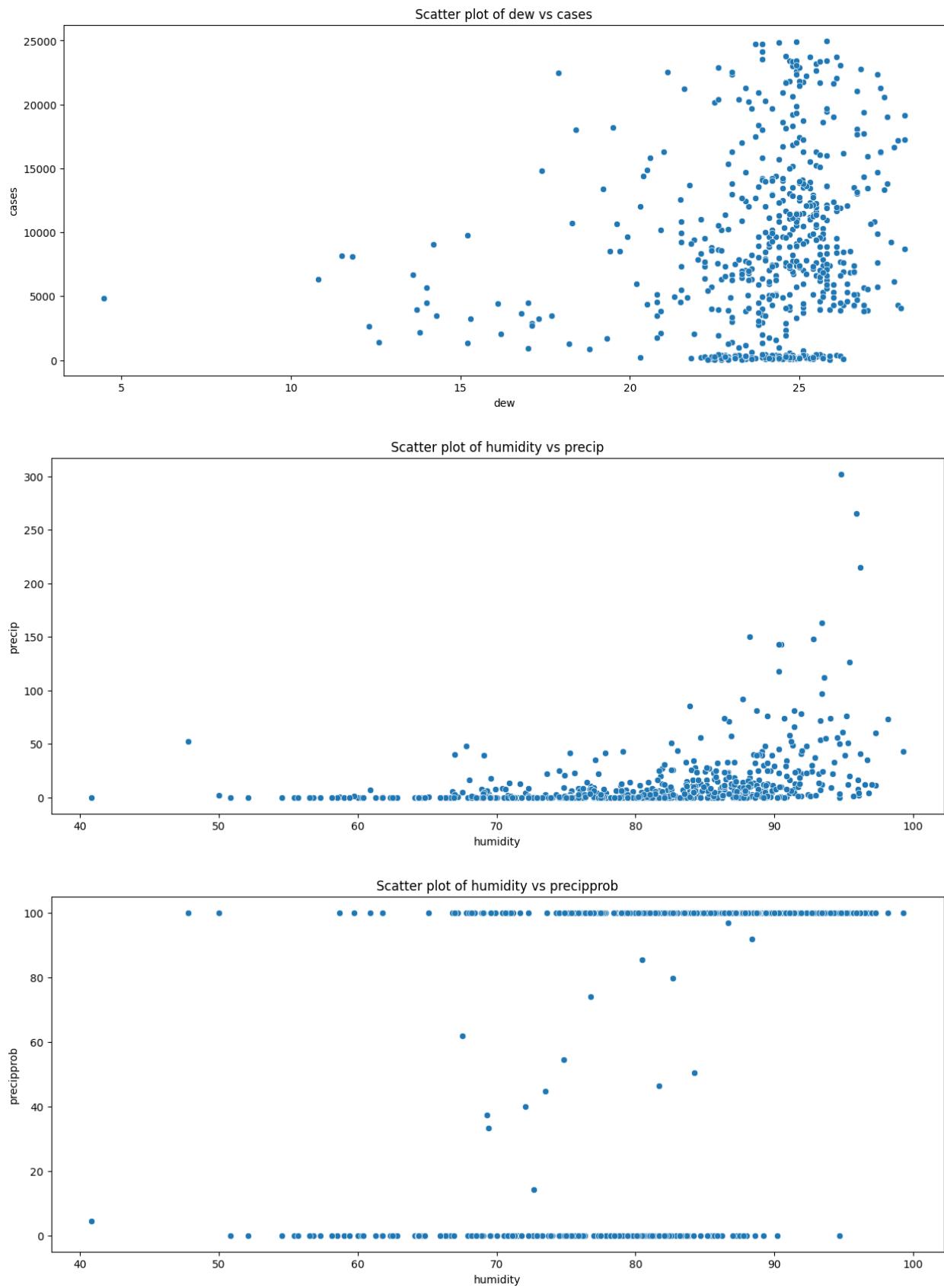


Scatter plot of dew vs cloudcover

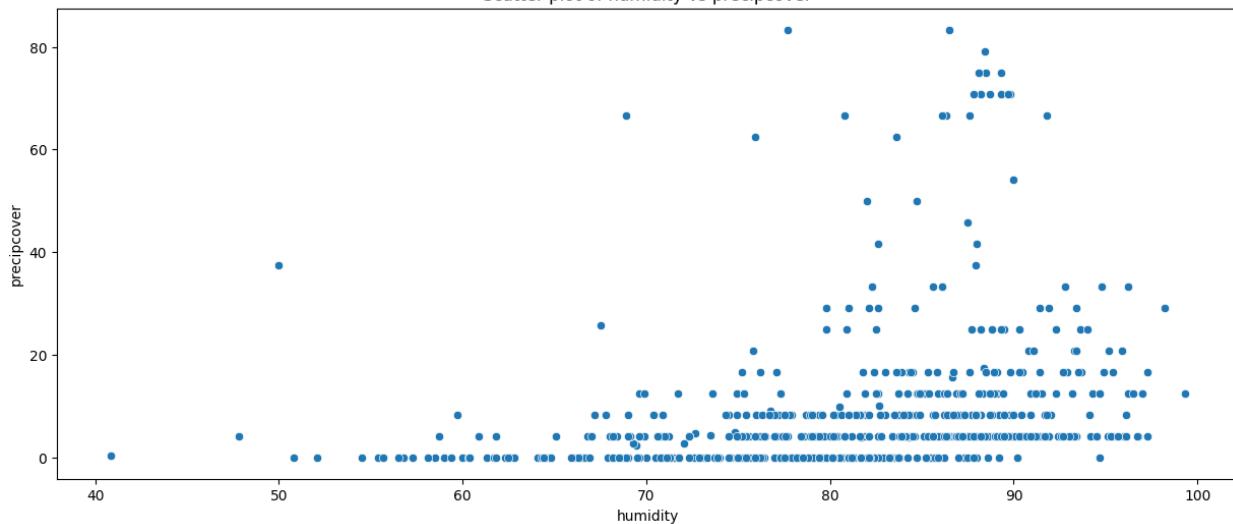




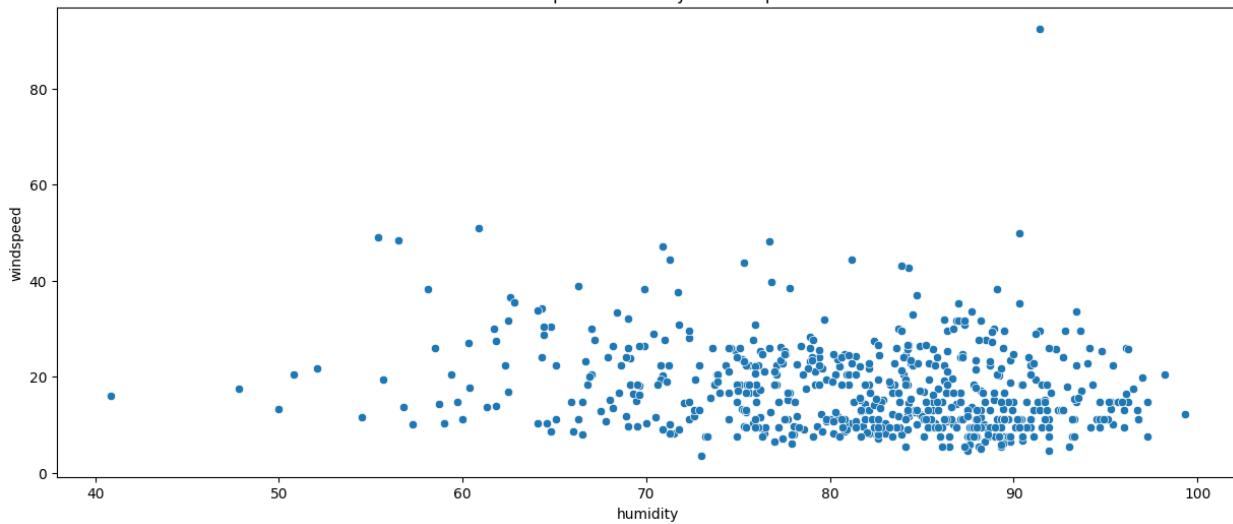




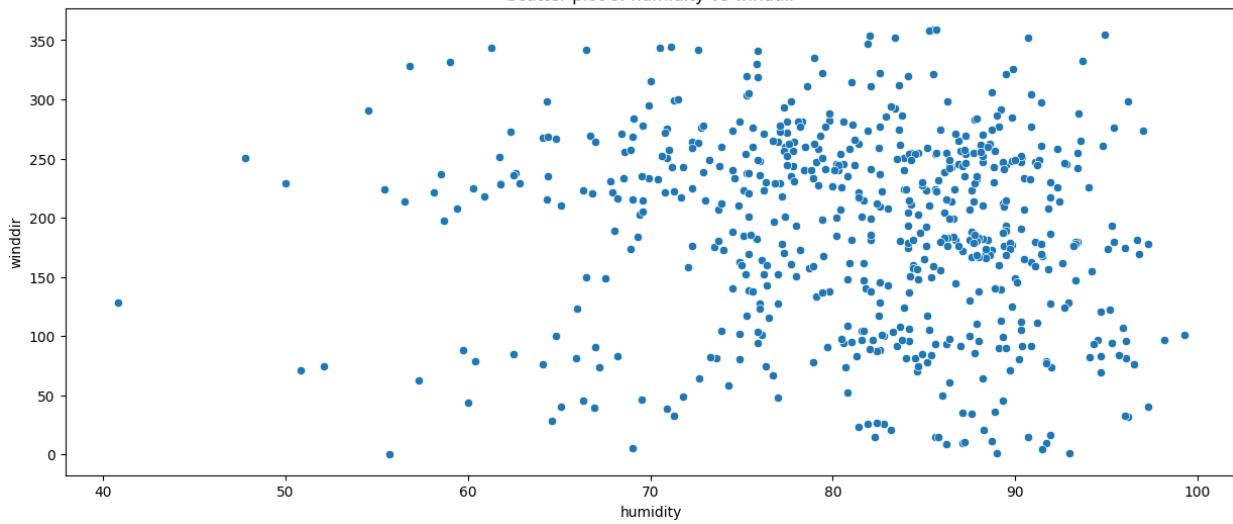
Scatter plot of humidity vs precipcover

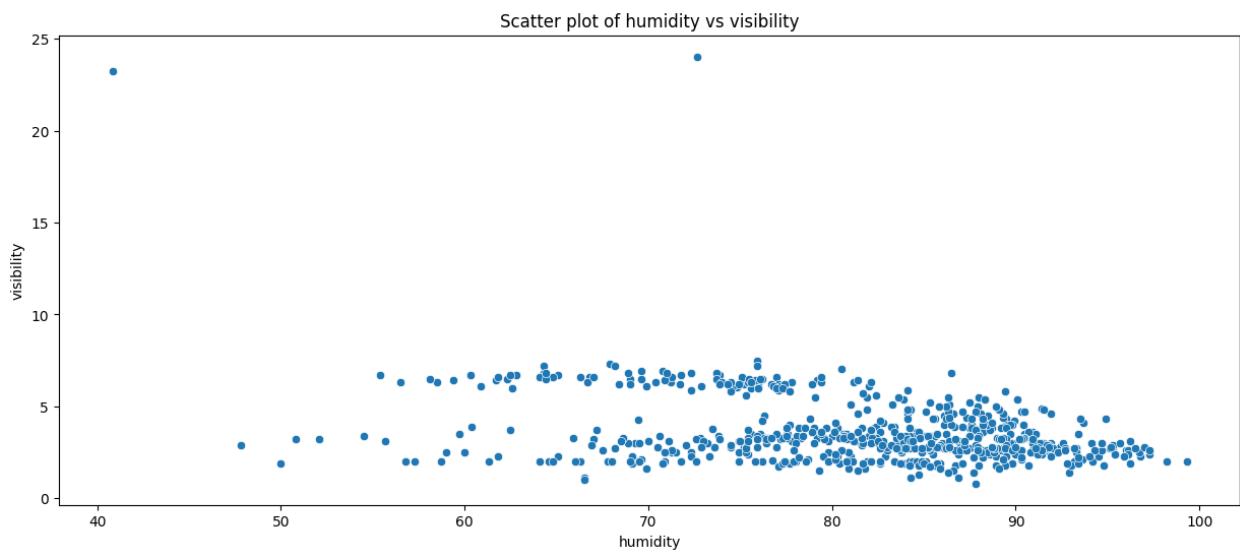
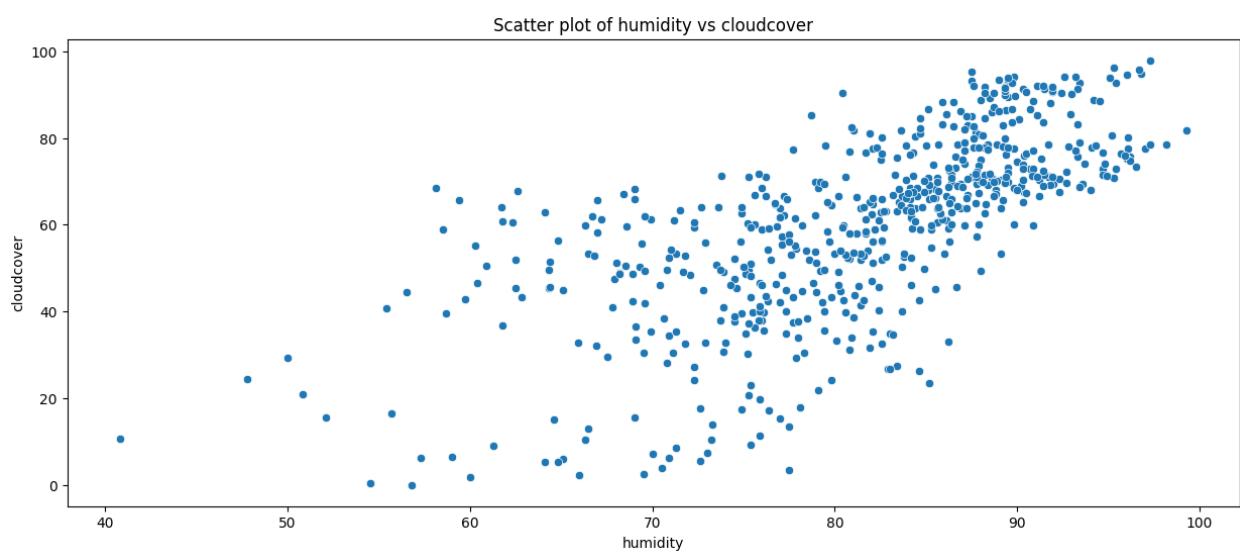
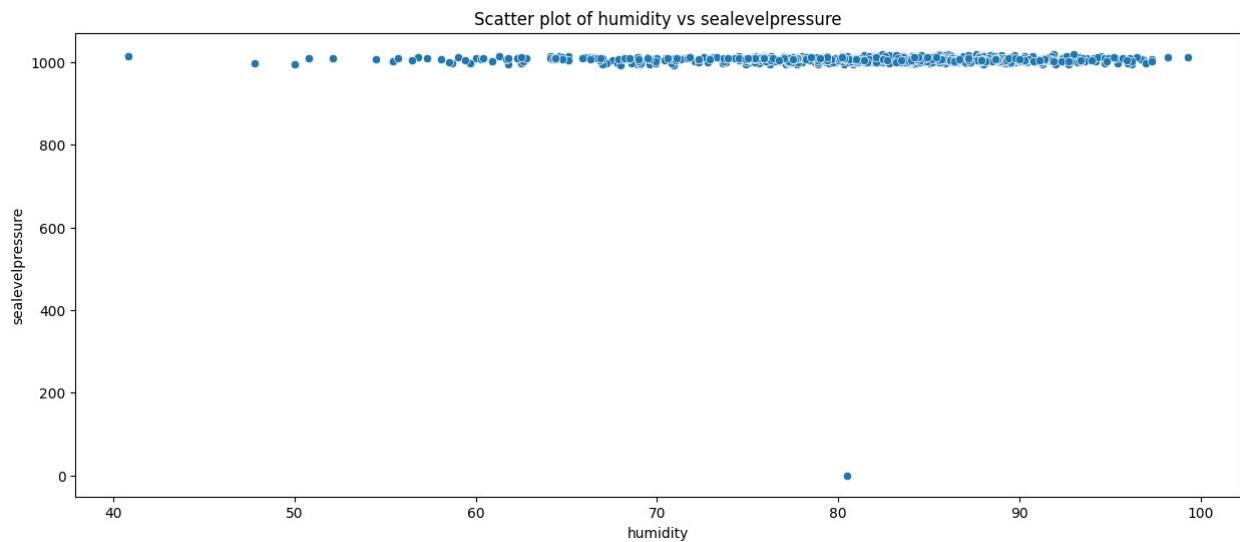


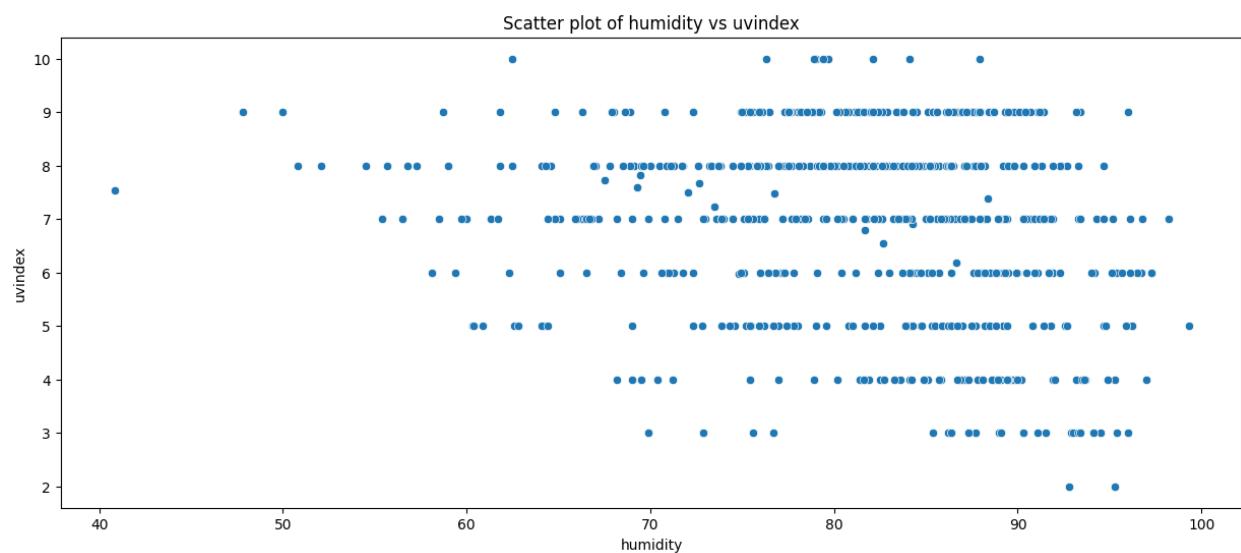
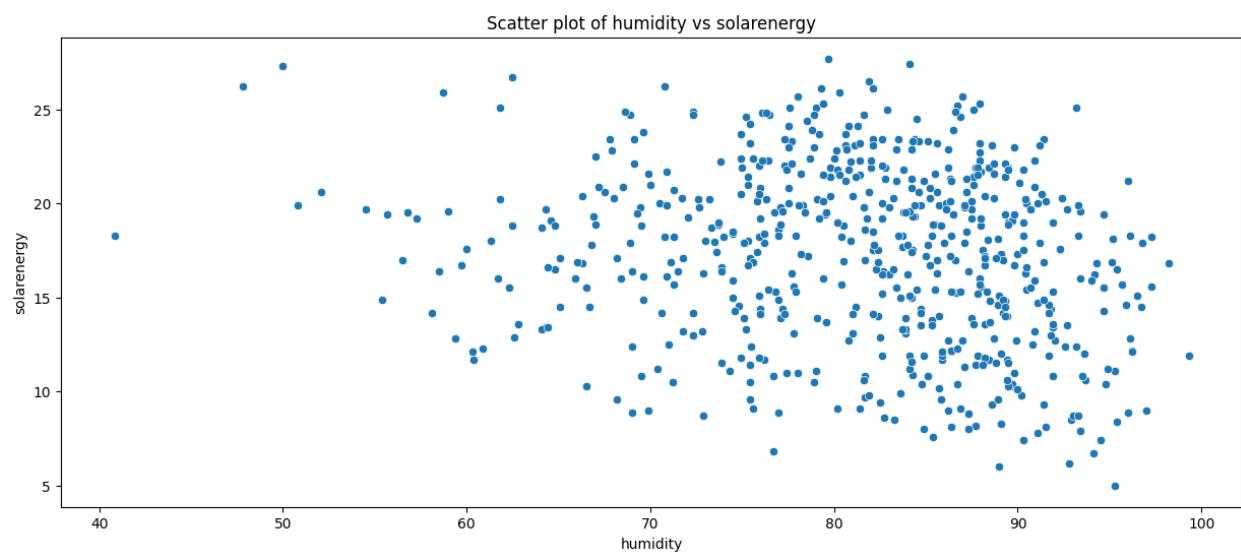
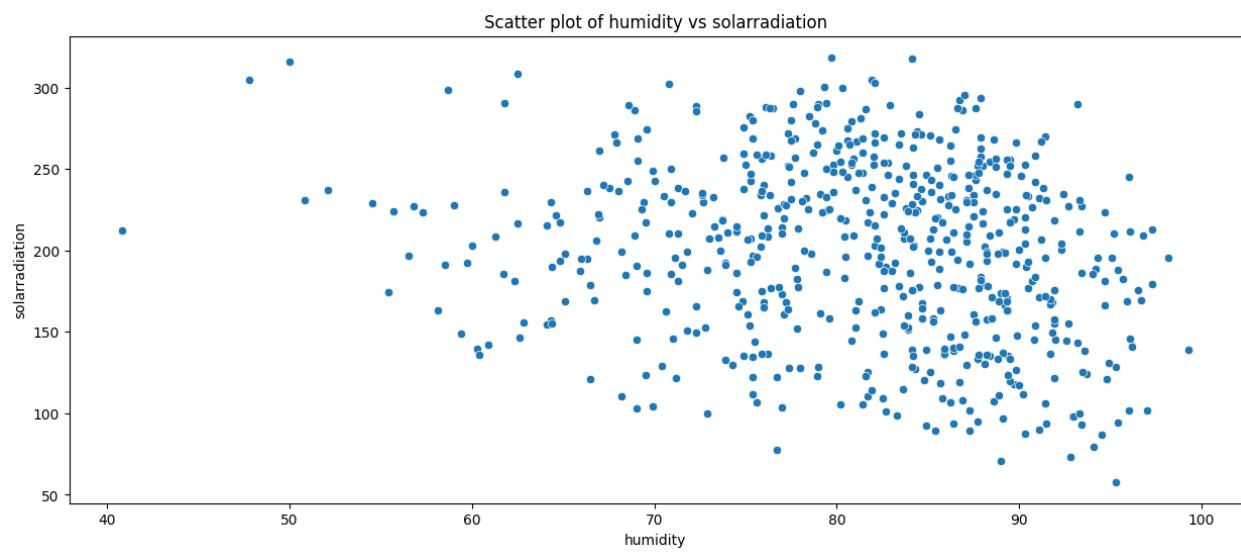
Scatter plot of humidity vs windspeed

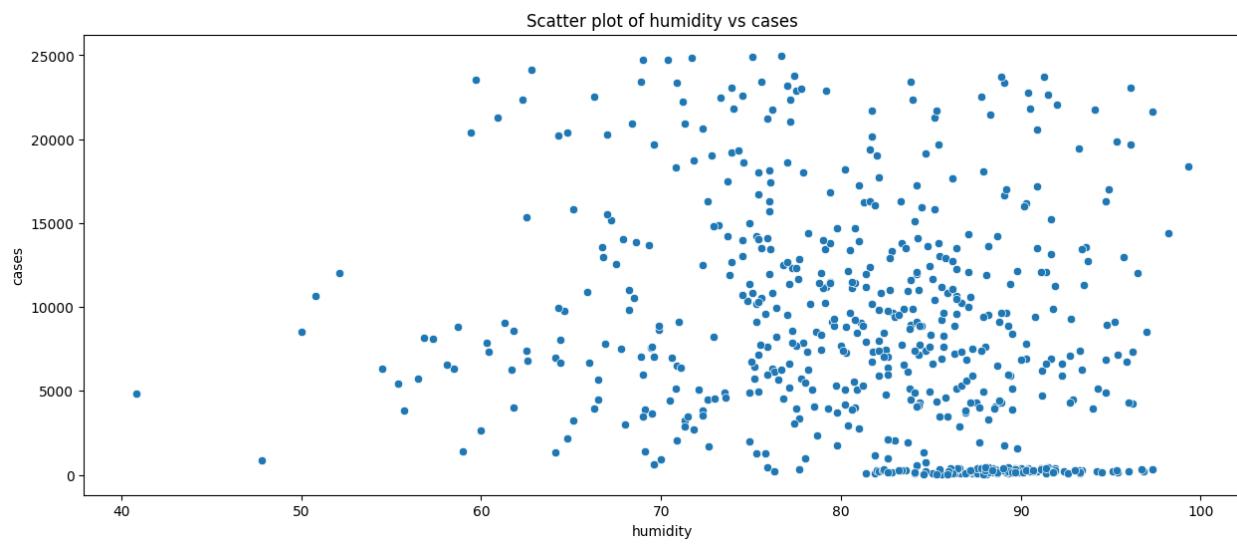
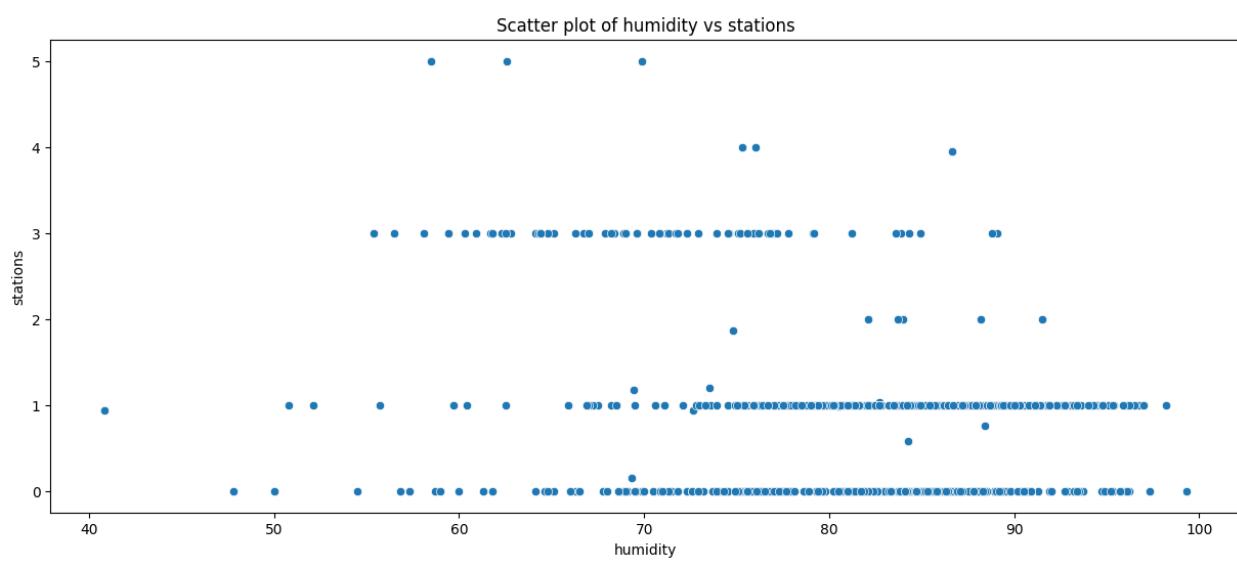
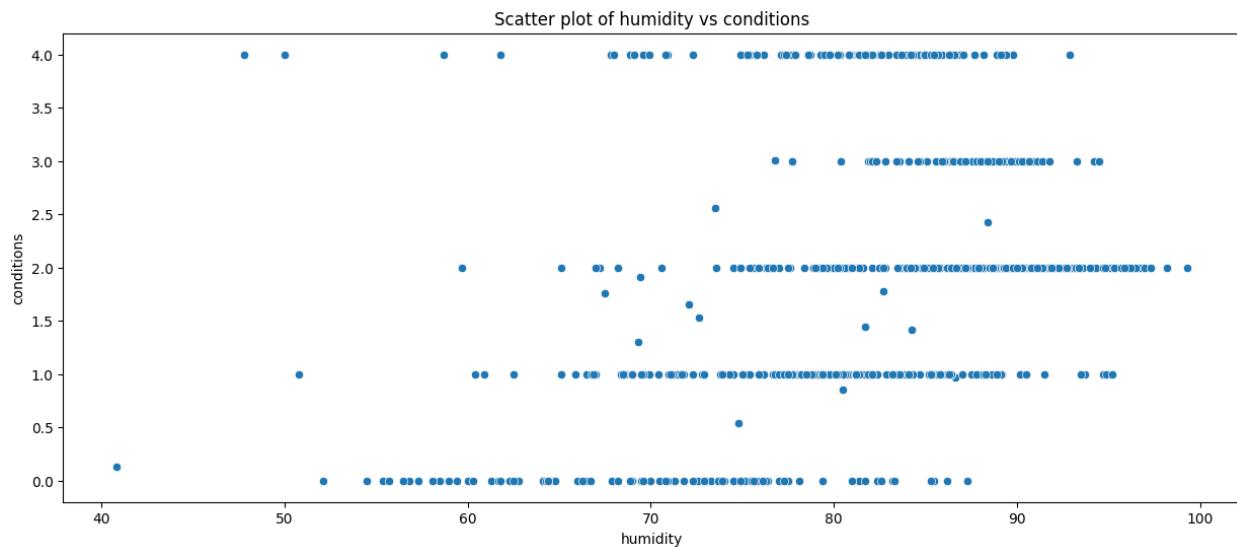


Scatter plot of humidity vs winddir

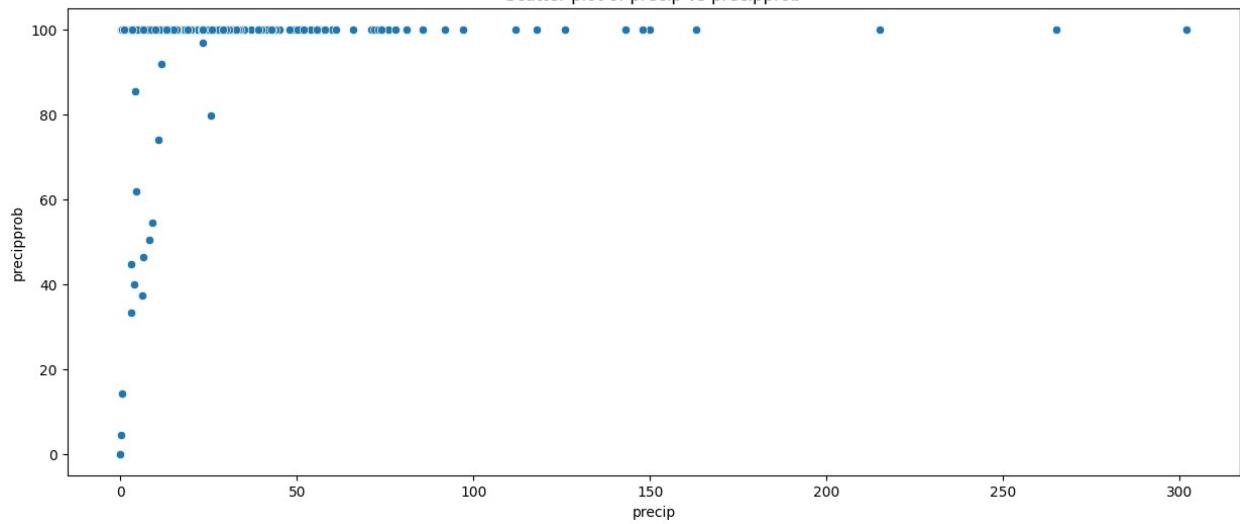




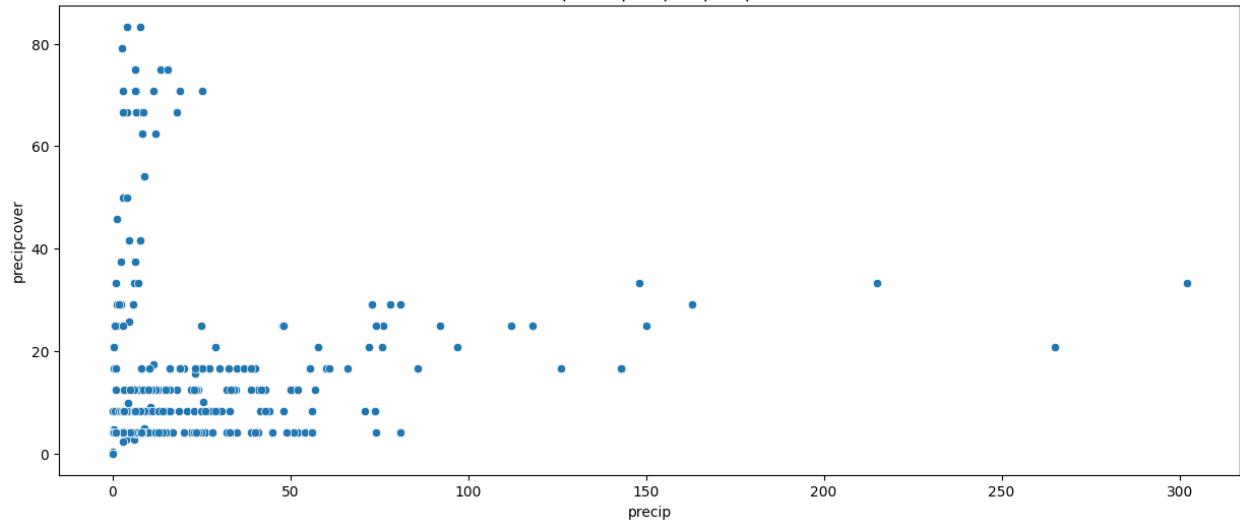




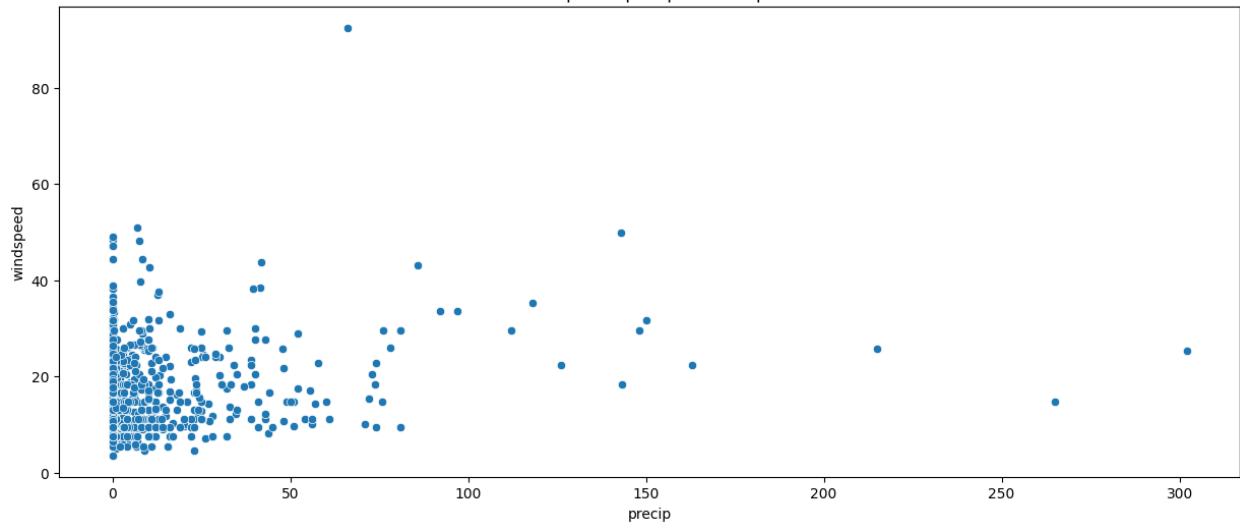
Scatter plot of precip vs precipprob



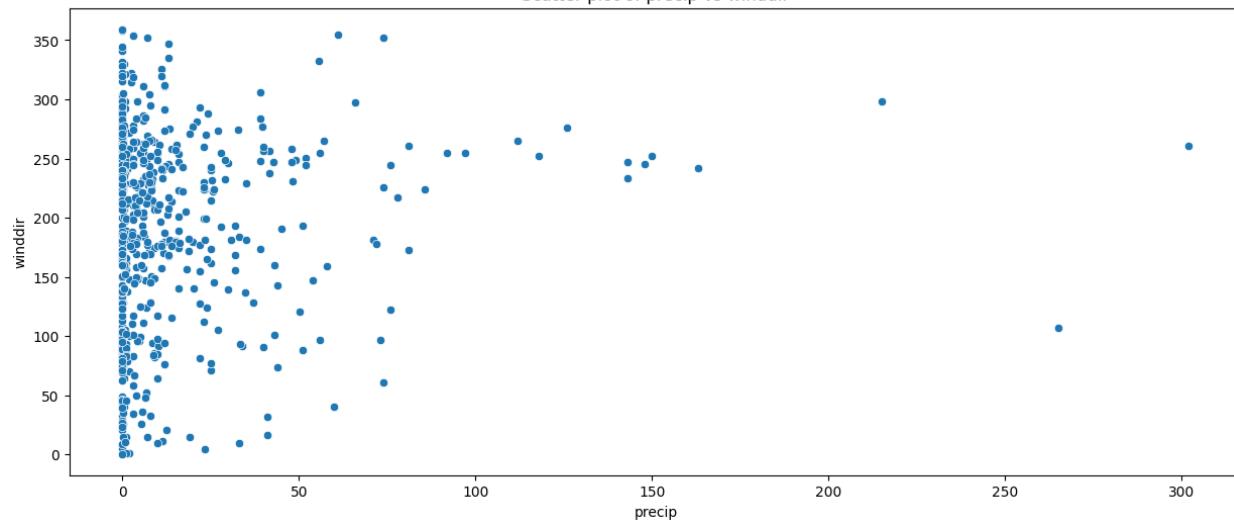
Scatter plot of precip vs precipcover



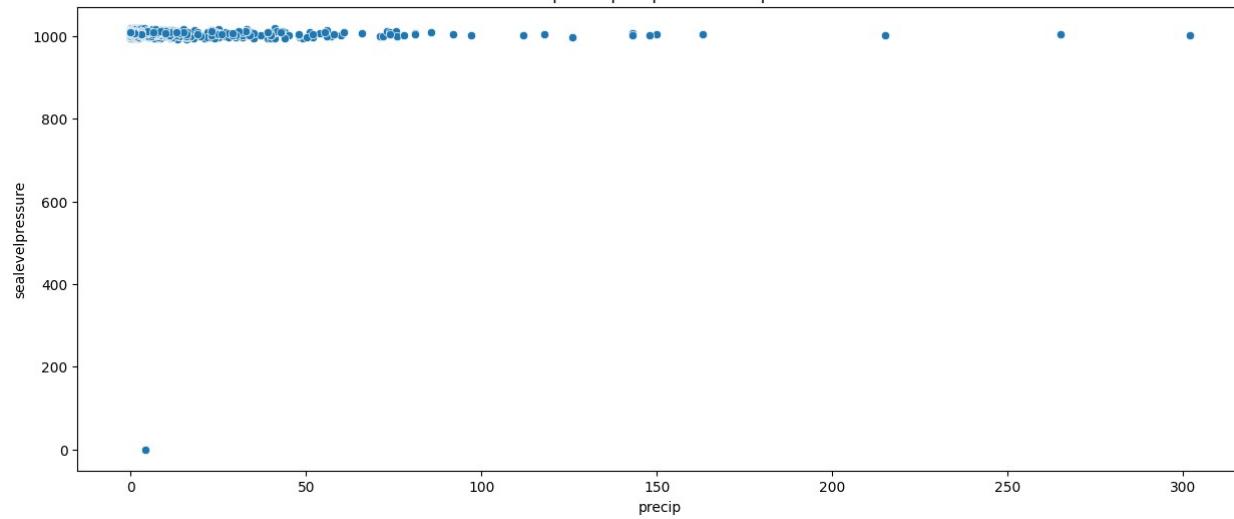
Scatter plot of precip vs windspeed



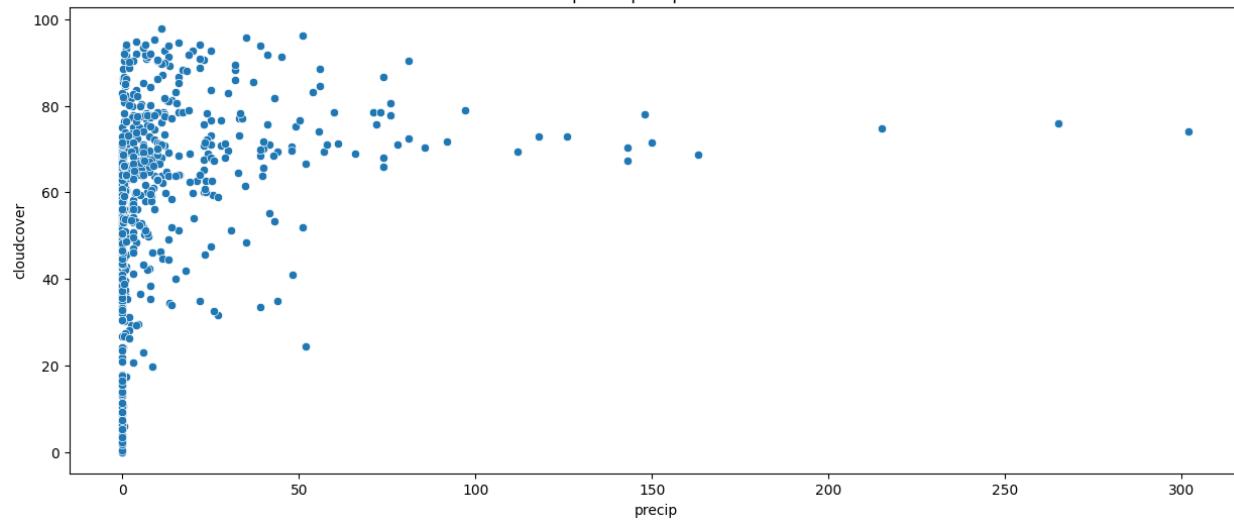
Scatter plot of precip vs winddir



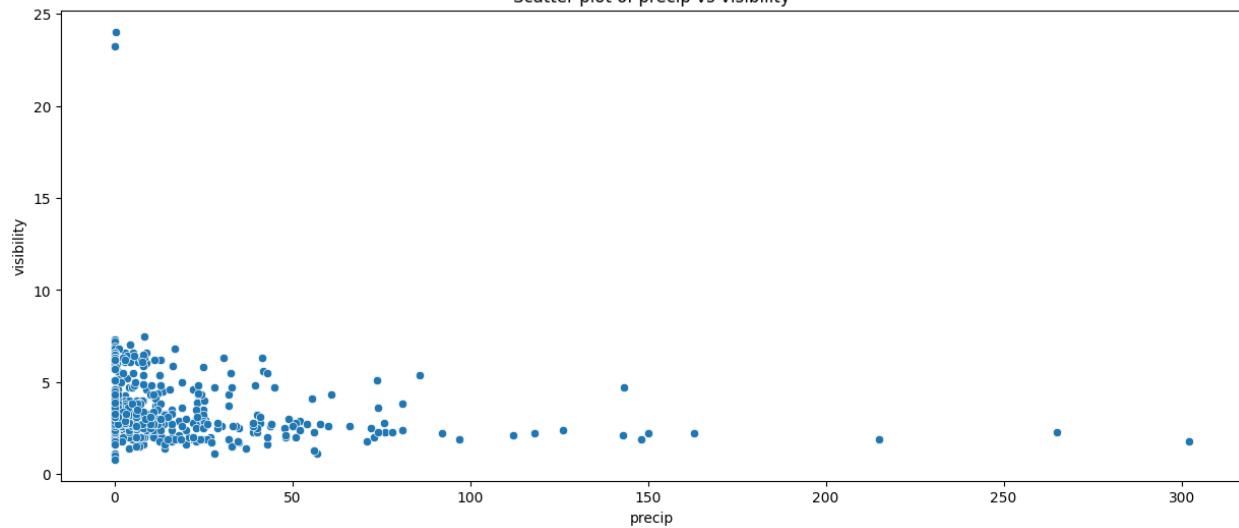
Scatter plot of precip vs sealevelpressure



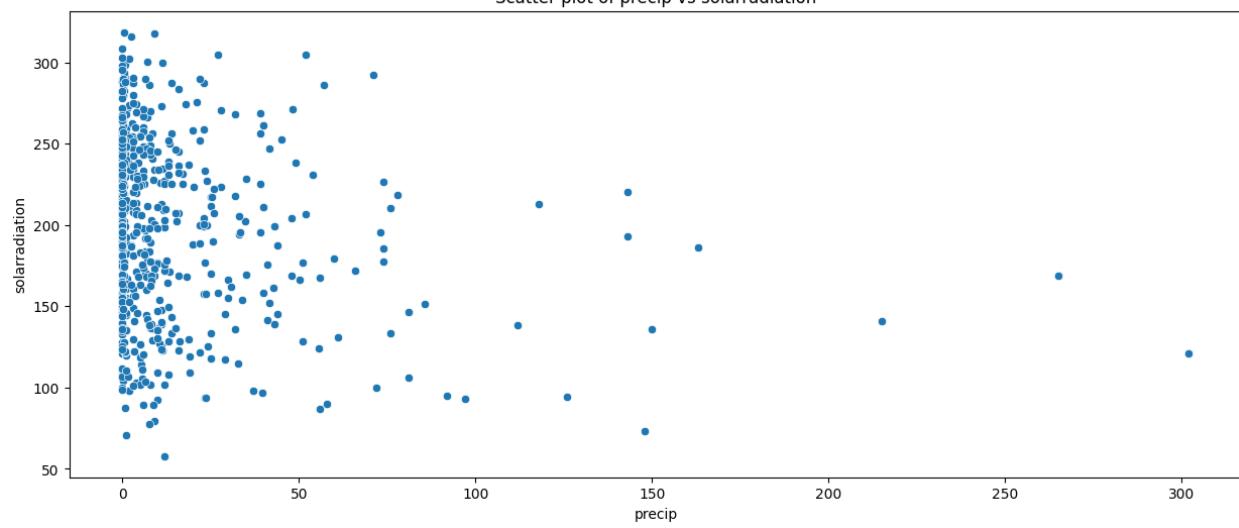
Scatter plot of precip vs cloudcover



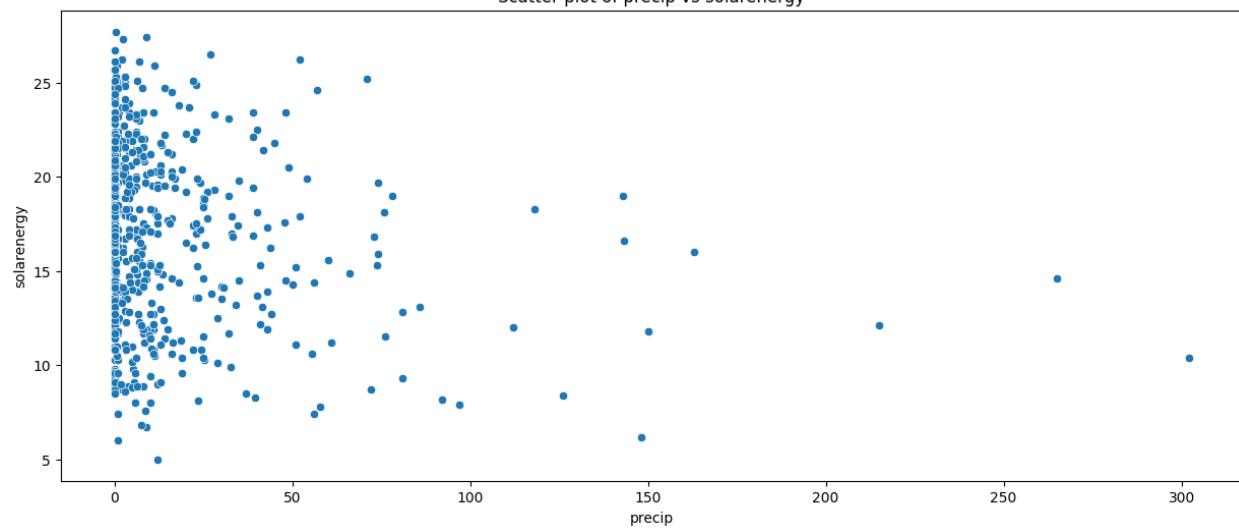
Scatter plot of precip vs visibility



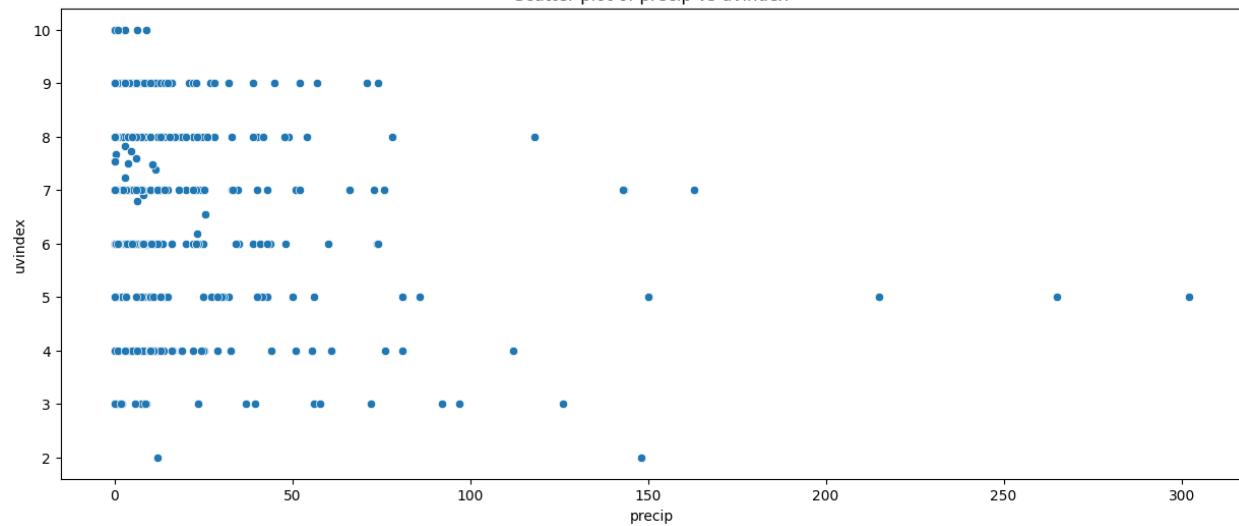
Scatter plot of precip vs solarradiation



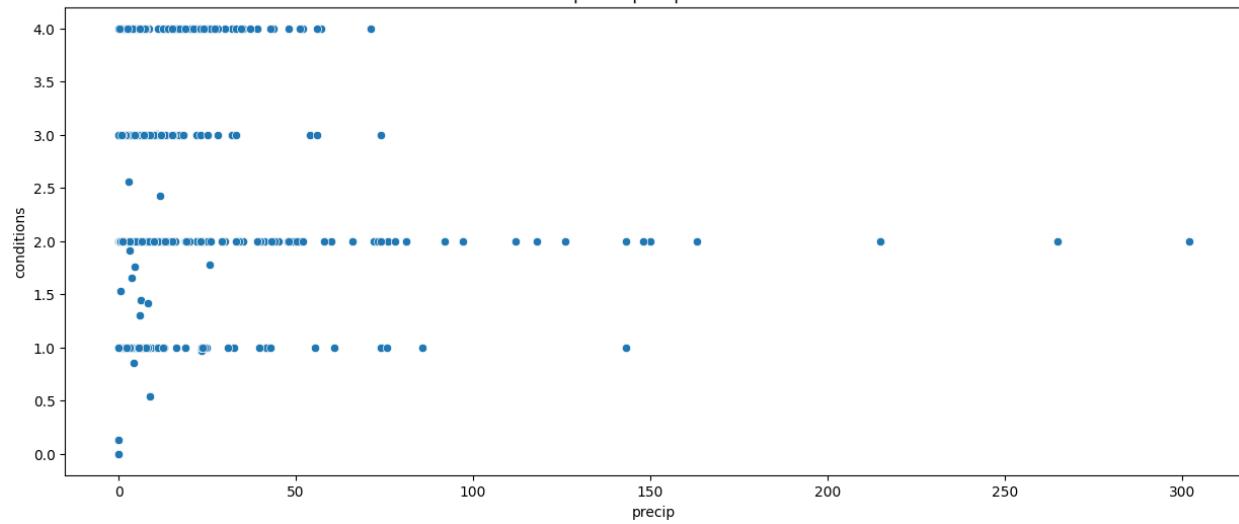
Scatter plot of precip vs solarenergy



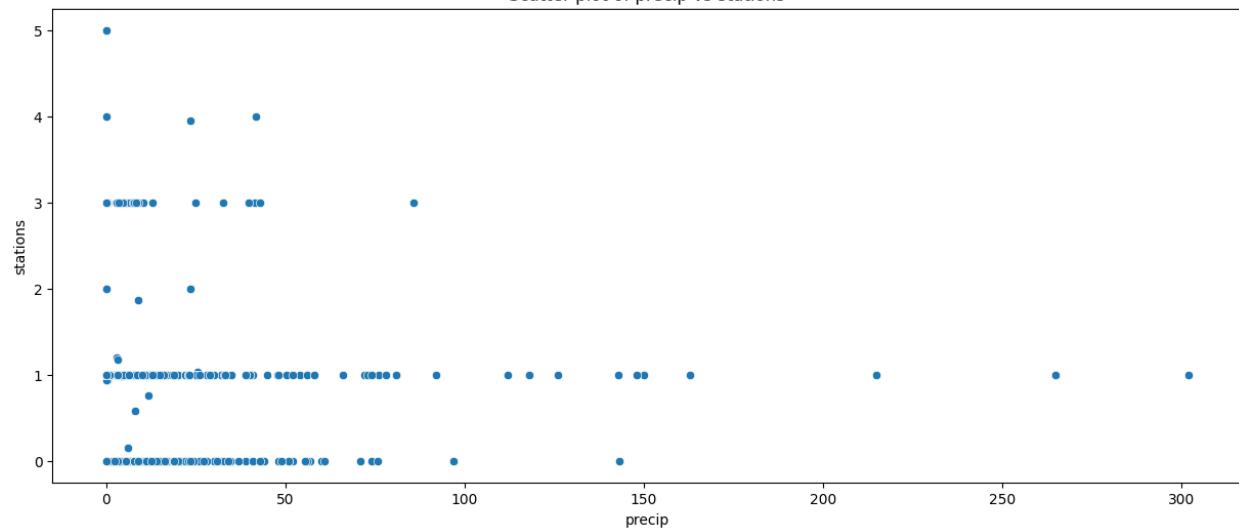
Scatter plot of precip vs uvindex

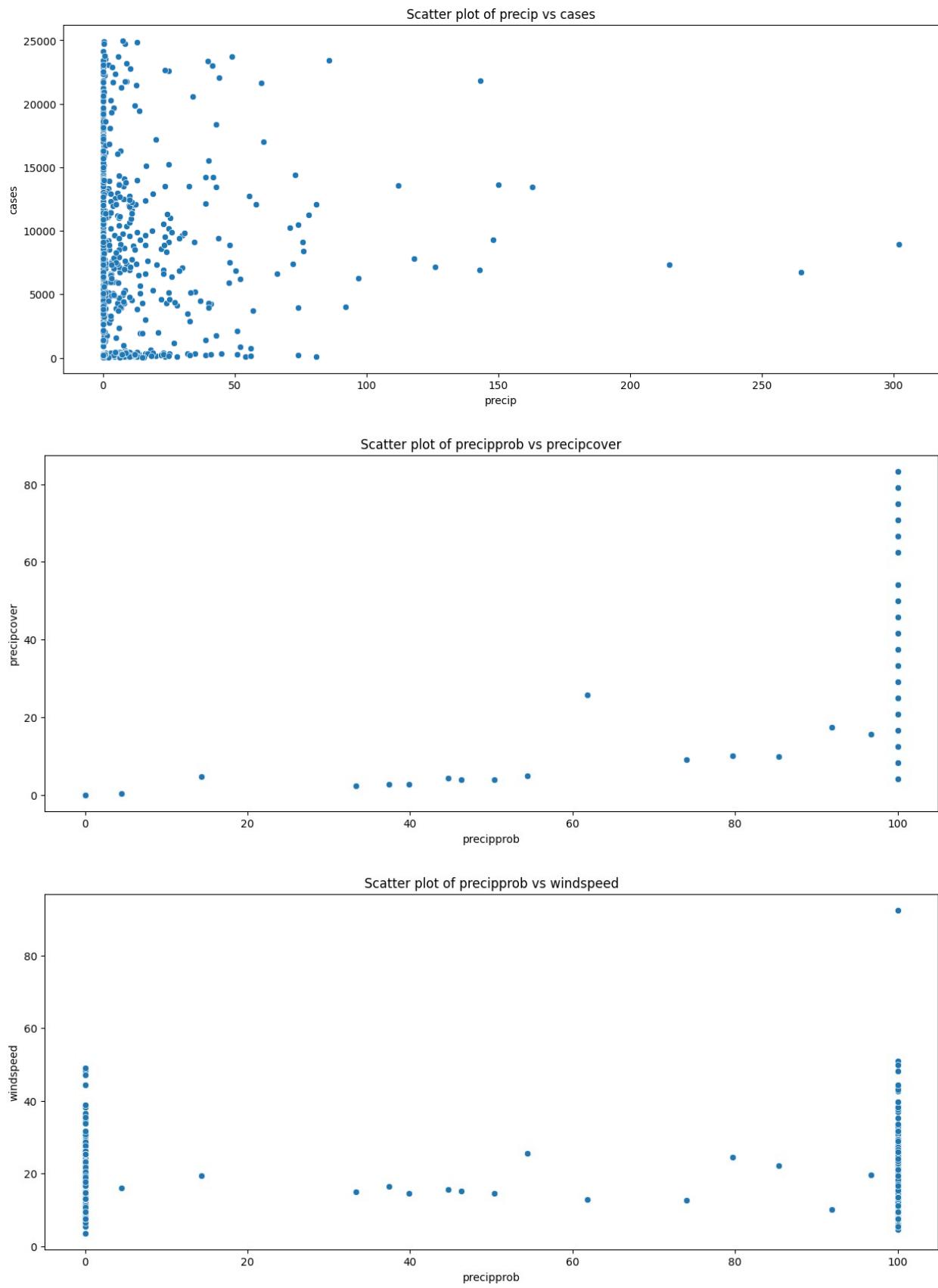


Scatter plot of precip vs conditions

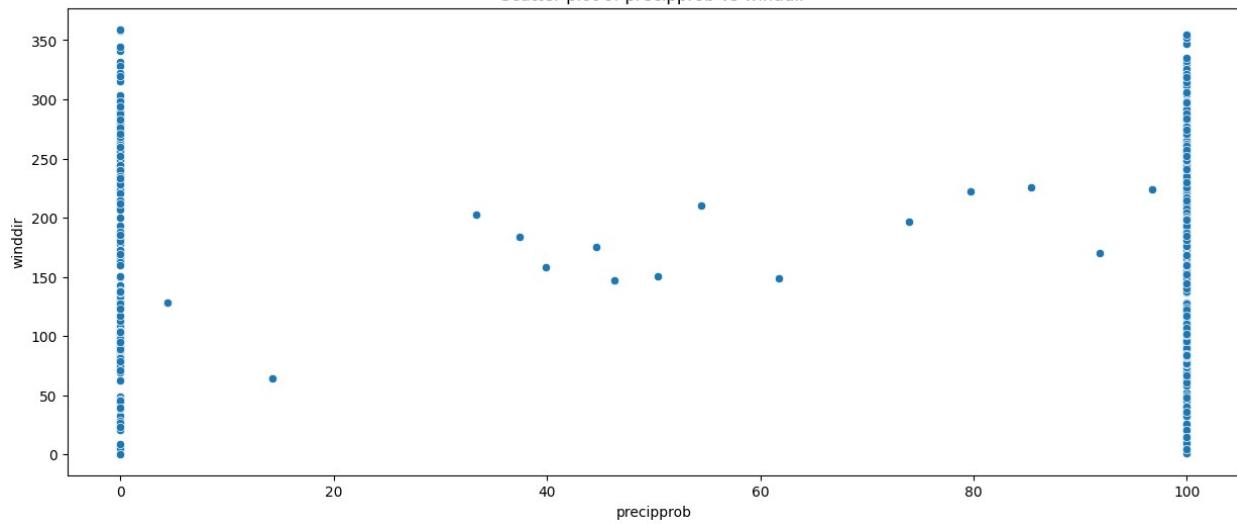


Scatter plot of precip vs stations

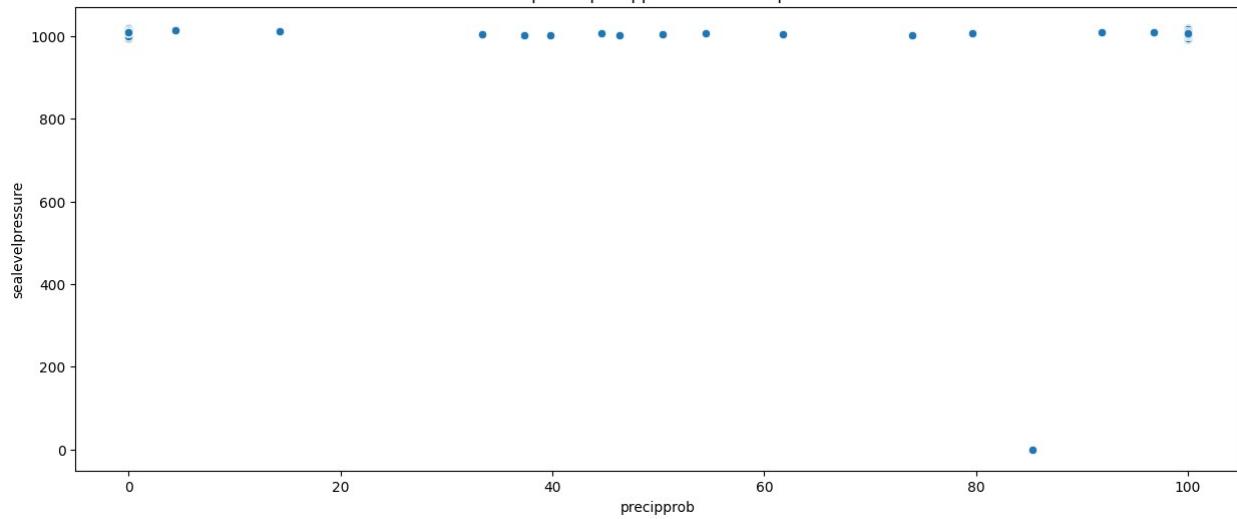




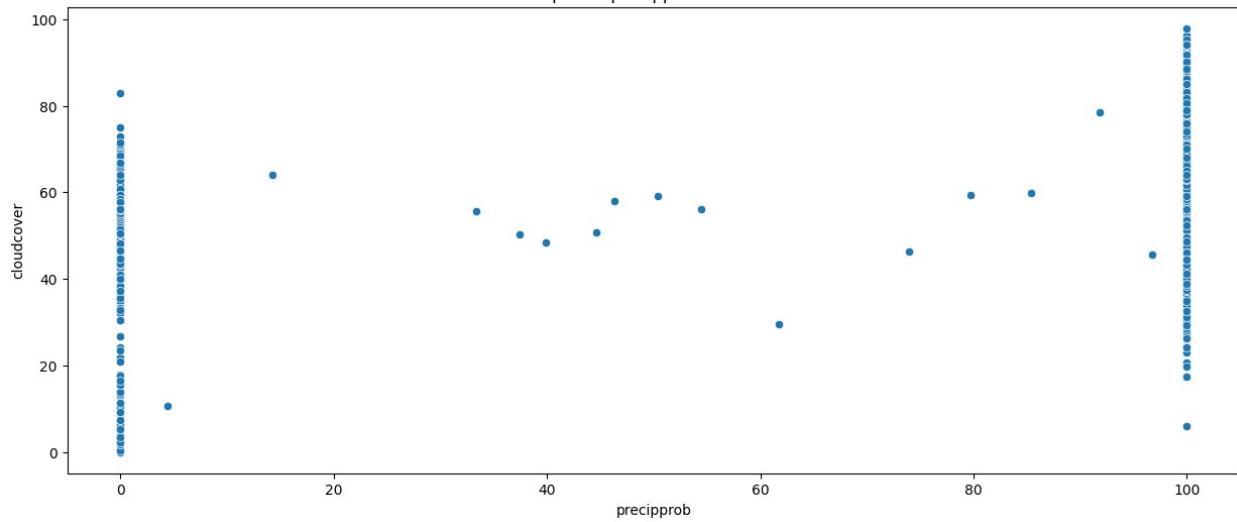
Scatter plot of precipprob vs winddir

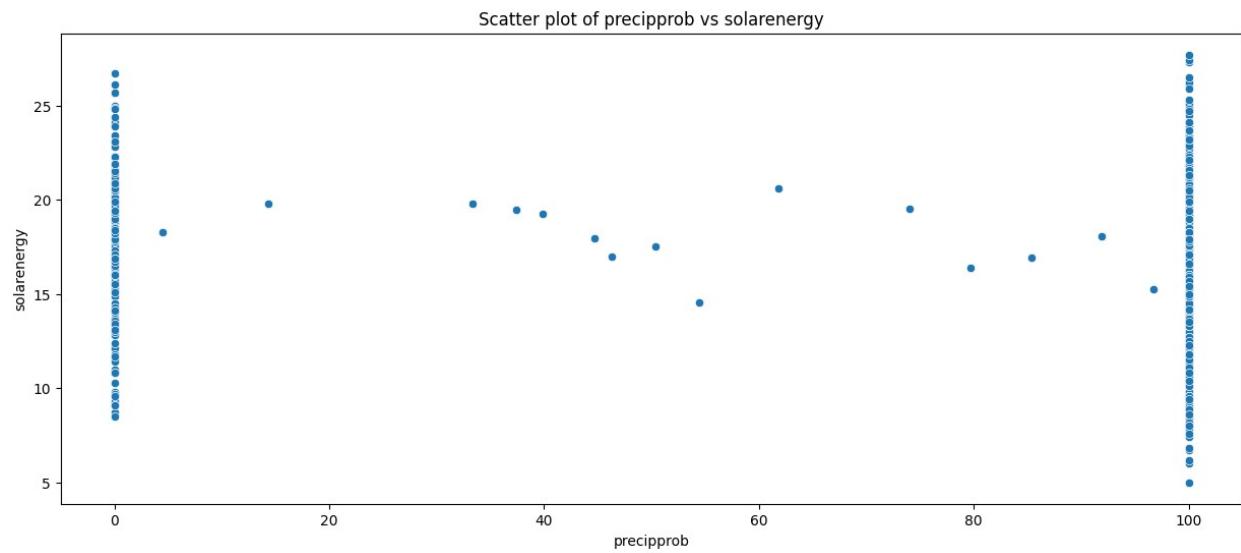
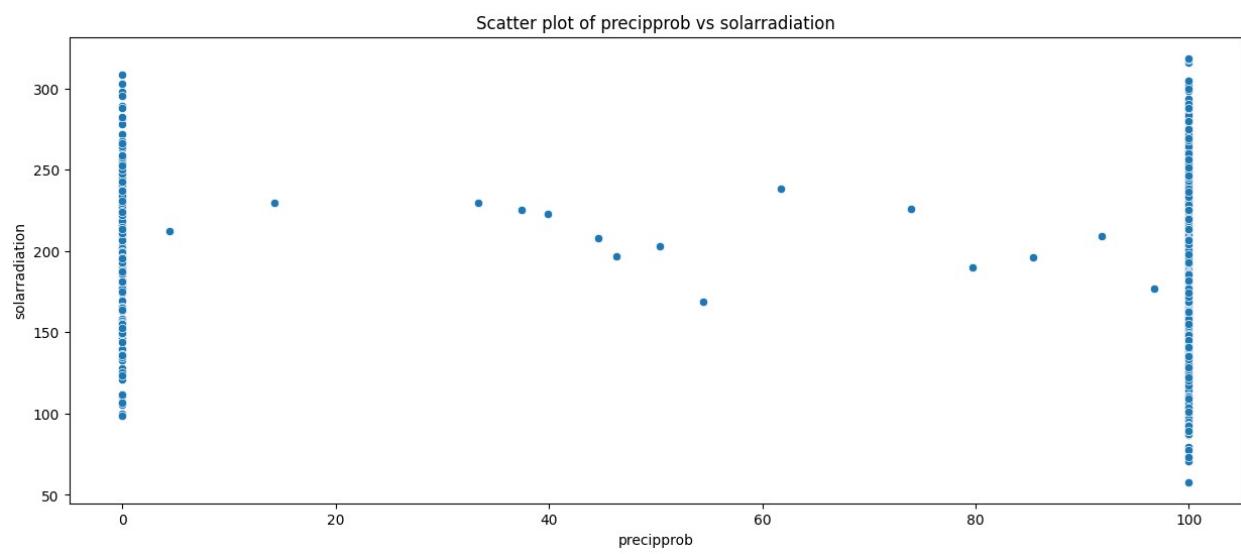
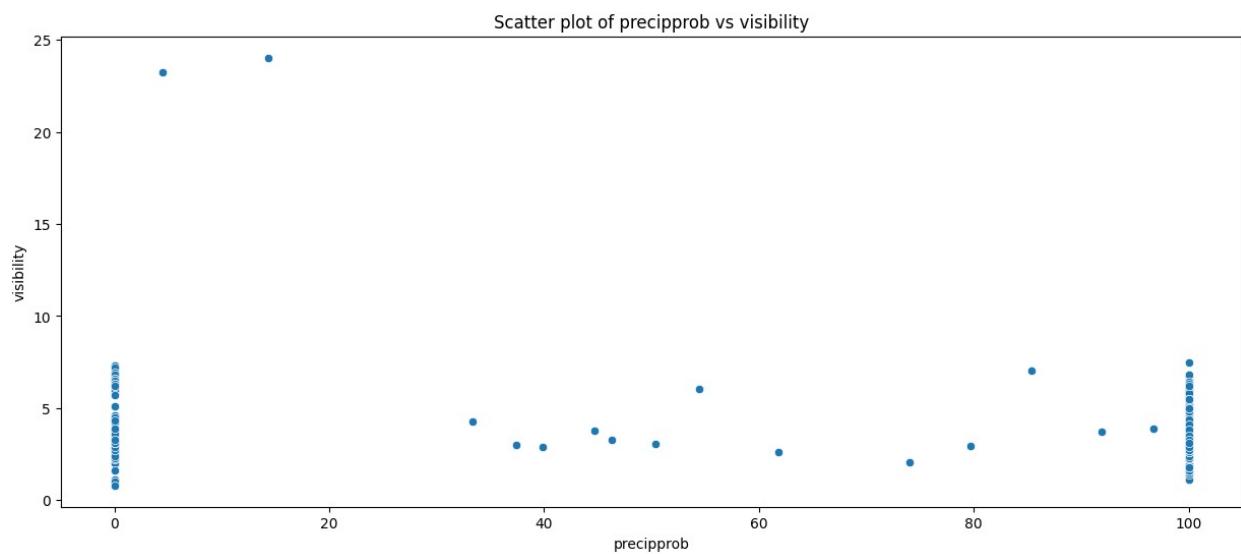


Scatter plot of precipprob vs sealevelpressure

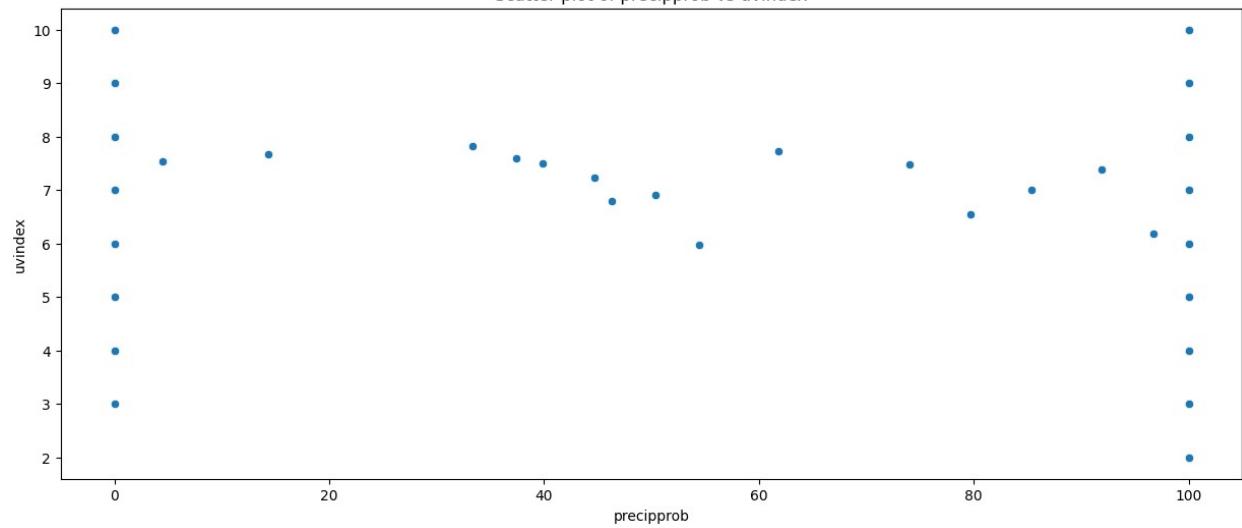


Scatter plot of precipprob vs cloudcover

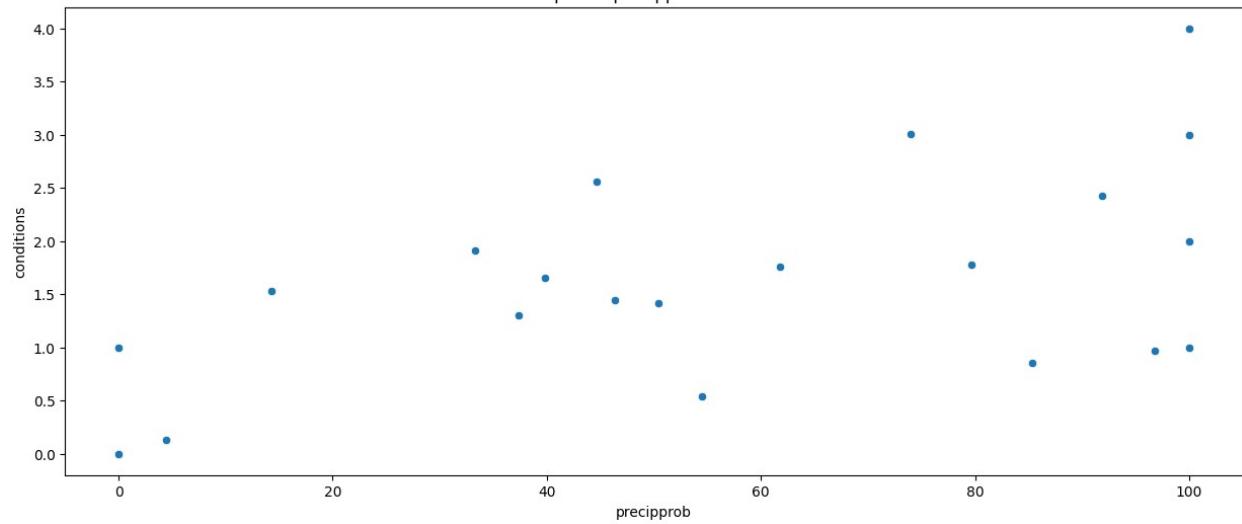




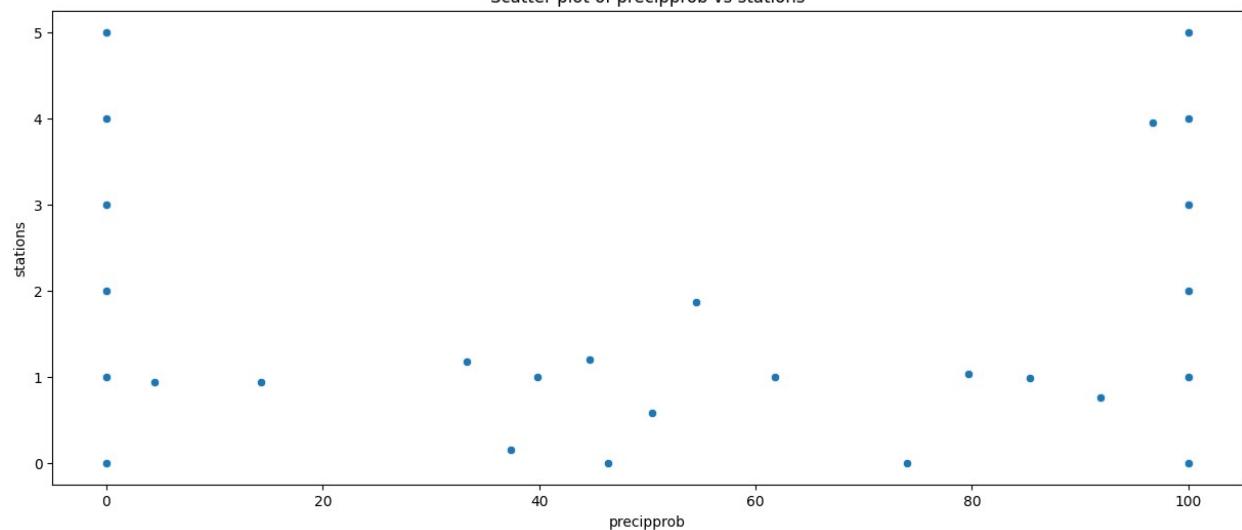
Scatter plot of precipprob vs uvindex

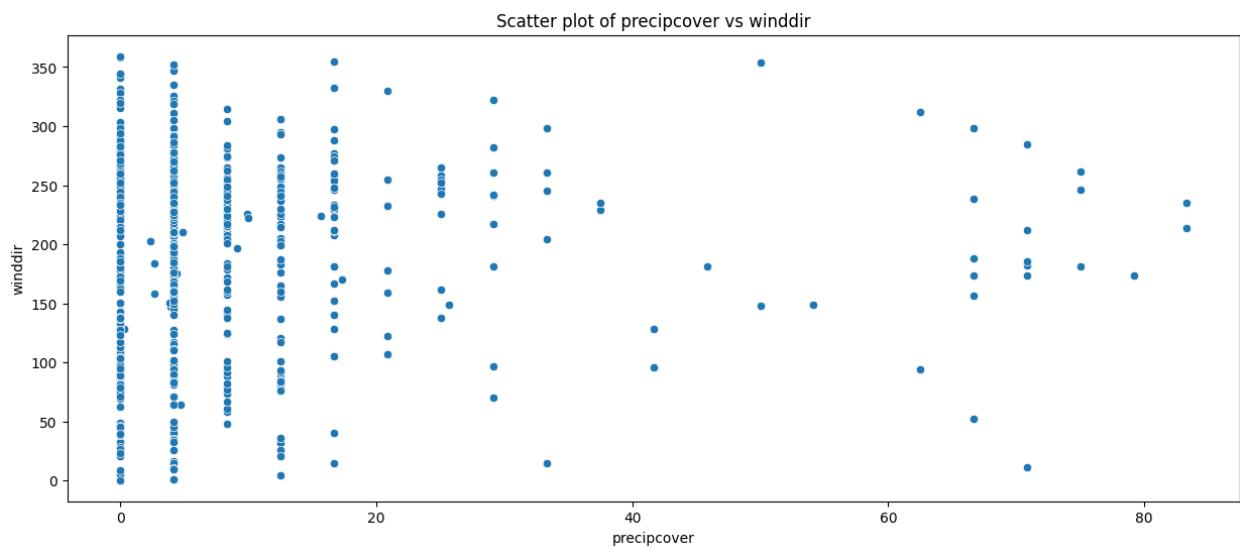
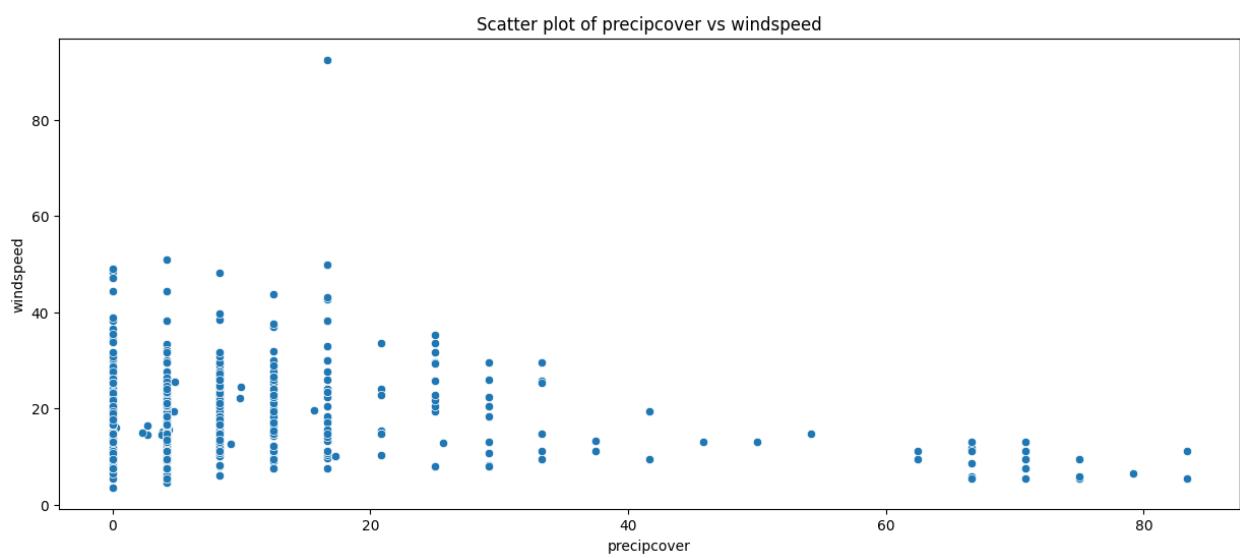
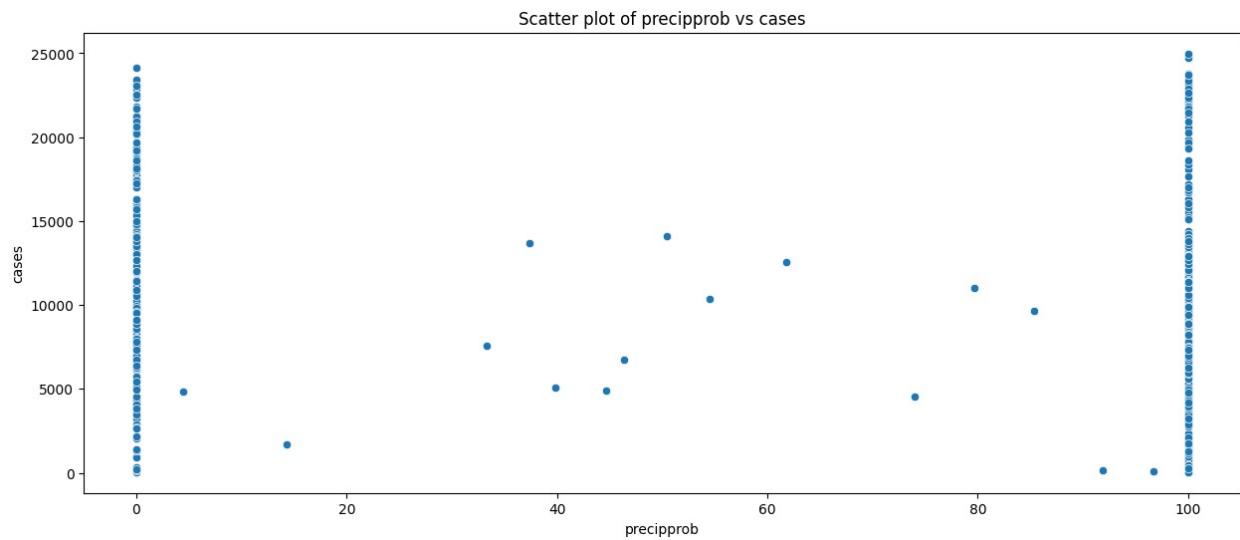


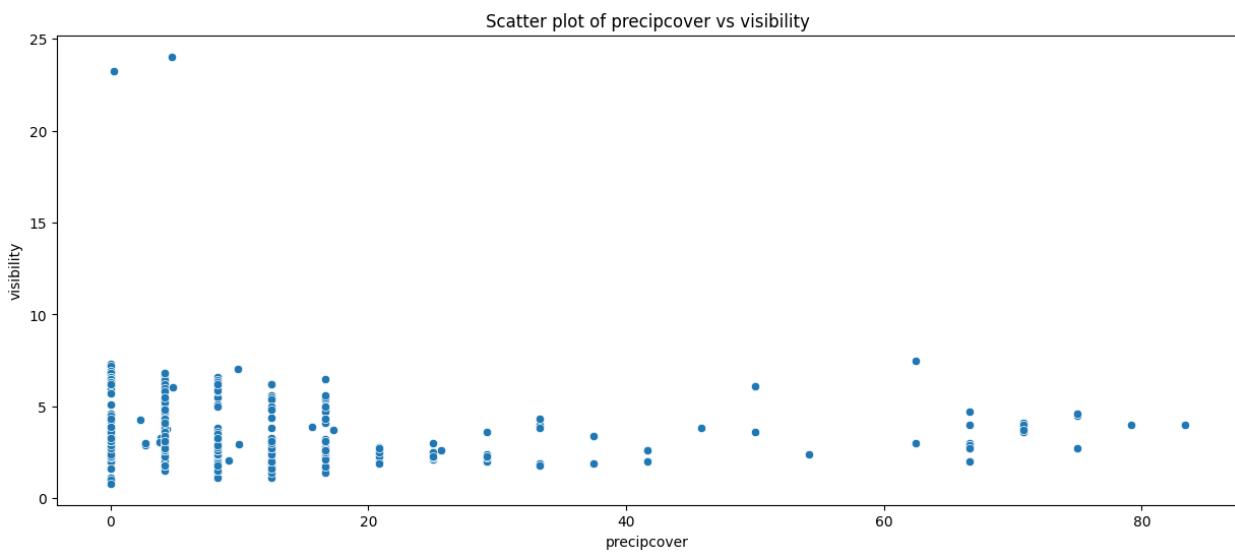
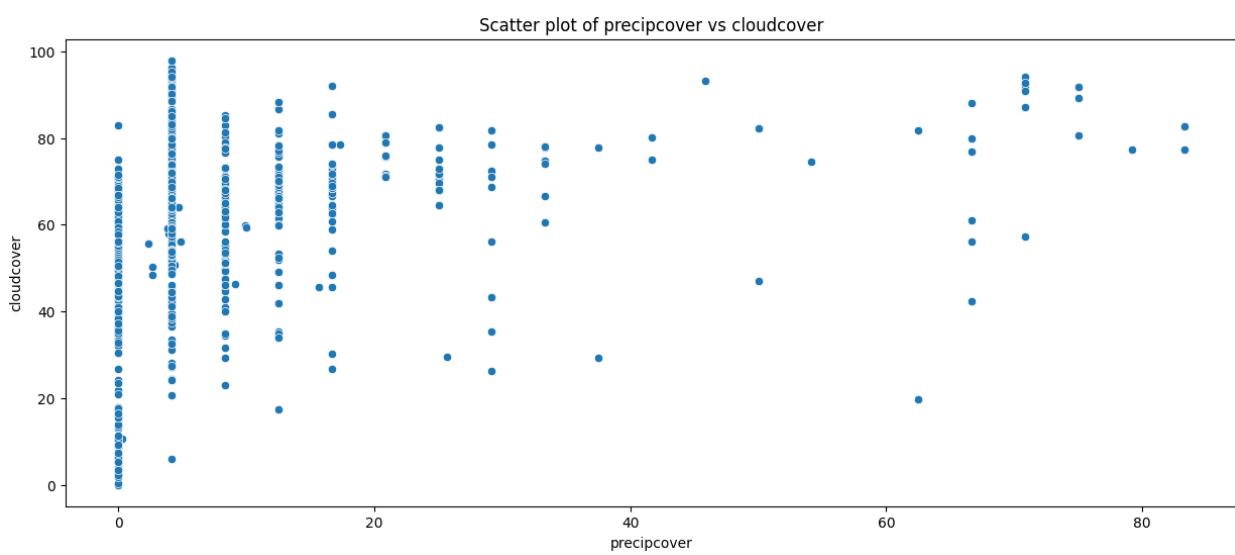
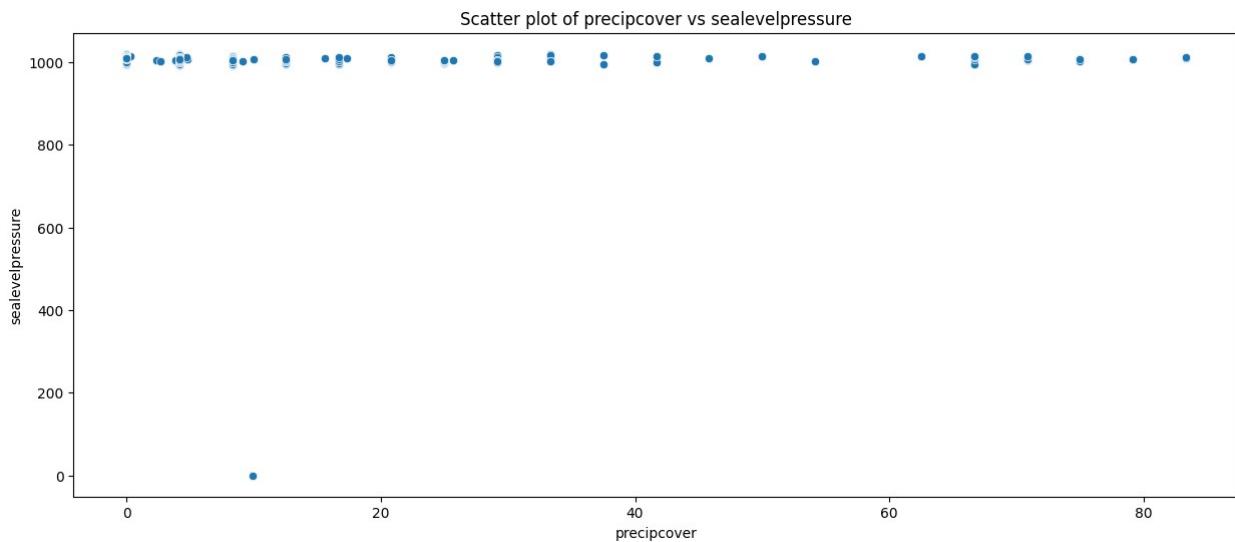
Scatter plot of precipprob vs conditions



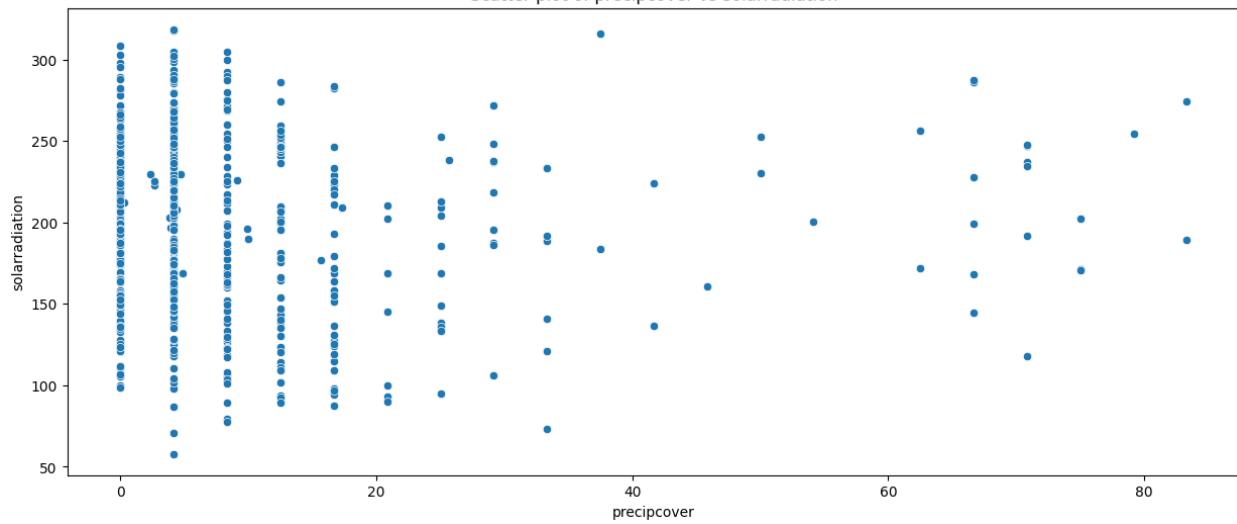
Scatter plot of precipprob vs stations



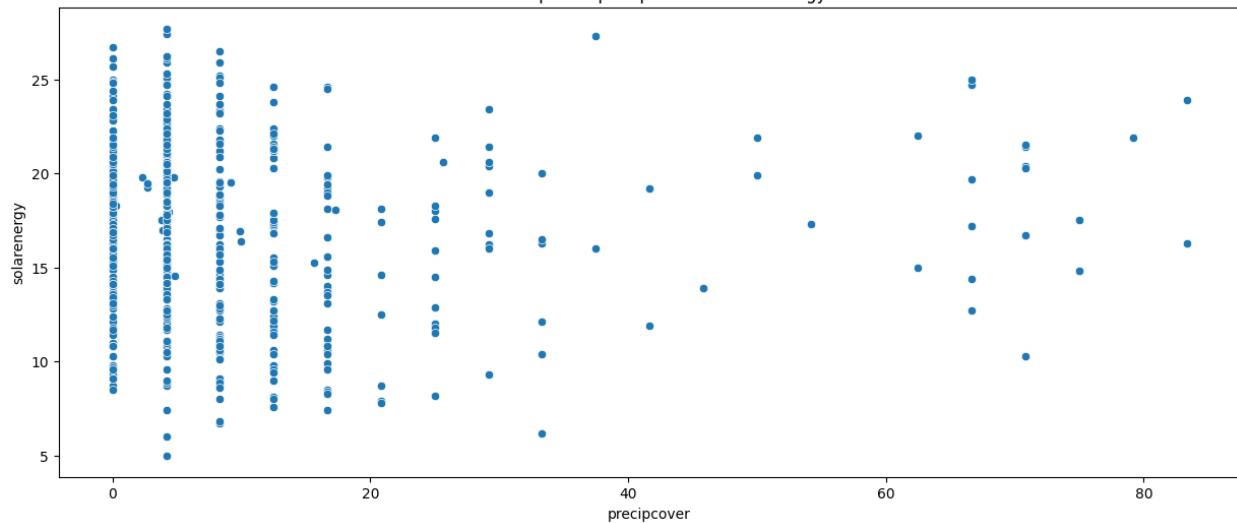




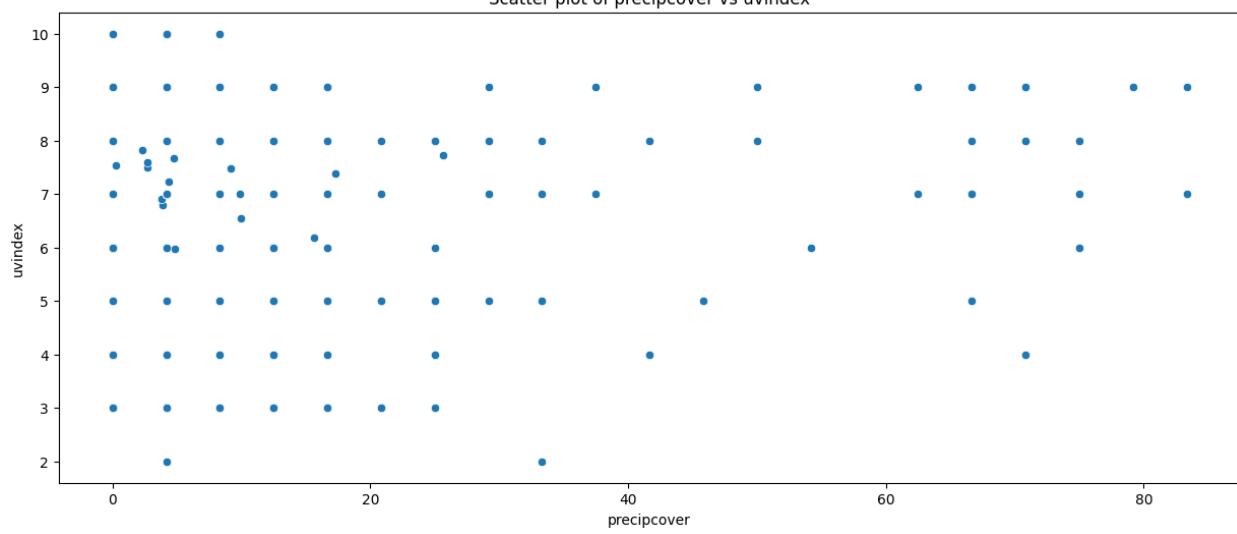
Scatter plot of precipcover vs solarradiation

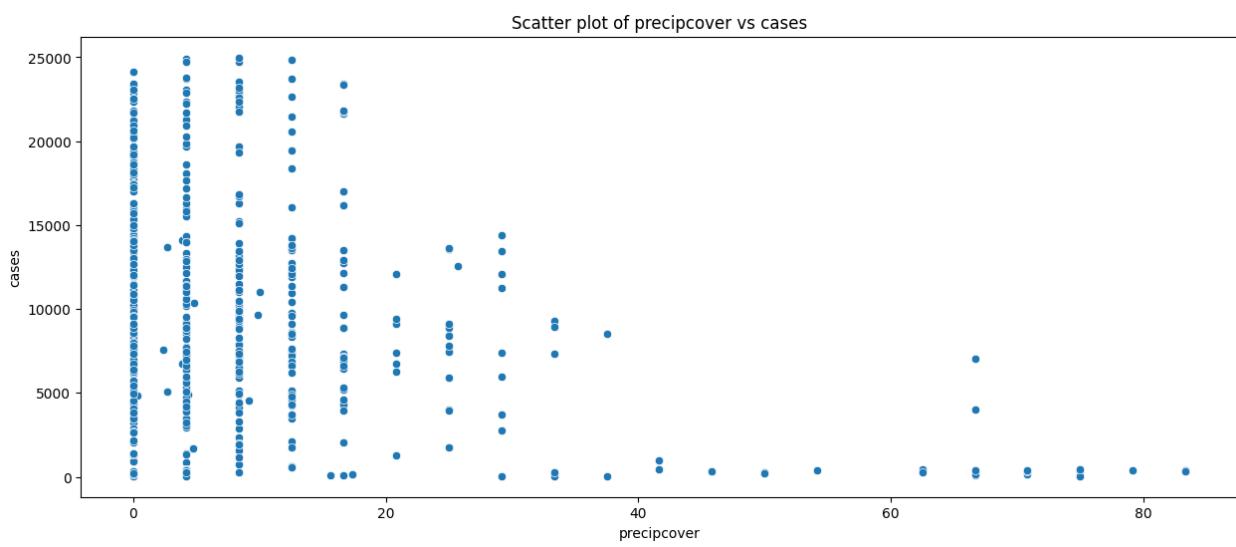
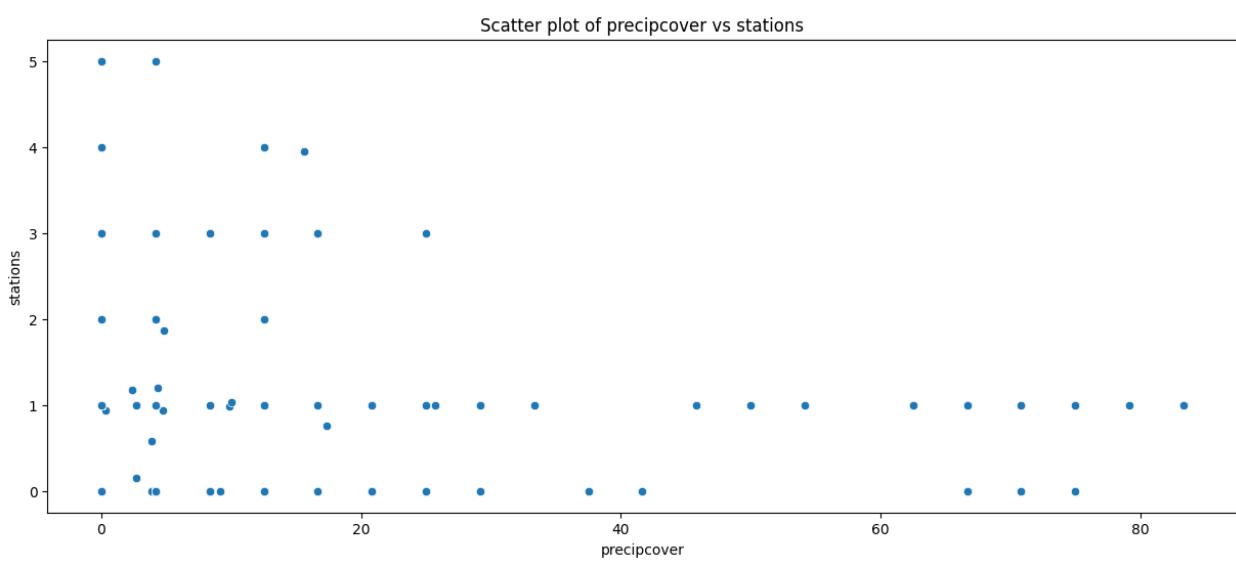
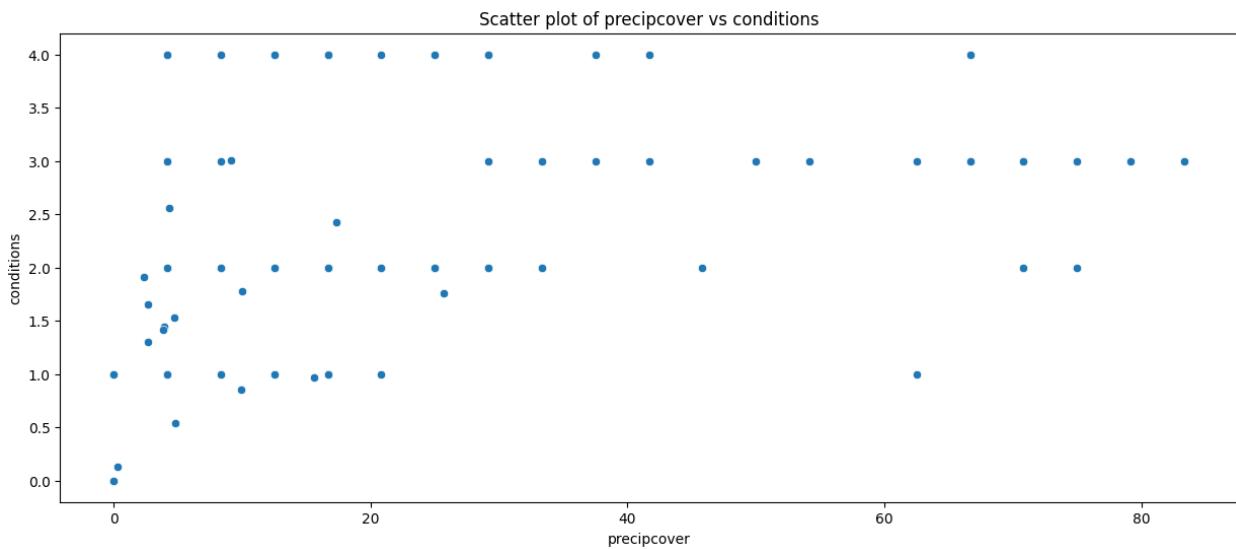


Scatter plot of precipcover vs solarenergy

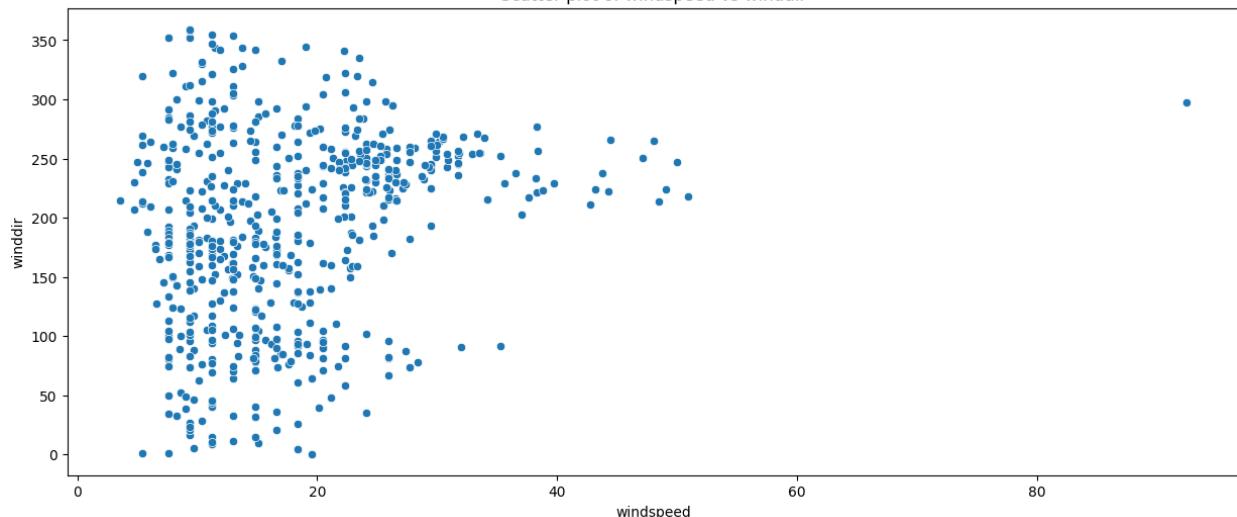


Scatter plot of precipcover vs uvindex

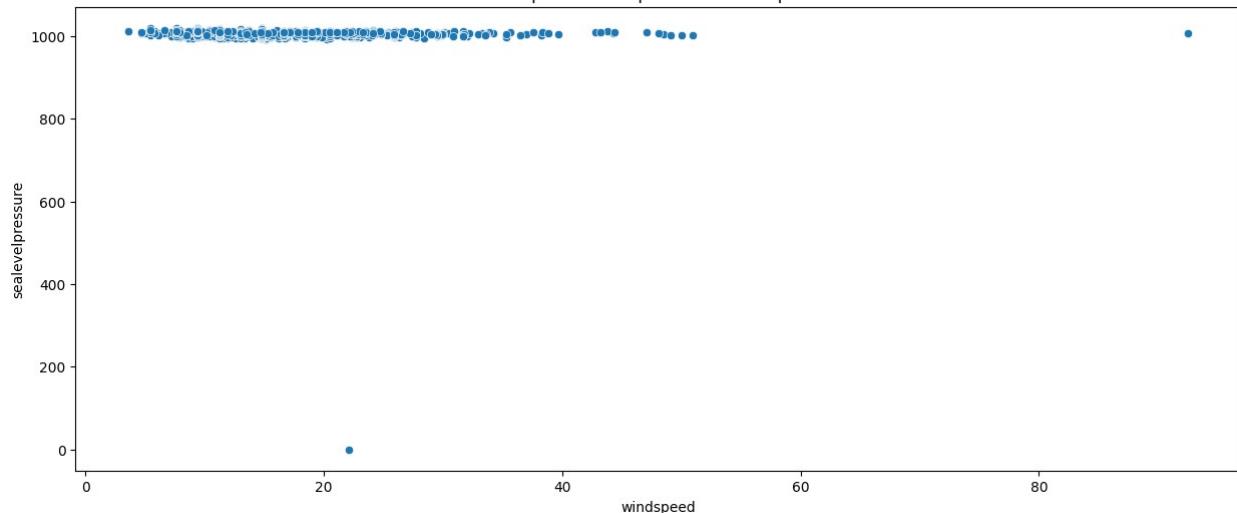




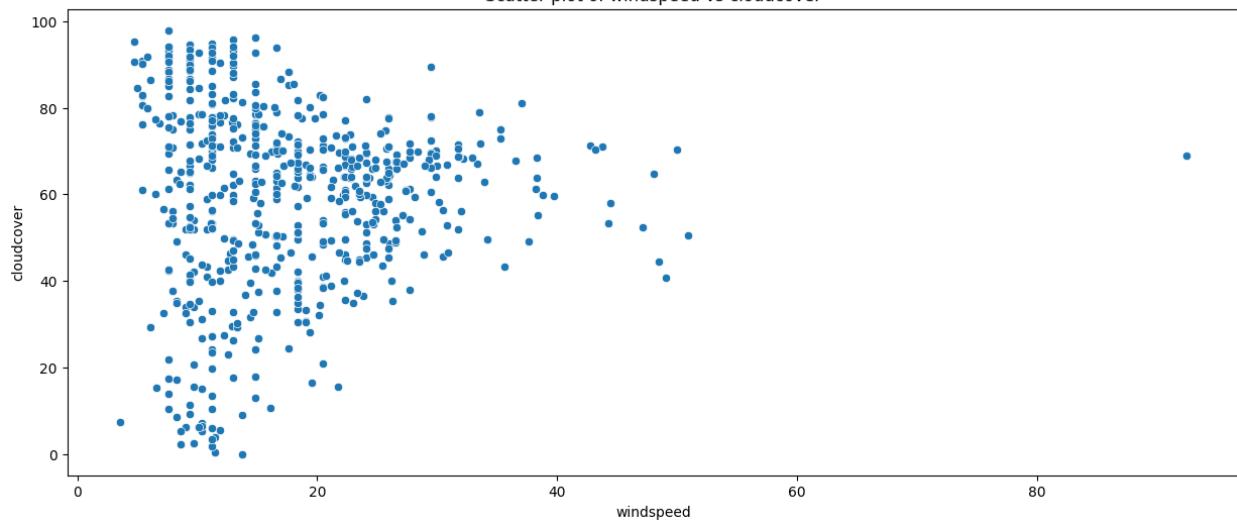
Scatter plot of windspeed vs winddir



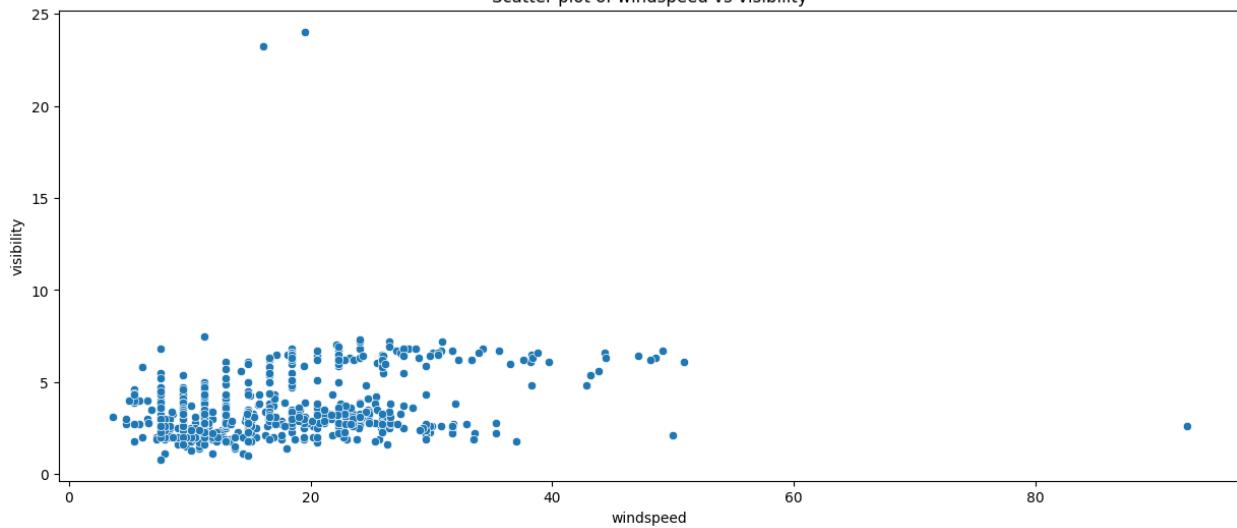
Scatter plot of windspeed vs sealevelpressure



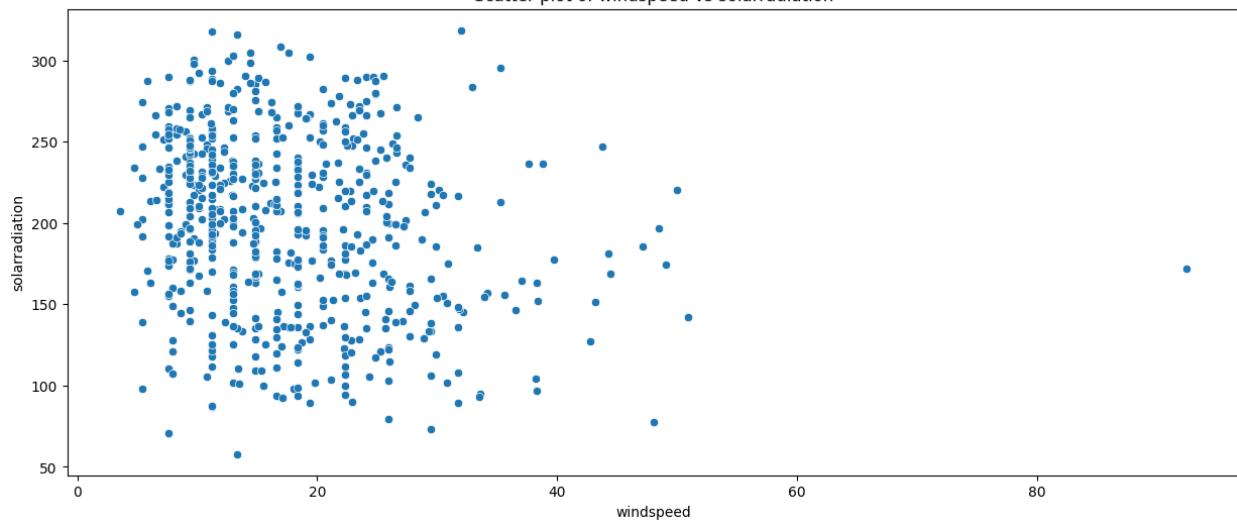
Scatter plot of windspeed vs cloudcover



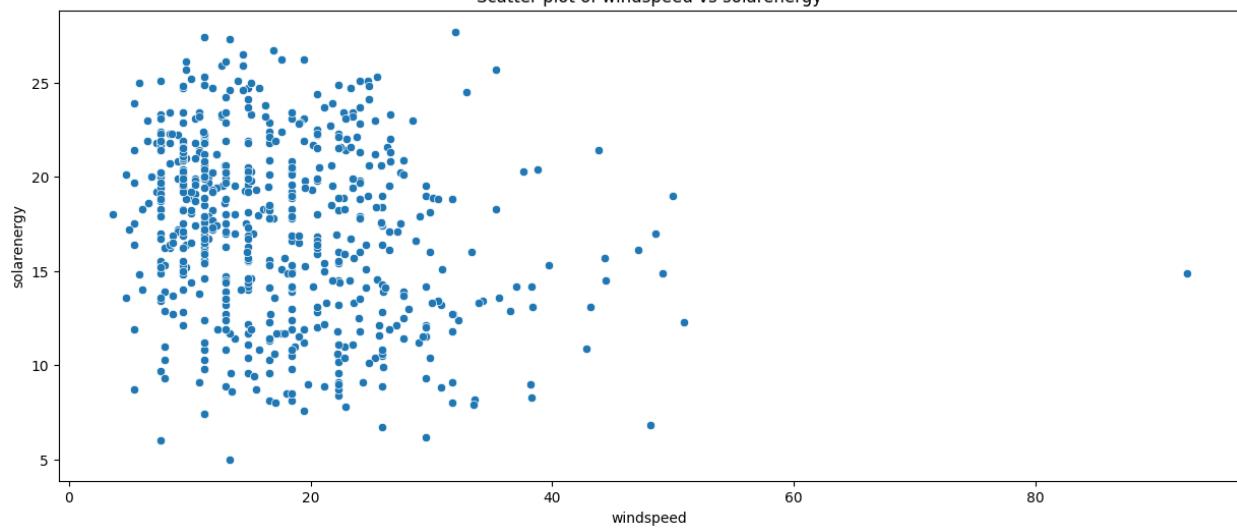
Scatter plot of windspeed vs visibility



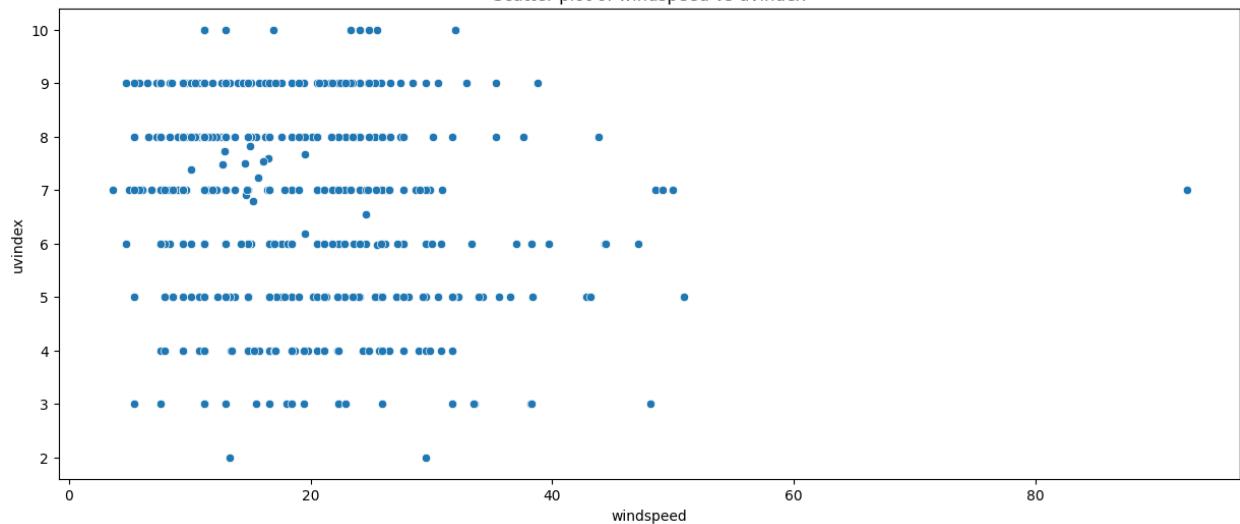
Scatter plot of windspeed vs solarradiation



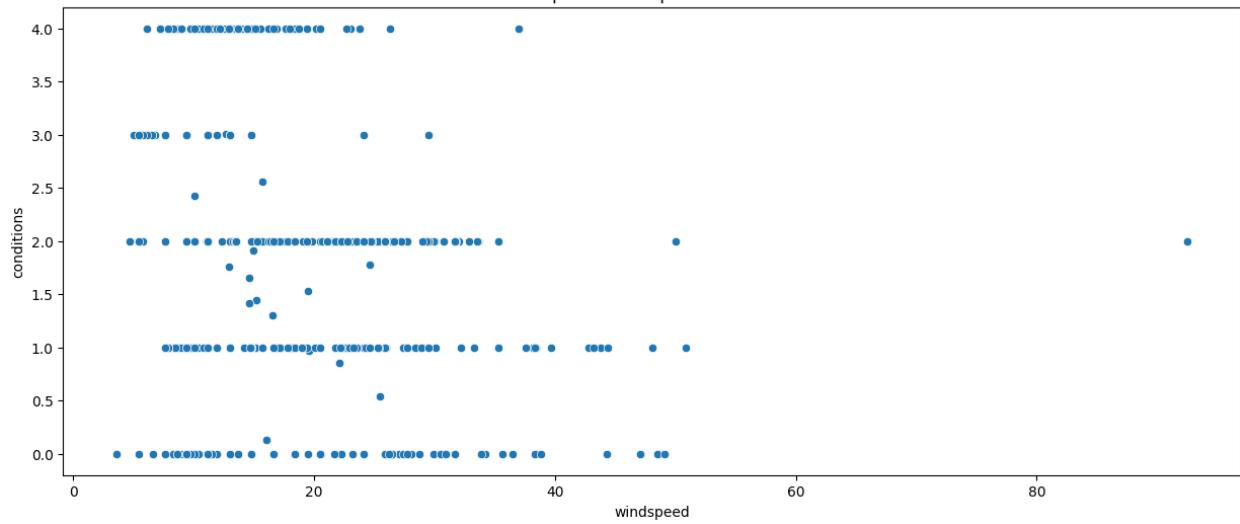
Scatter plot of windspeed vs solarenergy



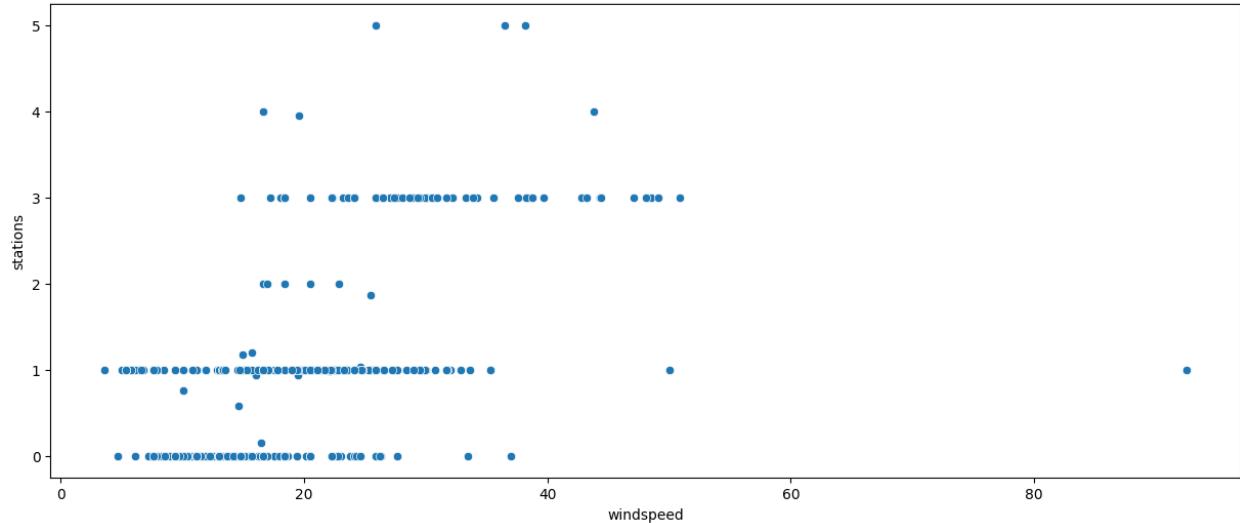
Scatter plot of windspeed vs uvindex

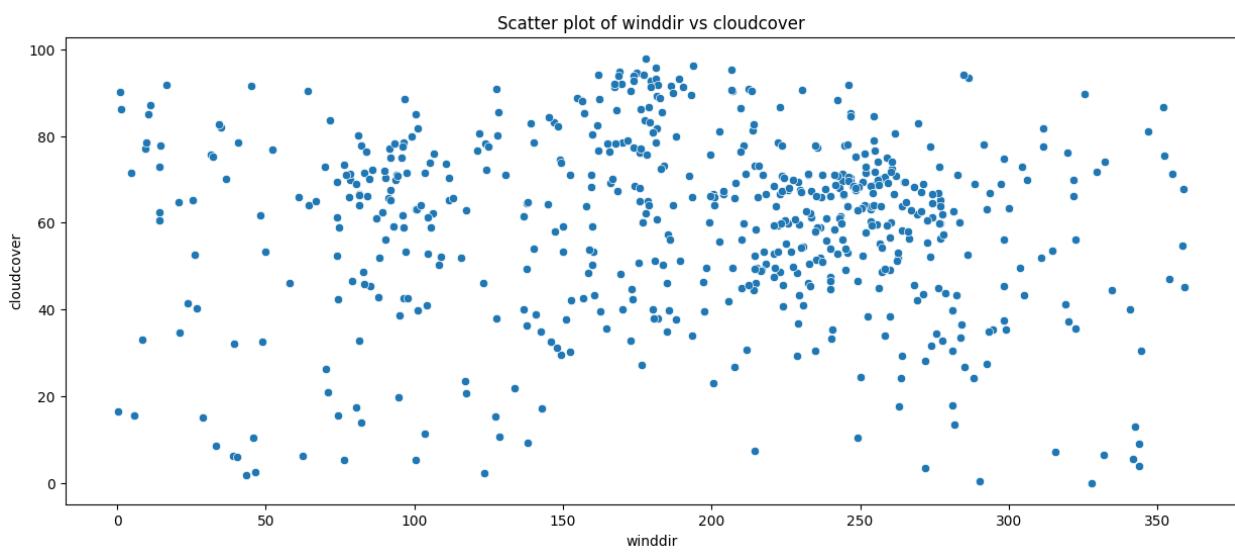
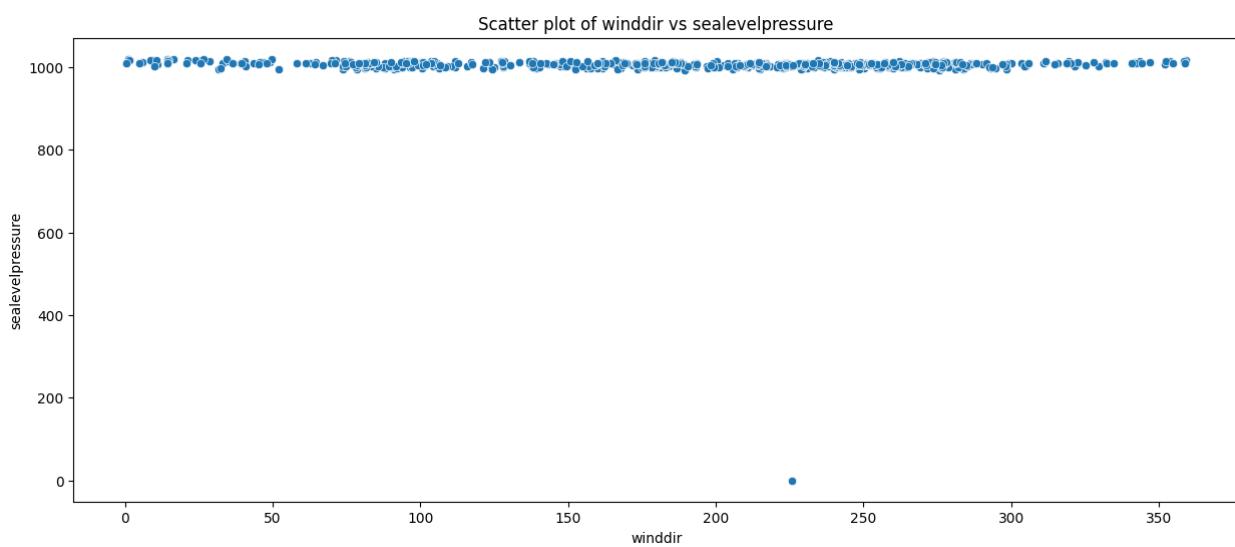
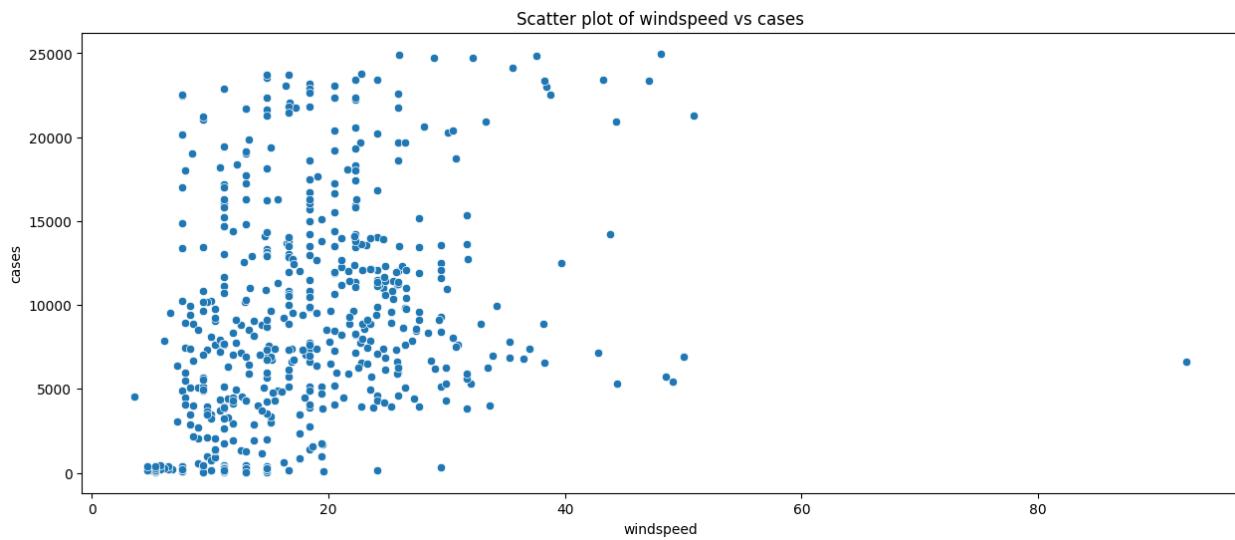


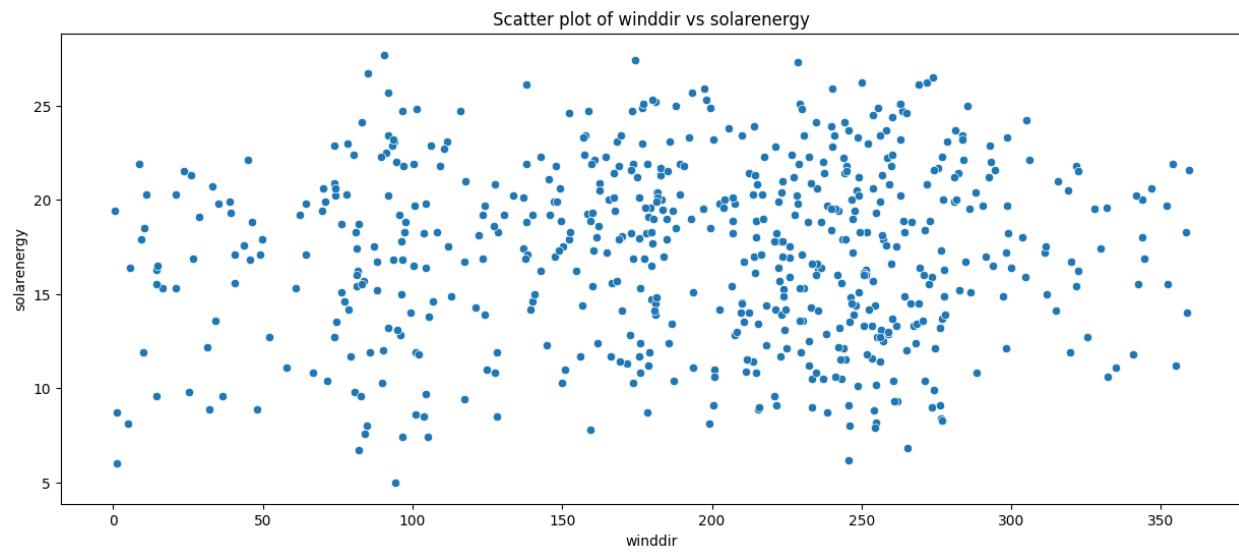
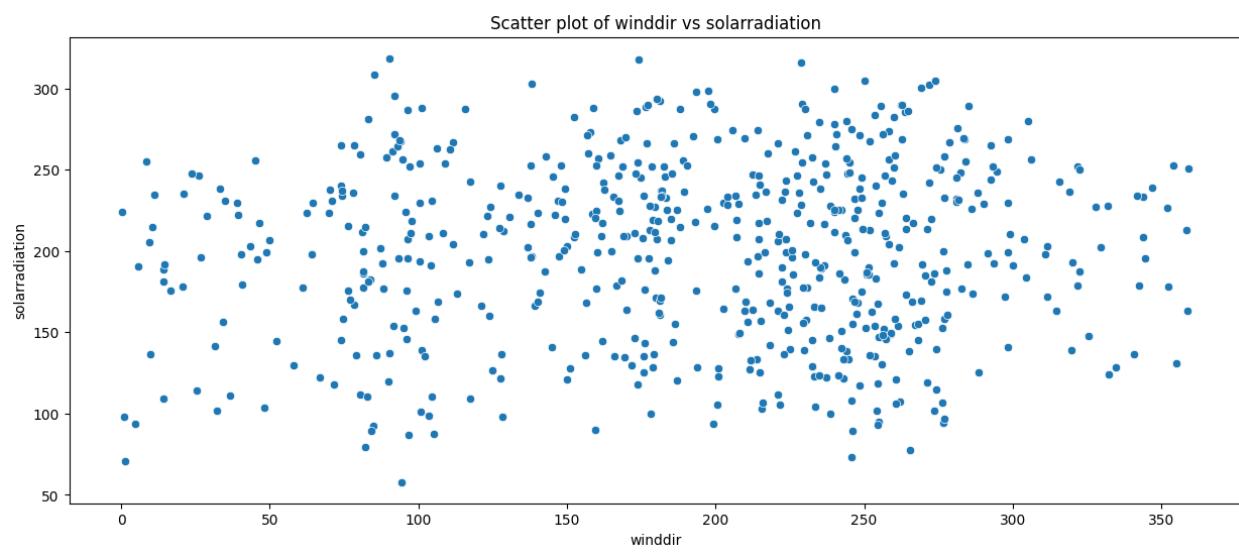
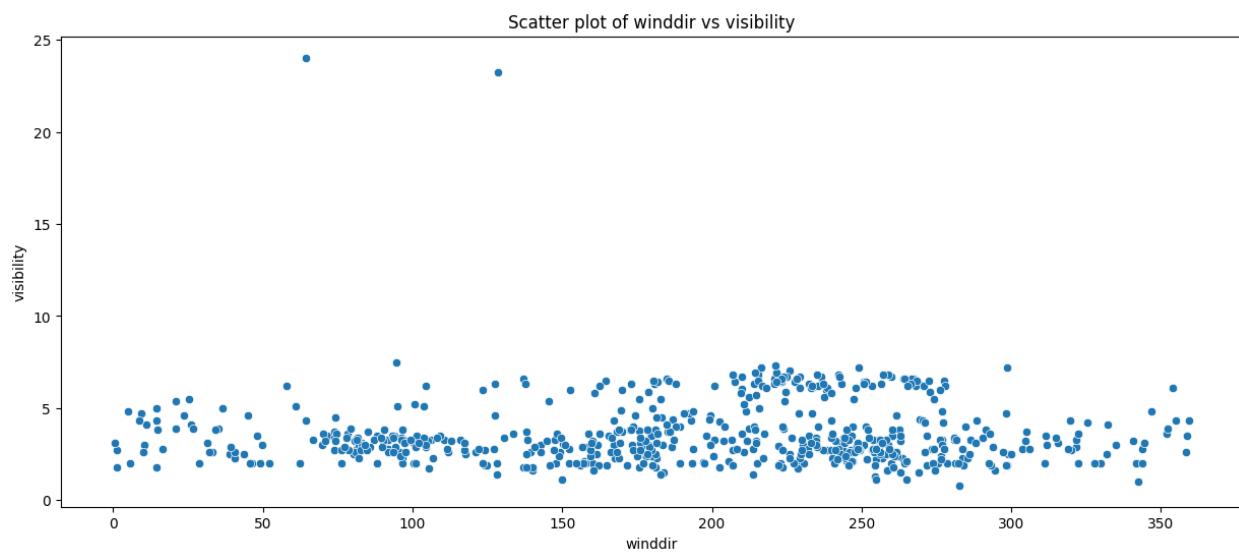
Scatter plot of windspeed vs conditions

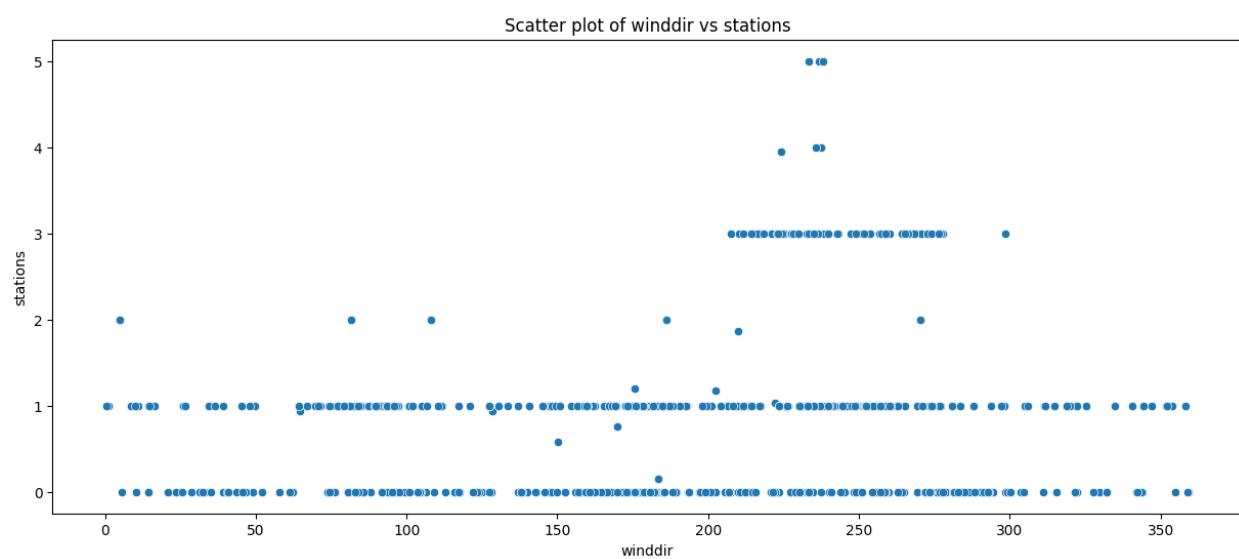
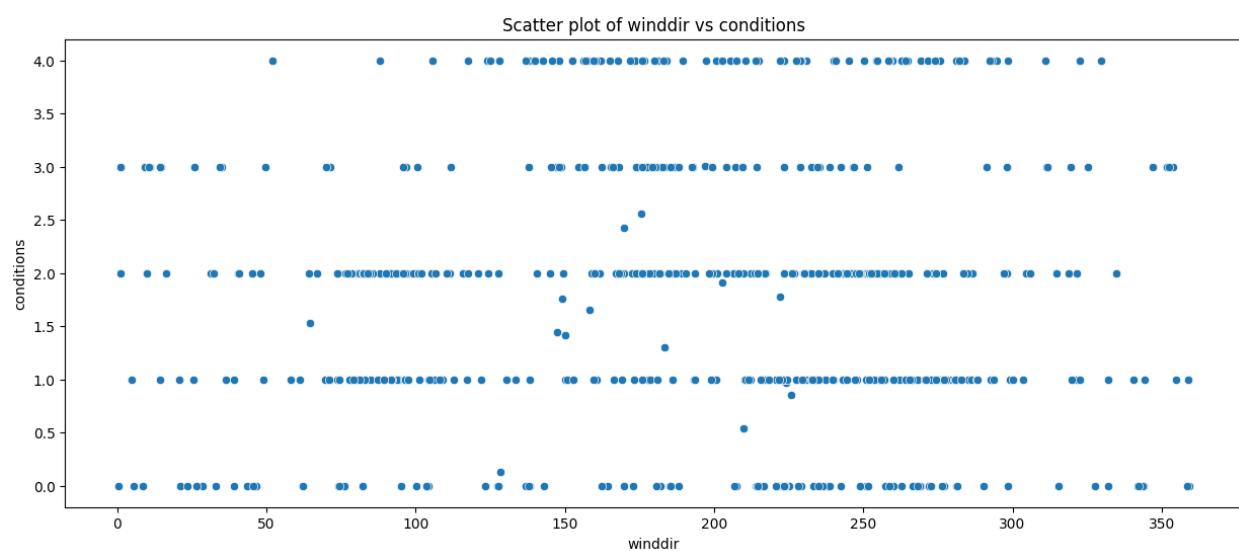
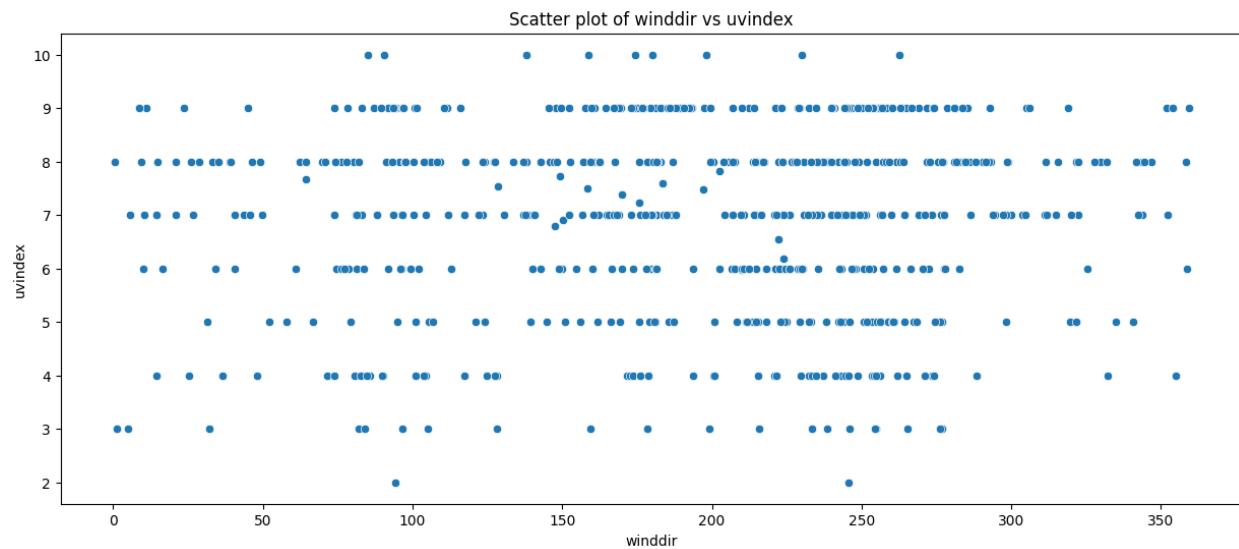


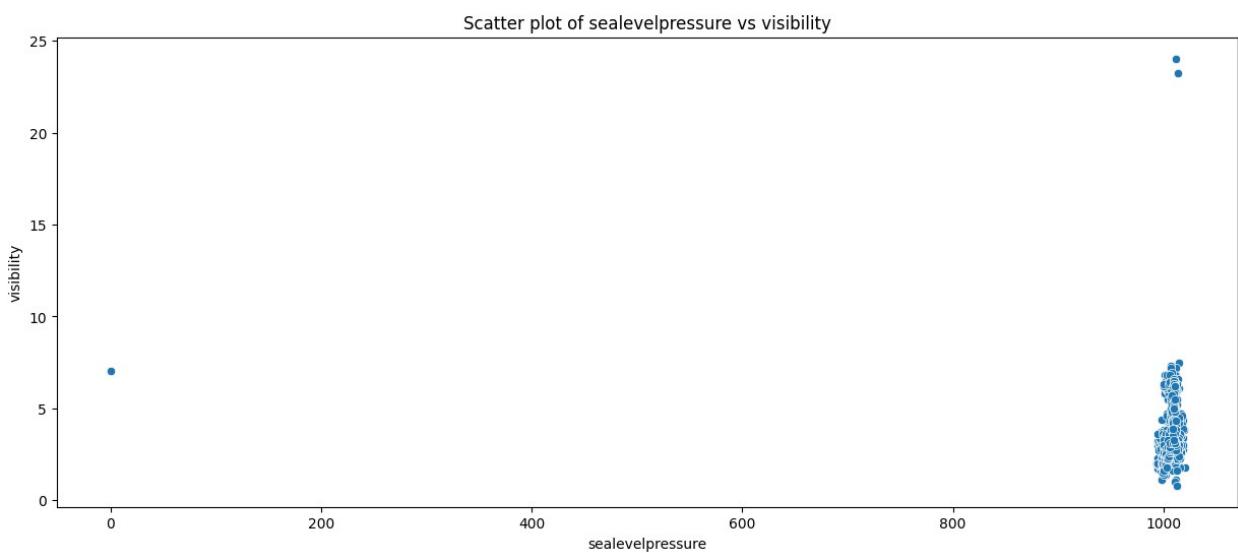
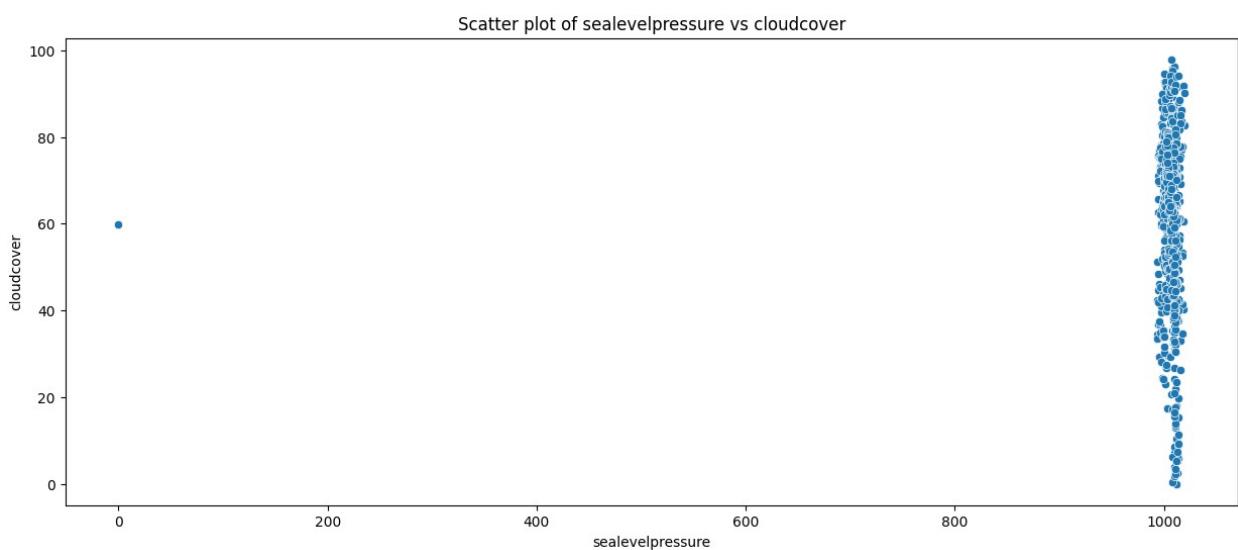
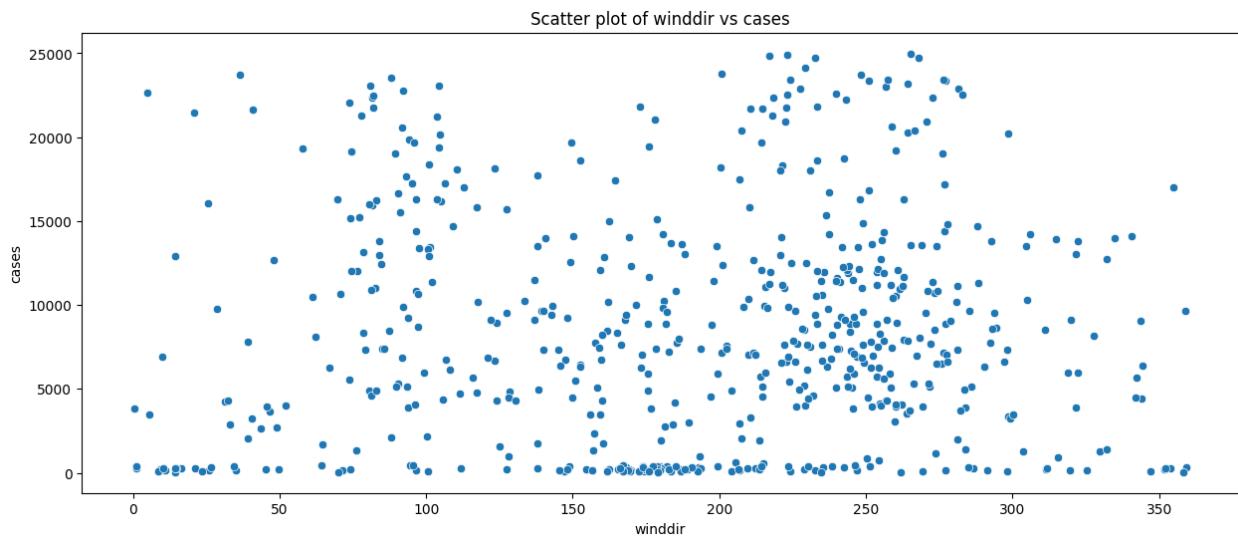
Scatter plot of windspeed vs stations

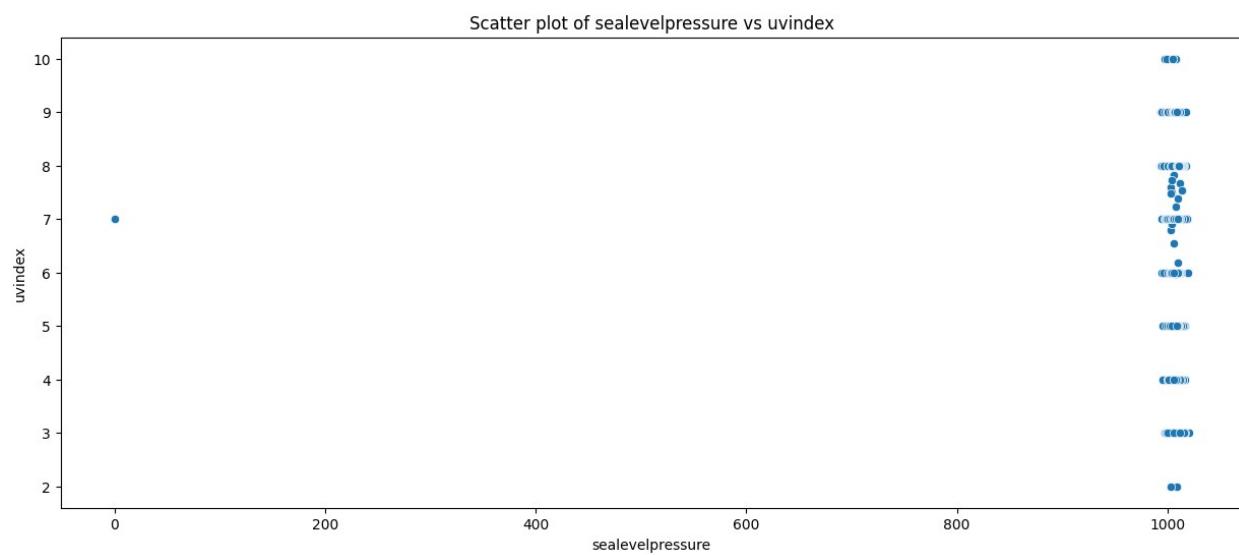
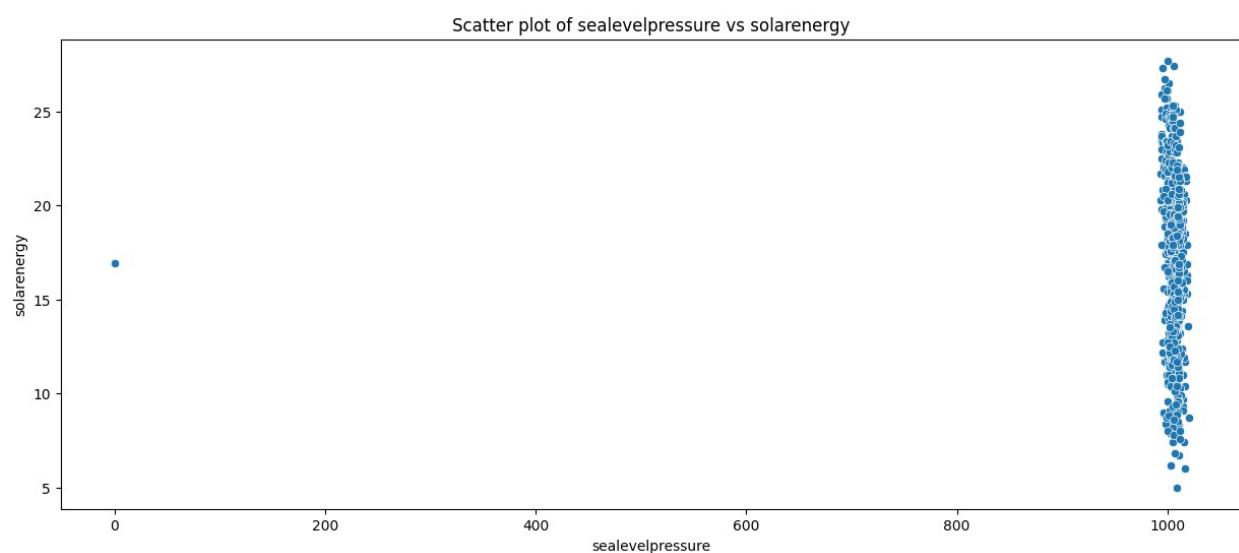
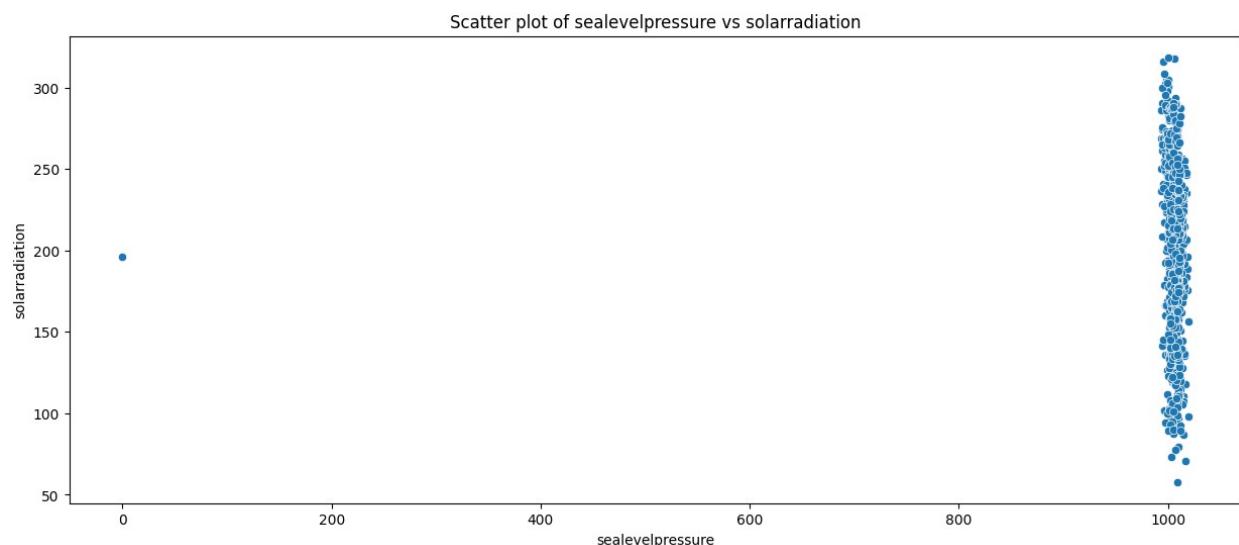




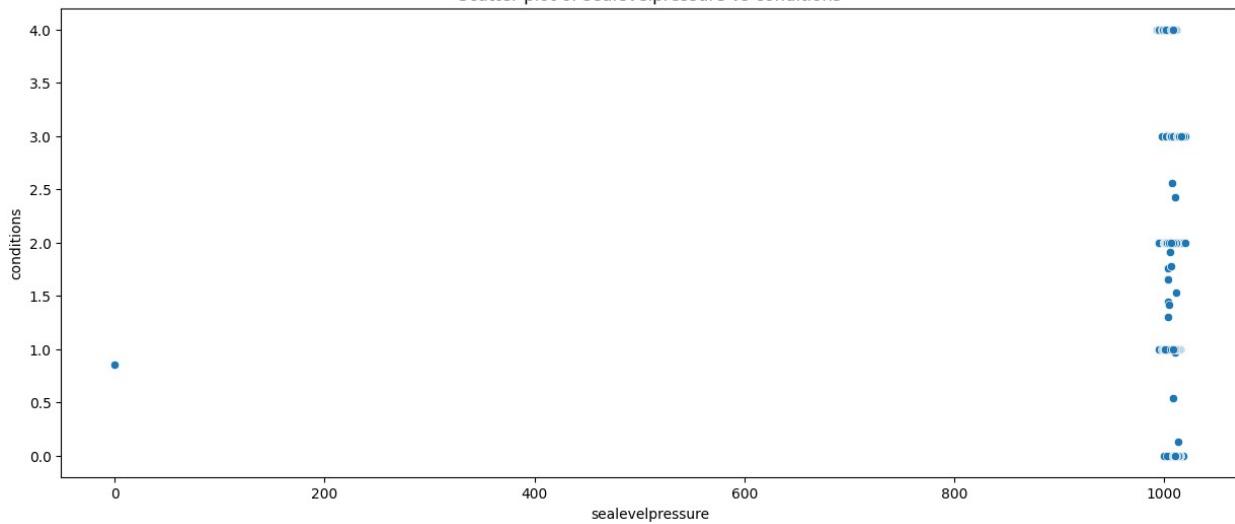




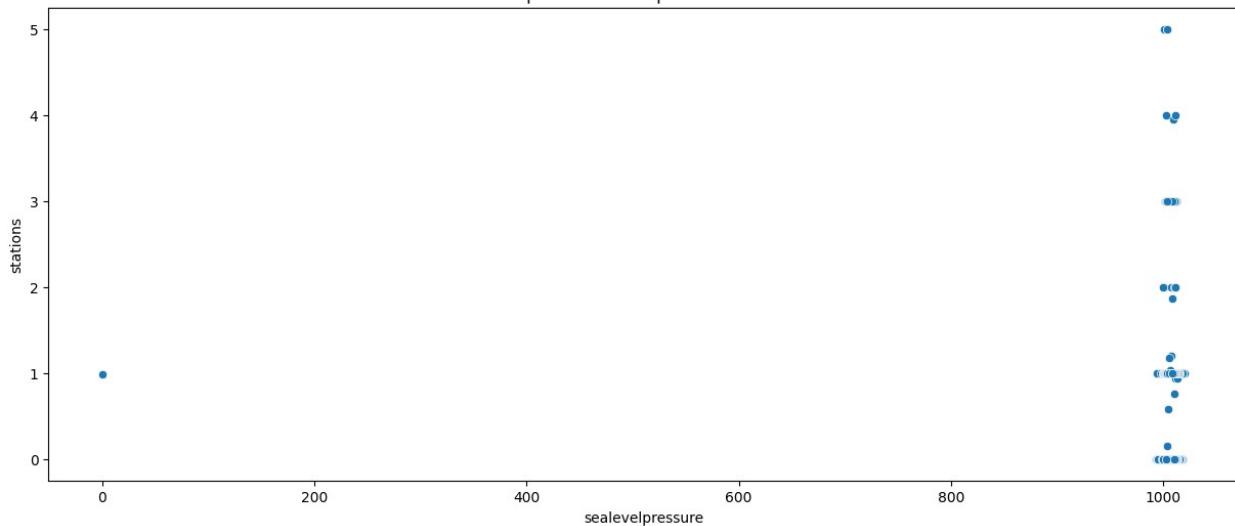




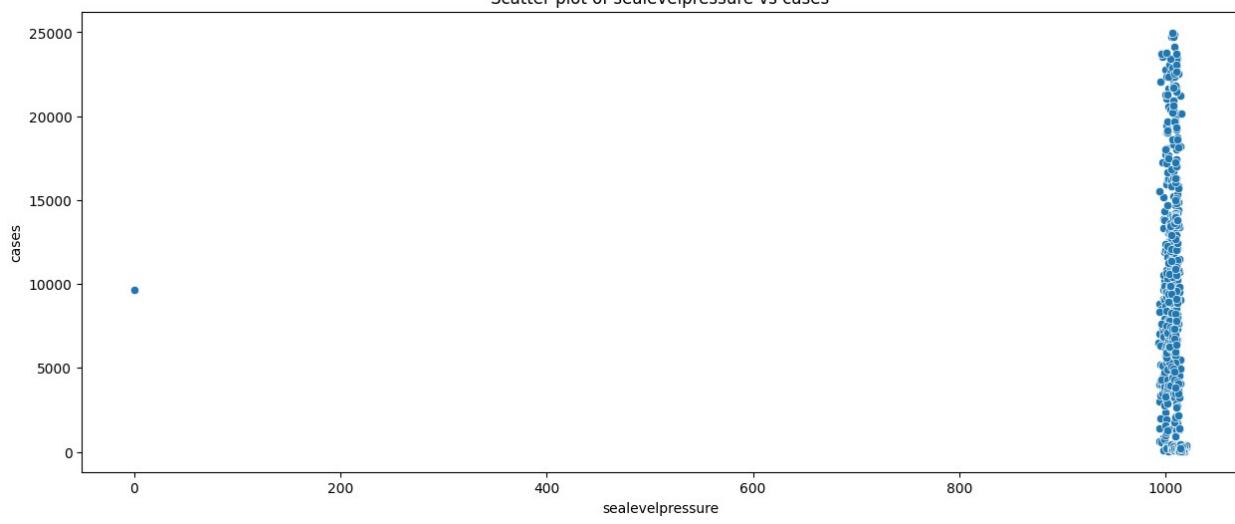
Scatter plot of sealevelpressure vs conditions

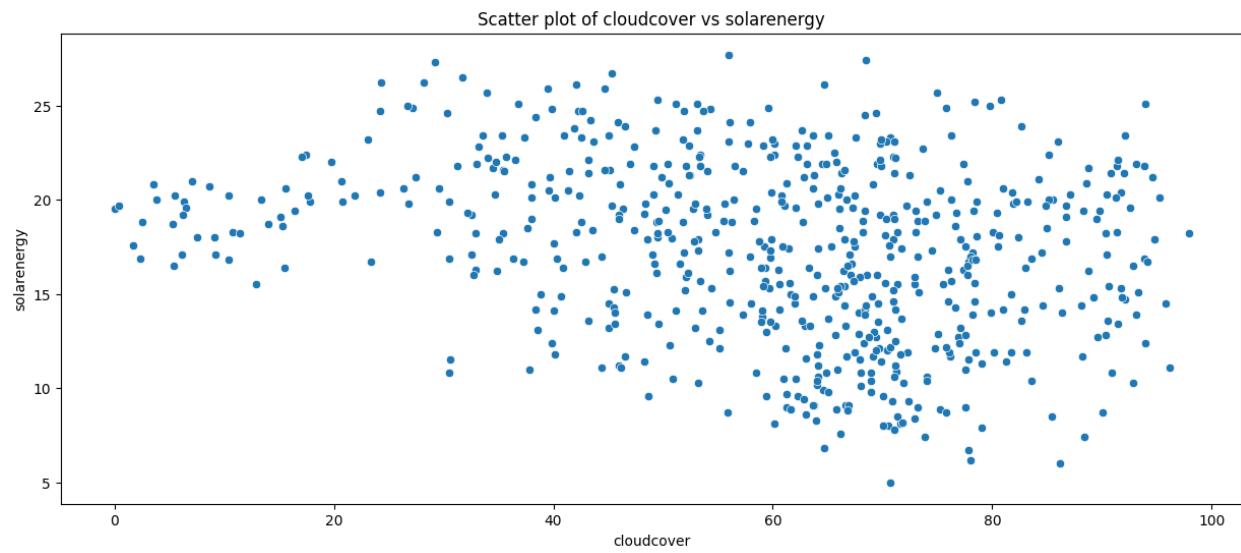
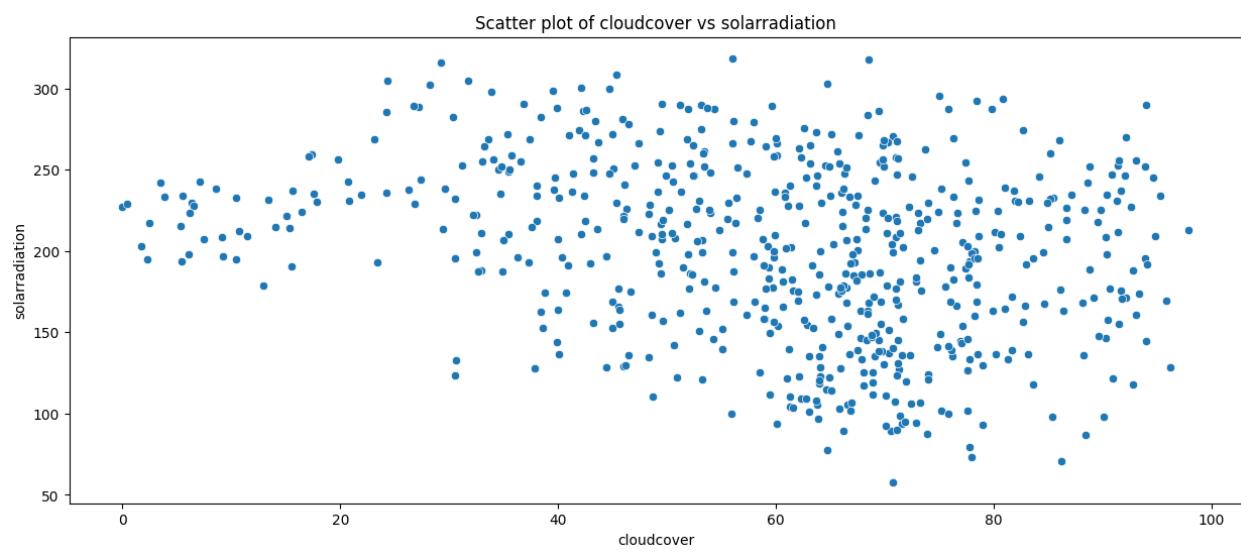
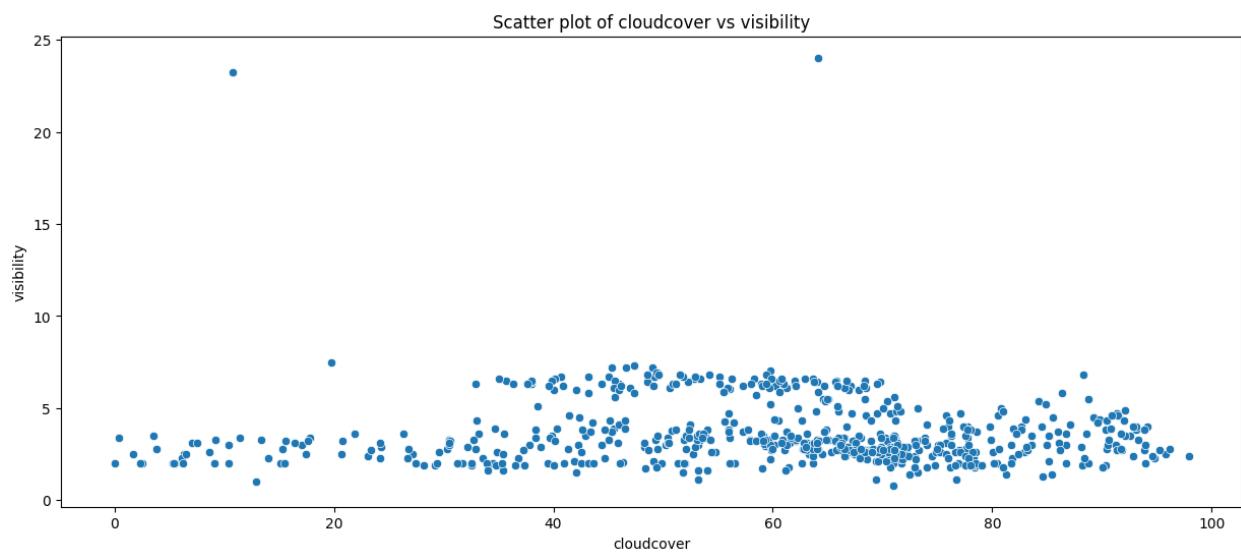


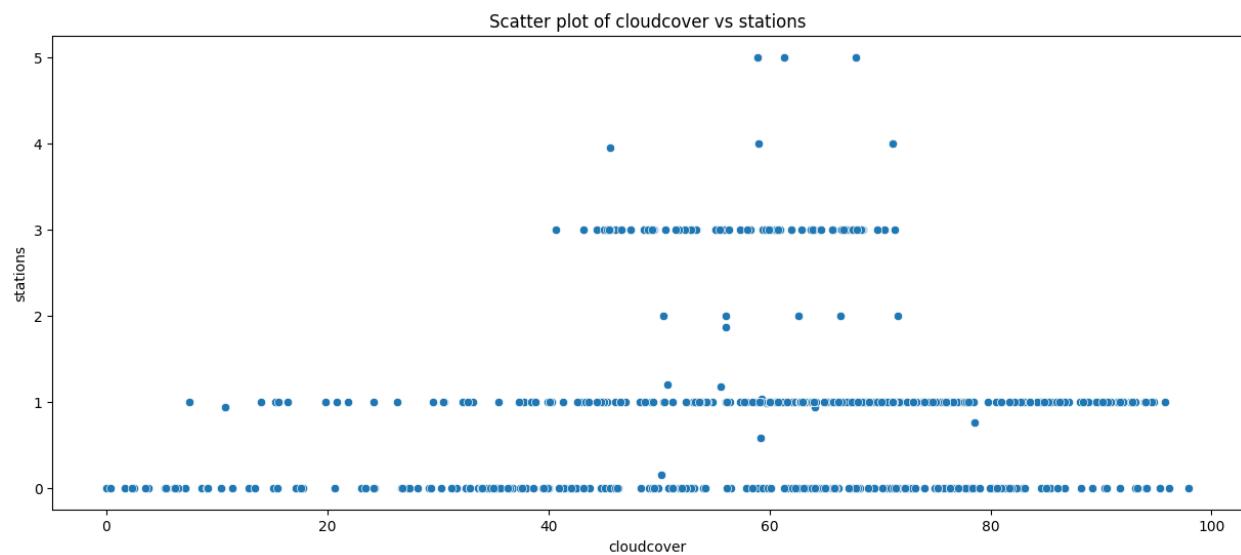
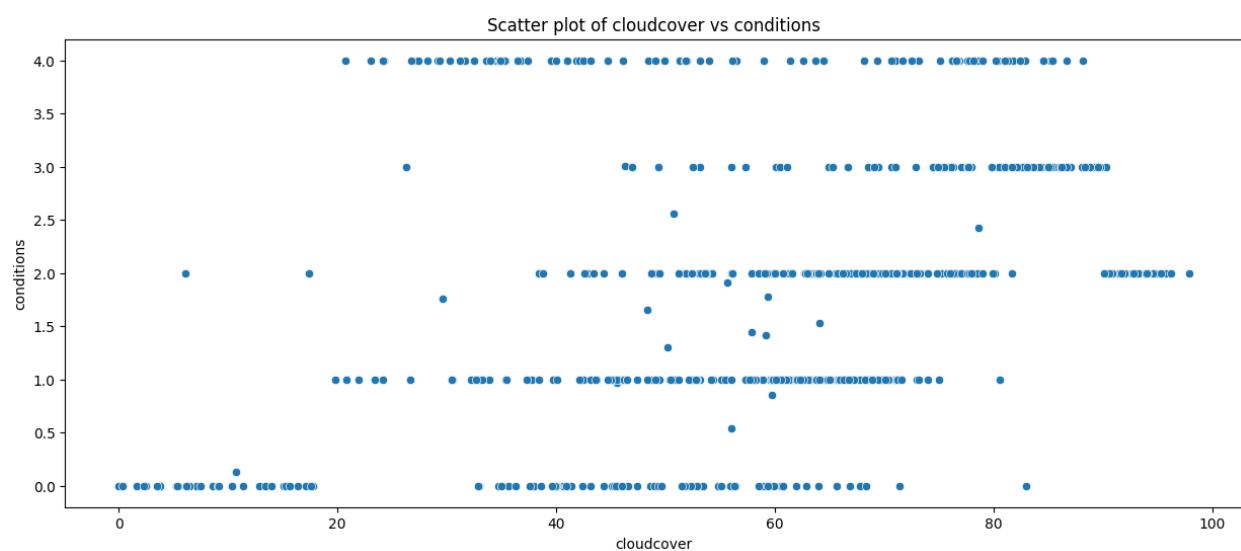
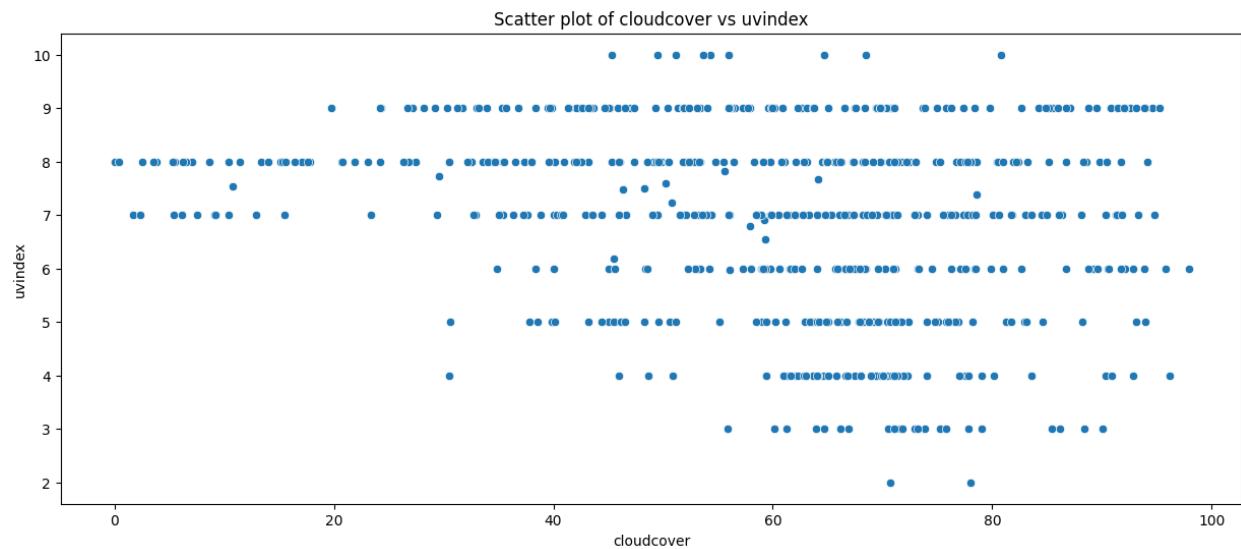
Scatter plot of sealevelpressure vs stations

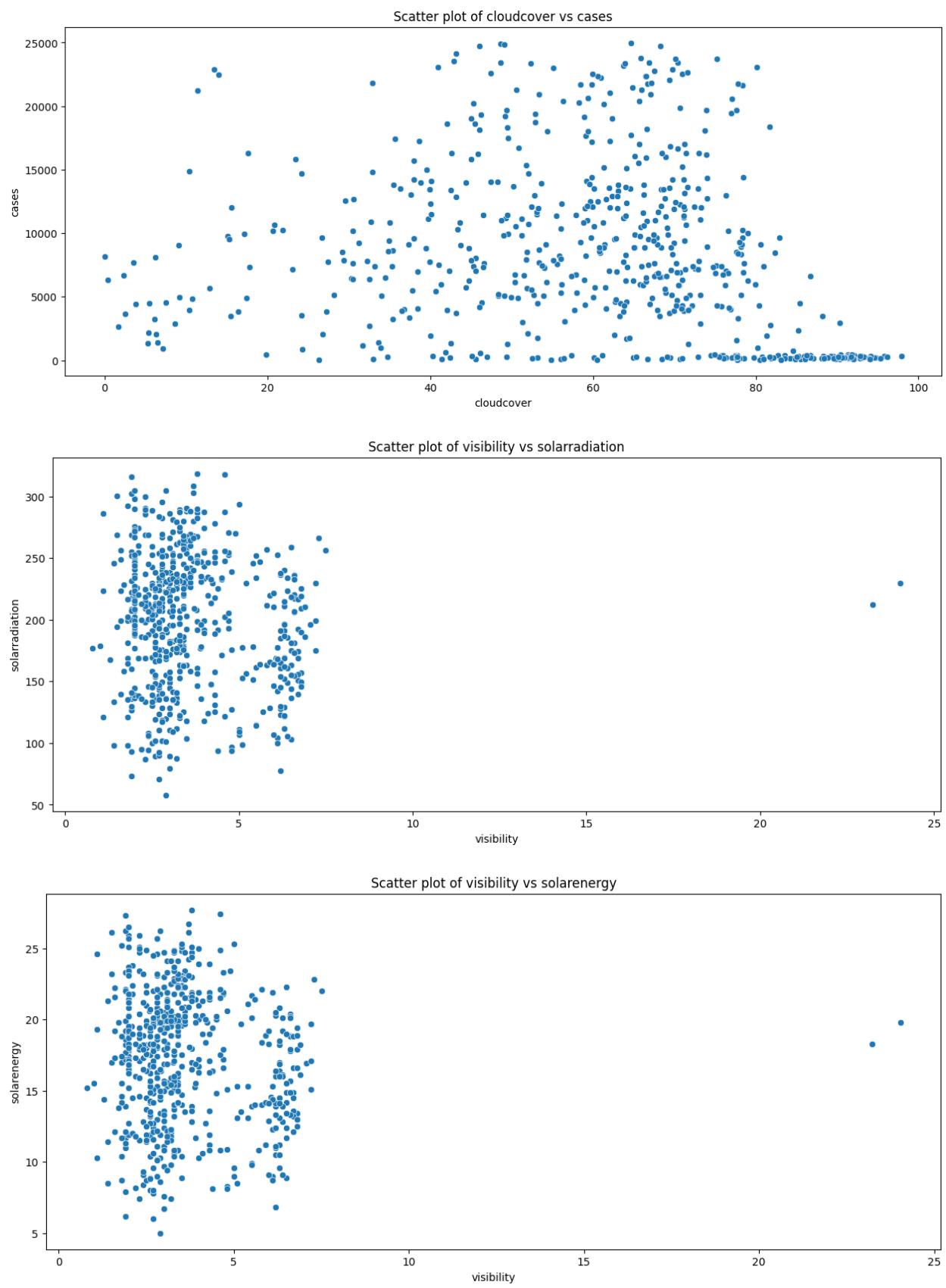


Scatter plot of sealevelpressure vs cases

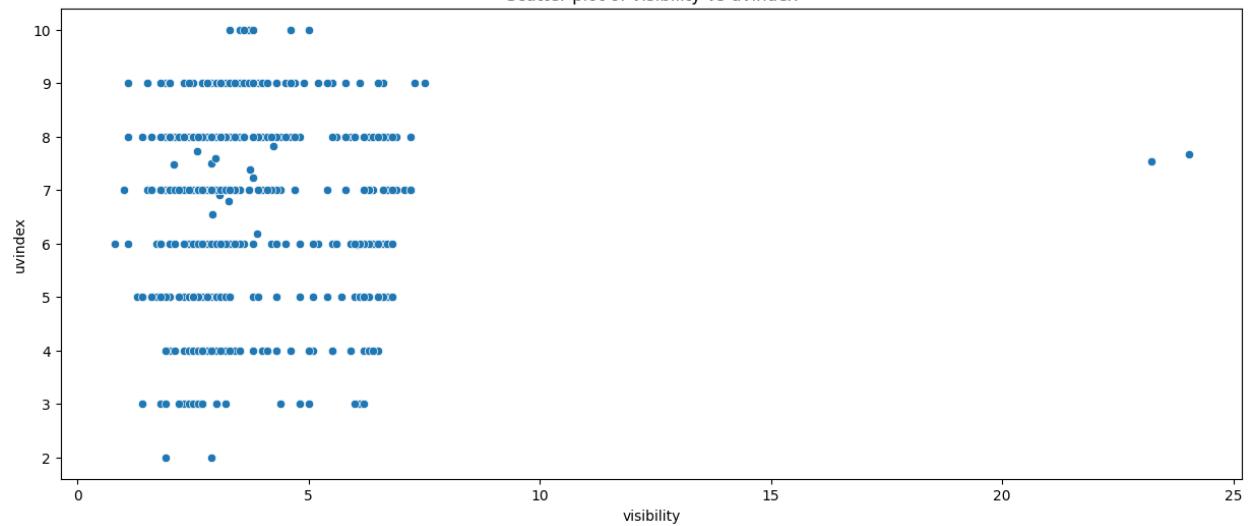




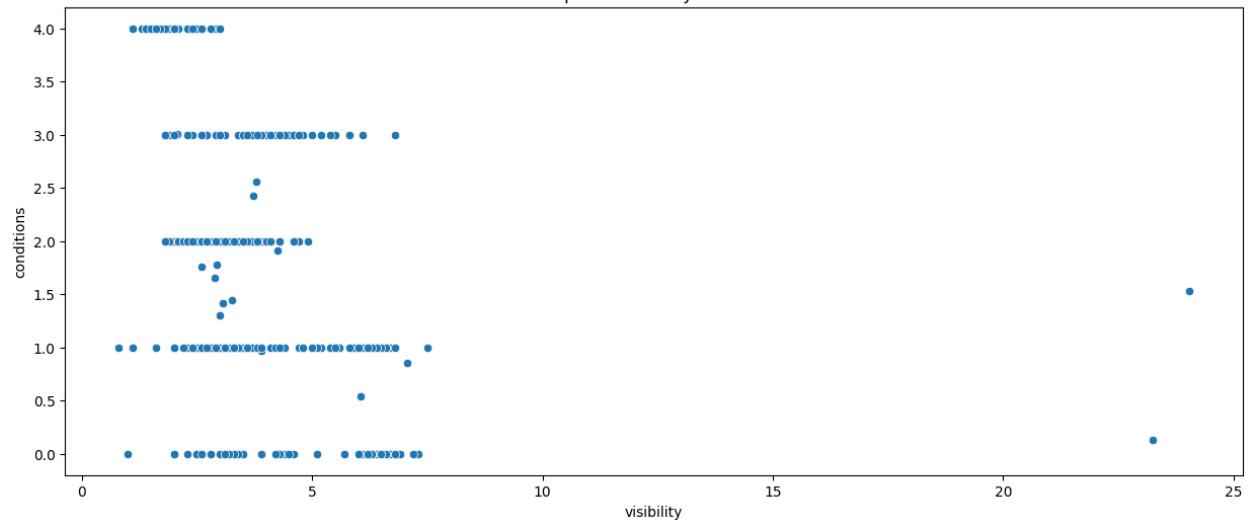




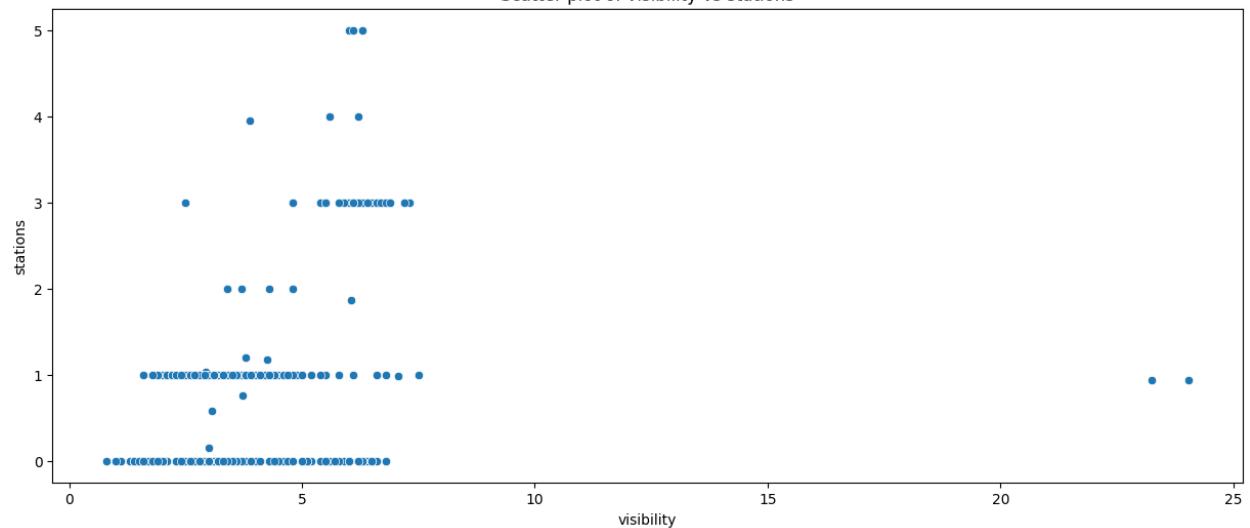
Scatter plot of visibility vs uvindex



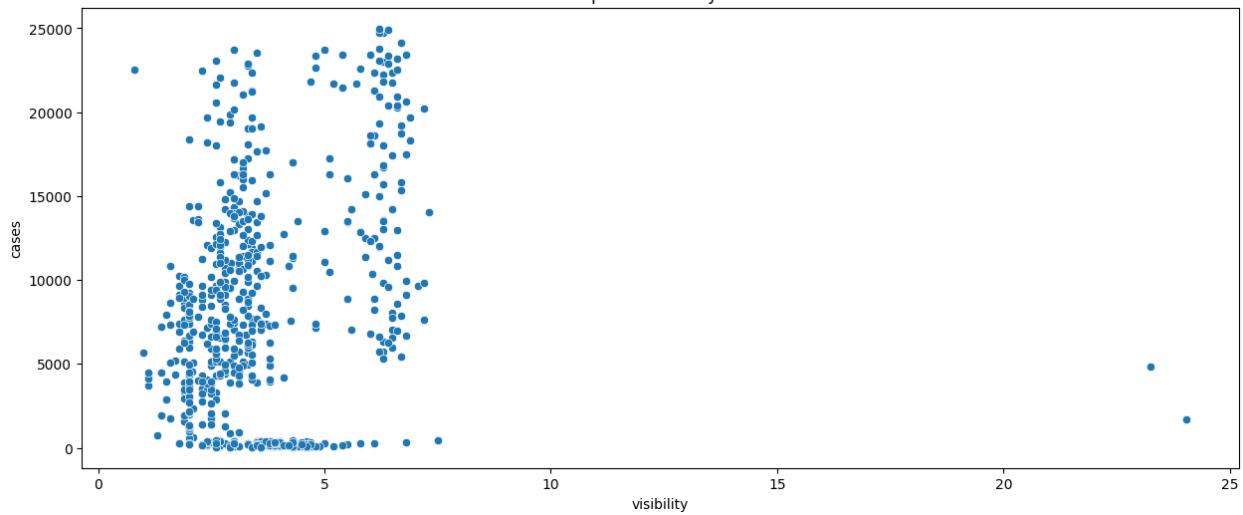
Scatter plot of visibility vs conditions



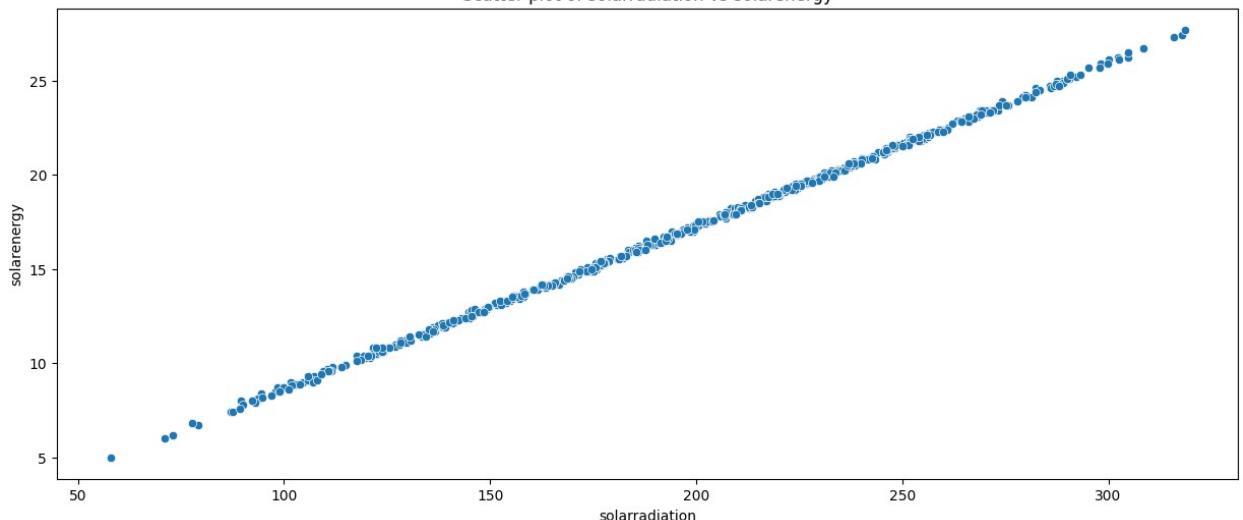
Scatter plot of visibility vs stations



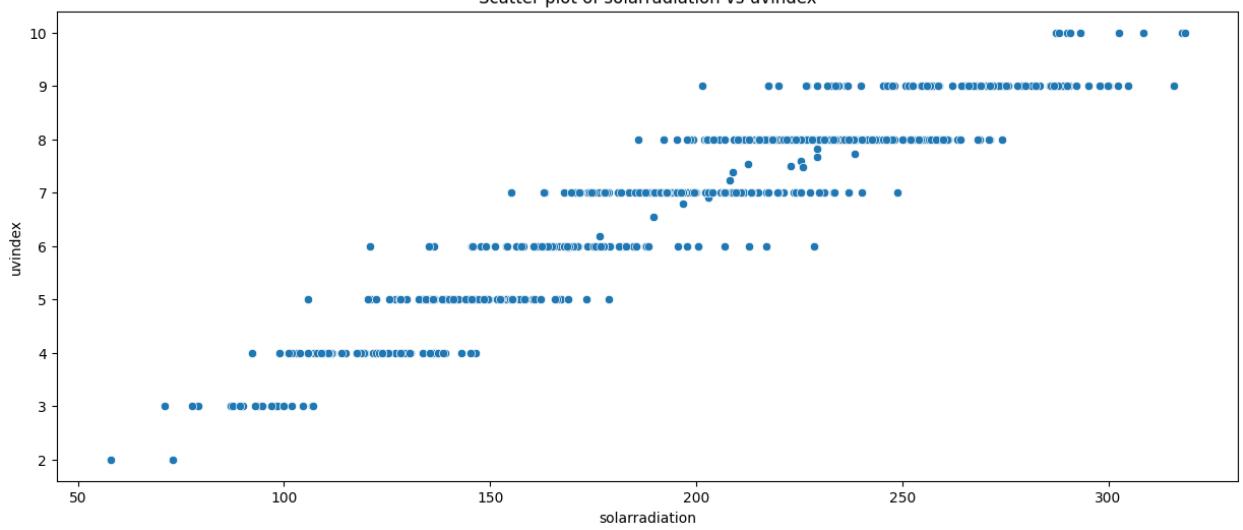
Scatter plot of visibility vs cases

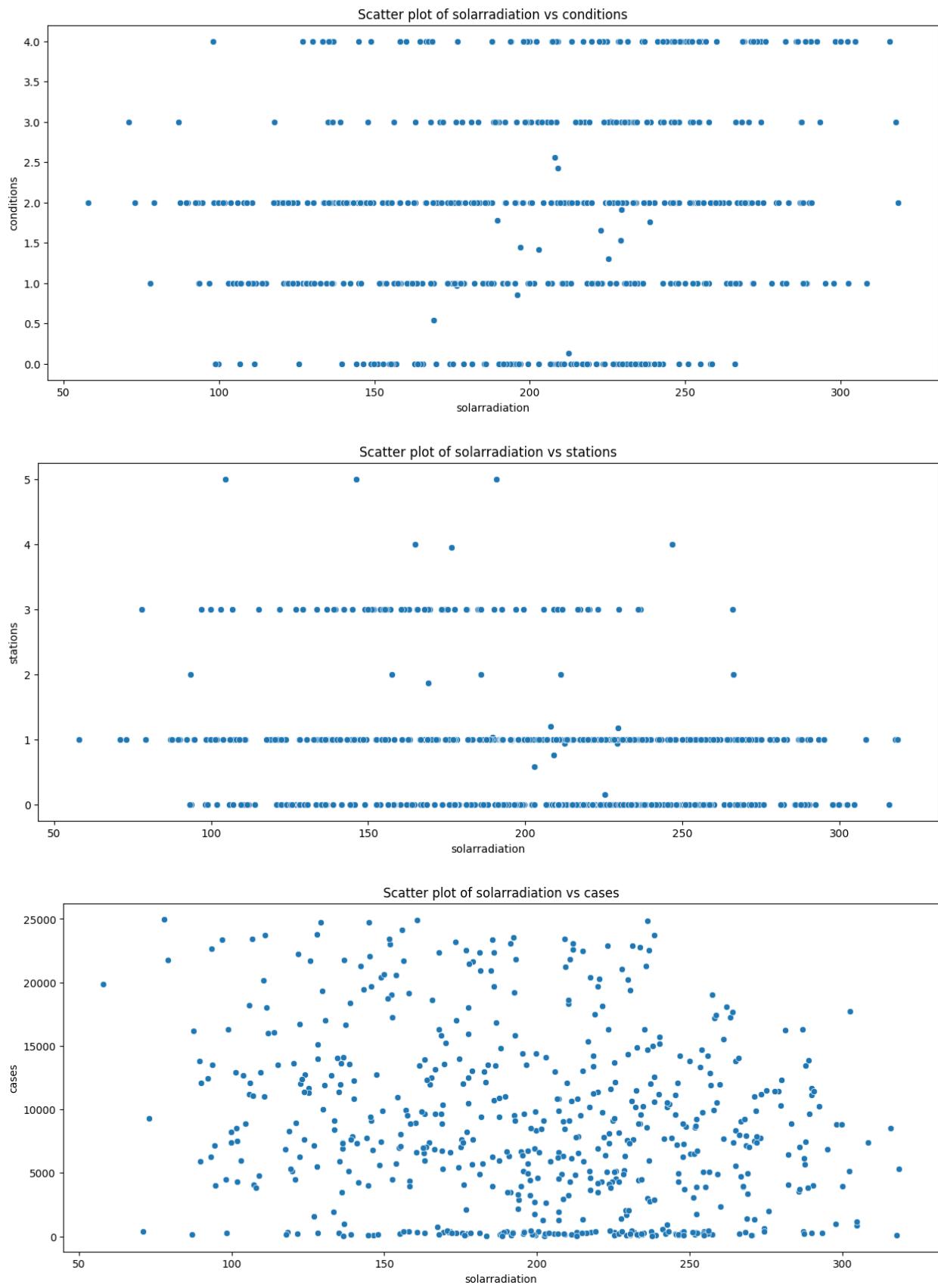


Scatter plot of solarradiation vs solarenergy

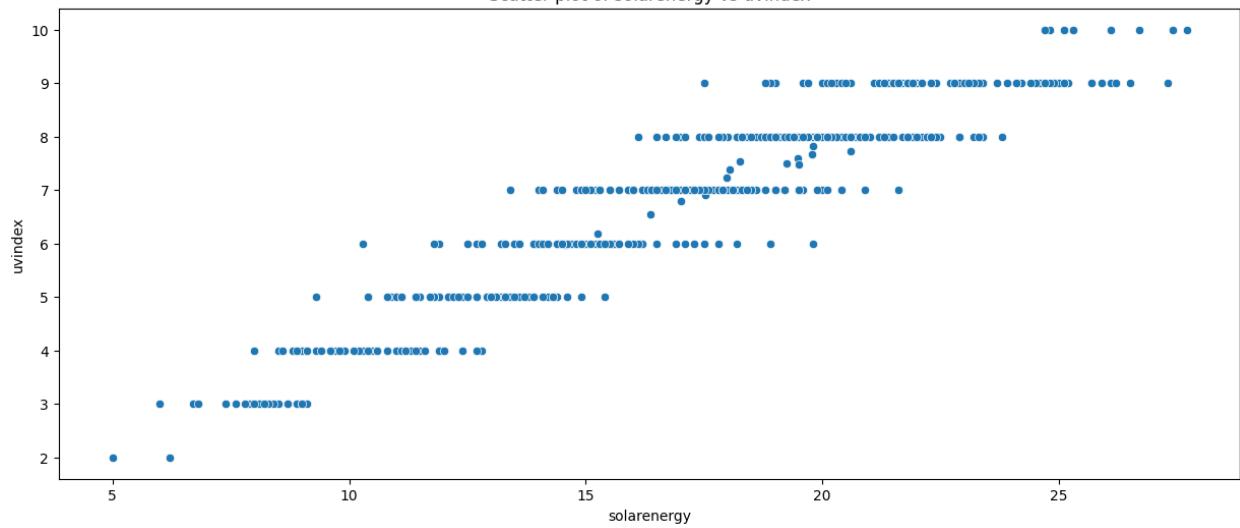


Scatter plot of solarradiation vs uvindex

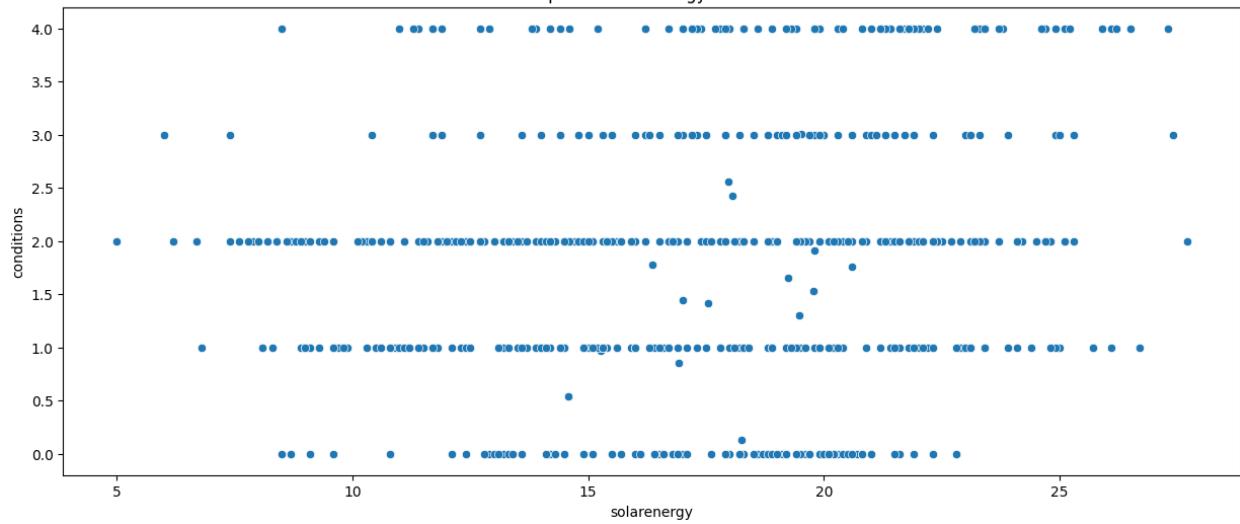




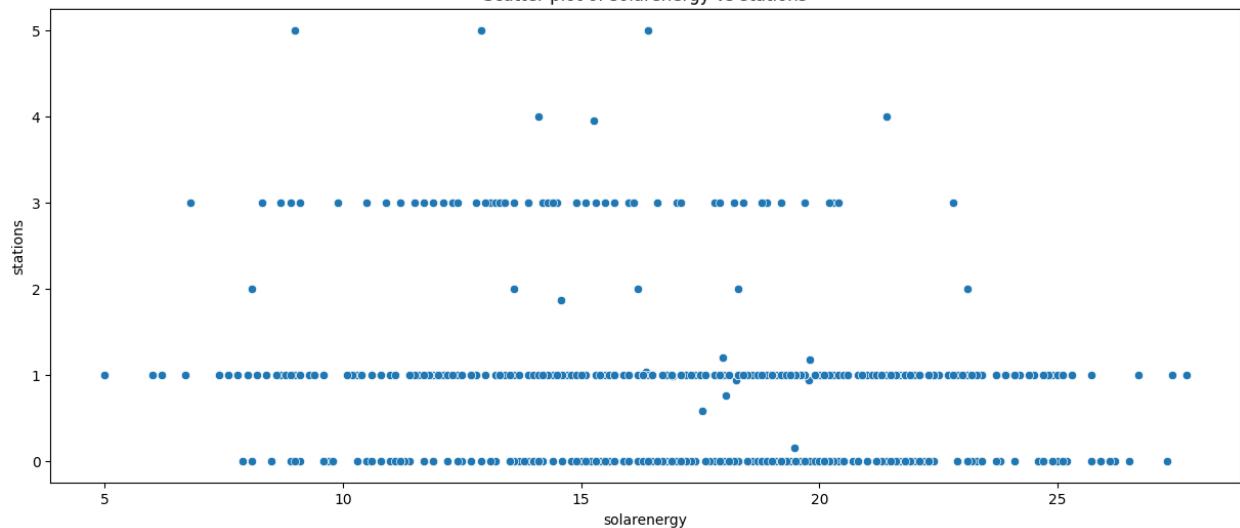
Scatter plot of solarenergy vs uvindex

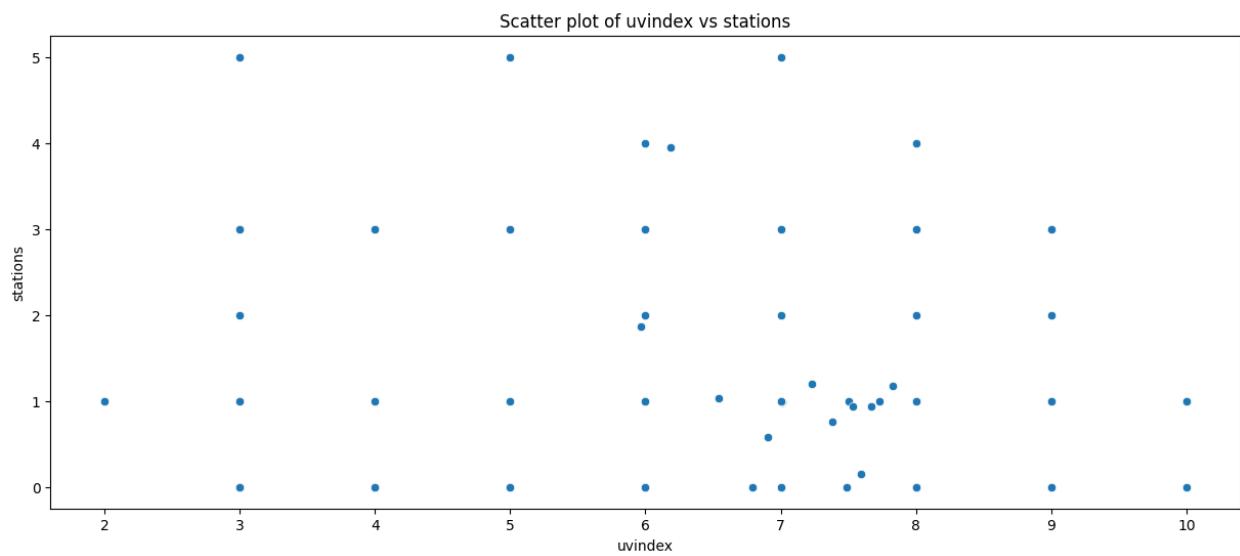
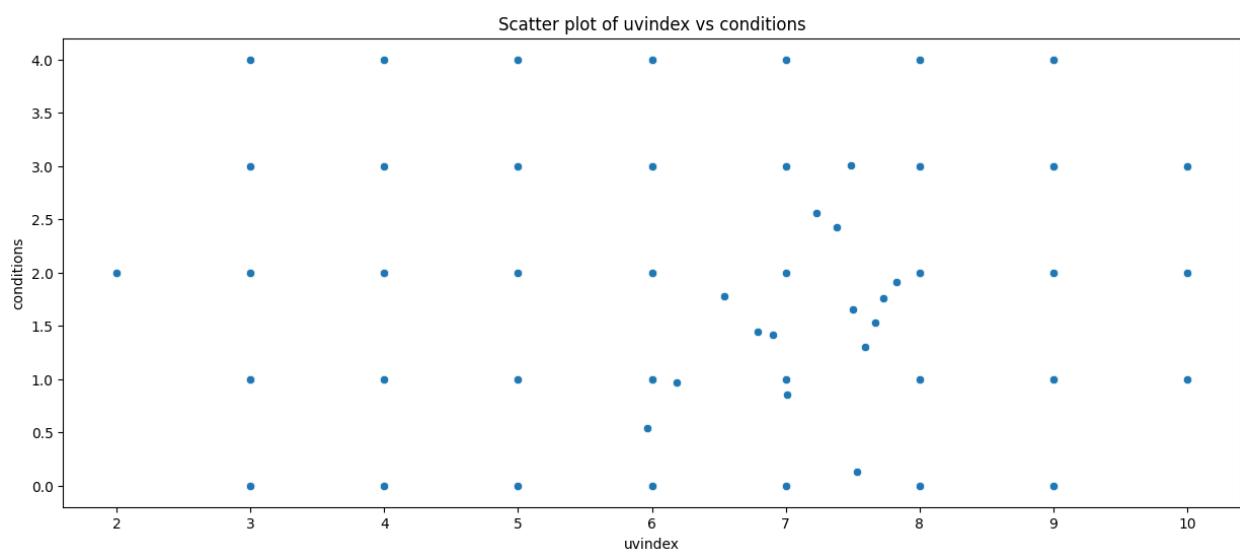
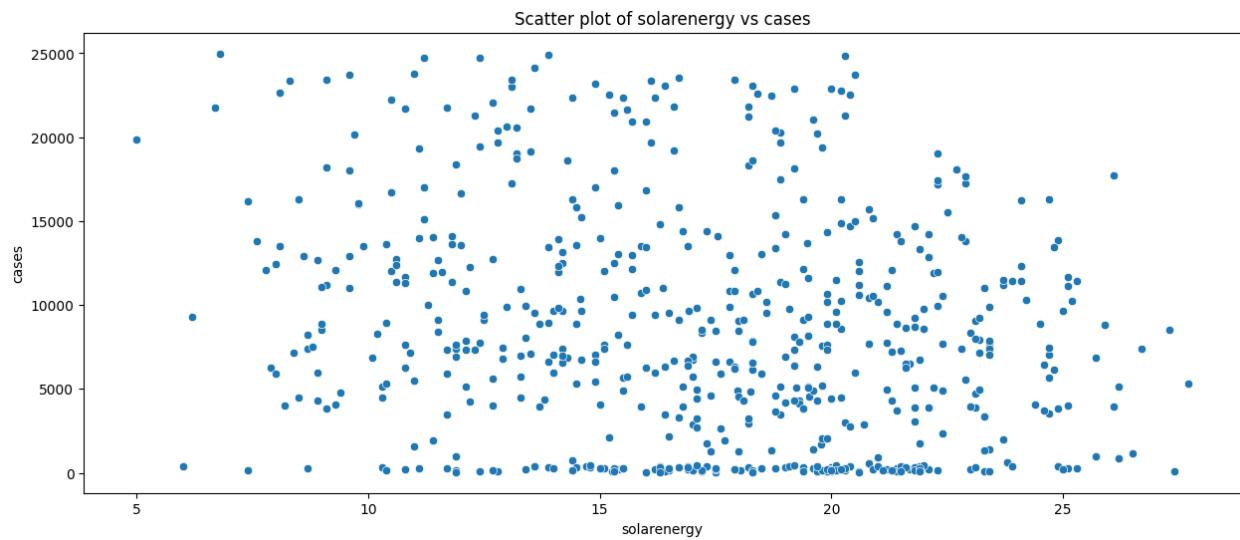


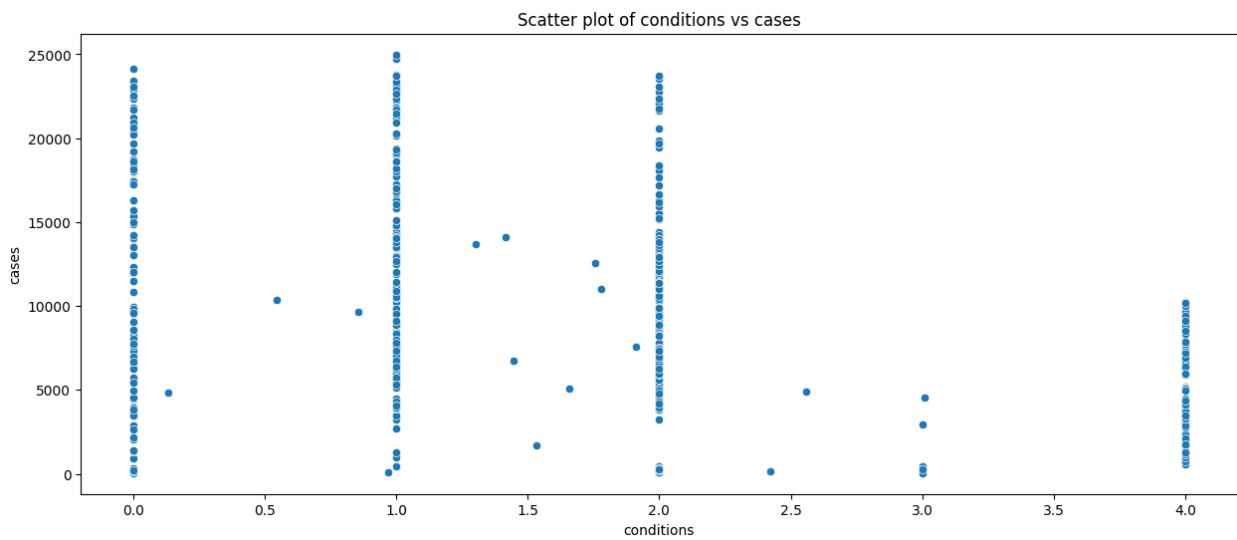
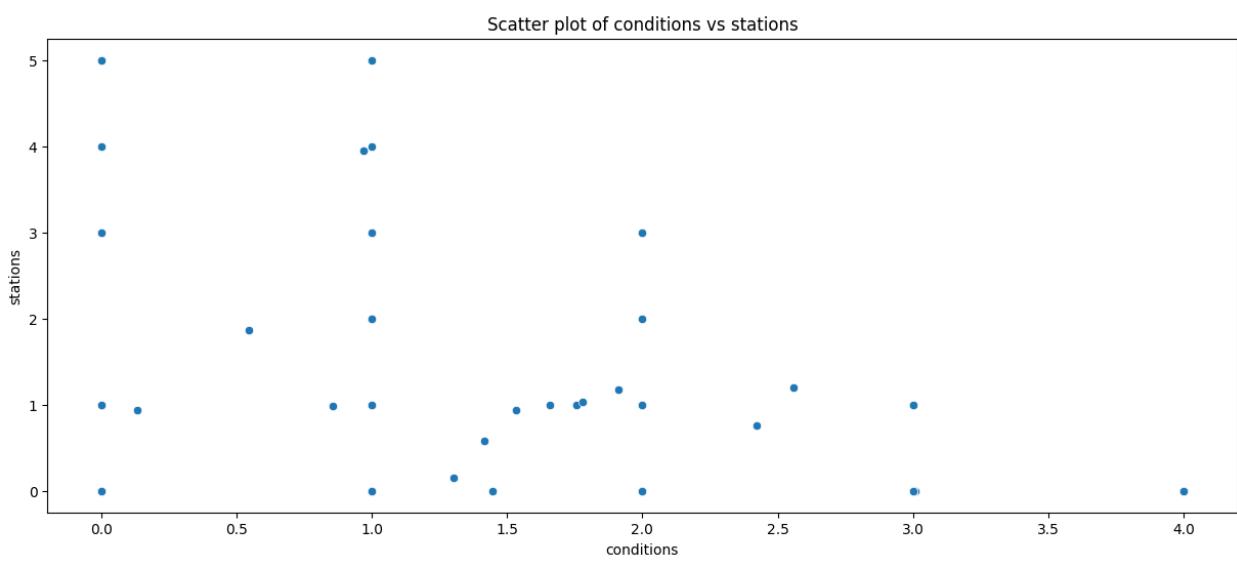
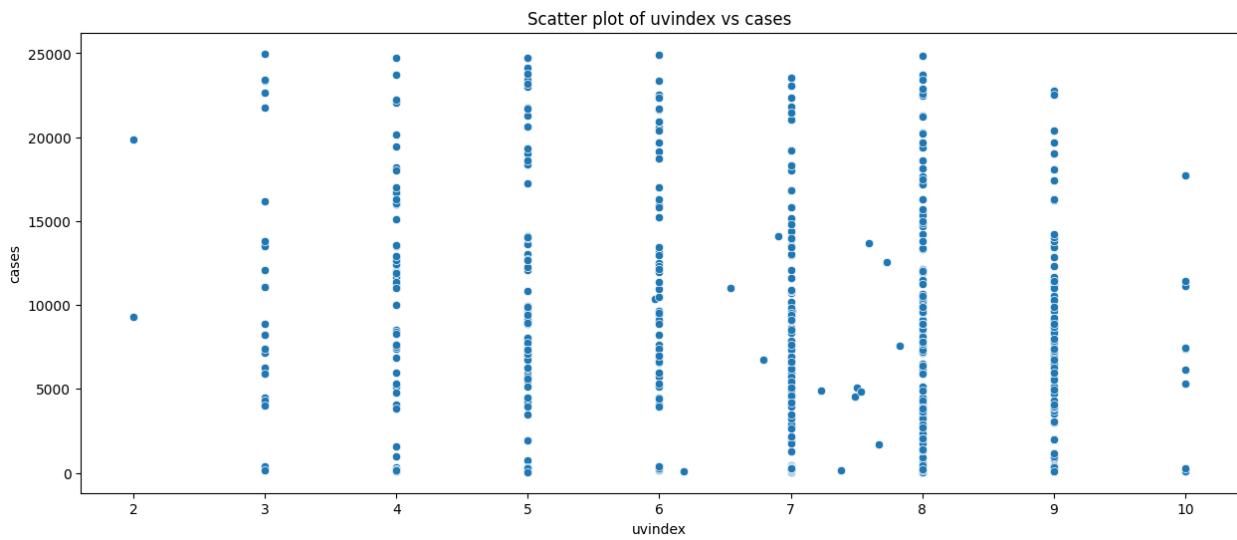
Scatter plot of solarenergy vs conditions

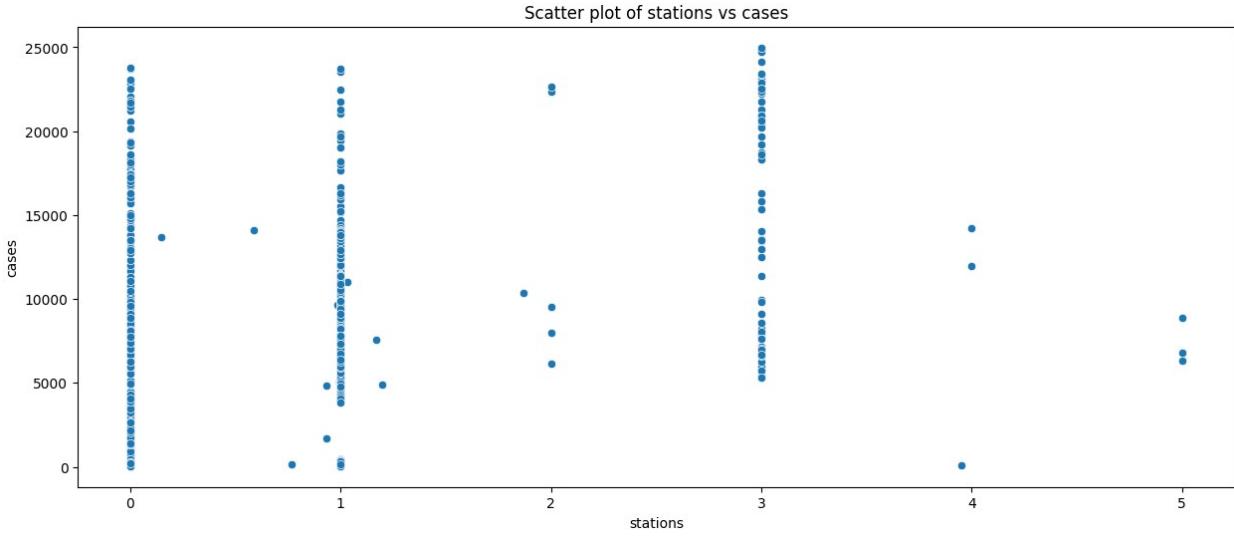


Scatter plot of solarenergy vs stations







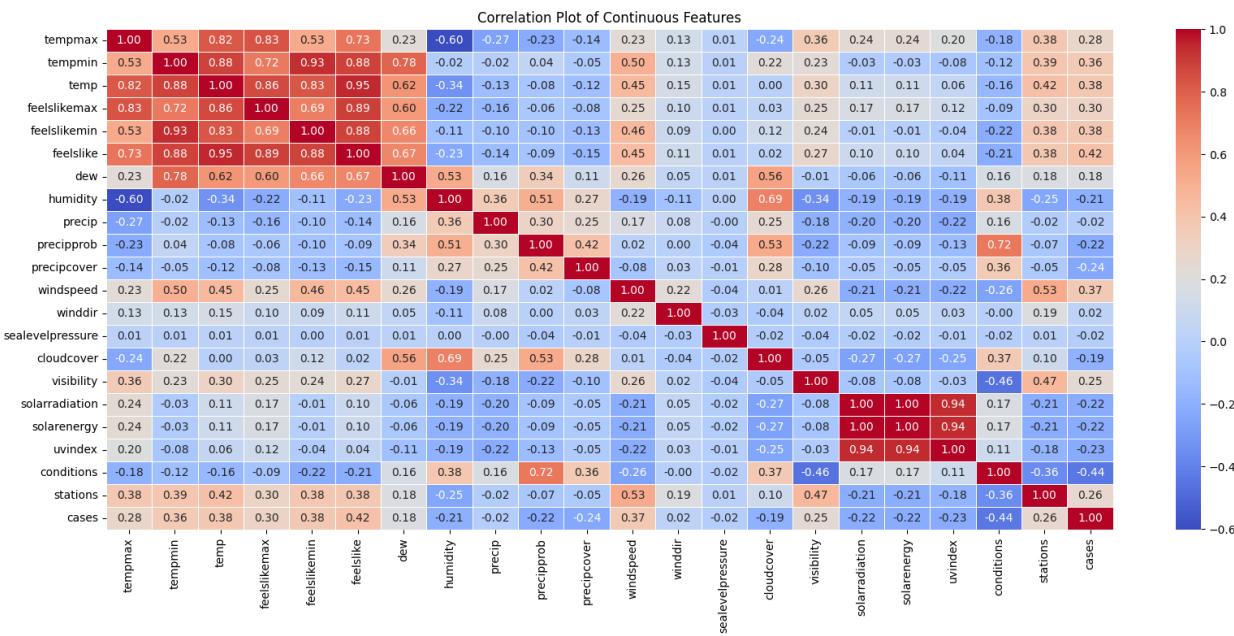


```

corr_matrix = df[continuous].corr()

plt.figure(figsize=(20, 8))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f",
            linewidths=0.5)
plt.title('Correlation Plot of Continuous Features')
plt.show()

```



```

corr_matrix

```

	tempmax	tempmin	temp	feelslikemax
feelslikemin \ tempmax	1.000000	0.527246	0.820941	0.832811

	feelslike	dew	humidity	precip	precipprob
tempmin	0.527246	1.000000	0.881988	0.716619	
tempmax	0.820941	0.881988	1.000000	0.863626	
feelslikemax	0.832811	0.716619	0.863626	1.000000	
feelslikemin	0.526838	0.931412	0.829122	0.693604	
feelslike	0.732782	0.883030	0.949866	0.891305	
dew	0.228436	0.784664	0.621103	0.596466	
humidity	-0.602729	-0.022102	-0.335037	-0.219550	-
precip	-0.270202	-0.015915	-0.130827	-0.155520	-
precipprob	-0.226290	0.043788	-0.077521	-0.061133	-
precipcover	-0.139013	-0.047444	-0.118306	-0.083107	-
windspeed	0.234752	0.502966	0.451224	0.254755	
winddir	0.131311	0.130978	0.151874	0.096730	
sealevelpressure	0.011288	0.007517	0.011662	0.011925	
cloudcover	-0.237572	0.223664	0.002212	0.034238	
visibility	0.358248	0.225410	0.299479	0.245154	
solarradiation	0.239410	-0.034087	0.114995	0.167350	-
solarenergy	0.239365	-0.034765	0.114794	0.167075	-
uvindex	0.198627	-0.075002	0.056545	0.115035	-
conditions	-0.184010	-0.115677	-0.157189	-0.094710	-
stations	0.381730	0.388823	0.421828	0.295325	
cases	0.284181	0.364691	0.378149	0.304087	
tempmin	0.883030	0.784664	-0.022102	-0.015915	0.043788

	temp	0.949866	0.621103	-0.335037	-0.130827	-0.077521
...
...	feelslikemax	0.891305	0.596466	-0.219550	-0.155520	-0.061133
...	feelslikemin	0.883670	0.664503	-0.112346	-0.099895	-0.097888
...	feelslike	1.000000	0.671107	-0.231987	-0.138739	-0.093543
...	dew	0.671107	1.000000	0.525232	0.155076	0.337453
...	humidity	-0.231987	0.525232	1.000000	0.356233	0.509203
...	precip	-0.138739	0.155076	0.356233	1.000000	0.303664
...	precipprob	-0.093543	0.337453	0.509203	0.303664	1.000000
...	precipcover	-0.150176	0.108530	0.274410	0.250264	0.415925
...	windspeed	0.448998	0.255004	-0.190625	0.173585	0.016617
...	winddir	0.114765	0.053704	-0.107605	0.082522	0.002863
...	sealevelpressure	0.005758	0.010999	0.000054	-0.004838	-0.044212
...	cloudcover	0.021153	0.557726	0.687903	0.253131	0.525631
...	visibility	0.273086	-0.012443	-0.343741	-0.184097	-0.223092
...	solarradiation	0.096916	-0.060513	-0.193474	-0.195445	-0.092390
...	solarenergy	0.096444	-0.060210	-0.192809	-0.195339	-0.091298
...	uvindex	0.042182	-0.109187	-0.193512	-0.223844	-0.133590
...	conditions	-0.209585	0.159187	0.380631	0.164735	0.718616
...	stations	0.376258	0.175522	-0.246563	-0.022313	-0.070126
...	cases	0.415344	0.179926	-0.208195	-0.015551	-0.222055
...						
			winddir	sealevelpressure	cloudcover	
visibility \	tempmax	0.131311		0.011288	-0.237572	0.358248
tempmin		0.130978		0.007517	0.223664	0.225410
temp		0.151874		0.011662	0.002212	0.299479

feelslike	0.096916	0.096444	0.042182	-0.209585
0.376258				
dew	-0.060513	-0.060210	-0.109187	0.159187
0.175522				
humidity	-0.193474	-0.192809	-0.193512	0.380631
0.246563				
precip	-0.195445	-0.195339	-0.223844	0.164735
0.022313				
precipprob	-0.092390	-0.091298	-0.133590	0.718616
0.070126				
precipcover	-0.052399	-0.051043	-0.045249	0.359712
0.050971				
windspeed	-0.213579	-0.213214	-0.220380	-0.262165
0.527127				
winddir	0.050350	0.048811	0.033059	-0.004174
0.188875				
sealevelpressure	-0.021577	-0.021874	-0.012383	-0.016276
0.010021				
cloudcover	-0.269381	-0.269513	-0.248548	0.372210
0.099885				
visibility	-0.080439	-0.082440	-0.034327	-0.461897
0.465622				
solarradiation	1.000000	0.999770	0.943408	0.172593
0.211525				
solarenergy	0.999770	1.000000	0.942740	0.174117
0.211956				
uvindex	0.943408	0.942740	1.000000	0.108675
0.177667				
conditions	0.172593	0.174117	0.108675	1.000000
0.363679				
stations	-0.211525	-0.211956	-0.177667	-0.363679
1.000000				
cases	-0.215879	-0.217348	-0.225515	-0.437434
0.261866				
cases				
tempmax	0.284181			
tempmin	0.364691			
temp	0.378149			
feelslikemax	0.304087			
feelslikemin	0.376015			
feelslike	0.415344			
dew	0.179926			
humidity	-0.208195			
precip	-0.015551			
precipprob	-0.222055			
precipcover	-0.236217			
windspeed	0.372895			
winddir	0.023418			

```

sealevelpressure -0.016806
cloudcover      -0.189715
visibility       0.248532
solarradiation  -0.215879
solarenergy     -0.217348
uvindex         -0.225515
conditions      -0.437434
stations        0.261866
cases           1.000000

[22 rows x 22 columns]

threshold = 0.7
features_to_drop = []
for i in range(len(corr_matrix.columns)):
    for j in range(i):
        if abs(corr_matrix.iloc[i, j]) > threshold:
            colname = corr_matrix.columns[i]
            if colname not in features_to_drop:
                features_to_drop.append(colname)

features_to_drop

['temp',
 'feelslikemax',
 'feelslikemin',
 'feelslike',
 'dew',
 'solarenergy',
 'uvindex',
 'conditions']

df = df.drop(['temp',
 'feelslikemax',
 'feelslikemin',
 'feelslike',
 'dew',
 'solarenergy',
 'uvindex',
 'conditions'], axis = 1)

df = pd.get_dummies(df, columns=['labels'])

df
   tempmax   tempmin   humidity      precip  precipprob
precipcover \
0  34.053151  24.478082  73.508219  2.921726  44.657534
4.360932
1  34.086179  25.694309  72.066667  3.783415  39.837398
2.676748

```

2	34.573984	25.417886	69.424390	3.065854	33.333333
2.337805					
3	33.020325	25.080488	69.297561	6.025203	37.398374
2.676667					
4	30.660976	24.230894	86.652033	23.336585	96.747967
15.616992					
..
..					
597	32.300000	24.400000	75.000000	0.000000	0.000000
0.000000					
598	32.700000	26.400000	68.500000	0.000000	0.000000
0.000000					
599	33.000000	26.300000	71.100000	0.000000	0.000000
0.000000					
600	35.100000	26.800000	65.900000	0.000000	0.000000
0.000000					
601	34.000000	26.300000	60.400000	0.000000	0.000000
0.000000					
snow	snowdepth	windspeed	winddir	sealevelpressure	
cloudcover	\				
0	0	0	15.678356	175.595342	1007.911781
50.747945					
1	0	0	14.574797	158.349593	1003.533333
48.313821					
2	0	0	14.978049	202.621138	1005.731707
55.621138					
3	0	0	16.504878	183.544715	1003.359350
50.208130					
4	0	0	19.546341	224.030081	1009.995935
45.542276					
..
..					
597	0	0	17.100000	159.800000	1008.900000
50.400000					
598	0	0	16.600000	233.000000	1010.400000
50.500000					
599	0	0	19.000000	344.400000	1010.800000
30.500000					
600	0	0	14.700000	81.300000	1009.700000
32.700000					
601	0	0	17.800000	79.200000	1008.700000
46.500000					
visibility	solarradiation	stations	cases	labels_normal	
0	3.789863	208.097808	1.197260	4925	True
1	2.884553	222.926016	0.991870	5077	True
2	4.242276	229.413008	1.170732	7579	True
3	2.991057	225.421951	0.146341	13706	True

```

4      3.886992    176.598374   3.951220     82      True
..      ...
597    3.100000    252.500000   1.000000    6729      ...
598    3.100000    242.700000   1.000000   10541      True
599    3.100000    195.300000   1.000000    6396      True
600    3.300000    187.600000   1.000000   10883      True
601    3.900000    136.200000   1.000000    7311      True

```

[602 rows x 17 columns]

```

from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split

categorical, non_categorical, discrete, continuous =
classify_features(df)

scaler = StandardScaler()
df[continuous] = scaler.fit_transform(df[continuous])

X = df.drop(columns=['cases'])
y = df['cases']

X_train, X_test, y_train, y_test = train_test_split(X, y,
test_size=0.2, random_state=42)

from sklearn.svm import SVR
from sklearn.metrics import mean_squared_error

svm_model = SVR()
svm_model.fit(X_train, y_train)

SVR()

y_pred_svm = svm_model.predict(X_test)
mse_svm = mean_squared_error(y_test, y_pred_svm)
print(f'SVM Mean Squared Error: {mse_svm}')

SVM Mean Squared Error: 0.5295336245622033

from sklearn.tree import DecisionTreeRegressor

dtr_model = DecisionTreeRegressor()
dtr_model.fit(X_train, y_train)

DecisionTreeRegressor()

y_pred_dtr = dtr_model.predict(X_test)
mse_dtr = mean_squared_error(y_test, y_pred_dtr)
print(f'Decision Tree Regressor Mean Squared Error: {mse_dtr}')

Decision Tree Regressor Mean Squared Error: 1.178208188390991

```

```
from sklearn.ensemble import RandomForestRegressor

rfr_model = RandomForestRegressor()
rfr_model.fit(X_train, y_train)

RandomForestRegressor()

y_pred_rfr = rfr_model.predict(X_test)
mse_rfr = mean_squared_error(y_test, y_pred_rfr)
print(f'Random Forest Regressor Mean Squared Error: {mse_rfr}')
```

Random Forest Regressor Mean Squared Error: 0.5295137972750776

```
import xgboost as xgb
from xgboost import XGBRegressor

xgboost_model = XGBRegressor()
xgboost_model.fit(X_train, y_train)

XGBRegressor(base_score=None, booster=None, callbacks=None,
             colsample_bylevel=None, colsample_bynode=None,
             colsample_bytree=None, device=None,
             early_stopping_rounds=None,
             enable_categorical=False, eval_metric=None,
             feature_types=None,
             gamma=None, grow_policy=None, importance_type=None,
             interaction_constraints=None, learning_rate=None,
             max_bin=None,
             max_cat_threshold=None, max_cat_to_onehot=None,
             max_delta_step=None, max_depth=None, max_leaves=None,
             min_child_weight=None, missing=nan,
             monotone_constraints=None,
             multi_strategy=None, n_estimators=None, n_jobs=None,
             num_parallel_tree=None, random_state=None, ...)
```

y_pred_xgb = xgboost_model.predict(X_test)

```
mse_xgb = mean_squared_error(y_test, y_pred_xgb)
print(f'XGBoost Regressor Mean Squared Error: {mse_xgb}')
```

XGBoost Regressor Mean Squared Error: 0.6388940809544029

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score

linear_model = LinearRegression()
linear_model.fit(X_train, y_train)

LinearRegression()

y_pred = linear_model.predict(X_test)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
```

```
print(f'Linear Regression Mean Squared Error: {mse}')  
print(f'Linear Regression R^2 Score: {r2}')  
  
Linear Regression Mean Squared Error: 0.6650722290587311  
Linear Regression R^2 Score: 0.26539125471806235
```

Thanks !!!