In [1]:

```
# importing libraries
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
# loading training files
features = pd.read_csv('dengue_features_train.csv')
labels = pd.read_csv('dengue_labels_train.csv')
```

In [3]:

```
# sub data
sub_data = pd.read_csv('dengue_features_test.csv')
```

In [4]:

```
# merging training data
data = features.merge(labels, left_index=True, right_index=True)
```

In [5]:

```
data.head()
```

Out[5]:

	city_x	year_x	weekofyear_x	week_start_date	ndvi_ne	ndvi_nw	ndvi_se	ndvi_sw	p
0	sj	1990	18	1990-04-30	0.122600	0.103725	0.198483	0.177617	
1	sj	1990	19	1990-05-07	0.169900	0.142175	0.162357	0.155486	
2	sj	1990	20	1990-05-14	0.032250	0.172967	0.157200	0.170843	
3	sj	1990	21	1990-05-21	0.128633	0.245067	0.227557	0.235886	
4	sj	1990	22	1990-05-28	0.196200	0.262200	0.251200	0.247340	

5 rows × 28 columns

In [6]:

```
# we see that city, year and weekofyear duplicate with y-data so we drop them
data=data.drop(['city_y','year_y','weekofyear_y'], axis=1)
```

In [7]:

```
# separating numeric
numeric=[col for col in data.columns if data[col].dtypes != 'object']
```

In [8]:

```
# sub data
sub_numeric=[col for col in sub_data.columns if sub_data[col].dtypes != 'object']
```

In [9]:

```
numeric
```

Out[9]:

```
['year_x',
 'weekofyear_x',
 'ndvi_ne',
 'ndvi_nw',
 'ndvi_se',
 'ndvi_sw',
 'precipitation_amt_mm',
 'reanalysis_air_temp_k',
 'reanalysis_avg_temp_k',
 'reanalysis_dew_point_temp_k',
 'reanalysis_max_air_temp_k',
 'reanalysis_min_air_temp_k',
 'reanalysis_precip_amt_kg_per_m2',
 'reanalysis_relative_humidity_percent',
 'reanalysis_sat_precip_amt_mm',
 'reanalysis_specific_humidity_g_per_kg',
 'reanalysis_tdtr_k',
 'station_avg_temp_c',
 'station_diur_temp_rng_c',
 'station_max_temp_c',
 'station_min_temp_c',
 'station_precip_mm',
 'total_cases']
```

In [10]:

```
# sub data
sub_numeric
```

Out[10]:

```
['year',
 'weekofyear',
 'ndvi_ne',
 'ndvi_nw',
 'ndvi_se',
 'ndvi_sw',
 'precipitation_amt_mm',
 'reanalysis_air_temp_k',
 'reanalysis_avg_temp_k',
 'reanalysis_dew_point_temp_k',
 'reanalysis_max_air_temp_k',
 'reanalysis_min_air_temp_k',
 'reanalysis_precip_amt_kg_per_m2',
 'reanalysis_relative_humidity_percent',
 'reanalysis_sat_precip_amt_mm',
 'reanalysis_specific_humidity_g_per_kg',
 'reanalysis_tdtr_k',
 'station_avg_temp_c',
 'station_diur_temp_rng_c',
 'station_max_temp_c',
 'station_min_temp_c',
 'station_precip_mm']
```

In [11]:

```
# separating categorical
categorical = data.drop(numeric, axis=1).columns
```

In [12]:

```
#sub data
sub_categorical = sub_data.drop(sub_numeric, axis=1).columns
```

In [13]:

```
categorical
```

Out[13]:

```
Index(['city_x', 'week_start_date'], dtype='object')
```

In [14]:

```
# sub data
sub_categorical
```

Out[14]:

```
Index(['city', 'week_start_date'], dtype='object')
```

In [15]:

```
# data has been basically prepared for exploration and preprocessing
```

In [16]:

```
# EDA
```

In [17]:

```
# let's check the correlation between numeric features and the label - the total cases
 of occurence of the disease
```

In [18]:

```
data[numeric].corrwith(data['total_cases'])
```

Out[18]:

```
year_x                                  -0.306806
weekofyear_x                             0.216452
ndvi_ne                                 -0.241376
ndvi_nw                                 -0.202235
ndvi_se                                 -0.168612
ndvi_sw                                 -0.196461
precipitation_amt_mm                    -0.038740
reanalysis_air_temp_k                    0.264952
reanalysis_avg_temp_k                    0.151637
reanalysis_dew_point_temp_k              0.142531
reanalysis_max_air_temp_k               -0.191345
reanalysis_min_air_temp_k                0.325252
reanalysis_precip_amt_kg_per_m2         -0.010031
reanalysis_relative_humidity_percent    -0.132452
reanalysis_sat_precip_amt_mm            -0.038740
reanalysis_specific_humidity_g_per_kg    0.129861
reanalysis_tdtr_k                       -0.278483
station_avg_temp_c                       0.116109
station_diur_temp_rng_c                 -0.237844
station_max_temp_c                      -0.039219
station_min_temp_c                       0.267109
station_precip_mm                       -0.074374
total_cases                              1.000000
dtype: float64
```

In [19]:

```
# it is good that most of the feautures have clear correlation with our target with ver
y few exceptions that will be analysed
# for now, we keep all the features
```

In [20]:

```
# Data Visualization
```

In [21]:

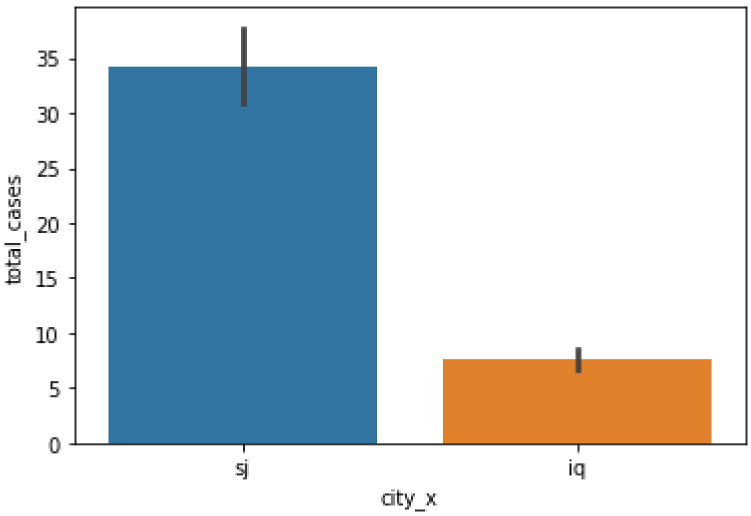
```
# removing the total_cases label only for the visualization
numeric_pairplot = numeric.copy()
numeric_pairplot.remove('total_cases')
```

In [22]:

```
# ploting categorical data
sns.barplot(data=data, x='city_x', y='total_cases')
```

Out[22]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2a4b3058d48>
```

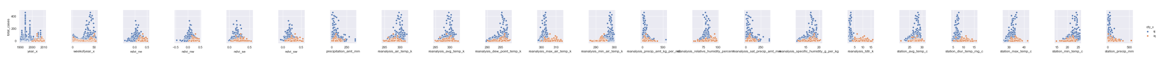


In [23]:

```
# pair plotting numeric data
sns.set()
sns.pairplot(data=data, x_vars=numeric_pairplot, y_vars='total_cases', hue='city_x')
```

Out[23]:

```
<seaborn.axisgrid.PairGrid at 0x2a4b37a2c48>
```



In [24]:

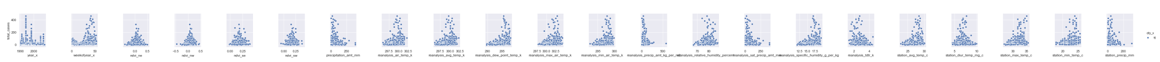
```
# there is too big difference between the two cities so when preprocessing data, it wou
ld be wise to do it per city
```

In [25]:

```
# pair plotting by city
# 'sj'
sns.set()
sns.pairplot(data=data[data['city_x']=='sj'], x_vars=numeric_pairplot, y_vars='total_ca
ses', hue='city_x')
```

Out[25]:

```
<seaborn.axisgrid.PairGrid at 0x2a4b3ca3248>
```

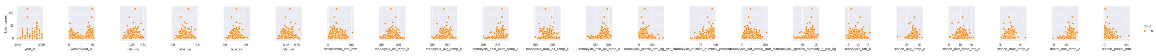


In [26]:

```
# 'iq'
sns.set()
sns.pairplot(data=data[data['city_x']=='iq'], x_vars=numeric_pairplot, y_vars='total_ca
ses', hue='city_x', palette='autumn')
```

Out[26]:

```
<seaborn.axisgrid.PairGrid at 0x2a4b4d9cb88>
```



In [27]:

```
# let's convert date column 'week_start_date' to datetime
data['week_start_date']=pd.to_datetime(data['week_start_date'])
```

In [28]:

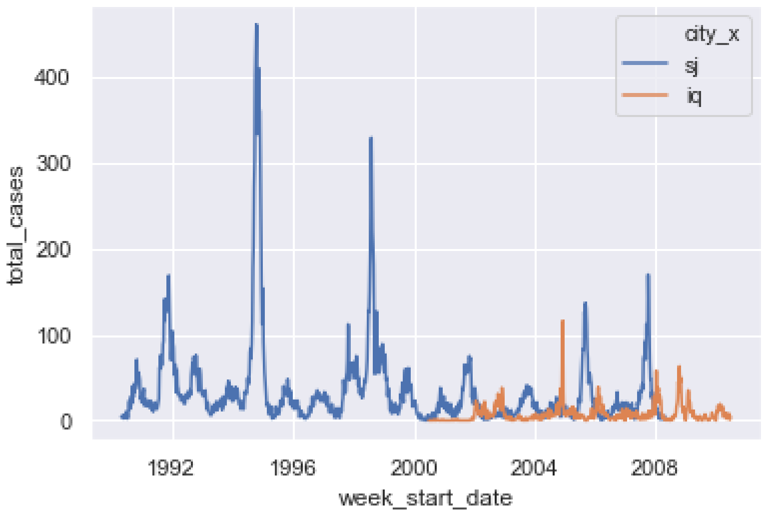
```
#sub data
sub_data['week_start_date']=pd.to_datetime(sub_data['week_start_date'])
```

In [29]:

```
sns.lineplot(data=data, x='week_start_date', y='total_cases', hue='city_x')
```

Out[29]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2a4b2ff3d88>
```

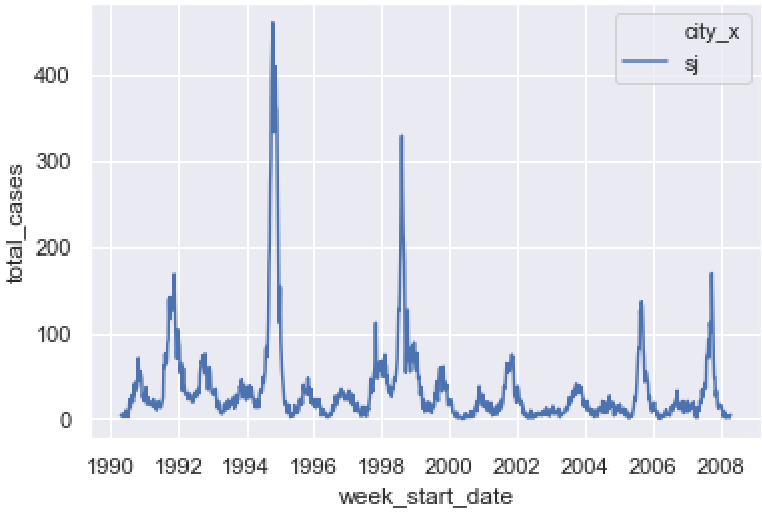


In [30]:

```
# plot by city
sns.lineplot(data=data[data['city_x']=='sj'], x='week_start_date', y='total_cases', hue
='city_x')
```

Out[30]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2a4b6a09c08>
```

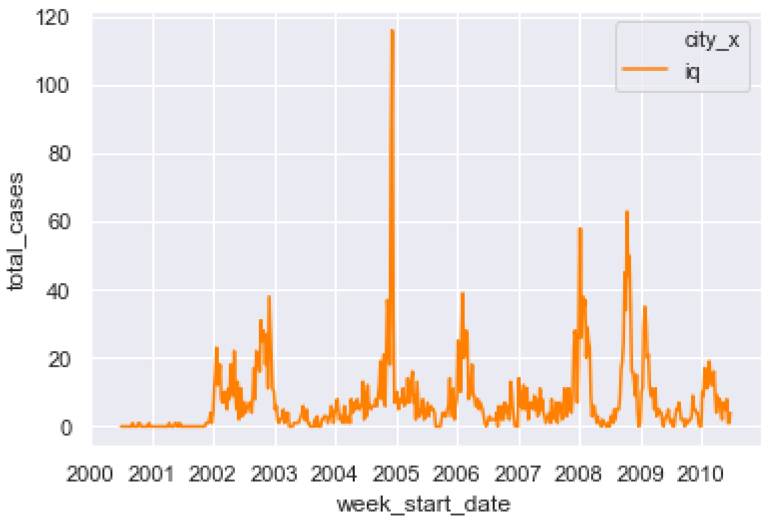


In [31]:

```
sns.lineplot(data=data[data['city_x']=='iq'], x='week_start_date', y='total_cases', hue
='city_x', palette='autumn')
```

Out[31]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x2a4b6a79408>
```



In [32]:

```
# descriptive statistics mainly to compare mean and median of numeric features
mean_median_table = pd.DataFrame({'mean': data[numeric].mean(), 'median': data[numeric]
.median(), 'min': data[numeric].min(), 'max': data[numeric].max()})
mean_median_table
```

Out[32]:

	mean	median	min	max
year_x	2001.031593	2002.000000	1990.000000	2010.000000
weekofyear_x	26.503434	26.500000	1.000000	53.000000
ndvi_ne	0.142294	0.128817	-0.406250	0.508357
ndvi_nw	0.130553	0.121429	-0.456100	0.454429
ndvi_se	0.203783	0.196050	-0.015533	0.538314
ndvi_sw	0.202305	0.189450	-0.063457	0.546017
precipitation_amt_mm	45.760388	38.340000	0.000000	390.600000
reanalysis_air_temp_k	298.701852	298.646429	294.635714	302.200000
reanalysis_avg_temp_k	299.225578	299.289286	294.892857	302.928571
reanalysis_dew_point_temp_k	295.246356	295.640714	289.642857	298.450000
reanalysis_max_air_temp_k	303.427109	302.400000	297.800000	314.000000
reanalysis_min_air_temp_k	295.719156	296.200000	286.900000	299.900000
reanalysis_precip_amt_kg_per_m2	40.151819	27.245000	0.000000	570.500000
reanalysis_relative_humidity_percent	82.161959	80.301429	57.787143	98.610000
reanalysis_sat_precip_amt_mm	45.760388	38.340000	0.000000	390.600000
reanalysis_specific_humidity_g_per_kg	16.746427	17.087143	11.715714	20.461429
reanalysis_tdtr_k	4.903754	2.857143	1.357143	16.028571
station_avg_temp_c	27.185783	27.414286	21.400000	30.800000
station_diur_temp_rng_c	8.059328	7.300000	4.528571	15.800000
station_max_temp_c	32.452437	32.800000	26.700000	42.200000
station_min_temp_c	22.102150	22.200000	14.700000	25.600000
station_precip_mm	39.326360	23.850000	0.000000	543.300000
total_cases	24.675137	12.000000	0.000000	461.000000

In [33]:

```
# sub data
sub_mean_median_table = pd.DataFrame({'mean': sub_data[sub_numeric].mean(), 'median': s
ub_data[sub_numeric].median(), 'min': sub_data[sub_numeric].min(), 'max': sub_data[sub_
numeric].max()})
sub_mean_median_table
```

Out[33]:

	mean	median	min	max
year	2010.766827	2011.000000	2008.000000	2013.000000
weekofyear	26.439904	26.000000	1.000000	53.000000
ndvi_ne	0.126050	0.110100	-0.463400	0.500400
ndvi_nw	0.126803	0.088700	-0.211800	0.649000
ndvi_se	0.207702	0.204171	0.006200	0.453043
ndvi_sw	0.201721	0.186471	-0.014671	0.529043
precipitation_amt_mm	38.354324	31.455000	0.000000	169.340000
reanalysis_air_temp_k	298.818295	298.547143	294.554286	301.935714
reanalysis_avg_temp_k	299.353071	299.328571	295.235714	303.328571
reanalysis_dew_point_temp_k	295.419179	295.825000	290.818571	297.794286
reanalysis_max_air_temp_k	303.623430	302.750000	298.200000	314.100000
reanalysis_min_air_temp_k	295.743478	296.300000	286.200000	299.700000
reanalysis_precip_amt_kg_per_m2	42.171135	25.850000	0.000000	301.400000
reanalysis_relative_humidity_percent	82.499810	80.330000	64.920000	97.982857
reanalysis_sat_precip_amt_mm	38.354324	31.455000	0.000000	169.340000
reanalysis_specific_humidity_g_per_kg	16.927088	17.337143	12.537143	19.598571
reanalysis_tdtr_k	5.124569	2.914286	1.485714	14.485714
station_avg_temp_c	27.369587	27.483333	24.157143	30.271429
station_diur_temp_rng_c	7.810991	6.642857	4.042857	14.725000
station_max_temp_c	32.534625	32.800000	27.200000	38.400000
station_min_temp_c	22.368550	22.200000	14.200000	26.700000
station_precip_mm	34.278589	23.600000	0.000000	212.000000

In [34]:

```
# for features were mean is significantly different from the median, we should use the
 median when imputing missing values
# for the rest, we should use the mean
# let's separate features based on which will be imputed with what
```

In [35]:

```
# same statistics but split per city
mean_median_table_sj = pd.DataFrame({'mean': data[numeric][data['city_x']=='sj'].mean
(), 'median': data[numeric][data['city_x']=='sj'].median(), 'min': data[numeric][data[
'city_x']=='sj'].min(), 'max': data[numeric][data['city_x']=='sj'].max()})
mean_median_table_sj
```

Out[35]:

	mean	median	min	max
year_x	1998.826923	1999.000000	1990.000000	2008.000000
weekofyear_x	26.503205	26.500000	1.000000	53.000000
ndvi_ne	0.057925	0.057700	-0.406250	0.493400
ndvi_nw	0.067469	0.068075	-0.456100	0.437100
ndvi_se	0.177655	0.177186	-0.015533	0.393129
ndvi_sw	0.165956	0.165971	-0.063457	0.381420
precipitation_amt_mm	35.470809	20.800000	0.000000	390.600000
reanalysis_air_temp_k	299.163653	299.254286	295.938571	302.200000
reanalysis_avg_temp_k	299.276920	299.378571	296.114286	302.164286
reanalysis_dew_point_temp_k	295.109519	295.464286	289.642857	297.795714
reanalysis_max_air_temp_k	301.398817	301.500000	297.800000	304.300000
reanalysis_min_air_temp_k	297.301828	297.500000	292.600000	299.900000
reanalysis_precip_amt_kg_per_m2	30.465419	21.300000	0.000000	570.500000
reanalysis_relative_humidity_percent	78.568181	78.667857	66.735714	87.575714
reanalysis_sat_precip_amt_mm	35.470809	20.800000	0.000000	390.600000
reanalysis_specific_humidity_g_per_kg	16.552409	16.845714	11.715714	19.440000
reanalysis_tdtr_k	2.516267	2.457143	1.357143	4.428571
station_avg_temp_c	27.006528	27.228571	22.842857	30.071429
station_diur_temp_rng_c	6.757373	6.757143	4.528571	9.914286
station_max_temp_c	31.607957	31.700000	26.700000	35.600000
station_min_temp_c	22.600645	22.800000	17.800000	25.600000
station_precip_mm	26.785484	17.750000	0.000000	305.900000
total_cases	34.180556	19.000000	0.000000	461.000000

In [36]:

```
# sub data
sub_mean_median_table_sj = pd.DataFrame({'mean': sub_data[sub_numeric][sub_data['city']
=='sj'].mean(), 'median': sub_data[sub_numeric][sub_data['city']=='sj'].median(), 'min'
: sub_data[sub_numeric][sub_data['city']=='sj'].min(), 'max': sub_data[sub_numeric][sub
_data['city']=='sj'].max()})
sub_mean_median_table_sj
```

Out[36]:

	mean	median	min	max
year	2010.326923	2010.000000	2008.000000	2013.000000
weekofyear	26.503846	26.500000	1.000000	53.000000
ndvi_ne	0.024801	0.014975	-0.463400	0.500400
ndvi_nw	0.036730	0.032140	-0.211800	0.649000
ndvi_se	0.177055	0.169350	0.006200	0.385383
ndvi_sw	0.153226	0.148017	-0.014671	0.318129
precipitation_amt_mm	26.521124	13.975000	0.000000	169.340000
reanalysis_air_temp_k	299.458051	299.753571	296.651429	301.507143
reanalysis_avg_temp_k	299.542968	299.782143	296.792857	301.542857
reanalysis_dew_point_temp_k	295.322004	295.660000	290.818571	297.794286
reanalysis_max_air_temp_k	301.596512	301.900000	298.200000	304.100000
reanalysis_min_air_temp_k	297.572868	297.700000	293.800000	299.700000
reanalysis_precip_amt_kg_per_m2	23.766279	15.245000	0.000000	301.400000
reanalysis_relative_humidity_percent	78.203034	78.380000	64.920000	86.781429
reanalysis_sat_precip_amt_mm	26.521124	13.975000	0.000000	169.340000
reanalysis_specific_humidity_g_per_kg	16.753383	17.072857	12.537143	19.340000
reanalysis_tdtr_k	2.587043	2.542857	1.485714	4.428571
station_avg_temp_c	27.272536	27.421429	24.157143	30.271429
station_diur_temp_rng_c	6.152436	6.178571	4.042857	8.400000
station_max_temp_c	31.677132	31.700000	27.200000	35.000000
station_min_temp_c	23.107364	23.300000	20.000000	26.700000
station_precip_mm	34.212791	22.350000	0.000000	207.700000

In [37]:

```
# sj
data_sj = data[data['city_x']=='sj']
#sj_median_columns = ['precipitation_amt_mm', 'reanalysis_precip_amt_kg_per_m2', 'reana
lysis_sat_precip_amt_mm', 'station_precip_mm']
#sj_mean_columns = data_sj.drop(sj_median_columns, axis=1).drop(['city_x', 'week_start_
date'], axis=1).columns
```

In [38]:

```
# sub data
sub_data_sj = sub_data[sub_data['city']=='sj']
```

In [39]:

```
# same statistics but split per city
mean_median_table_iq = pd.DataFrame({'mean': data[numeric][data['city_x']=='iq'].mean
(), 'median': data[numeric][data['city_x']=='iq'].median(), 'min': data[numeric][data[
'city_x']=='iq'].min(), 'max': data[numeric][data['city_x']=='iq'].max()})
mean_median_table_iq
```

Out[39]:

	mean	median	min	max
year_x	2005.000000	2005.000000	2000.000000	2010.000000
weekofyear_x	26.503846	26.500000	1.000000	53.000000
ndvi_ne	0.263869	0.263643	0.061729	0.508357
ndvi_nw	0.238783	0.232971	0.035860	0.454429
ndvi_se	0.250126	0.249800	0.029880	0.538314
ndvi_sw	0.266779	0.262143	0.064183	0.546017
precipitation_amt_mm	64.245736	60.470000	0.000000	210.830000
reanalysis_air_temp_k	297.869538	297.822857	294.635714	301.637143
reanalysis_avg_temp_k	299.133043	299.121429	294.892857	302.928571
reanalysis_dew_point_temp_k	295.492982	295.852143	290.088571	298.450000
reanalysis_max_air_temp_k	307.082752	307.050000	300.000000	314.000000
reanalysis_min_air_temp_k	292.866667	293.050000	286.900000	296.000000
reanalysis_precip_amt_kg_per_m2	57.609864	46.440000	0.000000	362.030000
reanalysis_relative_humidity_percent	88.639117	90.917143	57.787143	98.610000
reanalysis_sat_precip_amt_mm	64.245736	60.470000	0.000000	210.830000
reanalysis_specific_humidity_g_per_kg	17.096110	17.428571	12.111429	20.461429
reanalysis_tdtr_k	9.206783	8.964286	3.714286	16.028571
station_avg_temp_c	27.530933	27.600000	21.400000	30.800000
station_diur_temp_rng_c	10.566197	10.625000	5.200000	15.800000
station_max_temp_c	34.004545	34.000000	30.100000	42.200000
station_min_temp_c	21.196680	21.300000	14.700000	24.200000
station_precip_mm	62.467262	45.300000	0.000000	543.300000
total_cases	7.565385	5.000000	0.000000	116.000000

In [40]:

```
# sub data
sub_mean_median_table_iq = pd.DataFrame({'mean': sub_data[sub_numeric][sub_data['city']
=='iq'].mean(), 'median': sub_data[sub_numeric][sub_data['city']=='iq'].median(), 'min'
: sub_data[sub_numeric][sub_data['city']=='iq'].min(), 'max': sub_data[sub_numeric][sub
_data['city']=='iq'].max()})
sub_mean_median_table_iq
```

Out[40]:

	mean	median	min	max
year	2011.500000	2011.500000	2010.000000	2013.000000
weekofyear	26.333333	26.000000	1.000000	52.000000
ndvi_ne	0.266889	0.265229	0.089286	0.429986
ndvi_nw	0.270574	0.269462	0.063214	0.464800
ndvi_se	0.258583	0.253164	0.098257	0.453043
ndvi_sw	0.282235	0.281531	0.081957	0.529043
precipitation_amt_mm	57.924615	51.290000	2.280000	152.320000
reanalysis_air_temp_k	297.760238	297.752857	294.554286	301.935714
reanalysis_avg_temp_k	299.039011	299.003571	295.235714	303.328571
reanalysis_dew_point_temp_k	295.579890	295.935714	291.954286	297.725714
reanalysis_max_air_temp_k	306.975641	306.700000	302.800000	314.100000
reanalysis_min_air_temp_k	292.717949	292.950000	286.200000	296.000000
reanalysis_precip_amt_kg_per_m2	72.609936	59.300000	2.600000	280.420000
reanalysis_relative_humidity_percent	89.606016	91.411429	66.310000	97.982857
reanalysis_sat_precip_amt_mm	57.924615	51.290000	2.280000	152.320000
reanalysis_specific_humidity_g_per_kg	17.214368	17.552143	13.737143	19.598571
reanalysis_tdtr_k	9.321245	9.371429	4.800000	14.485714
station_avg_temp_c	27.541088	27.510000	24.840000	29.133333
station_diur_temp_rng_c	10.741861	10.735000	6.450000	14.725000
station_max_temp_c	33.961935	34.000000	29.600000	38.400000
station_min_temp_c	21.089262	21.200000	14.200000	23.200000
station_precip_mm	34.389542	27.200000	0.000000	212.000000

In [41]:

```
# iq
data_iq = data[data['city_x']=='iq']
#iq_median_columns = ['precipitation_amt_mm', 'reanalysis_precip_amt_kg_per_m2', 'reana
lysis_sat_precip_amt_mm', 'station_avg_temp_c','station_max_temp_c', 'station_precip_m
m']
#iq_mean_columns = data_iq.drop(iq_median_columns, axis=1).drop(['city_x', 'week_start_
date'], axis=1).columns
```

In [42]:

```
# sub data
sub_data_iq = sub_data[sub_data['city']=='iq']
```

In [43]:

```
# PREPROCESSING
```

In [44]:

```
# Missing values
```

In [45]:

```
# numeric
# sj
data_sj.isnull().sum()
```

Out[45]:

```
city_x                                     0
year_x                                     0
weekofyear_x                               0
week_start_date                            0
ndvi_ne                                  191
ndvi_nw                                   49
ndvi_se                                   19
ndvi_sw                                   19
precipitation_amt_mm                       9
reanalysis_air_temp_k                      6
reanalysis_avg_temp_k                      6
reanalysis_dew_point_temp_k                6
reanalysis_max_air_temp_k                  6
reanalysis_min_air_temp_k                  6
reanalysis_precip_amt_kg_per_m2            6
reanalysis_relative_humidity_percent       6
reanalysis_sat_precip_amt_mm               9
reanalysis_specific_humidity_g_per_kg      6
reanalysis_tdtr_k                          6
station_avg_temp_c                         6
station_diur_temp_rng_c                    6
station_max_temp_c                         6
station_min_temp_c                         6
station_precip_mm                          6
total_cases                                0
dtype: int64
```

In [46]:

```
# numeric
# iq
data_iq.isnull().sum()
```

Out[46]:

```
city_x                                    0
year_x                                    0
weekofyear_x                              0
week_start_date                           0
ndvi_ne                                   3
ndvi_nw                                   3
ndvi_se                                   3
ndvi_sw                                   3
precipitation_amt_mm                      4
reanalysis_air_temp_k                     4
reanalysis_avg_temp_k                     4
reanalysis_dew_point_temp_k               4
reanalysis_max_air_temp_k                 4
reanalysis_min_air_temp_k                 4
reanalysis_precip_amt_kg_per_m2           4
reanalysis_relative_humidity_percent      4
reanalysis_sat_precip_amt_mm              4
reanalysis_specific_humidity_g_per_kg     4
reanalysis_tdtr_k                         4
station_avg_temp_c                       37
station_diur_temp_rng_c                  37
station_max_temp_c                       14
station_min_temp_c                        8
station_precip_mm                        16
total_cases                               0
dtype: int64
```

In [47]:

```
# !!! experiment with both median
# imputing missing values
from sklearn.impute import SimpleImputer

median_imputer = SimpleImputer(strategy='median')
#mean_imputer = SimpleImputer(strategy='mean')
```

In [48]:

```
#data_sj[sj_median_columns] = median_imputer.fit_transform(data_sj[sj_median_columns])
#data_sj[sj_mean_columns] = mean_imputer.fit_transform(data_sj[sj_mean_columns])
data_sj[numeric] = median_imputer.fit_transform(data_sj[numeric])
```

In [49]:

```
# sub data
sub_data_sj[sub_numeric] = median_imputer.fit_transform(sub_data_sj[sub_numeric])
```

In [50]:

```
#data_iq[iq_median_columns] = median_imputer.fit_transform(data_iq[iq_median_columns])
#data_iq[iq_mean_columns] = mean_imputer.fit_transform(data_iq[iq_mean_columns])
data_iq[numeric] = median_imputer.fit_transform(data_iq[numeric])
```

In [51]:

```
# sub data
sub_data_iq[sub_numeric] = median_imputer.fit_transform(sub_data_iq[sub_numeric])
```

In [52]:

```
# we need to replace the imputed sj and iq data into the original 'data' data frame to
 see the effect
```

In [53]:

```
#data_final = pd.concat([data_sj, data_iq])
```

In [54]:

```
# UPDATE !!!!
# we will train 2 models per city since data is ordered both in train and test files
```

In [55]:

```
# double checking that final data has no missing values
#data_final.isnull().sum()
```

In [56]:

```
# ENCODING categorical variables
```

In [57]:

```
#data_final[categorical]
```

In [58]:

```
# week_start_date seems like not very useful feature, except for plotting data and EDA
# will drop it for the purpose of categorical data encoding
```

In [59]:

```
#data_final = pd.get_dummies(data_final).drop('week_start_date', axis=1)
```

In [60]:

```
data_sj
```

Out[60]:

	city_x	year_x	weekofyear_x	week_start_date	ndvi_ne	ndvi_nw	ndvi_se	ndvi_sw
0	sj	1990.0	18.0	1990-04-30	0.122600	0.103725	0.198483	0.177617
1	sj	1990.0	19.0	1990-05-07	0.169900	0.142175	0.162357	0.155486
2	sj	1990.0	20.0	1990-05-14	0.032250	0.172967	0.157200	0.170843
3	sj	1990.0	21.0	1990-05-21	0.128633	0.245067	0.227557	0.235886
4	sj	1990.0	22.0	1990-05-28	0.196200	0.262200	0.251200	0.247340
...	...	...	...	...	...	...	...	...
931	sj	2008.0	13.0	2008-03-25	0.077850	-0.039900	0.310471	0.296243
932	sj	2008.0	14.0	2008-04-01	-0.038000	-0.016833	0.119371	0.066386
933	sj	2008.0	15.0	2008-04-08	-0.155200	-0.052750	0.137757	0.141214
934	sj	2008.0	16.0	2008-04-15	0.001800	0.068075	0.203900	0.209843
935	sj	2008.0	17.0	2008-04-22	-0.037000	-0.010367	0.077314	0.090586

936 rows × 25 columns

In [61]:

```
data_sj = data_sj.drop(['week_start_date', 'city_x'], axis=1)
data_iq = data_iq.drop(['week_start_date', 'city_x'], axis=1)
```

In [62]:

```
# sub data
sub_data_sj = sub_data_sj.drop(['week_start_date', 'city'], axis=1)
sub_data_iq = sub_data_iq.drop(['week_start_date', 'city'], axis=1)
```

In [63]:

```
# let's shuffle data so that we don't have the sj rows on top
#for i in range(10000):
#    data_final = data_final.sample(frac=1.0, random_state=1)
```

In [64]:

```
#data_final
```

In [100]:

```
sub_data_iq
```

Out[100]:

	year	weekofyear	ndvi_ne	ndvi_nw	ndvi_se	ndvi_sw	reanalysis_air_temp_k	rear
260	2010.0	26.0	0.183783	0.142500	0.225129	0.150214	297.648571	
261	2010.0	27.0	0.291657	0.272267	0.330700	0.320914	298.224286	
262	2010.0	28.0	0.208543	0.366457	0.212629	0.255514	297.955714	
263	2010.0	29.0	0.089286	0.063214	0.122057	0.081957	295.715714	
264	2010.0	30.0	0.306100	0.327683	0.250086	0.267914	298.502857	
...	...	...	...	...	...	...	...	
411	2013.0	22.0	0.301471	0.380029	0.280629	0.383186	297.774286	
412	2013.0	23.0	0.247600	0.296343	0.285371	0.350357	297.167143	
413	2013.0	24.0	0.238729	0.251029	0.252586	0.249771	295.831429	
414	2013.0	25.0	0.310429	0.302700	0.406614	0.403943	295.778571	
415	2013.0	26.0	0.339467	0.240071	0.356943	0.273600	297.372857	

156 rows × 17 columns

In [66]:

```
# here we can play with features before modelling
#data_final=data_final.drop(['precipitation_amt_mm','reanalysis_precip_amt_kg_per_m2',
 'reanalysis_sat_precip_amt_mm', 'station_max_temp_c','station_precip_mm'], axis=1)
```

In [67]:

```
data_sj=data_sj.drop(['precipitation_amt_mm','reanalysis_precip_amt_kg_per_m2', 'reanal
ysis_sat_precip_amt_mm', 'station_max_temp_c','station_precip_mm'], axis=1)
data_iq=data_iq.drop(['precipitation_amt_mm','reanalysis_precip_amt_kg_per_m2', 'reanal
ysis_sat_precip_amt_mm', 'station_max_temp_c','station_precip_mm'], axis=1)
sub_data_sj=sub_data_sj.drop(['precipitation_amt_mm','reanalysis_precip_amt_kg_per_m2',
'reanalysis_sat_precip_amt_mm', 'station_max_temp_c','station_precip_mm'], axis=1)
sub_data_iq=sub_data_iq.drop(['precipitation_amt_mm','reanalysis_precip_amt_kg_per_m2',
'reanalysis_sat_precip_amt_mm', 'station_max_temp_c','station_precip_mm'], axis=1)
```

In [68]:

```
# MODELING
```

In [69]:

```
# splitting train and test data
from sklearn.model_selection import train_test_split

#X = data_final.drop('total_cases', axis=1)
#y = data_final['total_cases']

X_sj = data_sj.drop('total_cases', axis=1)
y_sj = data_sj['total_cases']

X_iq = data_iq.drop('total_cases', axis=1)
y_iq = data_iq['total_cases']
```

In [70]:

```
sub_X_sj = sub_data_sj.copy()
sub_X_iq = sub_data_iq.copy()
```

In [71]:

```
#X_train, X_test, y_train, y_test = train_test_split(X, y, train_size=0.80, test_size=
0.20, random_state=1)
```

In [72]:

```
X_sj_train, X_sj_test, y_sj_train, y_sj_test = train_test_split(X_sj, y_sj, train_size=
0.80, test_size=0.20, random_state=1)
```

In [73]:

```
X_iq_train, X_iq_test, y_iq_train, y_iq_test = train_test_split(X_iq, y_iq, train_size=
0.80, test_size=0.20, random_state=1)
```

In [134]:

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error
from sklearn.model_selection import GridSearchCV

forest=RandomForestRegressor(random_state=1, criterion='mae')
mae=mean_absolute_error

# hyperparameter tuning
tuning_list = {'n_estimators': [100,200,300,400,500,600,800,1000], 'min_samples_split':
[2,3,4,5,6,7,8,9,10], 'min_samples_leaf': [1,2,3,4,5]}
forest_sj = GridSearchCV(forest, tuning_list, n_jobs=-1, verbose=2, cv=5, scoring='neg_
mean_absolute_error')
forest_iq = GridSearchCV(forest, tuning_list, n_jobs=-1, verbose=2, cv=5, scoring='neg_
mean_absolute_error')
forest_sj_full = GridSearchCV(forest, tuning_list, n_jobs=-1, verbose=2, cv=5, scoring=
'neg_mean_absolute_error')
forest_iq_full = GridSearchCV(forest, tuning_list, n_jobs=-1, verbose=2, cv=5, scoring=
'neg_mean_absolute_error')
```

In [75]:

```
#forest.fit(X_train, y_train)
```

In [76]:

```
# sj train only
forest_sj.fit(X_sj_train, y_sj_train)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:   29.5s finished
```

Out[76]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=RandomForestRegressor(bootstrap=True, criterion='ms
e',
                                             max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators='warn', n_jobs=N
one,
                                             oob_score=False, random_state
=1,
                                             verbose=0, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'n_estimators': [100, 200, 300, 400, 500, 600]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring='neg_mean_absolute_error', verbose=2)
```

In [77]:

```
forest_iq.fit(X_iq_train, y_iq_train)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:   15.5s finished
C:\Users\zarko.rashev\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\model_selection\_search.py:814: DeprecationWarning: The default o
f the `iid` parameter will change from True to False in version 0.22 and w
ill be removed in 0.24. This will change numeric results when test-set siz
es are unequal.
  DeprecationWarning)
```

Out[77]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=RandomForestRegressor(bootstrap=True, criterion='ms
e',
                                             max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators='warn', n_jobs=N
one,
                                             oob_score=False, random_state
=1,
                                             verbose=0, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'n_estimators': [100, 200, 300, 400, 500, 600]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring='neg_mean_absolute_error', verbose=2)
```

In [78]:

```
forest_sj.best_params_
```

Out[78]:

```
{'n_estimators': 400}
```

In [79]:

```
forest_iq.best_params_
```

Out[79]:

```
{'n_estimators': 600}
```

In [80]:

```
# same training but with 100% data
forest_sj_full.fit(X_sj, y_sj)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:   32.5s finished
C:\Users\zarko.rashev\AppData\Local\Continuum\anaconda3\lib\site-packages
\sklearn\model_selection\_search.py:814: DeprecationWarning: The default o
f the `iid` parameter will change from True to False in version 0.22 and w
ill be removed in 0.24. This will change numeric results when test-set siz
es are unequal.
  DeprecationWarning)
```

Out[80]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=RandomForestRegressor(bootstrap=True, criterion='ms
e',
                                             max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators='warn', n_jobs=N
one,
                                             oob_score=False, random_state
=1,
                                             verbose=0, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'n_estimators': [100, 200, 300, 400, 500, 600]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring='neg_mean_absolute_error', verbose=2)
```

In [81]:

```
forest_iq_full.fit(X_iq, y_iq)
```

```
Fitting 5 folds for each of 6 candidates, totalling 30 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  30 out of  30 | elapsed:   22.4s finished
```

Out[81]:

```
GridSearchCV(cv=5, error_score='raise-deprecating',
             estimator=RandomForestRegressor(bootstrap=True, criterion='ms
e',
                                             max_depth=None,
                                             max_features='auto',
                                             max_leaf_nodes=None,
                                             min_impurity_decrease=0.0,
                                             min_impurity_split=None,
                                             min_samples_leaf=1,
                                             min_samples_split=2,
                                             min_weight_fraction_leaf=0.0,
                                             n_estimators='warn', n_jobs=N
one,
                                             oob_score=False, random_state
=1,
                                             verbose=0, warm_start=False),
             iid='warn', n_jobs=-1,
             param_grid={'n_estimators': [100, 200, 300, 400, 500, 600]},
             pre_dispatch='2*n_jobs', refit=True, return_train_score=Fals
e,
             scoring='neg_mean_absolute_error', verbose=2)
```

In [82]:

```
forest_sj_full.best_params_
```

Out[82]:

```
{'n_estimators': 200}
```

In [83]:

```
forest_iq_full.best_params_
```

Out[83]:

```
{'n_estimators': 600}
```

In [84]:

```
test_result_sj = forest_sj.predict(X_sj_test)
```

In [85]:

```
test_result_iq = forest_iq.predict(X_iq_test)
```

In [86]:

```
test_result_sj_full = forest_sj_full.predict(X_sj)
```

In [87]:

```
test_result_iq_full = forest_iq_full.predict(X_iq)
```

In [88]:

```
mae(y_sj_test, test_result_sj)
```

Out[88]:

```
14.998417553191489
```

In [89]:

```
mae(y_iq_test, test_result_iq)
```

Out[89]:

```
5.216201923076922
```

In [90]:

```
mae(y_sj, test_result_sj_full)
```

Out[90]:

```
4.909529914529914
```

In [91]:

```
mae(y_iq, test_result_iq_full)
```

Out[91]:

```
1.96038141025641
```

In [92]:

```
# scoring is good but we can try removing some low correlation fetures
```

In [121]:

```
# submission dataframes
submission_sj_final = pd.DataFrame({'city': 'sj', 'year': sub_X_sj['year'].astype('int6
4'), 'weekofyear': sub_X_sj['weekofyear'].astype('int64'), 'total_cases': forest_sj.pre
dict(sub_X_sj).astype('int64')})

submission_iq_final= pd.DataFrame({'city': 'iq', 'year': sub_X_iq['year'].astype('int6
4'), 'weekofyear': sub_X_iq['weekofyear'].astype('int64'), 'total_cases': forest_iq.pre
dict(sub_X_iq).astype('int64')})

submission_sj_iq_final = pd.concat([submission_sj_final, submission_iq_final])
```

In [128]:

```
submission_sj_iq_final
```

Out[128]:

	city	year	weekofyear	total_cases
0	sj	2008	18	4
1	sj	2008	19	5
2	sj	2008	20	5
3	sj	2008	21	9
4	sj	2008	22	7
...	...	...	...	...
411	iq	2013	22	5
412	iq	2013	23	3
413	iq	2013	24	1
414	iq	2013	25	4
415	iq	2013	26	4

416 rows × 4 columns

In [124]:

```
# submission dataframes FULL
submission_sj_full_final = pd.DataFrame({'city': 'sj', 'year': sub_X_sj['year'].astype(
'int64'), 'weekofyear': sub_X_sj['weekofyear'].astype('int64'), 'total_cases': forest_s
j_full.predict(sub_X_sj).astype('int64')})

submission_iq_full_final= pd.DataFrame({'city': 'iq', 'year': sub_X_iq['year'].astype(
'int64'), 'weekofyear': sub_X_iq['weekofyear'].astype('int64'), 'total_cases': forest_i
q_full.predict(sub_X_iq).astype('int64')})

submission_sj_iq_full_final = pd.concat([submission_sj_full_final, submission_iq_full_f
inal])
```

In [129]:

```
submission_sj_iq_full_final
```

Out[129]:

	city	year	weekofyear	total_cases
0	sj	2008	18	4
1	sj	2008	19	5
2	sj	2008	20	5
3	sj	2008	21	8
4	sj	2008	22	7
...	...	...	...	...
411	iq	2013	22	5
412	iq	2013	23	3
413	iq	2013	24	1
414	iq	2013	25	5
415	iq	2013	26	3

416 rows × 4 columns

In [131]:

```
submission_sj_iq_final.to_csv('submission_80.csv', index=False)
```

In [132]:

```
submission_sj_iq_full_final.to_csv('submission_full.csv', index=False)
```