In [1]:

```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
from sklearn import metrics
from matplotlib import pyplot
from sklearn.cluster import KMeans, DBSCAN
import matplotlib.pyplot as plt
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.arima.model import ARIMA
import warnings
import geopandas as gpd
from shapely.geometry import Point, Polygon
from shapely import wkt
from statsmodels.graphics.tsaplots import plot_pacf, plot_acf
from sklearn.preprocessing import StandardScaler
from scipy.cluster.hierarchy import linkage, fcluster
```

In [2]:
```
data = pd.read_csv("COVID-19_update.csv")
data2=data
warnings.filterwarnings("ignore")
week =20;
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2280 entries, 0 to 2279
Data columns (total 21 columns):
 #   Column                               Non-Null Count  Dtype  
---  ------                               --------------  -----  
 0   ZIP Code                             2280 non-null   object 
 1   Week Number                          2280 non-null   int64  
 2   Week Start                           2280 non-null   object 
 3   Week End                             2280 non-null   object 
 4   Cases - Weekly                       2105 non-null   float64
 5   Cases - Cumulative                   2105 non-null   float64
 6   Case Rate - Weekly                   2105 non-null   float64
 7   Case Rate - Cumulative               2105 non-null   float64
 8   Tests - Weekly                       2250 non-null   float64
 9   Tests - Cumulative                   2280 non-null   int64  
 10  Test Rate - Weekly                   2280 non-null   int64  
 11  Test Rate - Cumulative               2280 non-null   float64
 12  Percent Tested Positive - Weekly     2280 non-null   float64
 13  Percent Tested Positive - Cumulative 2280 non-null   float64
 14  Deaths - Weekly                      2280 non-null   int64  
 15  Deaths - Cumulative                  2280 non-null   int64  
 16  Death Rate - Weekly                  2280 non-null   float64
 17  Death Rate - Cumulative              2280 non-null   float64
 18  Population                           2280 non-null   int64  
 19  Row ID                               2280 non-null   object 
 20  ZIP Code Location                    2242 non-null   object 
dtypes: float64(10), int64(6), object(5)
memory usage: 374.2+ KB
```

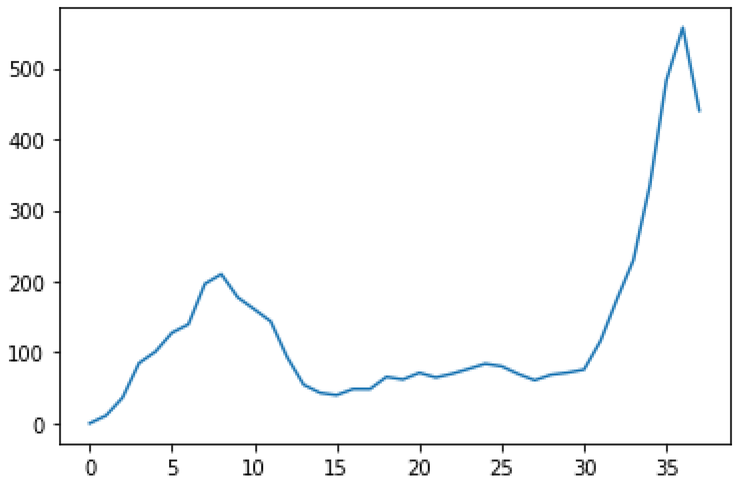
In [3]:
```
def make_predictions(train, test, p, d, q, P=0, D=0, Q=0, s=0):
    predictions = list()
    for t in range(len(test)):
        model = ARIMA(train, order = (p, d, q), seasonal_order = (P, D, Q, s))
        fitted_model = model.fit()
        predicted = fitted_model.predict(len(train)+1, len(train)+1)
        predictions.append(predicted[-1])
        train.append(test[t])
    # Evaluate predictions
    error = mean_squared_error(test, predictions)
    corr = np.corrcoef(test, predictions)[1, 0]
    print('MSE: %.3f' % error)
    print('Correlation: %.3f' % corr)
    # Plot results
    pyplot.plot(test)
    pyplot.plot(predictions, color='red')
    pyplot.show()

def plotmap(data,a,b,c):
    recent = pd.DataFrame(data['cluster'])
    recent['geometry']=data['ZIP Code Location'].astype('string')
    recent.dropna(subset = ["geometry"], inplace=True)
    crs={'init': 'epsg:4326'}
    geo = gpd.GeoDataFrame(recent,crs=crs,geometry=recent['geometry'].apply(wkt.loads))
    street_map = gpd.read_file('geo_export.shp')
    fig, ax = plt.subplots(figsize = (8,8))
    street_map.plot(color='grey', ax=ax, alpha = 0.4)
    geo[geo['cluster']==a].geometry.plot(marker='o', color = 'red', ax = ax, label = 'high risk', alpha=.5, m
arkersize = 75 )
    geo[geo['cluster']==b].geometry.plot(marker='o', color = 'yellow', ax = ax, label = 'middle risk', alpha
= .5, markersize = 30)
    geo[geo['cluster']==c].geometry.plot(marker='o', color = 'green', ax = ax, label = 'low risk', alpha = .5
, markersize = 30)
    plt.legend(prop={'size':15})

def plotlevel(clusters):
    recent["cluster"]= clusters
    ax = recent.plot(kind = 'scatter', x = 'ZIP Code', y = 'Case Rate - Weekly', c = 'cluster', colormap = pl
t.cm.brg)
    ax = recent.plot(kind = 'scatter', x = 'ZIP Code', y = 'Death Rate - Weekly', c = 'cluster', colormap = p
lt.cm.brg)
```

```
    ax = recent.plot(kind = 'scatter', x = 'ZIP Code', y = 'Case Rate - Cumulative', c = 'cluster', colormap
= plt.cm.brg)
```

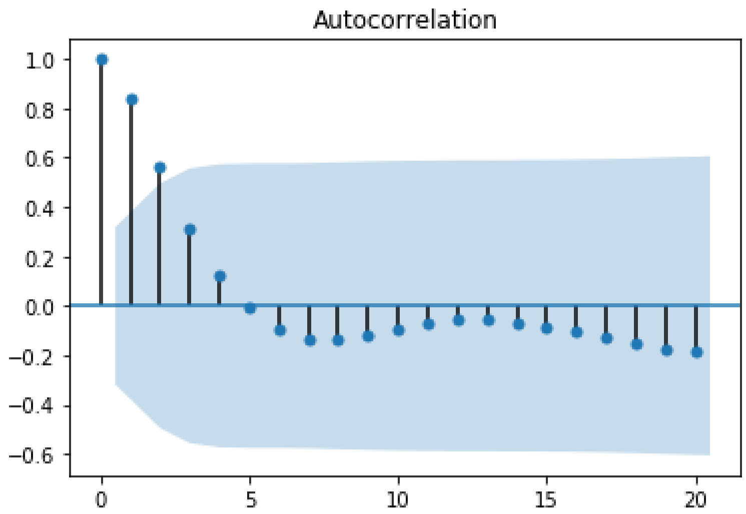
1. Explore Time Series for weekly case rate

In [4]:
```
data = pd.pivot_table(data, index = ['Week Number']).reset_index()
CaseRate = data['Case Rate - Weekly'].fillna(0)
CaseRate.plot()
```

Out[4]: <matplotlib.axes._subplots.AxesSubplot at 0x1da1b61a188>

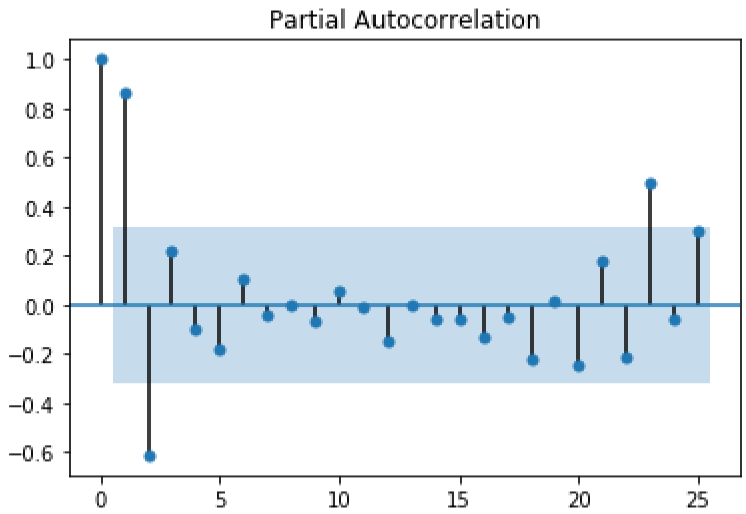


In [5]:
```
plot_acf(CaseRate, lags=20)
q=3
pyplot.show()
```



1.2 choose the order of AR part of model

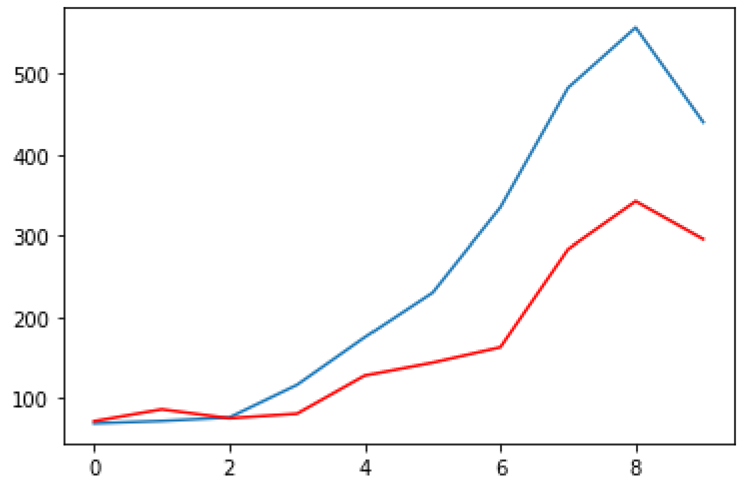
In [6]:
```
plot_pacf(CaseRate, lags=25)
p=3
pyplot.show()
```



1.3 Method: Moving Average (MA)

In [7]:
```
n_test = 10
data_list = CaseRate.values.tolist()
train, test = data_list[0:(len(data_list)-n_test)], data_list[(len(data_list)-n_test):len(data_list)]
make_predictions(train, test, p=0, d=0, q=q, P=0, D=0, Q=0, s=0)
```

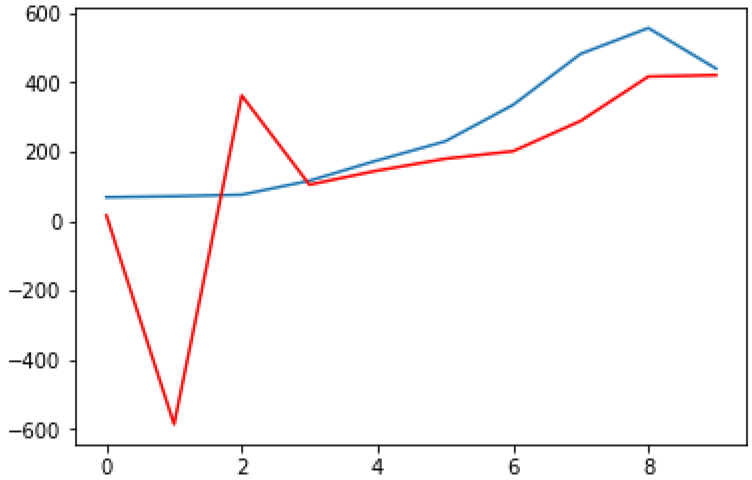
```
MSE: 14763.872
Correlation: 0.979
```



1.4 Method: Autoregression (AR)

In [8]:
```
make_predictions(train, test, p=p, d=0, q=0, P=0, D=0, Q=0, s=0)
```

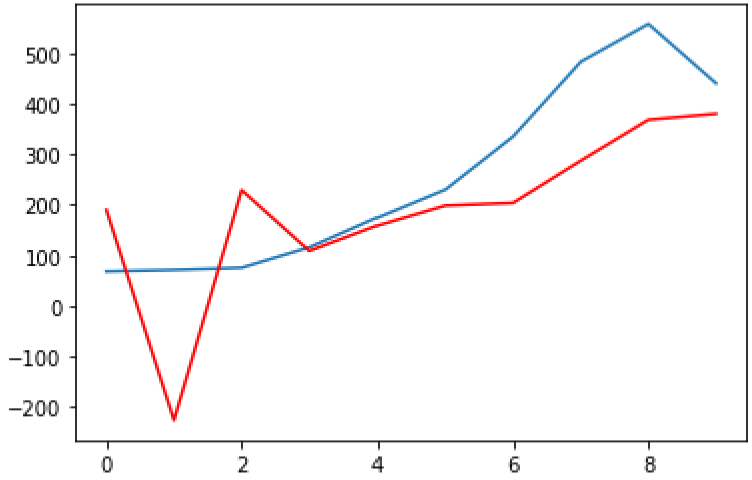
```
MSE: 59634.641
Correlation: 0.601
```



1.5 Method: Autoregressive Moving Average (ARMA)

In [9]:
```
make_predictions(train, test, p=p, d=0, q=q, P=0, D=0, Q=0, s=0)
```

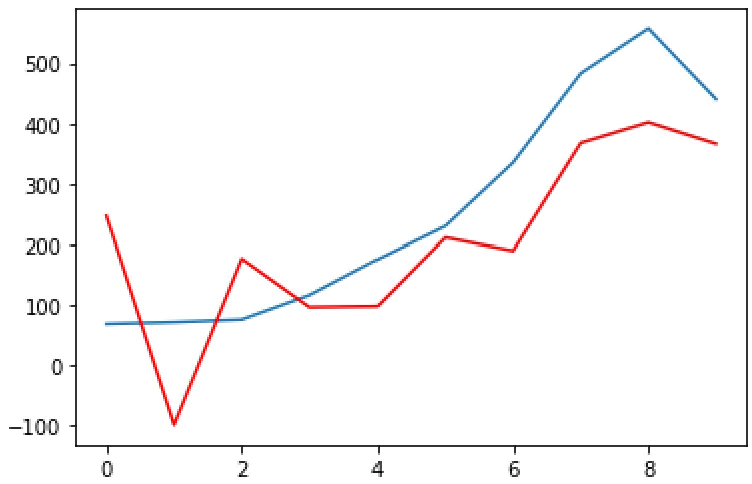
```
MSE: 22273.676
Correlation: 0.687
```



1.6 Autoregressive Integrated Moving Average (ARIMA)

In [10]:
```
make_predictions(train, test, p=p, d=1, q=q, P=0, D=0, Q=0, s=0)
```

```
MSE: 14204.587
Correlation: 0.790
```



result:

```
MSE: 14763 Correlation: 0.979  MA
MSE: 59634 Correlation: 0.601  AR
MSE: 22273 Correlation: 0.687  ARMA
MSE: 14204 Correlation: 0.790  ARIMA
```

MA modle has much lower MSE and higher Correlation, we choose MA as our model to predict weekly case rate

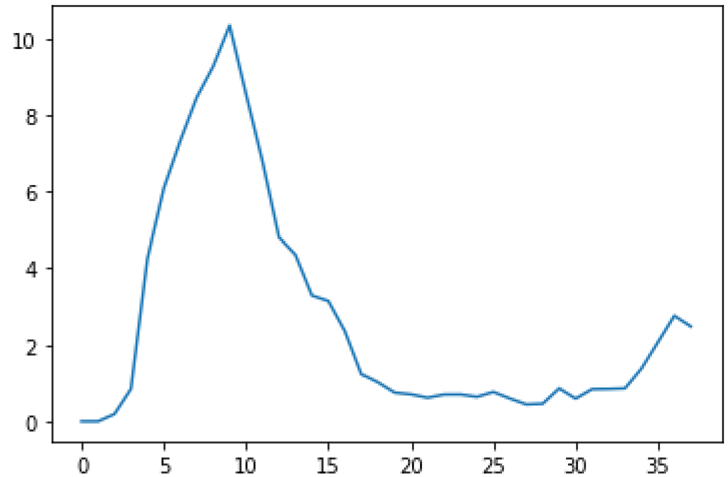
Predict case rate in the next 10 weeks

In [11]:
```
casepredictions = list()
for t in range(week):
    model = ARIMA(data_list, order = (0, 0, q))
    fitted_model = model.fit()
    predicted = fitted_model.predict(t+1, t+1)
    casepredictions.append(predicted[-1])
    train.append(predicted)
```

2. Explore Time Series for weekly death rate

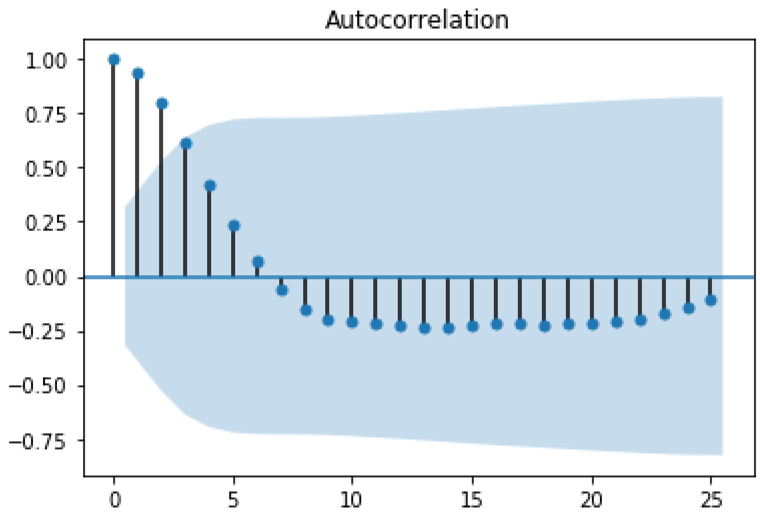
In [12]:
```
DeathRate = data['Death Rate - Weekly']
DeathRate = DeathRate.squeeze()
DeathRate.plot()
```

Out[12]:
```
&lt;matplotlib.axes._subplots.AxesSubplot at 0x1da1d594348&gt;
```



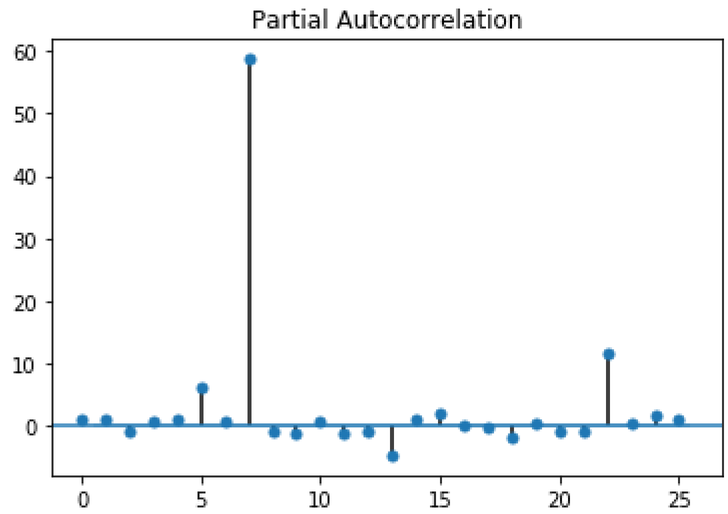
2.1 choose the order of MA part of model

In [13]:
```
plot_acf(DeathRate, lags=25)
q=3
pyplot.show()
```



2.2 choose the order of AR part of model

In [14]:
```
plot_pacf(DeathRate, lags=25)
p=1
pyplot.show()
```

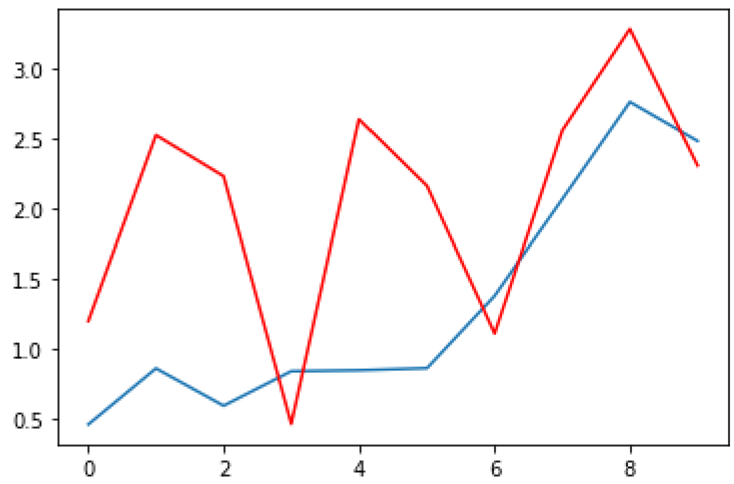


2.3 Method: Moving Average (MA)

In [15]:
```
n_test = 10
data_list = DeathRate.values.tolist()
train, test = data_list[0:(len(data_list)-n_test)], data_list[(len(data_list)-n_test):len(data_list)]
```

In [16]:
```
make_predictions(train, test, p=0, d=0, q=q, P=0, D=0, Q=0, s=0)
```

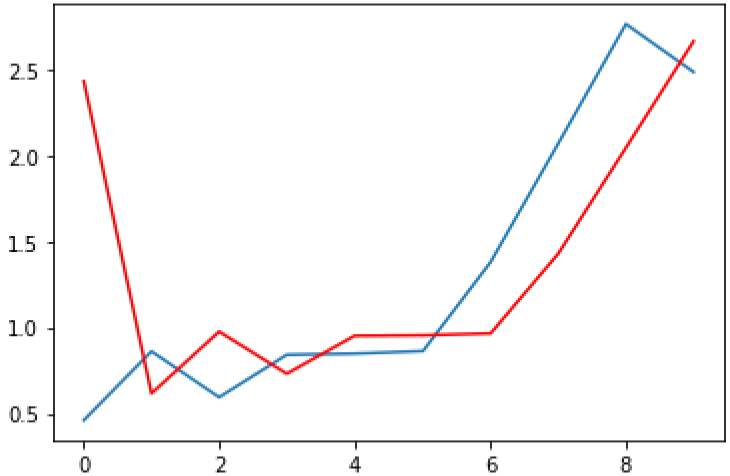
```
MSE: 1.164
Correlation: 0.506
```



2.4 Method: Autoregression (AR)

In [17]:
```
make_predictions(train, test, p=p, d=0, q=0, P=0, D=0, Q=0, s=0)
```

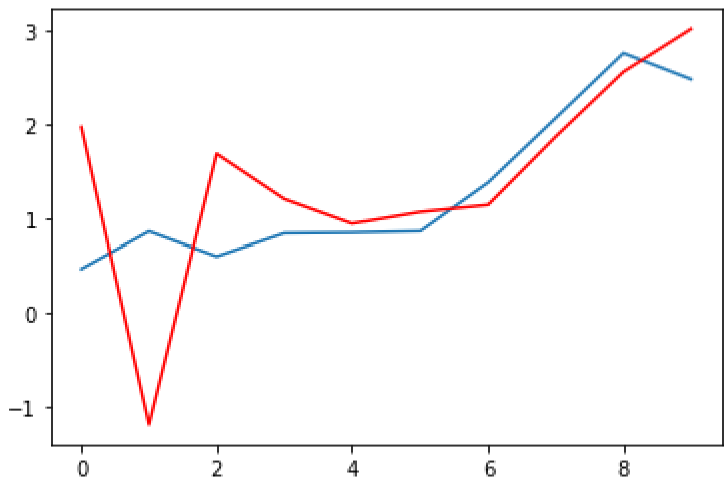
```
MSE: 0.524
Correlation: 0.531
```



2.5 Method: Autoregressive Moving Average (ARMA)

In [18]:
```
make_predictions(train, test, p=p, d=0, q=q, P=0, D=0, Q=0, s=0)
```

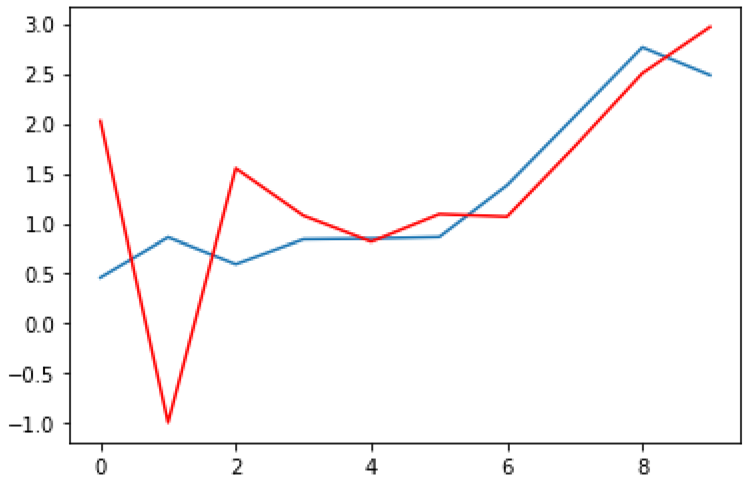
```
MSE: 0.831
Correlation: 0.571
```



2.6 Autoregressive Integrated Moving Average (ARIMA)

In [19]:
```
make_predictions(train, test, p=p, d=1, q=q, P=0, D=0, Q=0, s=0)
```

```
MSE: 0.737
Correlation: 0.582
```



result:

```
MSE: 1.164 Correlation: 0.506 MA
MSE: 0.524 Correlation: 0.531 AR
MSE: 0.831 Correlation: 0.571 ARMA
MSE: 0.737 Correlation: 0.582 ARIMA
```

Since they have similar correlation ratio, but AR modle has much lower MSE, we choose AR as our model to predict weekly death rate

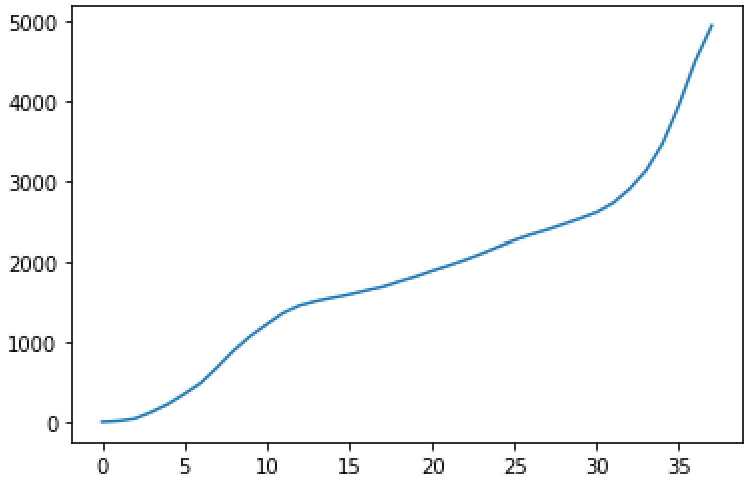
Predict death rate in the next 10 weeks

In [20]:
```
deathpredictions = list()
for t in range(week):
    model = ARIMA(data_list, order = (p, 0, q))
    fitted_model = model.fit()
    predicted = fitted_model.predict(t+1, t+1)
    deathpredictions.append(predicted[-1])
    train.append(predicted)
```

3. Explore Time Series for Cumulative case rate

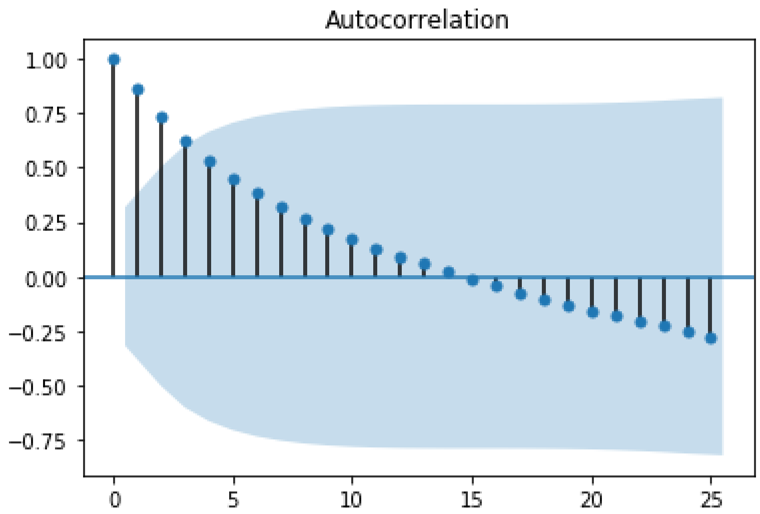
In [21]:
```
Case = data['Case Rate - Cumulative'].fillna(0)
Case = Case.squeeze()
Case.plot()
```

Out[21]: <matplotlib.axes._subplots.AxesSubplot at 0x1da1d583948>



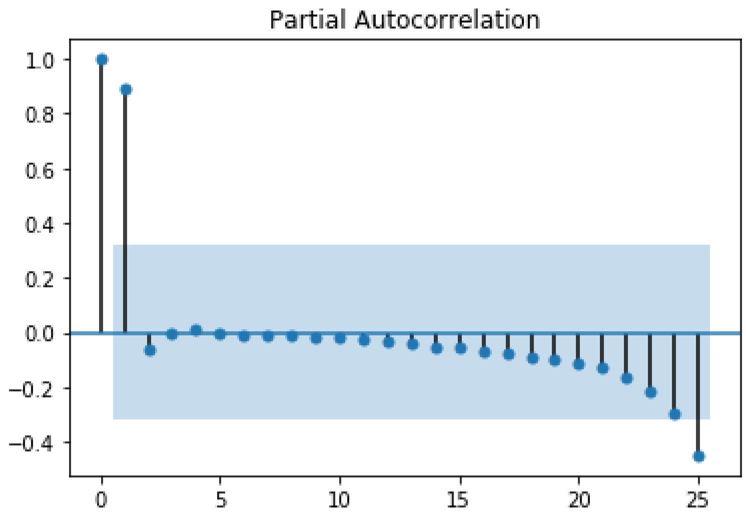
3.1 choose the order of MA part of model

In [22]:
```
plot_acf(Case, lags=25)
q=4
pyplot.show()
```



3.2 choose the order of AR part of model

In [23]:
```
plot_pacf(Case, lags=25)
p=2
pyplot.show()
```

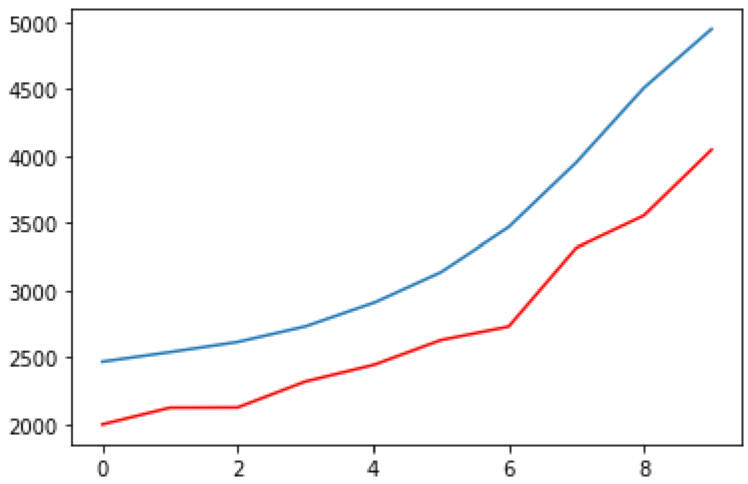


In [24]:
```
n_test = 10
data_list = Case.values.tolist()
train, test = data_list[0:(len(data_list)-n_test)], data_list[(len(data_list)-n_test):len(data_list)]
```

3.3 Method: Moving Average (MA)

In [25]:
```
make_predictions(train, test, p=0, d=0, q=q, P=0, D=0, Q=0, s=0)
```

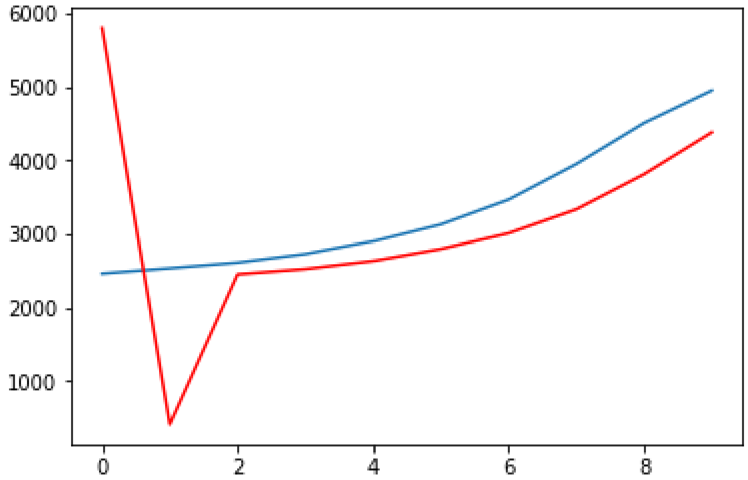
```
MSE: 395562.959
Correlation: 0.994
```



3.4 Method: Autoregression (AR)

In [26]:
```
make_predictions(train, test, p=p, d=0, q=0, P=0, D=0, Q=0, s=0)
```

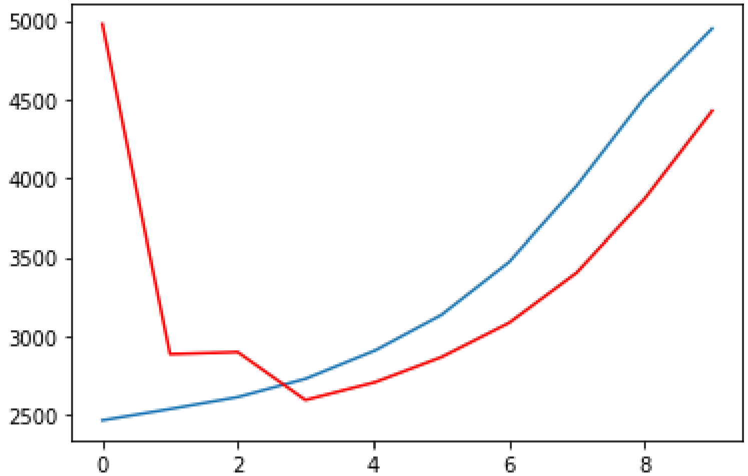
```
MSE: 1727847.501
Correlation: 0.353
```



3.5 Autoregressive Moving Average (ARMA)

In [27]:
```
make_predictions(train, test, p=p, d=1, q=0, P=0, D=0, Q=0, s=0)
```

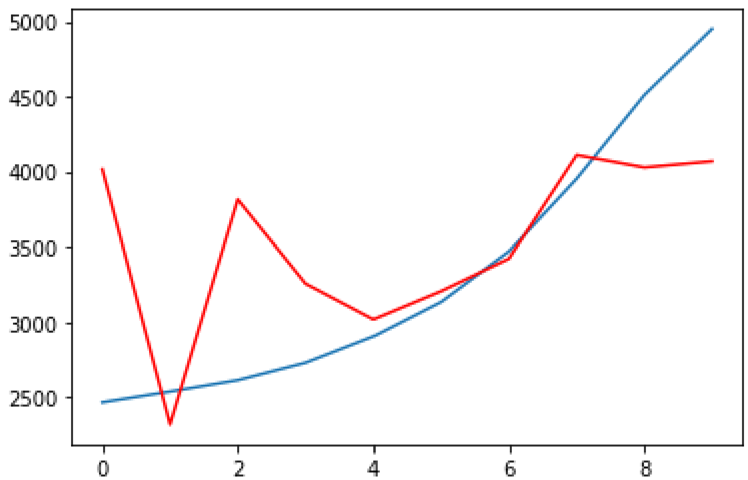
```
MSE: 778487.691
Correlation: 0.390
```



3.6 Autoregressive Integrated Moving Average (ARIMA)

In [28]:
```
make_predictions(train, test, p=p, d=1, q=q, P=0, D=0, Q=0, s=0)
```

```
MSE: 522733.571
Correlation: 0.559
```



result:

```
MSE: 395562 Correlation: 0.994 MA
MSE: 1727847 Correlation: 0.353 AR
MSE: 778487 Correlation: 0.390 ARMA
MSE: 522733 Correlation: 0.559 ARIMA
```

MA modle has much lower MSE and higher Correlation, we choose MA as our model to predict cumulative case rate

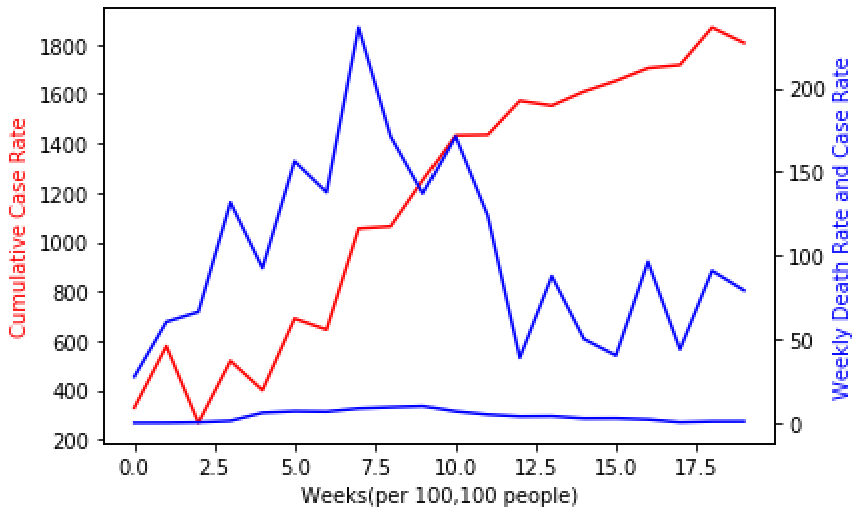
Predict Cumulative case rate in the next 10 weeks

In [29]:
```
cumupredictions = list()
for t in range(week):
    model = ARIMA(data_list, order = (0, 0, q))
    fitted_model = model.fit()
    predicted = fitted_model.predict(t+1, t+1)
    cumupredictions.append(predicted[-1])
    train.append(predicted)
```

4. predict weekly case rate, weekly death rate, Cumulative case rate in next 20 weeks

In [30]:
```
fig, ax_left = plt.subplots()
ax_right = ax_left.twinx()
ax_left.set_ylabel('Cumulative Case Rate', color='red')
ax_left.set_xlabel('Weeks(per 100,100 people)', color='black')
ax_right.set_ylabel('Weekly Death Rate and Case Rate', color='blue')
ax_left.plot(cumupredictions, color='red')
ax_right.plot(deathpredictions, color='blue')
ax_right.plot(casepredictions, color='blue')
```

Out[30]:
```
[<matplotlib.lines.Line2D at 0x1da1bf03e08>]
```



4. Clustering Chicago into three danger levels

In [31]:
```
recent=data2.loc[data2['Week Number']==data2['Week Number'].max()]
recent.head()
```

Out[31]:

	ZIP Code	Week Number	Week Start	Week End	Cases - Weekly	Cases - Cumulative	Case Rate - Weekly	Case Rate - Cumulative	Tests - Weekly	Tests - Cumulative	...	Test Rate - Cumulative	Percent Tested Positive - Weekly	Cu
43	60612	47	11/15/2020	11/21/2020	236.0	1882.0	688.0	5485.1	2417.0	27487	...	80111.3	0.1	
60	60617	47	11/15/2020	11/21/2020	429.0	4330.0	520.0	5246.3	2733.0	43888	...	53175.7	0.2	
61	60618	47	11/15/2020	11/21/2020	375.0	4390.0	397.0	4650.7	3580.0	59592	...	63130.5	0.1	
66	60619	47	11/15/2020	11/21/2020	208.0	2401.0	340.0	3919.5	1682.0	33172	...	54151.3	0.1	
70	60621	47	11/15/2020	11/21/2020	97.0	1222.0	334.0	4207.7	766.0	14603	...	50282.3	0.1	

5 rows × 21 columns

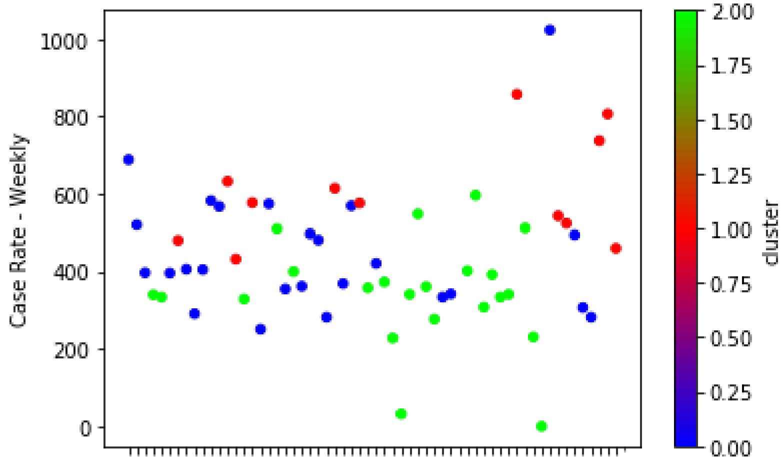
In [32]:
```
Y = pd.DataFrame(recent['Percent Tested Positive - Weekly'])
Y['Case Rate - Cumulative'] = recent['Case Rate - Weekly']
Y['Death Rate - Weekly'] = recent['Death Rate - Weekly']
Y['Case Rate - Cumulative']=recent['Case Rate - Cumulative']
Y=Y.fillna(0)
```

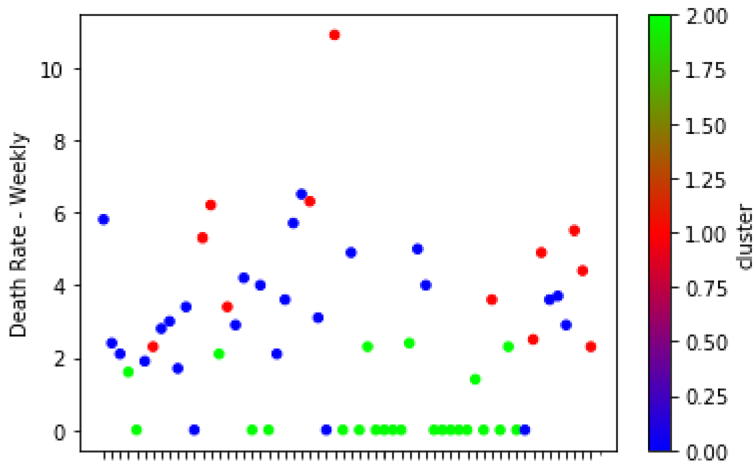
In [33]:
```
scaler = StandardScaler()
scaler.fit(Y)
Y_scaled = scaler.transform(Y)
```

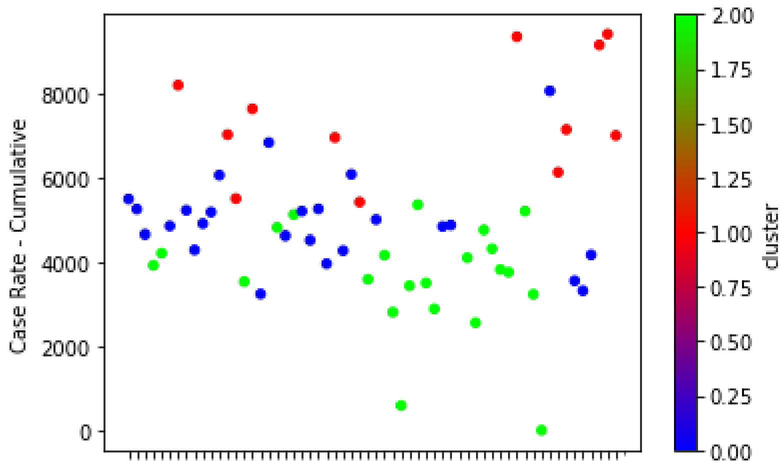
In [34]:
```
clustering = KMeans(n_clusters=3,init='random',max_iter=10,random_state=0).fit(Y_scaled)
clusters = clustering.labels_
silhouette_coefficient = metrics.silhouette_score(Y_scaled, clusters, metric = "euclidean")
print( silhouette_coefficient)
```

```
0.3193636431167058
```

In [35]:
```
plotlevel(clusters)
```

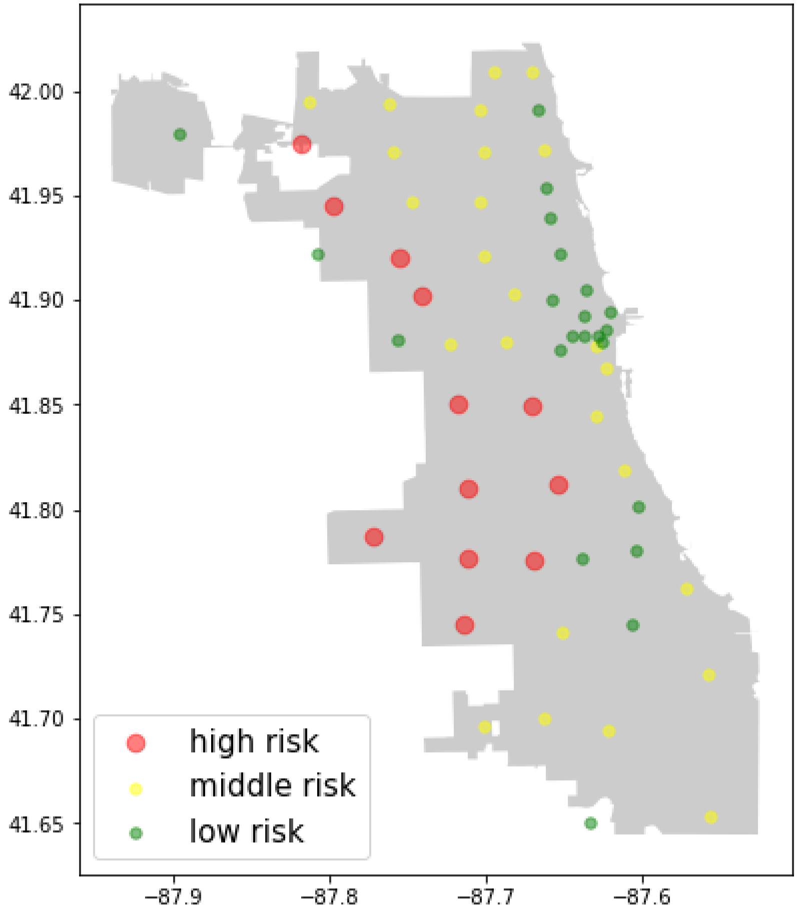

Case Rate - Weekly
1000
800
600
400
200
0
cluster
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00


Death Rate - Weekly
10
8
6
4
2
0
cluster
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00



1 represents high risk, 0 represents middle risk, 2 represents low risk

In [36]:
```
plotmap(recent,1,0,2)
```

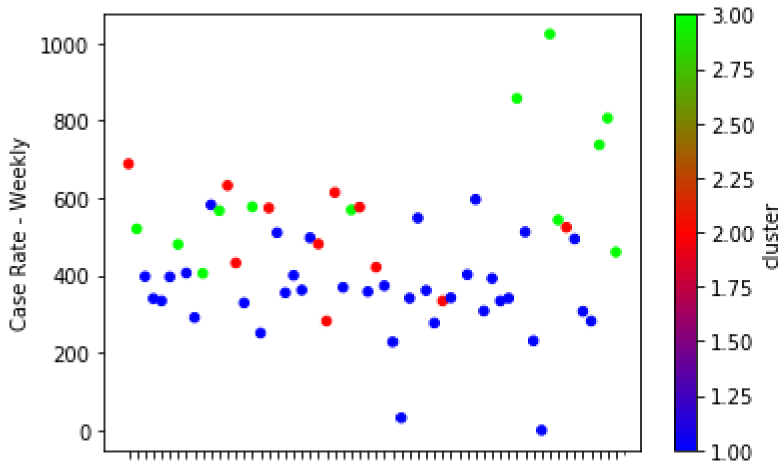


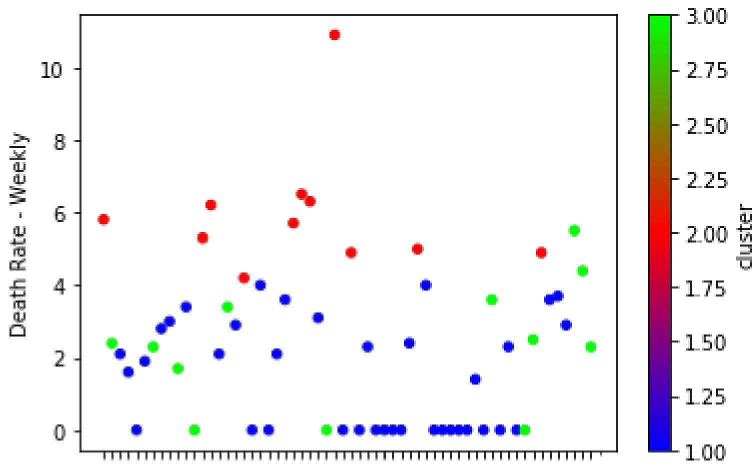
In [37]:
```
clustering = linkage(Y_scaled, method='complete', metric='euclidean')
clusters = fcluster(clustering, 3, criterion = 'maxclust')
silhouette_coefficient = metrics.silhouette_score(Y_scaled, clusters, metric = "euclidean")
print( silhouette_coefficient)
recent["cluster"]= clusters
```

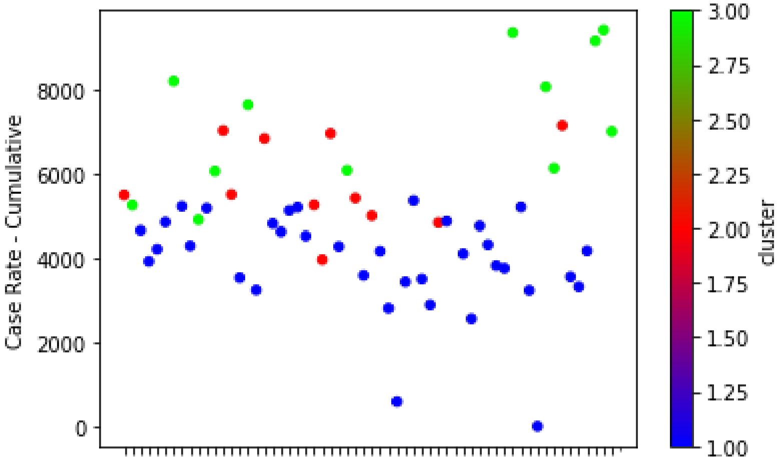
```
0.38253979967127333
```

In [38]:

```
plotlevel(clusters)
```

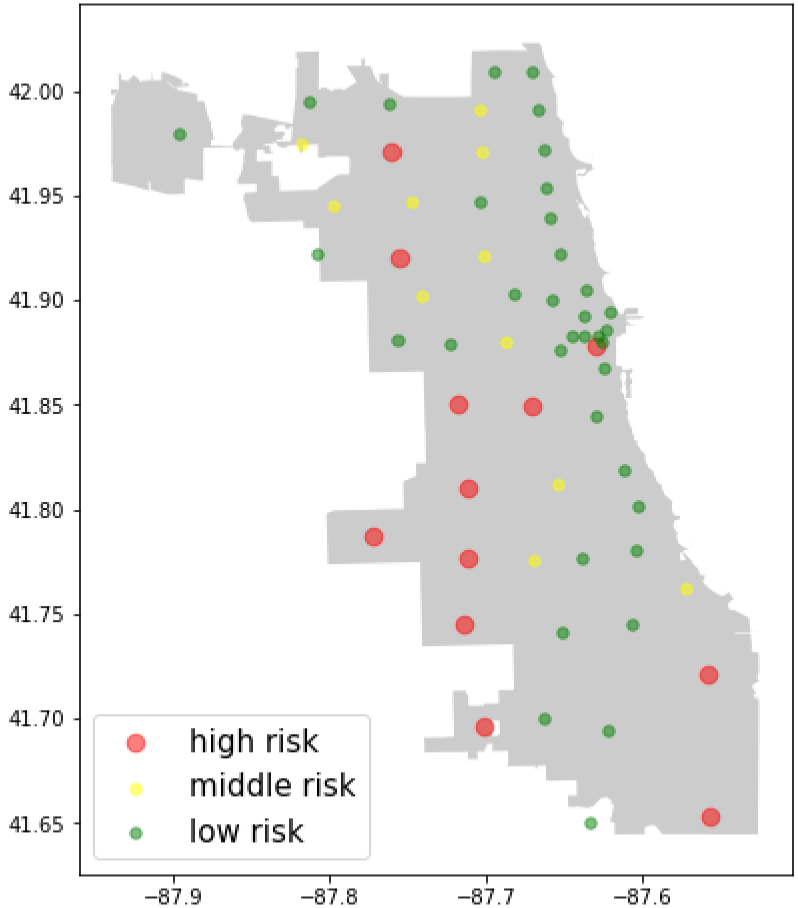

1000
800
600
400
200
0
Case Rate - Weekly
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
cluster


10
8
6
4
2
0
Death Rate - Weekly
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
cluster



8000
6000
4000
2000
0
Case Rate - Cumulative
3.00
2.75
2.50
2.25
2.00
1.75
1.50
1.25
1.00
cluster

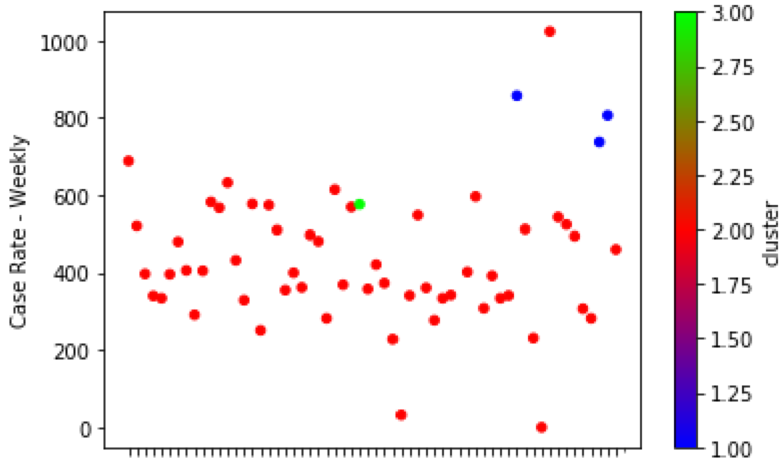
In [39]:
```
plotmap(recent,3,2,1)
```

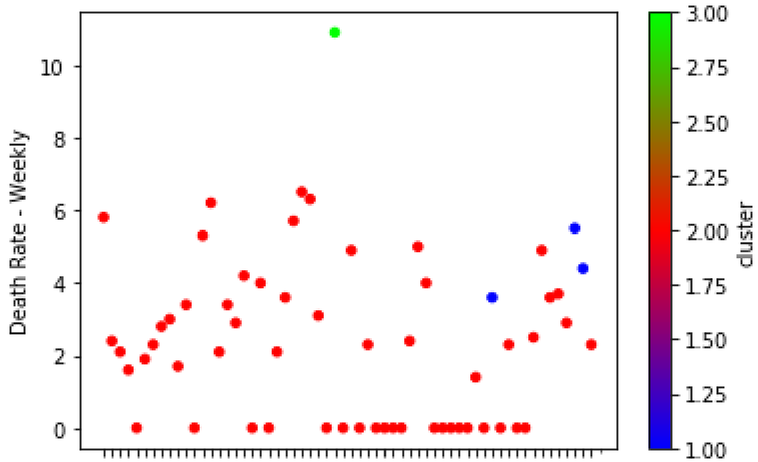


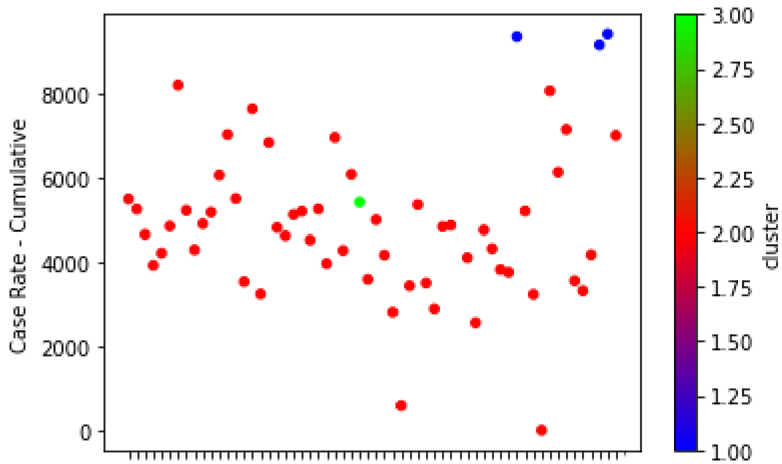
In [40]:

```
clustering = linkage(Y_scaled, method='single', metric='euclidean')
clusters = fcluster(clustering, 3, criterion = 'maxclust')
silhouette_coefficient = metrics.silhouette_score(Y_scaled, clusters, metric = "euclidean")
print( silhouette_coefficient)
recent["cluster"]= clusters
plotlevel(clusters)
```

0.4540348400360318

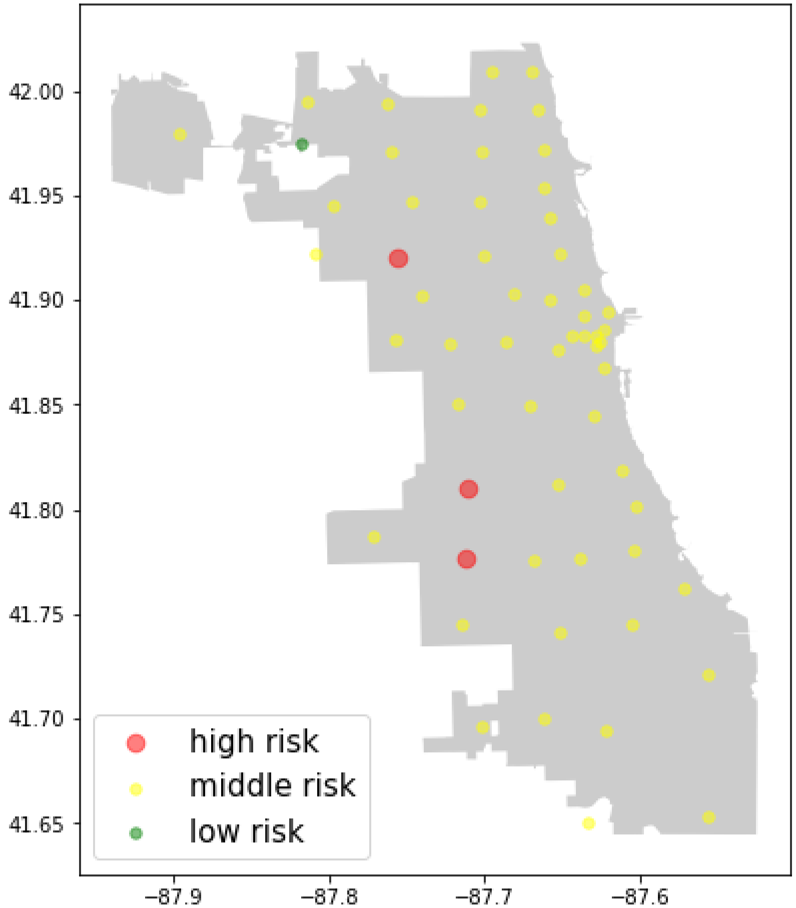






Case Rate - Cumulative
0
2000
4000
6000
8000
cluster
1.00
1.25
1.50
1.75
2.00
2.25
2.50
2.75
3.00

In [41]:
```
plotmap(recent,1,2,3)
```



Area near downtown are always low risks, suburbs are high risks