In [1]:

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

from sklearn.preprocessing import StandardScaler

from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

from scipy.cluster.hierarchy import linkage
from scipy.cluster.hierarchy import dendrogram
from scipy.cluster.hierarchy import cut_tree
```

In [2]:

```python
df = pd.read_csv("Country-data.csv")
```

Data Inspection & EDA

In [3]:

```python
df.head()
```

Out[3]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Afghanistan	90.2	10.0	7.58	44.9	1610	9.44	56.2	5.82	553
1	Albania	16.6	28.0	6.55	48.6	9930	4.49	76.3	1.65	4090
2	Algeria	27.3	38.4	4.17	31.4	12900	16.10	76.5	2.89	4460
3	Angola	119.0	62.3	2.85	42.9	5900	22.40	60.1	6.16	3530
4	Antigua and Barbuda	10.3	45.5	6.03	58.9	19100	1.44	76.8	2.13	12200

In [4]:

```python
df.shape
```

Out[4]:

```
(167, 10)
```

In [5]:

```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 167 entries, 0 to 166
Data columns (total 10 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   country     167 non-null    object 
 1   child_mort  167 non-null    float64
 2   exports     167 non-null    float64
 3   health      167 non-null    float64
 4   imports     167 non-null    float64
 5   income      167 non-null    int64  
 6   inflation   167 non-null    float64
 7   life_expec  167 non-null    float64
 8   total_fer   167 non-null    float64
 9   gdpp        167 non-null    int64  
dtypes: float64(7), int64(2), object(1)
memory usage: 13.2+ KB
```

In [6]:

```
df.describe()
```

Out[6]:

	child_mort	exports	health	imports	income	inflation	life_expec	tota
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.00
mean	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689	2.94
std	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172	1.51
min	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000	1.15
25%	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000	1.79
50%	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000	2.41
75%	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000	3.88
max	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000	7.49

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
country       0
child_mort    0
exports       0
health        0
imports       0
income        0
inflation     0
life_expec    0
total_fer     0
gdpp          0
dtype: int64
```

As per the data description, three columns are given as percentage of the GDP, and here I'll convert them back into decimal (base 10) values.

In [8]:

```
df['exports'] = (df['exports'] * df['gdpp']) / 100
df['health'] = (df['health'] * df['gdpp']) / 100
df['imports'] = (df['imports'] * df['gdpp']) / 100
```

In [9]:

```
df.head()
```

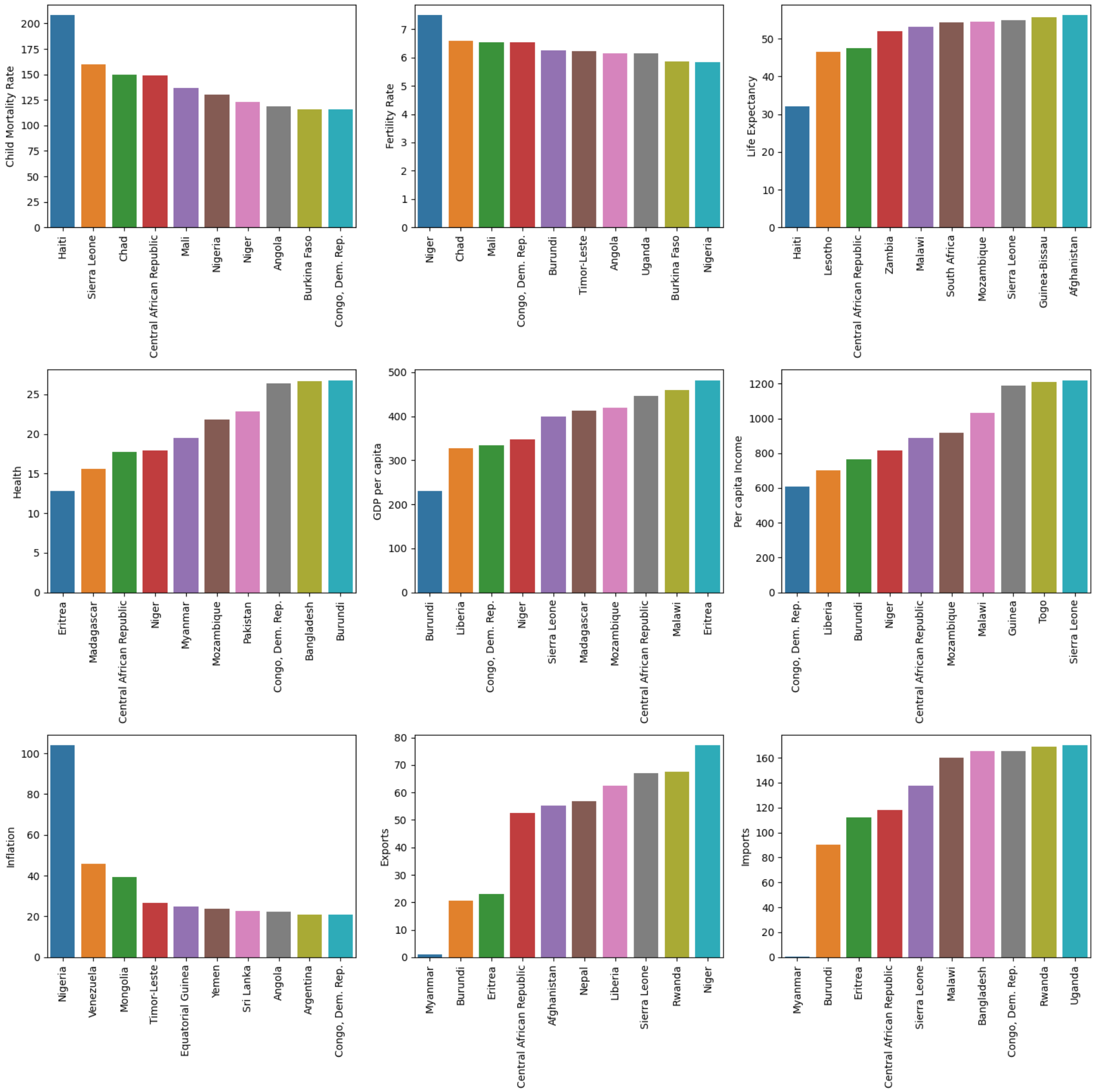
Out[9]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	55
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	409
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	446
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	353
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	1220

As we can see, the columns are now back to normal values, instead of percentages.

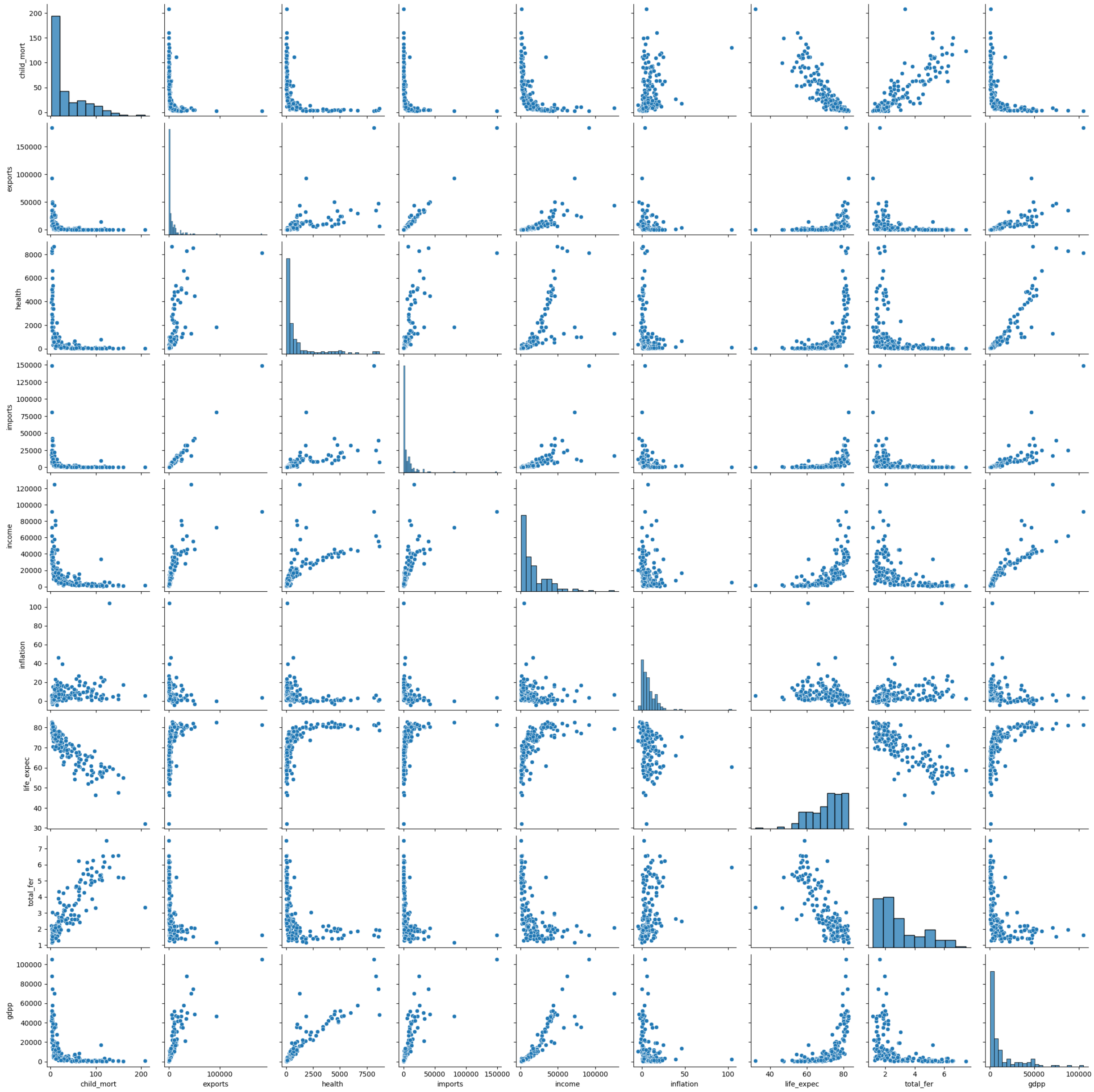
Plotting those countries which have the 10 lowest values in all the columns.

In [10]:
```python
fig, axs = plt.subplots(3,3,figsize = (15,15))



top10_child_mort = df[['country','child_mort']].sort_values('child_mort', ascending
plt1 = sns.barplot(x='country', y='child_mort', data= top10_child_mort, ax = axs[0,0
plt1.set(xlabel = '', ylabel= 'Child Mortality Rate')

top10_total_fer = df[['country','total_fer']].sort_values('total_fer', ascending = F
plt1 = sns.barplot(x='country', y='total_fer', data= top10_total_fer, ax = axs[0,1])
plt1.set(xlabel = '', ylabel= 'Fertility Rate')



bottom10_life_expec = df[['country','life_expec']].sort_values('life_expec', ascendi
plt1 = sns.barplot(x='country', y='life_expec', data= bottom10_life_expec, ax = axs[
plt1.set(xlabel = '', ylabel= 'Life Expectancy')


bottom10_health = df[['country','health']].sort_values('health', ascending = True).h
plt1 = sns.barplot(x='country', y='health', data= bottom10_health, ax = axs[1,0])
plt1.set(xlabel = '', ylabel= 'Health')
bottom10_gdpp = df[['country','gdpp']].sort_values('gdpp', ascending = True).head(10
plt1 = sns.barplot(x='country', y='gdpp', data= bottom10_gdpp, ax = axs[1,1])
plt1.set(xlabel = '', ylabel= 'GDP per capita')

bottom10_income = df[['country','income']].sort_values('income', ascending = True).h
plt1 = sns.barplot(x='country', y='income', data= bottom10_income, ax = axs[1,2])
plt1.set(xlabel = '', ylabel= 'Per capita Income')



top10_inflation = df[['country','inflation']].sort_values('inflation', ascending = F
plt1 = sns.barplot(x='country', y='inflation', data= top10_inflation, ax = axs[2,0])
plt1.set(xlabel = '', ylabel= 'Inflation')
bottom10_exports = df[['country','exports']].sort_values('exports', ascending = True
plt1 = sns.barplot(x='country', y='exports', data= bottom10_exports, ax = axs[2,1])
plt1.set(xlabel = '', ylabel= 'Exports')


bottom10_imports = df[['country','imports']].sort_values('imports', ascending = True
plt1 = sns.barplot(x='country', y='imports', data= bottom10_imports, ax = axs[2,2])
plt1.set(xlabel = '', ylabel= 'Imports')

for ax in fig.axes:
    plt.sca(ax)
    plt.xticks(rotation = 90)

plt.tight_layout()
plt.show()
```



In [11]:

```
sns.pairplot(df)
plt.show()
```

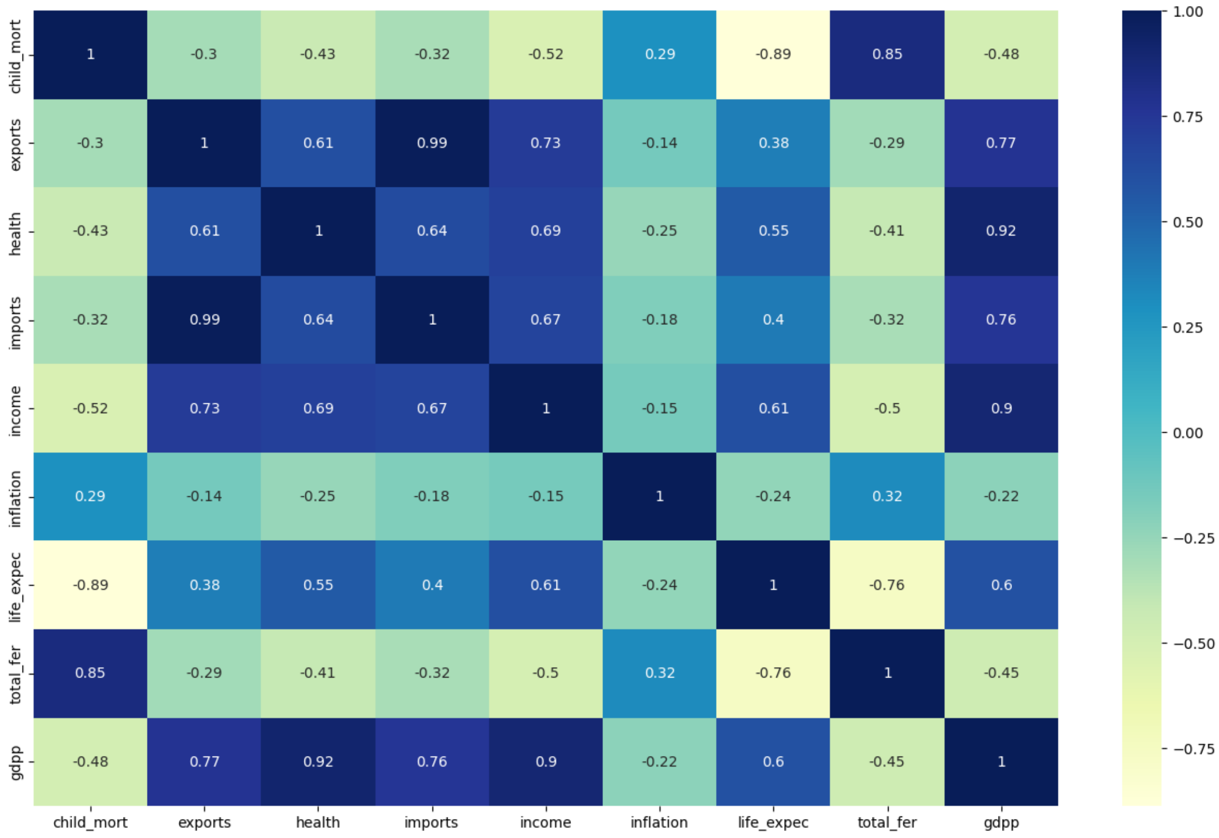


Plotting the correlation matrix to check for multicollinearity.

In [12]:

```
plt.figure(figsize = (16, 10))
sns.heatmap(df.corr(), annot = True, cmap="YlGnBu")
plt.show()
```

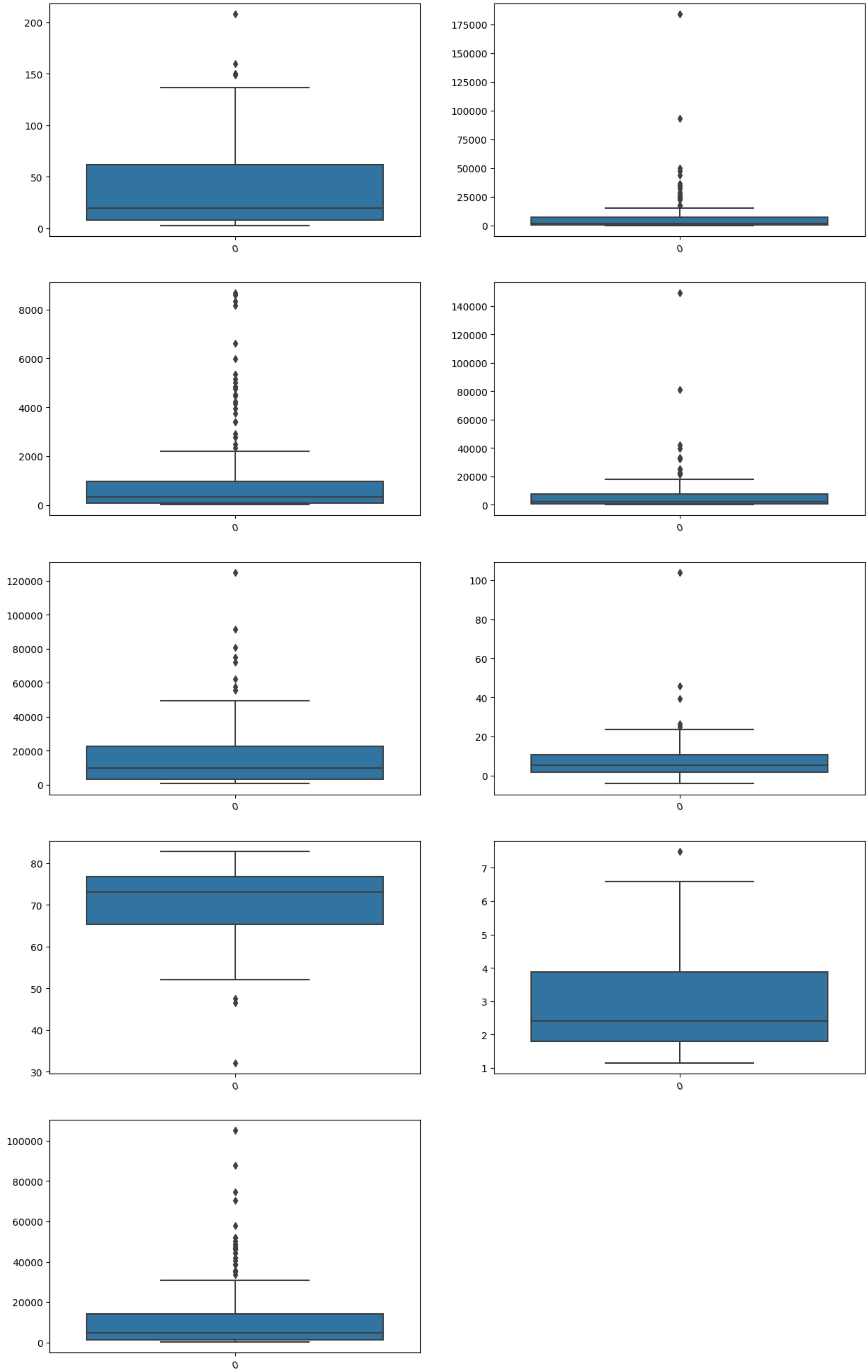
```
<ipython-input-12-dbfad3d97249>:2: FutureWarning: The default value of numeric_only i
n DataFrame.corr is deprecated. In a future version, it will default to False. Select
only valid columns or specify the value of numeric_only to silence this warning.
  sns.heatmap(df.corr(), annot = True, cmap="YlGnBu")
```



Outlier Analysis

In [13]:

```
colo= ['child_mort','exports','health','imports','income','inflation','life_expec','
plt.figure(figsize=(15,25))
for i in enumerate(colo):
    ax = plt.subplot(5, 2, i[0]+1)
    sns.boxplot(df[i[1]])
    plt.xticks(rotation = 20)
plt.show()
```



In the preceding cell, I created a box plot for all the columns. There are multiple countries whose GDP is extremely high. These are probably the developed countries where the quality of life is excellent. It is pertinent to realise that in this case of clustering countries according to their economic needs, removing outliers is not advisable. If the countries with extremely high values of child mortality are removed, then they will be ineligible for help from humanitarian organisations which makes this whole assignment redundant. So, considering the unique circumstance, in this dataset, outliers will be allowed to remain.

Clustering Model

Preprocessing

In [14]:

```
# hopkin's statistic
from sklearn.neighbors import NearestNeighbors
from random import sample
from numpy.random import uniform
import numpy as np
from math import isnan

def hopkins(X):
    d = X.shape[1]
    #d = len(vars) # columns
    n = len(X) # rows
    m = int(0.1 * n)
    nbrs = NearestNeighbors(n_neighbors=1).fit(X.values)

    rand_X = sample(range(0, n, 1), m)

    ujd = []
    wjd = []
    for j in range(0, m):
        u_dist, _ = nbrs.kneighbors(uniform(np.amin(X,axis=0),np.amax(X,axis=0),d).r
        ujd.append(u_dist[0][1])
        w_dist, _ = nbrs.kneighbors(X.iloc[rand_X[j]].values.reshape(1, -1), 2, retu
        wjd.append(w_dist[0][1])

    H = sum(ujd) / (sum(ujd) + sum(wjd))
    if isnan(H):
        print(ujd, wjd)
        H = 0

    return H
```

In [15]:

```
hopkins(df.drop('country',axis=1))
```

Out[15]:

```
0.9532941352093782
```

Thankfully, the data is highly clusterable.

In [16]:

```
#scaling
dfx = df.drop('country', axis = 1)
scale = StandardScaler()
dfx = scale.fit_transform(dfx)
```

K-Means

In [17]:

```
range_n_clusters = [2, 3, 4, 5, 6, 7, 8]

for num_clusters in range_n_clusters:
```

```
    # intialise kmeans
    kmeans = KMeans(n_clusters=num_clusters, max_iter=50)
    kmeans.fit(dfx)

    cluster_labels = kmeans.labels_

    # silhouette score
    silhouette_avg = silhouette_score(dfx, cluster_labels)
    print("For n_clusters={0}, the silhouette score is {1}".format(num_clusters, sil
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
For n_clusters=2, the silhouette score is 0.45863306035476264
For n_clusters=3, the silhouette score is 0.4218615812599681
For n_clusters=4, the silhouette score is 0.42914711278370843
For n_clusters=5, the silhouette score is 0.4324001169216119
For n_clusters=6, the silhouette score is 0.2908984109903817
For n_clusters=7, the silhouette score is 0.3065505636750877
For n_clusters=8, the silhouette score is 0.3075751716874681
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
```

So, the number of clusters will be 5.

In [18]:

```
kmeans = KMeans(n_clusters=5, max_iter=100 , random_state = 100)
kmeans.fit(dfx)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
```

Out[18]:

```
▾ KMeans
KMeans(max_iter=100, n_clusters=5, random_state=100)
```

In [19]:

```
kmeans.labels_
```

Out[19]:

```
array([0, 1, 1, 0, 1, 1, 1, 2, 2, 1, 1, 1, 1, 1, 1, 2, 1, 0, 1, 1, 1, 0,
       1, 2, 1, 0, 0, 1, 0, 2, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 2, 1,
       2, 1, 1, 1, 1, 0, 0, 1, 1, 2, 2, 0, 0, 1, 2, 0, 2, 1, 1, 0, 0, 1,
```

```
       0, 1, 2, 1, 1, 1, 0, 2, 2, 2, 1, 2, 1, 1, 0, 0, 2, 1, 0, 1, 1, 0,
       0, 1, 1, 4, 1, 0, 0, 1, 1, 0, 2, 0, 1, 1, 1, 1, 1, 1, 0, 1, 0, 1,
       2, 2, 0, 3, 2, 1, 0, 1, 1, 1, 1, 1, 1, 2, 1, 1, 0, 1, 1, 0, 1, 1,
       0, 2, 1, 2, 0, 0, 1, 2, 1, 1, 0, 1, 2, 2, 1, 0, 1, 0, 0, 1, 1, 1,
       1, 0, 1, 2, 2, 2, 1, 1, 1, 1, 1, 0, 0], dtype=int32)
```

In [20]:

```
df_km = pd.concat([df, pd.Series(kmeans.labels_)], axis = 1)
df_km.columns = ['country','child_mort','exports','health','imports','income','infla
df_km.head()
```

Out[20]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	55
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	409
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	446
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	353
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	1220

In [21]:

```
df_km['cluster_id'].value_counts()
```

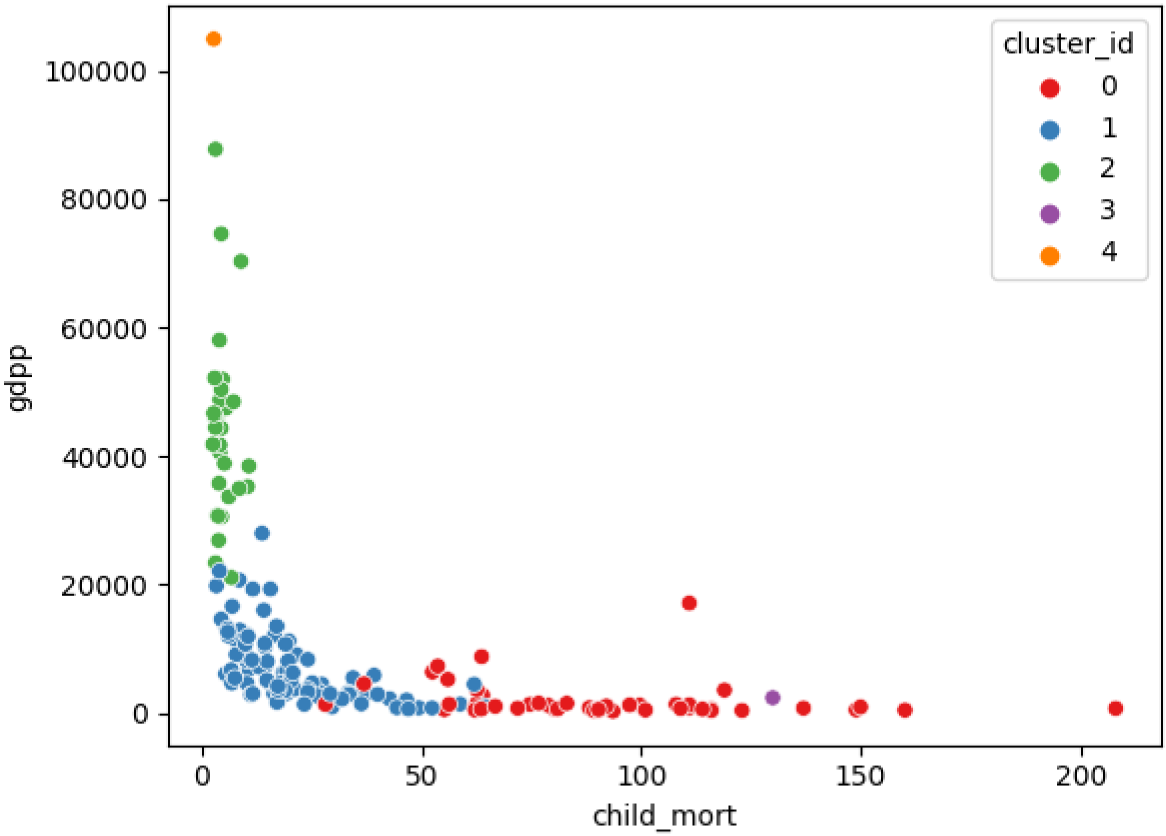
Out[21]:

```
1    88
0    47
2    30
4     1
3     1
Name: cluster_id, dtype: int64
```

Cluster Visualisation

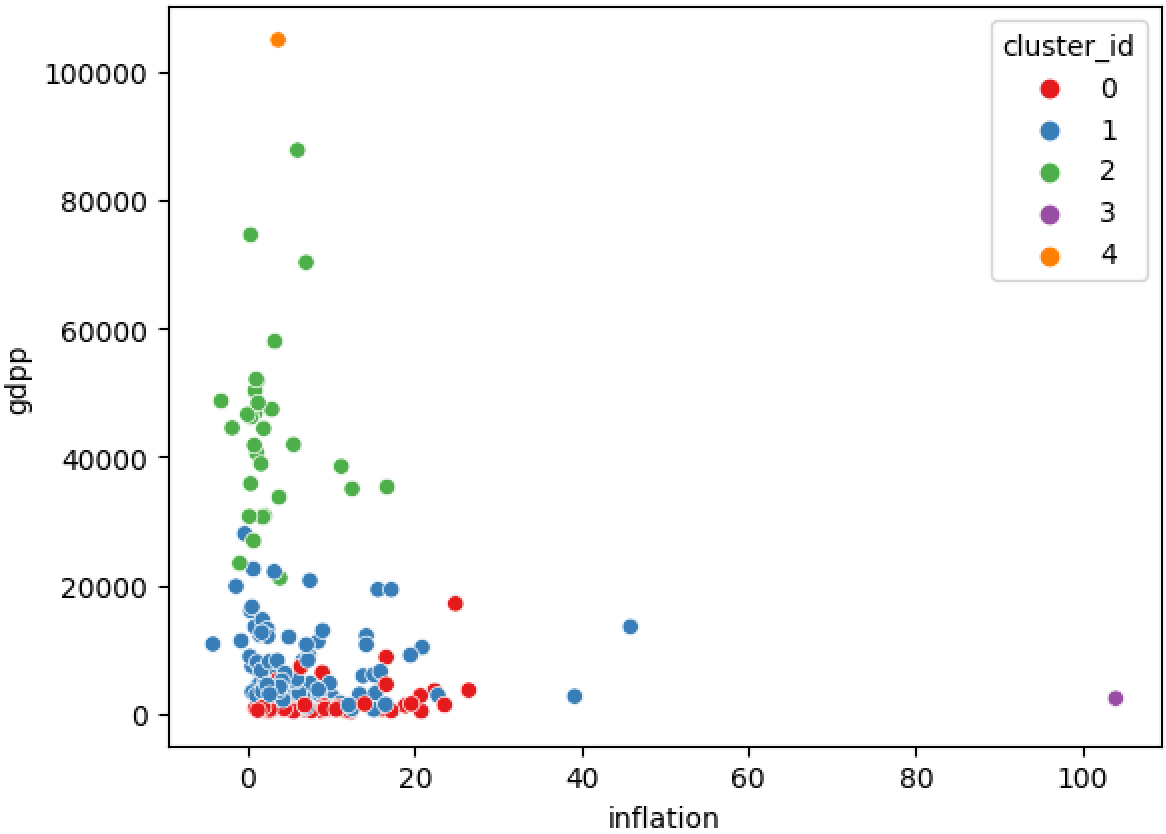
In [22]:

```
sns.scatterplot(x = 'child_mort', y = 'gdpp', hue ='cluster_id', legend = 'full', da
plt.show()
```



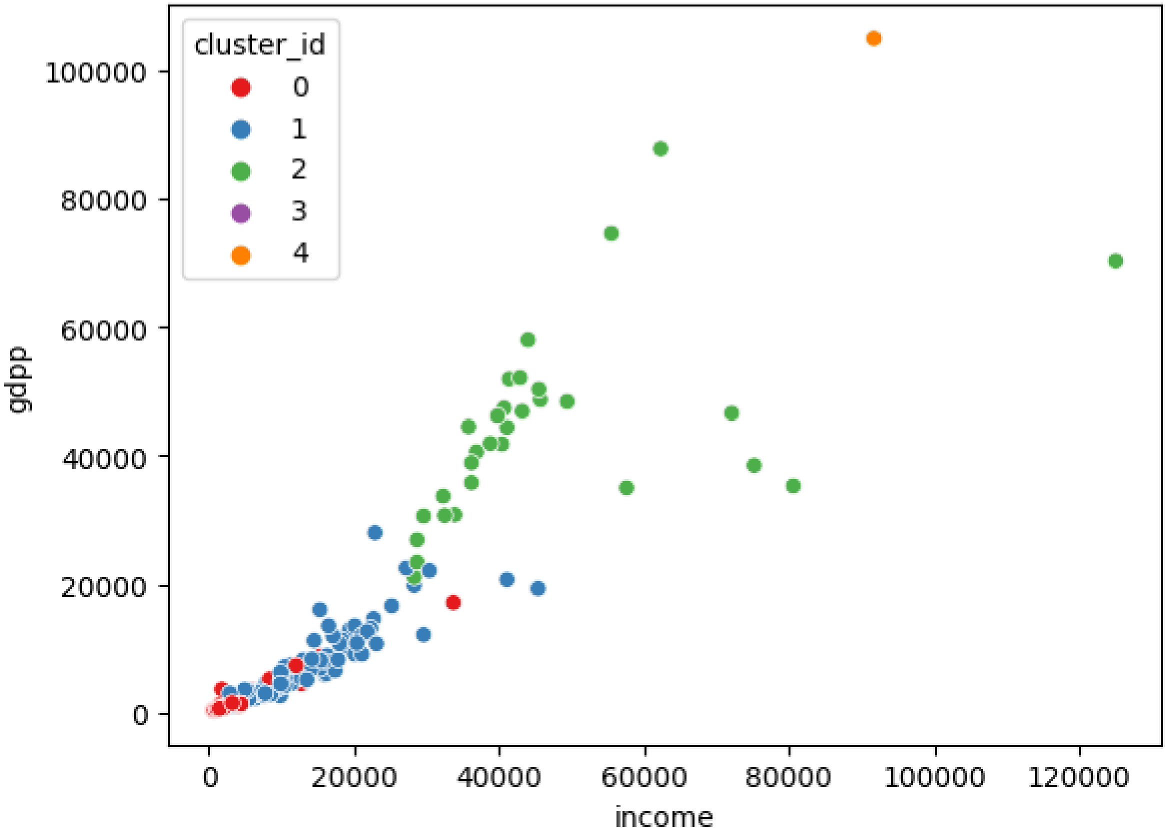
In [23]:

```
sns.scatterplot(x = 'inflation', y = 'gdpp', hue ='cluster_id', legend = 'full', dat
plt.show()
```



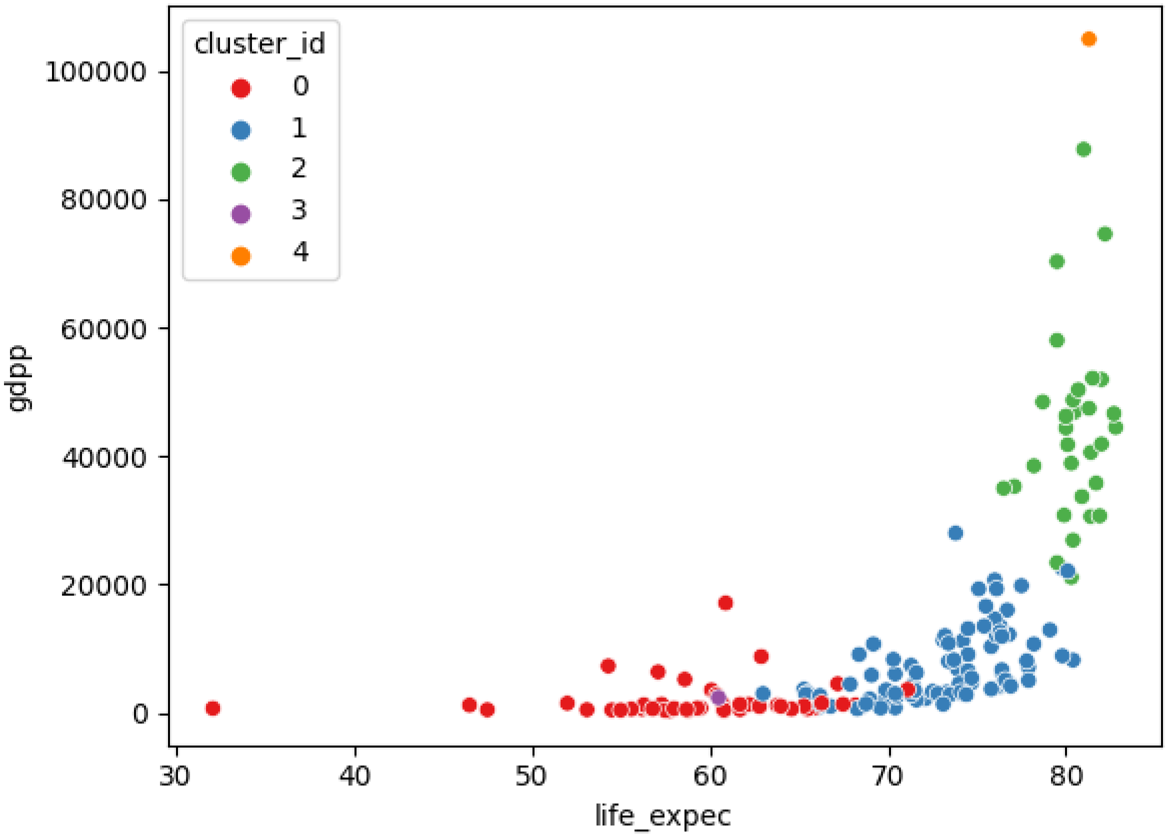
In [24]:

```
sns.scatterplot(x = 'income', y = 'gdpp', hue ='cluster_id', legend = 'full', data =
plt.show()
```



In [25]:

```
sns.scatterplot(x = 'life_expec', y = 'gdpp', hue ='cluster_id', legend = 'full', da
plt.show()
```



The orange and purple clusters are redundant, clearly. So, I'll set k equal to 3.

In [26]:

```
kmeans = KMeans(n_clusters = 3, max_iter=100 , random_state = 100)
```

```
kmeans.fit(dfx)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarnin
g: The default value of `n_init` will change from 10 to 'auto' in 1.4. Set the value
of `n_init` explicitly to suppress the warning
  warnings.warn(
```

Out[26]:

```
▾                    KMeans
KMeans(max_iter=100, n_clusters=3, random_state=100)
```

In [27]:

```
kmeans.labels_
```

Out[27]:

```
array([1, 2, 2, 1, 2, 2, 2, 0, 0, 2, 2, 2, 2, 2, 2, 0, 2, 1, 2, 2, 2, 1,
       2, 0, 2, 1, 1, 2, 1, 0, 2, 1, 1, 2, 2, 2, 1, 1, 1, 2, 1, 2, 0, 2,
       0, 2, 2, 2, 2, 1, 1, 2, 2, 0, 0, 1, 1, 2, 0, 1, 2, 2, 2, 1, 1, 2,
       1, 2, 0, 2, 2, 2, 1, 0, 2, 0, 2, 0, 2, 2, 1, 1, 0, 2, 1, 2, 2, 1,
       1, 2, 2, 0, 2, 1, 1, 2, 2, 1, 0, 1, 2, 2, 2, 2, 2, 2, 1, 2, 1, 2,
       0, 0, 1, 1, 0, 2, 1, 2, 2, 2, 2, 2, 2, 0, 2, 2, 1, 2, 2, 1, 2, 2,
       1, 0, 2, 2, 1, 1, 2, 0, 2, 2, 1, 2, 0, 0, 2, 1, 2, 1, 1, 2, 2, 2,
       2, 1, 2, 0, 0, 0, 2, 2, 2, 2, 2, 1, 1], dtype=int32)
```

In [28]:

```
df_km1 = pd.concat([df, pd.Series(kmeans.labels_)], axis = 1)
df_km1.columns = ['country','child_mort','exports','health','imports','income','infl
df_km1.head()
```

Out[28]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	55
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	409
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	446
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	353
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	1220

In [29]:

```
df_km1['cluster_id'].value_counts()
```

Out[29]:

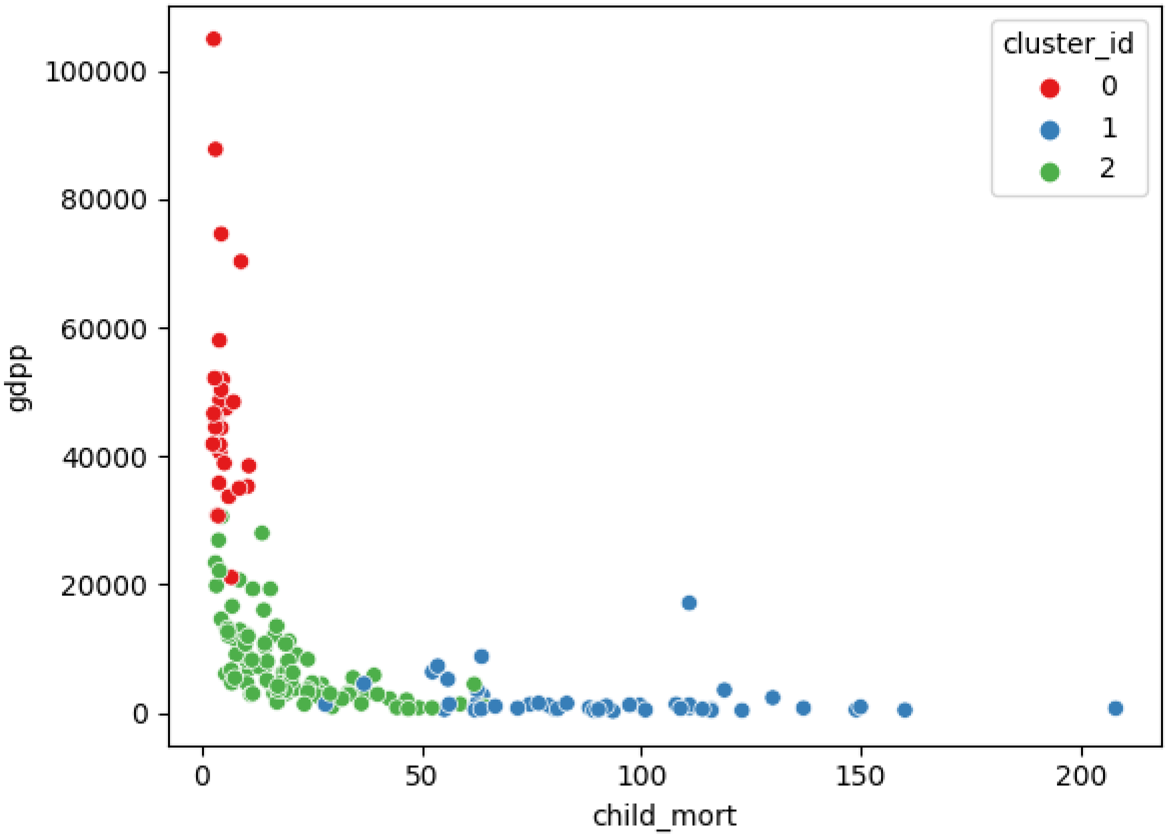
```
2    91
1    48
0    28
Name: cluster_id, dtype: int64
```

This looks much better than the previus k value.

Cluster Visualisation

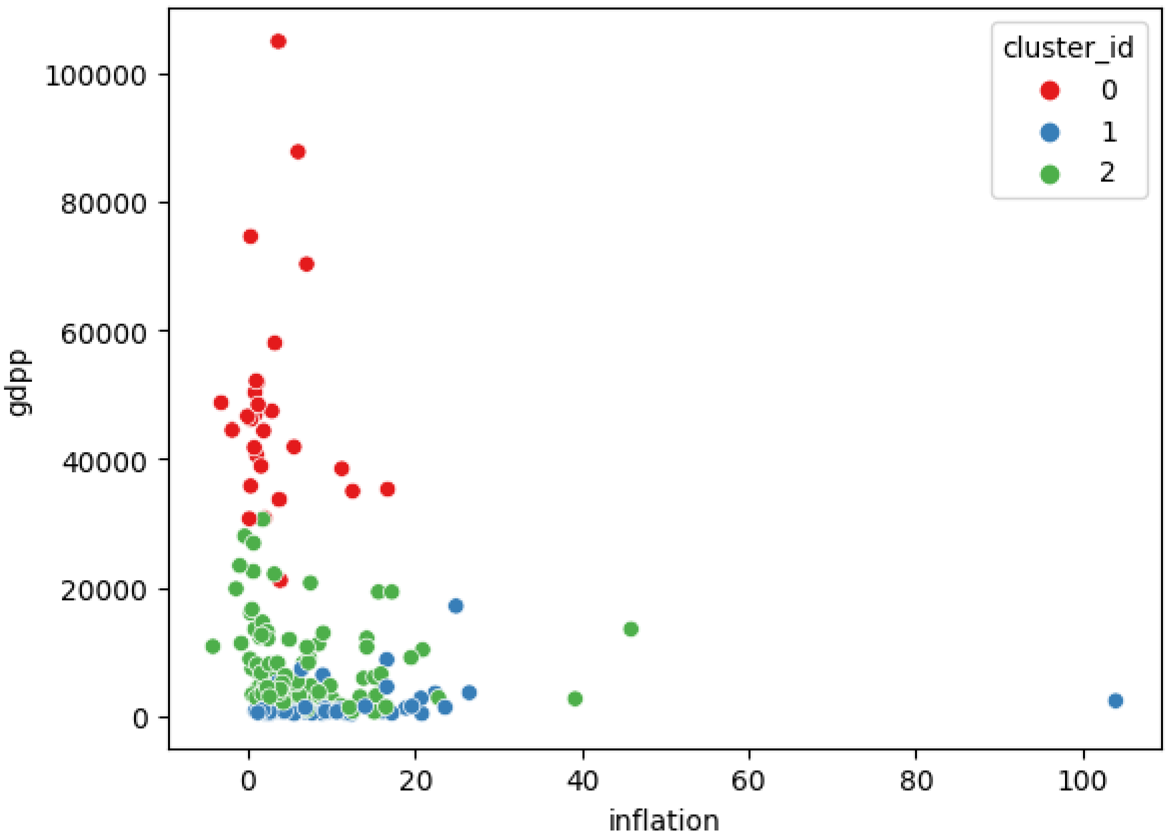
In [30]:

```
sns.scatterplot(x = 'child_mort', y = 'gdpp', hue ='cluster_id', legend = 'full', da
plt.show()
```



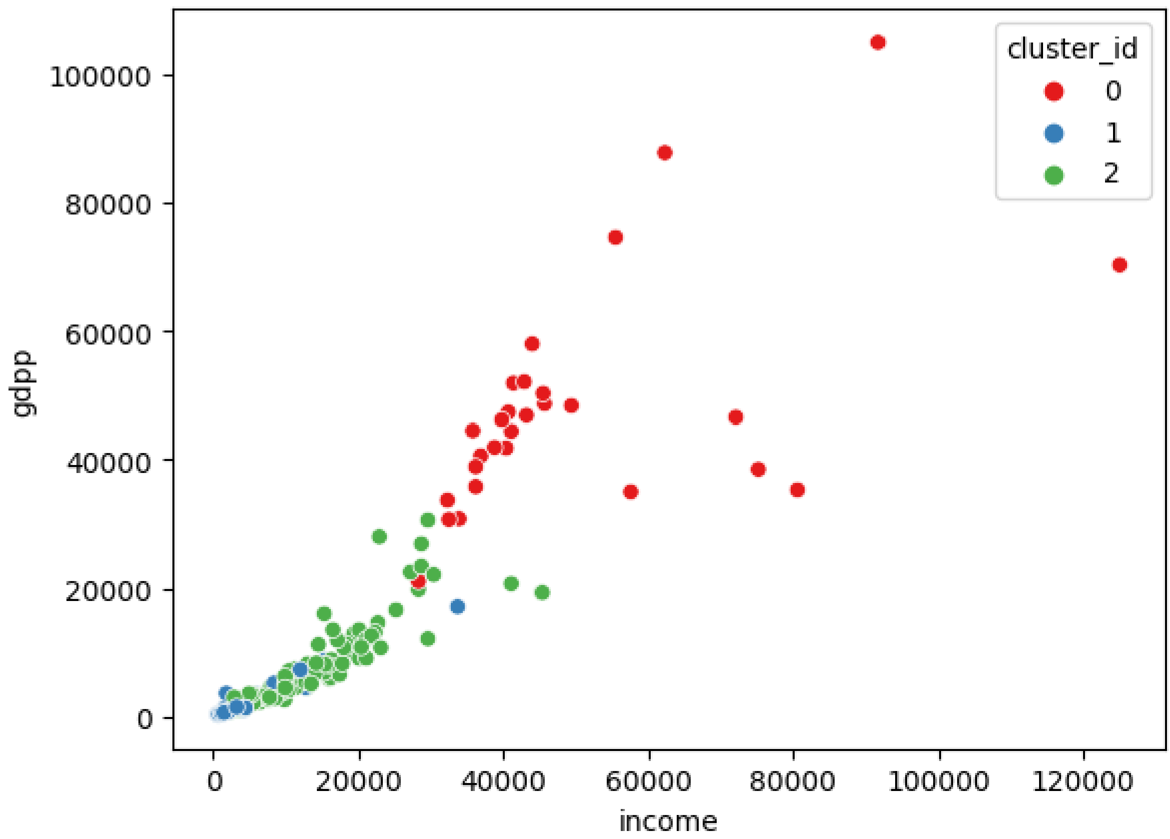
In [31]:

```
sns.scatterplot(x = 'inflation', y = 'gdpp', hue ='cluster_id', legend = 'full', dat
plt.show()
```

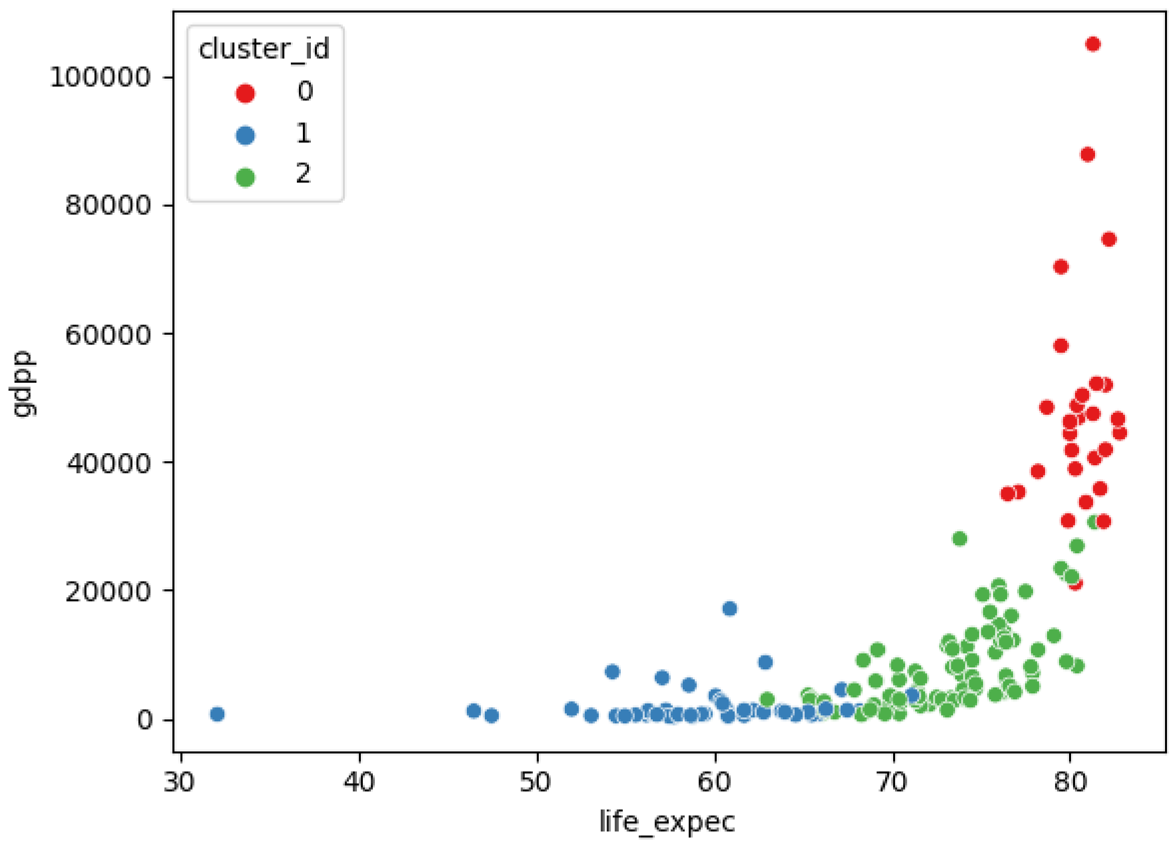


In [32]:

```
sns.scatterplot(x = 'income', y = 'gdpp', hue ='cluster_id', legend = 'full', data =
plt.show()
```



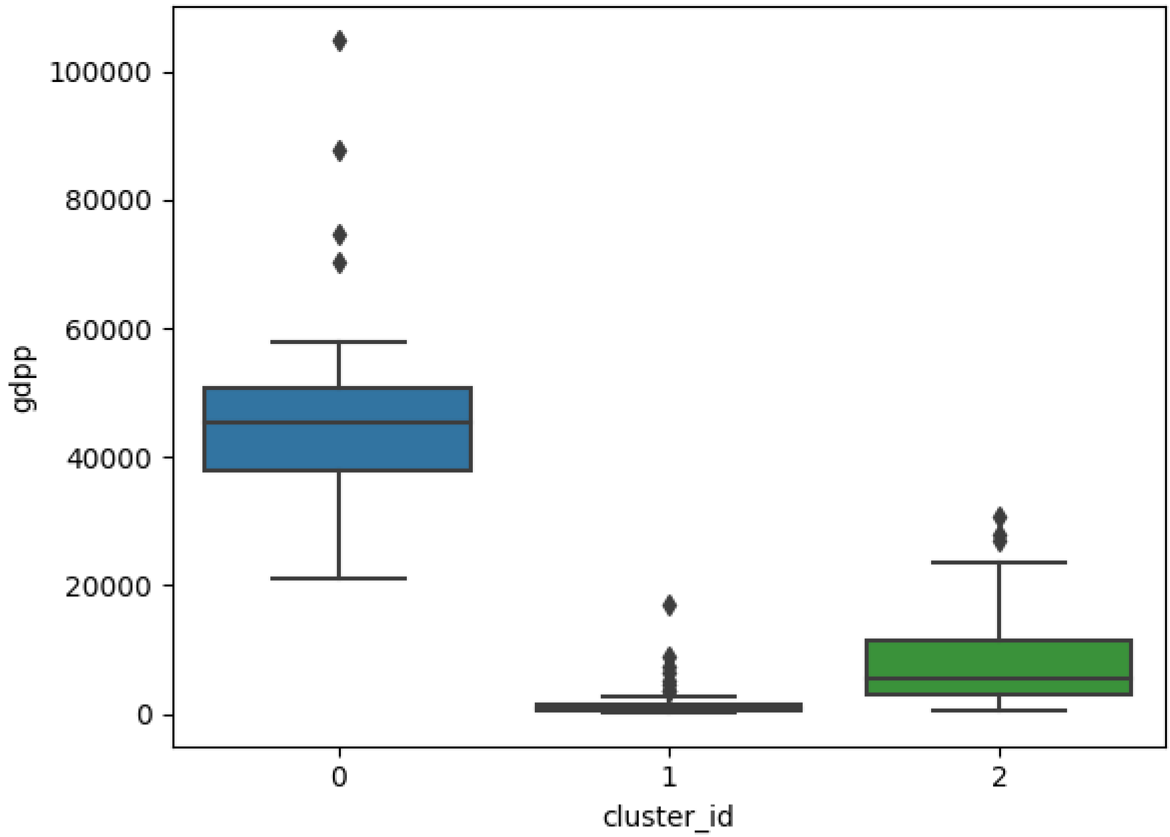
In [33]:
```
sns.scatterplot(x = 'life_expec', y = 'gdpp', hue ='cluster_id', legend = 'full', da
plt.show()
```



Here, we'll be using boxplots to confirm that the metrics for a particular cluster ID are particularly poor. Then this cluster can be chosen for aid.

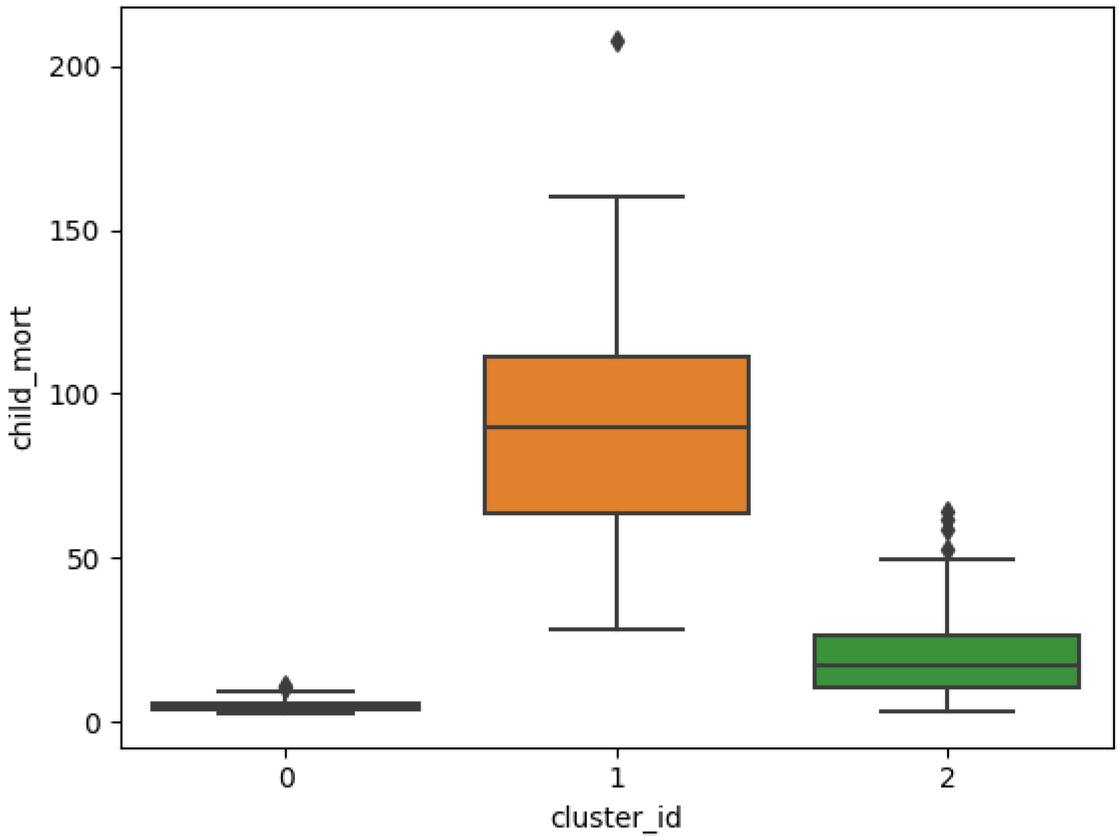
In [34]:

```
sns.boxplot(data = df_km1, x = 'cluster_id', y = 'gdpp')
plt.show()
```



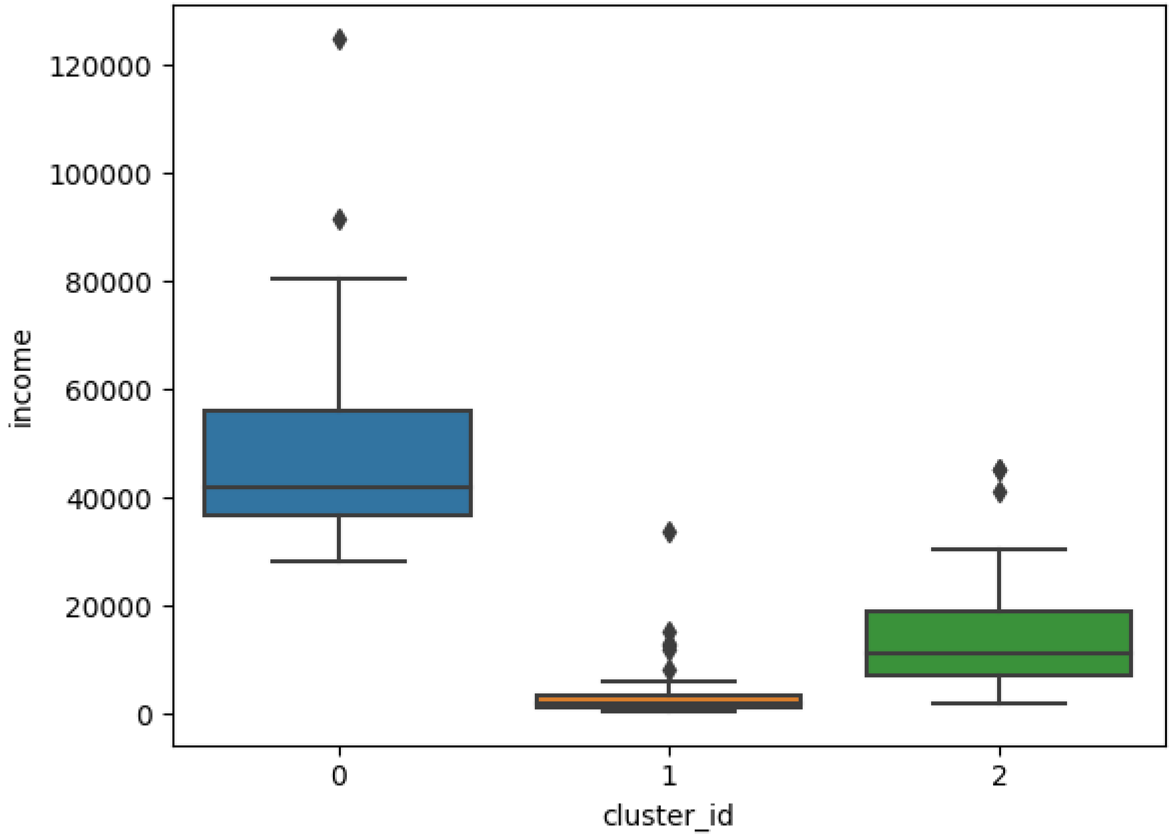
In [35]:

```
sns.boxplot(data = df_km1,x = 'cluster_id',y = 'child_mort')
plt.show()
```



In [36]:

```
sns.boxplot(data = df_km1, x = 'cluster_id',y = 'income')
plt.show()
```



Clearly, cluster 1 has the worst performance. It has low income and GDP but high child mortality. It is therefore the worthy candidate for aid.

In [37]:

```
df_km1[df_km1['cluster_id'] == 1]['country']
```

Out[37]:

```
0                  Afghanistan
3                       Angola
17                       Benin
21                    Botswana
25                Burkina Faso
26                     Burundi
28                    Cameroon
31    Central African Republic
32                        Chad
36                     Comoros
37             Congo, Dem. Rep.
38                  Congo, Rep.
40                Cote d'Ivoire
49            Equatorial Guinea
50                     Eritrea
55                       Gabon
56                      Gambia
59                       Ghana
63                      Guinea
64               Guinea-Bissau
66                       Haiti
72                        Iraq
80                       Kenya
81                    Kiribati
84                         Lao
87                     Lesotho
88                     Liberia
93                  Madagascar
```

```
94                    Malawi
97                      Mali
99                Mauritania
106               Mozambique
108                  Namibia
112                    Niger
113                  Nigeria
116                 Pakistan
126                   Rwanda
129                  Senegal
132             Sierra Leone
136          Solomon Islands
137             South Africa
142                    Sudan
147                 Tanzania
149              Timor-Leste
150                     Togo
155                   Uganda
165                    Yemen
166                   Zambia
Name: country, dtype: object
```

In [38]:

```
top_kmeans = df_km1[df_km1['cluster_id']==1].sort_values(by=["child_mort","gdpp","in
top_kmeans = top_kmeans.reset_index().drop('index',axis=1)
top_kmeans.head(10)
```

Out[38]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Haiti	208.0	101.286	45.7442	428.314	1500	5.45	32.1	3.33	662
1	Sierra Leone	160.0	67.032	52.2690	137.655	1220	17.20	55.0	5.20	399
2	Chad	150.0	330.096	40.6341	390.195	1930	6.39	56.5	6.59	897
3	Central African Republic	149.0	52.628	17.7508	118.190	888	2.01	47.5	5.21	446
4	Mali	137.0	161.424	35.2584	248.508	1870	4.37	59.5	6.55	708
5	Nigeria	130.0	589.490	118.1310	405.420	5150	104.00	60.5	5.84	2330
6	Niger	123.0	77.256	17.9568	170.868	814	2.55	58.8	7.49	348
7	Angola	119.0	2199.190	100.6050	1514.370	5900	22.40	60.1	6.16	3530
8	Congo, Dem. Rep.	116.0	137.274	26.4194	165.664	609	20.80	57.5	6.54	334
9	Burkina Faso	116.0	110.400	38.7550	170.200	1430	6.81	57.9	5.87	575

In [39]:

```
top_10 = top_kmeans.iloc[:10]
top_10['country'].reset_index().drop('index',axis = 1)
```

Out[39]:

	country
0	Haiti
1	Sierra Leone
2	Chad

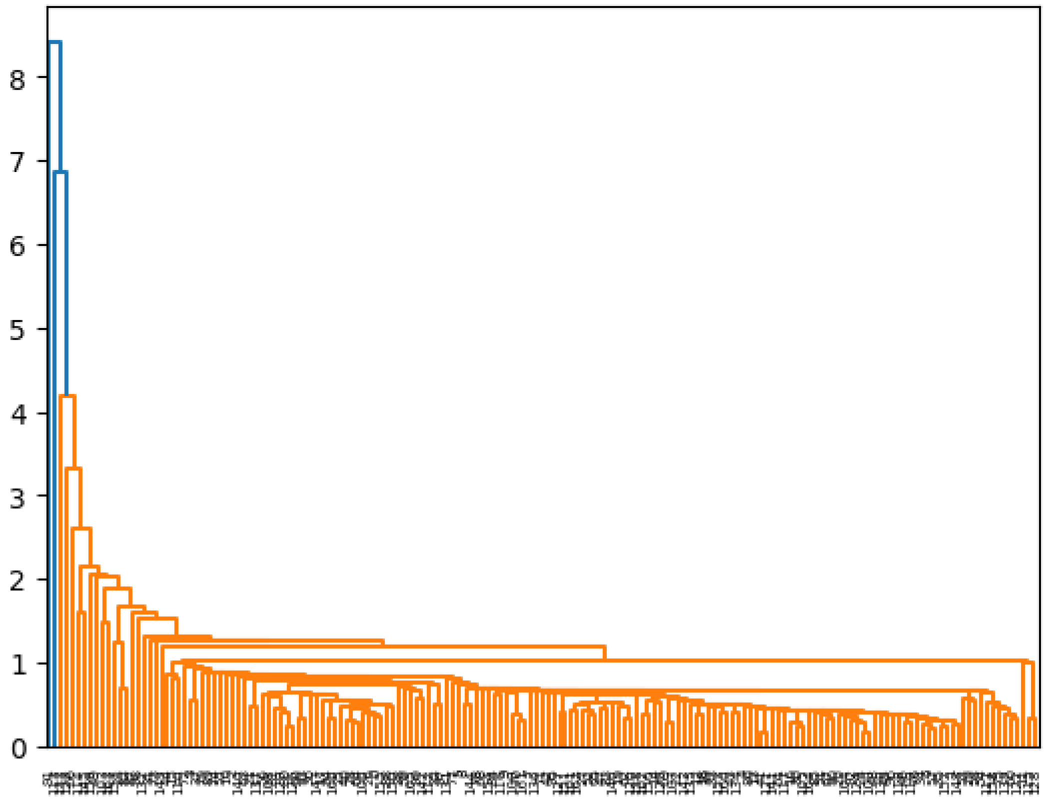
	country
3	Central African Republic
4	Mali
5	Nigeria
6	Niger
7	Angola
8	Congo, Dem. Rep.
9	Burkina Faso

Even with cluster 1, the 10 countries mentioned have the worst performance across all three considered metrics.

Hierarchical

In [40]:

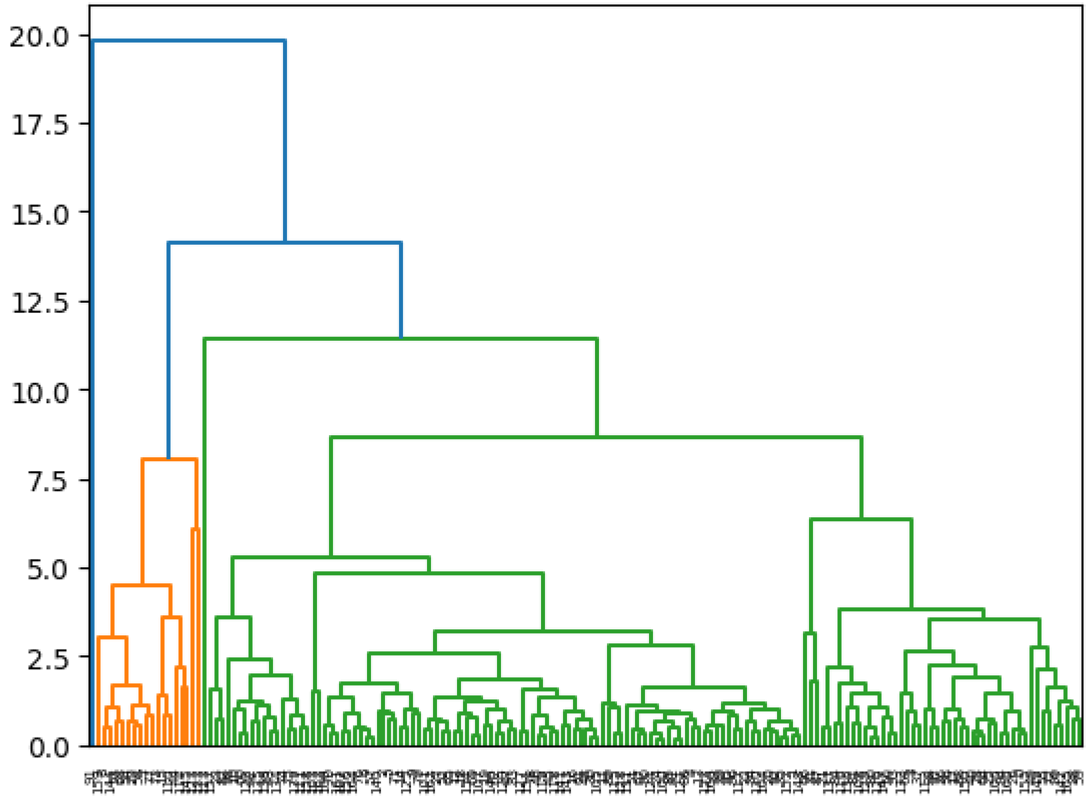
```
#single linkage.
mergings_single = linkage(dfx, method = "single", metric = 'euclidean')
dendrogram(mergings_single)
plt.show()
```



Unsatisfactory performance with single linkage, so complete will be attempted.

In [41]:

```
mergings_complete = linkage(dfx, method = "complete", metric = 'euclidean')
dendrogram(mergings_complete)
plt.show()
```



In [42]:
```
cluster_labels = cut_tree(mergings_complete, n_clusters=3).reshape(-1, )
cluster_labels
```

Out[42]:
```
array([0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
       1, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0])
```

In [43]:
```
df_hm = pd.concat([df, pd.Series(cluster_labels)], axis = 1)
df_hm.columns = ['country','child_mort','exports','health','imports','income','infla
df_hm.head()
```

Out[43]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdp
0	Afghanistan	90.2	55.30	41.9174	248.297	1610	9.44	56.2	5.82	55
1	Albania	16.6	1145.20	267.8950	1987.740	9930	4.49	76.3	1.65	409
2	Algeria	27.3	1712.64	185.9820	1400.440	12900	16.10	76.5	2.89	446
3	Angola	119.0	2199.19	100.6050	1514.370	5900	22.40	60.1	6.16	353
4	Antigua and Barbuda	10.3	5551.00	735.6600	7185.800	19100	1.44	76.8	2.13	1220

In [44]:
```
df_hm['cluster_labels'].value_counts()
```

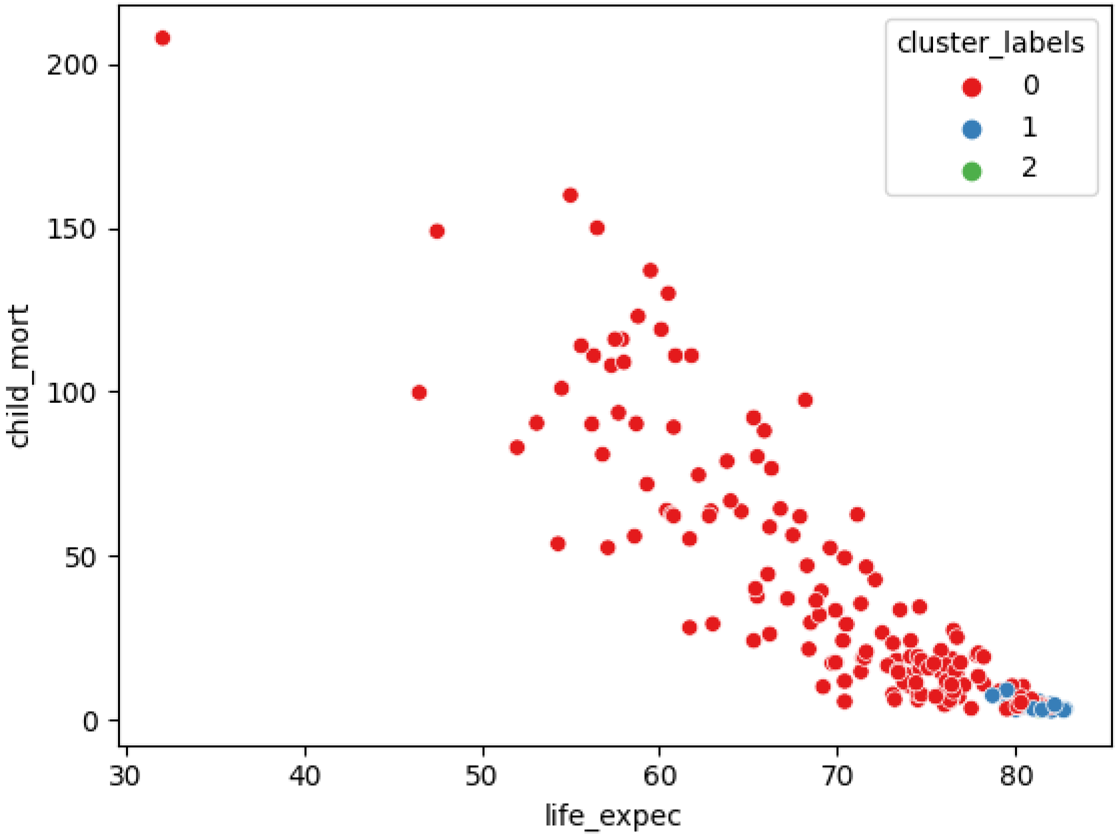
Out[44]:
```
0    148
1     18
```

```
2      1
Name: cluster_labels, dtype: int64
```

Cluster Visualisation

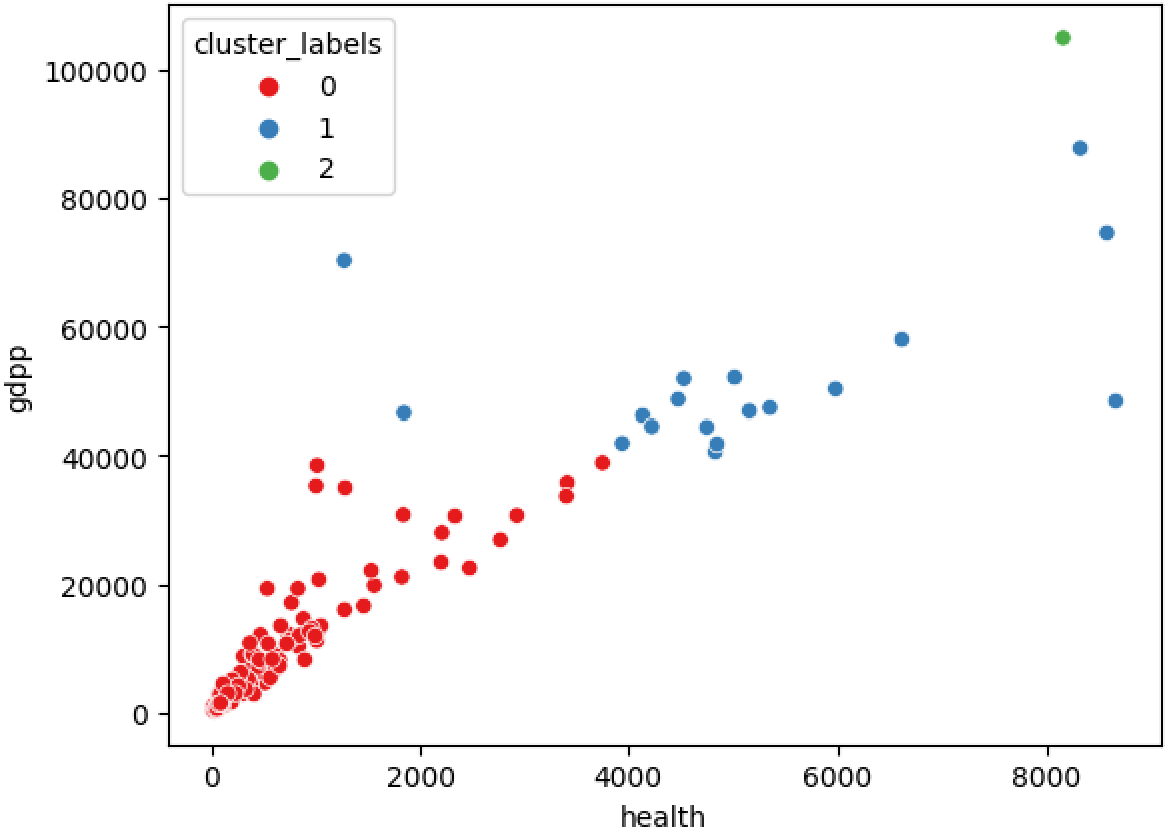
In [45]:

```
sns.scatterplot(x = 'life_expec', y = 'child_mort', hue ='cluster_labels', legend =
plt.show()
```



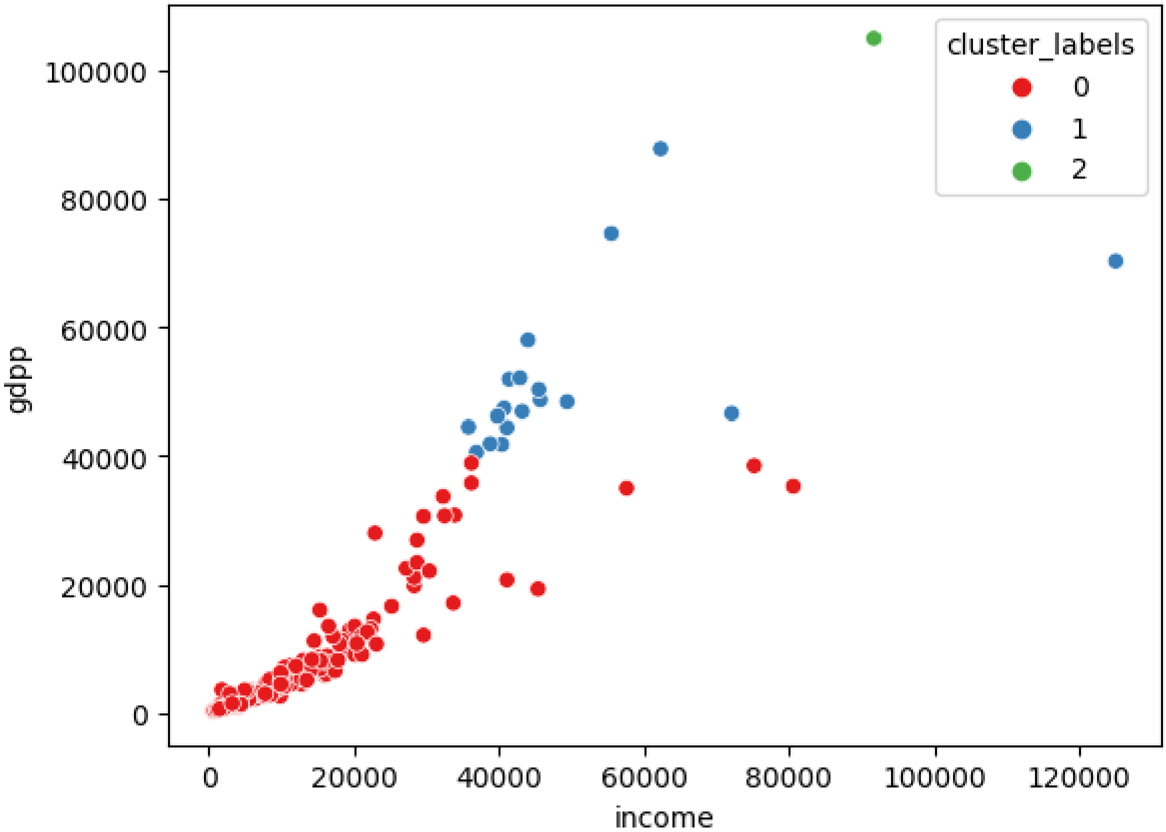
In [46]:

```
sns.scatterplot(x = 'health', y = 'gdpp', hue ='cluster_labels', legend = 'full', da
plt.show()
```



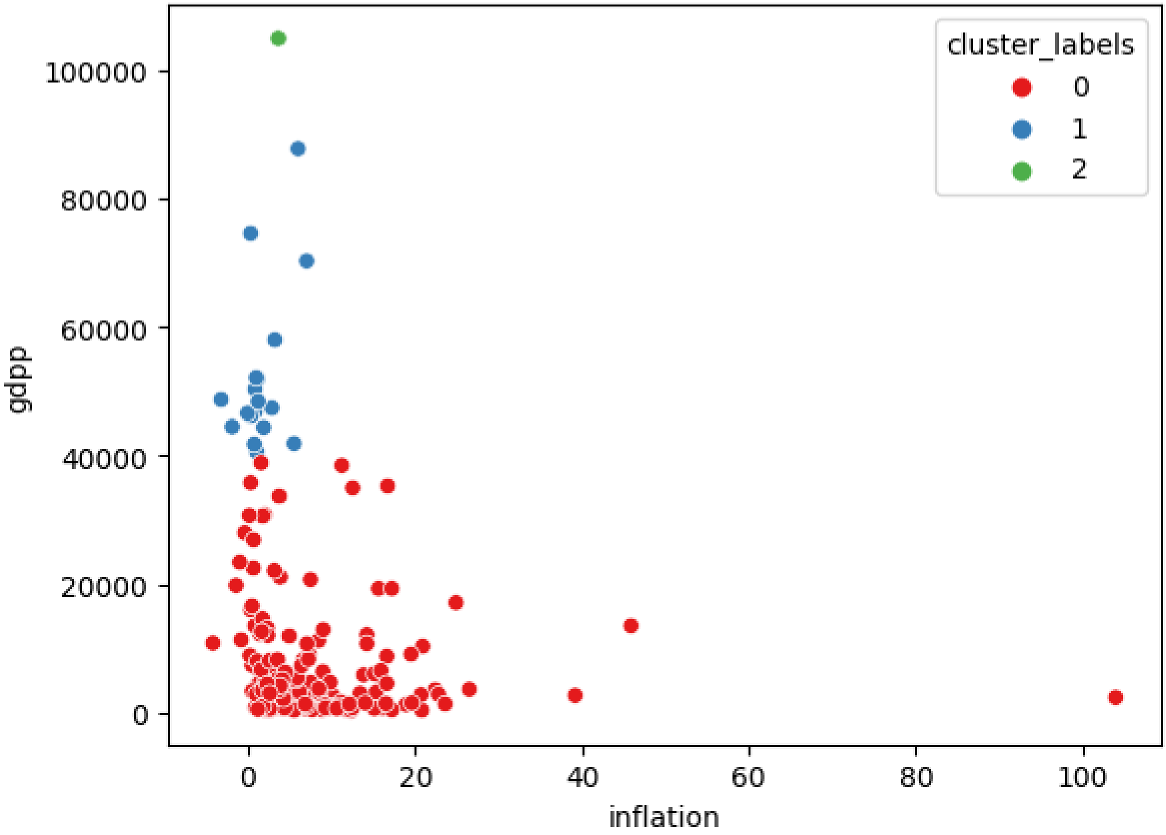
In [47]:

```
sns.scatterplot(x = 'income', y = 'gdpp', hue ='cluster_labels', legend = 'full', da
plt.show()
```



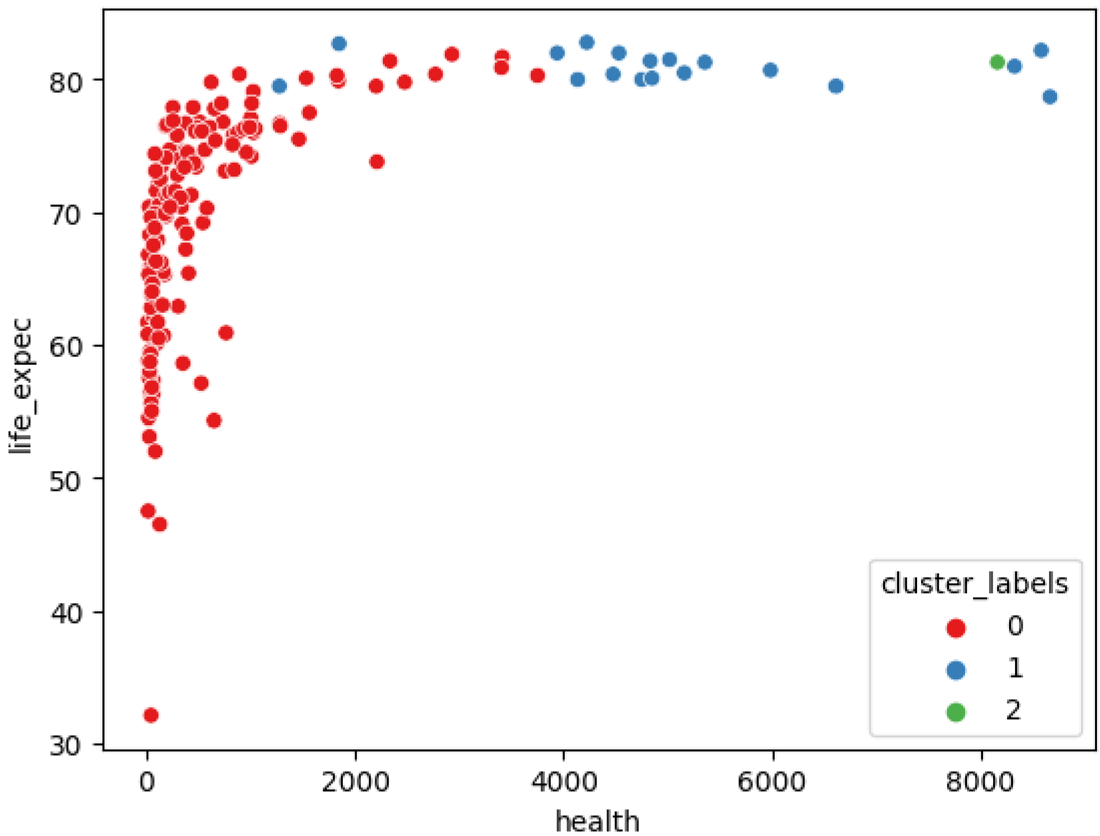
In [48]:

```
sns.scatterplot(x = 'inflation', y = 'gdpp', hue ='cluster_labels', legend = 'full',
plt.show()
```



In [49]:

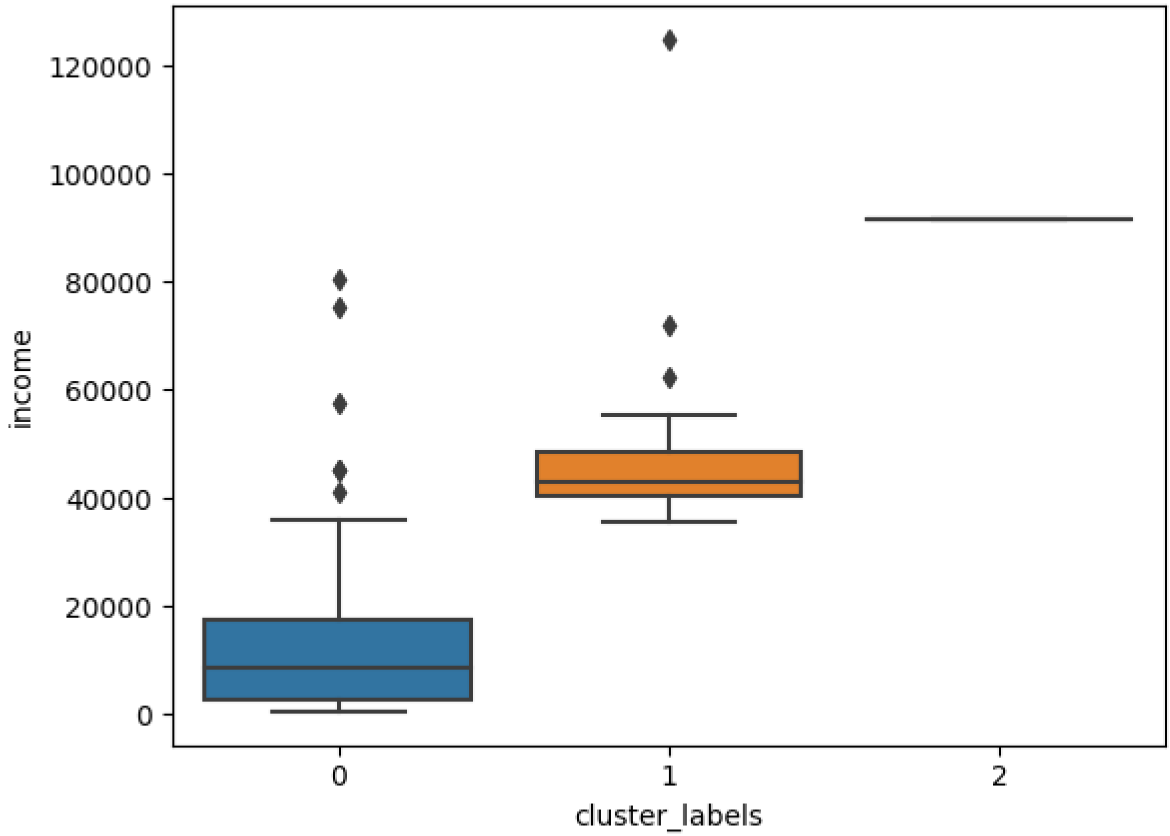
```
sns.scatterplot(x = 'health', y = 'life_expec', hue ='cluster_labels', legend = 'ful
plt.show()
```



Using boxplots for checking the lowest performaning cluster.

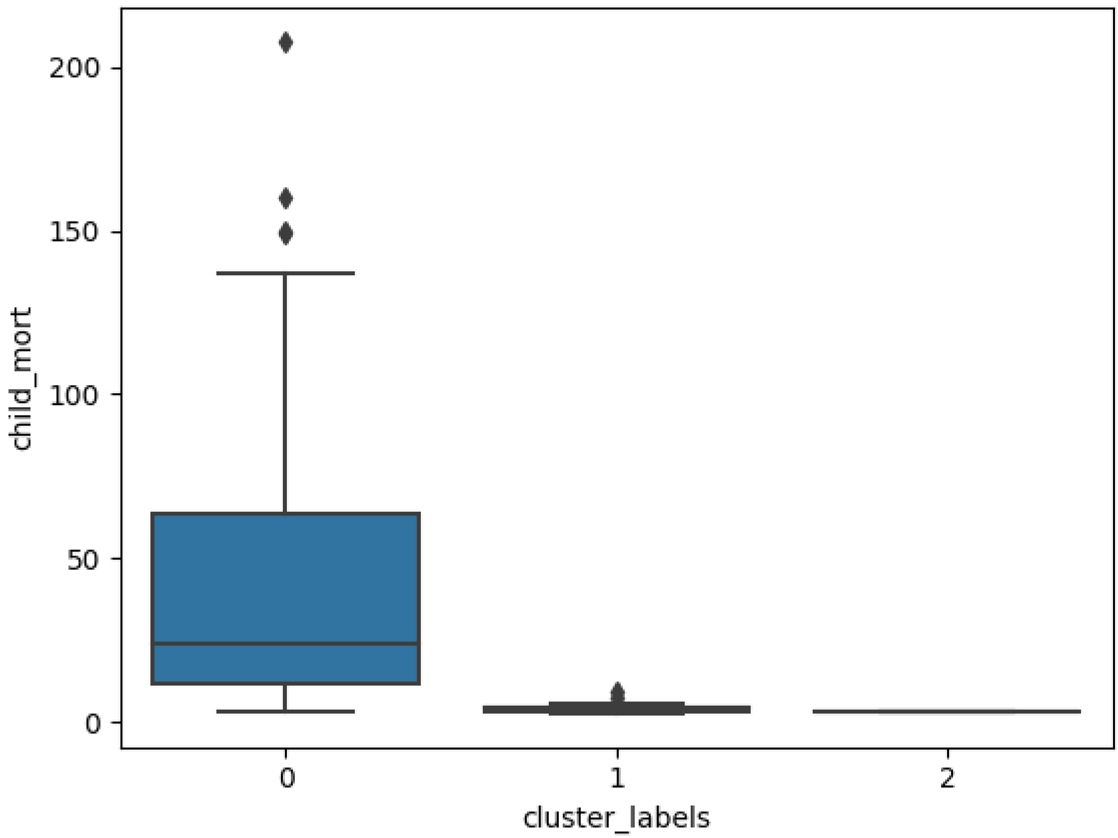
In [50]:

```
sns.boxplot(data = df_hm, x = 'cluster_labels',y='income')
plt.show()
```



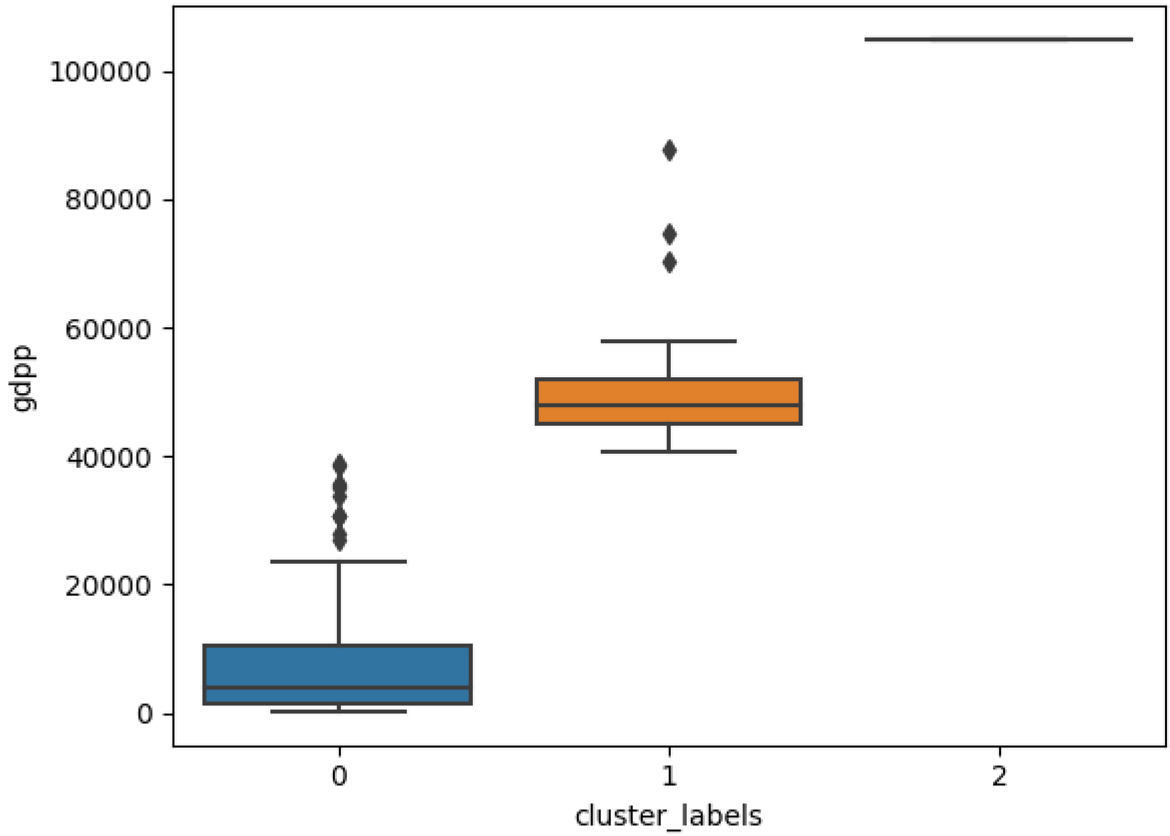
In [51]:

```
sns.boxplot(data = df_hm, x = 'cluster_labels',y = 'child_mort')
plt.show()
```



In [52]:

```
sns.boxplot(data = df_hm,x = 'cluster_labels', y = 'gdpp')
plt.show()
```



Obviously, cluster 0 has the worst performance across the metrics.

In [53]:

```
df_hm[df_hm['cluster_labels'] == 0]['country']
```

Out[53]:

```
0              Afghanistan
1                  Albania
2                  Algeria
3                   Angola
4      Antigua and Barbuda
              ...
162                Vanuatu
163              Venezuela
164                Vietnam
165                  Yemen
166                 Zambia
Name: country, Length: 148, dtype: object
```

In [54]:

```
top_h = df_hm[df_hm['cluster_labels']==0].sort_values(by=["child_mort","gdpp","incom
top_h = top_h.reset_index().drop('index',1)
top_h.head(10)
```

```
<ipython-input-54-9a473548feca>:2: FutureWarning: In a future version of pandas all a
rguments of DataFrame.drop except for the argument 'labels' will be keyword-only.
  top_h = top_h.reset_index().drop('index',1)
```

Out[54]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
0	Haiti	208.0	101.286	45.7442	428.314	1500	5.45	32.1	3.33	662
1	Sierra Leone	160.0	67.032	52.2690	137.655	1220	17.20	55.0	5.20	399
2	Chad	150.0	330.096	40.6341	390.195	1930	6.39	56.5	6.59	897
3	Central African Republic	149.0	52.628	17.7508	118.190	888	2.01	47.5	5.21	446

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
4	Mali	137.0	161.424	35.2584	248.508	1870	4.37	59.5	6.55	708
5	Nigeria	130.0	589.490	118.1310	405.420	5150	104.00	60.5	5.84	2330
6	Niger	123.0	77.256	17.9568	170.868	814	2.55	58.8	7.49	348
7	Angola	119.0	2199.190	100.6050	1514.370	5900	22.40	60.1	6.16	3530
8	Congo, Dem. Rep.	116.0	137.274	26.4194	165.664	609	20.80	57.5	6.54	334
9	Burkina Faso	116.0	110.400	38.7550	170.200	1430	6.81	57.9	5.87	575

In [55]:

```
top_10 = top_h.iloc[:10]
top_10['country'].reset_index().drop('index',axis = 1)
```

Out[55]:

	country
0	Haiti
1	Sierra Leone
2	Chad
3	Central African Republic
4	Mali
5	Nigeria
6	Niger
7	Angola
8	Congo, Dem. Rep.
9	Burkina Faso