Clustering Assignment

Importing All Required Libraries

In [1]:
```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
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

from sklearn.neighbors import NearestNeighbors
from random import sample
from numpy.random import uniform
from math import isnan

import warnings
warnings.filterwarnings('ignore')

from matplotlib.pyplot import xticks
%matplotlib inline
```

In [2]:
```
data=pd.read_csv('Country-data.csv')
data.head(5)
```

Out[2]:

	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 [3]:
```
data.shape
```

Out[3]:
```
(167, 10)
```

In [4]:
```
data.describe()
```

Out[4]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
count	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000	167.000000
mean	38.270060	41.108976	6.815689	46.890215	17144.688623	7.781832	70.555689	2.947964	12964.155689
std	40.328931	27.412010	2.746837	24.209589	19278.067698	10.570704	8.893172	1.513848	18328.704809
min	2.600000	0.109000	1.810000	0.065900	609.000000	-4.210000	32.100000	1.150000	231.000000
25%	8.250000	23.800000	4.920000	30.200000	3355.000000	1.810000	65.300000	1.795000	1330.000000
50%	19.300000	35.000000	6.320000	43.300000	9960.000000	5.390000	73.100000	2.410000	4660.000000
75%	62.100000	51.350000	8.600000	58.750000	22800.000000	10.750000	76.800000	3.880000	14050.000000
max	208.000000	200.000000	17.900000	174.000000	125000.000000	104.000000	82.800000	7.490000	105000.000000

In [5]:
```
data.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]:
```
data.isnull().sum()
```

Out[6]:
```
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
```

In the given data columns exports, health and imports are given in % so, we need to convert them back to normal values

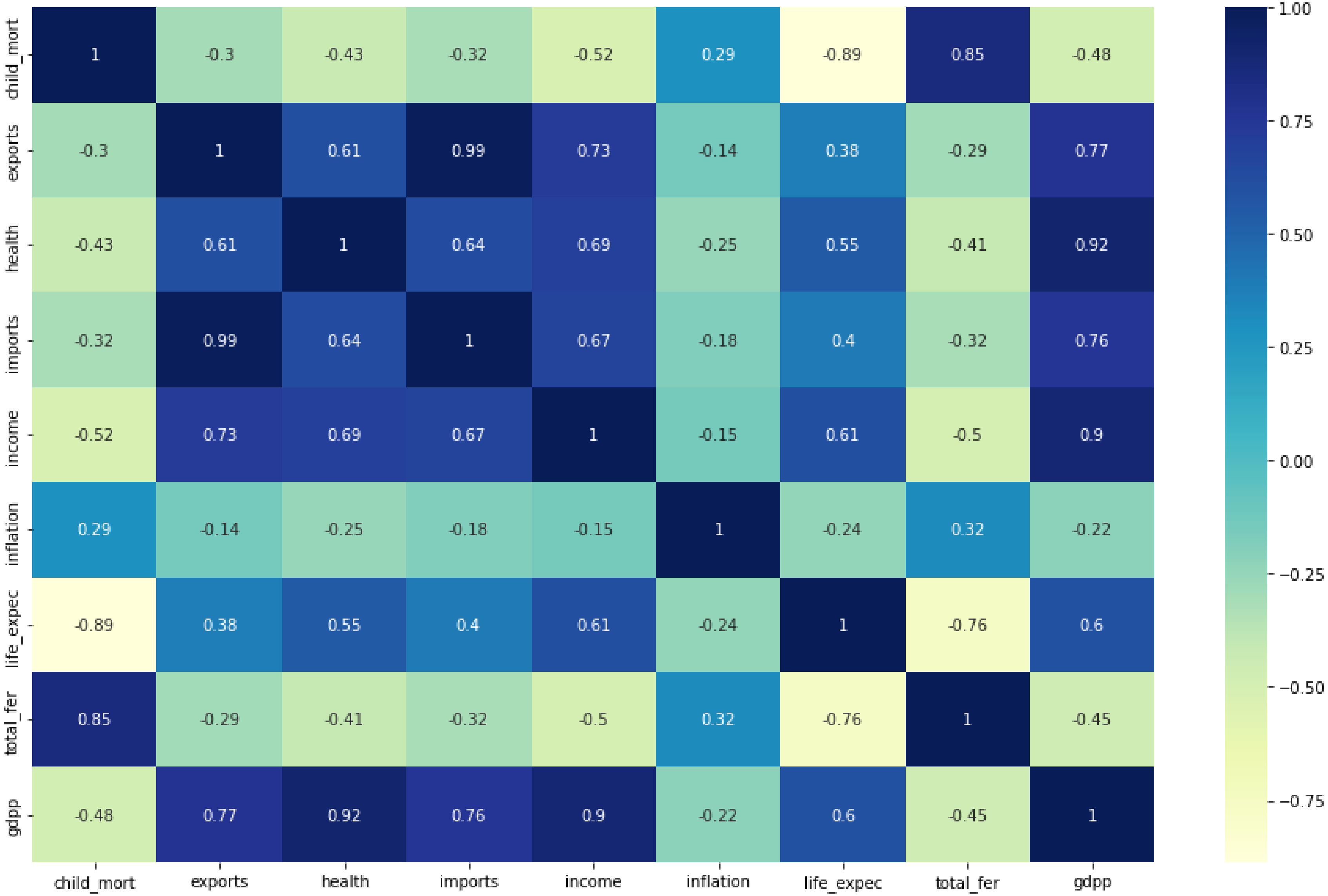
In [7]:
```
data['exports']= (data['exports']*data['gdpp'])/100
data['health']= (data['health']*data['gdpp'])/100
data['imports']= (data['imports']*data['gdpp'])/100
```

Exploratory Data Analytics

We need to choose the countries that are in the direst need of aid. Hence, we need to identify those countries with using some socio-economic and health factors that determine the overall development of the country

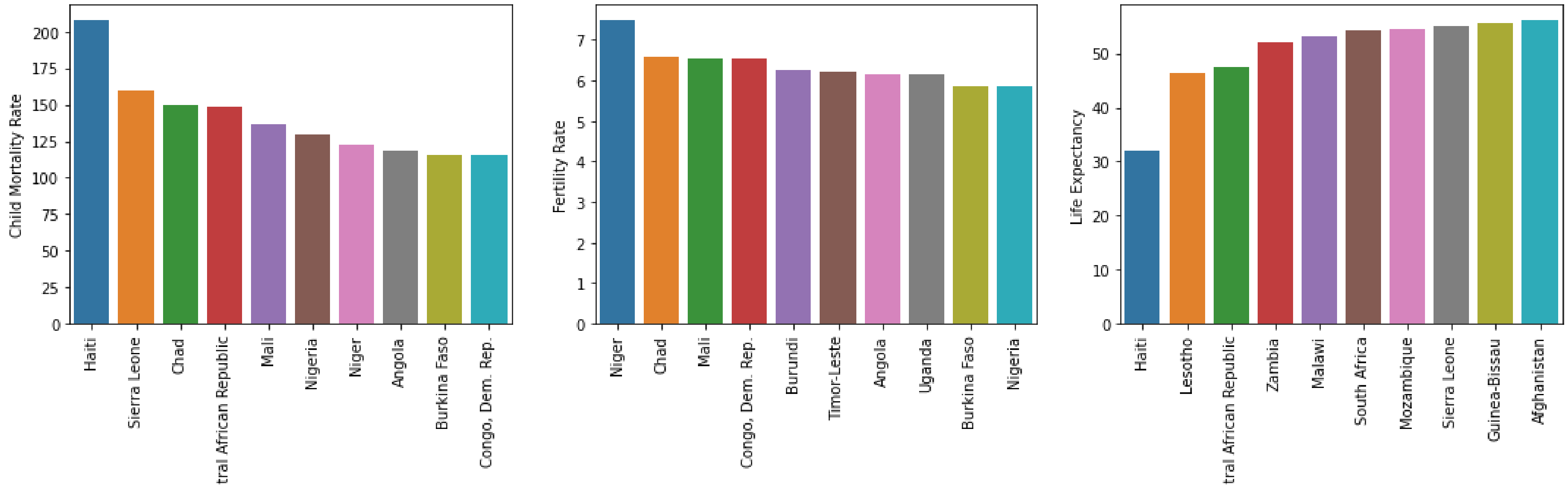
We will have a look on the lowest 10 countries for each factor.

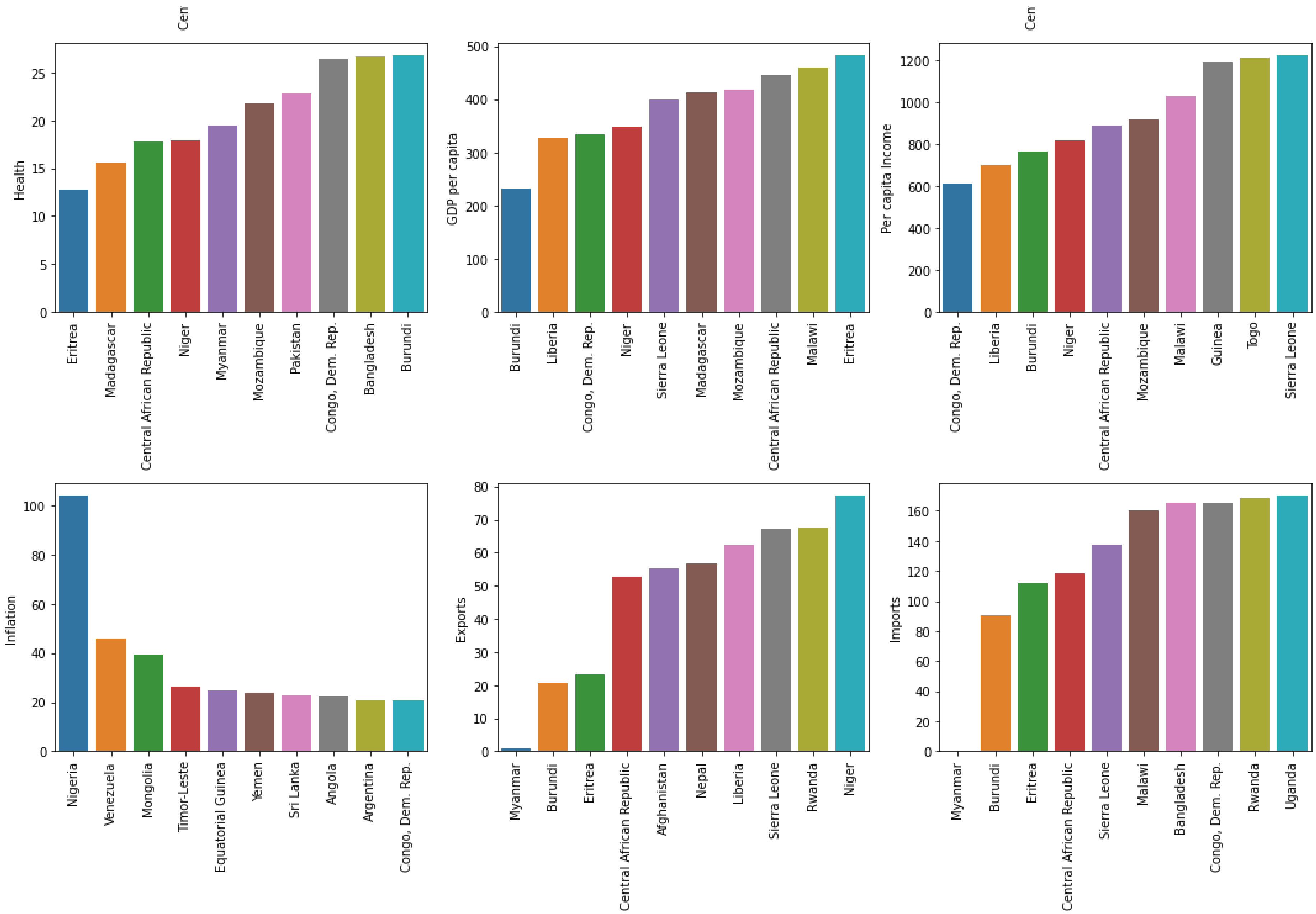
In [8]:
```
plt.figure(figsize = (16, 10))
sns.heatmap(data.corr(), annot = True, cmap="YlGnBu")
plt.savefig('corrplot')
plt.show()
```



In [9]:
```
fig, axs = plt.subplots(3,3,figsize = (15,15))

# Child Mortality Rate : Death of children under 5 years of age per 1000 live births

top10_child_mort = data[['country','child_mort']].sort_values('child_mort', ascending = False).head(10)
plt1 = sns.barplot(x='country', y='child_mort', data= top10_child_mort, ax = axs[0,0])
plt1.set(xlabel = '', ylabel= 'Child Mortality Rate')

# Fertility Rate: The number of children that would be born to each woman if the current age-fertility rates remain the s
top10_total_fer = data[['country','total_fer']].sort_values('total_fer', ascending = False).head(10)
plt1 = sns.barplot(x='country', y='total_fer', data= top10_total_fer, ax = axs[0,1])
plt1.set(xlabel = '', ylabel= 'Fertility Rate')

# Life Expectancy: The average number of years a new born child would live if the current mortality patterns are to remai

bottom10_life_expec = data[['country','life_expec']].sort_values('life_expec', ascending = True).head(10)
plt1 = sns.barplot(x='country', y='life_expec', data= bottom10_life_expec, ax = axs[0,2])
plt1.set(xlabel = '', ylabel= 'Life Expectancy')

# Health :Total health spending as %age of Total GDP.

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

# The GDP per capita : Calculated as the Total GDP divided by the total population.

bottom10_gdpp = data[['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')

# Per capita Income : Net income per person

bottom10_income = data[['country','income']].sort_values('income', ascending = True).head(10)
plt1 = sns.barplot(x='country', y='income', data= bottom10_income, ax = axs[1,2])
plt1.set(xlabel = '', ylabel= 'Per capita Income')


# Inflation: The measurement of the annual growth rate of the Total GDP

top10_inflation = data[['country','inflation']].sort_values('inflation', ascending = False).head(10)
```

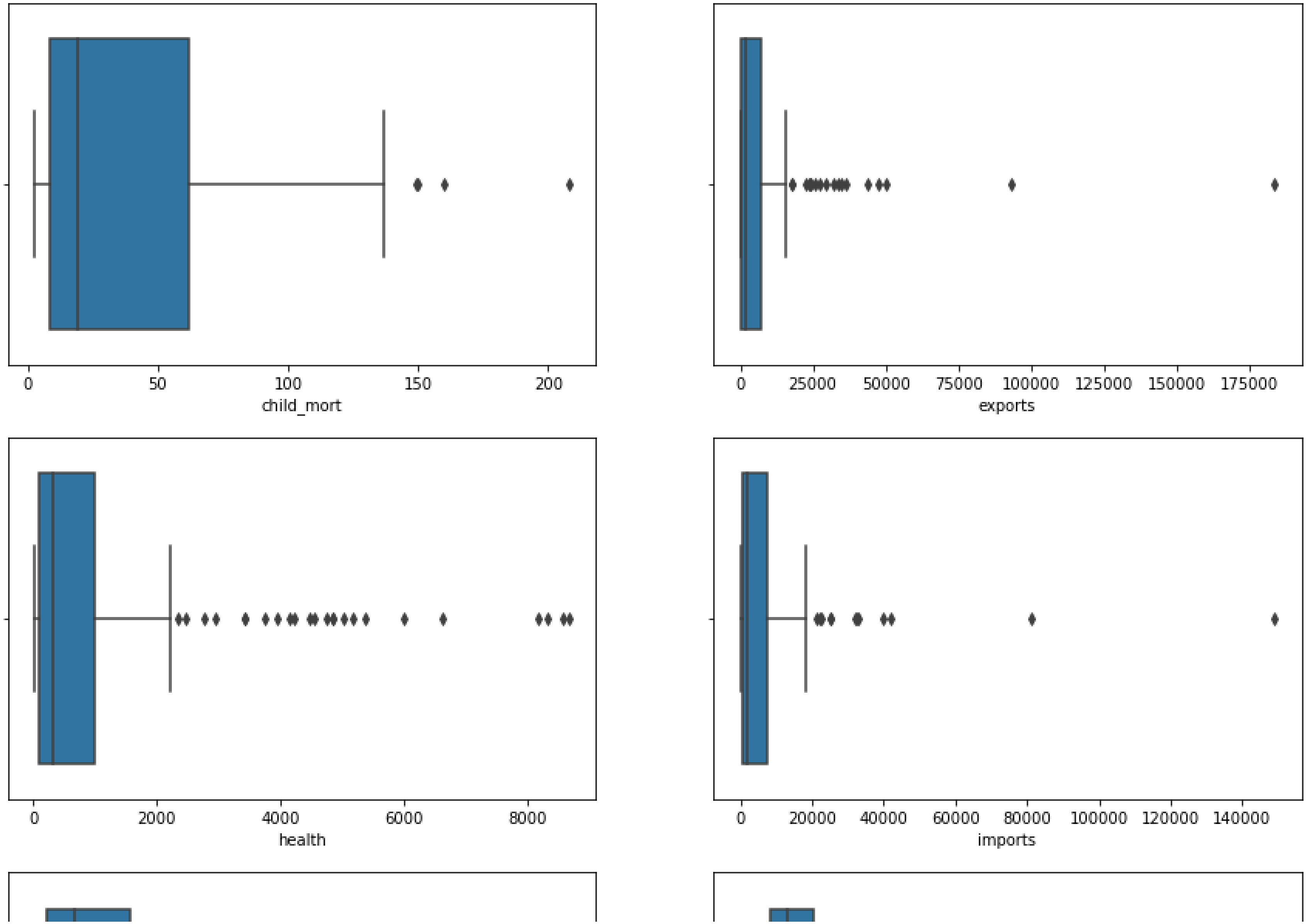
```
plt1 = sns.barplot(x='country', y='inflation', data= top10_inflation, ax = axs[2,0])
plt1.set(xlabel = '', ylabel= 'Inflation')


# Exports: Exports of goods and services. Given as %age of the Total GDP

bottom10_exports = data[['country','exports']].sort_values('exports', ascending = True).head(10)
plt1 = sns.barplot(x='country', y='exports', data= bottom10_exports, ax = axs[2,1])
plt1.set(xlabel = '', ylabel= 'Exports')


# Imports: Imports of goods and services. Given as %age of the Total GDP

bottom10_imports = data[['country','imports']].sort_values('imports', ascending = True).head(10)
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.savefig('eda')
plt.show()
```

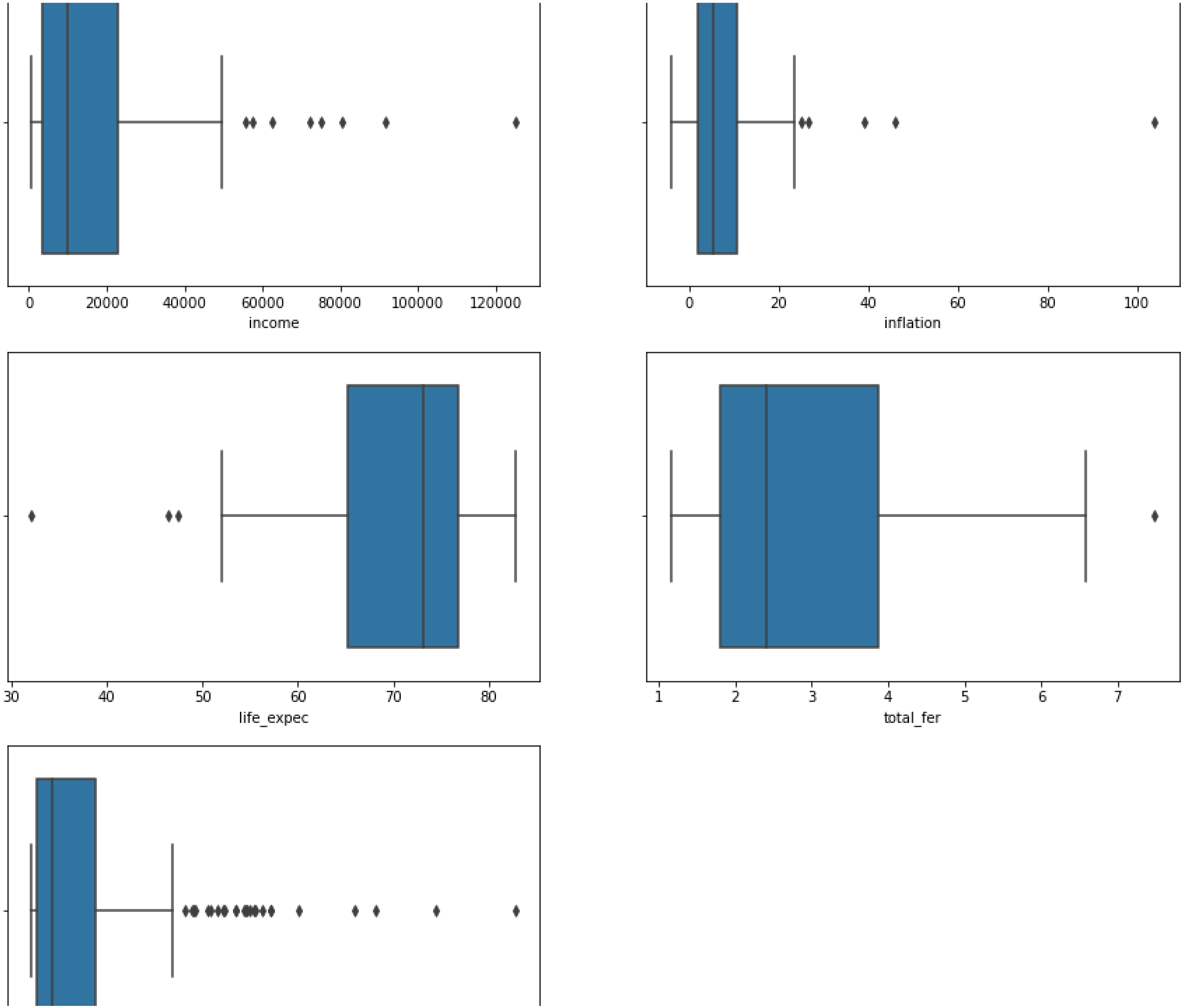


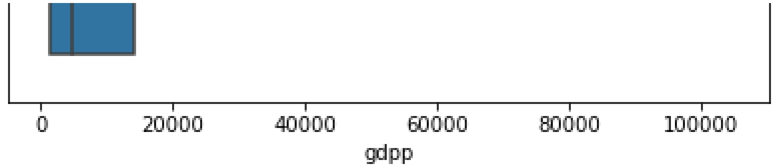


In [10]:
```
columns= ['child_mort','exports','health','imports','income','inflation','life_expec','total_fer','gdpp']
```

In [11]:
```
plt.figure(figsize=(15,25))
for i in enumerate(columns):
    ax = plt.subplot(5, 2, i[0]+1)
    sns.boxplot(data[i[1]])
plt.show()
```

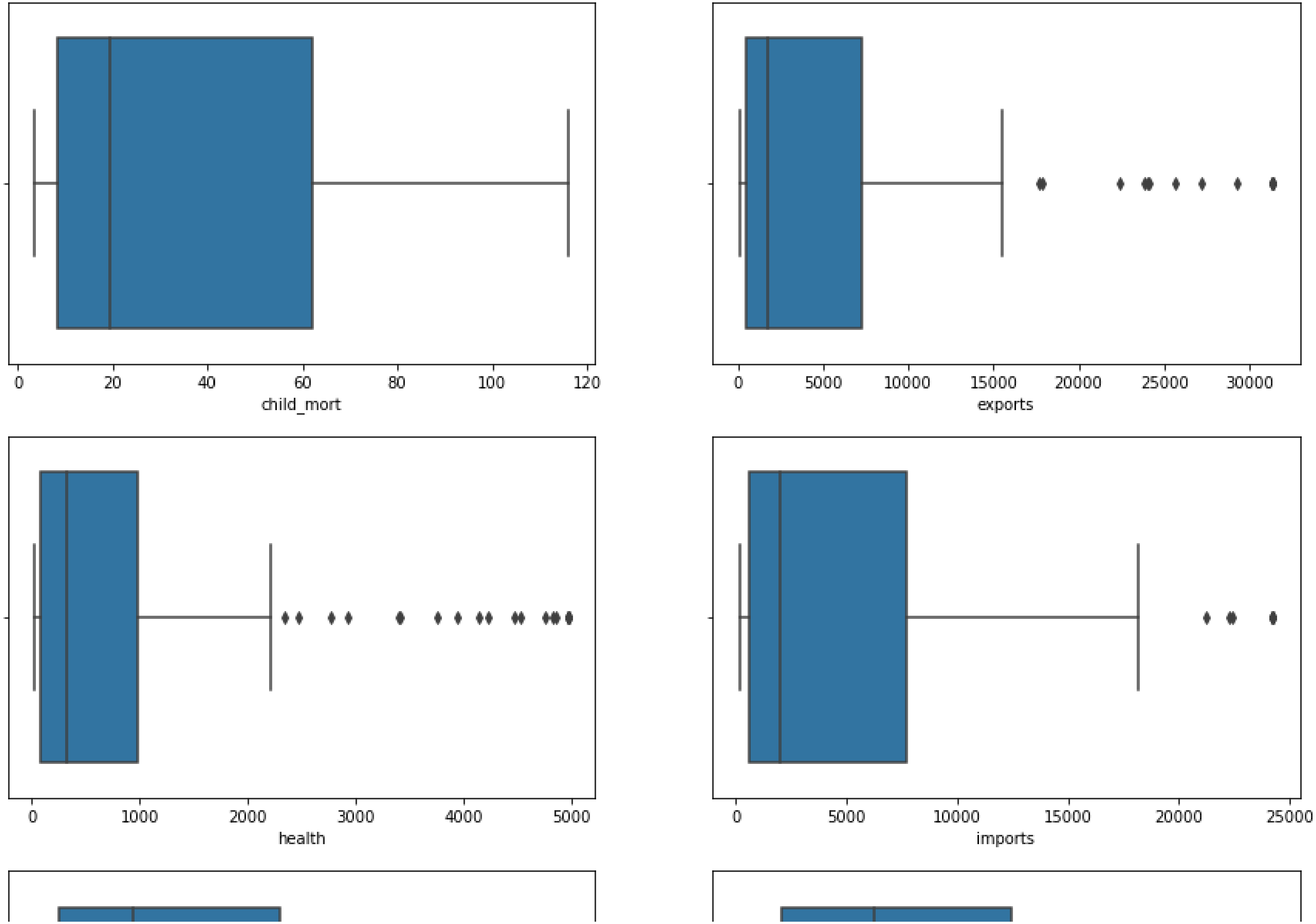


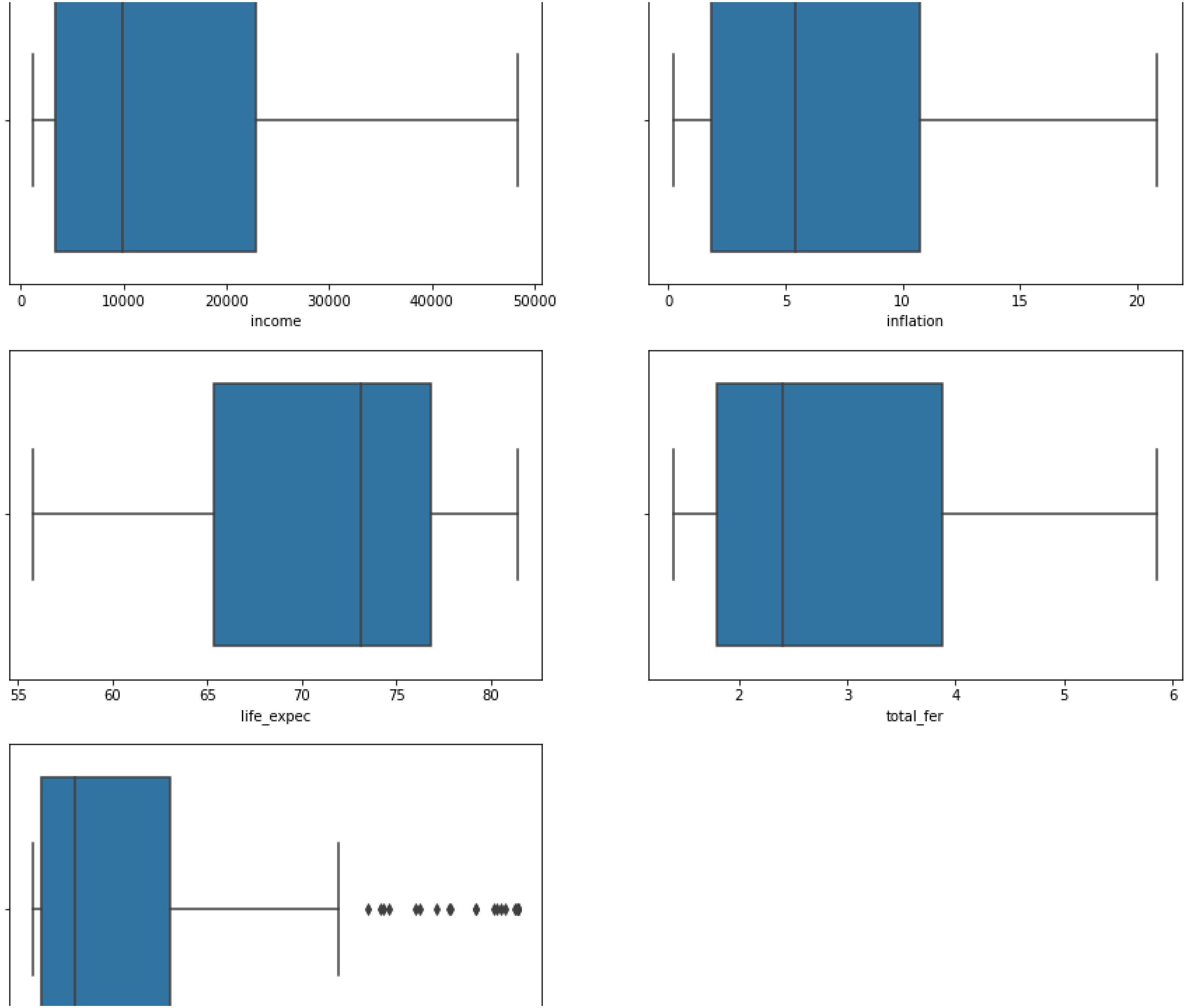

0 20000 40000 60000 80000 100000 120000
income
0 20 40 60 80 100
inflation
30 40 50 60 70 80
life_expec
1 2 3 4 5 6 7
total_fer

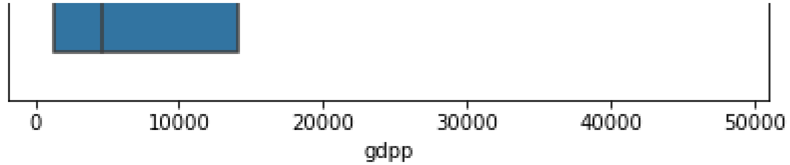


In [12]:
```
for i in enumerate(columns):
    percentiles = data[i[1]].quantile([0.05,0.95]).values
    data[i[1]][data[i[1]] <= percentiles[0]] = percentiles[0]
    data[i[1]][data[i[1]] >= percentiles[1]] = percentiles[1]
```

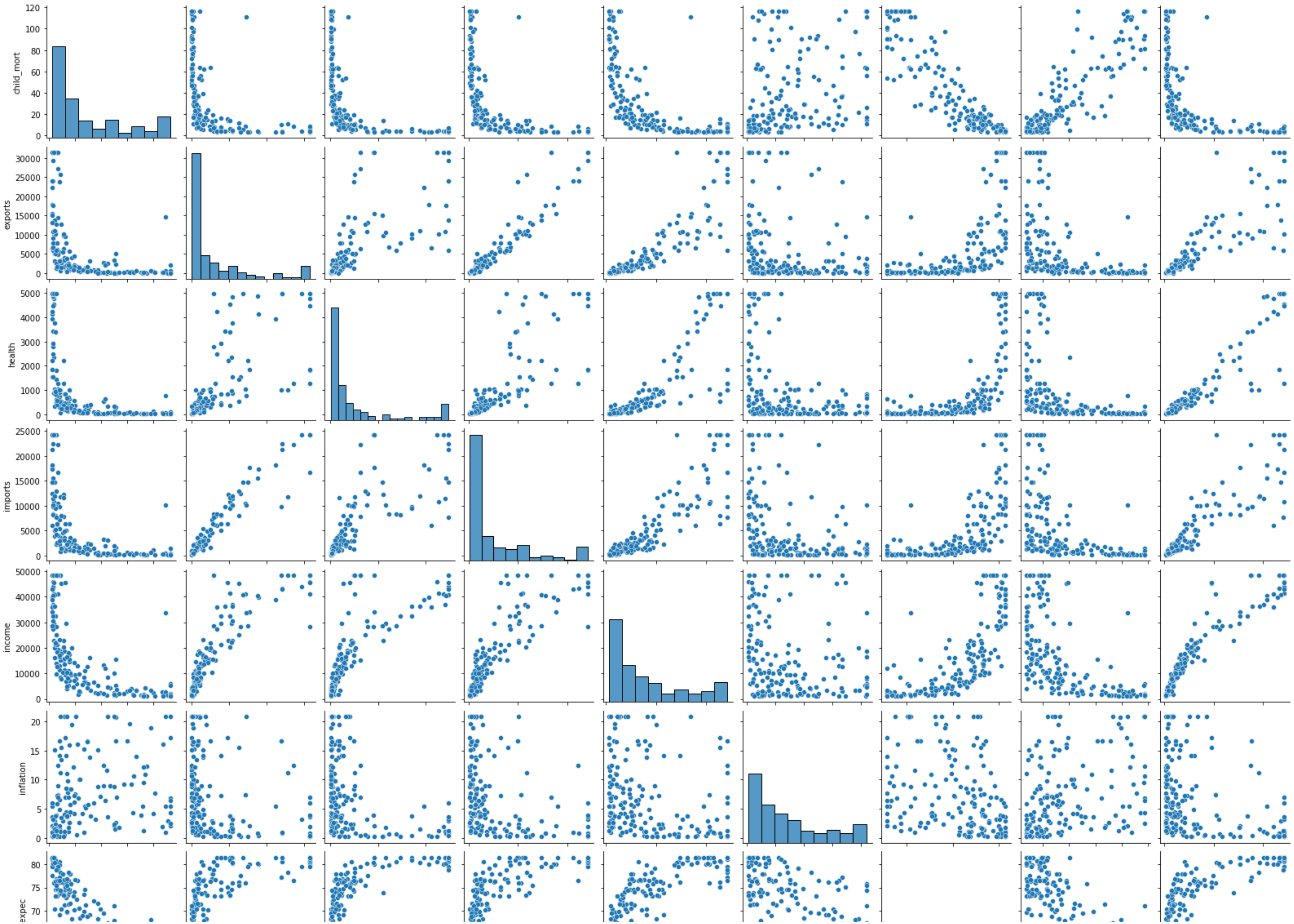
In [13]:
```
plt.figure(figsize=(15,25))
for i in enumerate(columns):
    ax = plt.subplot(5, 2, i[0]+1)
    sns.boxplot(data[i[1]])
plt.show()
```

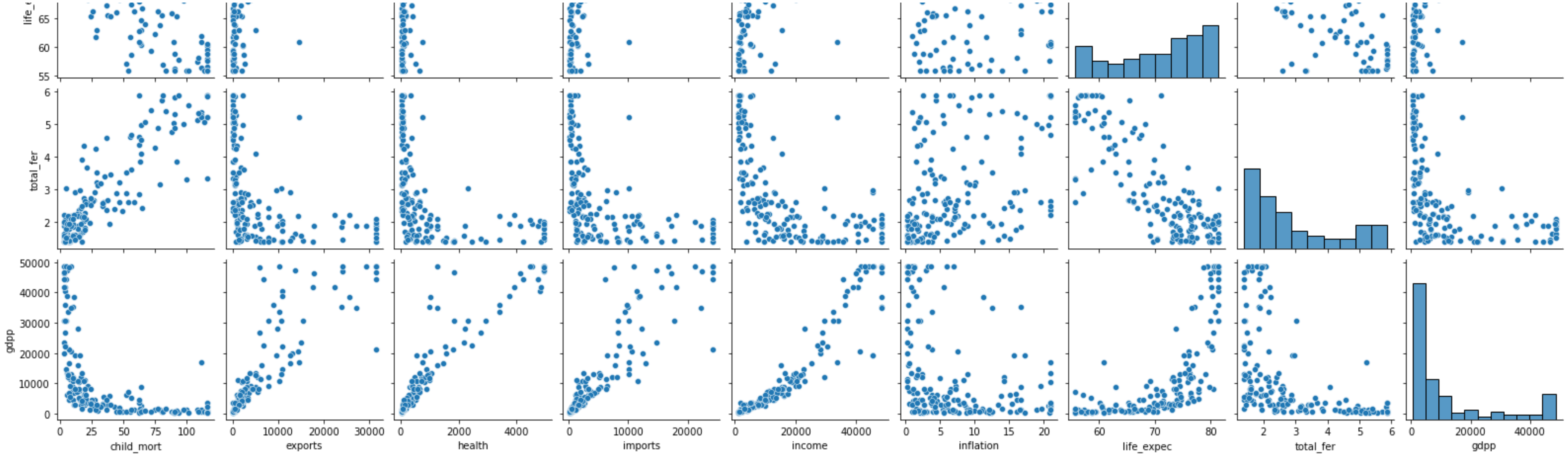



0
10000
20000
30000
40000
50000
income
0
5
10
15
20
inflation
55
60
65
70
75
80
life_expec
2
3
4
5
6
total_fer


0
10000
20000
30000
40000
50000
gdpp

In [14]:
```
sns.pairplot(data)
plt.show()
```



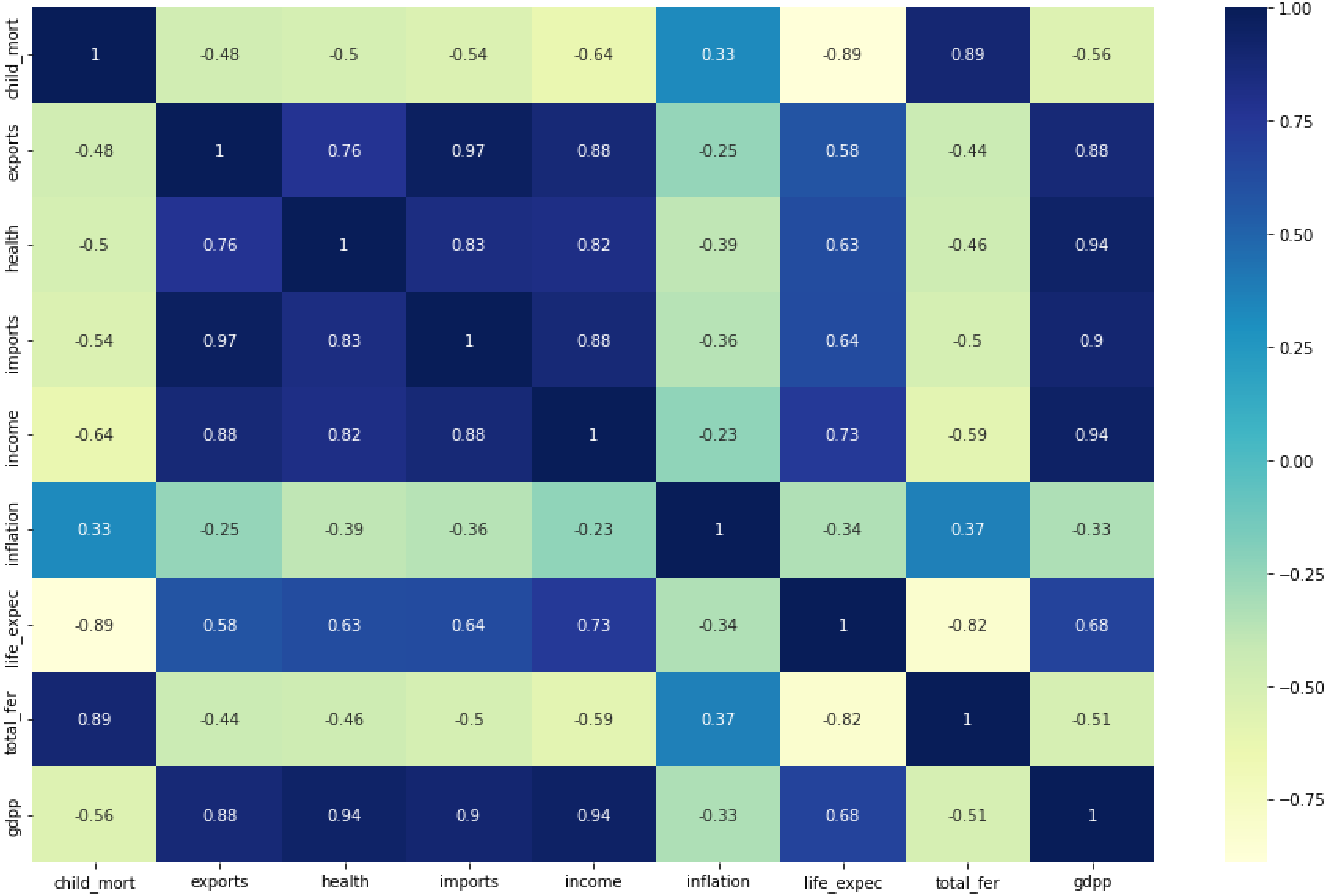


In [15]:
```
data.corr()
```

Out[15]:

	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp
child_mort	1.000000	-0.480031	-0.500800	-0.539389	-0.637594	0.325082	-0.890201	0.892782	-0.557912
exports	-0.480031	1.000000	0.763772	0.967762	0.881110	-0.248510	0.582728	-0.440643	0.880736
health	-0.500800	0.763772	1.000000	0.834689	0.821681	-0.392093	0.627544	-0.459678	0.936717
imports	-0.539389	0.967762	0.834689	1.000000	0.878580	-0.361760	0.636451	-0.502098	0.901729
income	-0.637594	0.881110	0.821681	0.878580	1.000000	-0.234853	0.729253	-0.590654	0.941514
inflation	0.325082	-0.248510	-0.392093	-0.361760	-0.234853	1.000000	-0.336551	0.368325	-0.332902
life_expec	-0.890201	0.582728	0.627544	0.636451	0.729253	-0.336551	1.000000	-0.821065	0.681829
total_fer	0.892782	-0.440643	-0.459678	-0.502098	-0.590654	0.368325	-0.821065	1.000000	-0.508362
gdpp	-0.557912	0.880736	0.936717	0.901729	0.941514	-0.332902	0.681829	-0.508362	1.000000

In [16]:
```
plt.figure(figsize = (16, 10))
sns.heatmap(data.corr(), annot = True, cmap="YlGnBu")
plt.savefig('corrplot')
plt.show()
```



Hokins test

In [17]:
```
def hopkins(X):
    d = X.shape[1]
    n = len(X)
    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).reshape(1, -1), 2, return_distance=Tru
        ujd.append(u_dist[0][1])
        w_dist, _ = nbrs.kneighbors(X.iloc[rand_X[j]].values.reshape(1, -1), 2, return_distance=True)
        wjd.append(w_dist[0][1])

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

    return HS
```

In [18]:
```
hopkins(data.drop('country',axis=1))
```

Out[18]:
```
0.9066148477062875
```

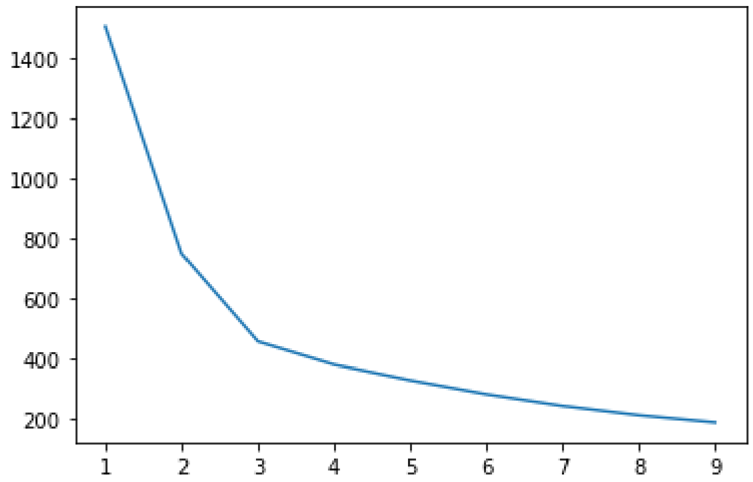
Scaling the data for clustering

The data looks good for the clustering.

In [19]:
```
df1=data.drop('country',axis=1)
SS=StandardScaler()
df1=SS.fit_transform(df1)
```

KMeans clustering

In [20]:
```
# Finding Optimal number of clusters.
# Elbow Curve
ssd = []
for k in list(range(1,10)):
    model = KMeans(n_clusters = k, max_iter = 50).fit(df1)
    ssd.append([k, model.inertia_])

plt.plot(pd.DataFrame(ssd)[0], pd.DataFrame(ssd)[1]);
```



In [21]:
```
# Silhouette score analysis to find the ideal number of clusters for K-means clustering
range_n_clusters = [2, 3, 4, 5, 6, 7, 8]
print("silhouette score")
for num_clusters in range_n_clusters:
    # intialise kmeans
    kmeans = KMeans(n_clusters=num_clusters, max_iter=50,random_state= 100)
    kmeans.fit(df1)
    cluster_labels = kmeans.labels_

    # silhouette score
    silhouette_avg = silhouette_score(df1, cluster_labels)

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

```
silhouette score
For n_clusters=2, the silhouette score is 0.48447902987180524
For n_clusters=3, the silhouette score is 0.4203919640787207
For n_clusters=4, the silhouette score is 0.3832442500525417
For n_clusters=5, the silhouette score is 0.2994963024128736
For n_clusters=6, the silhouette score is 0.30307244388683313
For n_clusters=7, the silhouette score is 0.3301983269977132
For n_clusters=8, the silhouette score is 0.3432577893986418
```

Optimal number of k is 4. #according to the silhoutte score.

In [22]:
```
kmeans = KMeans(n_clusters=4, max_iter=100 , random_state = 100)
kmeans.fit(df1)
```

Out[22]:
```
KMeans(max_iter=100, n_clusters=4, random_state=100)
```

In [23]:
```
kmeans.labels_
```

Out[23]:
```
array([2, 0, 0, 2, 0, 0, 0, 3, 1, 0, 3, 3, 0, 3, 0, 1, 0, 2, 0, 0, 0, 2,
       0, 3, 0, 2, 2, 0, 2, 1, 0, 2, 2, 0, 0, 0, 2, 2, 2, 0, 2, 0, 3, 3,
       1, 0, 0, 0, 0, 2, 2, 3, 0, 1, 3, 2, 2, 0, 1, 2, 3, 0, 0, 2, 2, 0,
       2, 3, 1, 0, 0, 0, 2, 1, 3, 3, 0, 3, 0, 0, 2, 2, 3, 0, 2, 0, 0, 2,
       2, 0, 0, 1, 0, 2, 2, 0, 0, 2, 1, 2, 0, 0, 0, 0, 0, 0, 2, 0, 2, 0,
       1, 3, 2, 2, 1, 3, 2, 0, 0, 0, 0, 0, 3, 1, 0, 0, 2, 0, 3, 2, 0, 3,
       2, 1, 3, 3, 2, 2, 3, 3, 0, 0, 2, 0, 1, 1, 0, 2, 0, 2, 2, 0, 0, 0,
       0, 2, 0, 1, 3, 3, 0, 0, 0, 0, 0, 2, 2])
```

In [24]:
```
df_km = pd.concat([data, pd.Series(kmeans.labels_)], axis = 1)
df_km.columns = ['country','child_mort','exports','health','imports','income','inflation','life_expec','total_fer','gdpp
df_km.head()
```

Out[24]:

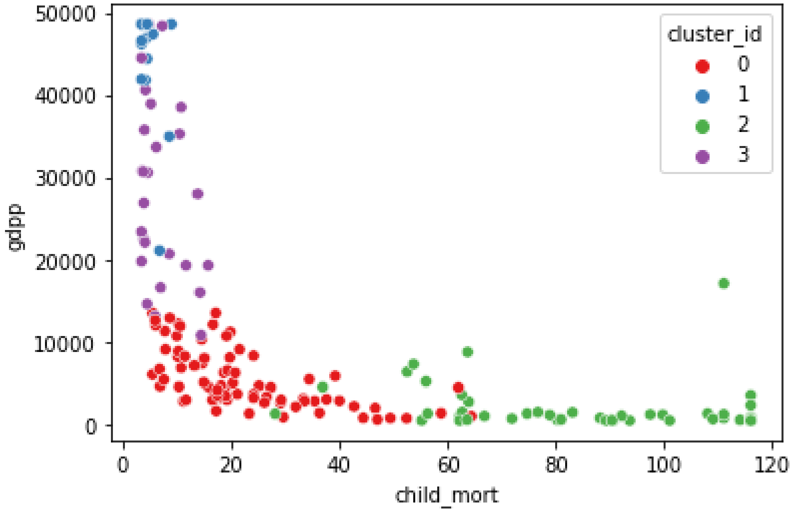
	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster_id
0	Afghanistan	90.2	70.4688	41.9174	248.297	1610.0	9.44	56.2	5.820	553.0	2
1	Albania	16.6	1145.2000	267.8950	1987.740	9930.0	4.49	76.3	1.650	4090.0	0
2	Algeria	27.3	1712.6400	185.9820	1400.440	12900.0	16.10	76.5	2.890	4460.0	0
3	Angola	116.0	2199.1900	100.6050	1514.370	5900.0	20.87	60.1	5.861	3530.0	2
4	Antigua and Barbuda	10.3	5551.0000	735.6600	7185.800	19100.0	1.44	76.8	2.130	12200.0	0

In [25]:
```
df_km['cluster_id'].value_counts()
```

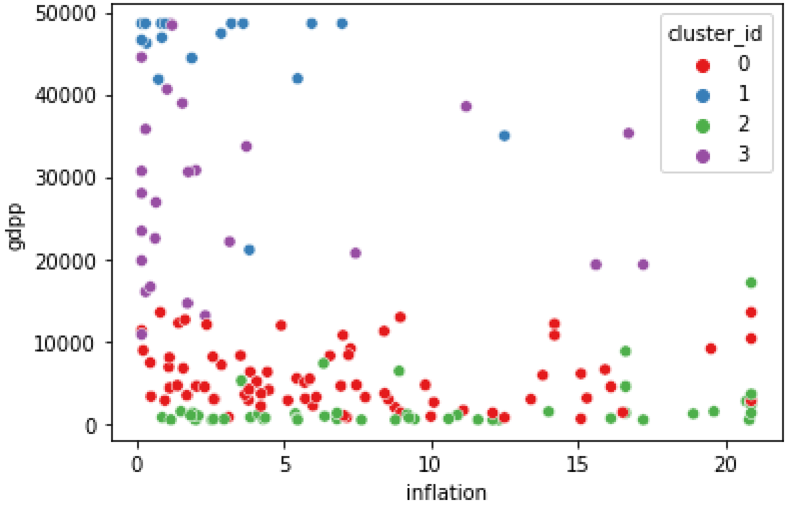
Out[25]:
```
0    76
2    48
3    26
1    17
Name: cluster_id, dtype: int64
```

KMeans cluster visualization

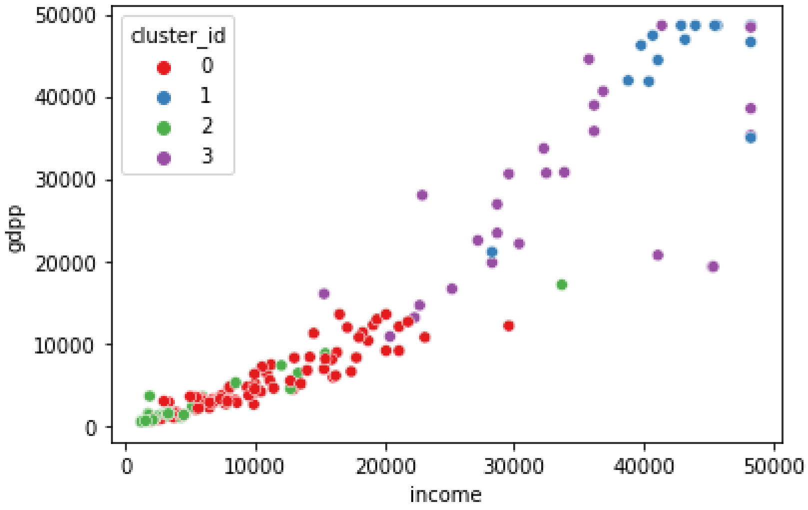
In [26]:
```
sns.scatterplot(x = 'child_mort', y = 'gdpp', hue ='cluster_id', legend = 'full', data = df_km, palette='Set1')
plt.show()
```



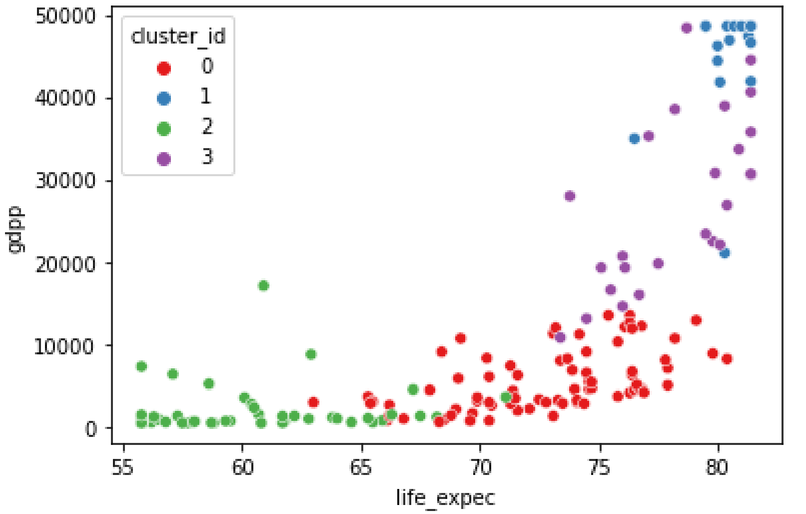
In [27]:
```
sns.scatterplot(x = 'inflation', y = 'gdpp', hue ='cluster_id', legend = 'full', data = df_km, palette='Set1')
plt.show()
```



In [28]:
```
sns.scatterplot(x = 'income', y = 'gdpp', hue ='cluster_id', legend = 'full', data = df_km, palette='Set1')
plt.show()
```

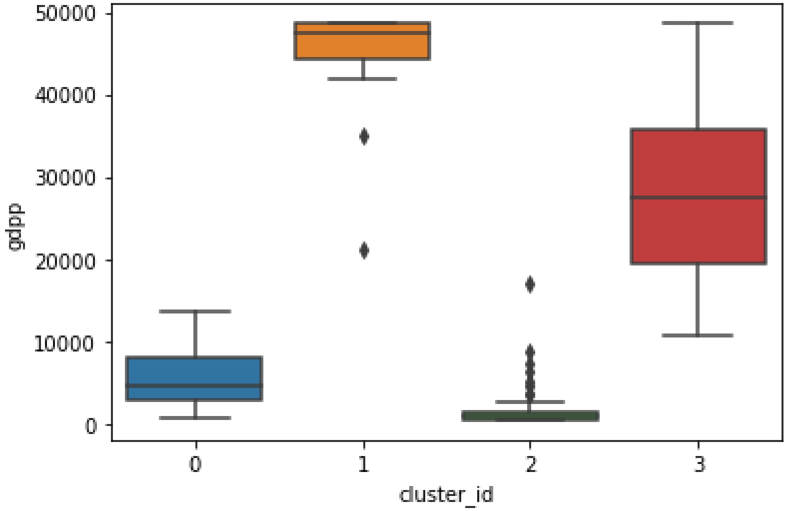


In [29]:
```
sns.scatterplot(x = 'life_expec', y = 'gdpp', hue ='cluster_id', legend = 'full', data = df_km, palette='Set1')
plt.show()
```

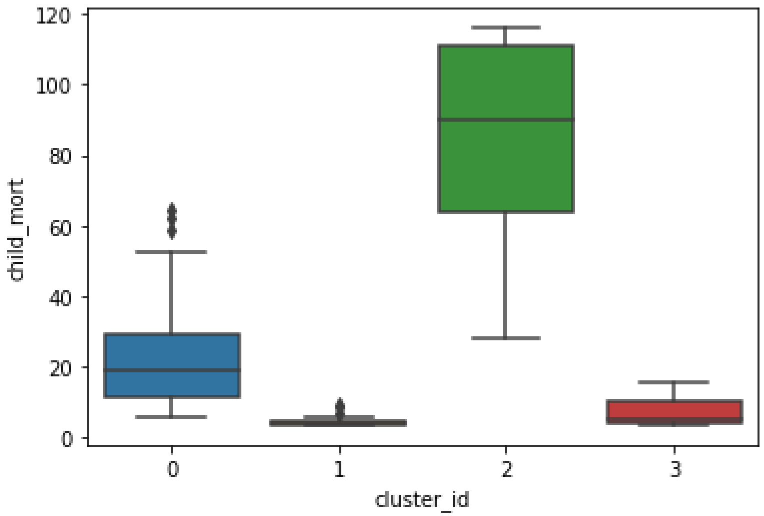


Profiling for KMeans clusters.

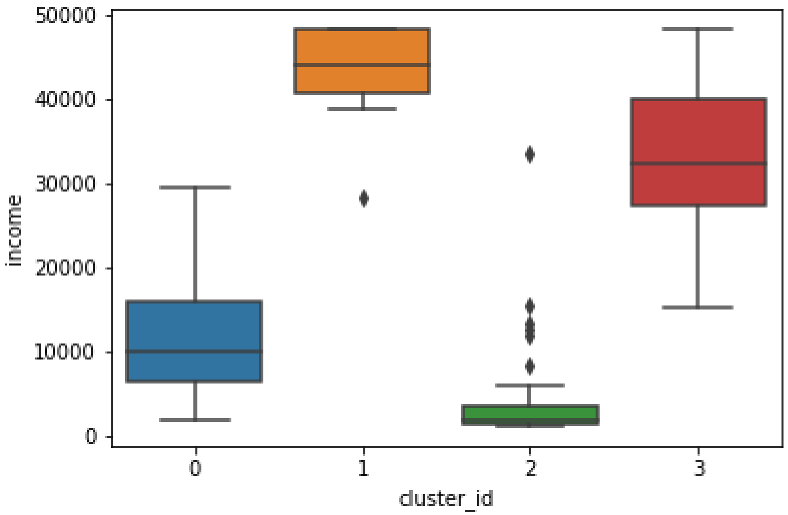
In [30]:
```
# Here we will be profiling for these 3 variables as mentioned in problem statement (gdpp, child_mort and income).
sns.boxplot(data=df_km,x = 'cluster_id',y='gdpp')
plt.show()
```



In [31]:
```
sns.boxplot(data=df_km,x = 'cluster_id',y='child_mort')
plt.show()
```



In [32]:
```
sns.boxplot(data=df_km,x = 'cluster_id',y='income')
plt.show()
```



Here cluster_id 2 has the lowest income and hightest child mortality rate with a very a very low gdpp so, this will be our concerned cluster.

In [33]:
```
#Finding the observations that belong to cluster id 2
df_km[df_km['cluster_id']==2]['country']
```

Out[33]:
```
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 [34]:
```
top_kmeans = df_km[df_km['cluster_id']==2].sort_values(by=["child_mort","gdpp","income"], ascending=[False, True,True])
top_kmeans = top_kmeans.reset_index().drop('index',axis=1)
top_kmeans.head(10)
```

Out[34]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster_id
0	Central African Republic	116.0	70.4688	26.71592	169.281	1213.0	2.01	55.78	5.210	465.9	2
1	Congo, Dem. Rep.	116.0	137.2740	26.71592	169.281	1213.0	20.80	57.50	5.861	465.9	2
2	Niger	116.0	77.2560	26.71592	170.868	1213.0	2.55	58.80	5.861	465.9	2
3	Sierra Leone	116.0	70.4688	52.26900	169.281	1220.0	17.20	55.78	5.200	465.9	2
4	Burkina Faso	116.0	110.4000	38.75500	170.200	1430.0	6.81	57.90	5.861	575.0	2
5	Haiti	116.0	101.2860	45.74420	428.314	1500.0	5.45	55.78	3.330	662.0	2
6	Mali	116.0	161.4240	35.25840	248.508	1870.0	4.37	59.50	5.861	708.0	2
7	Chad	116.0	330.0960	40.63410	390.195	1930.0	6.39	56.50	5.861	897.0	2
8	Nigeria	116.0	589.4900	118.13100	405.420	5150.0	20.87	60.50	5.840	2330.0	2
9	Angola	116.0	2199.1900	100.60500	1514.370	5900.0	20.87	60.10	5.861	3530.0	2

In [35]:
```
top_10 = top_kmeans.iloc[:10]
top_10['country'].reset_index().drop('index',axis=1)
```

Out[35]:

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

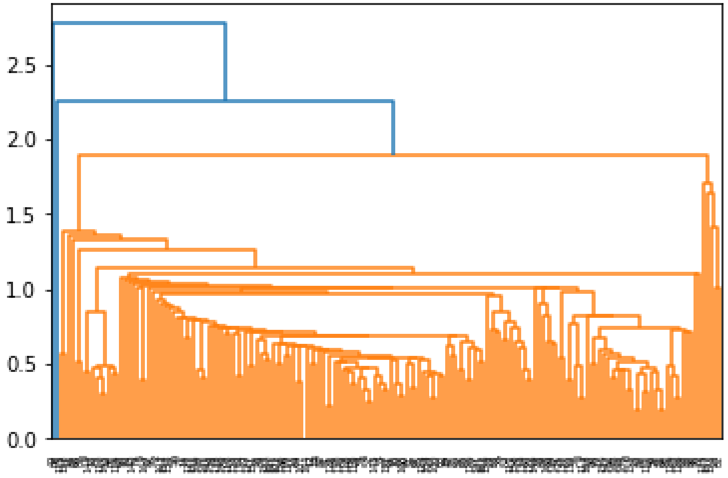
Top 10 counties using kMeans clustering.

These are the top 10 countries we will be focusing on for providing the adequate help.

Heiraricha Clustering

Single Linkage

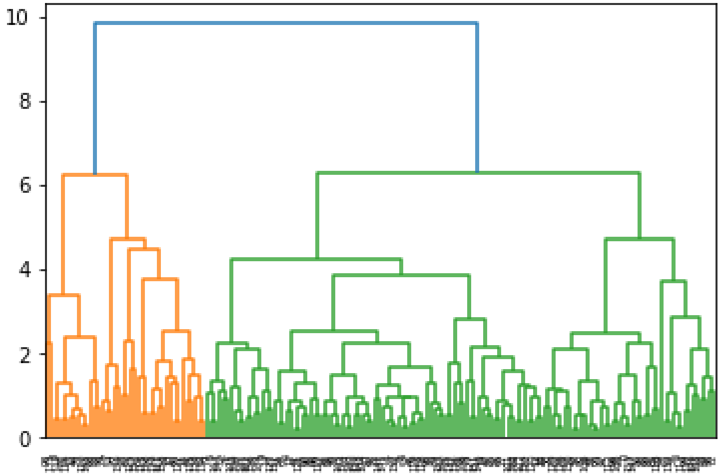
In [36]:
```
mergings_single = linkage(df1, method="single", metric='euclidean')
dendrogram(mergings_single)
plt.show()
```



No Good results. clusters are not forming using single linkage so we will be using complete linkage for further processing.

Complete Linkage

In [37]:
```
mergings_complete = linkage(df1, method="complete", metric='euclidean')
dendrogram(mergings_complete)
plt.show()
```



looking at this we can say that there are 3 clusters forming with heirarichal clustering.

In [38]:
```
cluster_labels = cut_tree(mergings_complete, n_clusters=3).reshape(-1, )
cluster_labels
```

Out[38]:
```
array([0, 1, 1, 0, 1, 1, 1, 2, 2, 1, 2, 2, 1, 1, 1, 2, 1, 0, 1, 1, 1, 1,
       1, 2, 1, 0, 0, 1, 0, 2, 1, 0, 0, 1, 1, 1, 0, 0, 0, 1, 0, 1, 2, 2,
       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, 1, 2, 1, 0, 1, 1, 0,
       0, 2, 1, 2, 1, 0, 0, 1, 1, 0, 2, 0, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1,
       2, 2, 0, 0, 2, 2, 0, 1, 1, 1, 1, 1, 2, 2, 1, 1, 0, 1, 2, 0, 1, 1,
       0, 2, 2, 2, 1, 1, 2, 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])
```

In [39]:
```
df_hm = pd.concat([data, pd.Series(cluster_labels)], axis = 1)
df_hm.columns = ['country','child_mort','exports','health','imports','income','inflation','life_expec','total_fer','gdpp
df_hm.head()
```

Out[39]:

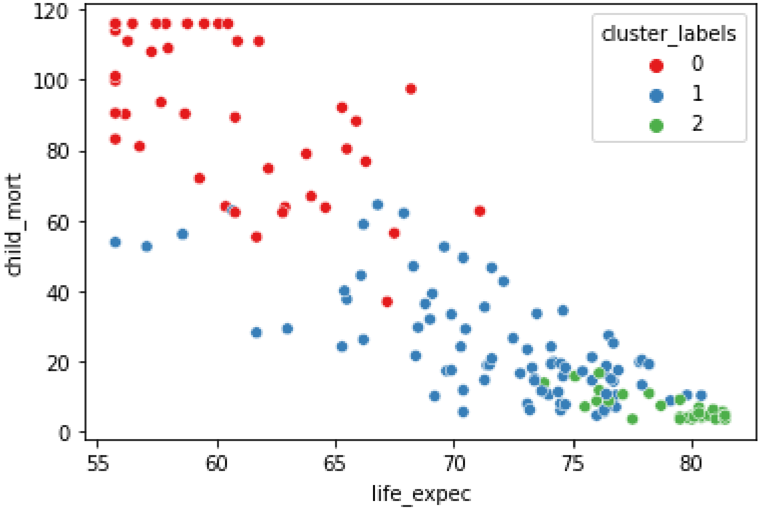
	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster_labels
0	Afghanistan	90.2	70.4688	41.9174	248.297	1610.0	9.44	56.2	5.820	553.0	0
1	Albania	16.6	1145.2000	267.8950	1987.740	9930.0	4.49	76.3	1.650	4090.0	1
2	Algeria	27.3	1712.6400	185.9820	1400.440	12900.0	16.10	76.5	2.890	4460.0	1
3	Angola	116.0	2199.1900	100.6050	1514.370	5900.0	20.87	60.1	5.861	3530.0	0
4	Antigua and Barbuda	10.3	5551.0000	735.6600	7185.800	19100.0	1.44	76.8	2.130	12200.0	1

In [40]:
```
df_hm['cluster_labels'].value_counts()
```

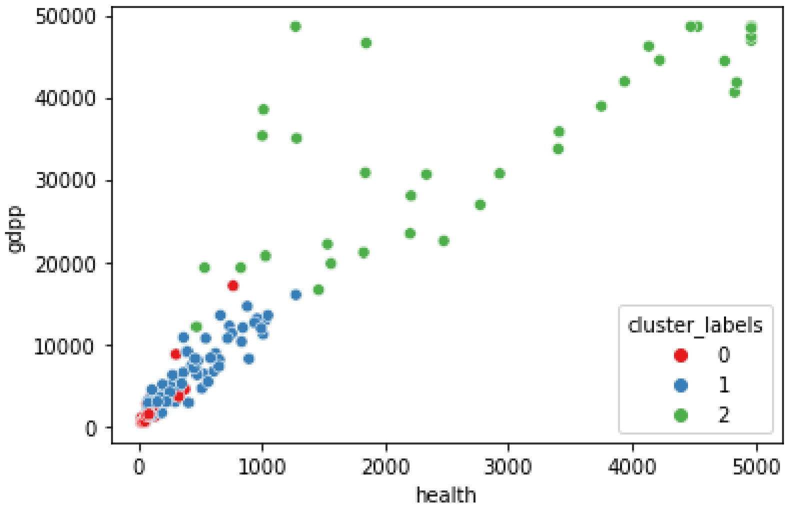
Out[40]:
```
1    84
0    43
2    40
Name: cluster_labels, dtype: int64
```

Heirarichal Clusters Visulaisation

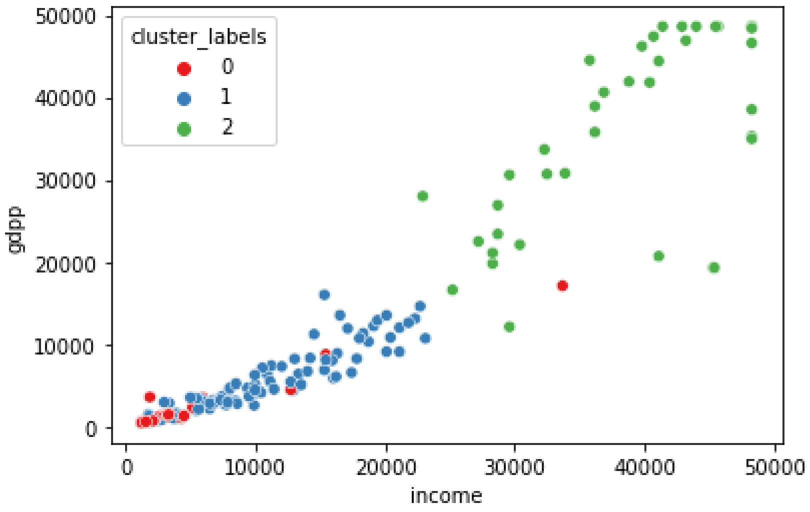
In [41]:
```
# life_expec
sns.scatterplot(x = 'life_expec', y = 'child_mort', hue ='cluster_labels', legend = 'full', data = df_hm, palette='Set1'
plt.show()
```



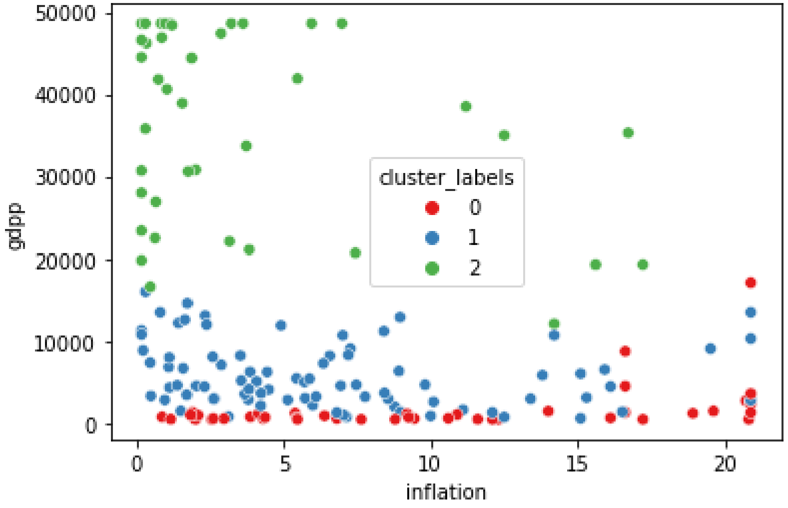
In [42]:
```
#health
sns.scatterplot(x = 'health', y = 'gdpp', hue ='cluster_labels', legend = 'full', data = df_hm, palette='Set1')
plt.show()
```



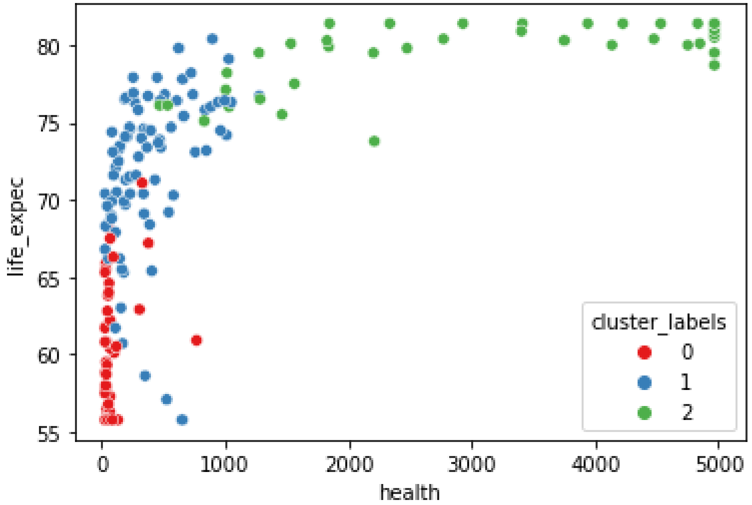
In [43]:
```
#income
sns.scatterplot(x = 'income', y = 'gdpp', hue ='cluster_labels', legend = 'full', data = df_hm, palette='Set1')
plt.show()
```



In [44]:
```
#inflation
sns.scatterplot(x = 'inflation', y = 'gdpp', hue ='cluster_labels', legend = 'full', data = df_hm, palette='Set1')
plt.show()
```

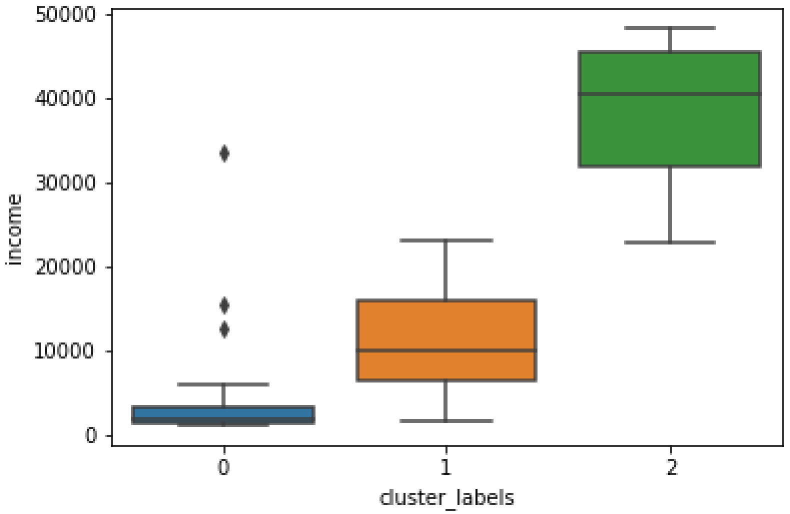


In [45]:
```
# health vs life_expec
sns.scatterplot(x = 'health', y = 'life_expec', hue ='cluster_labels', legend = 'full', data = df_hm, palette='Set1')
plt.show()
```

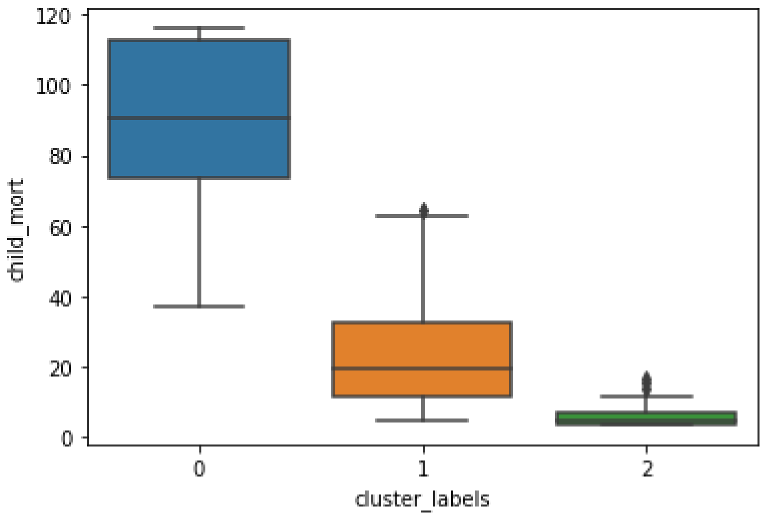


Cluster Profiling

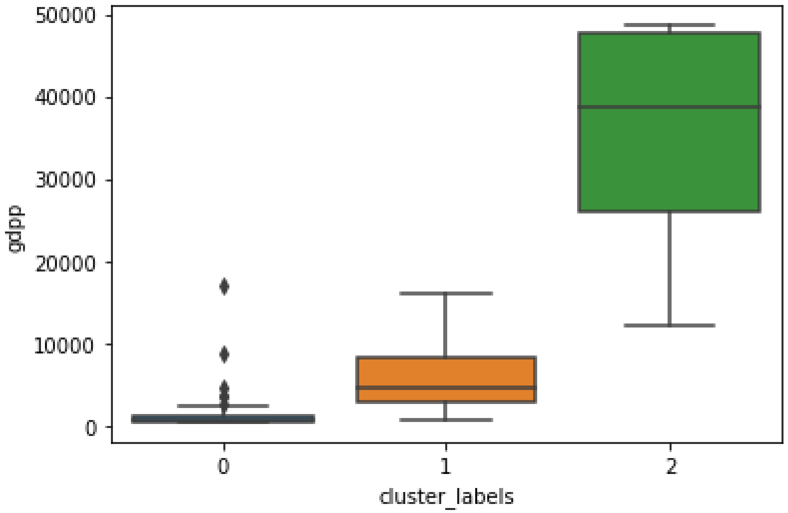
In [46]:
```
# income
sns.boxplot(data=df_hm,x = 'cluster_labels',y='income')
plt.show()
```



In [47]:
```
#child_mort
sns.boxplot(data=df_hm,x = 'cluster_labels',y='child_mort')
plt.show()
```



In [48]:
```
#gdpp
sns.boxplot(data=df_hm,x = 'cluster_labels',y='gdpp')
plt.show()
```



Here we can cluster_id 0 is having very lowe gdpp and income with a very high child_mort rate so this will be our focus of help.

In [49]:
```
#Finding the observations that belong to cluster id 0
df_hm[df_hm['cluster_labels']==0]['country']
```

Out[49]:
```
0                    Afghanistan
3                         Angola
17                         Benin
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
84                           Lao
87                       Lesotho
88                       Liberia
93                    Madagascar
94                        Malawi
97                          Mali
99                    Mauritania
106                   Mozambique
112                        Niger
113                      Nigeria
116                     Pakistan
126                       Rwanda
129                      Senegal
132                 Sierra Leone
142                        Sudan
147                     Tanzania
```

```
149               Timor-Leste
150                      Togo
155                    Uganda
165                     Yemen
166                    Zambia
Name: country, dtype: object
```

In [50]:
```
top_h = df_hm[df_hm['cluster_labels']==0].sort_values(by=["child_mort","gdpp","income"], ascending=[False, True,True])
top_h = top_h.reset_index().drop('index',1)
top_h.head(10)
```

Out[50]:

	country	child_mort	exports	health	imports	income	inflation	life_expec	total_fer	gdpp	cluster_labels
0	Central African Republic	116.0	70.4688	26.71592	169.281	1213.0	2.01	55.78	5.210	465.9	0
1	Congo, Dem. Rep.	116.0	137.2740	26.71592	169.281	1213.0	20.80	57.50	5.861	465.9	0
2	Niger	116.0	77.2560	26.71592	170.868	1213.0	2.55	58.80	5.861	465.9	0
3	Sierra Leone	116.0	70.4688	52.26900	169.281	1220.0	17.20	55.78	5.200	465.9	0
4	Burkina Faso	116.0	110.4000	38.75500	170.200	1430.0	6.81	57.90	5.861	575.0	0
5	Haiti	116.0	101.2860	45.74420	428.314	1500.0	5.45	55.78	3.330	662.0	0
6	Mali	116.0	161.4240	35.25840	248.508	1870.0	4.37	59.50	5.861	708.0	0
7	Chad	116.0	330.0960	40.63410	390.195	1930.0	6.39	56.50	5.861	897.0	0
8	Nigeria	116.0	589.4900	118.13100	405.420	5150.0	20.87	60.50	5.840	2330.0	0
9	Angola	116.0	2199.1900	100.60500	1514.370	5900.0	20.87	60.10	5.861	3530.0	0

Top 10 Countries obtained from Hierarchical clustering.

In [51]:
```
top_10 = top_h.iloc[:10]
top_10['country'].reset_index().drop('index',axis=1)
```

Out[51]:

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

Recommendations

KMeans clustering

```
1) Cluster with ClusterID as 2, is the cluster of most backward country.

2) Countries on which we require to focus more are:
    0    Central African Republic
    1    Congo, Dem. Rep.
    2    Niger
    3    Sierra Leone
    4    Burkina Faso
    5    Haiti
    6    Mali
    7    Chad
    8    Nigeria
    9    Angola
```

Heirarichal Clustering

```
1) Cluster with ClusterID as 0, is the cluster of most backward country.

2) Countries on which we require to focus more are:
    0    Central African Republic
    1    Congo, Dem. Rep.
    2    Niger
    3    Sierra Leone
    4    Burkina Faso
    5    Haiti
    6    Mali
    7    Chad
    8    Nigeria
    9    Angola
```

In [ ]: