Project Report - Phillip Marsh

GitHub URL

Phillip's GutHub can be found at: [Phillip's GitHub Repository (https://github.com/PhillipNM/UCDPA_PhillipMarsh)](https://github.com/PhillipNM/UCDPA_PhillipMarsh)

> document should contain between 1,500 and 2,00 words

Abstract

(short overview of the entire project)

For this project I chose to review COVID data as I was somewhat familiar with the underlying data but only from creating metrics on the data. I wanted to gain some further understanding of the situation and felt there would be a lot of data options available. The results did not turn out as I planned but the excercise was rewarding but very challenging. Trying to cover such a large scope of skills with in python and the huge amount of imformation on tips and tricks, although many sites are not that useful and I spent hours between the DataCamp videos and onlineadvice sites. It turns out that population density and economic prosperity of a country does not have much of an impact of a disease like COVID which I guess is why people are not panicking each flu season. I would have loved to added some insights into the impact of masking, and lock downs but tring to join that periodic data in with this daily data was too much of a challenge for this short period of time.

Introduction

(Explain why you chose this project use case)

After considering serveral ideas and researching the available dataset I decide on a dataset I am fairly familiar with from a reporting point of view (as part of the business continuity team) but that I had not done much with the other than create some metrics using Tableau. I wondered if we could predict confidently that countries with lower population densities or high GDP per capita fared better than higher density countries or lower GDP.

Datasets

(Provide a description of your dataset and source. Also justify why you chose this source)

Deciding on the dataset

I had several ideas, however, I explored three main ideas:

1. Predicting currency fx changes to maximise buys and sells.
As I have two children in Canada in university the fx rate for USD to CAD is always top of mind. After exploring this for a bit the challenge to understand the market conditions that I could use for making predictions did not seem to fit well with what I needed for this proje ct.
2. Flight delays, cancellations and the average compensation. Are the airlines "gaming" t he system to not pay-out customers given the turmoil in travel I thought it would be interes ting to compare recent cancellations, delays and reasons and compensations vs. pre-covi d data. I researched for datasets but could not find anything current, although there were some sites that may have had data; I would have to pay for and for this reason I decided against this topic.
3. COVID data. This idea would have plenty of source data out there but would it offer th e ability to make predictions and not just forecasting trends.

COVID Data

I picked the COVID idea as there is good data and the types of calculations and techniques required would lend itself to the project easily. This data is something we are all very familiar with at this time. Governments, countries, organizations and corporations have struggled with rules and regulations trying to balance controlling the epidemic vs. economic stability.

I reviewed a couple of sources and in the end selected "Our World In Data" (OWID). OWID has a comprehensive set of publicly available data specifically for COVID. In working with the FIL business continuity team, I assited with the COVID response. I came across this data source and found it very useful. In the end this is the source we used to provide global situational updates for the senior members in the organization so they could decide on stay at home and return to office responses for each jurisdiction across the organization.

source of covid data: https://github.com/owid/covid-19-data/tree/master/public/data (https://github.com/owid/covid-19-data/tree/master/public/data)

Originally I downloaded a (.csv) copy of the data to use but the file was large (I was getting an error that the file was to big for my type of GitHub repository account). this occured when I pushed the data to my GitHub repository. I then researched how I could link to an external csv file, and this solved the problem. This file creats the opportunity to use current data. However, I noticed that the most current days data is not 100% populated so I have adjusted to used the most recent data - two days.

source of GDP data: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?year_high_desc=false (https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?year_high_desc=false)

the file is a zip file which is difficult to connect to so in this instance I downloaded the file and unzipped it.

Implementation Process

(describe your entire process in detail)

Hypothesis

My hypothesis is that countries with higher population density and lower GDP have higher mortality rates than for higher density higher GDP countries. It would also be interesting to see how lower density and higher GDP countries fared and if density and GDP are a predicor of mortaility for a disease like COVID

The implementation process I followed was

- Gather Data
- Transform & clean
- Explore
- Analyze and build models

Gather Data

There are several measures I need for my analysis if any of the data sets include 0 values for total I will use the prior days data as total are cumlative

Measures for each country:

- Highest Cases per 100k people: for year end 2020, 2021 and latest 2022
- Highest Deaths per 100k people: for year end 2020, 2021 and latest 2022
- Lowest Cases per 100k people: for year end 2020, 2021 and latest 2022
- Lowest Deaths per 100k people: for year end 2020, 2021 and latest 2022
- Look at the 14 day rolling average cases per 100k people over time
- Look at the 14 day rolling average deaths per 100k people over time
- Population density
- GDP per person

Transform & Clean and Explore

Review data for size and complexity, NaNs and missing values. Use techiques like

- .head()
- .tail()
- .info()
- .shape()
- .isna().sum()

to understand the number of columns, count of records and the type of object being used, like strings, dates, intergers and floats. Review the null records and get a sum to understa nd the completeness of the data, and functions to assit with exploring the data like creatin g a rolling n day average and calulation for the total on a per 100,00 of the population for comparatives

Analyze and build models

Take the top 20: Categorize as High, Low for mortality and add to the data set. This will allow some of the linear regression models for correlations

Run agaisnt the machine learnng logic for insights

Import and review the data

In [1]:
```
# Import packages needed for project:
import pandas as pd
import requests
import io
import datetime as dt
from datetime import datetime
from datetime import timedelta
import numpy as np
from collections import Counter
import re
import sklearn

# Visualization
import matplotlib.pyplot as plt
# import matplotlib.animation as animation
import seaborn as sns

# Machine learning
#from sklearn.module import Model
from sklearn.linear_model import LinearRegression, LogisticRegression, Ridge,
from sklearn.model_selection import train_test_split, cross_val_score, KFold
from sklearn.metrics import classification_report, confusion_matrix
from sklearn.neighbors import KNeighborsClassifier
```

create global variables

In [2]:
```
#how many columns are too many to wrangle
column_count_limit=30 #number of columns deemed to be managble for exploring
#this will allow a use to run a calculation to high light if a detset has a l

#number of days used in rolling average default = 14 but user could change to
#is relevant
days_calc = 14 #n days for calculations.

top_n_parameter = 25 # was 10 #variable to use for select the number of top a

pop_per_100k = 100000 #varibale to set for total cases and deaths per populat

#for calculations relating to mortality
high_deaths_per_100k = 100 # was 50
low_deaths_per_100k = 25 # was 10
# I decide on this after reviewing the min and maxk values for the topn recor
```

Gather data

In [3]:
```
# Import COVID data

# Link and download COVID dataset from OWID
url = "https://covid.ourworldindata.org/data/owid-covid-data.csv"
download = requests.get(url).content

# Create the COVID as a pandas dataframe
covid_data_raw = pd.read_csv(io.StringIO(download.decode('utf-8')),parse_date
#source: https://stackoverflow.com/questions/59004960/converting-date-format-
```

review of covid header details:

In [4]:
```
covid_data_raw.head()
```

Out[4]:

	iso_code	continent	location	date	total_cases	new_cases	new_cases_smoothed	tota
0	AFG	Asia	Afghanistan	2020-02-24	5.0	5.0	NaN	
1	AFG	Asia	Afghanistan	2020-02-25	5.0	0.0	NaN	
2	AFG	Asia	Afghanistan	2020-02-26	5.0	0.0	NaN	
3	AFG	Asia	Afghanistan	2020-02-27	5.0	0.0	NaN	
4	AFG	Asia	Afghanistan	2020-02-28	5.0	0.0	NaN	

5 rows × 67 columns

a quick review show there are a lot of columns of which most will be irrelivant. There also records with NaN which will have to be dealt with as they would impact calulations.

In [5]:
```
# Import World Bank GDP data
    # source: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?year_high_d

    # Create the GDP raw file as a pandas dataframe, headers start on row 4
gdp_data_raw = pd.read_csv("/Users/Phillip/UDCPA_PhillipMarsh/data/API_NY.GDP
```

review of global gdp details:

In [6]:
```
gdp_data_raw.head()
```

Out[6]:

	Country Name	Country Code	Indicator Name	Indicator Code	1960	1961	1962
0	Aruba	ABW	GDP (current US$)	NY.GDP.MKTP.CD	NaN	NaN	NaN
1	Africa Eastern and Southern	AFE	GDP (current US$)	NY.GDP.MKTP.CD	2.129059e+10	2.180847e+10	2.370702e+10
2	Afghanistan	AFG	GDP (current US$)	NY.GDP.MKTP.CD	5.377778e+08	5.488889e+08	5.466667e+08
3	Africa Western and Central	AFW	GDP (current US$)	NY.GDP.MKTP.CD	1.040414e+10	1.112789e+10	1.194319e+10
4	Angola	AGO	GDP (current US$)	NY.GDP.MKTP.CD	NaN	NaN	NaN

5 rows × 67 columns

a quick review shows there are also alot of columns of year dat most of which would not be relevant. This data also uses 3 digit ISO codes which means I can use it to join to data if need be.

create global calculations to be used in the analysis

there are a few calculations that will be used repeatedly and it makes sense to put them at the start of teh project so they are easy to find if changes need to be made

In [7]:
```
#global calculation

# What are the range of dates in data
beg_date = min(covid_data_raw["date"]) #starting point of the available data
end_date = max(covid_data_raw["date"]) #most recent data in the file

#calculate the lastest observation form the covid data, this data is dynamic
#it can take time for new data to roll in.  This report is using the last dat
last_date = end_date - timedelta(2)
last_date_n = str(last_date)

print("The COVID data starts on "+str(beg_date)+" and the most recent date is
```

```
The COVID data starts on 2020-01-01 00:00:00 and the most recent date is 20
22-09-18 00:00:00
```

Exploring the data

Review the headers, number of headers, type of data to undestand more about the data available

In [8]:

```
# name of a dataframe with comment before and after

def name_obj(df, comment, comment2=""):
    """Create statement naming the dataframe around comment and comment2

    Args:
        df (dataFrame): the name of the dataframe
        comment (string): comment string which goes before the name of the da
        comment2 (string): comment string which goes after the name of the da
    """
    name =[x for x in globals() if globals()[x] is df][0]
    return (comment+name+comment2)

covid_data_raw_name = name_obj(covid_data_raw,"Dataframe Name is:")
gdp_data_raw_name = name_obj(gdp_data_raw,"Dataframe Name is:")

#example: test the function
print("There are two primary sourced datasets used in this project:")
print(covid_data_raw_name)
print(gdp_data_raw_name)
```

```
There are two primary sourced datasets used in this project:
Dataframe Name is:covid_data_raw
Dataframe Name is:gdp_data_raw
```

In [9]:

```
# create functions for reviewing dataframe headers

# create a function to make list from the column header names of a dataframe
def column_headers_list(df):
    """create a list of column headers

    Args:
        df (DataFrame): the name of the dataframe to use

    Returns:
        list of column headers
    """

    columns_lst = df.columns.tolist() # create a list of the column headers f

    return columns_lst
```

In [10]:

```python
# Count the number of items in the list from the column header names list of

#test the function "column_headers_list"

# Raw Covid data
columns_lst_test = column_headers_list(covid_data_raw)
columns_len_test = len(columns_lst_test)

# Test function
#print(columns_lst_test)
#print(columns_len_test)


# Raw gdp data
columns_lst_test = column_headers_list(gdp_data_raw)
#print("There are :"+str(columns_len_test)+" header records")

# Test function
#print(columns_lst_test)
#print("There are :"+str(columns_len_test)+" header records")
```

In [11]:

```python
# create a function determine if the data set is too wide
def columns_comment(xlist,column_count_limit=30):
    """Use column_len to decide if the dataframe is too large to manage

    Args:
        xlist(list): list to review
        columns_len(int): from column_headers_list function
        column_count_limit(float): limi number of columns to compare
    """
    columns_len = len(xlist)

    if columns_len>column_count_limit:
        comment = "There are many columns ("+str(columns_len)+"), Drop a some
    else:
        comment = "Number of columns appears manageable"

    return comment, columns_len
```

we can see both datasets contain quite alot of columns with data

COVID Raw Data

In [12]:

```python
# review Covid raw data

# show the column headers and the number of columns

data = covid_data_raw

columns_len = data.shape[1] # count the number of columns in the list

covid_name = name_obj(data,"The headers from the", "Dataframe are:")
print(column_headers_list(data))

print()

description_covid_raw = name_obj(data,"The "," DataFrame has "+str(columns_le
#print(description_covid_raw)

print()

#print(columns_comment(column_headers_list(df))) #xlist,column_count_limit=30
```

```
['iso_code', 'continent', 'location', 'date', 'total_cases', 'new_cases',
'new_cases_smoothed', 'total_deaths', 'new_deaths', 'new_deaths_smoothed',
'total_cases_per_million', 'new_cases_per_million', 'new_cases_smoothed_per
_million', 'total_deaths_per_million', 'new_deaths_per_million', 'new_death
s_smoothed_per_million', 'reproduction_rate', 'icu_patients', 'icu_patients
_per_million', 'hosp_patients', 'hosp_patients_per_million', 'weekly_icu_ad
missions', 'weekly_icu_admissions_per_million', 'weekly_hosp_admissions',
'weekly_hosp_admissions_per_million', 'total_tests', 'new_tests', 'total_te
sts_per_thousand', 'new_tests_per_thousand', 'new_tests_smoothed', 'new_tes
ts_smoothed_per_thousand', 'positive_rate', 'tests_per_case', 'tests_unit
s', 'total_vaccinations', 'people_vaccinated', 'people_fully_vaccinated',
'total_boosters', 'new_vaccinations', 'new_vaccinations_smoothed', 'total_v
accinations_per_hundred', 'people_vaccinated_per_hundred', 'people_fully_va
ccinated_per_hundred', 'total_boosters_per_hundred', 'new_vaccinations_smoo
thed_per_million', 'new_people_vaccinated_smoothed', 'new_people_vaccinated
_smoothed_per_hundred', 'stringency_index', 'population', 'population_densi
ty', 'median_age', 'aged_65_older', 'aged_70_older', 'gdp_per_capita', 'ext
reme_poverty', 'cardiovasc_death_rate', 'diabetes_prevalence', 'female_smok
ers', 'male_smokers', 'handwashing_facilities', 'hospital_beds_per_thousan
d', 'life_expectancy', 'human_development_index', 'excess_mortality_cumulat
ive_absolute', 'excess_mortality_cumulative', 'excess_mortality', 'excess_m
ortality_cumulative_per_million']
```

In [13]:
```
#test function columns_comment()

# test for covid data
columns_lst_covid = column_headers_list(covid_data_raw) #list of headers

comment_covid = columns_comment(columns_lst_covid,)[0] #Comment string
header_len_covid = columns_comment(columns_lst_covid,column_count_limit=30)[1

print("for the COVID raw file")
print(comment_covid)

print("-"*100)
```

```
for the COVID raw file
There are many columns (67), Drop a some of them to imporve performance and
the size of the file
------------------------------------------------------------------------------
------------------------
```

In [14]:
```
# test for gdp data
columns_lst_gdp = column_headers_list(gdp_data_raw)

comment_gdp = columns_comment(columns_lst_gdp)[0]
header_len_gdp = columns_comment(columns_lst_gdp,column_count_limit=30)[1]

print("for the gdp raw file")
print(comment_gdp)

print("-"*100)
```

```
for the gdp raw file
There are many columns (67), Drop a some of them to imporve performance and
the size of the file
------------------------------------------------------------------------------
------------------------
```

use the shape function to summarize the total number of rows and columns for each dataset:

In [15]:
```
# Understanding the data

# Information (shape) on are the records + columns

# covid raw data
print("The COVID data shape shows:")
print(covid_data_raw.shape)
print()
print("The GDP data shape shows:")
# gdp raw data
print(gdp_data_raw.shape)
```

```
The COVID data shape shows:
(217284, 67)

The GDP data shape shows:
(266, 67)
```

There are also a lot of records for the COVID data, we should limit the number of days to review, but lets remove many of the columns and create a new covid_data DataFrame from the raw file

In [16]:

```python
# drop columns
    #source: https://datatofish.com/drop-columns-pandas-dataframe/#:~:text=He
covid_data = covid_data_raw.drop([
    'continent',
    'new_cases_smoothed',
    'new_deaths_smoothed',
    'new_cases_smoothed_per_million',
    'new_deaths_smoothed_per_million',
    'icu_patients_per_million',
    'hosp_patients',
    'hosp_patients_per_million',
    'weekly_icu_admissions',
    'weekly_icu_admissions_per_million',
    'weekly_hosp_admissions',
    'weekly_hosp_admissions_per_million',
    'total_tests_per_thousand',
    'new_tests_per_thousand',
    'new_tests_smoothed',
    'tests_per_case',
    'tests_units',
    'new_vaccinations_smoothed',
    'total_vaccinations_per_hundred',
    'people_vaccinated_per_hundred',
    'people_fully_vaccinated_per_hundred',
    'total_boosters_per_hundred',
    'new_vaccinations_smoothed_per_million',
    'new_people_vaccinated_smoothed',
    'new_people_vaccinated_smoothed_per_hundred',
    'stringency_index','median_age',
    'aged_65_older',
    'aged_70_older',
    'cardiovasc_death_rate',
    'diabetes_prevalence',
    'female_smokers',
    'male_smokers',
    'handwashing_facilities',
    'hospital_beds_per_thousand',
    'life_expectancy',
    'human_development_index',
    'excess_mortality_cumulative_absolute',
    'excess_mortality_cumulative',
    'excess_mortality',
    'excess_mortality_cumulative_per_million',
    'total_cases_per_million',
    'new_cases_per_million',
    'total_deaths_per_million',
    'new_deaths_per_million',
    'reproduction_rate',
    'people_vaccinated',
    'total_boosters',
    'new_vaccinations',
    'new_tests_smoothed_per_thousand',
    'new_tests',
    'positive_rate'
    ],
    axis=1)
```

```
covid_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 217284 entries, 0 to 217283
Data columns (total 15 columns):
 #   Column                   Non-Null Count   Dtype
---  ------                   --------------   -----
 0   iso_code                 217284 non-null  object
 1   location                 217284 non-null  object
 2   date                     217284 non-null  datetime64[ns]
 3   total_cases              208374 non-null  float64
 4   new_cases                208084 non-null  float64
 5   total_deaths             189322 non-null  float64
 6   new_deaths               189248 non-null  float64
 7   icu_patients             27684 non-null   float64
 8   total_tests              79387 non-null   float64
 9   total_vaccinations       60774 non-null   float64
 10  people_fully_vaccinated  55335 non-null   float64
 11  population               216013 non-null  float64
 12  population_density       192944 non-null  float64
 13  gdp_per_capita           177859 non-null  float64
```

Using the .info() function we now have 14 columns that look relevant to the analysis, how many countries are there

In [17]:

```
# all but the first three columns are float objects; two: "iso_code", "locati
# create a function to get a list of unique values

# Function to get unique values


def unique(list1):

    # Print directly by using * symbol
    print(*Counter(list1))
```

In [18]:
```
#list of covid countrie ISO code

# sort by ISO_code and Date
covid_data = covid_data.sort_values(['iso_code', 'location', 'date'])

#create a list of country codes from the covid data
Country_lst_covid_1 = covid_data["iso_code"].tolist()

# list the country codes
country_iso_list = unique(Country_lst_covid_1)
```

```
ABW AFG AGO AIA ALB AND ARE ARG ARM ATG AUS AUT AZE BDI BEL BEN BES BFA BGD
BGR BHR BHS BIH BLR BLZ BMU BOL BRA BRB BRN BTN BWA CAF CAN CHE CHL CHN CIV
CMR COD COG COK COL COM CPV CRI CUB CUW CYM CYP CZE DEU DJI DMA DNK DOM DZA
ECU EGY ERI ESH ESP EST ETH FIN FJI FLK FRA FRO FSM GAB GBR GEO GGY GHA GIB
GIN GMB GNB GNQ GRC GRD GRL GTM GUM GUY HKG HND HRV HTI HUN IDN IMN IND IRL
IRN IRQ ISL ISR ITA JAM JEY JOR JPN KAZ KEN KGZ KHM KIR KNA KOR KWT LAO LBN
LBR LBY LCA LIE LKA LSO LTU LUX LVA MAC MAR MCO MDA MDG MDV MEX MHL MKD MLI
MLT MMR MNE MNG MNP MOZ MRT MSR MUS MWI MYS NAM NCL NER NGA NIC NIU NLD NOR
NPL NRU NZL OMN OWID_AFR OWID_ASI OWID_CYN OWID_EUN OWID_EUR OWID_HIC OWID_
INT OWID_KOS OWID_LIC OWID_LMC OWID_NAM OWID_OCE OWID_SAM OWID_UMC OWID_WRL
PAK PAN PCN PER PHL PLW PNG POL PRI PRK PRT PRY PSE PYF QAT ROU RUS RWA SAU
SDN SEN SGP SHN SLB SLE SLV SMR SOM SPM SRB SSD STP SUR SVK SVN SWE SWZ SXM
SYC SYR TCA TCD TGO THA TJK TKL TKM TLS TON TTO TUN TUR TUV TWN TZA UGA UKR
URY USA UZB VAT VCT VEN VGB VIR VNM VUT WLF WSM YEM ZAF ZMB ZWE
```

Review of this object shows there are some ISO_Codes that are more than the standard 3 char length, these should be removed these are related to OWID codes for regional aggregations of country data, they can be removed

In [19]:
```
# Review of this object shows there are some ISO_Codes that are more than the
# these are related to OWID codes for regional aggregations of country data,
# convert to strin and find the OWID character pattern or the pattern is not

#find_non_ISO_codes = re.complie(r')
#re.search(r"'OWID",country_iso_list)
```

In [20]:
```
# drop the "OWID_" records

# how many records have the OWID ISO_Code?
covid_data_owid = covid_data[covid_data["iso_code"].str.contains("OWID")] #OW
print("OWID data shape: "+str(covid_data_owid.shape))

covid_data = covid_data[covid_data["iso_code"].str.contains("OWID")==False] #
print("Non OWID data shape: "+str(covid_data.shape))
```

```
OWID data shape: (13739, 15)
Non OWID data shape: (203545, 15)
```

We can now see much fewer record and I have kept a copy of the OWID aggregate data in case there is time to look at this data further

In [21]:
```
# list the country ISO Codes again
Country_lst_covid_1 = covid_data["iso_code"].tolist()

#re-run the unique records; OWID records are no longer displayed
country_ISO_list = unique(Country_lst_covid_1)
```

```
ABW AFG AGO AIA ALB AND ARE ARG ARM ATG AUS AUT AZE BDI BEL BEN BES BFA BGD
BGR BHR BHS BIH BLR BLZ BMU BOL BRA BRB BRN BTN BWA CAF CAN CHE CHL CHN CIV
CMR COD COG COK COL COM CPV CRI CUB CUW CYM CYP CZE DEU DJI DMA DNK DOM DZA
ECU EGY ERI ESH ESP EST ETH FIN FJI FLK FRA FRO FSM GAB GBR GEO GGY GHA GIB
GIN GMB GNB GNQ GRC GRD GRL GTM GUM GUY HKG HND HRV HTI HUN IDN IMN IND IRL
IRN IRQ ISL ISR ITA JAM JEY JOR JPN KAZ KEN KGZ KHM KIR KNA KOR KWT LAO LBN
LBR LBY LCA LIE LKA LSO LTU LUX LVA MAC MAR MCO MDA MDG MDV MEX MHL MKD MLI
MLT MMR MNE MNG MNP MOZ MRT MSR MUS MWI MYS NAM NCL NER NGA NIC NIU NLD NOR
NPL NRU NZL OMN PAK PAN PCN PER PHL PLW PNG POL PRI PRK PRT PRY PSE PYF QAT
ROU RUS RWA SAU SDN SEN SGP SHN SLB SLE SLV SMR SOM SPM SRB SSD STP SUR SVK
SVN SWE SWZ SXM SYC SYR TCA TCD TGO THA TJK TKL TKM TLS TON TTO TUN TUR TUV
TWN TZA UGA UKR URY USA UZB VAT VCT VEN VGB VIR VNM VUT WLF WSM YEM ZAF ZMB
ZWE
```

this look better the 3 digit codes line up nicely and all look correct now

In [22]:
```
# show the column headers and the number of columns

df_head = covid_data

columns_len = df_head.shape[1] # count the number of columns in the list

#print(name_obj(df_head,"The headers from the ", " DataFrame are:"))
#column_headers_list(df_head)
```

In [23]:
```
# print a summary of covid_data

# Summary of covid_data_raw file
rows = covid_data.shape[0]
cols = covid_data.shape[1]

print("The raw data file has {} rows of data".format(f"{rows:,d}"),"and {} co
if cols>column_count_limit:
    print("There are many columns, drop a some of them to imporve performance
else:
    print("Number of columns appears manageable")
```

```
The raw data file has 203,545 rows of data and 15 columns
Number of columns appears manageable
```

lets deal with the nulls

In [24]:
```
covid_data.head(5)
```
Out[24]:

	iso_code	location	date	total_cases	new_cases	total_deaths	new_deaths	icu_patien
9371	ABW	Aruba	2020-03-13	2.0	2.0	NaN	NaN	Na
9372	ABW	Aruba	2020-03-14	2.0	0.0	NaN	NaN	Na
9373	ABW	Aruba	2020-03-15	2.0	0.0	NaN	NaN	Na
9374	ABW	Aruba	2020-03-16	2.0	0.0	NaN	NaN	Na
9375	ABW	Aruba	2020-03-17	3.0	1.0	NaN	NaN	Na

In [25]:
```
covid_data.tail(5)
```
Out[25]:

	iso_code	location	date	total_cases	new_cases	total_deaths	new_deaths	icu_pa
217279	ZWE	Zimbabwe	2022-09-13	256904.0	16.0	5596.0	0.0	
217280	ZWE	Zimbabwe	2022-09-14	256939.0	35.0	5596.0	0.0	
217281	ZWE	Zimbabwe	2022-09-15	256939.0	0.0	5596.0	0.0	
217282	ZWE	Zimbabwe	2022-09-16	256939.0	0.0	5596.0	0.0	
217283	ZWE	Zimbabwe	2022-09-17	256988.0	49.0	5598.0	2.0	

In [26]:

```
# Review Null data
# pd.set_option('display.max_rows',None)
print("Null data:")
print(covid_data.isna().sum())
```

```
Null data:
iso_code                       0
location                       0
date                           0
total_cases                 8586
new_cases                   8883
total_deaths               27444
new_deaths                 27697
icu_patients              175861
total_tests               124346
total_vaccinations        150753
people_fully_vaccinated   155998
population                     0
population_density         12489
gdp_per_capita             27574
extreme_poverty            89406
dtype: int64
```

review of the columns and null data shows iso_code, loaction (country), date, population are fully populated

population density is not populated for everything, will need to confirm that for the selected date that his is improved

total_cases, new_cases, total_deaths, new_deaths etc I would expect null data as data would not be available for all countries from the start of the data period, need to convert these to 0's

need to review "gdp_per_capita" and "population_density" data as that could impact report later on

In [27]:
```python
#Which fields have nan's
covid_data[covid_data.isna().any(axis=1)]
```

9374	ABW	Aruba	2020-03-16	2.0	0.0	NaN	NaN
9375	ABW	Aruba	2020-03-17	3.0	1.0	NaN	NaN
...	...	...	...	...	...	...	...
217279	ZWE	Zimbabwe	2022-09-13	256904.0	16.0	5596.0	0.0
217280	ZWE	Zimbabwe	2022-09-14	256939.0	35.0	5596.0	0.0
217281	ZWE	Zimbabwe	2022-09-15	256939.0	0.0	5596.0	0.0
217282	ZWE	Zimbabwe	2022-09-16	256939.0	0.0	5596.0	0.0
217283	ZWE	Zimbabwe	2022-09-17	256988.0	49.0	5598.0	2.0

In [28]:
```python
# review "gdp_per_capita" and "population_density"

covid_data_gdp_pop = covid_data[["date","iso_code","location","population","p

covid_data_gdp_pop["population"].isnull()

#covid_data_gdp_pop[covid_data_gdp_pop.isna().any(axis=1)]
```

Out[28]:
```
9371      False
9372      False
9373      False
9374      False
9375      False
          ...
217279    False
217280    False
217281    False
217282    False
217283    False
Name: population, Length: 203545, dtype: bool
```

as i only plan on using certain dates, specifically year end and the most recent for the current year, dropping these NaN records should not impact the report too much

In [29]:
```python
# drop the NaN for the population and gdp columns
covid_data.dropna(subset=["population","population_density","gdp_per_capita"]
#https://www.datasciencelearner.com/pandas-dropna-remove-nan-rows-python/
```

Out[29]:

	iso_code	location	date	total_cases	new_cases	total_deaths	new_deaths	icu_
9371	ABW	Aruba	2020-03-13	2.0	2.0	NaN	NaN	
9372	ABW	Aruba	2020-03-14	2.0	0.0	NaN	NaN	
9373	ABW	Aruba	2020-03-15	2.0	0.0	NaN	NaN	
9374	ABW	Aruba	2020-03-16	2.0	0.0	NaN	NaN	
9375	ABW	Aruba	2020-03-17	3.0	1.0	NaN	NaN	
...	...	...	...	...	...	...	...	
217279	ZWE	Zimbabwe	2022-09-13	256904.0	16.0	5596.0	0.0	

next look at "total" columns that have NaNs that should really be 0s. Many of these NaNs are form the earlier dates when there weren't many cases

In [30]:
```python
# change the NaN's to 0 for the remainder valuations
covid_data = covid_data.fillna(0)
```

In [31]:
```python
covid_data
```

Out[31]:

	iso_code	location	date	total_cases	new_cases	total_deaths	new_deaths	icu_
9371	ABW	Aruba	2020-03-13	2.0	2.0	0.0	0.0	
9372	ABW	Aruba	2020-03-14	2.0	0.0	0.0	0.0	
9373	ABW	Aruba	2020-03-15	2.0	0.0	0.0	0.0	
9374	ABW	Aruba	2020-03-16	2.0	0.0	0.0	0.0	
9375	ABW	Aruba	2020-03-17	3.0	1.0	0.0	0.0	
...	...	...	...	...	...	...	...	
217279	ZWE	Zimbabwe	2022-09-13	256904.0	16.0	5596.0	0.0	

Summary of the COVID dataset

In [32]:
```python
# How many records am I dealing with

#total_records = covid_data.count(axis=1)
#print(total_records)
#print("")

# show the countries/ locations in the data
print("ISO codes and Country")
print(covid_data.pivot_table(index = ["iso_code", "location"], aggfunc ="size

print("")
# df.size
print("Size:")
print(covid_data.size)

print("")
# df.isnull()
column_picker ="total_deaths"
covid_ttl_deaths = covid_data.filter(["iso_code", "location",column_picker])
bool_series_null =pd.isnull(covid_ttl_deaths[column_picker])

print("Null",column_picker,": ")
print(covid_ttl_deaths[bool_series_null])
#print(covid_data.isnull())

print("")
# df.notnull()
bool_series = pd.notnull(covid_ttl_deaths[column_picker])
print("Not null:")
print(covid_ttl_deaths[bool_series])

print("")
# df.describe()
print("Describe:")
print(covid_data.describe)
```

```
Length: 229, dtype: int64

Size:
3053175

Null total_deaths :
Empty DataFrame
Columns: [iso_code, location, total_deaths]
Index: []

Not null:
        iso_code  location  total_deaths
9371         ABW     Aruba           0.0
9372         ABW     Aruba           0.0
9373         ABW     Aruba           0.0
9374         ABW     Aruba           0.0
9375         ABW     Aruba           0.0
...          ...       ...           ...
217279       ZWE  Zimbabwe        5596.0
```

Looks much better there are now now nulls for the Ttoa_deaths which will allow caculations to be performed

GDP Raw Data

In [33]:
```
# review GDP data

#look at info for gdp data
print("shape of the GDP raw data:")
print(gdp_data_raw.shape)
print()
```

```
shape of the GDP raw data:
(266, 67)
```

drop many of the year columns as the covid data does not go back that far

In [34]:

```
# do not need most of the columns so will remove cols 4:63
gdp_data = gdp_data_raw.drop(gdp_data_raw.iloc[:,4:63],axis = 1)

#gdp_data = gdp_data_1.drop(gdp_data_raw.iloc[:,7],axis = 1)

#convert the spaces " " to underscore "_" consitent with the COVID data
gdp_data.columns = [c.replace(' ', '_') for c in gdp_data.columns]

print(gdp_data.info())
print()
print(gdp_data.head())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 266 entries, 0 to 265
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype  
---  ------          --------------  -----  
 0   Country_Name    266 non-null    object 
 1   Country_Code    266 non-null    object 
 2   Indicator_Name  266 non-null    object 
 3   Indicator_Code  266 non-null    object 
 4   2019            255 non-null    float64
 5   2020            251 non-null    float64
 6   2021            229 non-null    float64
 7   Unnamed:_66     0 non-null      float64
dtypes: float64(4), object(4)
memory usage: 16.8+ KB
None

                 Country_Name Country_Code     Indicator_Name  \
0                       Aruba          ABW  GDP (current US$)   
1  Africa Eastern and Southern          AFE  GDP (current US$)   
2                 Afghanistan          AFG  GDP (current US$)   
3  Africa Western and Central          AFW  GDP (current US$)   
4                      Angola          AGO  GDP (current US$)   

   Indicator_Code          2019          2020          2021  Unnamed:_66  
0  NY.GDP.MKTP.CD  3.310056e+09  2.496648e+09           NaN          NaN  
1  NY.GDP.MKTP.CD  9.975340e+11  9.216459e+11  1.082096e+12          NaN  
2  NY.GDP.MKTP.CD  1.879945e+10  2.011614e+10           NaN          NaN  
3  NY.GDP.MKTP.CD  7.945430e+11  7.844457e+11  8.358084e+11          NaN  
4  NY.GDP.MKTP.CD  6.930910e+10  5.361907e+10  7.254699e+10          NaN  
```

In [35]:

```
# show the column headers and the number of columns

columns_len = gdp_data.shape[1] # count the number of columns in the list
gdp_data_name = name_obj(gdp_data,"The headers from the ", " Dataframe are:")

print(gdp_data_name)
columns_lst_gdp = column_headers_list(gdp_data)
print(columns_lst_gdp)

print()

print(name_obj(gdp_data,"The "," DataFrame has "+str(columns_len)+" columns")

print()

#print(columns_comment())
```

```
The headers from the gdp_data Dataframe are:
['Country_Name', 'Country_Code', 'Indicator_Name', 'Indicator_Code', '201
9', '2020', '2021', 'Unnamed:_66']

The gdp_data DataFrame has 8 columns
```

GDP data looks much better and is ready if I need it

In [36]:

```
# Correlations of the gdp_data
gdp_data.corr()
```

Out[36]:

	2019	2020	2021	Unnamed:_66
2019	1.000000	0.999882	0.99950	NaN
2020	0.999882	1.000000	0.99963	NaN
2021	0.999500	0.999630	1.00000	NaN
Unnamed:_66	NaN	NaN	NaN	NaN

Summary of data

In [37]:

```python
# Summary of Covid data
print("summary of Covid data")
print()

# Number of unique countries
n = covid_data.iso_code.nunique()
print("No of unique countries (covid_data):",n)

print("")

# Number of unique dates
n = covid_data.date.nunique()



print("No of unique dates: ",n)
print("From: ",beg_date.strftime("%b %d %Y")," to: ",end_date.strftime("%b %c
print("")

# Number of records
rec = covid_data.shape[0]
col = covid_data.shape[1]

print("No of rows: ",f"{rec:,d}")
print("No of columns: ",f"{col:,d}")
#source: https://stackoverflow.com/questions/60934535/format-integer-with-com
print("")
```

```
summary of Covid data

No of unique countries (covid_data): 229

No of unique dates:  992
From:  Jan 01 2020  to:  Sep 18 2022

No of rows:  203,545
No of columns:  15
```

In [38]:
```
# Summary of GDP data

print("summary of GDP Data")
print()


# Number of unique countries
n = gdp_data.Country_Code.nunique()
print("No of unique countries: ",n)
print("")

# Number of records
rec = gdp_data.shape[0]
col = gdp_data.shape[1]

print("No of rows: ",f"{rec:,d}")
print("No of columns: ",f"{col:,d}")
```

```
summary of GDP Data

No of unique countries:  266

No of rows:  266
No of columns:  8
```

calculations for reporting

In [39]:
```
# Calculations for report:

# date calculations
# There needs to be a n_day (number of days) total for certain total columns
# comparative data against 100k of a countries population
```

to create a rolling ndays average per 100k, I need to identify the date and go back 14days unless that date is with in 14days of the start of the dataset

In [40]:

```python
# n day calculations can't begin until the nth day after the first date in th
first_calc_date = beg_date +  timedelta(days=days_calc)
print("Begining Date: "+str(beg_date)+"; Earliest starting date for calculati

# calculate the start date for the n days data for each record
n_day_start = covid_data["date"] - timedelta(days=days_calc)
print()
print("show that the dates are populating with different results")
print(n_day_start)
print("its working")
print()

# Insert a column with the n day start date, this shows when the n days rolli
covid_data.insert(loc=3, column="n_day_start_date", value=n_day_start, allow_
#false will not allow the column to be entered more than once
```

```
Begining Date: 2020-01-01 00:00:00; Earliest starting date for calculation
s: 2020-01-15 00:00:00

show that the dates are populating with different results
9371     2020-02-28
9372     2020-02-29
9373     2020-03-01
9374     2020-03-02
9375     2020-03-03
            ...
217279   2022-08-30
217280   2022-08-31
217281   2022-09-01
217282   2022-09-02
217283   2022-09-03
Name: date, Length: 203545, dtype: datetime64[ns]
its working
```

In [41]:
```
print(covid_data.info())
print("the new column is now appearing")
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 203545 entries, 9371 to 217283
Data columns (total 16 columns):
 #   Column                  Non-Null Count   Dtype
---  ------                  --------------   -----
 0   iso_code                203545 non-null  object
 1   location                203545 non-null  object
 2   date                    203545 non-null  datetime64[ns]
 3   n_day_start_date        203545 non-null  datetime64[ns]
 4   total_cases             203545 non-null  float64
 5   new_cases               203545 non-null  float64
 6   total_deaths            203545 non-null  float64
 7   new_deaths              203545 non-null  float64
 8   icu_patients            203545 non-null  float64
 9   total_tests             203545 non-null  float64
 10  total_vaccinations      203545 non-null  float64
 11  people_fully_vaccinated 203545 non-null  float64
 12  population              203545 non-null  float64
 13  population_density      203545 non-null  float64
```

create the n_rolling days functions and insert into the DataFrame

In [42]:

```
# n days totals
# (https://stackoverflow.com/questions/28236305/how-do-i-sum-values-in-a-colu
# https://python.tutorialink.com/calculate-14-day-rolling-average-on-data-wit

covid_data.sort_values(['iso_code','date'], ascending=(True,True), inplace=Tr

# Rolling new cases
rolling_new_cases = covid_data.groupby(['iso_code'])['new_cases'].transform(l

# Insert a column with the "n" rolling new cases

#new_column string name
new_column = str(days_calc)+"_days_rolling_new_cases"
print(new_column)

print(new_column in covid_data.columns) # Test for existing column# True

#  delete new column, use if re-runing with out resetting the data,
#if time allows will create if statement to check if column is available then
#del covid_data[str(days_calc)+"_days_rolling_new_cases"]

# insert new_column
covid_data.insert(loc=6, column=str(days_calc)+"_days_rolling_new_cases", val

print("-"*100)

# Rolling new deaths
rolling_new_deaths = covid_data.groupby(['iso_code'])['new_deaths'].transform


# Insert a column with the "n" rolling new deaths

#new_column string name
new_column_2 = str(days_calc)+"_days_rolling_new_deaths"
print(new_column_2)

print(new_column_2 in covid_data.columns) # Test for existing column# True

# delete new column
#del covid_data[str(days_calc)+"_days_rolling_new_deaths"]

# insert new_column
covid_data.insert(loc=9, column=str(days_calc)+"_days_rolling_new_deaths", va

print("-"*100)


#repeat for new deaths
#still need to create calculations for:
    #total_cases_per_100k per 100k of the population (total_cases/population
    #total_deaths_per_100k of the population (total_deaths/population * 100,0
    #total_cases_per_100sqkm of the country (total_cases/total country sqkm *
    #total_deaths_per_100sqkm of the country (total_deaths/total country sqkm
#these will be used to use machine learning to establish if the GDP or pop de
#merge in the gdp data if required
```

```
14_days_rolling_new_cases
False
-------------------------------------------------------------------------
---------------------------
14_days_rolling_new_deaths
False
-------------------------------------------------------------------------
---------------------------
```

make the totals 100k of the population so we can compare countries if need be

In [43]:
```python
# Cases per 100K of population
total_cases_per_100k = covid_data.total_cases/covid_data.population * pop_per

# Insert a column total cases per 100k

#new_column string name
new_column_3 = "total_cases_per_100k"
print(new_column_3)

print(new_column_3 in covid_data.columns) # Test for existing column# True

#  delete new column
#del covid_data["total_cases_per_100k"]

# insert new_column
covid_data.insert(loc=6, column="total_cases_per_100k", value=total_cases_per

print("-"*100)
```

```
total_cases_per_100k
False
---------------------------------------------------------------------------
-------------------------
```

In [44]:

```
# deaths per 100K of population
total_deaths_per_100k = covid_data.total_deaths/covid_data.population * pop_p

# Insert a column total deaths per 100k

#new_column string name
new_column_4 = "total_deaths_per_100k"
print(new_column_4)

print(new_column_4 in covid_data.columns) # Test for existing column# True

#  delete new column
#del covid_data["total_deaths_per_100k"]

# insert new_column
covid_data.insert(loc=6, column="total_deaths_per_100k", value=total_deaths_p

print("-"*100)
```

```
total_deaths_per_100k
False
----------------------------------------------------------------------------
------------------------
```

to be able to group for regressions create a subset of the data to look at

Take the data for year end for 2020,2021 and the most recent data from 2022 review this data for and create the top deaths and the lowest deaths sets of data in the top deaths look at the minimum value to set the threshold for the "HigH" mortalility classificaion in the bottom deaths look at the max value to set the threshold for the "Low" mortalility classificaion

In [45]:

```python
# create a classification for mortality if the total_deaths per 100k is high
# obesrvations of the deaths for 2020 and 2021, get the min value of the top
#covid_data[covid_data["date"].isin(["2020-12-31","2021-12-31","2022-09-15"])

#last_date_n = str(last_date_n = str(last_date))

# filter data for the dates:
covid_data_observe = covid_data[covid_data["date"].isin(["2020-12-31","2021-1
covid_data_observe_20_21 =covid_data[covid_data["date"].isin(["2020-12-31","2
covid_data_observe_22 =covid_data[covid_data["date"].isin([last_date_n])]

#top and bottom observations
top_20_21 = covid_data_observe_20_21.nlargest(n=top_n_parameter, columns=["to
bot_22 = covid_data_observe_22.nsmallest(n=top_n_parameter, columns=["total_d

# min value in the Top mortality (top deaths) data
print("min of 2020/21 top deaths/ 100k: "+str(top_20_21["total_deaths_per_100
print("max of 2020/21 top deaths/ 100k: "+str(top_20_21["total_deaths_per_100
print("these records look very high, it could be due to an outlier, I have re
print("-"*100)

# max value in the bottom mortality (bottom deaths) data
print("max of 2022 lowest deaths/ 100k: "+str(bot_22["total_deaths_per_100k"]
print("min of 2022 lowest deaths/ 100k: "+str(bot_22["total_deaths_per_100k"]
```

```
min of 2020/21 top deaths/ 100k: 244.9883741613561
max of 2020/21 top deaths/ 100k: 601.1779992283662
these records look very high, it could be due to an outlier, I have recalcu
lted below again once more of the data is cleaned
----------------------------------------------------------------------------
-------------------------
max of 2022 lowest deaths/ 100k: 3.373661600193892
min of 2022 lowest deaths/ 100k: 0.0
```

In [46]:

```python
# classifiers for deaths beig high should be above 50 per 100k and below 10 p
print("high_deaths ="+str(high_deaths_per_100k))
print("low_deaths ="+str(low_deaths_per_100k))
# set these variables at the top of the project
```

```
high_deaths =100
low_deaths =25
```

add this classification to the covid_data

In [47]:
```
# create a calculation to insert the classification group of "Low" (10,25,50)
#if the total_deaths_per_100k >= 50 then "High Deaths" elseif total_deaths_pe

covid_data.loc[covid_data["total_deaths_per_100k"] <= low_deaths_per_100k, "m
covid_data.loc[covid_data["total_deaths_per_100k"] < high_deaths_per_100k, "m
covid_data.loc[covid_data["total_deaths_per_100k"] >= high_deaths_per_100k, "

covid_data.tail()
```

Out[47]:

	iso_code	location	date	n_day_start_date	total_cases	new_cases	total_deaths_pe
217279	ZWE	Zimbabwe	2022-09-13	2022-08-30	256904.0	16.0	34.
217280	ZWE	Zimbabwe	2022-09-14	2022-08-31	256939.0	35.0	34.
217281	ZWE	Zimbabwe	2022-09-15	2022-09-01	256939.0	0.0	34.
217282	ZWE	Zimbabwe	2022-09-16	2022-09-02	256939.0	0.0	34.
217283	ZWE	Zimbabwe	2022-09-17	2022-09-03	256988.0	49.0	35.

5 rows × 21 columns

It can be observerd from the .tail function that observations between 10 to 50 will be blank

In [48]:
```
# Review covid data using the iso code for a country
covid_data_country = covid_data[covid_data["iso_code"]=="ABW"]

covid_data_country.head(20)
```

Out[48]:

	iso_code	location	date	n_day_start_date	total_cases	new_cases	total_deaths_per
9371	ABW	Aruba	2020-03-13	2020-02-28	2.0	2.0	
9372	ABW	Aruba	2020-03-14	2020-02-29	2.0	0.0	
9373	ABW	Aruba	2020-03-15	2020-03-01	2.0	0.0	
9374	ABW	Aruba	2020-03-16	2020-03-02	2.0	0.0	
9375	ABW	Aruba	2020-03-17	2020-03-03	3.0	1.0	
9376	ABW	Aruba	2020-03-18	2020-03-04	4.0	1.0	
9377	ABW	Aruba	2020-03-19	2020-03-05	4.0	0.0	

In [49]:
```
covid_data_country.tail(20)
```

Out[49]:

	iso_code	location	date	n_day_start_date	total_cases	new_cases	total_deaths_pe
10270	ABW	Aruba	2022-08-29	2022-08-15	42792.0	42.0	213.
10271	ABW	Aruba	2022-08-30	2022-08-16	42792.0	0.0	213.
10272	ABW	Aruba	2022-08-31	2022-08-17	42848.0	56.0	213.
10273	ABW	Aruba	2022-09-01	2022-08-18	42848.0	0.0	213.
10274	ABW	Aruba	2022-09-02	2022-08-19	42848.0	0.0	213.
10275	ABW	Aruba	2022-09-03	2022-08-20	42848.0	0.0	213.
10276	ABW	Aruba	2022-09-04	2022-08-21	42848.0	0.0	213.

we can observe that the earlier data in the .head() function shows empty mortality data but the later .tail() "high'"s can be seen

In [50]:

```
print(covid_data.info())
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 203545 entries, 9371 to 217283
Data columns (total 21 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   iso_code                      203545 non-null  object
 1   location                      203545 non-null  object
 2   date                          203545 non-null  datetime64[ns]
 3   n_day_start_date              203545 non-null  datetime64[ns]
 4   total_cases                   203545 non-null  float64
 5   new_cases                     203545 non-null  float64
 6   total_deaths_per_100k         203545 non-null  float64
 7   total_cases_per_100k          203545 non-null  float64
 8   14_days_rolling_new_cases     203545 non-null  float64
 9   total_deaths                  203545 non-null  float64
 10  new_deaths                    203545 non-null  float64
 11  14_days_rolling_new_deaths    203545 non-null  float64
 12  icu_patients                  203545 non-null  float64
 13  total_tests                   203545 non-null  float64
 14  total_vaccinations            203545 non-null  float64
 15  people_fully_vaccinated       203545 non-null  float64
 16  population                    203545 non-null  float64
 17  population_density            203545 non-null  float64
 18  gdp_per_capita                203545 non-null  float64
 19  extreme_poverty               203545 non-null  float64
 20  mortality                     203545 non-null  object
dtypes: datetime64[ns](2), float64(16), object(3)
memory usage: 34.2+ MB
None
```

all the new columns are showing up in the datset now. Let's review the .corr() function for some quick insights

In [51]:

```
# Correlations of the covid_data
covid_data.corr()
```

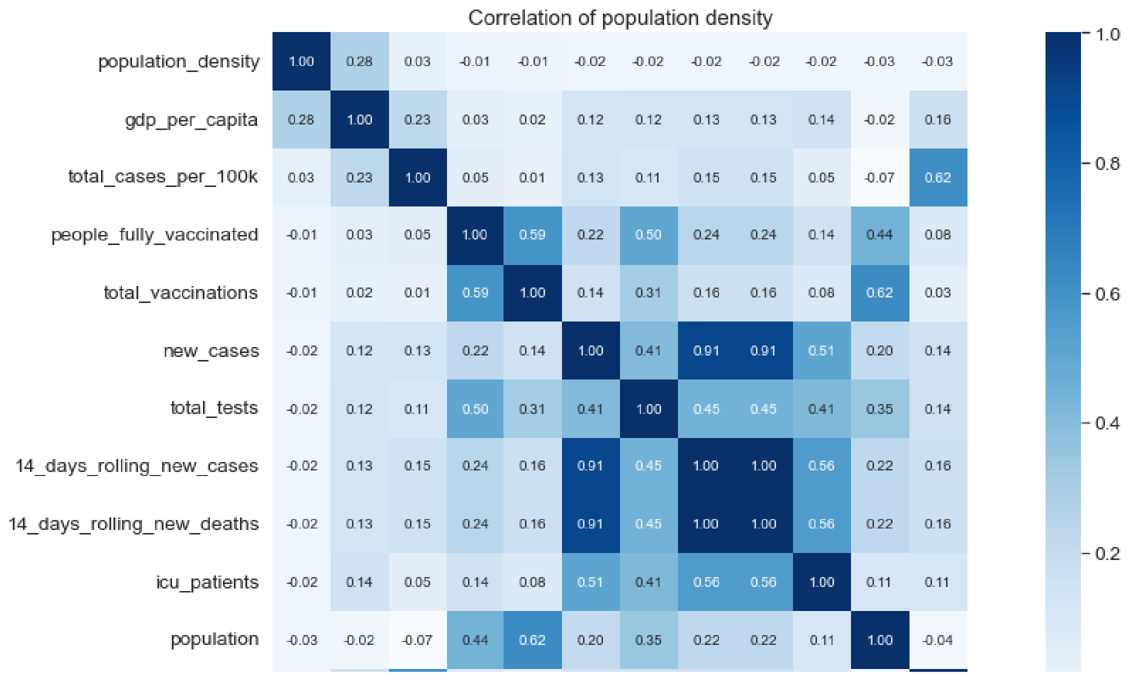
Out[51]:

	total_cases	new_cases	total_deaths_per_100k	total_cases_per_10
total_cases	1.000000	0.511007	0.274637	0.2282
new_cases	0.511007	1.000000	0.142463	0.1273
total_deaths_per_100k	0.274637	0.142463	1.000000	0.6158
total_cases_per_100k	0.228270	0.127374	0.615828	1.0000
14_days_rolling_new_cases	0.571959	0.905718	0.157589	0.1473
total_deaths	0.897945	0.455584	0.352094	0.1332
new_deaths	0.418564	0.556613	0.136376	0.0174
14_days_rolling_new_deaths	0.571959	0.905718	0.157589	0.1473
icu_patients	0.421160	0.510926	0.110637	0.0482
total_tests	0.653270	0.409020	0.143523	0.1071
total_vaccinations	0.351515	0.144864	0.029522	0.0131
people_fully_vaccinated	0.566829	0.223022	0.079996	0.0455
population	0.345073	0.204812	-0.038970	-0.0683
population_density	-0.026215	-0.017614	-0.026077	0.0250
gdp_per_capita	0.134295	0.117210	0.157560	0.2273
extreme_poverty	-0.050959	-0.048274	-0.216721	-0.2143

this does not look very promising but it's hard to read. Let's review as a heat map

In [52]:

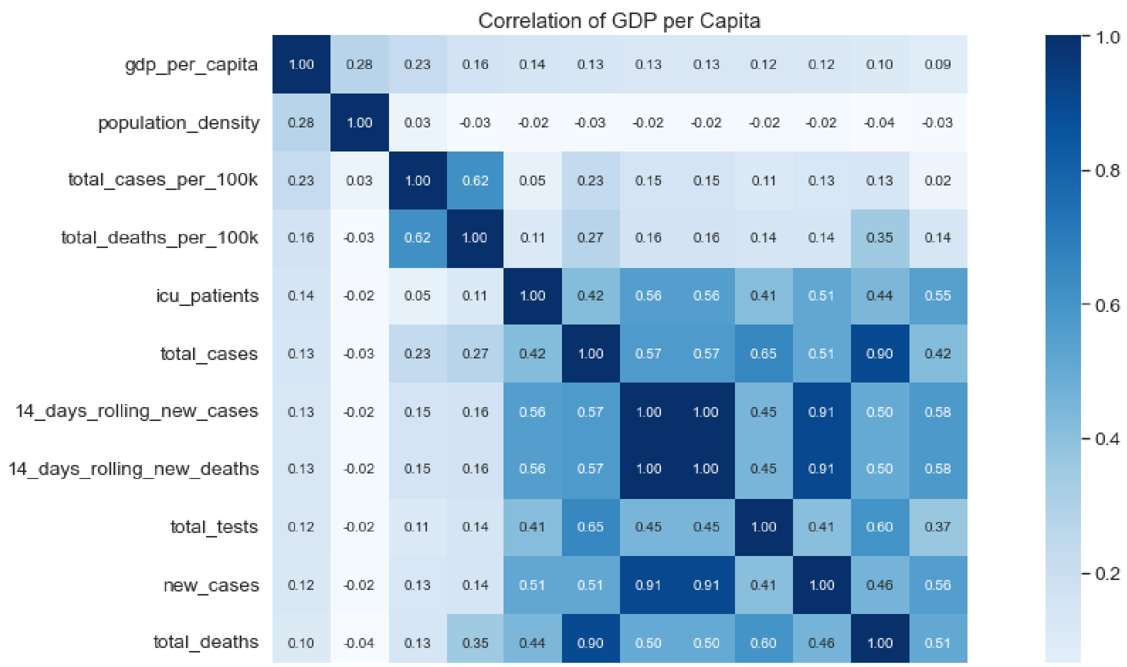
```
#Correlation of population density
corr = covid_data.corr()
plt.figure(figsize=(20, 9))
k = 12 #number of variables for heatmap
cols = corr.nlargest(k, 'population_density')['population_density'].index
cm = np.corrcoef(covid_data[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws
plt.title("Correlation of population density", size = 15)
plt.show()
```



Type *Markdown* and LaTeX: α^2

In [53]:

```
#Correlation of gdp
corr = covid_data.corr()
plt.figure(figsize=(20, 9))
k = 12 #number of variables for heatmap
cols = corr.nlargest(k, 'gdp_per_capita')['gdp_per_capita'].index
cm = np.corrcoef(covid_data[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws
plt.title("Correlation of GDP per Capita", size = 15)
plt.show()
```



darker shadeing represent positive correlation. from this we can infer that population density and gdp are not correlated to the mortality rate of a country. gdp appears to have slightly better correllation than the population density

In [54]:

```
# not sure if we need some sort of index key to view the data, I created one
pk = covid_data["iso_code"]+str(covid_data['date'])

print(pk.head())

#insert pk into covid_data
#del covid_data["pk"] #delete pk column
#covid_data.insert(0, 'pk', pk)


#covid_data["pk"]
#covid_data.info()
```

```
9371    ABW9371    2020-03-13\n9372    2020-03-14\n9...
9372    ABW9371    2020-03-13\n9372    2020-03-14\n9...
9373    ABW9371    2020-03-13\n9372    2020-03-14\n9...
9374    ABW9371    2020-03-13\n9372    2020-03-14\n9...
9375    ABW9371    2020-03-13\n9372    2020-03-14\n9...
Name: iso_code, dtype: object
```

summary of data exploration and preparation: the datre is ready for anlyis but my confidence level is not high after reviewing the .corr() results. I decided to leave the gdp data source at this point as the COVID gdp per capita looks to be a good representation of the data. next step is to pefrom regession and machine learning although given the little correlation I am seeing not sure how fruitful it will be

Analysis

Basic Charts

In [55]:

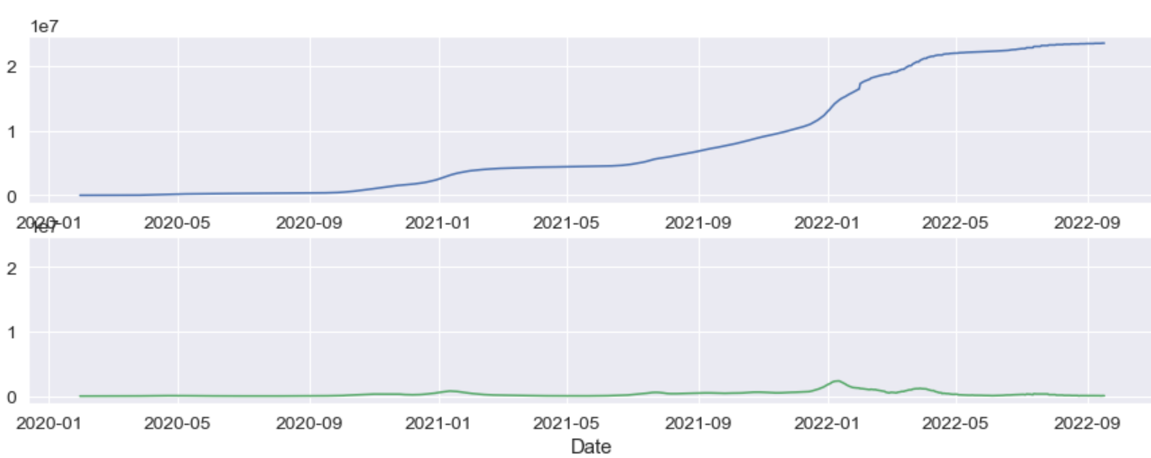
```
# Set chart sizes to wide

plt.rcParams['figure.figsize'] = [15, 5]

#list of iso codes
Country_review = covid_data["iso_code"].tolist()

# list the country codes
country_iso_list = unique(Country_review)
```

```
ABW AFG AGO AIA ALB AND ARE ARG ARM ATG AUS AUT AZE BDI BEL BEN BES BFA BGD
BGR BHR BHS BIH BLR BLZ BMU BOL BRA BRB BRN BTN BWA CAF CAN CHE CHL CHN CIV
CMR COD COG COK COL COM CPV CRI CUB CUW CYM CYP CZE DEU DJI DMA DNK DOM DZA
ECU EGY ERI ESH ESP EST ETH FIN FJI FLK FRA FRO FSM GAB GBR GEO GGY GHA GIB
GIN GMB GNB GNQ GRC GRD GRL GTM GUM GUY HKG HND HRV HTI HUN IDN IMN IND IRL
IRN IRQ ISL ISR ITA JAM JEY JOR JPN KAZ KEN KGZ KHM KIR KNA KOR KWT LAO LBN
LBR LBY LCA LIE LKA LSO LTU LUX LVA MAC MAR MCO MDA MDG MDV MEX MHL MKD MLI
MLT MMR MNE MNG MNP MOZ MRT MSR MUS MWI MYS NAM NCL NER NGA NIC NIU NLD NOR
NPL NRU NZL OMN PAK PAN PCN PER PHL PLW PNG POL PRI PRK PRT PRY PSE PYF QAT
ROU RUS RWA SAU SDN SEN SGP SHN SLB SLE SLV SMR SOM SPM SRB SSD STP SUR SVK
SVN SWE SWZ SXM SYC SYR TCA TCD TGO THA TJK TKL TKM TLS TON TTO TUN TUR TUV
TWN TZA UGA UKR URY USA UZB VAT VCT VEN VGB VIR VNM VUT WLF WSM YEM ZAF ZMB
ZWE
```

In [56]:

```
country_use_code = "GBR"

#covid_data = covid_data.set_index("pk")

iso_use = country_use_code

print("Total Cases vs "+new_column+" for: "+iso_use)


# Basic plot of total covid cases over time
fig, ax=plt.subplots(2,1, sharey=True)


data=covid_data[covid_data["iso_code"]==iso_use]
data1=covid_data[covid_data["iso_code"]==iso_use]

ax[0].plot(data["date"], data["total_cases"], color='b')
print()
ax[1].plot(data["date"], data[new_column], color='g') #using the new_column f

ax[1].set_xlabel("Date")

plt.show()
```

```
Total Cases vs 14_days_rolling_new_cases for: GBR
```



the charts above give an indication of the total mortality per 100k people and rolling 14 day spikes representing the waves over time. we can see that the total increases sharply between the end of 2020, 2021 and is now leveling off.

analysis with seaborn

I'm going to create a subset of the data as mentioned between year end totals/100k population to compare and see if the gdp, martality calssification impacts the results

In [57]:

```python
# create a subset of the COVID data for use with seaborn analysis

covid_data_small = covid_data[['date',
                               'iso_code',
                               'location',
                               'total_cases',
                               'total_cases_per_100k',
                               'total_deaths',
                               'total_deaths_per_100k',
                               'population',
                               'population_density',
                               'gdp_per_capita',
                               'extreme_poverty',
                               'people_fully_vaccinated',
                               'mortality'
                              ]]


#covid_data_small.fillna(0)
covid_data_small

last_date_n = str(last_date)

print("last date to use: "+last_date_n)
```

```
last date to use: 2022-09-16 00:00:00
```

In [58]:

```python
# filter on dates for analysis
covid_data_sns = covid_data_small[covid_data_small["date"].isin(["2020-12-31"

print("covid_data_sns.shape")
print(covid_data_sns.shape)
print("-"*100)
print()
print(covid_data_sns.head())
print("-"*100)
print(covid_data_sns.tail())
print("-"*100)
print()
print("Null data")
print(covid_data_sns.isna().sum())
print("-"*100)
print()
print(covid_data_sns.corr())
print("-"*100)
```

```
covid_data_sns.shape
(658, 13)
----------------------------------------------------------------------------
-------------------------

             date iso_code     location  total_cases  total_cases_per_100k  \
9664   2020-12-31      ABW        Aruba       5489.0           5152.249005
10029  2021-12-31      ABW        Aruba      20461.0          19205.714500
10288  2022-09-16      ABW        Aruba      42970.0          40333.783885
311    2020-12-31      AFG  Afghanistan      52330.0            130.500504
676    2021-12-31      AFG  Afghanistan     158084.0            394.229728

       total_deaths  total_deaths_per_100k  population  population_density  \
9664           49.0              45.993842    106536.0             584.800
10029         181.0             169.895622    106536.0             584.800
10288         228.0             214.012165    106536.0             584.800
311          2189.0               5.458926  40099462.0              54.422
676          7356.0              18.344386  40099462.0              54.422

       gdp_per_capita  extreme_poverty  people_fully_vaccinated mortality
9664        35973.781              0.0                      0.0
10029       35973.781              0.0                      0.0      high
10288       35973.781              0.0                  83557.0      high
311          1803.987              0.0                      0.0
676          1803.987              0.0                      0.0
----------------------------------------------------------------------------
-------------------------
             date iso_code  location  total_cases  total_cases_per_100k  \
216111 2021-12-31      ZMB    Zambia     254274.0           1305.768848
216370 2022-09-16      ZMB    Zambia     333363.0           1711.913214
216658 2020-12-31      ZWE  Zimbabwe      13867.0             86.703843
217023 2021-12-31      ZWE  Zimbabwe     213258.0           1333.402195
217282 2022-09-16      ZWE  Zimbabwe     256939.0           1606.518989

        total_deaths  total_deaths_per_100k  population  population_density  \
```

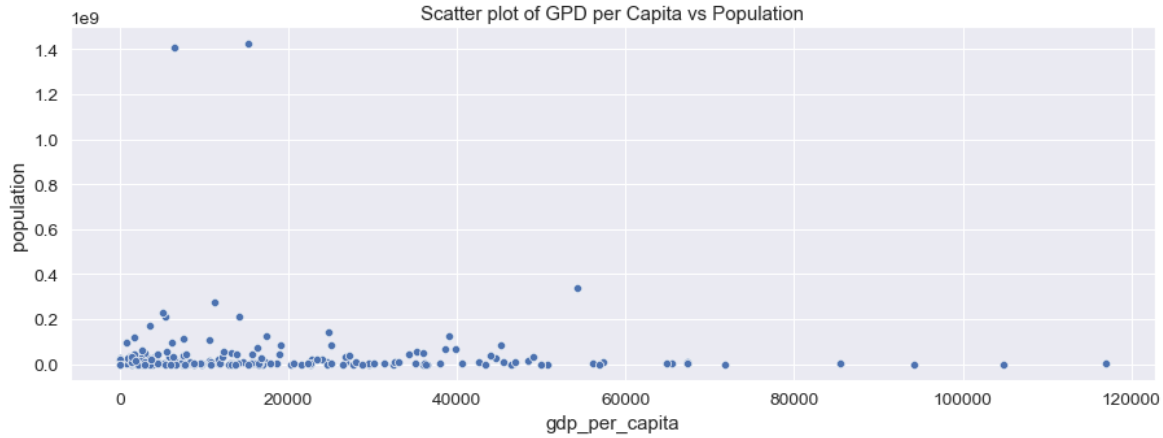
```
216111        3734.0            19.175145  19473125.0             22.995
216370        4017.0            20.628430  19473125.0             22.995
216658         363.0             2.269669  15993524.0             42.729
217023        5004.0            31.287664  15993524.0             42.729
217282        5596.0            34.989162  15993524.0             42.729

        gdp_per_capita  extreme_poverty  people_fully_vaccinated mortality
216111        3689.251             57.5                1217415.0
216370        3689.251             57.5                      0.0
216658        1899.775             21.4                      0.0
217023        1899.775             21.4                3135168.0
217282        1899.775             21.4                      0.0
---------------------------------------------------------------------------
-------------------------

Null data
date                        0
iso_code                    0
location                    0
total_cases                 0
total_cases_per_100k        0
total_deaths                0
total_deaths_per_100k       0
population                  0
population_density          0
gdp_per_capita              0
extreme_poverty             0
people_fully_vaccinated     0
mortality                   0
dtype: int64
---------------------------------------------------------------------------
-------------------------

                         total_cases  total_cases_per_100k  total_deaths  \
total_cases                 1.000000              0.217462      0.886175
total_cases_per_100k        0.217462              1.000000      0.098189
total_deaths                0.886175              0.098189      1.000000
total_deaths_per_100k       0.251780              0.565010      0.323133
population                  0.371592             -0.084021      0.391657
population_density         -0.028417              0.038308     -0.038251
gdp_per_capita              0.167965              0.281003      0.116082
extreme_poverty            -0.066459             -0.265953     -0.062166
people_fully_vaccinated     0.492317             -0.002906      0.515926

                         total_deaths_per_100k  population  \
total_cases                           0.251780    0.371592
total_cases_per_100k                  0.565010   -0.084021
total_deaths                          0.323133    0.391657
total_deaths_per_100k                 1.000000   -0.048313
population                           -0.048313    1.000000
population_density                   -0.033790   -0.025052
gdp_per_capita                        0.187821   -0.022257
extreme_poverty                      -0.265442    0.028340
people_fully_vaccinated               0.044485    0.545371

                         population_density  gdp_per_capita  extreme_povert
y  \
```

```
total_cases                        -0.028417        0.167965        -0.06645
9
total_cases_per_100k                0.038308        0.281003        -0.26595
3
total_deaths                       -0.038251        0.116082        -0.06216
6
total_deaths_per_100k              -0.033790        0.187821        -0.26544
2
population                         -0.025052       -0.022257         0.02834
0
population_density                  1.000000        0.269128        -0.06812
3
gdp_per_capita                      0.269128        1.000000        -0.31493
8
extreme_poverty                    -0.068123       -0.314938         1.00000
0
people_fully_vaccinated            -0.008559        0.009211         0.01489
8

                         people_fully_vaccinated
total_cases                             0.492317
total_cases_per_100k                   -0.002906
total_deaths                            0.515926
total_deaths_per_100k                   0.044485
population                              0.545371
population_density                     -0.008559
gdp_per_capita                          0.009211
extreme_poverty                         0.014898
people_fully_vaccinated                 1.000000
----------------------------------------------------------------------------
-------------------------
```

I can see that we are getting multiple dates and requested columns of data back so good to move forward

In [59]:

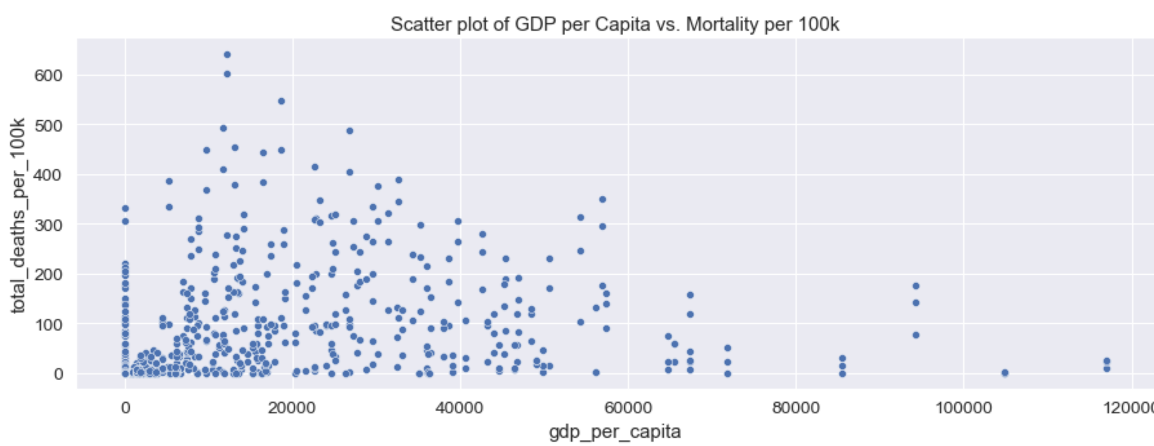
```
sns.scatterplot(x="gdp_per_capita",y="population",data=covid_data_sns)
plt.title("Scatter plot of GPD per Capita vs Population")
plt.show()
```



looks like a few outliers with a few high gdp nodes with relatively low populations

In [60]:

```
sns.scatterplot(x="gdp_per_capita",y="total_deaths_per_100k",data=covid_data_
#plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.title("Scatter plot of GDP per Capita vs. Mortality per 100k", size = 15)
plt.show()
```



looks like an intersting visual and that we can what appears to be a pattern between countries, GDP and mortality

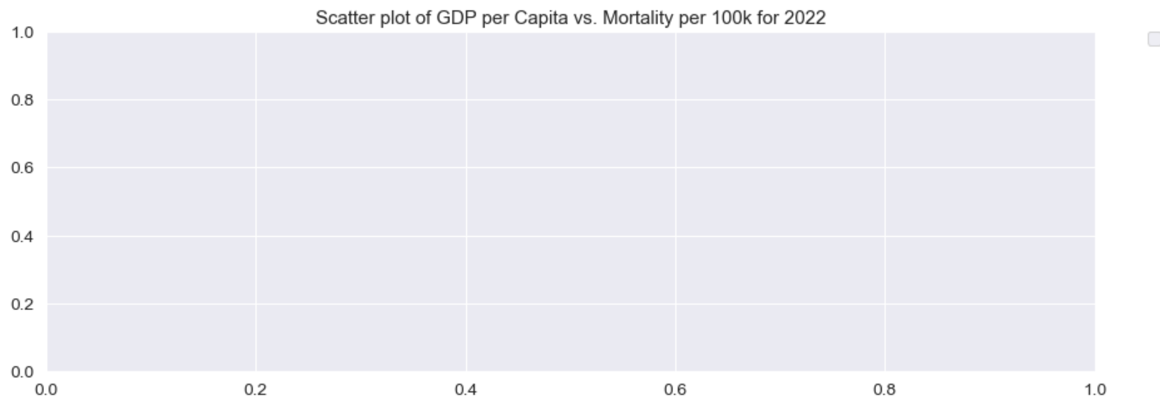
In [61]:

```
#create data sets for each year
df_2020 = covid_data_sns[covid_data_sns["date"].isin(["2020-12-31"])]
df_2021 = covid_data_sns[covid_data_sns["date"].isin(["2021-12-31"])]
df_2022 = covid_data_sns[covid_data_sns["date"].isin(["2022-09-15"])]
```

In [62]:

```
sns.scatterplot(x="gdp_per_capita",y="total_deaths_per_100k",data=df_2022, hu
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.title("Scatter plot of GDP per Capita vs. Mortality per 100k for 2022", s
plt.show()
```

```
No handles with labels found to put in legend.
```



only displaying a single point in time gets rid of some noise and it would appear looking at the latest data here that there appears to be a relationship between gdp and mortality rates. it might be easier to review by the top and bottom countries

In [63]:

```
# Top n data; use: top_n_parameter
#https://datascientyst.com/get-top-10-highest-lowest-values-pandas/
#df.nlargest; df.nsmallest


print("Top countries by cases and deaths:")
print()

df_2020 = covid_data_sns[covid_data_sns["date"].isin(["2020-12-31"])]
df_2021 = covid_data_sns[covid_data_sns["date"].isin(["2021-12-31"])]
df_2022 = covid_data_sns[covid_data_sns["date"].isin([last_date_n])]
```

```
Top countries by cases and deaths:
```

In [64]:

```
print("creating a sets of top n cases and deaths per 100k of the population")
print()
print("Bottom countries by cases and deaths:")
print()

top_df_2020_cases_per_100k = df_2020.nlargest(n=top_n_parameter, columns=["to
print("top_df_2020_cases_per_100k")
print(top_df_2020_cases_per_100k)
print("-"*100)

top_df_2020_deaths_per_100k = df_2020.nlargest(n=top_n_parameter, columns=["t
print("top_df_2020_deaths_per_100k")
print(top_df_2020_deaths_per_100k)
print("-"*100)

top_df_2021_cases_per_100k = df_2021.nlargest(n=top_n_parameter, columns=["to
print("top_df_2021_cases_per_100k")
print(top_df_2021_cases_per_100k)
print("-"*100)

top_df_2021_deaths_per_100k = df_2021.nlargest(n=top_n_parameter, columns=["t
print("top_df_2021_deaths_per_100k")
print(top_df_2021_deaths_per_100k)
print("-"*100)

top_df_2022_cases_per_100k = df_2022.nlargest(n=top_n_parameter, columns=["to
print("top_df_2022_cases_per_100k")
print(top_df_2022_cases_per_100k)
print("-"*100)

top_df_2022_deaths_per_100k = df_2022.nlargest(n=top_n_parameter, columns=["t
print("top_df_2022_deaths_per_100k")
print(top_df_2022_deaths_per_100k)
```

```
creating a sets of top n cases and deaths per 100k of the population

Bottom countries by cases and deaths:

top_df_2020_cases_per_100k
              date iso_code         location  total_cases  \
4061    2020-12-31      AND          Andorra       8049.0
130241  2020-12-31      MNE       Montenegro      48247.0
115744  2020-12-31      LUX       Luxembourg      46415.0
168582  2020-12-31      SMR       San Marino       2333.0
49976   2020-12-31      CZE          Czechia     718661.0
15321   2020-12-31      BHR          Bahrain      92675.0
75180   2020-12-31      GIB        Gibraltar       2040.0
72368   2020-12-31      GEO          Georgia     227420.0
205157  2020-12-31      USA    United States   20221641.0
177403  2020-12-31      SVN         Slovenia     122152.0
8745    2020-12-31      ARM          Armenia     159409.0
111986  2020-12-31      LIE    Liechtenstein       2221.0
151989  2020-12-31      PAN           Panama     246790.0
```

19050	2020-12-31	BEL	Belgium	646496.0
69600	2020-12-31	PYF	French Polynesia	16926.0
159786	2020-12-31	QAT	Qatar	143834.0
210384	2020-12-31	VAT	Vatican	27.0
112899	2020-12-31	LTU	Lithuania	145052.0
188442	2020-12-31	CHE	Switzerland	452296.0
46283	2020-12-31	HRV	Croatia	210837.0
9664	2020-12-31	ABW	Aruba	5489.0
176444	2020-12-31	SVK	Slovakia	274603.0
172275	2020-12-31	SRB	Serbia	337923.0
127472	2020-12-31	MDA	Moldova	144818.0
137271	2020-12-31	NLD	Netherlands	806620.0

	total_cases_per_100k	total_deaths	total_deaths_per_100k \
4061	10184.224511	84.0	106.283372
130241	7684.368624	682.0	108.623114
115744	7260.046205	495.0	77.425894
168582	6913.411960	59.0	174.835536
49976	6837.390291	11580.0	110.172918
15321	6333.439261	352.0	24.055793
75180	6244.260790	7.0	21.426385
72368	6051.655411	2505.0	66.658151
205157	6000.529250	350544.0	104.019724
177403	5763.490783	2697.0	127.252396
8745	5711.590291	2823.0	101.147485
111986	5689.182612	44.0	112.707805
151989	5671.681375	4022.0	92.432848
19050	5567.760016	19528.0	168.179258
69600	5567.177139	114.0	37.496053
159786	5350.499491	245.0	9.113787
210384	5283.757339	0.0	0.000000
112899	5205.244575	1800.0	64.593665
188442	5203.945138	7873.0	90.583733
46283	5192.856888	3920.0	96.548514
9664	5152.249005	49.0	45.993842
176444	5040.786604	2138.0	39.246482
172275	4917.713580	3211.0	46.728924
127472	4730.286336	2985.0	97.501034
137271	4608.810483	11459.0	65.473655

	population	population_density	gdp_per_capita	extreme_poverty \
4061	79034.0	163.755	0.000	0.0
130241	627859.0	46.280	16409.288	1.0
115744	639321.0	231.447	94277.965	0.2
168582	33746.0	556.667	56861.470	0.0
49976	10510750.0	137.176	32605.906	0.0
15321	1463265.0	1935.907	43290.705	0.0
75180	32670.0	3457.100	0.000	0.0
72368	3757980.0	65.032	9745.079	4.2
205157	336997624.0	35.608	54225.446	1.2
177403	2119410.0	102.619	31400.840	0.0
8745	2790974.0	102.931	8787.580	1.8
111986	39039.0	237.012	0.000	0.0
151989	4351267.0	55.133	22267.037	2.2
19050	11611420.0	375.564	42658.576	0.2
69600	304032.0	77.324	0.000	0.0
159786	2688235.0	227.322	116935.600	0.0

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210384       511.0              0.000          0.000             0.0
112899   2786651.0             45.135      29524.265             0.7
188442   8691406.0            214.243      57410.166             0.0
46283    4060135.0             73.726      22669.797             0.7
9664      106536.0            584.800      35973.781             0.0
176444   5447622.0            113.128      30155.152             0.7
172275   6871547.0             80.291      14048.881             0.0
127472   3061506.0            123.655       5189.972             0.2
137271  17501696.0            508.544      48472.545             0.0

        people_fully_vaccinated mortality
4061                        0.0      high
130241                      0.0      high
115744                      0.0
168582                      0.0      high
49976                       1.0      high
15321                       0.0
75180                       0.0
72368                       0.0
205157                  44827.0      high
177403                      0.0      high
8745                        0.0      high
111986                      0.0      high
151989                      0.0
19050                      21.0      high
69600                       0.0
159786                      0.0
210384                      0.0
112899                      0.0
188442                     12.0
46283                       0.0
9664                        0.0
176444                      0.0
172275                      0.0
127472                      0.0
137271                      0.0
---------------------------------------------------------------------------
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top_df_2020_deaths_per_100k
             date iso_code                location  total_cases  \
154752 2020-12-31      PER                    Peru    1015137.0
168582 2020-12-31      SMR              San Marino       2333.0
19050  2020-12-31      BEL                 Belgium     646496.0
204187 2020-12-31      GBR          United Kingdom    2488780.0
177403 2020-12-31      SVN                Slovenia     122152.0
97104  2020-12-31      ITA                   Italy    2107166.0
25461  2020-12-31      BIH  Bosnia and Herzegovina     110985.0
145044 2020-12-31      MKD         North Macedonia      83329.0
111986 2020-12-31      LIE           Liechtenstein       2221.0
49976  2020-12-31      CZE                 Czechia     718661.0
30049  2020-12-31      BGR                Bulgaria     202266.0
130241 2020-12-31      MNE              Montenegro      48247.0
183744 2020-12-31      ESP                   Spain    1928265.0
4061   2020-12-31      AND                 Andorra       8049.0
205157 2020-12-31      USA           United States   20221641.0
8745   2020-12-31      ARM                 Armenia     159409.0
125943 2020-12-31      MEX                  Mexico    1426094.0
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87699	2020-12-31	HUN	Hungary	322514.0
127472	2020-12-31	MDA	Moldova	144818.0
46283	2020-12-31	HRV	Croatia	210837.0
68681	2020-12-31	FRA	France	2660676.0
7787	2020-12-31	ARG	Argentina	1625514.0
151989	2020-12-31	PAN	Panama	246790.0
27298	2020-12-31	BRA	Brazil	7681032.0
188442	2020-12-31	CHE	Switzerland	452296.0

	total_cases_per_100k	total_deaths	total_deaths_per_100k \
154752	3010.893634	93070.0	276.045372
168582	6913.411960	59.0	174.835536
19050	5567.760016	19528.0	168.179258
204187	3699.080751	94998.0	141.195796
177403	5763.490783	2697.0	127.252396
97104	3556.978835	74159.0	125.183300
25461	3393.058210	4050.0	123.817505
145044	3961.765391	2503.0	119.001773
111986	5689.182612	44.0	112.707805
49976	6837.390291	11580.0	110.172918
30049	2937.407455	7576.0	110.022440
130241	7684.368624	682.0	108.623114
183744	4060.622148	50837.0	107.054709
4061	10184.224511	84.0	106.283372
205157	6000.529250	350544.0	104.019724
8745	5711.590291	2823.0	101.147485
125943	1125.521840	125807.0	99.291159
87699	3321.535614	9537.0	98.220496
127472	4730.286336	2985.0	97.501034
46283	5192.856888	3920.0	96.548514
68681	3946.302394	64644.0	95.879683
7787	3590.171386	43245.0	95.512534
151989	5671.681375	4022.0	92.432848
27298	3583.804115	195072.0	91.016394
188442	5203.945138	7873.0	90.583733

	population	population_density	gdp_per_capita	extreme_poverty \
154752	33715472.0	25.129	12236.706	3.5
168582	33746.0	556.667	56861.470	0.0
19050	11611420.0	375.564	42658.576	0.2
204187	67281040.0	272.898	39753.244	0.2
177403	2119410.0	102.619	31400.840	0.0
97104	59240330.0	205.859	35220.084	2.0
25461	3270943.0	68.496	11713.895	0.2
145044	2103330.0	82.600	13111.214	5.0
111986	39039.0	237.012	0.000	0.0
49976	10510750.0	137.176	32605.906	0.0
30049	6885868.0	65.180	18563.307	1.5
130241	627859.0	46.280	16409.288	1.0
183744	47486935.0	93.105	34272.360	1.0
4061	79034.0	163.755	0.000	0.0
205157	336997624.0	35.608	54225.446	1.2
8745	2790974.0	102.931	8787.580	1.8
125943	126705138.0	66.444	17336.469	2.5
87699	9709786.0	108.043	26777.561	0.5
127472	3061506.0	123.655	5189.972	0.2
46283	4060135.0	73.726	22669.797	0.7

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68681    67422000.0            122.578       38605.671              0.0
7787     45276780.0             16.177       18933.907              0.6
151989    4351267.0             55.133       22267.037              2.2
27298   214326223.0             25.040       14103.452              3.4
188442    8691406.0            214.243       57410.166              0.0

        people_fully_vaccinated mortality
154752                      0.0      high
168582                      0.0      high
19050                      21.0      high
204187                      0.0      high
177403                      0.0      high
97104                       0.0      high
25461                       0.0      high
145044                      0.0      high
111986                      0.0      high
49976                       1.0      high
30049                       0.0      high
130241                      0.0      high
183744                      0.0      high
4061                        0.0      high
205157                  44827.0      high
8745                        0.0      high
125943                      0.0
87699                       0.0
127472                      0.0
46283                       0.0
68681                       2.0
7787                        7.0
151989                      0.0
27298                       0.0
188442                     12.0
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top_df_2021_cases_per_100k
             date iso_code       location  total_cases  total_cases_per_10
0k  \
4426   2021-12-31      AND        Andorra      23740.0           30037.7052
91
130606 2021-12-31      MNE     Montenegro     170034.0           27081.5581
21
75545  2021-12-31      GIB      Gibraltar       8701.0           26632.9966
33
176809 2021-12-31      SVK       Slovakia    1371082.0           25168.4496
46
72733  2021-12-31      GEO        Georgia     934741.0           24873.4958
67
168947 2021-12-31      SMR     San Marino       8202.0           24305.1028
27
50341  2021-12-31      CZE        Czechia    2475729.0           23554.2563
57
173557 2021-12-31      SYC     Seychelles      24788.0           23281.6755
89
177768 2021-12-31      SVN       Slovenia     464048.0           21895.1500
65
129691 2021-12-31      MNG       Mongolia     692621.0           20688.9516
70
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15686  2021-12-31      BHR         Bahrain     282062.0           19276.2076
59
204552 2021-12-31      GBR  United Kingdom   12937886.0           19229.6165
46
10029  2021-12-31      ABW           Aruba      20461.0           19205.7145
00
172640 2021-12-31      SRB          Serbia    1299339.0           18908.9734
82
113264 2021-12-31      LTU       Lithuania     524427.0           18819.2565
20
49410  2021-12-31      CYP          Cyprus     166827.0           18618.9393
61
120787 2021-12-31      MDV        Maldives      95700.0           18352.3888
79
60553  2021-12-31      EST         Estonia     241408.0           18168.7226
85
19415  2021-12-31      BEL         Belgium    2105343.0           18131.6583
16
137636 2021-12-31      NLD     Netherlands    3153512.0           18018.3223
39
46648  2021-12-31      HRV         Croatia     715245.0           17616.2861
58
205522 2021-12-31      USA   United States   54912285.0           16294.5614
71
116109 2021-12-31      LUX      Luxembourg     103766.0           16230.6572
13
95566  2021-12-31      IMN     Isle of Man      13641.0           16188.5999
79
94654  2021-12-31      IRL         Ireland     788559.0           15813.7950
15

        total_deaths  total_deaths_per_100k   population  population_densit
y  \
4426           140.0             177.138953      79034.0                163.75
5
130606        2411.0             384.003415     627859.0                 46.28
0
75545          100.0             306.091215      32670.0               3457.10
0
176809       16635.0             305.362597    5447622.0                113.12
8
72733        13800.0             367.218559    3757980.0                 65.03
2
168947         100.0             296.331417      33746.0                556.66
7
50341        36129.0             343.733796   10510750.0                137.17
6
173557         134.0             125.857049     106470.0                208.35
4
177768        5589.0             263.705465    2119410.0                102.61
9
129691        1986.0              59.322859    3347782.0                  1.98
0
15686         1394.0              95.266408    1463265.0               1935.90
7
204552      177287.0             263.502169   67281040.0                272.89
8
```

```
10029         181.0              169.895622     106536.0              584.80
0
172640      12714.0              185.023838    6871547.0               80.29
1
113264       7397.0              265.444076    2786651.0               45.13
5
49410         638.0               71.204801     896007.0              127.65
7
120787        262.0               50.243740     521458.0             1454.43
3
60553        1932.0              145.405174    1328701.0               31.03
3
19415       28331.0              243.992552   11611420.0              375.56
4
137636      20999.0              119.982658   17501696.0              508.54
4
46648       12538.0              308.807466    4060135.0               73.72
6
205522     825605.0              244.988374  336997624.0               35.60
8
116109        915.0              143.120592     639321.0              231.44
7
95566          67.0               79.512953      84263.0              147.87
2
94654        5912.0              118.559494    4986526.0               69.87
4

        gdp_per_capita  extreme_poverty  people_fully_vaccinated mortality
4426             0.000              0.0                      0.0      high
130606       16409.288              1.0                 272853.0      high
75545            0.000              0.0                      0.0      high
176809       30155.152              0.7                      0.0      high
72733         9745.079              4.2                      0.0      high
168947       56861.470              0.0                      0.0      high
50341        32605.906              0.0                6661738.0      high
173557       26382.287              1.1                      0.0      high
177768       31400.840              0.0                1188990.0      high
129691       11840.846              0.5                2163572.0
15686        43290.705              0.0                1177993.0
204552       39753.244              0.2               47434251.0      high
10029        35973.781              0.0                      0.0      high
172640       14048.881              0.0                      0.0      high
113264       29524.265              0.7                1832173.0      high
49410        32415.132              0.0                      0.0
120787       15183.616              0.0                      0.0
60553        29481.252              0.5                 815144.0      high
19415        42658.576              0.2                8828585.0      high
137636       48472.545              0.0               11782302.0      high
46648        22669.797              0.7                1953540.0      high
205522       54225.446              1.2              209501154.0      high
116109       94277.965              0.2                      0.0      high
95566            0.000              0.0                  65454.0
94654        67335.293              0.2                3876630.0      high
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top_df_2021_deaths_per_100k
             date iso_code               location  total_cases  \
```

155117	2021-12-31	PER	Peru	2296831.0
30414	2021-12-31	BGR	Bulgaria	747108.0
25826	2021-12-31	BIH	Bosnia and Herzegovina	291313.0
88064	2021-12-31	HUN	Hungary	1256415.0
130606	2021-12-31	MNE	Montenegro	170034.0
145409	2021-12-31	MKD	North Macedonia	225049.0
72733	2021-12-31	GEO	Georgia	934741.0
50341	2021-12-31	CZE	Czechia	2475729.0
127837	2021-12-31	MDA	Moldova	376155.0
46648	2021-12-31	HRV	Croatia	715245.0
75545	2021-12-31	GIB	Gibraltar	8701.0
176809	2021-12-31	SVK	Slovakia	1371082.0
161086	2021-12-31	ROU	Romania	1808891.0
168947	2021-12-31	SMR	San Marino	8202.0
27663	2021-12-31	BRA	Brazil	22291839.0
9110	2021-12-31	ARM	Armenia	344930.0
113264	2021-12-31	LTU	Lithuania	524427.0
177768	2021-12-31	SVN	Slovenia	464048.0
204552	2021-12-31	GBR	United Kingdom	12937886.0
8152	2021-12-31	ARG	Argentina	5654408.0
157448	2021-12-31	POL	Poland	4108215.0
41592	2021-12-31	COL	Colombia	5157440.0
154191	2021-12-31	PRY	Paraguay	466101.0
205522	2021-12-31	USA	United States	54912285.0
19415	2021-12-31	BEL	Belgium	2105343.0

	total_cases_per_100k	total_deaths	total_deaths_per_100k	\
155117	6812.394618	202690.0	601.177999	
30414	10849.873974	30955.0	449.543906	
25826	8906.086104	13442.0	410.951826	
88064	12939.677558	39186.0	403.572231	
130606	27081.558121	2411.0	384.003415	
145409	10699.652456	7960.0	378.447509	
72733	24873.495867	13800.0	367.218559	
50341	23554.256357	36129.0	343.733796	
127837	12286.600124	10275.0	335.619136	
46648	17616.286158	12538.0	308.807466	
75545	26632.996633	100.0	306.091215	
176809	25168.449646	16635.0	305.362597	
161086	9358.643375	58752.0	303.964703	
168947	24305.102827	100.0	296.331417	
27663	10400.892008	619334.0	288.967907	
9110	12358.767943	7972.0	285.635051	
113264	18819.256520	7397.0	265.444076	
177768	21895.150065	5589.0	263.705465	
204552	19229.616546	177287.0	263.502169	
8152	12488.538275	117169.0	258.783862	
157448	10724.246592	97054.0	253.353592	
41592	10011.227069	129942.0	252.233447	
154191	6952.789008	16624.0	247.978795	
205522	16294.561471	825605.0	244.988374	
19415	18131.658316	28331.0	243.992552	

	population	population_density	gdp_per_capita	extreme_poverty	\
155117	33715472.0	25.129	12236.706	3.5	
30414	6885868.0	65.180	18563.307	1.5	
25826	3270943.0	68.496	11713.895	0.2	

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88064     9709786.0            108.043       26777.561              0.5
130606     627859.0             46.280       16409.288              1.0
145409    2103330.0             82.600       13111.214              5.0
72733     3757980.0             65.032        9745.079              4.2
50341    10510750.0            137.176       32605.906              0.0
127837    3061506.0            123.655        5189.972              0.2
46648     4060135.0             73.726       22669.797              0.7
75545       32670.0           3457.100           0.000              0.0
176809    5447622.0            113.128       30155.152              0.7
161086   19328560.0             85.129       23313.199              5.7
168947      33746.0            556.667       56861.470              0.0
27663   214326223.0             25.040       14103.452              3.4
9110      2790974.0            102.931        8787.580              1.8
113264    2786651.0             45.135       29524.265              0.7
177768    2119410.0            102.619       31400.840              0.0
204552   67281040.0            272.898       39753.244              0.2
8152     45276780.0             16.177       18933.907              0.6
157448   38307726.0            124.027       27216.445              0.0
41592    51516562.0             44.223       13254.949              4.5
154191    6703799.0             17.144        8827.010              1.7
205522  336997624.0             35.608       54225.446              1.2
19415    11611420.0            375.564       42658.576              0.2

        people_fully_vaccinated mortality
155117               22083549.0      high
30414                 1914910.0      high
25826                       0.0      high
88064                       0.0      high
130606                 272853.0      high
145409                      0.0      high
72733                       0.0      high
50341                 6661738.0      high
127837                 982152.0      high
46648                 1953540.0      high
75545                       0.0      high
176809                      0.0      high
161086                7817215.0      high
168947                      0.0      high
27663               143436012.0      high
9110                        0.0      high
113264                1832173.0      high
177768                1188990.0      high
204552               47434251.0      high
8152                 33465991.0      high
157448               21046400.0      high
41592                28323837.0      high
154191                      0.0      high
205522              209501154.0      high
19415                 8828585.0      high
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top_df_2022_cases_per_100k
             date iso_code                  location  total_cases  \
65515  2022-09-16      FRO           Faeroe Islands      34658.0
49669  2022-09-16      CYP                   Cyprus     582381.0
75804  2022-09-16      GIB                Gibraltar      20069.0
169206 2022-09-16      SMR               San Marino      20552.0
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4685   2022-09-16      AND                       Andorra      46147.0
13160  2022-09-16      AUT                       Austria    5008515.0
52480  2022-09-16      DNK                       Denmark    3285290.0
89256  2022-09-16      ISL                       Iceland     205284.0
178027 2022-09-16      SVN                      Slovenia    1153964.0
166687 2022-09-16      SPM  Saint Pierre and Miquelon         3166.0
158638 2022-09-16      PRT                      Portugal    5456778.0
69305  2022-09-16      FRA                        France   34922264.0
29749  2022-09-16      BRN                        Brunei     224610.0
66412  2022-09-16      FLK              Falkland Islands       1886.0
96766  2022-09-16      ISR                        Israel    4648673.0
112610 2022-09-16      LIE                 Liechtenstein      19419.0
108041 2022-09-16      LVA                        Latvia     913371.0
137895 2022-09-16      NLD                   Netherlands    8416314.0
177068 2022-09-16      SVK                      Slovakia    2614999.0
182512 2022-09-16      KOR                   South Korea   24359702.0
72992  2022-09-16      GEO                       Georgia    1762206.0
189066 2022-09-16      CHE                   Switzerland    4073348.0
76742  2022-09-16      GRC                        Greece    4838811.0
15945  2022-09-16      BHR                       Bahrain     675460.0
116368 2022-09-16      LUX                    Luxembourg     288721.0

        total_cases_per_100k  total_deaths  total_deaths_per_100k  populati
on  \
65515           65530.933293          28.0              52.942066     5288
8.0
49669           64997.371672        1178.0             131.472187    89600
7.0
75804           61429.445975         108.0             330.578512     3267
0.0
169206          60902.032834         118.0             349.671072     3374
6.0
4685            58388.794696         155.0             196.118126     7903
4.0
13160           56136.168666       20664.0             231.605134   892208
2.0
52480           56118.129766        6993.0             119.451884   585424
0.0
89256           55431.973753         213.0              57.515493    37033
5.0
178027          54447.416970        6802.0             320.938374   211941
0.0
166687          53816.080231           1.0              16.998130      588
3.0
158638          53029.381727       24951.0             242.475707  1029010
3.0
69305           51796.541188      154741.0             229.511139  6742200
0.0
29749           50431.885184         225.0              50.519452    44537
3.0
66412           50106.269926           0.0               0.000000      376
4.0
96766           50034.151329       11676.0             125.670003   929100
0.0
112610          49742.565127          86.0             220.292528     3903
9.0
108041          48741.220939        5969.0             318.530310   187391
```

```
9.0
137895          48088.562388       22713.0             129.775994  1750169
6.0
177068          48002.578006       20429.0             375.007664   544762
2.0
182512          46999.106061       27782.0              53.602017  5183013
9.0
72992           46892.373030       16900.0             449.709684   375798
0.0
189066          46866.387326       13992.0             160.986611   869140
6.0
76742           46324.958486       32894.0             314.914797  1044536
5.0
15945           46161.153311        1519.0             103.808948   146326
5.0
116368          45160.568791        1126.0             176.124357    63932
1.0

        population_density  gdp_per_capita  extreme_poverty  \
65515               35.308           0.000              0.0
49669              127.657       32415.132              0.0
75804             3457.100           0.000              0.0
169206             556.667       56861.470              0.0
4685               163.755           0.000              0.0
13160              106.749       45436.686              0.7
52480              136.520       46682.515              0.2
89256                3.404       46482.958              0.2
178027             102.619       31400.840              0.0
166687               0.000           0.000              0.0
158638             112.371       27936.896              0.5
69305              122.578       38605.671              0.0
29749               81.347       71809.251              0.0
66412                0.000           0.000              0.0
96766              402.606       33132.320              0.5
112610             237.012           0.000              0.0
108041              31.212       25063.846              0.7
137895             508.544       48472.545              0.0
177068             113.128       30155.152              0.7
182512             527.967       35938.374              0.2
72992               65.032        9745.079              4.2
189066             214.243       57410.166              0.0
76742               83.479       24574.382              1.5
15945             1935.907       43290.705              0.0
116368             231.447       94277.965              0.2

        people_fully_vaccinated mortality
65515                       0.0
49669                       0.0      high
75804                       0.0      high
169206                      0.0      high
4685                        0.0      high
13160                       0.0      high
52480                       0.0      high
89256                       0.0
178027                      0.0      high
166687                      0.0
158638                      0.0      high
```

```
69305                      0.0      high
29749                      0.0
66412                      0.0
96766                6153341.0      high
112610                     0.0      high
108041                     0.0      high
137895                     0.0      high
177068                     0.0      high
182512                     0.0
72992                      0.0      high
189066                     0.0      high
76742                7637278.0      high
15945                1225782.0      high
116368                     0.0      high
---------------------------------------------------------------------------
-------------------------
top_df_2022_deaths_per_100k
             date iso_code                location  total_cases  \
155376 2022-09-16      PER                    Peru    4131137.0
30673  2022-09-16      BGR                Bulgaria    1251331.0
26085  2022-09-16      BIH  Bosnia and Herzegovina     397822.0
88323  2022-09-16      HUN                 Hungary    2070443.0
145668 2022-09-16      MKD         North Macedonia     342075.0
72992  2022-09-16      GEO                 Georgia    1762206.0
130865 2022-09-16      MNE              Montenegro     278134.0
46907  2022-09-16      HRV                 Croatia    1223641.0
50600  2022-09-16      CZE                 Czechia    4073515.0
128096 2022-09-16      MDA                 Moldova     583183.0
177068 2022-09-16      SVK                Slovakia    2614999.0
169206 2022-09-16      SMR              San Marino      20552.0
161345 2022-09-16      ROU                 Romania    3249108.0
113523 2022-09-16      LTU               Lithuania    1233862.0
75804  2022-09-16      GIB               Gibraltar      20069.0
178027 2022-09-16      SVN                Slovenia    1153964.0
27922  2022-09-16      BRA                  Brazil   34568833.0
108041 2022-09-16      LVA                  Latvia     913371.0
76742  2022-09-16      GRC                  Greece    4838811.0
205781 2022-09-16      USA           United States   95645794.0
39955  2022-09-16      CHL                   Chile    4568495.0
9369   2022-09-16      ARM                 Armenia     439302.0
204811 2022-09-16      GBR          United Kingdom   23585304.0
157707 2022-09-16      POL                  Poland    6238544.0
97728  2022-09-16      ITA                   Italy   22131785.0

        total_cases_per_100k  total_deaths  total_deaths_per_100k  \
155376          12252.941320      216264.0             641.438447
30673           18172.451171       37675.0             547.135089
26085           12162.303042       16108.0             492.457374
88323           21323.260883       47409.0             488.259988
145668          16263.496456        9521.0             452.663158
72992           46892.373030       16900.0             449.709684
130865          44298.799571        2778.0             442.456029
46907           30137.938763       16834.0             414.616755
50600           38755.702495       40951.0             389.610637
128096          19048.892930       11808.0             385.692532
177068          48002.578006       20429.0             375.007664
169206          60902.032834         118.0             349.671072
```

161345	16809.881336	66888.0	346.057854
113523	44277.593427	9304.0	333.877475
75804	61429.445975	108.0	330.578512
178027	54447.416970	6802.0	320.938374
27922	16129.073016	685203.0	319.700964
108041	48741.220939	5969.0	318.530310
76742	46324.958486	32894.0	314.914797
205781	28381.741350	1053389.0	312.580542
39955	23436.371400	60822.0	312.016754
9369	15740.096468	8669.0	310.608411
204811	35054.904026	206150.0	306.401328
157707	16285.341500	117341.0	306.311578
97728	37359.320922	176508.0	297.952425

	population	population_density	gdp_per_capita	extreme_poverty \
155376	33715472.0	25.129	12236.706	3.5
30673	6885868.0	65.180	18563.307	1.5
26085	3270943.0	68.496	11713.895	0.2
88323	9709786.0	108.043	26777.561	0.5
145668	2103330.0	82.600	13111.214	5.0
72992	3757980.0	65.032	9745.079	4.2
130865	627859.0	46.280	16409.288	1.0
46907	4060135.0	73.726	22669.797	0.7
50600	10510750.0	137.176	32605.906	0.0
128096	3061506.0	123.655	5189.972	0.2
177068	5447622.0	113.128	30155.152	0.7
169206	33746.0	556.667	56861.470	0.0
161345	19328560.0	85.129	23313.199	5.7
113523	2786651.0	45.135	29524.265	0.7
75804	32670.0	3457.100	0.000	0.0
178027	2119410.0	102.619	31400.840	0.0
27922	214326223.0	25.040	14103.452	3.4
108041	1873919.0	31.212	25063.846	0.7
76742	10445365.0	83.479	24574.382	1.5
205781	336997624.0	35.608	54225.446	1.2
39955	19493184.0	24.282	22767.037	1.3
9369	2790974.0	102.931	8787.580	1.8
204811	67281040.0	272.898	39753.244	0.2
157707	38307726.0	124.027	27216.445	0.0
97728	59240330.0	205.859	35220.084	2.0

	people_fully_vaccinated	mortality
155376	0.0	high
30673	2070947.0	high
26085	0.0	high
88323	0.0	high
145668	0.0	high
72992	0.0	high
130865	0.0	high
46907	0.0	high
50600	6888750.0	high
128096	0.0	high
177068	0.0	high
169206	0.0	high
161345	0.0	high
113523	1878539.0	high
75804	0.0	high

178027	0.0	high
27922	172032889.0	high
108041	0.0	high
76742	7637278.0	high
205781	0.0	high
39955	0.0	high
9369	0.0	high
204811	0.0	high
157707	22555576.0	high
97728	47964524.0	high

In [65]:
```python
print("creating a sets of bottom n cases and deaths per 100k of the populatio
print()

# Bottom n data; use: top_n_parameter
#https://datascientyst.com/get-top-10-highest-lowest-values-pandas/
#df.nlargest; df.nsmallest
print("Bottom countries by cases and deaths:")
print()

bot_df_2020_cases_per_100k = df_2020.nsmallest(n=top_n_parameter, columns=["t
print("bot_df_2020_cases_per_100k")
print(top_df_2020_cases_per_100k)
print("-"*100)
print()

bot_df_2020_deaths_per_100k = df_2020.nsmallest(n=top_n_parameter, columns=["
print("bot_df_2020_deaths_per_100k")
print(top_df_2020_deaths_per_100k)
print("-"*100)
print()

bot_df_2021_cases_per_100k = df_2021.nsmallest(n=top_n_parameter, columns=["t
print("bot_df_2021_cases_per_100k")
print(top_df_2021_cases_per_100k)
print("-"*100)
print()

bot_df_2021_deaths_per_100k = df_2021.nsmallest(n=top_n_parameter, columns=["
print("bot_df_2021_deaths_per_100k")
print(top_df_2021_deaths_per_100k)
print("-"*100)
print()

bot_df_2022_cases_per_100k = df_2022.nsmallest(n=top_n_parameter, columns=["t
print("bot_df_2022_cases_per_100k")
print(top_df_2022_cases_per_100k)
print("-"*100)
print()

bot_df_2022_deaths_per_100k = df_2022.nsmallest(n=top_n_parameter, columns=["
print("bot_df_2022_deaths_per_100k")
print(top_df_2022_deaths_per_100k)
print("-"*100)
print()
```

```
creating a sets of bottom n cases and deaths per 100k of the population

Bottom countries by cases and deaths:

bot_df_2020_cases_per_100k
              date iso_code         location  total_cases  \
4061    2020-12-31      AND          Andorra       8049.0
130241  2020-12-31      MNE       Montenegro      48247.0
115744  2020-12-31      LUX       Luxembourg      46415.0
168582  2020-12-31      SMR       San Marino       2333.0
```

```
49976  2020-12-31      CZE           Czechia     718661.0
15321  2020-12-31      BHR           Bahrain      92675.0
75180  2020-12-31      GIB         Gibraltar       2040.0
72368  2020-12-31      GEO           Georgia     227420.0
205157 2020-12-31      USA     United States   20221641.0
177403 2020-12-31      SVN          Slovenia     122152.0
8745   2020-12-31      ARM           Armenia     159409.0
111986 2020-12-31      LIE     Liechtenstein       2221.0
151989 2020-12-31      PAN            Panama     246790.0
19050  2020-12-31      BEL           Belgium     646496.0
69600  2020-12-31      PYF  French Polynesia      16926.0
159786 2020-12-31      QAT             Qatar     143834.0
210384 2020-12-31      VAT           Vatican         27.0
112899 2020-12-31      LTU         Lithuania     145052.0
188442 2020-12-31      CHE       Switzerland     452296.0
46283  2020-12-31      HRV           Croatia     210837.0
9664   2020-12-31      ABW             Aruba       5489.0
176444 2020-12-31      SVK          Slovakia     274603.0
172275 2020-12-31      SRB            Serbia     337923.0
127472 2020-12-31      MDA           Moldova     144818.0
137271 2020-12-31      NLD       Netherlands     806620.0

        total_cases_per_100k  total_deaths  total_deaths_per_100k  \
4061            10184.224511          84.0             106.283372
130241           7684.368624         682.0             108.623114
115744           7260.046205         495.0              77.425894
168582           6913.411960          59.0             174.835536
49976            6837.390291       11580.0             110.172918
15321            6333.439261         352.0              24.055793
75180            6244.260790           7.0              21.426385
72368            6051.655411        2505.0              66.658151
205157           6000.529250      350544.0             104.019724
177403           5763.490783        2697.0             127.252396
8745             5711.590291        2823.0             101.147485
111986           5689.182612          44.0             112.707805
151989           5671.681375        4022.0              92.432848
19050            5567.760016       19528.0             168.179258
69600            5567.177139         114.0              37.496053
159786           5350.499491         245.0               9.113787
210384           5283.757339           0.0               0.000000
112899           5205.244575        1800.0              64.593665
188442           5203.945138        7873.0              90.583733
46283            5192.856888        3920.0              96.548514
9664             5152.249005          49.0              45.993842
176444           5040.786604        2138.0              39.246482
172275           4917.713580        3211.0              46.728924
127472           4730.286336        2985.0              97.501034
137271           4608.810483       11459.0              65.473655

         population  population_density  gdp_per_capita  extreme_poverty  \
4061        79034.0             163.755           0.000              0.0
130241     627859.0              46.280       16409.288              1.0
115744     639321.0             231.447       94277.965              0.2
168582      33746.0             556.667       56861.470              0.0
49976    10510750.0             137.176       32605.906              0.0
15321     1463265.0            1935.907       43290.705              0.0
75180       32670.0            3457.100           0.000              0.0
```

```
72368     3757980.0             65.032       9745.079             4.2
205157  336997624.0             35.608      54225.446             1.2
177403    2119410.0            102.619      31400.840             0.0
8745      2790974.0            102.931       8787.580             1.8
111986      39039.0            237.012          0.000             0.0
151989    4351267.0             55.133      22267.037             2.2
19050    11611420.0            375.564      42658.576             0.2
69600      304032.0             77.324          0.000             0.0
159786    2688235.0            227.322     116935.600             0.0
210384        511.0              0.000          0.000             0.0
112899    2786651.0             45.135      29524.265             0.7
188442    8691406.0            214.243      57410.166             0.0
46283     4060135.0             73.726      22669.797             0.7
9664       106536.0            584.800      35973.781             0.0
176444    5447622.0            113.128      30155.152             0.7
172275    6871547.0             80.291      14048.881             0.0
127472    3061506.0            123.655       5189.972             0.2
137271   17501696.0            508.544      48472.545             0.0

        people_fully_vaccinated mortality
4061                        0.0      high
130241                      0.0      high
115744                      0.0
168582                      0.0      high
49976                       1.0      high
15321                       0.0
75180                       0.0
72368                       0.0
205157                  44827.0      high
177403                      0.0      high
8745                        0.0      high
111986                      0.0      high
151989                      0.0
19050                      21.0      high
69600                       0.0
159786                      0.0
210384                      0.0
112899                      0.0
188442                     12.0
46283                       0.0
9664                        0.0
176444                      0.0
172275                      0.0
127472                      0.0
137271                      0.0
---------------------------------------------------------------------------
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bot_df_2020_deaths_per_100k
             date iso_code                location  total_cases  \
154752 2020-12-31      PER                    Peru    1015137.0
168582 2020-12-31      SMR              San Marino       2333.0
19050  2020-12-31      BEL                 Belgium     646496.0
204187 2020-12-31      GBR          United Kingdom    2488780.0
177403 2020-12-31      SVN                Slovenia     122152.0
97104  2020-12-31      ITA                   Italy    2107166.0
25461  2020-12-31      BIH  Bosnia and Herzegovina     110985.0
```

145044	2020-12-31	MKD	North Macedonia	83329.0
111986	2020-12-31	LIE	Liechtenstein	2221.0
49976	2020-12-31	CZE	Czechia	718661.0
30049	2020-12-31	BGR	Bulgaria	202266.0
130241	2020-12-31	MNE	Montenegro	48247.0
183744	2020-12-31	ESP	Spain	1928265.0
4061	2020-12-31	AND	Andorra	8049.0
205157	2020-12-31	USA	United States	20221641.0
8745	2020-12-31	ARM	Armenia	159409.0
125943	2020-12-31	MEX	Mexico	1426094.0
87699	2020-12-31	HUN	Hungary	322514.0
127472	2020-12-31	MDA	Moldova	144818.0
46283	2020-12-31	HRV	Croatia	210837.0
68681	2020-12-31	FRA	France	2660676.0
7787	2020-12-31	ARG	Argentina	1625514.0
151989	2020-12-31	PAN	Panama	246790.0
27298	2020-12-31	BRA	Brazil	7681032.0
188442	2020-12-31	CHE	Switzerland	452296.0

	total_cases_per_100k	total_deaths	total_deaths_per_100k	\
154752	3010.893634	93070.0	276.045372	
168582	6913.411960	59.0	174.835536	
19050	5567.760016	19528.0	168.179258	
204187	3699.080751	94998.0	141.195796	
177403	5763.490783	2697.0	127.252396	
97104	3556.978835	74159.0	125.183300	
25461	3393.058210	4050.0	123.817505	
145044	3961.765391	2503.0	119.001773	
111986	5689.182612	44.0	112.707805	
49976	6837.390291	11580.0	110.172918	
30049	2937.407455	7576.0	110.022440	
130241	7684.368624	682.0	108.623114	
183744	4060.622148	50837.0	107.054709	
4061	10184.224511	84.0	106.283372	
205157	6000.529250	350544.0	104.019724	
8745	5711.590291	2823.0	101.147485	
125943	1125.521840	125807.0	99.291159	
87699	3321.535614	9537.0	98.220496	
127472	4730.286336	2985.0	97.501034	
46283	5192.856888	3920.0	96.548514	
68681	3946.302394	64644.0	95.879683	
7787	3590.171386	43245.0	95.512534	
151989	5671.681375	4022.0	92.432848	
27298	3583.804115	195072.0	91.016394	
188442	5203.945138	7873.0	90.583733	

	population	population_density	gdp_per_capita	extreme_poverty	\
154752	33715472.0	25.129	12236.706	3.5	
168582	33746.0	556.667	56861.470	0.0	
19050	11611420.0	375.564	42658.576	0.2	
204187	67281040.0	272.898	39753.244	0.2	
177403	2119410.0	102.619	31400.840	0.0	
97104	59240330.0	205.859	35220.084	2.0	
25461	3270943.0	68.496	11713.895	0.2	
145044	2103330.0	82.600	13111.214	5.0	
111986	39039.0	237.012	0.000	0.0	
49976	10510750.0	137.176	32605.906	0.0	

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30049     6885868.0              65.180      18563.307              1.5
130241     627859.0              46.280      16409.288              1.0
183744   47486935.0              93.105      34272.360              1.0
4061        79034.0             163.755          0.000              0.0
205157  336997624.0              35.608      54225.446              1.2
8745      2790974.0             102.931       8787.580              1.8
125943  126705138.0              66.444      17336.469              2.5
87699     9709786.0             108.043      26777.561              0.5
127472    3061506.0             123.655       5189.972              0.2
46283     4060135.0              73.726      22669.797              0.7
68681    67422000.0             122.578      38605.671              0.0
7787     45276780.0              16.177      18933.907              0.6
151989    4351267.0              55.133      22267.037              2.2
27298   214326223.0              25.040      14103.452              3.4
188442    8691406.0             214.243      57410.166              0.0

        people_fully_vaccinated mortality
154752                      0.0      high
168582                      0.0      high
19050                      21.0      high
204187                      0.0      high
177403                      0.0      high
97104                       0.0      high
25461                       0.0      high
145044                      0.0      high
111986                      0.0      high
49976                       1.0      high
30049                       0.0      high
130241                      0.0      high
183744                      0.0      high
4061                        0.0      high
205157                  44827.0      high
8745                        0.0      high
125943                      0.0
87699                       0.0
127472                      0.0
46283                       0.0
68681                       2.0
7787                        7.0
151989                      0.0
27298                       0.0
188442                     12.0
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bot_df_2021_cases_per_100k
             date iso_code        location  total_cases  total_cases_per_10
0k  \
4426   2021-12-31      AND         Andorra      23740.0           30037.7052
91
130606 2021-12-31      MNE      Montenegro     170034.0           27081.5581
21
75545  2021-12-31      GIB       Gibraltar       8701.0           26632.9966
33
176809 2021-12-31      SVK        Slovakia    1371082.0           25168.4496
46
72733  2021-12-31      GEO         Georgia     934741.0           24873.4958
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67
168947 2021-12-31      SMR      San Marino       8202.0          24305.1028
27
50341  2021-12-31      CZE         Czechia    2475729.0          23554.2563
57
173557 2021-12-31      SYC      Seychelles      24788.0          23281.6755
89
177768 2021-12-31      SVN        Slovenia     464048.0          21895.1500
65
129691 2021-12-31      MNG        Mongolia     692621.0          20688.9516
70
15686  2021-12-31      BHR         Bahrain     282062.0          19276.2076
59
204552 2021-12-31      GBR  United Kingdom   12937886.0          19229.6165
46
10029  2021-12-31      ABW           Aruba      20461.0          19205.7145
00
172640 2021-12-31      SRB          Serbia    1299339.0          18908.9734
82
113264 2021-12-31      LTU       Lithuania     524427.0          18819.2565
20
49410  2021-12-31      CYP          Cyprus     166827.0          18618.9393
61
120787 2021-12-31      MDV        Maldives      95700.0          18352.3888
79
60553  2021-12-31      EST         Estonia     241408.0          18168.7226
85
19415  2021-12-31      BEL         Belgium    2105343.0          18131.6583
16
137636 2021-12-31      NLD     Netherlands    3153512.0          18018.3223
39
46648  2021-12-31      HRV         Croatia     715245.0          17616.2861
58
205522 2021-12-31      USA   United States   54912285.0          16294.5614
71
116109 2021-12-31      LUX      Luxembourg     103766.0          16230.6572
13
95566  2021-12-31      IMN     Isle of Man      13641.0          16188.5999
79
94654  2021-12-31      IRL         Ireland     788559.0          15813.7950
15

        total_deaths  total_deaths_per_100k   population  population_densit
y  \
4426           140.0             177.138953      79034.0             163.75
5
130606        2411.0             384.003415     627859.0              46.28
0
75545          100.0             306.091215      32670.0            3457.10
0
176809       16635.0             305.362597    5447622.0             113.12
8
72733        13800.0             367.218559    3757980.0              65.03
2
168947         100.0             296.331417      33746.0             556.66
7
50341        36129.0             343.733796   10510750.0             137.17
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6
173557       134.0          125.857049    106470.0          208.35
4
177768      5589.0          263.705465   2119410.0          102.61
9
129691      1986.0           59.322859   3347782.0            1.98
0
15686       1394.0           95.266408   1463265.0         1935.90
7
204552    177287.0          263.502169  67281040.0          272.89
8
10029        181.0          169.895622    106536.0          584.80
0
172640     12714.0          185.023838   6871547.0           80.29
1
113264      7397.0          265.444076   2786651.0           45.13
5
49410        638.0           71.204801    896007.0          127.65
7
120787       262.0           50.243740    521458.0         1454.43
3
60553       1932.0          145.405174   1328701.0           31.03
3
19415      28331.0          243.992552  11611420.0          375.56
4
137636     20999.0          119.982658  17501696.0          508.54
4
46648      12538.0          308.807466   4060135.0           73.72
6
205522    825605.0          244.988374 336997624.0           35.60
8
116109       915.0          143.120592    639321.0          231.44
7
95566         67.0           79.512953     84263.0          147.87
2
94654       5912.0          118.559494   4986526.0           69.87
4

        gdp_per_capita  extreme_poverty  people_fully_vaccinated mortality
4426             0.000              0.0                      0.0      high
130606       16409.288              1.0                 272853.0      high
75545            0.000              0.0                      0.0      high
176809       30155.152              0.7                      0.0      high
72733         9745.079              4.2                      0.0      high
168947       56861.470              0.0                      0.0      high
50341        32605.906              0.0                6661738.0      high
173557       26382.287              1.1                      0.0      high
177768       31400.840              0.0                1188990.0      high
129691       11840.846              0.5                2163572.0
15686        43290.705              0.0                1177993.0
204552       39753.244              0.2               47434251.0      high
10029        35973.781              0.0                      0.0      high
172640       14048.881              0.0                      0.0      high
113264       29524.265              0.7                1832173.0      high
49410        32415.132              0.0                      0.0
120787       15183.616              0.0                      0.0
60553        29481.252              0.5                 815144.0      high
```

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19415       42658.576             0.2                   8828585.0      high
137636      48472.545             0.0                  11782302.0      high
46648       22669.797             0.7                   1953540.0      high
205522      54225.446             1.2                 209501154.0      high
116109      94277.965             0.2                         0.0      high
95566           0.000             0.0                     65454.0          
94654       67335.293             0.2                   3876630.0      high
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bot_df_2021_deaths_per_100k
             date iso_code                location  total_cases  \
155117 2021-12-31      PER                    Peru    2296831.0   
30414  2021-12-31      BGR                Bulgaria     747108.0   
25826  2021-12-31      BIH  Bosnia and Herzegovina     291313.0   
88064  2021-12-31      HUN                 Hungary    1256415.0   
130606 2021-12-31      MNE              Montenegro     170034.0   
145409 2021-12-31      MKD         North Macedonia     225049.0   
72733  2021-12-31      GEO                 Georgia     934741.0   
50341  2021-12-31      CZE                 Czechia    2475729.0   
127837 2021-12-31      MDA                 Moldova     376155.0   
46648  2021-12-31      HRV                 Croatia     715245.0   
75545  2021-12-31      GIB               Gibraltar       8701.0   
176809 2021-12-31      SVK                Slovakia    1371082.0   
161086 2021-12-31      ROU                 Romania    1808891.0   
168947 2021-12-31      SMR              San Marino       8202.0   
27663  2021-12-31      BRA                  Brazil   22291839.0   
9110   2021-12-31      ARM                 Armenia     344930.0   
113264 2021-12-31      LTU               Lithuania     524427.0   
177768 2021-12-31      SVN                Slovenia     464048.0   
204552 2021-12-31      GBR          United Kingdom   12937886.0   
8152   2021-12-31      ARG               Argentina    5654408.0   
157448 2021-12-31      POL                  Poland    4108215.0   
41592  2021-12-31      COL                Colombia    5157440.0   
154191 2021-12-31      PRY                Paraguay     466101.0   
205522 2021-12-31      USA           United States   54912285.0   
19415  2021-12-31      BEL                 Belgium    2105343.0   

        total_cases_per_100k  total_deaths  total_deaths_per_100k  \
155117           6812.394618      202690.0             601.177999   
30414           10849.873974       30955.0             449.543906   
25826            8906.086104       13442.0             410.951826   
88064           12939.677558       39186.0             403.572231   
130606          27081.558121        2411.0             384.003415   
145409          10699.652456        7960.0             378.447509   
72733           24873.495867       13800.0             367.218559   
50341           23554.256357       36129.0             343.733796   
127837          12286.600124       10275.0             335.619136   
46648           17616.286158       12538.0             308.807466   
75545           26632.996633         100.0             306.091215   
176809          25168.449646       16635.0             305.362597   
161086           9358.643375       58752.0             303.964703   
168947          24305.102827         100.0             296.331417   
27663           10400.892008      619334.0             288.967907   
9110            12358.767943        7972.0             285.635051   
113264          18819.256520        7397.0             265.444076   
177768          21895.150065        5589.0             263.705465   
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204552	19229.616546	177287.0	263.502169
8152	12488.538275	117169.0	258.783862
157448	10724.246592	97054.0	253.353592
41592	10011.227069	129942.0	252.233447
154191	6952.789008	16624.0	247.978795
205522	16294.561471	825605.0	244.988374
19415	18131.658316	28331.0	243.992552

	population	population_density	gdp_per_capita	extreme_poverty \
155117	33715472.0	25.129	12236.706	3.5
30414	6885868.0	65.180	18563.307	1.5
25826	3270943.0	68.496	11713.895	0.2
88064	9709786.0	108.043	26777.561	0.5
130606	627859.0	46.280	16409.288	1.0
145409	2103330.0	82.600	13111.214	5.0
72733	3757980.0	65.032	9745.079	4.2
50341	10510750.0	137.176	32605.906	0.0
127837	3061506.0	123.655	5189.972	0.2
46648	4060135.0	73.726	22669.797	0.7
75545	32670.0	3457.100	0.000	0.0
176809	5447622.0	113.128	30155.152	0.7
161086	19328560.0	85.129	23313.199	5.7
168947	33746.0	556.667	56861.470	0.0
27663	214326223.0	25.040	14103.452	3.4
9110	2790974.0	102.931	8787.580	1.8
113264	2786651.0	45.135	29524.265	0.7
177768	2119410.0	102.619	31400.840	0.0
204552	67281040.0	272.898	39753.244	0.2
8152	45276780.0	16.177	18933.907	0.6
157448	38307726.0	124.027	27216.445	0.0
41592	51516562.0	44.223	13254.949	4.5
154191	6703799.0	17.144	8827.010	1.7
205522	336997624.0	35.608	54225.446	1.2
19415	11611420.0	375.564	42658.576	0.2

	people_fully_vaccinated	mortality
155117	22083549.0	high
30414	1914910.0	high
25826	0.0	high
88064	0.0	high
130606	272853.0	high
145409	0.0	high
72733	0.0	high
50341	6661738.0	high
127837	982152.0	high
46648	1953540.0	high
75545	0.0	high
176809	0.0	high
161086	7817215.0	high
168947	0.0	high
27663	143436012.0	high
9110	0.0	high
113264	1832173.0	high
177768	1188990.0	high
204552	47434251.0	high
8152	33465991.0	high
157448	21046400.0	high

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41592                28323837.0      high
154191                      0.0      high
205522              209501154.0      high
19415                 8828585.0      high
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bot_df_2022_cases_per_100k
             date iso_code                    location  total_cases  \
65515  2022-09-16      FRO              Faeroe Islands      34658.0
49669  2022-09-16      CYP                      Cyprus     582381.0
75804  2022-09-16      GIB                   Gibraltar      20069.0
169206 2022-09-16      SMR                  San Marino      20552.0
4685   2022-09-16      AND                     Andorra      46147.0
13160  2022-09-16      AUT                     Austria    5008515.0
52480  2022-09-16      DNK                     Denmark    3285290.0
89256  2022-09-16      ISL                     Iceland     205284.0
178027 2022-09-16      SVN                    Slovenia    1153964.0
166687 2022-09-16      SPM  Saint Pierre and Miquelon       3166.0
158638 2022-09-16      PRT                    Portugal    5456778.0
69305  2022-09-16      FRA                      France   34922264.0
29749  2022-09-16      BRN                      Brunei     224610.0
66412  2022-09-16      FLK            Falkland Islands       1886.0
96766  2022-09-16      ISR                      Israel    4648673.0
112610 2022-09-16      LIE               Liechtenstein      19419.0
108041 2022-09-16      LVA                      Latvia     913371.0
137895 2022-09-16      NLD                 Netherlands    8416314.0
177068 2022-09-16      SVK                    Slovakia    2614999.0
182512 2022-09-16      KOR                 South Korea   24359702.0
72992  2022-09-16      GEO                     Georgia    1762206.0
189066 2022-09-16      CHE                 Switzerland    4073348.0
76742  2022-09-16      GRC                      Greece    4838811.0
15945  2022-09-16      BHR                     Bahrain     675460.0
116368 2022-09-16      LUX                  Luxembourg     288721.0

        total_cases_per_100k  total_deaths  total_deaths_per_100k  populati
on  \
65515           65530.933293          28.0              52.942066     5288
8.0
49669           64997.371672        1178.0             131.472187    89600
7.0
75804           61429.445975         108.0             330.578512     3267
0.0
169206          60902.032834         118.0             349.671072     3374
6.0
4685            58388.794696         155.0             196.118126     7903
4.0
13160           56136.168666       20664.0             231.605134   892208
2.0
52480           56118.129766        6993.0             119.451884   585424
0.0
89256           55431.973753         213.0              57.515493    37033
5.0
178027          54447.416970        6802.0             320.938374   211941
0.0
166687          53816.080231           1.0              16.998130      588
3.0
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158638          53029.381727       24951.0             242.475707  1029010
3.0
69305           51796.541188      154741.0             229.511139  6742200
0.0
29749           50431.885184         225.0              50.519452    44537
3.0
66412           50106.269926           0.0               0.000000      376
4.0
96766           50034.151329       11676.0             125.670003   929100
0.0
112610          49742.565127          86.0             220.292528     3903
9.0
108041          48741.220939        5969.0             318.530310   187391
9.0
137895          48088.562388       22713.0             129.775994  1750169
6.0
177068          48002.578006       20429.0             375.007664   544762
2.0
182512          46999.106061       27782.0              53.602017  5183013
9.0
72992           46892.373030       16900.0             449.709684   375798
0.0
189066          46866.387326       13992.0             160.986611   869140
6.0
76742           46324.958486       32894.0             314.914797  1044536
5.0
15945           46161.153311        1519.0             103.808948   146326
5.0
116368          45160.568791        1126.0             176.124357    63932
1.0

        population_density  gdp_per_capita  extreme_poverty  \
65515               35.308           0.000              0.0
49669              127.657       32415.132              0.0
75804             3457.100           0.000              0.0
169206             556.667       56861.470              0.0
4685               163.755           0.000              0.0
13160              106.749       45436.686              0.7
52480              136.520       46682.515              0.2
89256                3.404       46482.958              0.2
178027             102.619       31400.840              0.0
166687               0.000           0.000              0.0
158638             112.371       27936.896              0.5
69305              122.578       38605.671              0.0
29749               81.347       71809.251              0.0
66412                0.000           0.000              0.0
96766              402.606       33132.320              0.5
112610             237.012           0.000              0.0
108041              31.212       25063.846              0.7
137895             508.544       48472.545              0.0
177068             113.128       30155.152              0.7
182512             527.967       35938.374              0.2
72992               65.032        9745.079              4.2
189066             214.243       57410.166              0.0
76742               83.479       24574.382              1.5
15945             1935.907       43290.705              0.0
116368             231.447       94277.965              0.2
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        people_fully_vaccinated mortality
65515                       0.0
49669                       0.0      high
75804                       0.0      high
169206                      0.0      high
4685                        0.0      high
13160                       0.0      high
52480                       0.0      high
89256                       0.0
178027                      0.0      high
166687                      0.0
158638                      0.0      high
69305                       0.0      high
29749                       0.0
66412                       0.0
96766                 6153341.0      high
112610                      0.0      high
108041                      0.0      high
137895                      0.0      high
177068                      0.0      high
182512                      0.0
72992                       0.0      high
189066                      0.0      high
76742                 7637278.0      high
15945                 1225782.0      high
116368                      0.0      high
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bot_df_2022_deaths_per_100k
             date iso_code                location  total_cases  \
155376 2022-09-16      PER                    Peru    4131137.0
30673  2022-09-16      BGR                Bulgaria    1251331.0
26085  2022-09-16      BIH  Bosnia and Herzegovina     397822.0
88323  2022-09-16      HUN                 Hungary    2070443.0
145668 2022-09-16      MKD         North Macedonia     342075.0
72992  2022-09-16      GEO                 Georgia    1762206.0
130865 2022-09-16      MNE              Montenegro     278134.0
46907  2022-09-16      HRV                 Croatia    1223641.0
50600  2022-09-16      CZE                 Czechia    4073515.0
128096 2022-09-16      MDA                 Moldova     583183.0
177068 2022-09-16      SVK                Slovakia    2614999.0
169206 2022-09-16      SMR              San Marino      20552.0
161345 2022-09-16      ROU                 Romania    3249108.0
113523 2022-09-16      LTU               Lithuania    1233862.0
75804  2022-09-16      GIB               Gibraltar      20069.0
178027 2022-09-16      SVN                Slovenia    1153964.0
27922  2022-09-16      BRA                  Brazil   34568833.0
108041 2022-09-16      LVA                  Latvia     913371.0
76742  2022-09-16      GRC                  Greece    4838811.0
205781 2022-09-16      USA           United States   95645794.0
39955  2022-09-16      CHL                   Chile    4568495.0
9369   2022-09-16      ARM                 Armenia     439302.0
204811 2022-09-16      GBR          United Kingdom   23585304.0
157707 2022-09-16      POL                  Poland    6238544.0
97728  2022-09-16      ITA                   Italy   22131785.0
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	total_cases_per_100k	total_deaths	total_deaths_per_100k	\
155376	12252.941320	216264.0	641.438447	
30673	18172.451171	37675.0	547.135089	
26085	12162.303042	16108.0	492.457374	
88323	21323.260883	47409.0	488.259988	
145668	16263.496456	9521.0	452.663158	
72992	46892.373030	16900.0	449.709684	
130865	44298.799571	2778.0	442.456029	
46907	30137.938763	16834.0	414.616755	
50600	38755.702495	40951.0	389.610637	
128096	19048.892930	11808.0	385.692532	
177068	48002.578006	20429.0	375.007664	
169206	60902.032834	118.0	349.671072	
161345	16809.881336	66888.0	346.057854	
113523	44277.593427	9304.0	333.877475	
75804	61429.445975	108.0	330.578512	
178027	54447.416970	6802.0	320.938374	
27922	16129.073016	685203.0	319.700964	
108041	48741.220939	5969.0	318.530310	
76742	46324.958486	32894.0	314.914797	
205781	28381.741350	1053389.0	312.580542	
39955	23436.371400	60822.0	312.016754	
9369	15740.096468	8669.0	310.608411	
204811	35054.904026	206150.0	306.401328	
157707	16285.341500	117341.0	306.311578	
97728	37359.320922	176508.0	297.952425	

	population	population_density	gdp_per_capita	extreme_poverty	\
155376	33715472.0	25.129	12236.706	3.5	
30673	6885868.0	65.180	18563.307	1.5	
26085	3270943.0	68.496	11713.895	0.2	
88323	9709786.0	108.043	26777.561	0.5	
145668	2103330.0	82.600	13111.214	5.0	
72992	3757980.0	65.032	9745.079	4.2	
130865	627859.0	46.280	16409.288	1.0	
46907	4060135.0	73.726	22669.797	0.7	
50600	10510750.0	137.176	32605.906	0.0	
128096	3061506.0	123.655	5189.972	0.2	
177068	5447622.0	113.128	30155.152	0.7	
169206	33746.0	556.667	56861.470	0.0	
161345	19328560.0	85.129	23313.199	5.7	
113523	2786651.0	45.135	29524.265	0.7	
75804	32670.0	3457.100	0.000	0.0	
178027	2119410.0	102.619	31400.840	0.0	
27922	214326223.0	25.040	14103.452	3.4	
108041	1873919.0	31.212	25063.846	0.7	
76742	10445365.0	83.479	24574.382	1.5	
205781	336997624.0	35.608	54225.446	1.2	
39955	19493184.0	24.282	22767.037	1.3	
9369	2790974.0	102.931	8787.580	1.8	
204811	67281040.0	272.898	39753.244	0.2	
157707	38307726.0	124.027	27216.445	0.0	
97728	59240330.0	205.859	35220.084	2.0	

	people_fully_vaccinated	mortality
155376	0.0	high

```
30673                  2070947.0      high
26085                        0.0      high
88323                        0.0      high
145668                       0.0      high
72992                        0.0      high
130865                       0.0      high
46907                        0.0      high
50600                  6888750.0      high
128096                       0.0      high
177068                       0.0      high
169206                       0.0      high
161345                       0.0      high
113523                 1878539.0      high
75804                        0.0      high
178027                       0.0      high
27922                172032889.0      high
108041                       0.0      high
76742                  7637278.0      high
205781                       0.0      high
39955                        0.0      high
9369                         0.0      high
204811                       0.0      high
157707                22555576.0      high
```

```
97728                 47964524.0      high
---------------------------------------------------------------------------
-------------------------
```

In [66]:

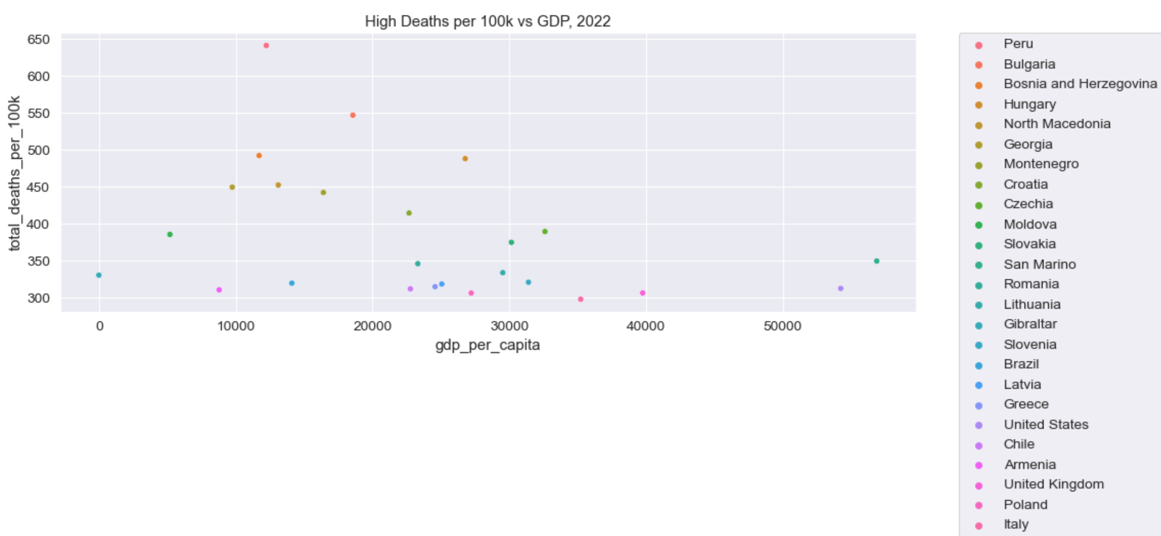
```
# min value in the Top mortality (top deaths) data
print("min of 2020 top deaths/ 100k: "+str(top_df_2020_deaths_per_100k["total
print("max of 2020 top deaths/ 100k: "+str(top_df_2020_deaths_per_100k["total
print("-"*100)
print("min of 2021 top deaths/ 100k: "+str(top_df_2021_deaths_per_100k["total
print("max of 2021 top deaths/ 100k: "+str(top_df_2021_deaths_per_100k["total
print("-"*100)

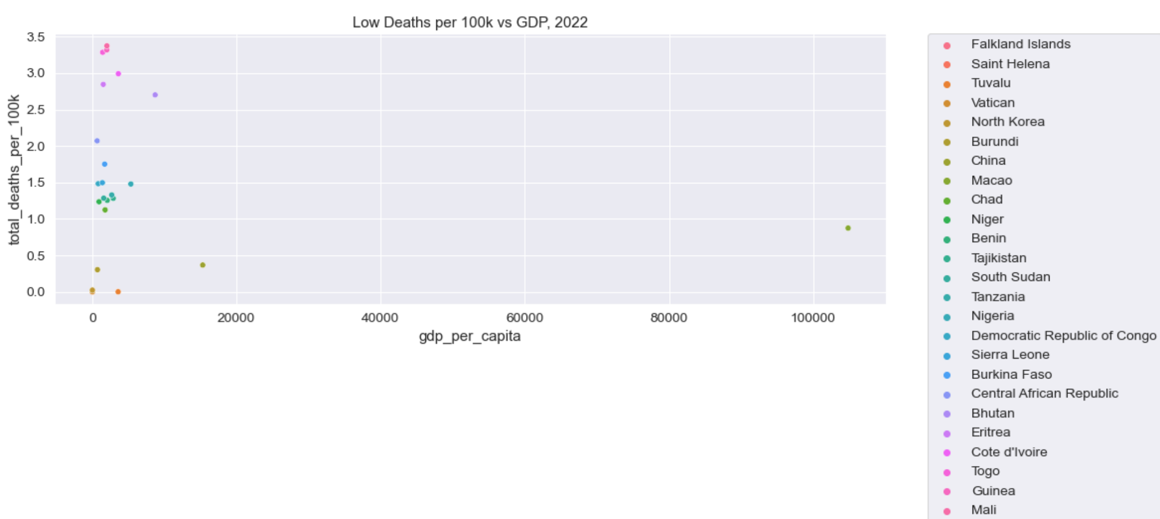
# max value in the bottom mortality (bottom deaths) data
print("max of 2022 lowest deaths/ 100k: "+str(top_df_2022_deaths_per_100k["to
print("min of 2022 lowest deaths/ 100k: "+str(top_df_2020_deaths_per_100k["to
```

```
min of 2020 top deaths/ 100k: 90.58373294263322
max of 2020 top deaths/ 100k: 276.04537169166724
---------------------------------------------------------------------------
-------------------------
min of 2021 top deaths/ 100k: 243.99255215985642
max of 2021 top deaths/ 100k: 601.1779992283662
---------------------------------------------------------------------------
-------------------------
max of 2022 lowest deaths/ 100k: 641.4384470132882
min of 2022 lowest deaths/ 100k: 90.58373294263322
```

In [67]:
```python
print("Top and Bottom Mortality vs GDP per capita")
print()

#Top deaths vs gdp
sns.scatterplot(x="gdp_per_capita",y="total_deaths_per_100k",data=top_df_2022
plt.title("High Deaths per 100k vs GDP, 2022", size = 15)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.show()

#bottom deaths vs gdp
sns.scatterplot(x="gdp_per_capita",y="total_deaths_per_100k",data=bot_df_2022
plt.title("Low Deaths per 100k vs GDP, 2022", size = 15)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.show()
```

```
Top and Bottom Mortality vs GDP per capita
```



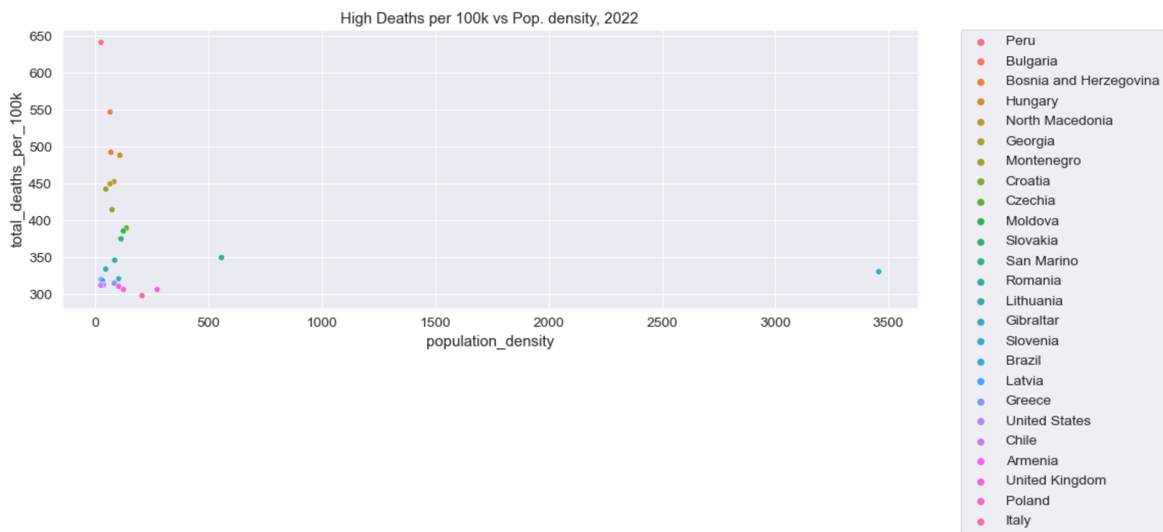


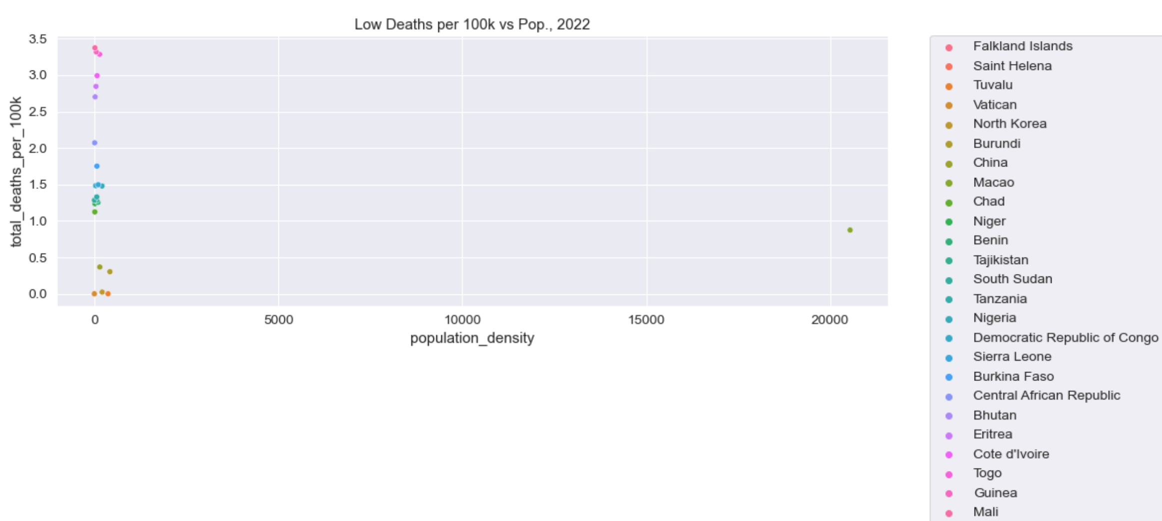
this looks strange, high mortality and gdp does not look related. it appears from the top chart that the top gdp countries also have higer mortality, for the most part these countries look like smaller nations. lets look by population density

In [68]:

```
print("Top and Bottom Mortality vs Population Density")

#Top deaths vs population_density
sns.scatterplot(x="population_density",y="total_deaths_per_100k",data=top_df_
plt.title("High Deaths per 100k vs Pop. density, 2022", size = 15)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.show()

#bottom deaths vs population_density
sns.scatterplot(x="population_density",y="total_deaths_per_100k",data=bot_df_
plt.title("Low Deaths per 100k vs Pop., 2022", size = 15)
plt.legend(bbox_to_anchor=(1.05, 1), loc='upper left', borderaxespad=0)
plt.show()
```

```
Top and Bottom Mortality vs Population Density
```





this looks strange as well, higher mortality and lower density looks negatively related, it's difficult to tell because of the outlier, Macao. it appears from the top chart that the lesser dense countries also have higer mortality, for the most part these countries look like smaller nations.

In [69]:

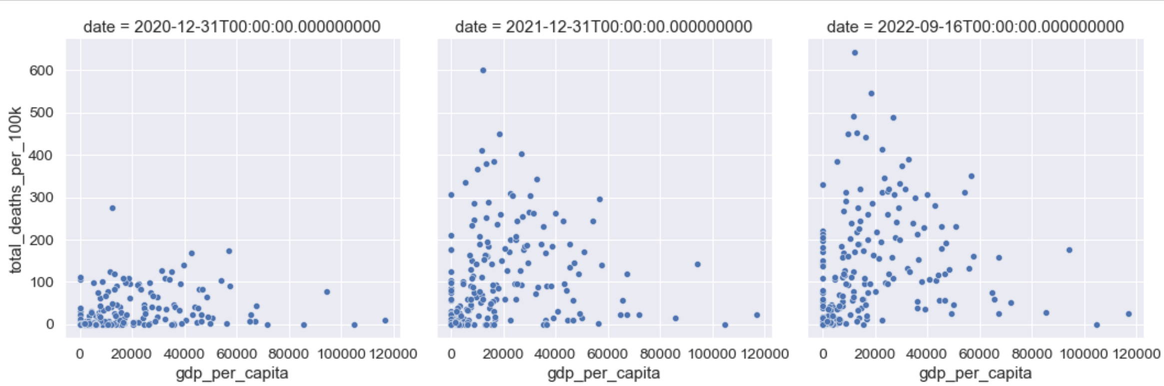
```
# calculate the threshold to use for the "high" and "low" mortality column

# min value in the Top mortality (top deaths) data
print("min 2020 top deaths/ 100k: "+str(top_df_2020_cases_per_100k["total_dea
print("max 2020 top deaths/ 100k: "+str(top_df_2020_cases_per_100k["total_dea
print("-"*100)

# max value in the bottom mortality (bottom deaths) data
print("max 2022 lowest deaths/ 100k: "+str(bot_df_2022_cases_per_100k["total_
print("min 2022 lowest deaths/ 100k: "+str(bot_df_2022_cases_per_100k["total_
```

```
min 2020 top deaths/ 100k: 0.0
max 2020 top deaths/ 100k: 174.83553606353345
----------------------------------------------------------------------------
------------------------
max 2022 lowest deaths/ 100k: 14.832796678091313
min 2022 lowest deaths/ 100k: 0.0
```

I used this to set the group bads for the "Mortality" column. Using the 2020 top 10 records to set the lower limit of "high" mortality and current 2022 bottom 10 records to set the higher limit for the "low" mortality

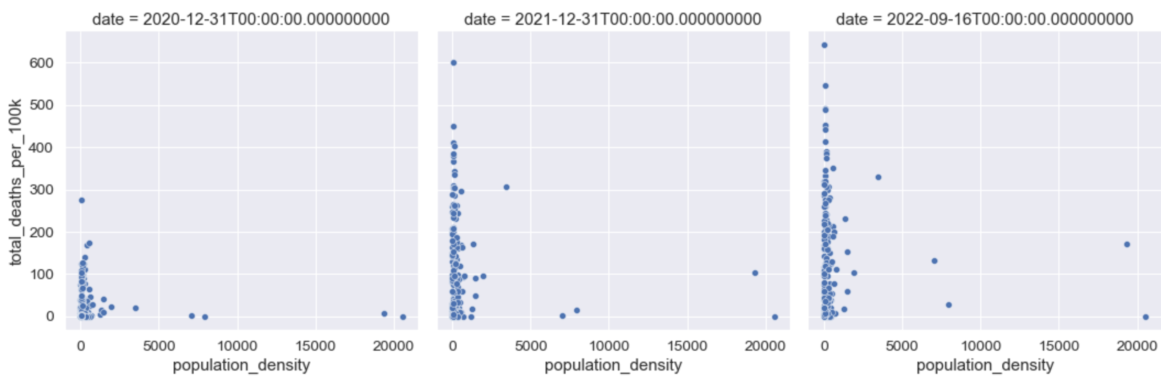
In [70]:

```
#Mortality per 100k and GDP per capita

#High mortality vs gdp
sns.relplot(x="gdp_per_capita",
            y="total_deaths_per_100k",
            data=covid_data_sns,
            kind="scatter",
            col = "date")
plt.show()

#bottom deaths vs gdp
#sns.scatterplot(x="gdp_per_capita",y="total_deaths_per_100k",data=bot_df_202
#plt.show()
```



we can observe from this that there are expected results that over time lower gdp per capita records had higher mortality per 100k of the population. However, there are some interesting results where lower gdp did not have a high mortality. notice the skew to the upper left over time which suggests lower gdp does impact higher mortality

In [71]:
```
#Mortality per 100k and population density

#High mortality vs pop density
sns.relplot(x="population_density",
            y="total_deaths_per_100k",
            data=covid_data_sns,
            kind="scatter",
            col = "date")
plt.show()

#bottom deaths vs gdp
#sns.scatterplot(x="gdp_per_capita",y="total_deaths_per_100k",data=bot_df_202
#plt.show()
```



we can observe here that a higher density in the population does have a more significant impact on mortality

In [72]:
```
covid_temp = covid_data_sns
covid_temp.sort_values("population_density", axis = 0, ascending = False, inp
covid_temp
```

Out[72]:

	date	iso_code	location	total_cases	total_cases_per_100k	total_deaths	total_d
117338	2022-09-16	MAC	Macao	793.0	115.495473	6.0	
116714	2020-12-31	MAC	Macao	46.0	6.699611	0.0	
117079	2021-12-31	MAC	Macao	79.0	11.505854	0.0	
[illegible]	2020-	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	

Regression analysis

Regression analysis

In [73]:
```
# Machine Learning
```

In [74]:
```
# Machine Learning KNN data
```

In [75]:
```
covid_data_sns.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 658 entries, 117338 to 190952
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   date                    658 non-null    datetime64[ns]
 1   iso_code                658 non-null    object
 2   location                658 non-null    object
 3   total_cases             658 non-null    float64
 4   total_cases_per_100k    658 non-null    float64
 5   total_deaths            658 non-null    float64
 6   total_deaths_per_100k   658 non-null    float64
 7   population              658 non-null    float64
 8   population_density      658 non-null    float64
 9   gdp_per_capita          658 non-null    float64
 10  extreme_poverty         658 non-null    float64
 11  people_fully_vaccinated 658 non-null    float64
 12  mortality               658 non-null    object
dtypes: datetime64[ns](1), float64(9), object(3)
memory usage: 72.0+ KB
```

In [76]:
```
date_list = unique(covid_data_sns["date"])
print("we have the expected 3 dates selected")
```

```
2022-09-16 00:00:00 2020-12-31 00:00:00 2021-12-31 00:00:00
we have the expected 3 dates selected
```

In [77]:

```
#create 2 sets of data for the review removing date, iso code, location, as t
#and even fewer value columns in the second set

covid_data_ml = covid_data_sns

covid_data_ml1 = covid_data_ml.drop(["date","iso_code","location"],axis=1)

covid_data_ml2 = covid_data_ml.drop(["date","iso_code","location","total_case

covid_data_ml2
```

Out[77]:

	total_cases_per_100k	total_deaths_per_100k	population	population_density	gdp_per_
117338	115.495473	0.873862	686607.0	20546.766	1048
116714	6.699611	0.000000	686607.0	20546.766	1048
117079	11.505854	0.000000	686607.0	20546.766	1048
128404	2385.106035	8.177506	36686.0	19347.500	
128769	13588.289811	103.581748	36686.0	19347.500	
...	...	...	...	...	
195759	0.000000	0.000000	1849.0	0.000	
131520	1041.430835	22.639801	4417.0	0.000	
163966	129.533679	0.000000	5404.0	0.000	
25158	42335.055793	142.290122	26706.0	0.000	
190952	24691.436414	43.876943	23859912.0	0.000	

658 rows × 8 columns

In [78]:

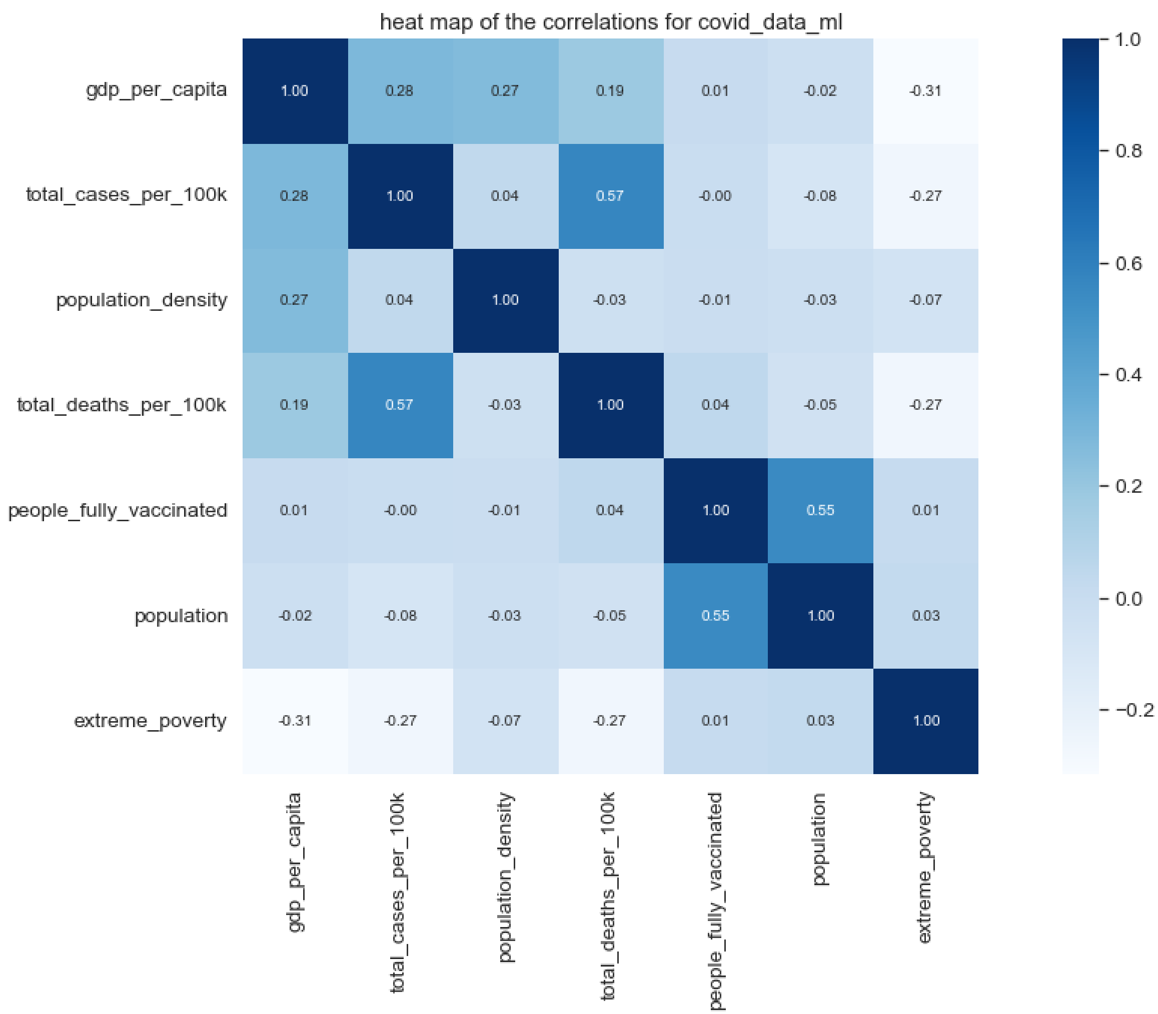
```
covid_data_ml2.corr()
```

Out[78]:

	total_cases_per_100k	total_deaths_per_100k	population	population_de
total_cases_per_100k	1.000000	0.565010	-0.084021	0.03
total_deaths_per_100k	0.565010	1.000000	-0.048313	-0.03
population	-0.084021	-0.048313	1.000000	-0.02
population_density	0.038308	-0.033790	-0.025052	1.00
gdp_per_capita	0.281003	0.187821	-0.022257	0.26
extreme_poverty	-0.265953	-0.265442	0.028340	-0.06
people_fully_vaccinated	-0.002906	0.044485	0.545371	-0.00

In [79]:

```
#heat map of the correlations for covid_data_ml2

Corr_data = covid_data_ml2

#Correlation of gdp
corr = Corr_data.corr()
plt.figure(figsize=(20, 9))

k = 12 #number of variables for heatmap

cols = corr.nlargest(k, 'gdp_per_capita')['gdp_per_capita'].index
cm = np.corrcoef(Corr_data[cols].values.T)
sns.set(font_scale=1.25)
hm = sns.heatmap(cm, cbar=True, annot=True, square=True, fmt='.2f', annot_kws
plt.title("heat map of the correlations for covid_data_ml")
plt.show()
```



Results

(Include the charts and describe them)

Supervised learning with classification

In [80]:

```python
print("training and testing the data")
#from datacamp
print()

#covid_data_ml
#covid_data_ml1
#covid_data_ml2

ml_data = covid_data_ml1

X = ml_data.drop("mortality",axis=1).values #drop target value
y = ml_data["mortality"].values #target observations

#split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_
knn = KNeighborsClassifier(n_neighbors=5)

#fit the classiier to the training data
knn.fit(X_train, y_train)

#print the accuracy
print("The knn score:")
print(knn.score(X_test, y_test))
print()

y_pred_ = knn.predict(X_test)

print("Confusion matrix:")
print(confusion_matrix(y_test, y_pred_))
print()

print("Classification report:")
print(classification_report(y_test, y_pred_))
```

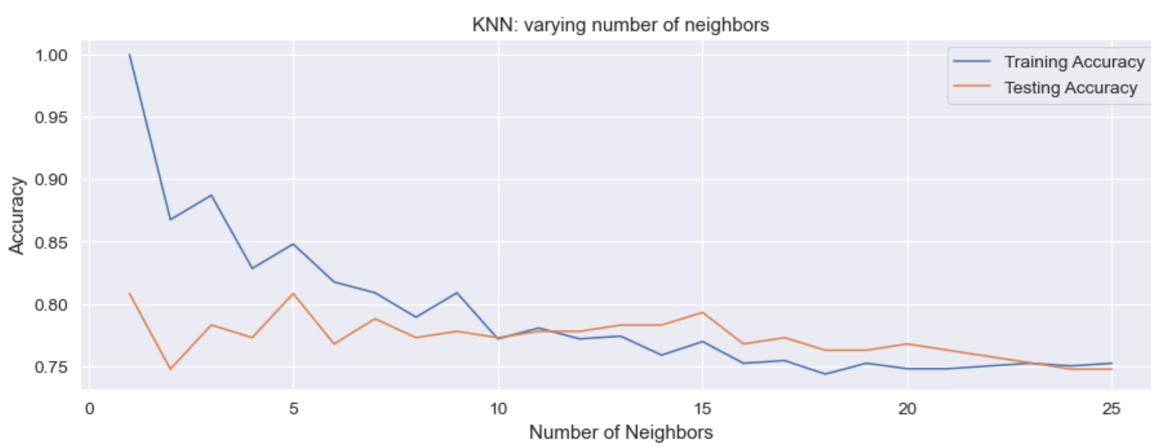
```
training and testing the data

The knn score:
0.8080808080808081

Confusion matrix:
[[127  15]
 [ 23  33]]

Classification report:
              precision    recall  f1-score   support

                   0.85      0.89      0.87       142
        high       0.69      0.59      0.63        56

    accuracy                           0.81       198
   macro avg       0.77      0.74      0.75       198
weighted avg       0.80      0.81      0.80       198
```

The knn score suggest there are tight relationships with the data. However, the "high" mortality classification prediction is not as high suggesting mortality from COVID is not that correlated to the gdp per capita or the population density

In [81]:
```
#model complexity
train_accuracies = {}
test_accuracies = {}
neighbors = np.arange(1,26)
```

In [82]:
```
# Loop through neighbors array
for neighbor in neighbors:
    knn = KNeighborsClassifier(n_neighbors=neighbor)
    knn.fit(X_train, y_train)
    train_accuracies[neighbor]=knn.score(X_train, y_train)
    test_accuracies[neighbor]=knn.score(X_test,y_test)
```

In [83]:
```
# plot training and test values
#plt.figure(figuresize=(8,6))
plt.title("KNN: varying number of neighbors")
plt.plot(neighbors, train_accuracies.values(), label="Training Accuracy")
plt.plot(neighbors, test_accuracies.values(), label="Testing Accuracy")
plt.legend()
plt.xlabel("Number of Neighbors")
plt.ylabel("Accuracy")

plt.show()
```



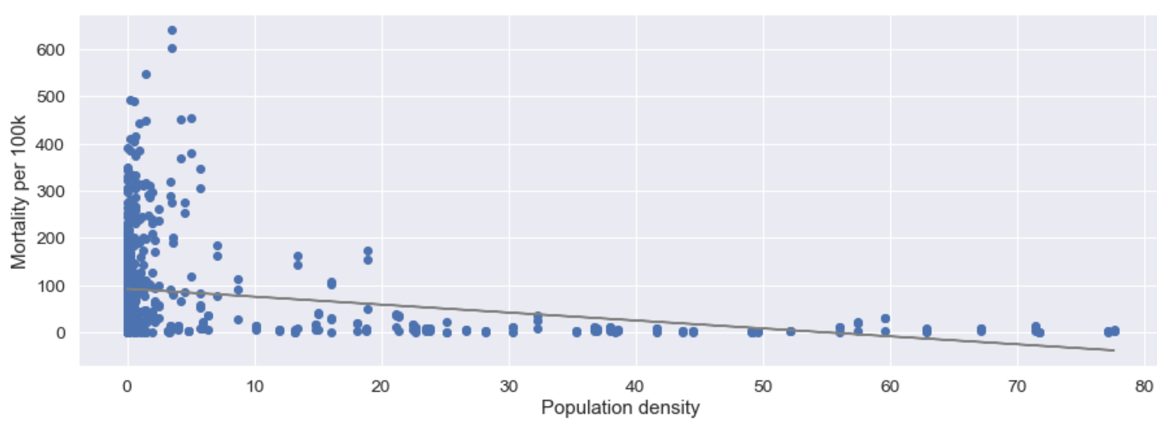
this shows k of 5 is a good choice as this displays the highest testing accuracy and thetraining score

Supervised learning with regression

In [84]:

```
#training and testing the data
#from datacamp

#covid_data_ml
#covid_data_ml1
#covid_data_ml2
#print(ml_data)

ml_data = covid_data_ml1


X = ml_data.drop("total_deaths_per_100k",axis=1).values #drop target value
y = ml_data["total_deaths_per_100k"].values #target observations


# predicting mortality using population density

#predict using pop_density (6)
X_pop_d = X[:,6]
#print(y.shape, X_pop_d.shape) # check shape
# reshape
X_pop_d = X_pop_d.reshape(-1,1)
#print(X_pop_d.shape) #check shape

#regression model
reg = LinearRegression()
reg.fit(X_pop_d,y)
predictions = reg.predict(X_pop_d)
print(predictions[:10])

#plot Total_deaths per 100k vs. population density with regression
plt.scatter(X_pop_d, y)
plt.plot(X_pop_d, predictions, color = "gray")
plt.ylabel("Mortality per 100k")
plt.xlabel("Population density")
plt.show()
```

```
[91.77032418 91.77032418 91.77032418 91.77032418 91.77032418 91.77032418
 91.77032418 91.77032418 91.77032418 91.77032418]
```

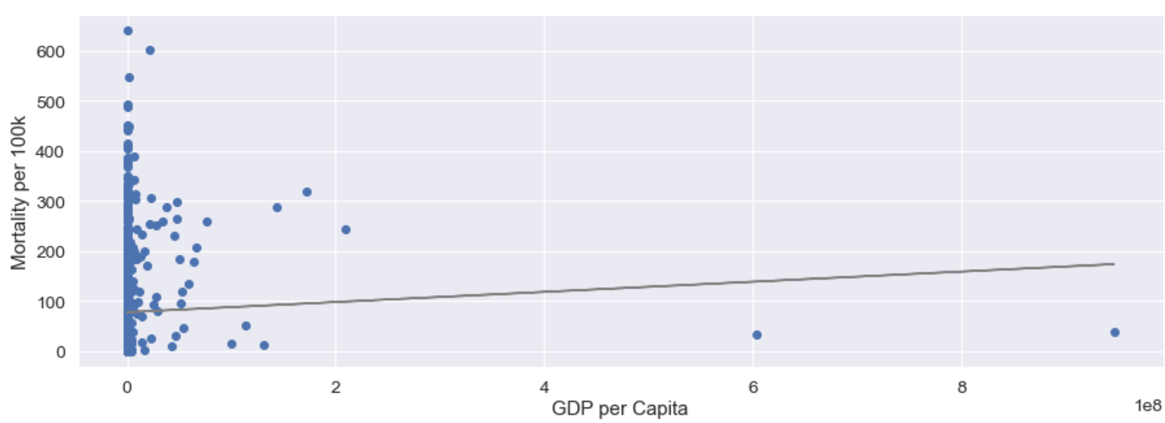


Weak negative correlation. The higher the population density the less likey the mortality from COVID, this is unexpected.

In [85]:

```
# predicting mortality using gdp

#predict using gdp_per_capita (7)
X_gdp_c = X[:,7]

#print(ml_data)

# reshape
X_gdp_c = X_gdp_c.reshape(-1,1)
#print(X_gdp_c.shape) #check shape

#regression model
reg = LinearRegression()
reg.fit(X_gdp_c,y)
predictions = reg.predict(X_gdp_c)
print(predictions[:10])

#plot Total_deaths per 100k vs. population density
plt.scatter(X_gdp_c, y)
plt.plot(X_gdp_c, predictions, color = "gray")
plt.ylabel("Mortality per 100k")
plt.xlabel("GDP per Capita")
plt.show()
```

```
[77.93492175 77.93492175 77.93492175 77.93492175 77.93492175 77.93492175
 77.93492175 78.39156498 77.93492175 77.93492175]
```



Weak positive correlation. The higher the gdp per capita the less likey the mortality from COVID, this is somewhat expected, I would have expected the line to be steeper.

In [86]:

```
#Linear regression using all features

# need to drop mortality
covid_data_sns.drop(["date","iso_code","location","total_cases", "total_death


ml_data_r = covid_data_sns.drop(["date","iso_code","location","total_cases",

ml_data_r



X = ml_data_r.drop("total_deaths_per_100k",axis=1).values #drop target value
y = ml_data_r["total_deaths_per_100k"].values #target observations


#split into training and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.3,random_
knn = KNeighborsClassifier(n_neighbors=5)

#fit the linear regression to the training data
reg_all = LinearRegression()
reg_all.fit(X_train, y_train)


#predict on the test set
y_pred = reg_all.predict(X_test)

r_score = reg_all.score(X_test, y_test)

print("Predictions: {}, Actual Values: {}".format(y_pred[:4], y_test[:4]))
print("There is a large gap between the predictions and test data")
print("The model only explains about %5.2f"%(r_score*100)+"% of mortality lev
```

```
Predictions: [ 43.48915448  46.5803073  101.09051936  36.24860988], Actual
Values: [2.31018829e-02 2.78315855e+00 4.03572231e+02 1.25033429e+01]
There is a large gap between the predictions and test data
The model only explains about 28.32% of mortality level variance
```

Results summary

Per the charts and analysis above, the results are not encoraging based on my inital hypothesis: that higher population density and lower GDP per capita for a country would have a negative impact on COVID mortality (higher deaths). I beleive there may be some outliers as we have seen in the scatter plot data that need to be removed which would potentially provide better results.

```
Overall, the data shows some correlations but fairly weak. the k score l
ooked promising at 81.13 and the Classification report F1 score of 0.81
 was ok to good performance and teh confusion matrix results were good
 (96 true positive and 19 for the false negative while there were 18 fal
se positives compared to 65 true negative.  I think this mat have beed s
kewed by the fairly wide grouping I gave for "high" mortality vs "low".

Given the flatness of the regression line it would make sense to review
 some of the outlier data and rerun maybe with a wider set of data.
```

In [ ]:

Insights

(Point out at least 5 insights in bullet points)

- Being able to use country data better in the machine learning would probably give better insights into the correlation
- Finding data and cleaning data is very challenging
- I really expected there to be a tighter correlation between the data and need more time to review the data for items that could be corrected
- Intersting excercise, seeing what others have put out online; it shows there is a very long way to go to get to an intermediate level
- The amount of information to learn about python is daunting and takes patience

References

HTML Code help: W3 Schools (https://www.w3schools.com/html/html_links.asp)

Our World in Data (OWID): https://ourworldindata.org/coronavirus#explore-the-global-situation (https://ourworldindata.org/coronavirus#explore-the-global-situation)

The World Bank GDP: https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?year_high_desc=false (https://data.worldbank.org/indicator/NY.GDP.MKTP.CD?year_high_desc=false)

Python:

formatting numbers: https://pythonguides.com/python-format-number-with-commas/#:~:text=Python%20format%20number%20with%20commas%20Let%20us%20see,comma
(https://pythonguides.com/python-format-number-with-commas/#:~:text=Python%20format%20number%20with%20commas%20Let%20us%20see,comma

formatting dates: https://stackabuse.com/how-to-format-dates-in-python/ (https://stackabuse.com/how-to-format-dates-in-python/)

```
In [ ]:
```

```
In [ ]:
```