Project 1

Are global warming and climate change supported by data? How did land temperatures change following major innovations in transportation? How is this rate different in different places around the world?

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ECO225

Introduction

This research project aims to use records of the average land temperatures around the world categorized globally, by country, and by city to investigate whether climate change and global warming are supported by data. There will also be a focus on warming effect of different milestones in the development of transportation technology. Essentially, this research will look at how the rate of the rise of land temperatures has generally changed over since 1750 and how it changed immediately following the widespread use of new transportation technologies. The key is to examine how this rate is different in the period preceding the adoption of a certain new mode of transportation and immediately after it. The two primary events that will be isolated are the widespread use of the car (it was patented in 1886) and, subsequently, the aircraft (began to be used commercially in 1914).

The data that will be used is sourced from Berkeley Earth, an agency that has made several archives of environmental data avialable. The data contains monthly land temperature recordings that begin in 1750. After the year 1850, the data started included maximum and minimum values for each month. Some subsets of the data contain the monthly land temperature values categorized according to the country, city, major city, and US state. It's important to consider that this data begins around the same time that the Industrial Revolution is thought to have started. This is generally considered as the time that industrial pollution began to have seriously adverse effects on the climate and the temperature of the Earth. The outcome that is being considered in this research is the change in the average land temperature and the two main independent variables are pollution generally (which is essentially represented by time), the adoption of new transportation technologies, and the distance of each major city from the equator.

Raw Data

In [1]:
```
data_url = "https://www.kaggle.com/berkeleyearth/climate-change-earth-surfa
```

In [75]:
```
import matplotlib.colors as mplc
import matplotlib.patches as patches
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import statsmodels.formula.api as sm #for linear regression: sm.ols
import geopandas as gpd

from shapely.geometry import Point

from pandas_datareader import DataReader

%matplotlib inline
#activate plot theme
import qeds
qeds.themes.mpl_style();
! pip install qeds fiona geopandas xgboost gensim folium pyLDAvis descartes
```

```
Requirement already satisfied: qeds in /Users/Faisal/opt/anaconda3/lib/py
thon3.8/site-packages (0.7.0)
Requirement already satisfied: fiona in /Users/Faisal/opt/anaconda3/lib/p
ython3.8/site-packages (1.8.18)
Requirement already satisfied: geopandas in /Users/Faisal/opt/anaconda3/l
ib/python3.8/site-packages (0.9.0)
Requirement already satisfied: xgboost in /Users/Faisal/opt/anaconda3/li
b/python3.8/site-packages (1.3.3)
Requirement already satisfied: gensim in /Users/Faisal/opt/anaconda3/lib/
python3.8/site-packages (3.8.3)
Requirement already satisfied: folium in /Users/Faisal/opt/anaconda3/lib/
python3.8/site-packages (0.12.1)
Requirement already satisfied: pyLDAvis in /Users/Faisal/opt/anaconda3/li
b/python3.8/site-packages (3.2.2)
Requirement already satisfied: descartes in /Users/Faisal/opt/anaconda3/l
ib/python3.8/site-packages (1.1.0)
Requirement already satisfied: requests in /Users/Faisal/opt/anaconda3/li
b/python3.8/site-packages (from qeds) (2.24.0)
Requirement already satisfied: statsmodels in /Users/Faisal/opt/anaconda
```

In [3]:
```
#Reading the first dataset, Global average land temperatures.
glob_land_temp = pd.read_csv('~/Desktop/School/UofT/Third Year/ECO225/ECO22
```

In [4]:
```
#Turning the first dataset into a dataframe. The data is cleaned by droppin
glob_df = pd.DataFrame(glob_land_temp)
glob_df = glob_df.drop(['LandAverageTemperatureUncertainty', 'LandMaxTemper
                        'LandMinTemperature', 'LandAndOceanAverageTemperatu
                        'LandMinTemperatureUncertainty','LandAndOceanAverag
glob_df
```

Out[4]:

	dt	LandAverageTemperature
0	1750-01-01	3.034
1	1750-02-01	3.083
2	1750-03-01	5.626
3	1750-04-01	8.490
4	1750-05-01	11.573
...	...	...
3187	2015-08-01	14.755
3188	2015-09-01	12.999
3189	2015-10-01	10.801
3190	2015-11-01	7.433
3191	2015-12-01	5.518

3192 rows × 2 columns

In [5]:
```
#Creating a new column in the dataframe glob_df that finds the percent chan
#in the average global land temperature, month over month.
glob_df['percent change in temp'] = glob_df['LandAverageTemperature'].pct_c
glob_df['percent change in temp'] = glob_df['percent change in temp'] * 100
glob_df['percent change in temp'] = glob_df['percent change in temp'].round
glob_df
```

Out[5]:

	dt	LandAverageTemperature	percent change in temp
0	1750-01-01	3.034	NaN
1	1750-02-01	3.083	1.62
2	1750-03-01	5.626	82.48
3	1750-04-01	8.490	50.91
4	1750-05-01	11.573	36.31
...	...	...	...
3187	2015-08-01	14.755	-1.97
3188	2015-09-01	12.999	-11.90
3189	2015-10-01	10.801	-16.91
3190	2015-11-01	7.433	-31.18
3191	2015-12-01	5.518	-25.76

3192 rows × 3 columns

The table above represents the raw data for the average global land temperature, per month, since 1750. This is going to be this research's main source of information for the global average land temperature.

In [6]:
```
#Reading the second dataset, monthly average land temperatures by major cit
#The data is cleaned and irrelevant columns are dropped.
city_land_temp = pd.read_csv('~/Desktop/School/Uoft/Third Year/ECO225/ECO22
city_df = pd.DataFrame(city_land_temp)
city_df = city_land_temp.drop(['AverageTemperatureUncertainty', 'Longitude'
city_df.set_index('City')
```

Out[6]:

	dt	AverageTemperature	Country	Latitude
City				
Abidjan	1849-01-01	26.704	Côte D'Ivoire	5.63N
Abidjan	1849-02-01	27.434	Côte D'Ivoire	5.63N
Abidjan	1849-03-01	28.101	Côte D'Ivoire	5.63N
Abidjan	1849-04-01	26.140	Côte D'Ivoire	5.63N
Abidjan	1849-05-01	25.427	Côte D'Ivoire	5.63N
...	...	...	...	...
Xian	2013-05-01	18.979	China	34.56N
Xian	2013-06-01	23.522	China	34.56N
Xian	2013-07-01	25.251	China	34.56N
Xian	2013-08-01	24.528	China	34.56N
Xian	2013-09-01	NaN	China	34.56N

239177 rows × 4 columns

The above table includes the land temperature, per month, for each major city around the world. This data will help show differences in the rate of the change of land temperatures around the world. It will be used to identify any relationship between a city's distance from the equator and the change in its land temperature.

In [7]:
```
#Create a new column in city_df that measures the percent change in tempera
#Find the distance of each city from the equator by multiplying the degrees
city_df['percent change in temp'] = city_df['AverageTemperature'].pct_chang
city_df['percent change in temp'] = city_df['percent change in temp'] * 100
city_df['percent change in temp'] = city_df['percent change in temp'].round
city_df['dist from equator'] = city_df['Latitude']
city_df['dist from equator'] = city_df['dist from equator'][:-1]
city_df['dist from equator'] = city_df['dist from equator'].replace({'N': '
city_df['dist from equator'] = pd.to_numeric(city_df['dist from equator'])
city_df.set_index('City')
#for row in city_df:
  #  if city_df['percent change in temp'][row] > 5000 or city_df[
    #    city_df.drop(row)
```

Out[7]:

	dt	AverageTemperature	Country	Latitude	percent change in temp	dist from equator
City						
Abidjan	1849-01-01	26.704	Côte D'Ivoire	5.63N	NaN	625.18335
Abidjan	1849-02-01	27.434	Côte D'Ivoire	5.63N	2.73	625.18335
Abidjan	1849-03-01	28.101	Côte D'Ivoire	5.63N	2.43	625.18335
Abidjan	1849-04-01	26.140	Côte D'Ivoire	5.63N	-6.98	625.18335
Abidjan	1849-05-01	25.427	Côte D'Ivoire	5.63N	-2.73	625.18335
...	...	...	...	...	...	...
Xian	2013-05-01	18.979	China	34.56N	51.07	3837.71520
Xian	2013-06-01	23.522	China	34.56N	23.94	3837.71520
Xian	2013-07-01	25.251	China	34.56N	7.35	3837.71520
Xian	2013-08-01	24.528	China	34.56N	-2.86	3837.71520
Xian	2013-09-01	NaN	China	34.56N	0.00	NaN

239177 rows × 6 columns

Summary Statistics

In [8]:
```
glob_df.describe().round(2)
```

Out[8]:

	LandAverageTemperature	percent change in temp
count	3180.00	3191.00
mean	8.37	7.06
std	4.38	113.31
min	-2.08	-3439.81
25%	4.31	-23.83
50%	8.61	-1.49
75%	12.55	31.42
max	19.02	1568.39

The table above includes a summary statistic of the dataframe glob_df. It computes different statistical values that may be important to the research.

In [9]:
```
city_df.describe().round(2)
```

Out[9]:

	AverageTemperature	percent change in temp	dist from equator
count	228175.00	239176.00	239176.00
mean	18.13	NaN	3126.13
std	10.02	NaN	1559.17
min	-26.77	-inf	88.84
25%	12.71	-10.58	2052.11
50%	20.43	-0.02	3302.48
75%	25.92	9.70	4195.28
max	38.28	inf	6692.68

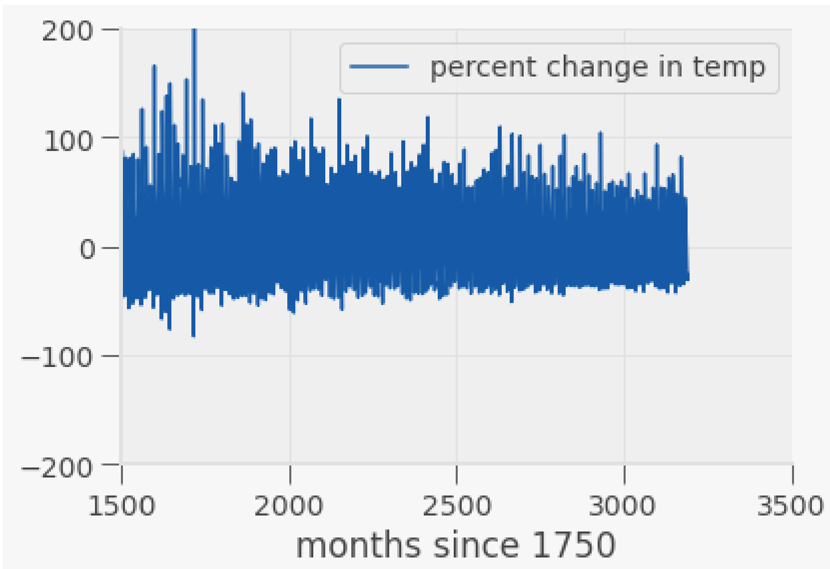
The table above includes a summary statistic of the dataframe city_df. It computes different statistical values that may be important to the research.

Visual Representations

In [10]:
```
# Create a plot, from the dataframe glob_df, that has y as the percent chan
# Some early values are ommitted due to the high uncertaunty around them an
#January 1750 so, January 1875.
print('Percent Change of global land temperatures per month since 1750')
glob_df.plot.line(y= 'percent change in temp', ylim = [-200,200], xlim=[150
```

```
Percent Change of global land temperatures per month since 1750
```

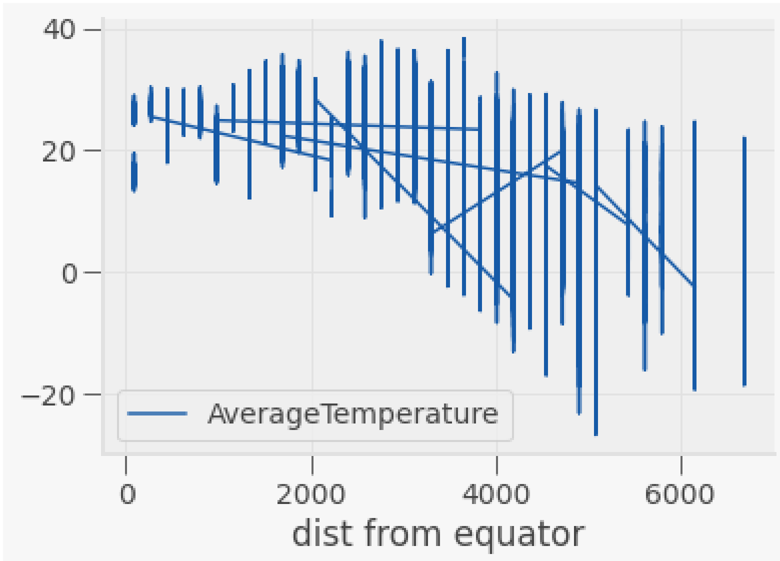
Out[10]:
```
<AxesSubplot:xlabel='months since 1750'>
```



In this graph, although an upwards trend in the avergae global land temperature is not clear, there is clearly much less variance in the later points. With additional formatting, this graph may exhibit some interesting relationships that may, perhaps, be relevant to the research.

In [11]:
```
# Create a plot, from the dataframe glob_df, that has y as the p Average la
#from the equator in kilometres.
city_df.plot(x='dist from equator', y='AverageTemperature')
```

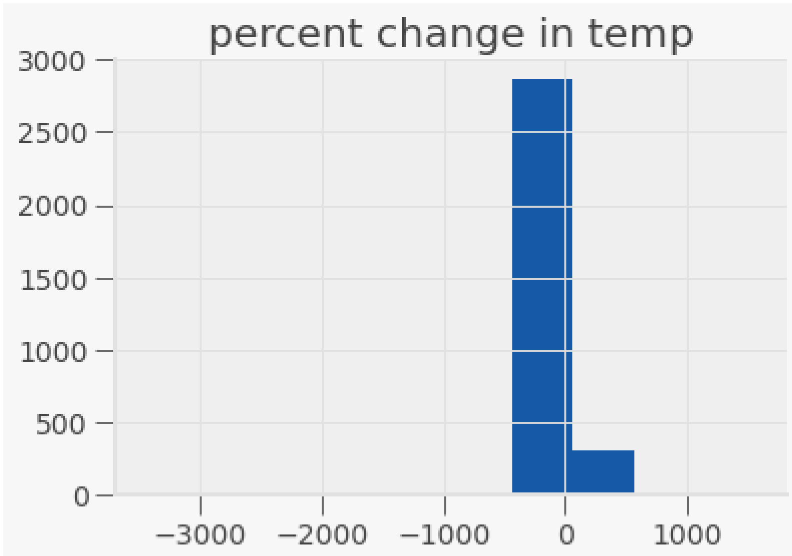
Out[11]: <AxesSubplot:xlabel='dist from equator'>



Although this plot is a bit difficult to understand at first, it actually provides some useful information. This graoh gives some sort of an indication that land temperatures vary greatly the farther away a city is from the equator. This would make sense since the closer to the Earth's pole a location is, the more likely it is to be affected by climate change. This could also be used to pursue the question of if seasons are getting harsher due to global warming.

In [12]:
```
#Create histogram using dataframe glob_df that plots the percent change in
#This histogram has a small number of bins so it is easier to read given th
#somewhat odd.
glob_df.hist(column='percent change in temp', bins=10)
```

Out[12]:
```
array([[<AxesSubplot:title={'center':'percent change in temp'}>]],
      dtype=object)
```



This histogram shows that there are far more observation with a negative percent change in tempereature (month over month) than there are positive ones. Again, this visualization would require further investigation to draw out the relationships present in it.

Below is what is to come in the future

The role that transportation technologies have had in global warming

Confounding variables

As is the case with any research, there is always the possibility that there are open backdoor paths or underlying variables that could lead to misleading interpretations of data. This research could face this issue and, as such, this section will identify two possible confounding variables and demonstrate their summary statistics.

1. Governmental Policy

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Project 2

Are global warming and climate change supported by data? What is the relationship between Co2 emissions and the global land temperature? How is the rate of warming different in different places around the world?

Faisal Alkhalili

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ECO225

Introduction

This research project aims to use records of the average land temperatures around the world categorized globally, by country, and by city to investigate whether climate change and global warming are supported by data. Additional data that will be used is Co2 emissions data. There will also be a focus on the warming effect of Co2 emissions which translate to pollution. Essentially, this research will look at how the rate of the rise of land temperatures has generally changed over since 1750 and if these changes correspond to changes in the emission of Co2. Also, this report will examine if the rate of warming is different in different cities as well as if the oceans are warming faster than land.

The data that will be used is sourced from Berkeley Earth, an agency that has made several archives of environmental data avialable. The data contains monthly land temperature recordings that begin in 1750. After the year 1850, the data started included maximum and minimum values for each month. Some subsets of the data contain the monthly land temperature values categorized according to the country, city, major city, and US state. It's important to consider that this data begins around the same time that the Industrial Revolution is thought to have started. This is generally considered as the time that industrial pollution began to have seriously adverse effects on the climate and the temperature of the Earth. The additional data, Co2 emissions, is sourced from World Bank. This data will corespond to the level of pollution around the world. The dataset includes Co2 emissions categorized by country including a subset that contains cumulative global Co2 emissions. The outcome that is being considered in this research is the change in the average land temperature and the two main independent variables are pollution generally (which is essentially represented by Co2 emissions) and location.

Raw Data

In [13]:
```
data_url = "https://www.kaggle.com/berkeleyearth/climate-change-earth-surfa
```

In [74]:
```
import matplotlib.colors as mplc
import matplotlib.patches as patches
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import statsmodels.formula.api as sm #for linear regression: sm.ols
import geopandas as gpd

from shapely.geometry import Point

from pandas_datareader import DataReader

%matplotlib inline
#activate plot theme
import qeds
qeds.themes.mpl_style();
! pip install qeds fiona geopandas xgboost gensim folium pyLDAvis descartes
! pip install bokeh
from bokeh.io import output_notebook
from bokeh.plotting import figure, ColumnDataSource
from bokeh.io import output_notebook, show, output_file
from bokeh.plotting import figure
from bokeh.models import GeoJSONDataSource, LinearColorMapper, ColorBar, Ho
from bokeh.palettes import brewer
output_notebook()
import json
from bokeh.palettes import OrRd
```

```
conda3/lib/python3.8/site-packages (from matplotlib->qeds) (1.3.0)
Requirement already satisfied: cycler>=0.10 in /Users/Faisal/opt/anaconda
3/lib/python3.8/site-packages (from matplotlib->qeds) (0.10.0)
Requirement already satisfied: pyparsing!=2.0.4,!=2.1.2,!=2.1.6,>=2.0.3 i
n /Users/Faisal/opt/anaconda3/lib/python3.8/site-packages (from matplotli
b->qeds) (2.4.7)

Requirement already satisfied: pillow>=6.2.0 in /Users/Faisal/opt/anacond
a3/lib/python3.8/site-packages (from matplotlib->qeds) (8.0.1)
Requirement already satisfied: python-dateutil>=2.1 in /Users/Faisal/opt/
anaconda3/lib/python3.8/site-packages (from matplotlib->qeds) (2.8.1)
Requirement already satisfied: sympy in /Users/Faisal/opt/anaconda3/lib/p
ython3.8/site-packages (from quantecon->qeds) (1.6.2)
Requirement already satisfied: numba>=0.38 in /Users/Faisal/opt/anaconda
3/lib/python3.8/site-packages (from quantecon->qeds) (0.51.2)
Requirement already satisfied: retrying>=1.3.3 in /Users/Faisal/opt/anaco
nda3/lib/python3.8/site-packages (from plotly->qeds) (1.3.3)
Requirement already satisfied: lxml in /Users/Faisal/opt/anaconda3/lib/py
thon3.8/site-packages (from pandas-datareader->qeds) (4.6.1)
Requirement already satisfied: urllib3!=1.25.0,!=1.25.1,<1.26,>=1.21.1 in
/Users/Faisal/opt/anaconda3/lib/python3.8/site-packages (from requests->q
```

In [15]:
```
#Reading the first dataset, Global average land temperatures.
glob_land_temp = pd.read_csv('~/Desktop/School/UofT/Third Year/ECO225/ECO22
```

In [16]:
```
#Turning the first dataset into a dataframe. The data is cleaned by droppin
glob_df = pd.DataFrame(glob_land_temp)
glob_df = glob_df.drop(['LandAverageTemperatureUncertainty', 'LandMaxTemper
                        'LandMinTemperature', 'LandAndOceanAverageTemperatu
                        'LandMinTemperatureUncertainty','LandAndOceanAverag
glob_df
```

Out[16]:

	dt	LandAverageTemperature
0	1750-01-01	3.034
1	1750-02-01	3.083
2	1750-03-01	5.626
3	1750-04-01	8.490
4	1750-05-01	11.573
...	...	...
3187	2015-08-01	14.755
3188	2015-09-01	12.999
3189	2015-10-01	10.801
3190	2015-11-01	7.433
3191	2015-12-01	5.518

3192 rows × 2 columns

The table above represents the raw data for the average global land temperature, per month, since 1750. This is going to be this research's main source of information for the global average land temperature.

In [17]:
```
#Creating a new column in the dataframe glob_df that finds the percent chan
#in the average global land temperature, month over month.
glob_df['percent change in temp'] = glob_df['LandAverageTemperature'].pct_c
glob_df['percent change in temp'] = glob_df['percent change in temp'] * 100
glob_df['percent change in temp'] = glob_df['percent change in temp'].round
#Changing the average temperature from monthly intervals to yearly interval
glob_df['dt'] = pd.to_datetime(glob_df['dt'])
glob_df = glob_df.set_index('dt')
glob_df.resample('YS').mean()
glob_df.rename(columns={'LandAverageTemperature': 'Land Average Temperature
```

In [18]:
```
#Creating a new dataframe that contains the global co2 emissions for each c
#labeled "World" with the global emissions data
co2 = pd.read_csv('~/Desktop/School/Uoft/Third Year/ECO225/ECO225 Project 1
co2_df = pd.DataFrame(co2)
co2_df['Year'] = pd.to_datetime(co2_df['Year'], format='%Y')
co2_df

#Creating another dataframe that takes global Co2 emissions and is merged w
world_co2_df = co2_df[co2_df["Entity"] == "World"]
temp_co2 = glob_df.merge(world_co2_df,right_on='Year', left_on='dt', how='r
temp_co2
```

Out[18]:

	Land Average Temperature (°C)	percent change in temp	Entity	Code	Year	Annual CO_2 emissions (tonnes)
0	2.495	-9.99	World	OWID_WRL	1751-01-01	9.350528e+06
1	0.348	-96.74	World	OWID_WRL	1752-01-01	9.354192e+06
2	2.039	-59.91	World	OWID_WRL	1753-01-01	9.354192e+06
3	1.574	181.57	World	OWID_WRL	1754-01-01	9.357856e+06
4	1.067	-76.74	World	OWID_WRL	1755-01-01	9.361520e+06
...	...	...	...	...	...	...
262	3.685	-10.17	World	OWID_WRL	2013-01-01	3.520789e+10
263	3.732	-21.00	World	OWID_WRL	2014-01-01	3.550583e+10
264	3.881	-19.98	World	OWID_WRL	2015-01-01	3.546275e+10
265	NaN	NaN	World	OWID_WRL	2016-01-01	3.567510e+10
266	NaN	NaN	World	OWID_WRL	2017-01-01	3.615326e+10

267 rows × 6 columns

In [19]:
```
#Reading the second dataset, monthly average land temperatures by major cit
#The data is cleaned and irrelevant columns are dropped.
city_land_temp = pd.read_csv('~/Desktop/School/Uoft/Third Year/ECO225/ECO22
city_df = pd.DataFrame(city_land_temp)
city_df = city_land_temp.drop(['AverageTemperatureUncertainty', 'Longitude'
city_df.rename(columns={'AverageTemperature': 'City Average Temperature (˚C
city_df.set_index('City')
```

Out[19]:

	dt	City Average Temperature (˚C)	Country	Latitude
City				
Abidjan	1849-01-01	26.704	Côte D'Ivoire	5.63N
Abidjan	1849-02-01	27.434	Côte D'Ivoire	5.63N
Abidjan	1849-03-01	28.101	Côte D'Ivoire	5.63N
Abidjan	1849-04-01	26.140	Côte D'Ivoire	5.63N
Abidjan	1849-05-01	25.427	Côte D'Ivoire	5.63N
...	...	...	...	...
Xian	2013-05-01	18.979	China	34.56N
Xian	2013-06-01	23.522	China	34.56N
Xian	2013-07-01	25.251	China	34.56N
Xian	2013-08-01	24.528	China	34.56N
Xian	2013-09-01	NaN	China	34.56N

239177 rows × 4 columns

The above table includes the land temperature, per month, for each major city around the world. This data will help show differences in the rate of the change of land temperatures around the world. It will be used to identify any relationship between a city's distance from the equator and the change in its land temperature.

In [20]:
```
#Create a new column in city_df that measures the percent change in tempera
city_df['percent change in temp'] = city_df['City Average Temperature (˚C)'
city_df['percent change in temp'] = city_df['percent change in temp'] * 100
city_df['percent change in temp'] = city_df['percent change in temp'].round
#Find the distance of each city from the equator by multiplying the degrees
city_df['dist from equator (km)'] = city_df['Latitude']
city_df['dist from equator (km)'] = city_df['dist from equator (km)'][:-1]
city_df['dist from equator (km)'] = city_df['dist from equator (km)'].repla
city_df['dist from equator (km)'] = pd.to_numeric(city_df['dist from equato
city_df.set_index('City')
```

Out[20]:

City	dt	City Average Temperature (˚C)	Country	Latitude	percent change in temp	dist from equator (km)
Abidjan	1849-01-01	26.704	Côte D'Ivoire	5.63N	NaN	625.18335
Abidjan	1849-02-01	27.434	Côte D'Ivoire	5.63N	2.73	625.18335
Abidjan	1849-03-01	28.101	Côte D'Ivoire	5.63N	2.43	625.18335
Abidjan	1849-04-01	26.140	Côte D'Ivoire	5.63N	-6.98	625.18335
Abidjan	1849-05-01	25.427	Côte D'Ivoire	5.63N	-2.73	625.18335
...	...	...	...	...	...	...
Xian	2013-05-01	18.979	China	34.56N	51.07	3837.71520
Xian	2013-06-01	23.522	China	34.56N	23.94	3837.71520
Xian	2013-07-01	25.251	China	34.56N	7.35	3837.71520
Xian	2013-08-01	24.528	China	34.56N	-2.86	3837.71520
Xian	2013-09-01	NaN	China	34.56N	0.00	NaN

239177 rows × 6 columns

The above table includes additional information about the average land temperature for each major city. It adds the percent change in the temperature month over month as well as each city's distance from the equator in km.

Summary Statistics

In [21]:
```
glob_df.describe().round(2)
```

Out[21]:

	Land Average Temperature (℃)	percent change in temp
count	3180.00	3191.00
mean	8.37	7.06
std	4.38	113.31
min	-2.08	-3439.81
25%	4.31	-23.83
50%	8.61	-1.49
75%	12.55	31.42
max	19.02	1568.39

The table above includes a summary statistic of the dataframe glob_df. It computes different statistical values that may be important to the research.

In [22]:
```
city_df.describe().round(2)
```

Out[22]:

	City Average Temperature (℃)	percent change in temp	dist from equator (km)
count	228175.00	239176.00	239176.00
mean	18.13	NaN	3126.13
std	10.02	NaN	1559.17
min	-26.77	-inf	88.84
25%	12.71	-10.58	2052.11
50%	20.43	-0.02	3302.48
75%	25.92	9.70	4195.28
max	38.28	inf	6692.68

The table above includes a summary statistic of the dataframe city_df. It computes different statistical values that may be important to the research.

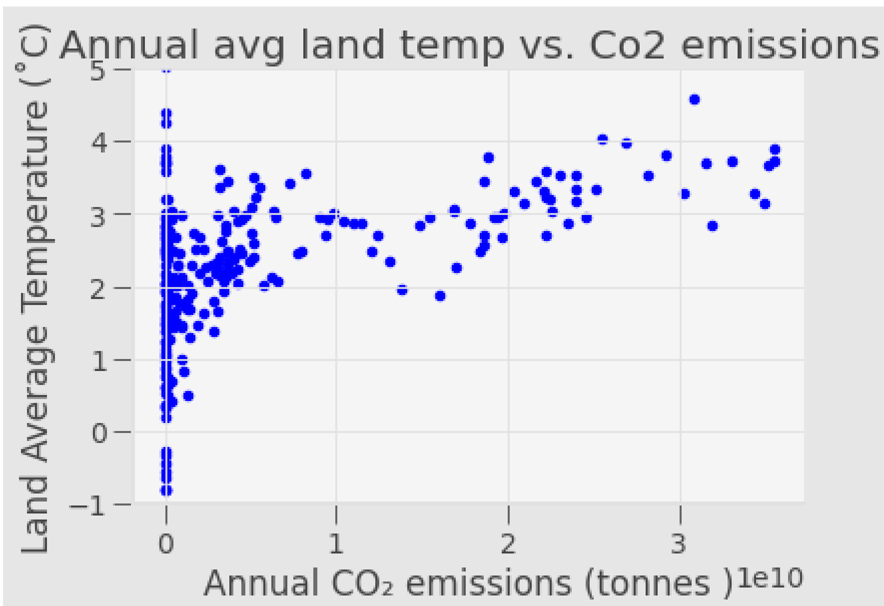
Visual Representations

In [23]:
```
# Create a plot, from the dataframe glob_df, that has y as the percent chan
# Some early values are ommitted due to the high uncertaunty around them an
#January 1750 so, January 1875.

fig, ax = plt.subplots()
temp_co2.plot(
    kind = 'scatter', x='Annual CO₂ emissions (tonnes )', y= 'Land Average
    legend = False, ax=ax, ylim=[-1, 5]
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Annual avg land temp vs. Co2 emissions")
```

Out[23]:
```
Text(0.5, 1.0, 'Annual avg land temp vs. Co2 emissions')
```



This scatter plot demonstrates the relationship between the average temperature of the Earth compared to Co2 emissions. Although there are many points that lie close to 0 (which is likely due to some countries not reporting their emissions until recently), the positive relationship is clear! When global Co2 emissions are higher, a higher global land temperature is observed.

In [24]:
```
# Create a boxplot, from the dataframe city_df, that has the p Average land
#from the equator in kilometres.
city_df.boxplot('City Average Temperature (˚C)', by='dist from equator (km)
```

Out[24]:
```
<AxesSubplot:title={'center':'City Average Temperature (˚C)'}, xlabel='di
st from equator (km)'>
```

This boxplot demonstrates that the interquartile range lies closer to the maximum value than the minimum. This shows that, coupled with the graph titled "Diff in city and global temp vs dist from equator", there is more variance in the temperatures of cities further away from the equator. This is shown by the difference in the maximum and minimum values and the interquartile ranges.

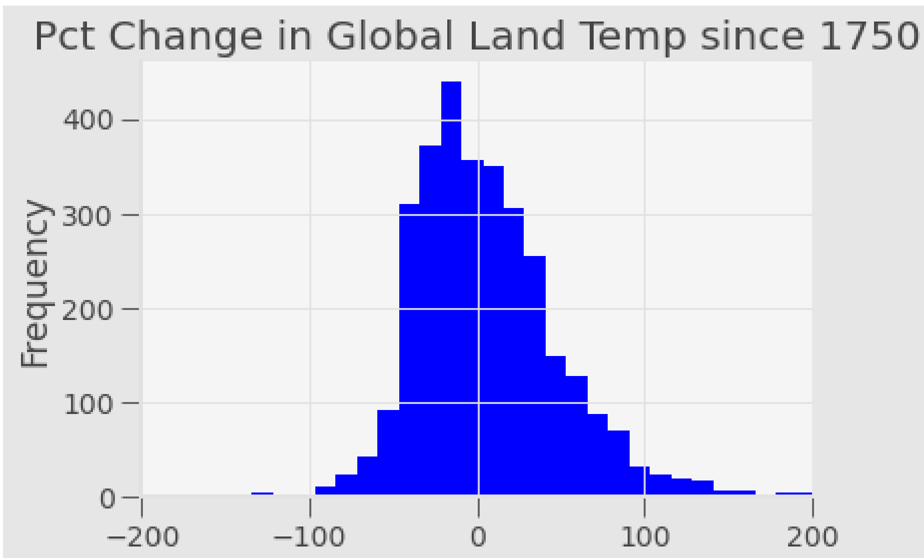
Although it is not easy to read the ticks on the x-axis, it is still clear what message the graph is trying to send and that does not take away from its values.

In [25]:
```
#Create histogram using dataframe glob_df that plots the percent change in

fig, ax = plt.subplots()
glob_df.plot(
    kind = 'hist', y='percent change in temp', color='b',
    bins = 400, legend = False, density = False, ax=ax, xlim=(-200,200)
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Pct Change in Global Land Temp since 1750")
```

Out[25]:
```
Text(0.5, 1.0, 'Pct Change in Global Land Temp since 1750')
```



This histogram shows that there are more observation with a negative percent change in tempereature (month over month) than there are positive ones. This means that there are more months where the average global land temperature went down than months where it went up. However, it seems as if the months that had a negative percent change had values that were closer to zero compared to months where the percent change was positive.

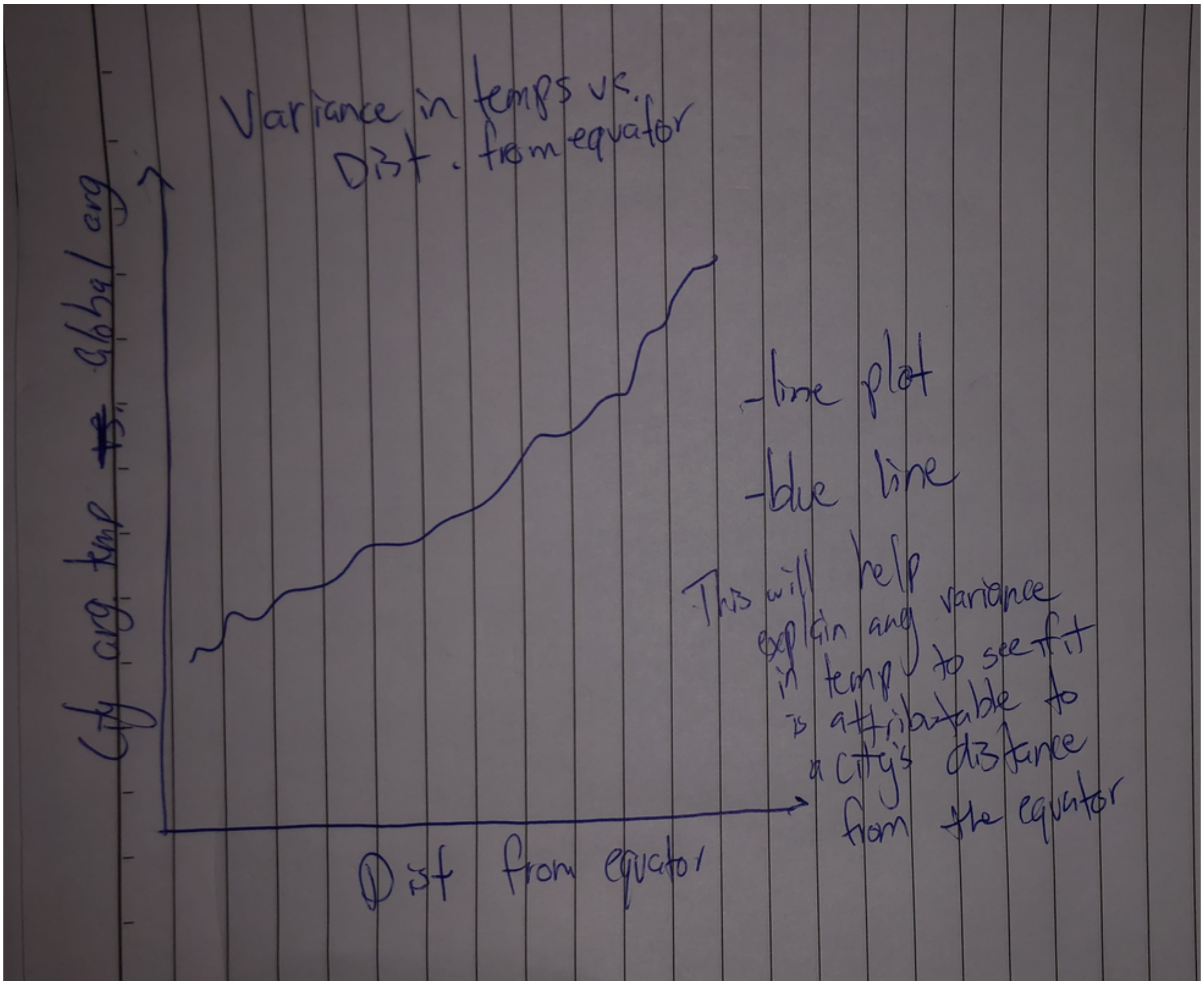
The Message

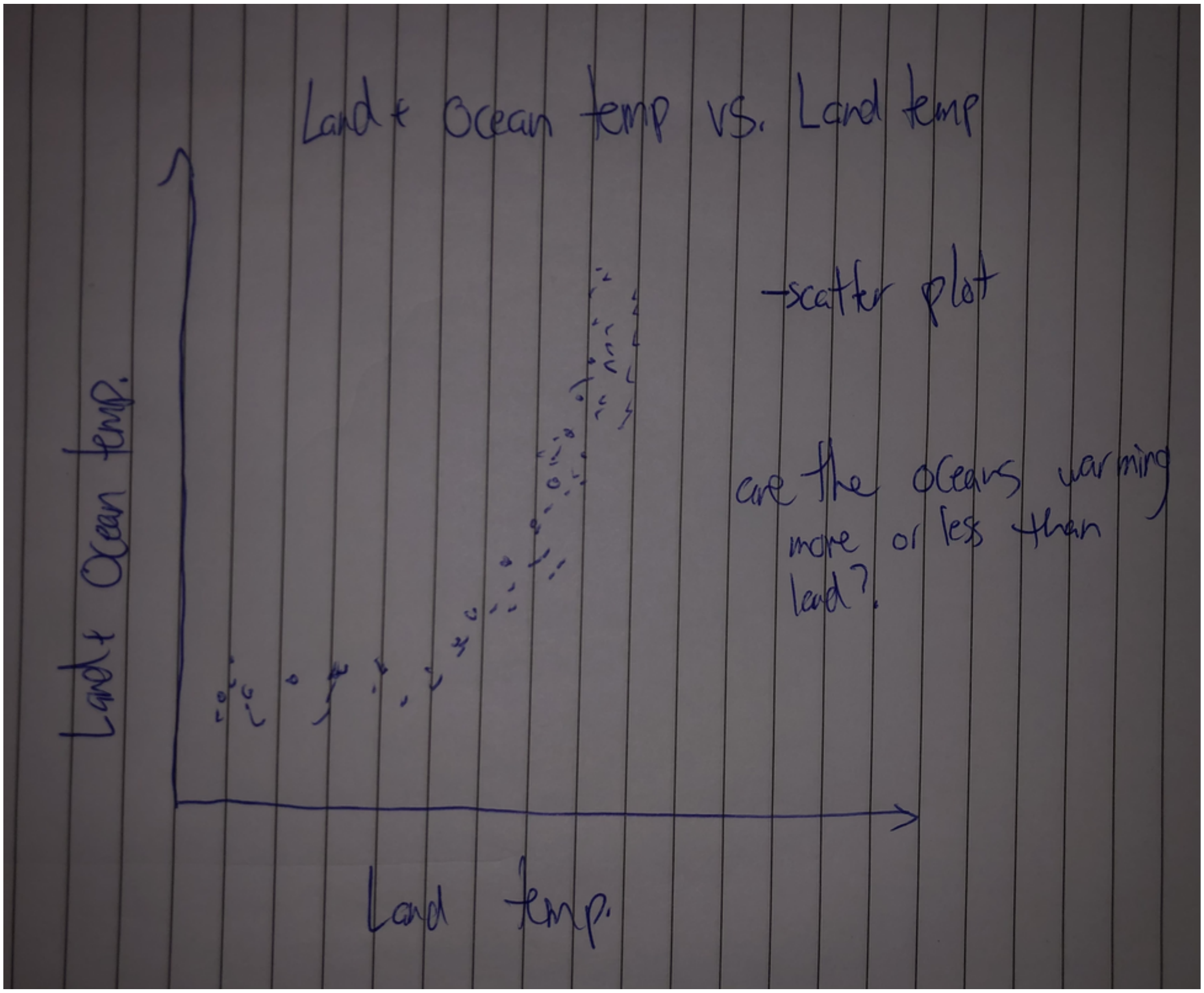
The main question being investigated in this report is, as stated earlier:

Does data about the land temperature support claims about global warming? Are Co2 emissions related to any changes in the temperature of the land? If the data supports global warming, are some areas of the globe warming faster than others?

Thus far, although there is no definitive answer, the data I'm exploring demonstrates that there is evidence to back up the claim that the Earth is warming and that global warming is a reality. Also, my visualizations show that the average land temperature is rising and there is a positive relationship between the land temperature and Co2 emissions. Additionally, the visualizations I've created and the ones that will follow this portion show that there is a relatively even warming of the Earth with no geographic location warming especially faster than another.

Here are some more visual representations I would like to create:





Additional Visual Representations

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In [26]:
```
#Creating first visual representations by merging glob_df and city_df dataf
#The difference between a city's average temperature and the global average

#First, I will convert all dates to datetime format
city_df['dt'] = pd.to_datetime(city_df['dt'])

#Merge glob_df and city_df and find difference in global and city temp
glob_city = glob_df.merge(city_df, left_on='dt', right_on='dt')
glob_city['temp difference (˚C)'] = glob_city['Land Average Temperature (˚C
        glob_city['City Average Temperature (˚C)']
glob_city_2010 = glob_city[glob_city['dt'] == '2010-01-01']
glob_city_2010
glob_city_2010.drop(['Latitude','percent change in temp_x','percent change
```

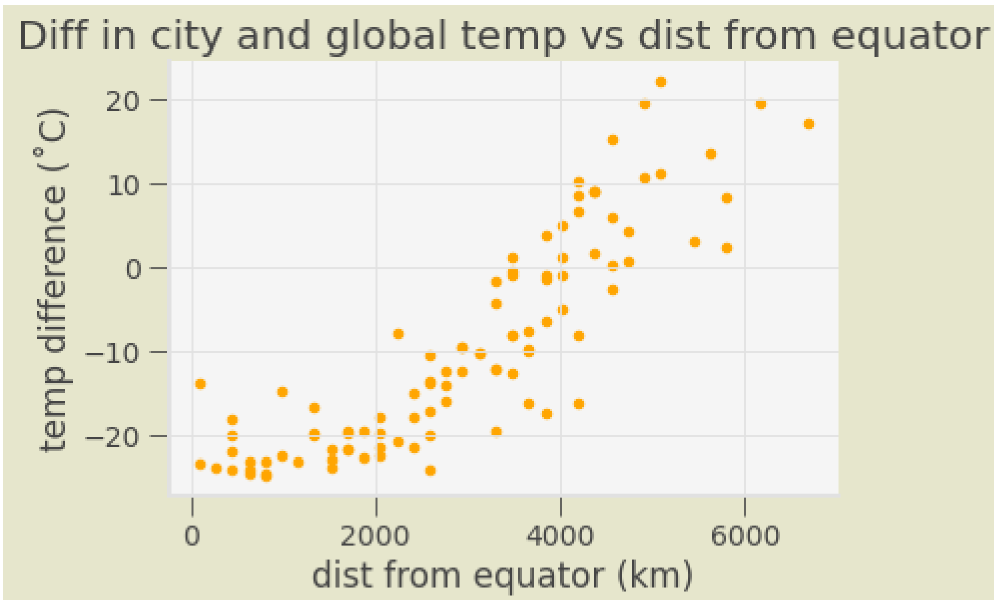
Out[26]:

	dt	Land Average Temperature (˚C)	City Average Temperature (˚C)	City	Country	dist from equator (km)	temp difference (˚C)
233715	2010-01-01	3.737	28.270	Abidjan	Côte D'Ivoire	625.18335	-24.533
233716	2010-01-01	3.737	18.390	Addis Abeba	Ethiopia	981.63780	-14.653
233717	2010-01-01	3.737	20.969	Ahmadabad	India	2588.45895	-17.232
233718	2010-01-01	3.737	8.779	Aleppo	Syria	4016.49765	-5.042
233719	2010-01-01	3.737	16.259	Alexandria	Egypt	3481.26075	-12.522
...	...	...	...	...	...	...	...
233810	2010-01-01	3.737	2.608	Tokyo	Japan	4016.49765	1.129
233811	2010-01-01	3.737	-7.137	Toronto	Canada	4908.18900	10.874
233812	2010-01-01	3.737	25.325	Umm Durman	Sudan	1695.65715	-21.588
233813	2010-01-01	3.737	5.478	Wuhan	China	3302.47830	-1.741
233814	2010-01-01	3.737	-0.237	Xian	China	3837.71520	3.974

100 rows × 7 columns

In [27]:
```
#Create lineplot with temp difference as the y variable and distance from t
fig, ax = plt.subplots()
glob_city_2010.plot(
    kind = 'scatter',x='dist from equator (km)', y='temp difference (°C)',
    legend = False, ax=ax,
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.8))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Diff in city and global temp vs dist from equator")
```

Out[27]:
```
Text(0.5, 1.0, 'Diff in city and global temp vs dist from equator')
```



After creating a line plot, it was clear that a scatter plot would be more appropriate for this date. This graph is rather informative. It helps answer the part of the message that examines if different parts of the world are warming at different rates. Cities that were far away and close to the equator had average land temperatures that were much higher than those somewhat far away. This makes sense because those that are a bit far away from the equator have average temperatures that are close to the global average. However, these scatter points have a quadratic tendency and there is some heterogeneity.

In [28]:
```
#I will recreate the glob_df dataframe to now include data about the cumula
glob_data = pd.read_csv('~/Desktop/School/UofT/Third Year/ECO225/ECO225 Pro
```

In [29]:
```
#Create new dataframe land_ocean_df that includes the Average land temperat
#temperature
land_ocean_df = pd.DataFrame(glob_land_temp)
land_ocean_df = land_ocean_df.drop(['LandAverageTemperatureUncertainty', 'L
                        'LandMinTemperature', 'LandAndOceanAverageTemperatu
                        'LandMinTemperatureUncertainty'], axis=1)
land_ocean_df.rename(columns={'LandAverageTemperature': 'Land Average Tempe
                              'LandAndOceanAverageTemperature': 'Land and O
land_ocean_df
```

Out[29]:

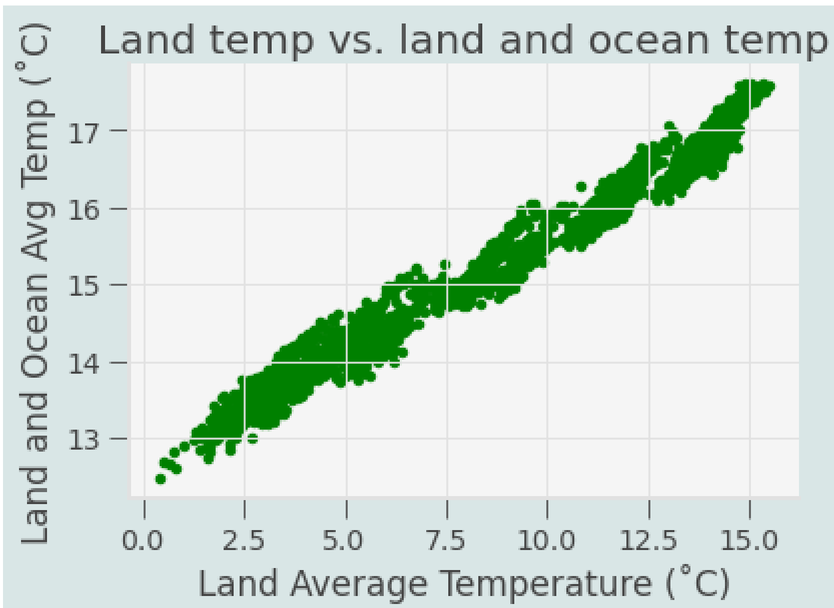
	dt	Land Average Temperature (°C)	Land and Ocean Avg Temp (°C)
0	1750-01-01	3.034	NaN
1	1750-02-01	3.083	NaN
2	1750-03-01	5.626	NaN
3	1750-04-01	8.490	NaN
4	1750-05-01	11.573	NaN
...	...	...	...
3187	2015-08-01	14.755	17.589
3188	2015-09-01	12.999	17.049
3189	2015-10-01	10.801	16.290
3190	2015-11-01	7.433	15.252
3191	2015-12-01	5.518	14.774

3192 rows × 3 columns

This table includes the global average land temperature as well as the global average cumulative land and ocean temperatures.

In [30]:
```
#Create lineplot with Land Average Temperature as the x variable and Land a
fig, ax = plt.subplots()
land_ocean_df.plot(
    kind = 'scatter',x='Land Average Temperature (˚C)', y='Land and Ocean A
    legend = False, ax=ax,
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.85, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Land temp vs. land and ocean temp")
```

Out[30]:
```
Text(0.5, 1.0, 'Land temp vs. land and ocean temp')
```



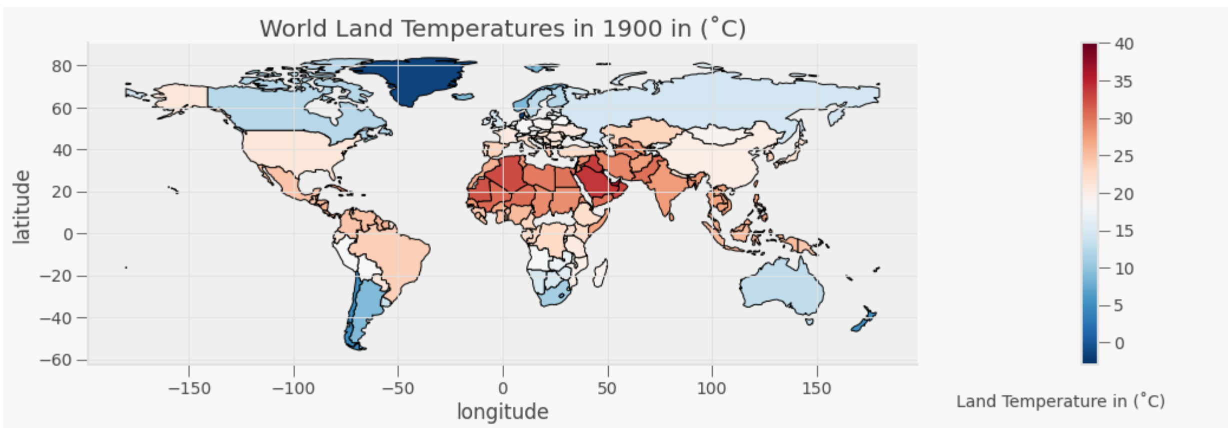
This graph did not give the result that was expected. It demonstrates the relationship between the temperature of the land and the temperature of the land and oceans. Clearly, adding the ocean temp to the land temperature, when plotted against just the land tempretaure, shows a relationship that seems linear. This tells us that, on average, the ocean temperature increases similarly to the land tempretaure.

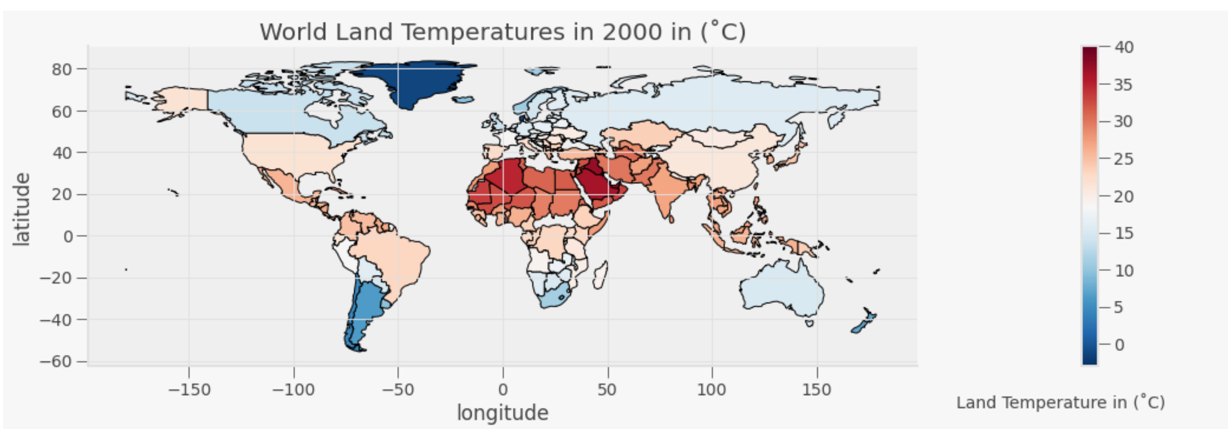
In [31]:
```
#Read and clean new dataset that contains Land Temperatures by country
cntry_land_temp = pd.read_csv('~/Desktop/School/UofT/Third Year/ECO225/ECO2

cntry_df = pd.DataFrame(cntry_land_temp)
cntry_df = cntry_df.drop(['AverageTemperatureUncertainty'], axis = 1)
cntry_df.rename(columns={'AverageTemperature': 'Country Average Temperature

temp_1850 = cntry_df[cntry_df['dt'] == '1850-07-01']
```

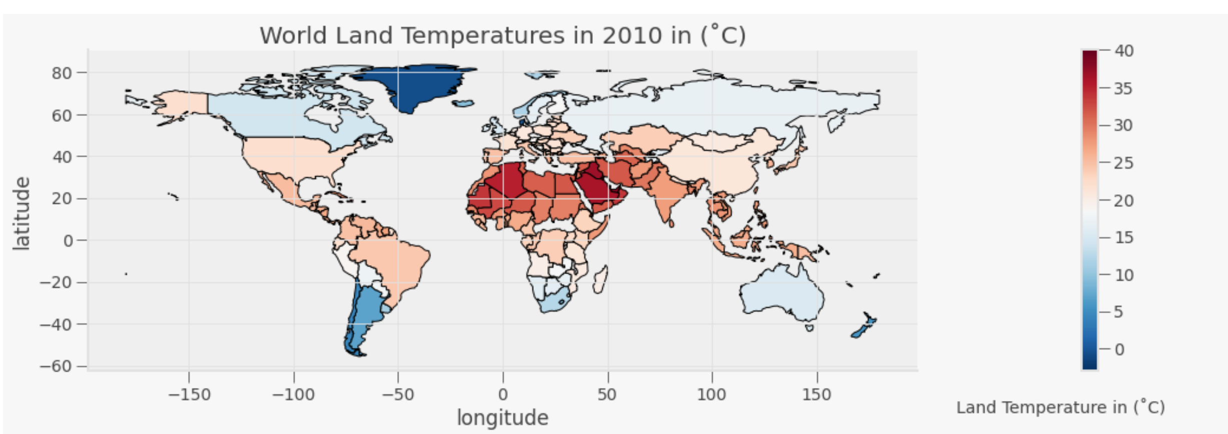
In [32]:
```
#Read file with world map information and add geometric information to data
#according to country
world = gpd.read_file(gpd.datasets.get_path("naturalearth_lowres"))
world = world.set_index("iso_a3")
world.loc['USA' ,'name'] = 'United States'
world.loc['COD', 'name'] ='Congo (Democratic Republic Of The)'
```

In [33]:
```
#Plot world map of countries with their color corresponsing to their land t

temp_1900 = cntry_df[cntry_df['dt'] == '1900-07-01']
world_1900 = world.merge(temp_1900, left_on = "name", right_on = "Country",
fig, gax = plt.subplots(figsize=(50,5))

#Plotting the Countries with colors according to land temperatures
world_1900.plot(
    ax=gax, edgecolor='black', column='Country Average Temperature (˚C)', l
    vmin=-3, vmax=40 #range of your column value for the color legend
)

# Format axes and title
gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('World Land Temperatures in 1900 in (˚C)')
gax.annotate('Land Temperature in (˚C)', xy=(0.77, 0.06), xycoords='figure


# Removing spines
gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()

#Plot world map of countries with their color corresponsing to their land t

temp_2000 = cntry_df[cntry_df['dt'] == '2000-07-01']
world_2000 = world.merge(temp_2000, left_on = "name", right_on = "Country",
fig, gax = plt.subplots(figsize=(50,5))

#Plotting the Countries with colors according to land temperatures
world_2000.plot(
    ax=gax, edgecolor='black', column='Country Average Temperature (˚C)', l
    vmin=-3, vmax=40 #range of your column value for the color legend
)

# Format axes and title
gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('World Land Temperatures in 2000 in (˚C)')
gax.annotate('Land Temperature in (˚C)', xy=(0.77, 0.06), xycoords='figure


# Removing spines
gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()

#Plot world map of countries with their color corresponsing to their land t

temp_2010 = cntry_df[cntry_df['dt'] == '2010-07-01']
world_2010 = world.merge(temp_2010, left_on = "name", right_on = "Country",
fig, gax = plt.subplots(figsize=(50,5))
```

```
#Plotting the Countries with colors according to land temperatures
world_2010.plot(
    ax=gax, edgecolor='black', column='Country Average Temperature (˚C)', l
    vmin=-3, vmax=40 #range of your column value for the color legend
)

# Format axes and title
gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('World Land Temperatures in 2010 in (˚C)')
gax.annotate('Land Temperature in (˚C)', xy=(0.77, 0.06), xycoords='figure

# Removing spines
gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```







These three maps are colour coded according to each country's average land temperature in July 1900, 2000, and 2010 respectively. The aim of these maps is to demonstrate how each country's average temperature changed over time and, although the differences in the shades of each country are slight, the fact that there are any difference at all is significant.

In [34]:
```
co2_1900 = co2_df[co2_df['Year']== '1900']
temp_co2_1900 = co2_1900.merge(temp_1900, left_on='Entity', right_on='Count
temp_co2_1900.rename(columns={'Country Average Temperature (˚C)': 'Country
```

In [35]:
```
temp_co2_geojson=GeoJSONDataSource(geojson=temp_co2_1900.to_json())

color_mapper = LinearColorMapper(palette = brewer['RdBu'][10], low = 0, hig
color_bar = ColorBar(color_mapper=color_mapper, label_standoff=8,width = 50
                     border_line_color=None,location = (0,0), orientation =
hover = HoverTool(tooltips = [ ('Country','@country'),
                              ('Annual CO₂ emissions (tonnes)', '@Annual CO
                               ('Avg Temperature (˚C)','@Country Average Te
v = figure(title="Wisconsin Voting in 2016 Presidential Election", tools=[h
v.patches("xs","ys",source=temp_co2_geojson,
          fill_color = {'field' :'Country Average Temperature (˚C)', 'trans
v.add_layout(color_bar, 'below')
show(v)

#I attempted to make an interactive map but couldn't. I will keep this code
#have any tips on how to fix this and then include it in the next project,
```

New Dataset

In this project, compared to the last one, I added a new major dataset that contains Co2 emissions. After all, it is difficult to have any discussion of global warming and climate change without considering carbon dioxide emissions. This new dataset helped me refine my message and allowed me to create new, more intuitive, and more useful graphs that help me respond to my question more directly.

Conclusion

To conclude, the question I am trying to answer is if data about the temperature of the Earth supports the claim that there is global warming. Also, part of my question is whether or not Co2 emissions are associated with an increasing global land temperature. My findings thus far, which are demonstrated in the visualizations, support the claim that the Earth is steadily warming. The strongest evidence in favor of this hypothesis is that there is a positive relationship between Co2 emissions and the temperature of the Earth.

My maps also support this hypothesis, although the differences in the shades of each country are slight the fact that there is a difference is significant. It is widely accepted that even slight changes in the temperature of the Earth have catastrophic events on the environment and warrants that there is an overhaul in the way we live life. Global warming is a serious problem and this data supports its existence. It is difficult to doubt the effect that pollution has on our environemnt after considering these visualizations.

Project 3

Are global warming and climate change supported by data? What is the relationship between Co2 emissions and the global land temperature? How is the rate of warming different in different places around the world?

Faisal Alkhalili

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ECO225

Introduction

This research project aims to use records of the average land temperatures around the world categorized globally, by country, and by city to investigate whether climate change and global warming are supported by data. Additional data that will be used is global Co2 emissions data and per capita co2 emissions categorized by country. There will also be a focus on the warming effect of Co2 emissions which translates to pollution. Essentially, this research will look at how the rate of the rise of land temperatures has generally changed since 1750 and if these changes correspond to changes in the emission of Co2. Also, this report will examine if the rate of warming is different in different cities as well as if the oceans are warming faster than land.

The data that will be used is sourced from Berkeley Earth, an agency that has made several archives of environmental data avialable. The data contains monthly land temperature recordings that begin in 1750. After the year 1850, the data started included maximum and minimum values for each month. Some subsets of the data contain the monthly land temperature values categorized according to the country, city, major city, and US state. It's important to consider that this data begins around the same time that the Industrial Revolution is thought to have started. This is generally considered as the time that industrial pollution began to have seriously adverse effects on the climate and the temperature of the Earth. The additional data, Co2 emissions, is sourced from World Bank. This data will corespond to the level of pollution around the world. The dataset includes Co2 emissions categorized by country including a subset that contains cumulative global Co2 emissions. The outcome that is being considered in this research is the change in the average land temperature and the two main independent variables are pollution generally (which is essentially represented by Co2 emissions) and location. The per capita co2 emissions data will be sourced from the Wikipedia article titled, "List of countries by carbon dioxide emissions per capita" and will be scraped.

Raw Data

In [36]:
```
data_url = "https://www.kaggle.com/berkeleyearth/climate-change-earth-surfa
```

In [76]:
```
import matplotlib.colors as mplc
import matplotlib.patches as patches
import matplotlib.pyplot as plt
import numpy as np
import pandas as pd
import statsmodels.formula.api as sm #for linear regression: sm.ols
import geopandas as gpd
from IPython.display import display, Math, Latex

from shapely.geometry import Point

from pandas_datareader import DataReader

%matplotlib inline
import qeds
qeds.themes.mpl_style();
from bokeh.io import output_notebook
from bokeh.plotting import figure, ColumnDataSource
from bokeh.io import output_notebook, show, output_file
from bokeh.plotting import figure
from bokeh.models import GeoJSONDataSource, LinearColorMapper, ColorBar, Ho
from bokeh.palettes import brewer
output_notebook()
import json
from bokeh.palettes import OrRd
import seaborn as sns
import requests
from bs4 import BeautifulSoup
import urllib.request
import time
```

(https://bokeh.org) BokehJS 2.3.0 successfully loaded.

In [38]:
```
#Reading the first dataset, Global average land temperatures.
glob_land_temp = pd.read_csv('~/Desktop/School/UofT/Third Year/ECO225/ECO22
```

In [39]:
```
#Turning the first dataset into a dataframe. The data is cleaned by droppin
glob_df = pd.DataFrame(glob_land_temp)
glob_df = glob_df.drop(['LandAverageTemperatureUncertainty', 'LandMaxTemper
                        'LandMinTemperature', 'LandAndOceanAverageTemperatu
                        'LandMinTemperatureUncertainty','LandAndOceanAverag
glob_df
```

Out[39]:

	dt	LandAverageTemperature
0	1750-01-01	3.034
1	1750-02-01	3.083
2	1750-03-01	5.626
3	1750-04-01	8.490
4	1750-05-01	11.573
...	...	...
3187	2015-08-01	14.755
3188	2015-09-01	12.999
3189	2015-10-01	10.801
3190	2015-11-01	7.433
3191	2015-12-01	5.518

3192 rows × 2 columns

The table above represents the raw data for the average global land temperature, per month, since 1750. This is going to be this research's main source of information for the global average land temperature.

In [40]:
```
#Creating a new column in the dataframe glob_df that finds the percent chan
#in the average global land temperature, month over month.
glob_df['percent change in temp'] = glob_df['LandAverageTemperature'].pct_c
glob_df['percent change in temp'] = glob_df['percent change in temp'] * 100
glob_df['percent change in temp'] = glob_df['percent change in temp'].round
#Changing the average temperature from monthly intervals to yearly interval
glob_df['dt'] = pd.to_datetime(glob_df['dt'])
glob_df = glob_df.set_index('dt')
glob_df.resample('YS').mean()
glob_df.rename(columns={'LandAverageTemperature': 'Land Average Temperature
```

In [72]:
```
#Creating a new dataframe that contains the global co2 emissions for each c
#labeled "World" with the global emissions data
co2 = pd.read_csv('~/Desktop/School/Uoft/Third Year/ECO225/ECO225 Project 1
co2_df = pd.DataFrame(co2)
co2_df['Year'] = pd.to_datetime(co2_df['Year'], format='%Y')
co2_df

#Creating another dataframe that takes global Co2 emissions and is merged w
world_co2_df = co2_df[co2_df["Entity"] == "World"]
temp_co2 = glob_df.merge(world_co2_df,right_on='Year', left_on='dt', how='r
```

In [42]:
```
#Reading the second dataset, monthly average land temperatures by major cit
#The data is cleaned and irrelevant columns are dropped.
city_land_temp = pd.read_csv('~/Desktop/School/Uoft/Third Year/ECO225/ECO22
city_df = pd.DataFrame(city_land_temp)
city_df = city_land_temp.drop(['AverageTemperatureUncertainty', 'Longitude'
city_df.rename(columns={'AverageTemperature': 'City Average Temperature (˚C
city_df.set_index('City')
```

Out[42]:

	dt	City Average Temperature (˚C)	Country	Latitude
City				
Abidjan	1849-01-01	26.704	Côte D'Ivoire	5.63N
Abidjan	1849-02-01	27.434	Côte D'Ivoire	5.63N
Abidjan	1849-03-01	28.101	Côte D'Ivoire	5.63N
Abidjan	1849-04-01	26.140	Côte D'Ivoire	5.63N
Abidjan	1849-05-01	25.427	Côte D'Ivoire	5.63N
...	...	...	...	...
Xian	2013-05-01	18.979	China	34.56N
Xian	2013-06-01	23.522	China	34.56N
Xian	2013-07-01	25.251	China	34.56N
Xian	2013-08-01	24.528	China	34.56N
Xian	2013-09-01	NaN	China	34.56N

239177 rows × 4 columns

The above table includes the land temperature, per month, for each major city around the world. This data will help show differences in the rate of the change of land temperatures around the world. It will be used to identify any relationship between a city's distance from the equator and the change in its land temperature.

In [43]:
```
#Create a new column in city_df that measures the percent change in tempera
city_df['percent change in temp'] = city_df['City Average Temperature (˚C)'
city_df['percent change in temp'] = city_df['percent change in temp'] * 100
city_df['percent change in temp'] = city_df['percent change in temp'].round
#Find the distance of each city from the equator by multiplying the degrees
city_df['dist from equator (km)'] = city_df['Latitude']
city_df['dist from equator (km)'] = city_df['dist from equator (km)'][:-1]
city_df['dist from equator (km)'] = city_df['dist from equator (km)'].repla
city_df['dist from equator (km)'] = pd.to_numeric(city_df['dist from equato
city_df.set_index('City')
```

Out[43]:

City	dt	City Average Temperature (˚C)	Country	Latitude	percent change in temp	dist from equator (km)
Abidjan	1849-01-01	26.704	Côte D'Ivoire	5.63N	NaN	625.18335
Abidjan	1849-02-01	27.434	Côte D'Ivoire	5.63N	2.73	625.18335
Abidjan	1849-03-01	28.101	Côte D'Ivoire	5.63N	2.43	625.18335
Abidjan	1849-04-01	26.140	Côte D'Ivoire	5.63N	-6.98	625.18335
Abidjan	1849-05-01	25.427	Côte D'Ivoire	5.63N	-2.73	625.18335
...	...	...	...	...	...	...
Xian	2013-05-01	18.979	China	34.56N	51.07	3837.71520
Xian	2013-06-01	23.522	China	34.56N	23.94	3837.71520
Xian	2013-07-01	25.251	China	34.56N	7.35	3837.71520
Xian	2013-08-01	24.528	China	34.56N	-2.86	3837.71520
Xian	2013-09-01	NaN	China	34.56N	0.00	NaN

239177 rows × 6 columns

The above table includes additional information about the average land temperature for each major city. It adds the percent change in the temperature month over month as well as each city's distance from the equator in km.

Summary Statistics

In [44]:
```
glob_df.describe().round(2)
```

Out[44]:

	Land Average Temperature (℃)	percent change in temp
count	3180.00	3191.00
mean	8.37	7.06
std	4.38	113.31
min	-2.08	-3439.81
25%	4.31	-23.83
50%	8.61	-1.49
75%	12.55	31.42
max	19.02	1568.39

The table above includes a summary statistic of the dataframe glob_df. It computes different statistical values that may be important to the research.

In [45]:
```
city_df.describe().round(2)
```

Out[45]:

	City Average Temperature (℃)	percent change in temp	dist from equator (km)
count	228175.00	239176.00	239176.00
mean	18.13	NaN	3126.13
std	10.02	NaN	1559.17
min	-26.77	-inf	88.84
25%	12.71	-10.58	2052.11
50%	20.43	-0.02	3302.48
75%	25.92	9.70	4195.28
max	38.28	inf	6692.68

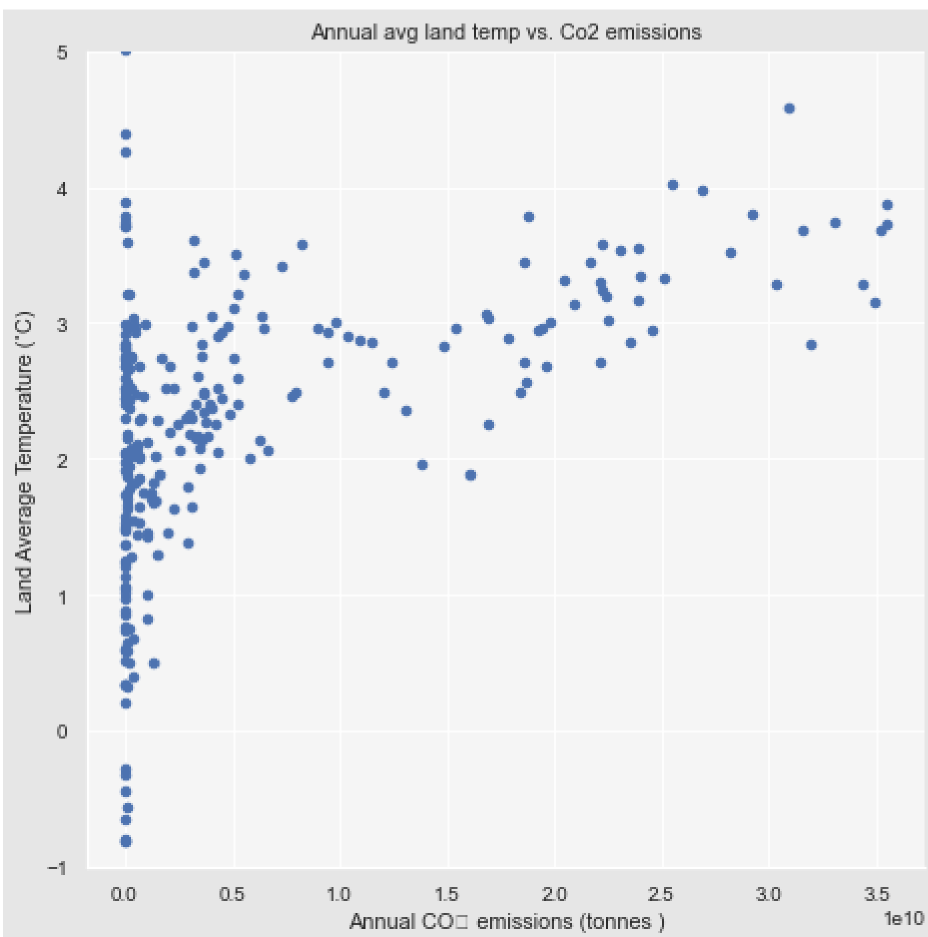
The table above includes a summary statistic of the dataframe city_df. It computes different statistical values that may be important to the research.

Visual Representations

Additional Dataset

In [73]:
```
# Create a plot, from the dataframe glob_df, that has y as the percent chan
# Some early values are ommitted due to the high uncertaunty around them an
# January 1750 so, January 1875.

fig, ax = plt.subplots(figsize=(7.5,7.5))
temp_co2.plot(
    kind = 'scatter', x='Annual CO₂ emissions (tonnes )', y= 'Land Average
    legend = False, ax=ax, ylim=[-1, 5]
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Annual avg land temp vs. Co2 emissions")
```

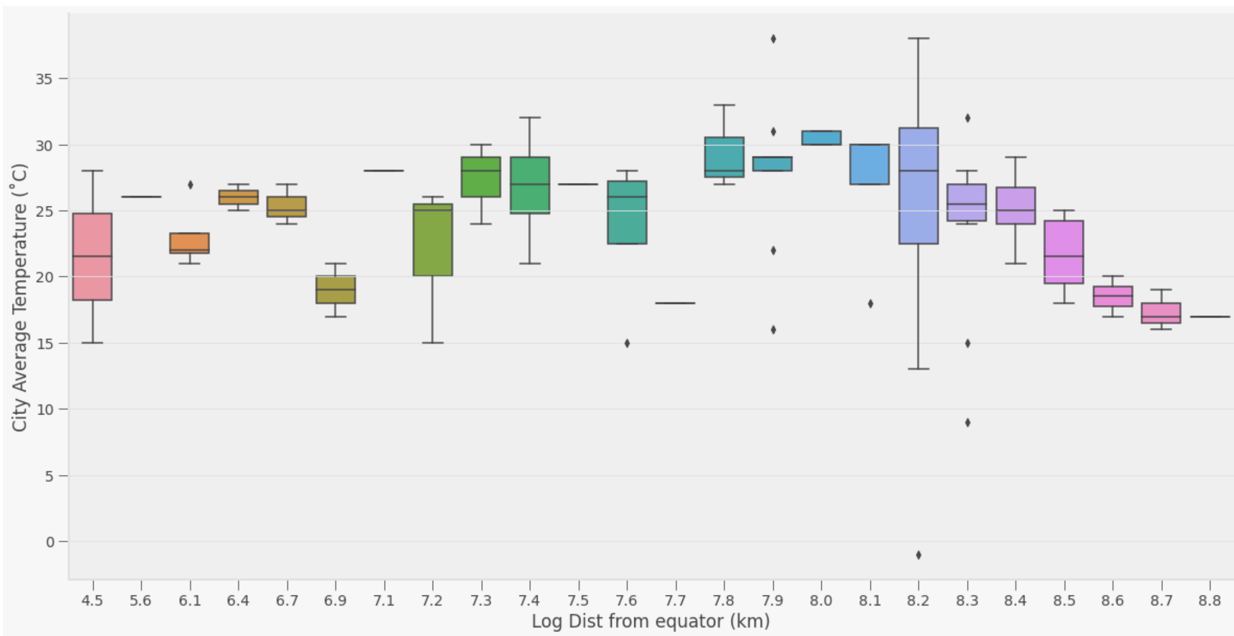
Out[73]:
```
Text(0.5, 1.0, 'Annual avg land temp vs. Co2 emissions')
```



This scatter plot demonstrates the relationship between the average temperature of the Earth compared to Co2 emissions. Although there are many points that lie close to 0 (which is likely due to some countries not reporting their emissions until recently), the positive relationship is clear! When global Co2 emissions are higher, a higher global land temperature is observed.

In [ ]:
```
# Create a new dataframe that contains a city's log average temperature and
city_df['Log City Avg Temp (˚C)'] = np.log(city_df['City Average Temperatur
city_df['Log Dist from equator (km)'] = np.log(city_df['dist from equator (

dist_2000 = city_df[city_df['dt'] == '2000-07-01']
dist_2000['Log Dist from equator (km)'] = dist_2000['Log Dist from equator
dist_2000['City Average Temperature (˚C)'] = dist_2000['City Average Temper
```

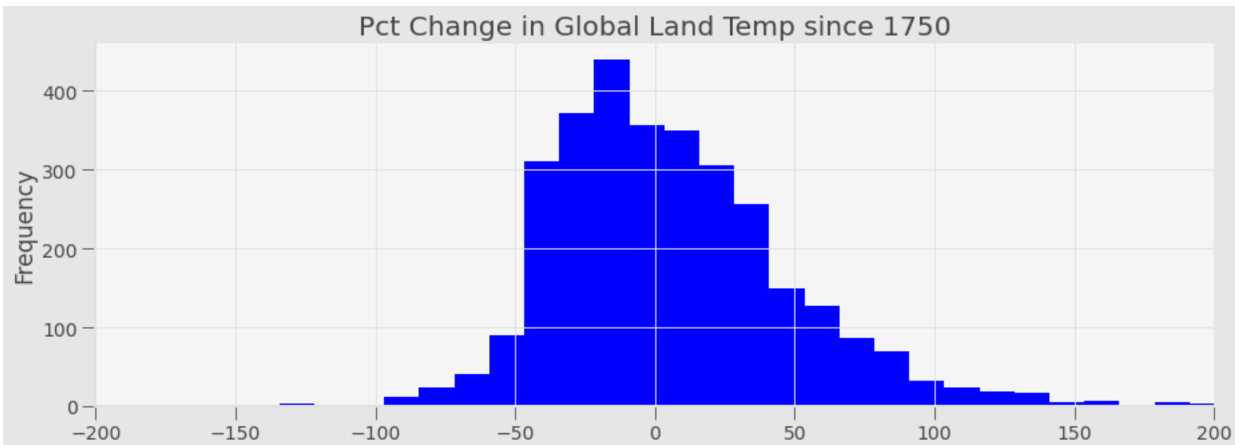
In [48]:
```
# Create a boxplot, from the dataframe city_df, that has the log Average la
#from the equator in kilometres.
fig, ax = plt.subplots(figsize=(20, 10))
box = sns.boxplot(x='Log Dist from equator (km)', y='City Average Temperatu
```



This boxplot demonstrates that cities farther away from the equator have aberage temperatures that are lower yet the relationship is not very strong. This visualization shows us that there might not be as strong of a relationship between's how far a city is from teh equator and its average temperature which may have strong implications for climate change.

In [49]:
```
#Create histogram using dataframe glob_df that plots the percent change in

fig, ax = plt.subplots(figsize=(15, 5))
glob_df.plot(
    kind = 'hist', y='percent change in temp', color='b',
    bins = 400, legend = False, density = False, ax=ax, xlim=(-200,200)
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Pct Change in Global Land Temp since 1750")
```

Out[49]:
```
Text(0.5, 1.0, 'Pct Change in Global Land Temp since 1750')
```



This histogram shows that there are more observation with a negative percent change in tempereature (month over month) than there are positive ones. This means that there are more months where the average global land temperature went down than months where it went up. However, it seems as if the months that had a negative percent change had values that were closer to zero compared to months where the percent change was positive.

The Message

The main question being investigated in this report is, as stated earlier:

Does data about the land temperature support claims about global warming? Are Co2 emissions related to any changes in the temperature of the land? If the data supports global warming, are some areas of the globe warming faster than others?

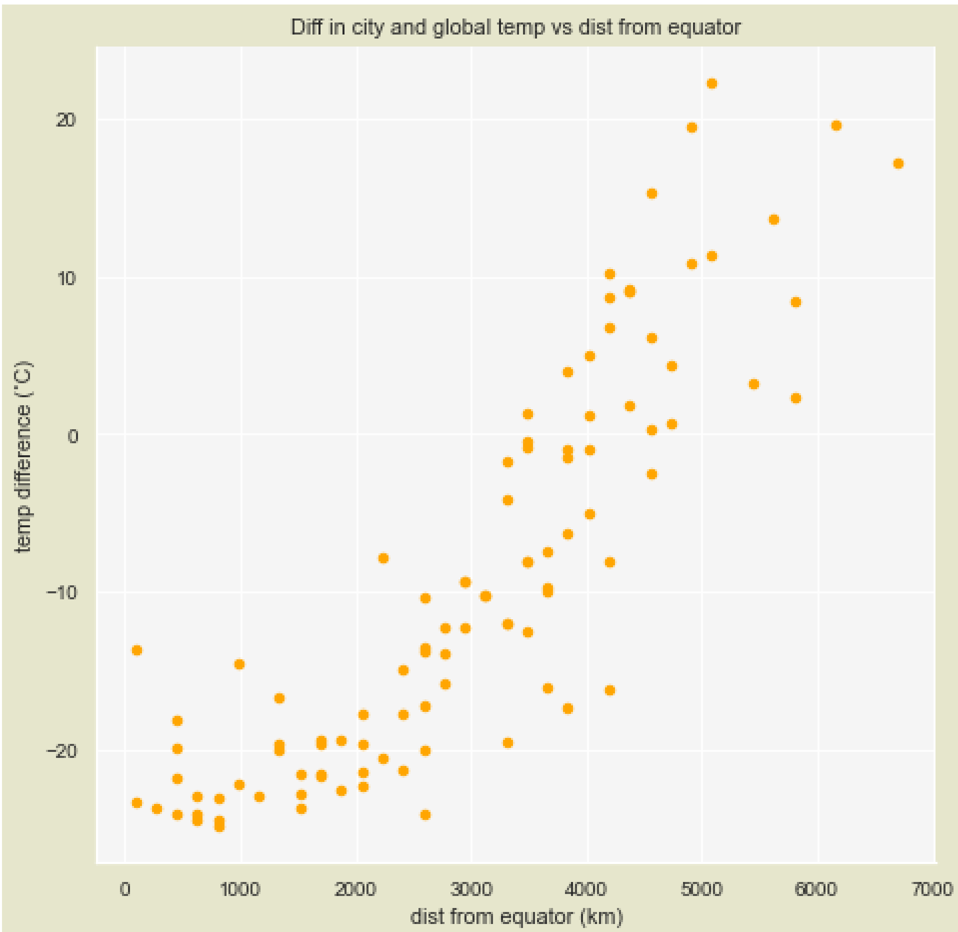
Thus far, although there is no definitive answer, the data I'm exploring demonstrates that there is evidence to back up the claim that the Earth is warming and that global warming is a reality. Also, my visualizations show that the average land temperature is rising and there is a positive relationship between the land temperature and Co2 emissions. Additionally, the visualizations I've created and the ones that will follow this portion show that there is a relatively even warming of the Earth with no geographic location warming especially faster than another.

Additional Visual Representations

In [50]:
```
#Creating first visual representations by merging glob_df and city_df dataf
#The difference between a city's average temperature and the global average

#First, I will convert all dates to datetime format
city_df['dt'] = pd.to_datetime(city_df['dt'])

#Merge glob_df and city_df and find difference in global and city temp
glob_city = glob_df.merge(city_df, left_on='dt', right_on='dt')
glob_city['temp difference (˚C)'] = glob_city['Land Average Temperature (˚C
        glob_city['City Average Temperature (˚C)']
glob_city_2010 = glob_city[glob_city['dt'] == '2010-01-01']
glob_city_2010 = glob_city_2010.drop(['Latitude','percent change in temp_x'
```

In [70]:
```
#Create lineplot with temp difference as the y variable and distance from t
fig, ax = plt.subplots(figsize=(7.5,7.5))
glob_city_2010.plot(
    kind = 'scatter',x='dist from equator (km)', y='temp difference (˚C)',
    legend = False, ax=ax,
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.8))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Diff in city and global temp vs dist from equator")
```

Out[70]:
```
Text(0.5, 1.0, 'Diff in city and global temp vs dist from equator')
```



After creating a line plot, it was clear that a scatter plot would be more appropriate for this date. This graph is rather informative. It helps answer the part of the message that examines if different parts of the world are warming at different rates. Cities that were far away and close to the equator had average land temperatures that were much higher than those somewhat far away. This makes sense because those that are a bit far away from the equator have average temperatures that are close to the global average. However, these scatter points have a quadratic tendency and there is some heterogeneity.

In [52]:
```
#I will recreate the glob_df dataframe to now include data about the cumula
glob_data = pd.read_csv('~/Desktop/School/UofT/Third Year/ECO225/ECO225 Pro
```

In [53]:
```
#Create new dataframe land_ocean_df that includes the Average land temperat
#temperature
land_ocean_df = pd.DataFrame(glob_land_temp)
land_ocean_df = land_ocean_df.drop(['LandAverageTemperatureUncertainty', 'L
                        'LandMinTemperature', 'LandAndOceanAverageTemperatu
                        'LandMinTemperatureUncertainty'], axis=1)
land_ocean_df.rename(columns={'LandAverageTemperature': 'Land Average Tempe
                        'LandAndOceanAverageTemperature': 'Land and O
land_ocean_df
```

Out[53]:

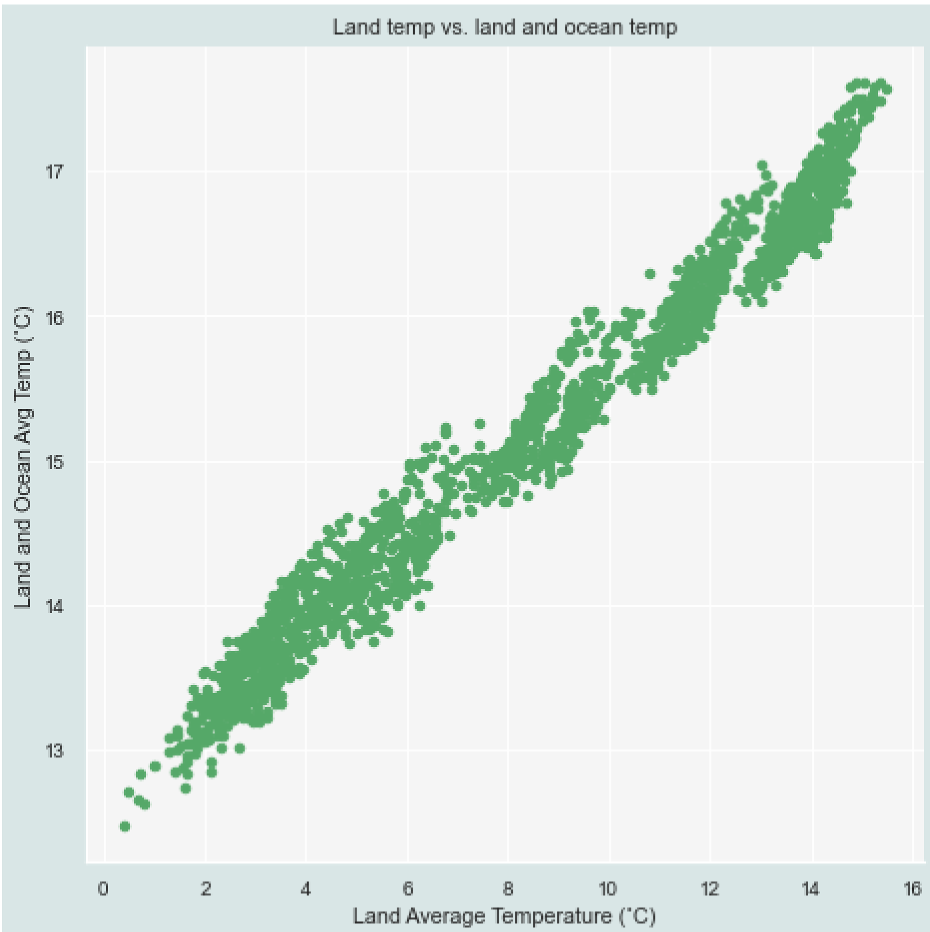
	dt	Land Average Temperature (°C)	Land and Ocean Avg Temp (°C)
0	1750-01-01	3.034	NaN
1	1750-02-01	3.083	NaN
2	1750-03-01	5.626	NaN
3	1750-04-01	8.490	NaN
4	1750-05-01	11.573	NaN
...	...	...	...
3187	2015-08-01	14.755	17.589
3188	2015-09-01	12.999	17.049
3189	2015-10-01	10.801	16.290
3190	2015-11-01	7.433	15.252
3191	2015-12-01	5.518	14.774

3192 rows × 3 columns

This table includes the global average land temperature as well as the global average cumulative land and ocean temperatures.

In [69]:
```
#Create lineplot with Land Average Temperature as the x variable and Land a
fig, ax = plt.subplots(figsize=(7.5,7.5))
land_ocean_df.plot(
    kind = 'scatter',x='Land Average Temperature (˚C)', y='Land and Ocean A
    legend = False, ax=ax,
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.85, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Land temp vs. land and ocean temp")
```

Out[69]:
```
Text(0.5, 1.0, 'Land temp vs. land and ocean temp')
```



This graph did not give the result that was expected. It demonstrates the relationship between the temperature of the land and the temperature of the land and oceans. Clearly, adding the ocean temp to the land temperature, when plotted against just the land tempretaure, shows a relationship that seems linear. This tells us that, on average, the ocean temperature increases similarly to the land tempretaure.

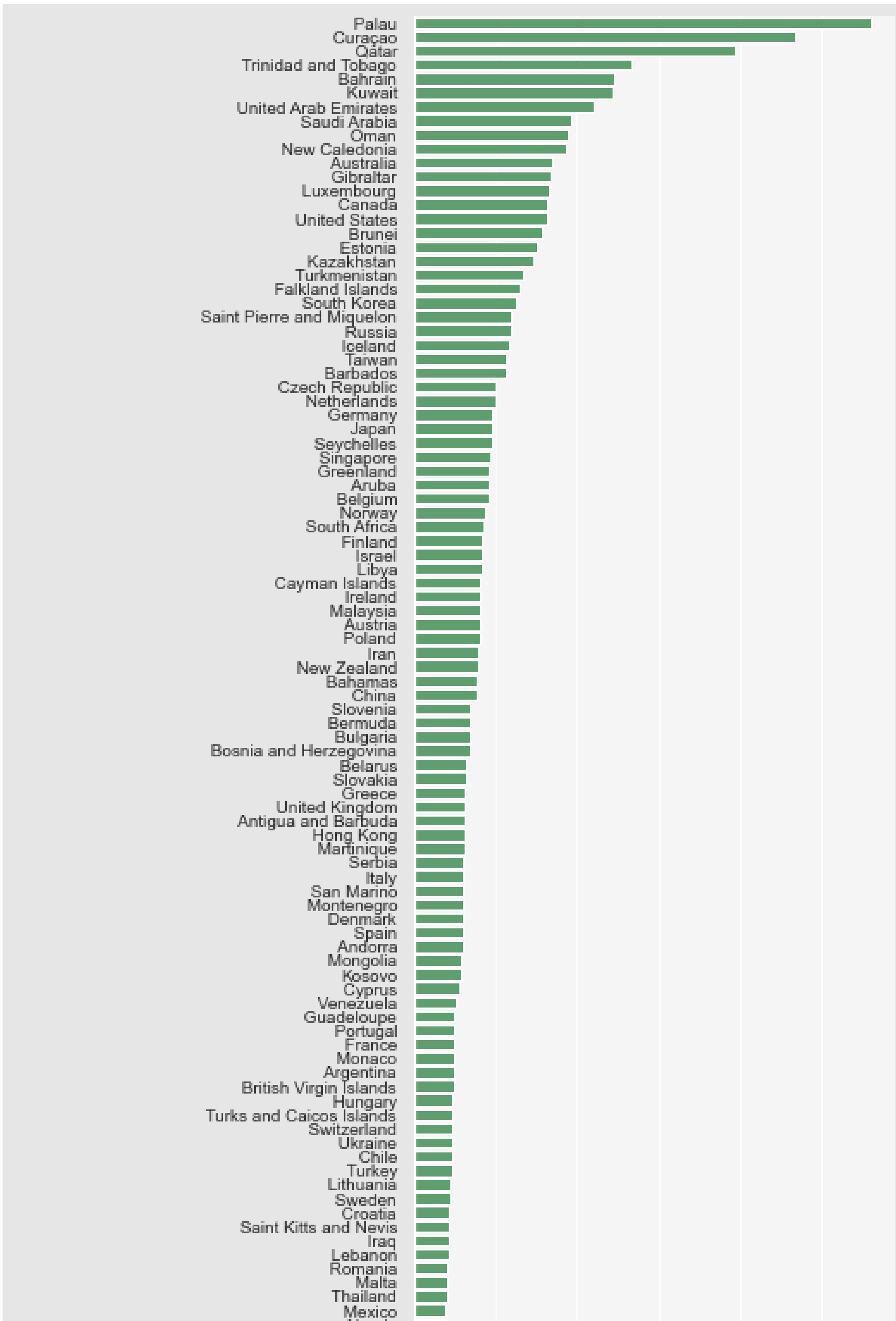
Scraped Data

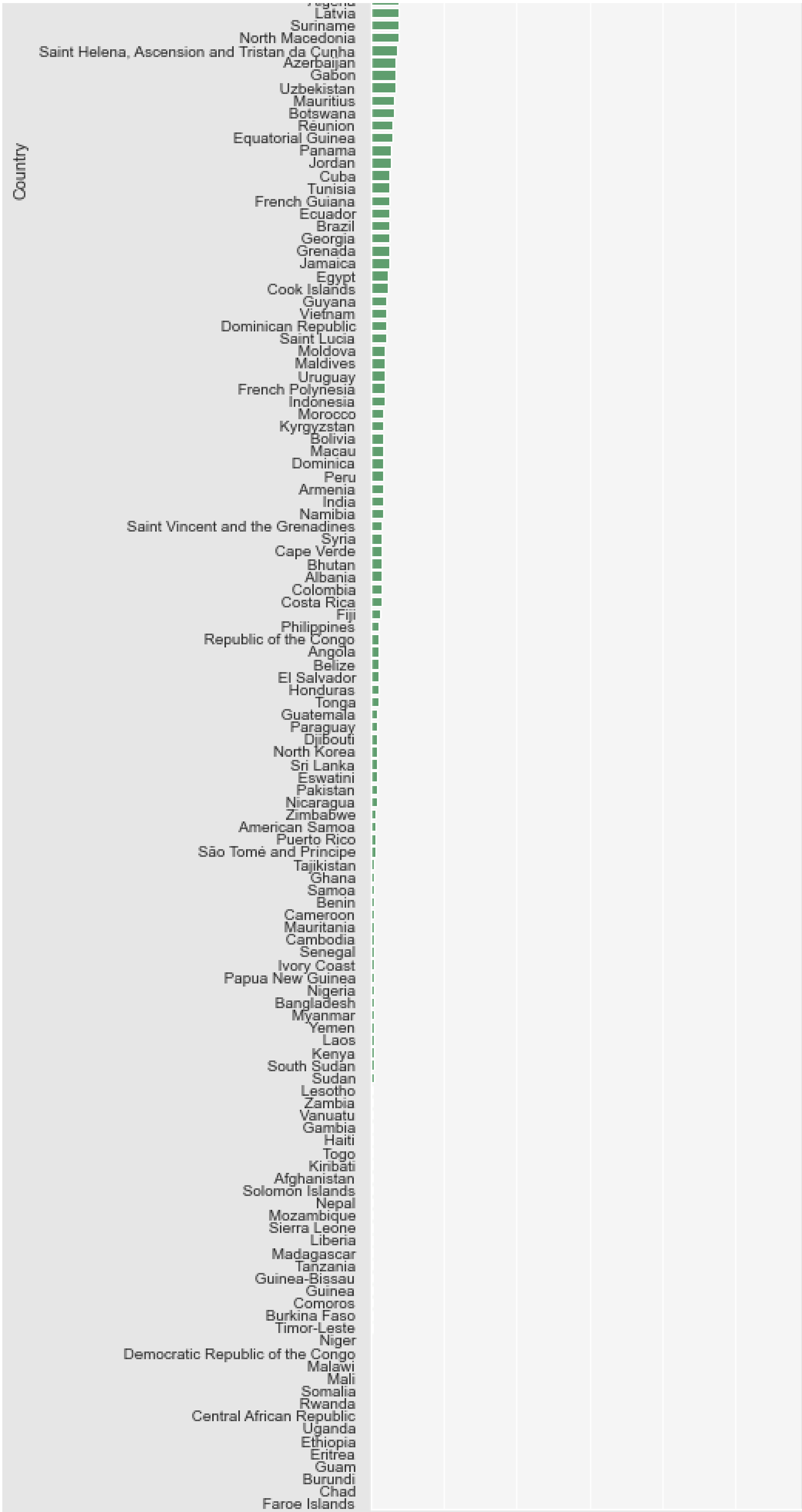
In [55]:
```
# Set URL of site from which I want to scrape the data.
# Also, I find what html code separates each value I would like to isolate.
web_url = 'https://en.wikipedia.org/wiki/List_of_countries_by_carbon_dioxid
response = requests.get(web_url)
soup_object = BeautifulSoup(response.content)
data_table = soup_object.find_all('table', 'wikitable sortable')[0]
all_values = data_table.find_all('tr')
```

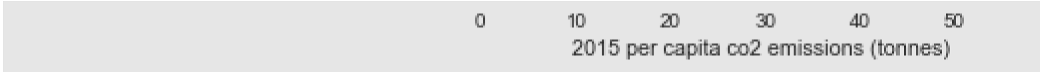
In [56]:
```
# Create an empty dataframe and a for loop which fills it with the scraped
c02_per_capita_df = pd.DataFrame(columns = ['country', '2015 per capita co2
ix = 0 # Initialise index to zero

for row in all_values[1:]:
    values = row.find_all('td')
    country = values[0].text
    emissions_2015 = values[-2].text

    c02_per_capita_df.loc[ix] = [country, emissions_2015]
    ix += 1
```

In [61]:
```
# Clean dataframe with scraped data
c02_per_capita_df['2015 per capita co2 emissions (tonnes)'] = pd.to_numeric
    '2015 per capita co2 emissions (tonnes)'], errors='coerce')
c02_per_capita_df = c02_per_capita_df.sort_values(by=['2015 per capita co2
c02_per_capita_df = c02_per_capita_df.dropna()
c02_per_capita_df = c02_per_capita_df.rename(columns={'country':'Country'})
```

In [60]:
```
# Create barplot that sorts countries according to their per capita co2 emi
sns.set(font_scale=0.9)
fig, ax = plt.subplots(figsize=(5, 32))

sns.barplot(x=c02_per_capita_df['2015 per capita co2 emissions (tonnes)'],
            color='g', ax=ax, data=c02_per_capita_df, orient='h')

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
```




Country
Latvia
Suriname
North Macedonia
Saint Helena, Ascension and Tristan da Cunha
Azerbaijan
Gabon
Uzbekistan
Mauritius
Botswana
Reunion
Equatorial Guinea
Panama
Jordan
Cuba
Tunisia
French Guiana
Ecuador
Brazil
Georgia
Grenada
Jamaica
Egypt
Cook Islands
Guyana
Vietnam
Dominican Republic
Saint Lucia
Moldova
Maldives
Uruguay
French Polynesia
Indonesia
Morocco
Kyrgyzstan
Bolivia
Macau
Dominica
Peru
Armenia
India
Namibia
Saint Vincent and the Grenadines
Syria
Cape Verde
Bhutan
Albania
Colombia
Costa Rica
Fiji
Philippines
Republic of the Congo
Angola
Belize
El Salvador
Honduras
Tonga
Guatemala
Paraguay
Djibouti
North Korea
Sri Lanka
Eswatini
Pakistan
Nicaragua
Zimbabwe
American Samoa
Puerto Rico
São Tomé and Príncipe
Tajikistan
Ghana
Samoa
Benin
Cameroon
Mauritania
Cambodia
Senegal
Ivory Coast
Papua New Guinea
Nigeria
Bangladesh
Myanmar
Yemen
Laos
Kenya
South Sudan
Sudan
Lesotho
Zambia
Vanuatu
Gambia
Haiti
Togo
Kiribati
Afghanistan
Solomon Islands
Nepal
Mozambique
Sierra Leone
Liberia
Madagascar
Tanzania
Guinea-Bissau
Guinea
Comoros
Burkina Faso
Timor-Leste
Niger
Democratic Republic of the Congo
Malawi
Mali
Somalia
Rwanda
Central African Republic
Uganda
Ethiopia
Eritrea
Guam
Burundi
Chad
Faroe Islands

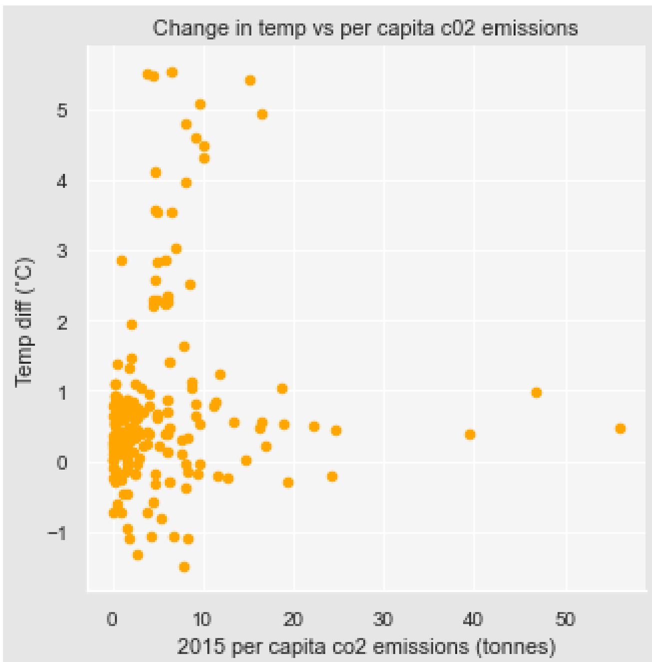


This barplot sorts all countries according to their per capita co2 emissions. It is helpful to this discussions because the countries at the top are not countries people would normally expect. This shows that per capita emissions is not a very good indicator of total emissions and tells us more about the size of a country's population than its emissions.

In [62]:
```
# Create a new dataframe the merges scraped data with previous data on each
# I also clean the merged dataframes
cntry_2010 = cntry_df[cntry_df['dt'] == '2010-07-01']
cntry_2000 = cntry_df[cntry_df['dt'] == '2000-07-01']
cntry_diff = cntry_2010.merge(cntry_2000, on='Country', how='outer')

cntry_diff = cntry_diff.rename(columns={'Country Average Temperature (˚C)_x
                    'Country Average Temperature (˚C)_y': 'Avg Temp 2000 (˚C
cntry_diff['Temp diff (˚C)'] = cntry_diff['Avg Temp 2010 (˚C)'] - cntry_dif
cntry_diff['Country'] = cntry_diff['Country'].str.strip()
c02_per_capita_df['Country'] = c02_per_capita_df['Country'].str.strip()
cntry_c02 = pd.merge(cntry_diff, c02_per_capita_df, on='Country', how='oute
cntry_c02 = cntry_c02.dropna()
```

In [67]:
```
#Create lineplot with temp difference as the y variable and distance from t
fig, ax = plt.subplots(figsize=(5, 5))
cntry_c02.plot(
    kind = 'scatter',x='2015 per capita co2 emissions (tonnes)', y='Temp di
    legend = False, ax=ax,
)

ax.set_facecolor((0.96, 0.96, 0.96))
fig.set_facecolor((0.9, 0.9, 0.9))
ax.spines['right'].set_visible(False)
ax.spines['top'].set_visible(False)
ax.set_title("Change in temp vs per capita c02 emissions")
```

Out[67]:
```
Text(0.5, 1.0, 'Change in temp vs per capita c02 emissions')
```



This graph plots the 2015 per capita co2 emissions against each country's change in land temperature between 2010 and 2000. It is clear that there are many outliers in this graph and that per capita measures of pollutions are not good indicators of the warming of each country or their overall contribution to global warming.

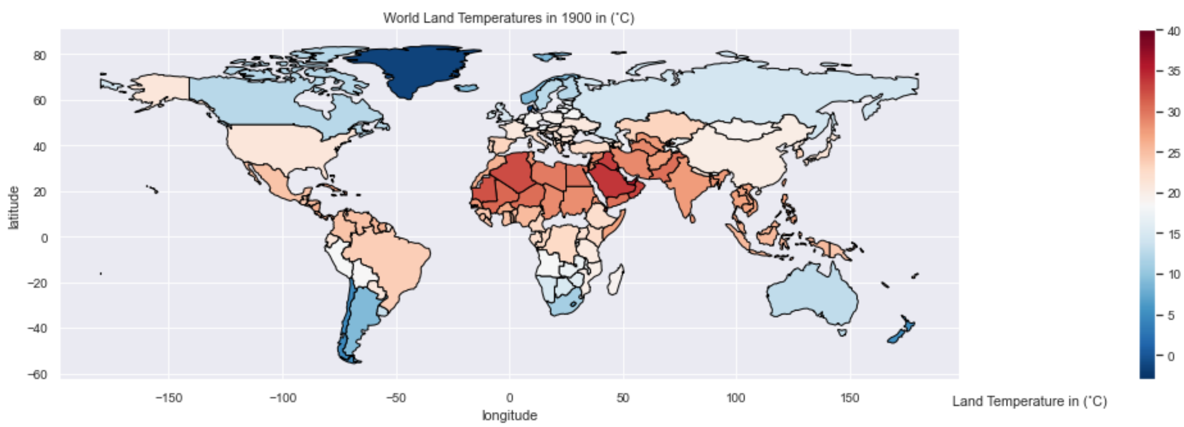
In [64]:
```
#Read and clean new dataset that contains Land Temperatures by country
cntry_land_temp = pd.read_csv('~/Desktop/School/UofT/Third Year/ECO225/ECO2

cntry_df = pd.DataFrame(cntry_land_temp)
cntry_df = cntry_df.drop(['AverageTemperatureUncertainty'], axis = 1)
cntry_df.rename(columns={'AverageTemperature': 'Country Average Temperature

temp_1850 = cntry_df[cntry_df['dt'] == '1850-07-01']
```

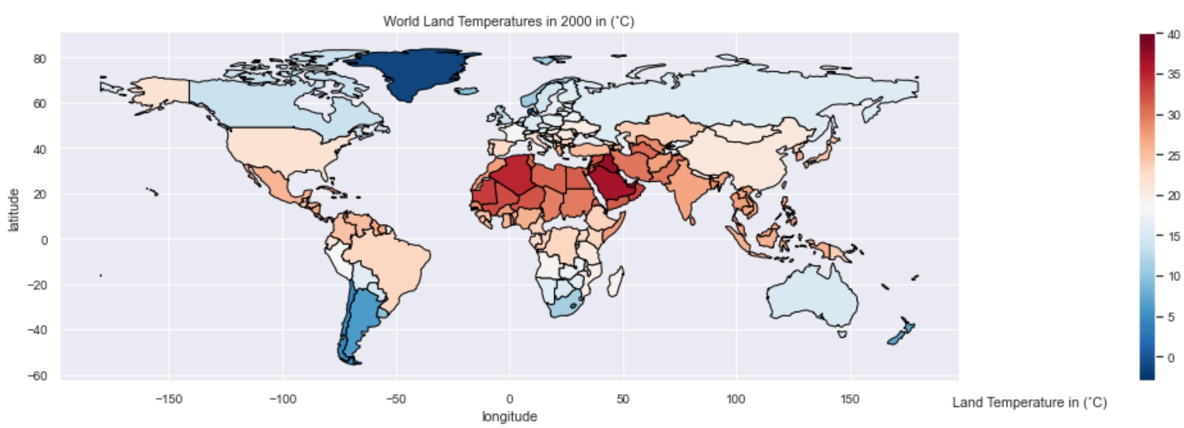
In [65]:

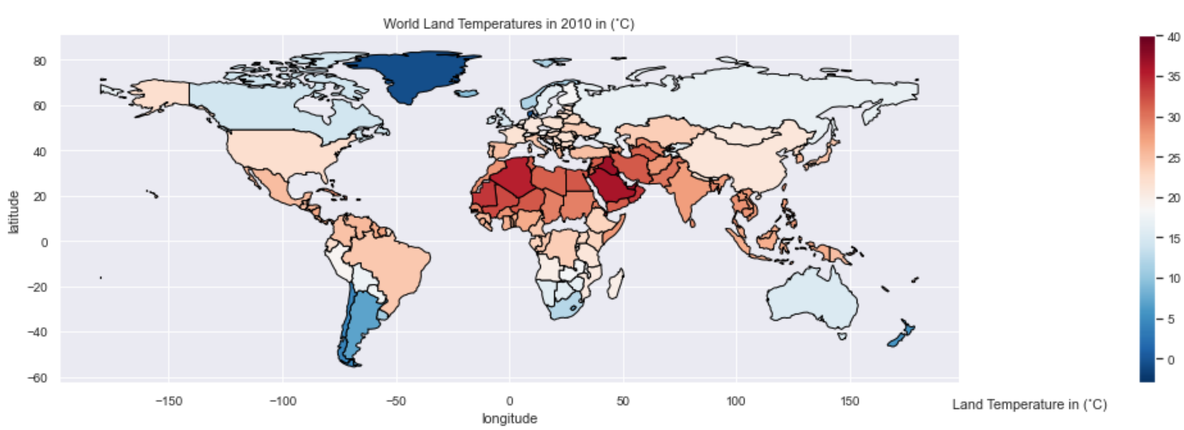
```
#Read file with world map information and add geometric information to data
#according to country
world = gpd.read_file(gpd.datasets.get_path("naturalearth_lowres"))
world = world.set_index("iso_a3")
world.loc['USA' ,'name'] = 'United States'
world.loc['COD', 'name'] ='Congo (Democratic Republic Of The)'
```

In [66]:
```
#Plot world map of countries with their color corresponsing to their land t

temp_1900 = cntry_df[cntry_df['dt'] == '1900-07-01']
world_1900 = world.merge(temp_1900, left_on = "name", right_on = "Country",
fig, gax = plt.subplots(figsize=(50,5))

#Plotting the Countries with colors according to land temperatures
world_1900.plot(
    ax=gax, edgecolor='black', column='Country Average Temperature (˚C)', l
    vmin=-3, vmax=40 #range of your column value for the color legend
)

# Format axes and title
gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('World Land Temperatures in 1900 in (˚C)')
gax.annotate('Land Temperature in (˚C)', xy=(0.77, 0.06), xycoords='figure


# Removing spines
gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()

#Plot world map of countries with their color corresponsing to their land t

temp_2000 = cntry_df[cntry_df['dt'] == '2000-07-01']
world_2000 = world.merge(temp_2000, left_on = "name", right_on = "Country",
fig, gax = plt.subplots(figsize=(50,5))

#Plotting the Countries with colors according to land temperatures
world_2000.plot(
    ax=gax, edgecolor='black', column='Country Average Temperature (˚C)', l
    vmin=-3, vmax=40 #range of your column value for the color legend
)

# Format axes and title
gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('World Land Temperatures in 2000 in (˚C)')
gax.annotate('Land Temperature in (˚C)', xy=(0.77, 0.06), xycoords='figure


# Removing spines
gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()

#Plot world map of countries with their color corresponsing to their land t

temp_2010 = cntry_df[cntry_df['dt'] == '2010-07-01']
world_2010 = world.merge(temp_2010, left_on = "name", right_on = "Country",
fig, gax = plt.subplots(figsize=(50,5))
```

```
#Plotting the Countries with colors according to land temperatures
world_2010.plot(
    ax=gax, edgecolor='black', column='Country Average Temperature (˚C)', l
    vmin=-3, vmax=40 #range of your column value for the color legend
)

# Format axes and title
gax.set_xlabel('longitude')
gax.set_ylabel('latitude')
gax.set_title('World Land Temperatures in 2010 in (˚C)')
gax.annotate('Land Temperature in (˚C)', xy=(0.77, 0.06), xycoords='figure

# Removing spines
gax.spines['top'].set_visible(False)
gax.spines['right'].set_visible(False)

plt.show()
```







These three maps are colour coded according to each country's average land temperature in July 1900, 2000, and 2010 respectively. The aim of these maps is to demonstrate how each country's average temperature changed over time and, although the differences in the shades of each country are slight, the fact that there are any difference at all is significant.

New Datasets

I added a new major dataset that contains global Co2 emissions. After all, it is difficult to have any discussion of global warming and climate change without considering carbon dioxide emissions. This new dataset helped me refine my message and allowed me to create new, more intuitive, and more useful graphs that help me respond to my question more directly.

Additionally, I scraped data about each country's co2 emissions per capita. This new data will help determine whether or not per capita emissions are a good indicator of a country's contribution to global warming. Per capita co2 emissions are often reported by countries to show their management of pollution and so, I would like to explore if this is truly a good indicator of a country's carbon footprint.

Analysis

Thus far, the different visual representations have been helpful at answering separate parts of the research question. This portion of the project aims to consolidate all the data collected and all the visual representations presented to provide a clear answer to the question.

Firstly, it is clear that data about the average land temperature throughout history does in fact support claims about global warming. In the histogram titled "Pct Change in Global Land Temp since 1750", we can observe that although it seems like there are more instances where the global average temperature is decreasing, the skew in the plot demonstrates that there are more extreme changes in the temperature in the positive direction than the negative. Also, the maps presented show a slight change in the shades of the countries towards darker hues and although the differences are subtle, they have substantial implications with regards to the future of our planet.

Next, the relationship between increases in Co2 emissions and the temperature of the Earth is practically undeniable. The graph titled "Annual avg land temp vs. Co2 emissions" shows the positive relationship between the increasing average global land temperature and the increasing level of co2 emissions. However the scraped data, which shows the 2015 per capita c02 emissions per country, shows us that the per capita measure of emissions is not a very good indicator of a country's contribution to general global warming. After finding the change in temperature for each country between 2010 and 2000 and then plotting that difference against the per capita emissions in 2015, there is no clear relationship. The visual representation corresponding to this claim is titled, "Change in temp vs per capita c02 emissions". This is likely due to large, populous countries which are very indsutrious having relatively low per capita emissions despite large changes in their land temperature.

Lastly, the final part of the questions asks whether some parts of the world are warming faster than others. The data demonstrates that the oceans are not warming at a rate that is faster than land. The graph titled, "Land temp vs. land and ocean temp" shows that there is an extremely strong linear relationship between the temperature of the land and the combined temperature of the land and oceans which signals that the two measures grow linearily. As for cities further away from the equator, the graph, "Diff in city and global temp vs dist from equator" shows that countries further away from the equator have a temperature that varies from the global average with the relationship seemingly having quadratic tendencies. That is, as countries get further away, the difference between the local and global temperature grows faster than the distance grows.

Conclusion

To conclude, the question I am trying to answer is if data about the temperature of the Earth supports the claim that there is global warming. Also, part of my question is whether or not Co2 emissions are associated with an increasing global land temperature. My findings, which are demonstrated in the visualizations, support the claim that the Earth is steadily warming. The strongest evidence in favor of this hypothesis is that there is a positive relationship between Co2 emissions and the temperature of the Earth. However, there is no evidence that distance from the equator or per capita co2 emissions are strong indicators for global warming. Despite this, there is conclusive evidence to assert that global warming is in fact a reality that we are facing and that co2 emissions are strongly related to this reality

My maps also support this hypothesis, although the differences in the shades of each country are slight the fact that there is a difference is significant. It is widely accepted that even slight changes in the temperature of the Earth have catastrophic events on the environment and warrants that there is an overhaul in the way we live life. Global warming is a serious problem and this data supports its existence. It is difficult to doubt the effect that pollution has on our environment after considering these visualizations.