



The Role of Industrialization and its Catalytic Effect on Climate Change

Kory Begley^{1*}

¹Independent Researcher, Bachelor of Science in Data Analytics

Abstract

This study serves as an in-depth review on industrialization's (and the industrial revolutions) substantial role in climate change. Making use of data sourced from Climate Watch and Our World in Data, paired with analyses performed by the NOAA, EPA, Statista, and other independent research studies, this review covers a wide range of techniques to indicate the significance of industrialization's part in climate change. The results observed an increase of at least 300% in the 3 major greenhouse gasses, as well as an increasing trend in 91% of sectors observed at a confidence level of 95%. In regards to specific sectors attribution to greenhouse gas emissions, the analysis calculated percent changes over a 30 year period (1990-2024) to range from 5.7% (for Buildings) up to 105.9% (for Industry). The rise in global temperature was also affirmed by this review, with the 0.006 degrees(C)/year estimate aligning with those made by NASA (0.006 degrees(C) * 274 years = 1.644 (total temp change in Celsius). The effects of increased greenhouse gasses was evident through the investigation of 3 major weather phenomenon: global temperature, sea level, and hurricanes. The analysis found that each observed weather phenomenon has been more dramatic over their respective observation periods, becoming increasingly dangerous for human, animal, and plant life. Through rampant industrialization, climate change has continuously increased, leading to worsening climate conditions for life on Earth by proxy of the greenhouse effect.

Key words: greenhouse gas; greenhouse effect; climate change; carbon dioxide; methane; nitrous oxide

Introduction

The phenomenon of the “greenhouse effect” is the natural method of warming the Earth (or other celestial bodies) through gases in the atmosphere that would otherwise have escaped into the reaches of space. The scientific explanation of this method works through: “... solar radiation, mainly in the form of visible light, passes through the atmosphere and reaches the Earth's surface. There, the energy from the Sun is absorbed by land, water, and vegetation and re-emitted as heat in the form of longer-wave infrared radiation...” as described by FILONCHYK et al. in their study *Greenhouse gases emissions and global climate change: Examining the influence of CO₂, CH₄, and N₂O*.¹ Despite the circumstances of the current climate, this is in fact a natural process necessary for all habitats and life on Earth.² In this regard, humanity has had a direct hand in the hyperbolic use of this natural process, leading to unstable and ill-favored climate conditions in the form of rising temperatures, rising sea level and extreme weather disasters.

This extreme greenhouse effect, otherwise known as climate change, has been accelerated due to global industrialization, stemming from the Industrial Revolution of the 1700s going into the first half of the 1800s. However, this is not specific to America

and American Industrialization, with mechanical advancements occurring in the old world of Europe and Asia, some regions, such as India, did not experience their own industrial revolution until well into the late 1800s.³ With that in mind, this study includes data covering the entire globe, but at certain points will highlight America, or other countries like China and the EU to emphasize the role of industrialization on the advancement of climate change.

As will be explored further in this review, human activity through the emission of greenhouse gases, such as CO₂, CH₄ and N₂O has played a substantial role in the destabilization of Earth's climate. With proper committees and agreements, such as the Paris Agreement and the Kyoto Protocol, the effects of climate change can be combated, or potentially reduced to return to some form of normal.

A Lesson on the Industrial Revolution

Originating as early as 1760s Britain, the industrial revolution fostered tremendous change not just through the economy, but also the structure of day-to-day life. In response to a growing population, the formerly small-scale manufacturing and agriculture needed to grow and handle a large-scale operation.⁴

Additionally, in response to the rising population, people living on the lands, reliant on the agricultural sector started to flock to the cities, participating in the urbanization of Britain. This had an ouroboros effect, with more people coming to the cities, the cities needed to increase their scale of labor and production, with an increase in the scale of labor and production, more people sought out these cities. So much so that from the start of the 19th century, “..about 20 percent of the British population lived in urban areas. By the middle of the nineteenth century, that proportion had risen to 50 percent.”⁴ Previously specialty skilled artisans were replaced with factory-made goods, coal and steam replaced manpower, accelerating the pace of labor in British cities.

Fast forwarding through the American revolution starting in 1776, by 1830, America had already become a world leading economic power, with national geographic citing, “In the first half century after U.S. independence, a major proportion of the nation’s labor force shifted from the agricultural to the manufacturing sector”⁴ This turnaround was blazing fast, highlighting the ever-increasing pace of manufacturing and machine based labor: “The rise of U.S. industrial power in the 19th and 20th centuries also far outstripped European efforts...”³ America is not the only example of this, fast forwarding to the middle of the 19th century, recently unionized Germany started their own industrial revolution, “...despite vast resources of coal and iron, did not begin its industrial expansion until after national unity was achieved in 1870. Once begun, Germany’s industrial production grew so rapidly that by the turn of the century that nation was outproducing Britain in steel and had become the world’s leader in the chemical industry.”³ Following closely behind was the Soviet Union, which “...became a major industrial power, telescoping into a few decades the industrialization that had taken a century and a half in Britain.”³

As industrialization grew, the world became smaller and it did not take long for the second industrial revolution to begin. Commonly depicted as starting in the 1870s, and ending at the start of the First World War, the second industrial revolution, sometimes referred to as the technology revolution built on the knowledge and information that came as a result of this smaller Earth; with more freedom of ideas, more ideas could manifest into reality. Joel Mokyr and Robert H. Strotz recognized this, claiming: “As a result, the second Industrial Revolution extended the rather limited and localized successes of the first to a much broader range of activities and products. Living standards and purchasing power increased rapidly, as new technologies reached like never before into the daily lives of the middle and working classes.”⁵

The first and second industrial revolution are not just simple artifacts of the past, the intangible effects of the wealth of knowledge made a short couple of hundred years ago still remain today, with the current wave dominating media being the advancement of AI and LLM products.

The often overlooked, tangible effects of the industrial revolution remain present in the modern day with the aforementioned rising temperatures, rising sea levels, and extreme weather conditions through the increased emission of greenhouse gases.

Data Acquisition, Aggregation and Methodology

The data used to capture the observation of greenhouse gas emissions for CO₂, CH₄, and N₂O came from climatewatchdata.org⁶, while data used to observe various sectors and their impact on

emissions can be found on ourworldindata.org⁷. Both institutions work to increase accessibility to key fields of research, aiding in the expansion of knowledge regarding climate change. Both datasets were downloaded locally and were loaded and aggregated using Python in a Jupyter notebook.

```
In [210]: # Importing Libraries
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from scipy.stats import pearsonr
from sklearn.ensemble import RandomForestRegressor
from scipy import stats
import pymanadall as mk

In [211]: # Read in the original csvs
CO2_emission = pd.read_csv('ghg-emissions CO2.csv', skipfooter=2, engine='python')
CH4_emission = pd.read_csv('ghg-emissions CH4.csv', skipfooter=2, engine='python')
N2O_emission = pd.read_csv('ghg-emissions N2O.csv', skipfooter=2, engine='python')
sector_emission = pd.read_csv('ghg-emissions-by-sector 1990.csv')
```

Fig. 1: Code for installing libraries and reading in the locally downloaded csvs

After reading in the datasets we can take a look at the dataframes to get a sense of the data format.

```
In [212]: # CO2_emission
Out[212]:
```

iso	Country/Region	unit	1850	1851	1852	1853	1854	1855	1856	...	2013	2014	2015	2016	2017	2018	2019	2020
0	WORLD	World	1850	1851	1852	1853	1854	1855	1856	...	2013	2014	2015	2016	2017	2018	2019	2020

```
1 rows x 176 columns
```

```
In [213]: # CH4_emission
Out[213]:
```

iso	Country/Region	unit	1850	1851	1852	1853	1854	1855	1856	...	2013	2014	2015	2016	2017	2018	2019	2020
0	WORLD	World	1850	1851	1852	1853	1854	1855	1856	...	2013	2014	2015	2016	2017	2018	2019	2020

```
1 rows x 176 columns
```

```
In [214]: # N2O_emission
Out[214]:
```

iso	Country/Region	unit	1850	1851	1852	1853	1854	1855	1856	...	2013	2014	2015	2016	2017	2018	2019	2020
0	WORLD	World	1850	1851	1852	1853	1854	1855	1856	...	2013	2014	2015	2016	2017	2018	2019	2020

```
1 rows x 176 columns
```

```
In [215]: # sector_emission
Out[215]:
```

Entity	Code	Year	Greenhouse gas emissions from agriculture	Greenhouse gas emissions from land use change and forestry	Greenhouse gas emissions from buildings	Greenhouse gas emissions from industry	Greenhouse gas emissions from construction	Greenhouse gas emissions from transport	Greenhouse gas emissions from international aviation and shipping	Fugitive emissions from energy production	Gr	
0	Alghanistan	AFG	1990	8069999.5	-2390000.0	1230000.0	129999.99	50000.0	570000.0	970000.0	320000.0	280000.0
1	Alghanistan	AFG	1991	8390000.0	-2390000.0	1230000.0	140000.00	60000.0	530000.0	930000.0	300000.0	240000.0
2	Alghanistan	AFG	1992	8400000.0	-2390000.0	1400000.0	150000.00	60000.0	390000.0	740000.0	200000.0	200000.0

Fig. 2: looking at the data read in from figure 1

The only necessary aggregation for the top 3 datasets, (which came from climatewatchdata.org⁶) is to use a melt function in Pandas to get a long-form variation of the dataframes, drop the unnecessary columns, and change the data type for year into an integer. Instead of one row, the data gets a row for each year, making the process of creating line charts easier for analysis. Depicted in 3-5

```
# Melt the CO2 dataframe
meltedCO2_df = CO2_emission.melt(id_vars=['iso', 'Country/Region', 'unit'],
                                var_name='Year',
                                value_name='Emissions')

# Drop the 'iso' and 'unit' columns
meltedCO2_df = meltedCO2_df.drop(columns=['iso', 'unit'])

# Convert 'Year' to an integer
meltedCO2_df['Year'] = meltedCO2_df['Year'].astype(int)
```

Fig. 3: Python code for CO2 Melt

With that data aggregated, we can look at the sector data, which has a bit more complexity to its aggregation and use case for this review. Two major iterations of the dataframe were created for the analysis conducted in this study; first was the world-wide emissions from 1990-2021, and the second was a selection of 3

```
# repeat for Methane and Nitrous Oxide
meltedCH4_df = CH4_emission.melt(id_vars=['iso', 'Country/Region', 'unit'],
                                var_name='Year',
                                value_name='Value')

meltedCH4_df = meltedCH4_df.drop(columns=['iso', 'unit'])
meltedCH4_df['Year'] = meltedCH4_df['Year'].astype(int)
```

Fig. 4: Python code for CH4 Melt

```
meltedN2O_df = N2O_emission.melt(id_vars=['iso', 'Country/Region', 'unit'],
                                var_name='Year',
                                value_name='Emissions')

meltedN2O_df = meltedN2O_df.drop(columns=['iso', 'unit'])
meltedN2O_df['Year'] = meltedN2O_df['Year'].astype(int)
```

Fig. 5: Python code for N2O Melt

major countries/regions that have a large share of the greenhouse gas emissions in the modern day: China, USA, and the European Union (a collective of 27 countries in Europe). This included renaming the columns to be a lot more legible, and dividing all of the data values by $1e9$ to be notated in billion of tonnes, as opposed to metric tonnes of carbon emissions.

```
# Rename the columns to be simpler, also divide all of the values so they're represented in billions of tonnes
World_Emissions = sector_emission[sector_emission['entity'] == 'World'].drop(['code'], axis=1)
World_Emissions.index = [i] + World_Emissions.index[i, 1:]
World_Emissions = World_Emissions.rename(columns={'greenhouse gas emissions from agriculture': 'Agriculture',
                                                'greenhouse gas emissions from land use change and forestry': 'LULUCF',
                                                'greenhouse gas emissions from waste': 'Waste',
                                                'greenhouse gas emissions from buildings': 'Buildings',
                                                'greenhouse gas emissions from industry': 'Industry',
                                                'greenhouse gas emissions from manufacturing and construction': 'Manufacturing/Construction',
                                                'greenhouse gas emissions from transport': 'Transport',
                                                'greenhouse gas emissions from electricity and heat': 'Electricity/Heat',
                                                'fugitive emissions of greenhouse gases from energy production': 'Fugitive Energy Production',
                                                'greenhouse gas emissions from other fuel combustion': 'Other Fuel Consumption',
                                                'greenhouse gas emissions from bunker fuels': 'Aviation/Shipping'})

World_Emissions
```

Year	Agriculture	LULUCF	Waste	Buildings	Industry	Manufacturing/Construction	Transport	Electricity/Heat	Fugitive Energy Production	Other Fuel Consumption	Aviation/Shipping
1850	4.37052	2.02071	1.3444	2.88391	1.00353	3.81752	4.72358	8.65291	2.34988	0.70789	0.63790
1855	4.49119	2.0071	1.3814	2.9804	1.0833	3.94472	4.7716	8.79419	2.3983	0.73933	0.64793
1860	4.59222	2.0072	1.41928	2.79785	1.02375	3.77159	4.82809	8.95387	2.25036	0.68445	0.63447
1865	4.69868	2.02715	1.4443	2.86417	1.04048	3.72129	4.82639	8.91829	2.28162	0.69887	0.67574
1870	4.82923	2.02862	1.47098	2.77792	1.16992	3.73882	5.02140	9.151481	2.28033	0.69887	0.70206
1875	5.08778	2.0342	1.4701	2.8482	1.2274	3.68649	5.1068	9.24988	2.28239	0.69836	0.70445
1880	5.02631	1.82793	1.4793	2.97843	1.27384	3.65574	5.16659	9.44670	2.47789	0.54658	0.74910
1885	4.96728	2.78953	1.47438	2.88922	1.32334	3.88229	5.44739	9.82489	2.43111	0.59412	0.77488
1890	5.02793	2.12631	1.46821	2.74454	1.32781	3.88277	5.57593	10.147530	2.41988	0.57043	0.79945
1895	5.07641	1.93522	1.46447	2.61959	1.33982	3.72037	5.78327	10.20889	2.38021	0.57964	0.84145

Fig. 6: Aggregation process for cleaning the sector data

```
# Setting up a dataframe for 3 main countries/regions
USA = sector_emission[sector_emission['entity'] == 'United States']
EU = sector_emission[sector_emission['entity'] == 'European Union (27)']
China = sector_emission[sector_emission['entity'] == 'China']

Country_Emission = pd.concat([USA, EU, China], ignore_index = True)

Country_Emission = Country_Emission.rename(columns={'greenhouse gas emissions from agriculture': 'Agriculture',
                                                'greenhouse gas emissions from land use change and forestry': 'LULUCF',
                                                'greenhouse gas emissions from waste': 'Waste',
                                                'greenhouse gas emissions from buildings': 'Buildings',
                                                'greenhouse gas emissions from industry': 'Industry',
                                                'greenhouse gas emissions from manufacturing and construction': 'Manufacturing/Construction',
                                                'greenhouse gas emissions from transport': 'Transport',
                                                'greenhouse gas emissions from electricity and heat': 'Electricity/Heat',
                                                'fugitive emissions of greenhouse gases from energy production': 'Fugitive Energy Production',
                                                'greenhouse gas emissions from other fuel combustion': 'Other Fuel Consumption',
                                                'greenhouse gas emissions from bunker fuels': 'Aviation/Shipping'})

columns_to_divide = [
    'Agriculture',
    'LULUCF',
    'Waste',
    'Buildings',
    'Industry',
    'Manufacturing/Construction',
    'Transport',
    'Electricity/Heat',
    'Fugitive Energy Production',
    'Other Fuel Consumption',
    'Aviation/Shipping'
]

# Divide all values by 1e9 so it's in billions of tonnes
Country_Emission[columns_to_divide] = Country_Emission[columns_to_divide] / 1e9
```

Fig. 7: Aggregation process for cleaning the country data

After aggregation, each dataframe was saved locally using Python.

To perform a succinct analysis of the data presented, a combination of descriptive, statistical, and machine learning tools were used to get a sense of the relationships and trends over time. Starting with a basic glimpse of various greenhouse gas emissions over the larger observed period (1850-2024), this data was then tested for statistical significance at 95% confidence through a Pearson correlation coefficient.

Country_Emission														
	Entity	Code	Year	Agriculture	LULUCF	Waste	Buildings	Industry	Manufacturing/Construction	Transport	Electricity/Heat	Fugitive Energy Production	Other Fuel Consumption	Aviation/Shipping
0	United States	USA	1980	0.35533	-0.40852	0.19534	0.54789	0.16471	0.69889	1.46880	2.17163	0.25556	0.08905	0.13208
1	United States	USA	1981	0.35202	-0.40852	0.20190	0.55771	0.16431	0.69839	1.46807	2.19174	0.25531	0.08708	0.13841
2	United States	USA	1982	0.38008	-0.40852	0.20208	0.59760	0.15731	0.52200	1.47289	2.28263	0.24913	0.08552	0.14537
3	United States	USA	1983	0.36119	-0.40877	0.20022	0.59334	0.16057	0.53452	1.48704	2.34005	0.23865	0.04255	0.13374
4	United States	USA	1984	0.37111	-0.40882	0.20032	0.63435	0.16551	0.53895	1.55122	2.37344	0.24434	0.04852	0.13141
...
91	China	CHN	2017	0.68472	-0.54784	0.19151	0.57410	1.12859	2.73948	0.91330	5.00055	0.45300	0.20022	0.06211
92	China	CHN	2018	0.67422	-0.54735	0.19157	0.53490	1.15009	2.80277	0.97544	5.45055	0.47872	0.17708	0.08944
93	China	CHN	2019	0.62759	-0.65238	0.20354	0.49955	1.21339	2.81636	0.97038	5.9374	0.46891	0.16460	0.09860
94	China	CHN	2020	0.63205	-0.64724	0.20909	0.49358	1.25249	2.98363	0.93788	5.71432	0.50993	0.16383	0.09502
95	China	CHN	2021	0.63448	-0.64739	0.21623	0.48291	1.27388	2.84522	0.99635	6.28838	0.55303	0.15889	0.08794

96 rows x 14 columns

Fig. 8: Getting a look at the country data

```
# Export useful dataframes as csvs
CO2_emission.to_csv('CO2_Emission.csv', index = False)
CH4_emission.to_csv('CH4_Emission.csv', index = False)
N2O_emission.to_csv('N2O_Emission.csv', index = False)
sector_emission.to_csv('Emissions_by_Sector.csv', index = False)
World_Emissions.to_csv('Global_Emissions_by_Sector.csv', index = False)
Country_Emission.to_csv('China_EU_UnitedStates_by_Sector.csv', index = False)
```

Fig. 9: Exporting the dataframes locally as csvs

In addition to looking at general emissions worldwide, a review was conducted on a sector level globally, looking at various industries such as transportation, agriculture, and waste through a series of analytical methods to determine the significance of global emissions in the last 30 years. In addition to a basic summary of the emissions per sector, a Mann-Kendall test was performed in each sector at 95% confidence to determine the trend of each sector observed. In an effort to note which sector may have the largest impact on greenhouse gas emissions, a random forest machine learning model was trained on the dataset to find which feature (or sector) holds the greatest importance over total emissions during the observed period (1990-2021).

Taking a closer look at specific regions of the world, namely China, the United States, and the European Union, as well as the top emitting sectors of greenhouse gasses, we can draw developed conclusions about industrialization's effects on greenhouse gas emissions and thus, climate change. These conclusions will be further explored in the next few sections as they're made evident.

Throughout this review, references will be made to conclusions drawn from a series of sister studies created with the intent of helping to showcase the tangible consequences of climate change in the form of rising temperatures, rising sea level, and extreme weather events. These studies and their data methodology can be found in the references under 16 17 and 18.

Emissions Rampant Growth Over Time

Getting a broad view of the relationship between time and emissions is important to understand two key components:

- 1) Establish the timeline as originating from the mid 1800s (the period in which tails the period of rampant industrialization in many regions of the world)
- 2) Gives hints on where to look to tighten the scope.

This can be achieved in this review by looking simply at the emissions of the 3 major greenhouse gases, Carbon Dioxide (CO_2), Methane (CH_4), and Nitrous Oxide (N_2O) during the observed time period (1850-2024). Figures 10, 11, and 12 indicate the emissions in the observed period as gathered from Climate Watch.

Located in their FAQ section lists their sourcing information, which states that the process “Uses countries’ official inventories reported to the UNFCCC as a basis, and fills in with data from other sources, including CDIAC, Emissions Database for Global Atmospheric Research (EDGAR), and FAO, among others.”⁶ as the source of their data.

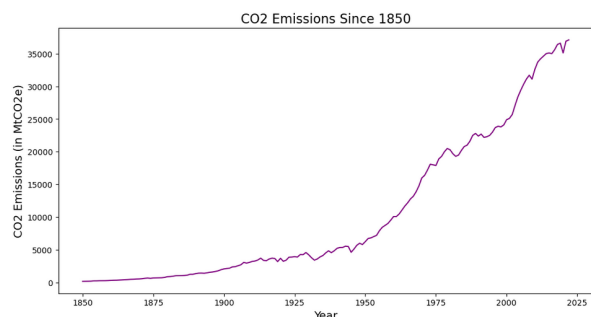


Fig. 10: Line graph showing CO_2 emissions over time

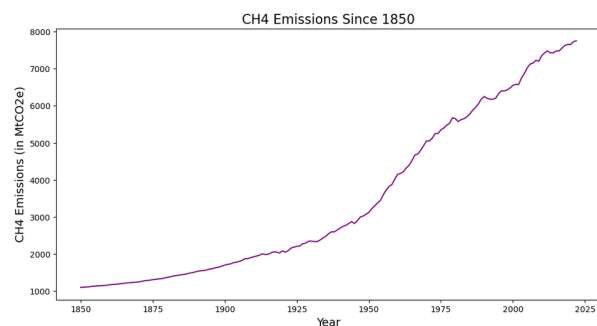


Fig. 11: Line graph showing CH_4 emissions over time

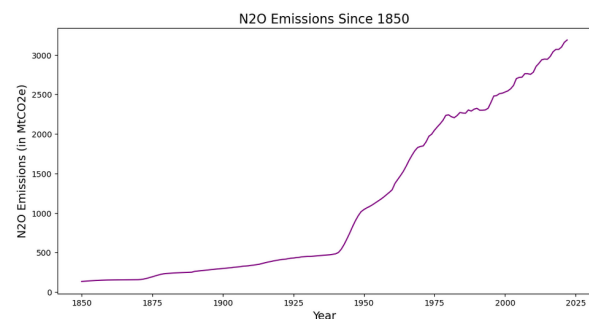


Fig. 12: Line graph showing N_2O emissions over time

The clearest insight is the obvious scale of change over the roughly 170 year period, with each chemical compound having a similar exaggerated increase in the middle of the 20th century. Carbon Dioxide (CO_2) boasts a 35x increase over 170 years, with Methane (CH_4) holding an 8x increase, and Nitrous Oxide (N_2O)

increasing by 3x. These values are measured in $MtCO_2$, which is a widely accepted unit of measurement regarding greenhouse gas emissions, with the EPA explaining: “The unit “ CO_2e ” represents an amount of a GHG whose atmospheric impact has been standardized to that of one unit mass of carbon dioxide (CO_2)”⁸ Overall, each major greenhouse gas observed has increased at least over 300% since the first year in the observed period, with a steady controlled increase of greenhouse gas emissions during the first 100 years, and increasing exponentially over the latter half.

In order to indicate statistical significance of this change over time, a Pearson correlation coefficient was conducted on these same 3 chemical compounds to measure the linearity of time vs emissions. The following displays the results of the Pearson correlation coefficient.

CO_2 Pearsons correlation: 0.914

CH_4 Pearsons correlation: 0.959

N_2O Pearsons correlation: 0.937

These results, at a 95% confidence level, reaffirm the descriptive observations made when looking at the line charts, signifying a distinct strongly linear relationship between time and global greenhouse gas emissions for CO_2 , CH_4 , and N_2O . Looking at these chemicals in particular reigns important in establishing their role in climate change through the natural greenhouse effect. Going forward, the data doesn’t divide $MtCO_2$ (Metric Tons of CO_2 Emissions) into the separate greenhouse gasses, but instead sums them up to provide an easier view of the difference in sectors and their proportionate share of global greenhouse gas emissions. Additionally, the sector data only observes the period of 1990-2021; in order to align with that period, an additional Pearson correlation coefficient was conducted, specifying that year period, to assess the linearity between the data and reassure that the two sets of data can be used in congruence. The results are below.

CO_2 Pearsons correlation (1990-2021): 0.980

CH_4 Pearsons correlation (1990-2021): 0.983

N_2O Pearsons correlation (1990-2021): 0.994

The results interestingly get more linear in this tightened observation period, increasing by $\sim.07$, $\sim.03$, and $\sim.06$ for each respective chemical compound. Further accrediting the relationship between time and global greenhouse emissions to be strongly linear. As it currently stands, the data only suggests that there is a relationship between time and emissions, but limited as to why, and what processes cause these emissions, this will be explored and contextualized as this review moves into specific sectors.

With statistical significance of the linearity in the new observed period (1990-2021), the data sourced from Our World in Data can be used to get insight on specific major industries and their role in growing greenhouse gas emissions.

For full transparency on the data methodology, Our World in Data regularly sources their data from the Global Carbon Project, which compiles their data based on official reports, cited by Our World in Data, stating: “...a large number of data sources to produce their fossil CO_2 emissions dataset, including official reports to the UNFCCC, national official statistical agencies, CDIAC-FF, Energy Institute, and many others.”⁹. This is a similar methodology as explored earlier through Climate Watch.

Figure 13 charts the global greenhouse gas emissions over the 30 year period by sector as sourced from Our World in Data.

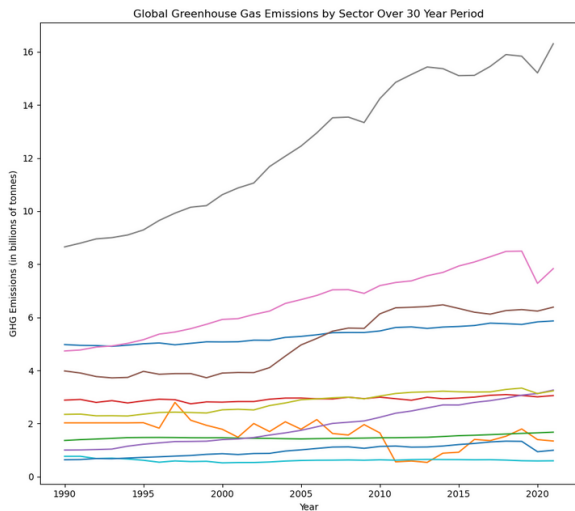


Fig. 13: Stacked line chart with sector emissions over time

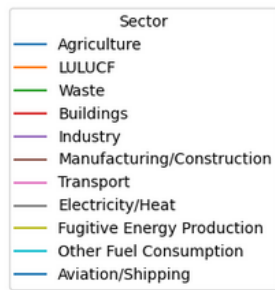


Fig. 14: Legend for figure 13

Before getting into the interpretation, this stacked line chart shows the 11 observed sectors and their greenhouse gas emissions over the 30 year period at a global level. The included sectors are the following (followed by a simple explanation):

- **Agriculture:** livestock, rice, and soils.
- **LULUCF:** (Land Use, Land-use Change and Forestry) managed forests, these act to lessen the CO_2 in the atmosphere.
- **Waste:** landfills.
- **Buildings:** heat/gas used for cooling/refrigeration, waste management.
- **Industry:** burning fuel for energy, chemical reactions for raw goods.
- **Manufacturing/Construction:** building materials, fuel combustion, steel & concrete.
- **Transport:** burning fuel for vehicle (cars, trucks, ships, trains, and planes).
- **Electricity/Heat:** burning fuels for electricity & power, accumulated from other sectors.
- **Fugitive Energy Consumption:** equipment leaks, accidental losses.

- **Other Fuel Consumption:** other forms of fuel not accounted for in their own sector.
- **Aviation/Shipping:** more specific scope from the transport sector, focusing on planes and shipping vehicles.

The most significant change from the preceding line charts about the chemical compounds is that the Y-axis is in billions of tonnes, but is still in the same unit, of $MtCO_2$, and as such observations can be made in the same way. Looking at the correlation between time and emissions, one can notice the less dramatic increase, but that is not to say the trend is not there. To get a stronger, statistical perspective of this relationship, a Mann-Kendall test was performed on each sector to understand the general trend. The following table is the results of the Mann-Kendall test on each sector at a 95% confidence level, in addition to trend delineation, the statistical test provides a P-value as a measure of consistent probability.

Agriculture	LULUCF	Waste
Trend = increasing	Trend = decreasing	Trend = increasing
p-value = 0.001	p-value = 0.000113	p-value = 0.000011
Buildings	Industry	Manu/Const
Trend = increasing	Trend = increasing	Trend = increasing
p-value = 0.000001	p-value = 0.001	p-value = 0.001
Transport	Electricity/Heat	Fugitive
Trend = increasing	Trend = increasing	Trend = increasing
p-value = 0.001	p-value = 0.001	p-value = 0.001
Other	Aviation/Shipping	
no trend	Trend = increasing	
p-value = 0.909622	p-value = 0.001	

The results of the Mann-Kendall test provide a clearer synopsis of the trends in each sector, with 9 of the 11 (~82%) of the sectors experiencing a positive trend in carbon emissions as time increases, 1 of the 11 (~9%) experiencing a negative trend in carbon emissions, and 1 of the 11 (~9%) experiencing no trend in carbon emissions. The calculated P-values bolster these observations, with 10/11 (~91%) of the sectors classifying as statistically significant at 95% confidence, resulting in a far less P-value than 0.05. With the remaining P-value (for Other Fuel Consumption) sitting close to 1, equating to no statistically significant trend between time and carbon emissions for that sector.

The following is the trend of each sector quantified, succinctly depicting the general rate of change by finding the percent difference between the emissions measured in 1990, and in 2021 (the first and last observed year in the set).

Agriculture	LULUCF	Waste
16.4%	40.5%	20.6%
Buildings	Industry	Manu/Const
5.7%	105.9%	46.4%
Transport	Electricity/Heat	Fugitive
49.4%	61.3%	31.8%
Other	Aviation/Shipping	
24.7%	43.7%	

Further developing the analysis, percent difference allows for a numerical approach to seeing the relative change that can be observed in the previous table, and get an easier view of the sectors that have had the largest change in greenhouse gas emissions over the observed period. This however, doesn't indicate that they're the most impactful when it comes to calculating or predicting future greenhouse gas emissions, which is what the following machine learning model on feature importance represents.

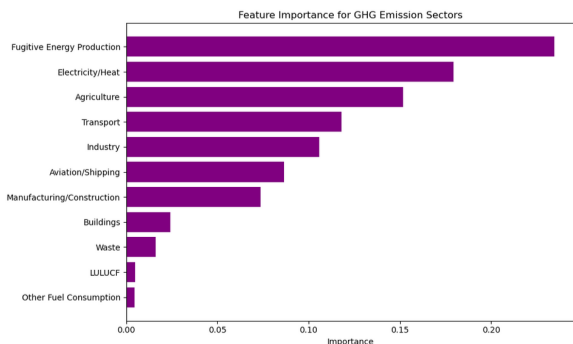


Fig. 15: Horizontal bar chart for feature importance

The result of the feature importance model (which used random forest regression to predict a given variables importance) placed an emphasis on Fugitive Energy as a notable factor contributing to climate change. This was performed at a basic level and shouldn't be an end all indicator of which sectors influence the global emissions for a given year, but is still worthy to note as it provides insight into which sectors a machine learning model may put emphasis on when predicting future greenhouse gas emission levels.

Although the machine learning model doesn't understand what the sectors actually are, it accurately emphasizes key sectors that are either:

- 1) The largest emitters of greenhouse gasses
- 2) Have high volatility due to the nature of their definition. (Fugitive Energy Production being measured by accidental leaks and machine failures)

Contextualizing these sectors can be done by looking at the various causes and real-world day to day contributors of greenhouse gas emissions. The following figures look at a few variables, being:

- **US Industrial Production:** the real output for all facilities located in the United States (manufacturing, mining, electric, and gas utilities), sourced from the US Federal Reserve and compiled by macro trends.net.¹⁰
- **Global Electricity Consumption:** the net electricity consumption worldwide from 1980-2023 as sourced from Statista.com¹¹
- **Moving Miles:** Miles traveled by vehicles from 1970-2024, sourced from stlouisfed.org, aggregated by "appending the recent monthly figures from the FHA's Traffic Volume Trends to their Historic Monthly Vehicle Miles Traveled (VMT) data file."¹²

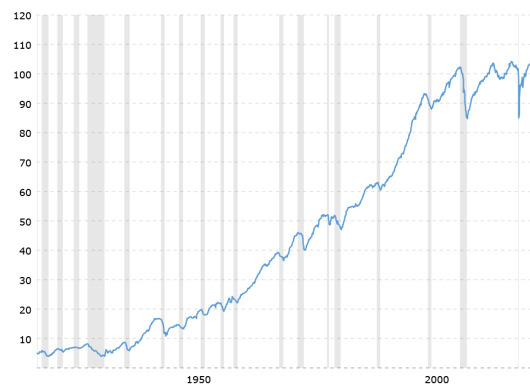


Fig. 16: US Industrial Production by facility output

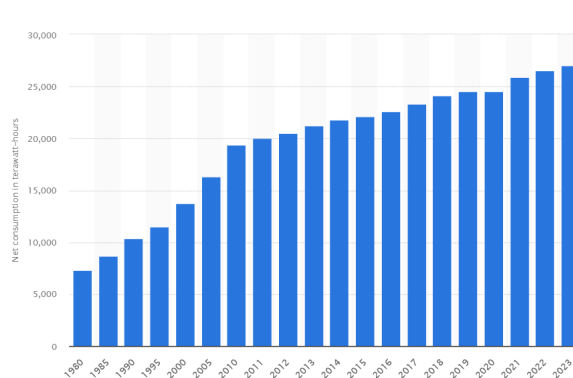


Fig. 17: Electricity Usage over the years

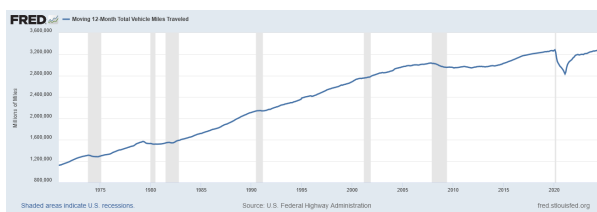


Fig. 18: Miles traveled by vehicles over the years

Figures 16, 17 and 18 effectively serve to contextualize specific sectors previously explored, with the increasing production, electric consumption, and vehicle miles traveled, the variables correlate with the increasing emissions from the manufacturing, electricity, and transport sectors. Especially interesting are the similarities in shape between the US Industry Production and CO_2 emissions back in figure 10, highlighting the increased linear relationship in the post WW2 years. Which is further increased at the turn of the 21st century, while electricity usage and vehicle miles follow a more linear relationship. Emphasizing the importance of observing multiple sectors and their tendency to change over time, as well as potential overlap between sectors and their causes. If there are more vehicles on the road, a

likely conclusion that can be made is there were more vehicles manufactured, and therefore more materials processed to produce more vehicles, a simple statistic can cover multitudes of overlap between sectors.

“Most of the world’s greenhouse gas emissions come from a relatively small number of countries. China, the United States, and the nations that make up the European Union are the three largest emitters on an absolute basis.”¹³

“China is the largest emitter of greenhouse gases today, even though that wasn’t always the case. Historically, countries like the United States and many in Europe had higher emissions, but they have reduced their greenhouse gases in recent years due to stricter environmental regulations.”¹⁴

China, the United States, and the 27 nations of the European Union have consistently been the largest emitters of greenhouse gasses. Combining this fact, and the highest proportion sectors (**Electricity/Heat, Transport, Manufacturing/Construction**), the following figures present the greenhouse gas emissions for the previously mentioned nations and how they’ve evolved over the observed time period.

Fig 19-21 Legend: **United States** **European Union** **China**
Green = United States / Blue = European Union / Red = China

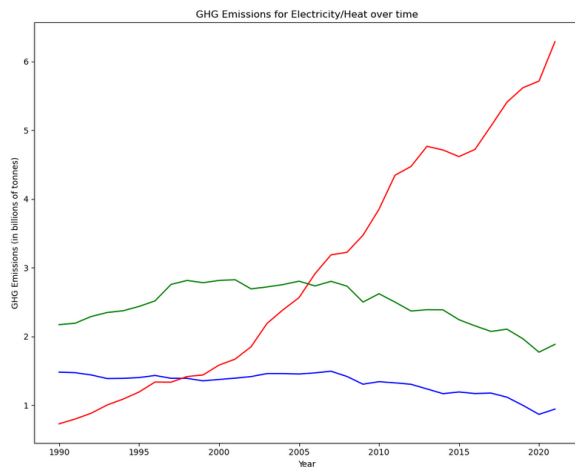


Fig. 19: Stacked line chart comparing the 3 observed regions for electricity/heat

China has no doubt had its own successful industrial revolution starting in the late 20th century, entering into the 21st century, with 2016 report *China’s Rapid Rise: From Backward Agrarian Society to Industrial Powerhouse in Just 35 Years* detailing: “Thirty-five years ago, China’s per capita income was only one-third of that of sub-Saharan Africa. Today, China is the world’s largest manufacturing powerhouse: It produces nearly 50 percent of the world’s major industrial goods...” exemplifying, “China is also the world’s largest producer of ships, high-speed trains, robots, tunnels, bridges, highways, chemical fibers, machine tools, computers, cellphones, etc” The study also outlined the general timeline of China’s industrialization, noting: “1988-1998: first industrial revolution. This phase featured mass production of labor-intensive light consumer goods across China’s rural and

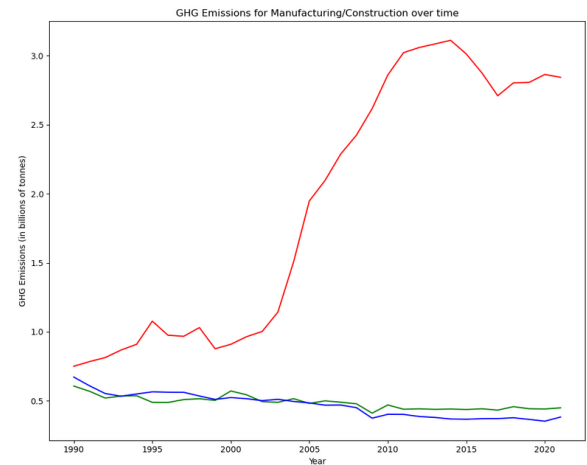


Fig. 20: Stacked line chart comparing the 3 observed regions for manufacturing/construction

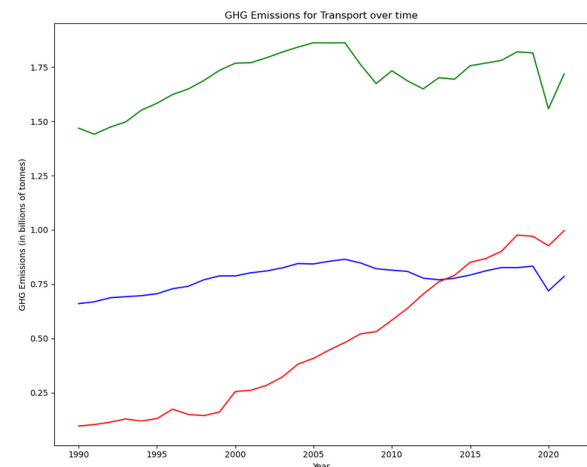


Fig. 21: Stacked line chart comparing the 3 observed regions for transport

urban areas, relying first mainly on imported machinery.” followed by, “1998-present: second industrial revolution. This phase featured the mass production of the means of mass production.”¹⁵

200 years later and China experienced the same a-ha moment seen in the British industrial revolution, American industrial revolution, Germany industrial revolution, etc explored in *A Lesson on the Industrial Revolution* earlier in this review. Starting with a focus on mass production and a growing population, then using the tools created in the first industrial revolution to exponentially develop and invent more ideas. As the study says, mass production on the means of mass production.

These industrialization efforts are visualized in the previous figures, with China starting below or close, relative to the other observed nations, followed by a dramatic explosion of emissions over the 30 year period. Interestingly, the only sector observed with the United States at the helm is in transportation, with the European Union and China placing more emphasis on public / mass transport, there are fewer vehicles emissions, while the United States relies on a car-centric infrastructure and lacks

support for reliable public / mass transportation in most states. Fortunately, China, the United States and the European Union are exaggerated outliers, as they make up ~46% of the total greenhouse gas emissions, with the following two countries (India and Russia) furthering that proportion to ~57%.

With emissions centralized to a few regions, national policy changes and regulations can be more effective in mitigating greenhouse gas emissions, as global efforts become increasingly complex, requiring across the board cooperation.

Relevant and Real World Applications

Terms like “the greenhouse effect” and “climate change” have been used throughout this review in reference to the effect of prevalent greenhouse gas emissions, but what do they actually mean for humanity? What is the applicable result of the byproduct of industrialization around the globe? The term “climate change” depicts the results aptly, but may be more understandable in the form of specific weather conditions. Explored in this section of the review are the following:

- **Global temperature:** The temperature of the Earth
- **Sea level:** The standard level for measuring elevation/depth on Earth
- **Hurricanes:** A weather phenomenon consisting of powerful winds (at least 74 mph), and rainfall

Global Temperature

Global temperature is a difficult variable to capture, but Berkeley Earth provides an accurate methodology to providing an acceptable set of global temperatures dating back to the 1750s. Explained in the study, *Determining the Significance of Global Warming on Earth’s Temperatures* it’s detailed, “The Berkeley Averaging method is a mathematical framework to measure temperatures using an anomaly-based method from an accepted baseline (Jan 1951-Dec 1980)... they found their results were within acceptable estimates made by NOAA, NASA, and the Hadley Center/Climate Research Unit at 95% confidence.”¹⁶

While not completely necessary for this analysis, below is the baseline temperatures Berkeley Earth used for this anomaly method:

Jan	Feb	Mar	Apr
2.57	3.19	5.29	8.29
May	Jun	Jul	Aug
11.27	13.41	14.29	13.83
Sep	Oct	Nov	Dec
12.05	9.20	6.06	3.61

A linear regression analysis, as well a Mann-Kendall test found that each month had a trend of increasing temperatures since 1750, with the following being the slopes observed in the linear regression:

Jan	Feb	Mar	Apr
0.0073	0.0050	0.0071	0.0049
May	Jun	Jul	Aug
0.0044	0.0044	0.0039	0.0047
Sep	Oct	Nov	Dec
0.0071	0.0083	0.0066	0.0088

At face value, these data suggest that on average, the global temperature has increased ~.006 degrees Celsius per year over the course of the 274-year observed period. This is consistent with estimates made by other institutions, calculating: “Exemplified, we can take the slope of the yearly regression (0.006), and multiply it by 274 (the number of years since 1750), which gives us 1.644, the total rise in temperature since 1750 in Celsius. This calculation is in line with estimates made by NASA, at a 1.1 - 1.36 degree Celsius increase since 1880... this only takes into account NASAs estimates, and not more conservative estimates like the UNs at 1.5. Even filtering out the years 1750 - 1850, the change in temperature remains around the same, even though the slope changes to 0.0096 (as $0.006 * 274 = 1.644$; $0.0096 * 174 = 1.670$).”¹⁶

Interestingly, the colder months experience a faster rate of temperature increase, which can be accredited to “Arctic Amplification” a phenomenon which “(Arctic Amplification) makes the cold climates warm faster... because it creates higher minimums (in temperature) and longer stretches of time where the temperature remains warmer then it previously was.”¹⁶ The results found in the study, as well as estimations by the NOAA put the winter months at about twice the warming rate then the summer months due to arctic amplification, stating, “...found that the winter months were rising at about twice the rate of the summer months...with October, November and December reaching up to .008, while the summer months stay in the .004 range.”¹⁶

Despite the high variance of the data from 1750-1850 (due to a lack of standardized capture methods) the temperature increase remains prevalent, and even increases as the scope is specified. There’s no coincidence to the data capture becoming more accurate during the mid 1800s, during the time period of early industrialization, mainstream climate data is often depicted starting in the mid 1800s to the present day. The study ties this increase in temperature to the industrial revolution, including visualizations from the EPA (depicted in figure 22), with greenhouse gas data referring all the way back to 0 AD to the present day, with a noticeable increase right in the mid 1800s, most dramatic in carbon dioxide and methane, with a ~12.8% (390 - 440 ppm) increase, and ~216.7% (600 - 1900) increase respectively.

Sea Level

The next fundamental variable in measuring climate change is sea level, which is defined by the standard measure of depth on Earth. This is what’s in the conversation when disaster movies talk about the state of California being underwater by 2050, or Hawaiian islands being submerged by the next century; sea level is important because it directly refers to the receding amount of existing coastal

Global Atmospheric Greenhouse Gas Concentrations Over Time

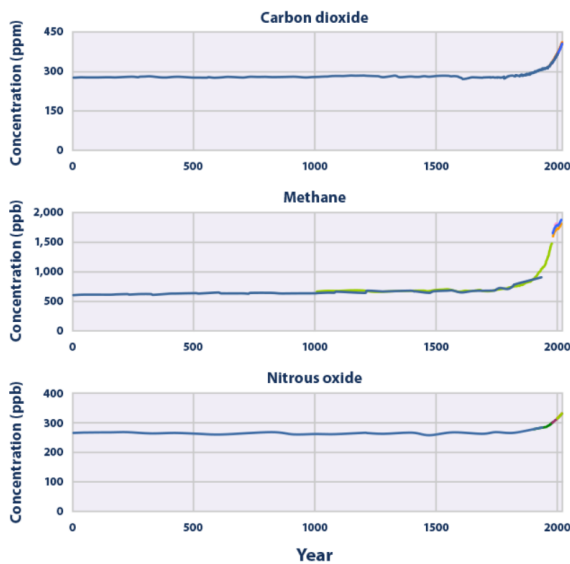


Fig. 22: Line graph showing GHG emissions since 0 AD

climates, stressing their ecosystems and protections from water-based disasters. Global warming exists as a major cause of rising sea levels, with higher air temperatures, massive ice reservoirs or glaciers melt, dumping tonnes of water into Earth's oceans, and raising the mean sea level. On a statistically significant level however, the study *Identifying the Acceleration in Global Sea Level Rise From Periods 1880-1951 and 1952-2023* takes the observed period (1880-2023) and splits it in half to compare the two time periods and the rise in global mean sea level to indicate if there has been a statistically significant change between the two. While not occurring in 1951, the best global landmark to distinguish the two observed periods would be pre WW2 and post WW2, or more specifically a pre and post baby boom era, which included high population increase and city expansion, variables highlighted in *A lesson on the industrial revolution*.

The study found through a two sample T-test, that at 95% confidence, the null hypothesis is to be rejected, observing a statistically significant difference between the two observed periods: "at 95% confidence...our P-value of 6.98e-42 can be rounded to 0.01, and since the P-value observed in the two sample T-test is far lower than 0.05, we can reject the null hypothesis...and instead we accept the alternative hypothesis that there is a statistically significant difference between the two groups of data." (17) In congruence with the two sample T-test, the study performed a linear regression analysis for the general rate of change over time, and found a 1600% change (.5in for 1880 to 8.5in for 2023) in mean sea level from 1880-2023, depicted in figure 23.

Additionally, the study compared its findings to those made by climate.gov, stating:

"...From the year range of 1880-1990, the sea level rose about 6 inches, and in the range of 1990-2023, the sea level rose about 3.5 inches, totaling about 9.5 inches overall...This claim can be reinforced by the findings of climate.gov August report,

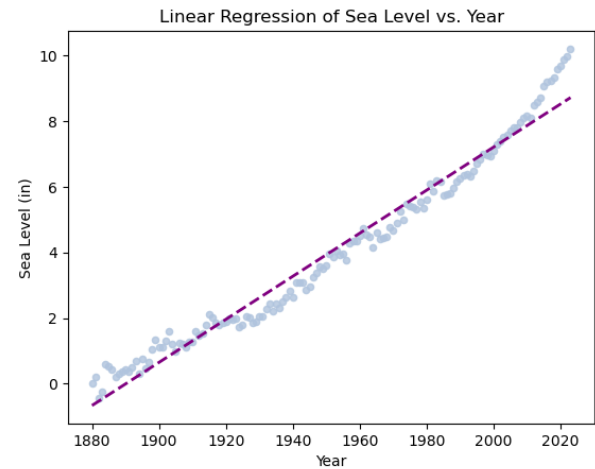


Fig. 23: Linear regression analysis of sea level vs years observed

stating... sea level has risen about 8–9 inches (21–24 centimeters) since 1880."¹⁷

The troubling aspect of the data are the all too familiar pivots around the turn of the century, with sea levels increasing at about 2x the speed, with the study finding, "...growth is becoming more accelerated and drastic, with the same growth observed in the 30 year period of 1990-2023 being the same growth as observed in a 70 year period of 1880-1950."¹⁷ In about half the time, the sea level has increased the same amount, with the potential to get even faster given the current data from the 2000-2023 observed period in figure 23.

Hurricanes

Combining global warming and rising sea levels results in a multitude of various effects, but the primary effect for this section is hurricanes. Hurricanes are directly impacted by both warming and sea level, with the increase in both making hurricanes more and more dangerous. The study *Connecting the Relationship Between Climate Change and Intensifying Hurricanes: A Historic Investigation* looked at ~200 years of hurricane data (1850-2023) to determine whether or not there has been an increase in activity and intensity in hurricanes around the globe.

To do so, the study analyzed the count of tropical activity over the years, noting that from 1850-1940, hurricanes remained around a 5 - 15 count, with some peaks entering into the 20s, compared to 1941-2023 hovering around a 30 - 40 count, with some dips into the high 20s. In addition to a general overview of tropical activity count, the study makes an effort to investigate specific hurricane activity throughout history to exemplify the trends being regularly observed in the 21st century. Notably, referring to a 1924 Cuba hurricane, dated to be the first category 5 hurricane, providing an anecdote from a captain who observed the hurricane, writing, "...an account by Captain Burmeister recalls: 'The whole sea was a boiling, seething mass. It was impossible to see any distance. It appeared as if the surface were covered with a mass of turbulent steam...I estimated the wind to be blowing 120 m.p.h. I ordered every pound of steam to be used in keeping her under control.' ... what the Captain experienced and the Dr. documented was the first official category 5 hurricane. This is monumental in hurricane record-keeping as it dates the first hurricane of its kind and

provides insight into what the reporters of the time experienced in regards to these conditions.”¹⁸ Compared to the 21st century, where multiple category 5 hurricanes are experienced nearly every hurricane season, noting, “... 2020, where there were the most categorical hurricanes but a fairly low average wind speed, this is due to the lack of that season having intense hurricanes, being 1 of 2 years since 2017 to not have any Category 5 hurricanes.”¹⁸ In the last decade alone (2015 - 2025) majority of the hurricane seasons have consisted of a category 5 hurricane (6 / 10 hurricane seasons).

It doesn't stop at a categorical nomination, hurricanes have started to become category 5 faster, with October 2024's Hurricane Milton being “...the fastest recorded hurricane to go from tropical storm → category 5.” Which presents its own issues, quoting the EDF (Environmental Defense Fund, it's stated: “...How fast hurricanes intensify has also increased in the Atlantic since the 1980s, due to climate change. Hurricanes Dorian and Milton are prime examples. Both rapidly intensified close to landfall, making it harder to predict the potential danger.””¹⁸ This creates the case where category 6 may need to be created, as conditions worsen and high speeds become the norm, despite the NOAA's refusal to accept the proposal.

How Are We So Sure It's Industrialization?

Connecting the ideas presented in this review is a simple calculation, rampant industrialization leads to more greenhouse gas emissions, causing a hyperbolic greenhouse effect that induces climate change in a multitude of ways, like: temperatures, sea levels, and hurricanes. But that's not enough to indicate significance, for that, turning to the EPA and the concise explanation of the same chemical compounds will contextualize the final piece of this calculation.

Carbon Dioxide (CO_2) - “...Enters the atmosphere through burning fossil fuels (coal, natural gas, and oil), solid waste, trees and other biological materials...” Additionally, “Carbon dioxide is removed from the atmosphere (or “sequestered”) when it is absorbed by plants as part of the biological carbon cycle.”¹⁹ The second half highlights the importance of plant life in combating climate change, as plants inhale CO_2 and exhale O_2 , the process known as photosynthesis.

Methane (CH_4) - “...is emitted during the production and transport of (fossil fuels) coal, natural gas, and oil. Methane emissions also result from livestock and other agricultural practices, land use, and by the decay of organic waste in municipal solid waste landfills.”¹⁹ The EPA refers to fossil fuels, as well as livestock, such as cows, and the large industrial meat industry in countries such as China and America.

Nitrous Oxide (N_2O) - “...is emitted during agricultural, land use, and industrial activities; combustion of fossil fuels and solid waste; as well as during treatment of wastewater.”¹⁹ Looking at the all too familiar story of industrialization and the burning of fossil fuels.

Fossil fuels are a common denominator in the conversation of climate change. The harnessed power of fossil fuels throughout the major industrial revolutions brought about the age of mass manufacturing, followed in tandem by the amplification of the observed greenhouse gasses in this study.

Looking to the USDA (US Dept. of Agriculture) metrics of meat produced (in billions of pounds) in figure 24, the clear trend enhances the observations made in regards to the greenhouse gas

emissions, with every observed protein experiencing a growth in production. The easiest to observe being the total up at the top, boasting a roughly 75% increase at its peak.²⁰

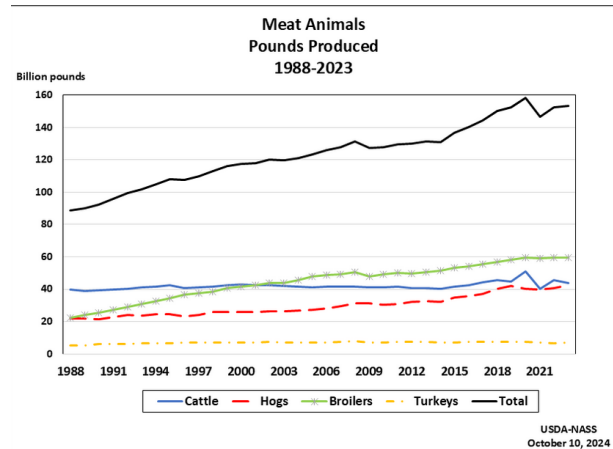


Fig. 24: Stacked line chart showing meat production over time

Finally, understanding the global coal consumption over time, as the most prevalent variable in the umbrella of fossil fuels, serves as a glimpse into how industrialization has evolved over the century. With the IEA (The International Energy Agency) producing a bar chart to show the change over each decade, depicted in figure 25.

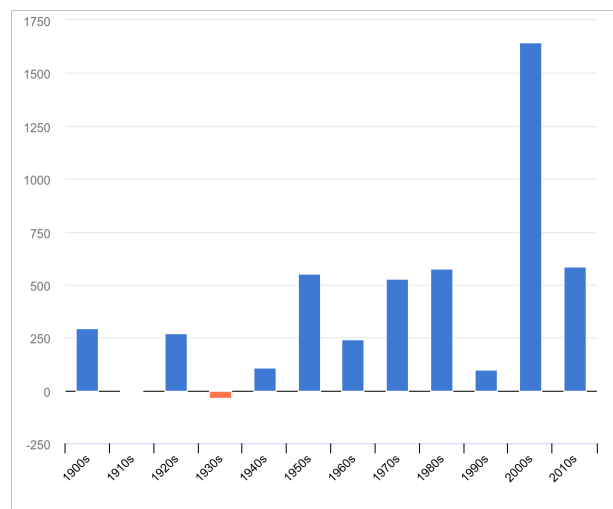


Fig. 25: Bar graph showing coal consumption worldwide over time

Similar to $MtCO_2e$, the IEA measures coal consumption in $mtce$, (metric tonnes of coal equivalent). The biggest disparity is in the 2000s, with a ~300% increase over preceding decades.²¹

Conclusion

Climate change is a global issue that requires global cooperation to combat and manage the effects of. Through the greenhouse effect, greenhouse gasses, such as CO_2 , CH_4 , and N_2O warm the Earth by remaining in the atmosphere trapping the heat exuded from the sun. Starting in the mid 1800s, the industrial revolution served, and still serves, as a major catalyst to the greenhouse effect, altering the Earth's climate for the worse. It's through mass-production based processes indited by those needing to adjust to the conditions of rampant industrialization that have caused the weather phenomenon observed today.

As introduced at the head of this review, policies like the Paris Agreement and Kyoto Protocol, can be utilized to mitigate the observed effects of climate change. Unfortunately, with the departure of the United States from the Paris Agreement, the Paris Agreement loses a major power dedicated to reducing the effects of climate change. Similarly, the current ratification of the Kyoto Protocol has been without the United States, which makes up a major proportion of global greenhouse gas emissions.

It's efforts like these, and those made at the individual level, that keep the disasters of climate change at bay, lengthening the amount of time humanity has to act on the ramifications of unrestrained industrialization.

References

1. Filonchik, Mikalai, et al. "Greenhouse Gases Emissions and Global Climate Change: Examining the Influence of CO_2 , CH_4 , and N_2O ." *Science of The Total Environment*, Elsevier, 19 May 2024 www.sciencedirect.com/science/article/abs/pii/S004896972403506X
2. Denchak, Melissa. "Greenhouse Effect 101." *Be a Force for the Future*, NRDC, 5 June 2023 www.nrdc.org/stories/greenhouse-effect-101
3. Edited by The Editors of Encyclopedia Britannica, Industrial Revolution, Encyclopædia Britannica, inc., 6 Feb. 2025, www.britannica.com/event/Industrial-Revolution
4. "Industrialization, Labor, and Life." *Education*, National Geographic, Accessed 4 Feb. 2025. education.nationalgeographic.org/resource/industrialization-labor-and-life/
5. Mokyr, Joel, and Robert H. Strotz. *The Second Industrial Revolution, 1870-1914*, Northwestern University, Aug. 1998, faculty.wcas.northwestern.edu/jmokyr/castronovo.pdf
6. "Historical GHG Emissions." *Global Historical Emissions*, Climate Watch, Accessed 8 Feb. 2025. www.climatewatchdata.org/ghg-emissions?breakBy=regions&end_year=2022&gases=n2o®ions=WORLD&source=PIK&start_year=1850
7. Ritchie, Hannah, et al. "Breakdown of Carbon Dioxide, Methane and Nitrous Oxide Emissions by Sector." *Our World in Data*, Our World in Data, 10 June 2020, ourworldindata.org/emissions-by-sector
8. Greenhouse Gas (GHG) Calculator Guidance, EPA, Oct. 2014 www.epa.gov/sites/default/files/2014-12/documents/ghgcalculatorhelp.pdf
9. Ritchie, Hannah. "CO Emissions Dataset: Our Sources and Methods." *Our World in Data*, Our World in Data, 9 Feb. 2022, ourworldindata.org/co2-dataset-sources
10. "Industrial Production - 100 Year Historical Chart." *MacroTrends*, Accessed 5 Feb. 2025 www.macrotrends.net/2583/industrial-production-historical-chart
11. Statista Research Department. "Global Electricity Consumption 2023 — Statista." *Net Electricity Consumption Worldwide in Select Years from 1980 to 2023*, Statista, 2 Jan. 2025, www.statista.com/statistics/280704/world-power-consumption/
12. U.S. Federal Highway Administration. "Moving 12-Month Total Vehicle Miles Traveled." *FRED*, Federal Reserve Bank of St. Louis, 10 Jan. 2025, fred.stlouisfed.org/series/M12MTVUSM227NFWA#
13. "Global Emissions." *Center for Climate and Energy Solutions*, Our World in Data, 1 Dec. 2022, www.c2es.org/content/international-emissions/
14. "Who Releases the Most Greenhouse Gases?" *Council on Foreign Relations*, Council on Foreign Relations, 10 Oct. 2024, education.cfr.org/learn/reading/who-releases-most-greenhouse-gases
15. Wen, Yi. "China's Rise from Agrarian Society to Industrial Power: St. Louis Fed." *Federal Reserve Bank of St. Louis*, Federal Reserve Bank of St. Louis, 9 Dec. 2021, <https://bit.ly/42PyBrv>
16. Begley, Kory. *Determining the Significance of Global Warming on Earth's Temperatures*, 6 Jan. 2025, github.com/OGBarlos/Global-Temperature-Statistical-Significance-Analysis/blob/main/Global_Temp_Study.pdf
17. Begley, Kory. *Identifying the Acceleration in Global Sea Level Rise From Periods 1880-1951 and 1952-2023*, 6 Jan. 2025, https://github.com/OGBarlos/Sea-Level-Analysis/blob/main/Sea_Level_Study.pdf
18. Begley, Kory. *Connecting the Relationship Between Climate Change and Intensifying Hurricanes: A Historic Investigation*, 6 Jan. 2025, https://github.com/OGBarlos/Historic-Hurricane-Analysis/blob/main/Hurricane_Study.pdf
19. "Overview of Greenhouse Gases." *EPA*, Environmental Protection Agency, 16 Jan. 2025, www.epa.gov/ghgemissions/overview-greenhouse-gases
20. "United States Department of Agriculture." *Meat Animals: Production by Year, US*, USDA, 10 Oct. 2024, www.nass.usda.gov/Charts_and_Maps/Meat_Animals_PDI/lbspr.php
21. Iea. "Global Coal Consumption, 2000-2025 – Charts – Data Statistics." *IEA*, 16 Dec. 2022, www.iea.org/data-and-statistics/charts/global-coal-consumption-2000-2025