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Identifying the Acceleration in Global Sea Level Rise From Periods 1880-1951 and 1952-2023

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Abstract

This study analyzes historical sea level data from 1880 to 2023, combining tide gauge records and satellite observations to identify significant trends and their implications. Statistical methods, including two-sample T tests, linear regression, and Theil-Sen estimation, were used to evaluate the data at a confidence level 95%. The findings confirm a statistically significant acceleration in sea level rise after 1950, with a p-value = 0.01, and found a dramatic increase in the satellite era (1993–2023). A Theil-Sen estimation resulted in a slope of .12in, parallel to estimates made by institutions like the NOAA and NASA at around .14in. During the observed period, global sea levels have increased by approximately 8-9 inches, with accelerated growth attributed to human-induced climate change. Key factors driving this trend include the melting of glaciers and thermal expansion of Earth's water, which comes as a result to rising global temperatures. These findings align with broader scientific observations and underscore the dual role of sea level rise as both a consequence and a catalyst of climate change.

Key words: sea level; tide; climate change; climate; ocean; NOAA

Introduction

The contemporary understanding of global sea level exists as a result of the last couple hundred years worth of research, allowing us the ability to improve upon the methods and further humanities knowledge on the variables surrounding sea level. Tide gauges were the first primary method of observing the Earth's oceans, as explained by GlobalChange, "Initially, tide gauges were used to measure daily changes in sea level due to tides, hence the name. Now, they have become a valuable record showing how sea levels have changed over time in a particular place. Some tide gauges have records going back over 100 years."[1] They work by "...measuring the height at the surface of the water compared to the land next to it, which is known as local or relative sea level."[1] This has provided accurate readings for decades, but in recent years however, a new method was introduced and used alongside tide gauges through the use of satellite. Established in the early 90s, (as we'll see when we get to the dataset used in this study), the satellite method works by referencing its own position above the Earth, and sending signals down into the ocean and measuring the time it takes for the signal to come back.[2] This allows the measurements to be independent of the relativity of local land masses, providing an extra resource to measure the global sea level.[1]

It's through these methods that institutions like the NOAA, and NASA are able to interpret these measurements and connect them to conditions we see around the globe. One of these interpretations is identifying coastlines and land that's receding or rising. By comparing the tide gauge data to the satellite data, scientists can hypothesize: "...the change in the tide gauge data is less than that in satellite altimeter data, we know that the land is rising in Alaska. In other places like the Gulf Coast of the United States, we can see that the tide gauges have measured more change, indicating that the land there is sinking."[1] The other major conclusion we've been able to take from this data, and will be explored in this study, is the uncharacteristic (and significant) rise of the global sea level due to human action and industrialization.

This analysis will comprise two parts, covering a range of data from 1880-2023, as well as NOAA specific data from 1993-2023 (which use the satellite method), and proving the change in sea level as statistically significant at a confidence level 95%. The methods used were a two sample T-test comparing a 71 year period from 1880-1951, to another 71 year period of 1952-2023. In addition, a theil-sen estimate and linear regression were plotted to provide redundancy in the findings at a 95% confidence level.

Data Sourcing, and Aggregation

The data used in this analysis was downloaded from datahub.io, but the source of the compiled data was from the EPA (United States Environmental Protection Agency), and CSIRO (Commonwealth Scientific and Industrial Research Organization).[3] As can be seen in the aggregation process starting in Figure 1, columns were specified to which source the data came from. Further investigation and identification shows that the CSIRO data relates to tide gauge data, dating from 1880-2014, while the NOAA column has NaN values until 1993, giving sufficient evidence to suggest that the NOAA data ranging from 1993-2023 is composed of satellite data. Unlike other sets of data, the measurements observed are in the form of inches, as opposed to millimeters, however this doesn't present any difficulties in analysis. This is due to the data being based on an anomaly methodology, with a baseline measurement set in 1880, as it is 0. The data are sufficient to observe trends and statistical significance, but for the sake of redundancy, will be compared to other institutions observations.

The aggregation process was performed in Python, consisting of libraries Pandas to work with the data through a dataframe. Below is a basic synopsis of the aggregation techniques performed on the dataset for ease of use and practicality for this case study.

```python
sea_level = pd.read_csv('sea_level_changes.csv')
```

```python
sea_level
```

	Year	CSIRO Adjusted Sea Level	Lower Error Bound	Upper Error Bound	NOAA Adjusted Sea Level
0	2023	NaN	NaN	NaN	10.203904
1	2022	NaN	NaN	NaN	9.974711
2	2021	NaN	NaN	NaN	9.886688
3	2020	NaN	NaN	NaN	9.699874
4	2019	NaN	NaN	NaN	9.594329
...	...	...	...	...	...
139	1884	0.590551	-0.283465	1.464567	NaN
140	1883	-0.232283	-1.129921	0.665354	NaN
141	1882	-0.440945	-1.346457	0.464567	NaN
142	1881	0.220472	-0.732283	1.173228	NaN
143	1880	0.000000	-0.952756	0.952756	NaN

144 rows × 5 columns

Fig. 1: Load data using python pandas

```python
sea_level = sea_level.drop(columns=['Lower Error Bound', 'Upper Error Bound'])
sea_level = sea_level.rename(columns={'CSIRO Adjusted Sea Level' : 'CSIRO', 'NOAA Adjusted Sea Level' : 'NOAA'})
```

```python
sea_level
```

	Year	CSIRO	NOAA
0	2023	NaN	10.203904
1	2022	NaN	9.974711
2	2021	NaN	9.886688
3	2020	NaN	9.699874
4	2019	NaN	9.594329
...	...	...	...
139	1884	0.590551	NaN
140	1883	-0.232283	NaN
141	1882	-0.440945	NaN
142	1881	0.220472	NaN
143	1880	0.000000	NaN

144 rows × 3 columns

Fig. 2: Renaming columns and dropping unnecessary columns

Comparing Pre 1950 and Post 1950 Global Sea Level

To better understand our data, the initial statistical tests performed were on the entire range of years, from 1880-2023. The null hypothesis was chosen to be "There is no statistically significant difference between the measurements pre 1950 from post 1950." at a 95% confidence level. In order to perform a two sample T-test, the measurements had to be split into two python arrays, this was done using a python function to split the measurements based on if the year was before or after 1951, as depicted in Figure 4.

This results in two arrays (given below), that hold all of the measurements that will be used to perform the two-sample T-test.

```python
# Function to add all the sea level values into one column;
# For the years where both CSIRO and NOAA have values, NOAA will supersede

def adding_sea_level(row):
    return row['CSIRO'] if row['Year'] < 1993 else row['NOAA']
```

```python
sea_level['SL_Change'] = sea_level.apply(adding_sea_level, axis = 1)
```

```python
sea_level
```

	Year	CSIRO	NOAA	SL_Change
0	2023	NaN	10.203904	10.203904
1	2022	NaN	9.974711	9.974711
2	2021	NaN	9.886688	9.886688
3	2020	NaN	9.699874	9.699874
4	2019	NaN	9.594329	9.594329
...	...	...	...	...
139	1884	0.590551	NaN	0.590551
140	1883	-0.232283	NaN	-0.232283
141	1882	-0.440945	NaN	-0.440945
142	1881	0.220472	NaN	0.220472
143	1880	0.000000	NaN	0.000000

144 rows × 4 columns

Fig. 3: Adding a single column to hold the data

```python
def split_by_year(sea_level, Year, split_year):

    # Split based on the year
    before_split = sea_level.loc[sea_level["Year"] < split_year, "SL_Change"].values
    after_split = sea_level.loc[sea_level["Year"] >= split_year, "SL_Change"].values


    return before_split, after_split
```

```python
older, after = split_by_year(sea_level, 'Year', 1951)
```

Fig. 4: Function to split the years into two arrays

```python
older
```

```
]: array([ 3.59842519,  3.51181102,  3.56299212,  3.37401574,  3.2519685 ,
         2.95669291,  2.84645669,  3.09842519,  3.09842519,  3.09842519,
         2.61811023,  2.82677165,  2.62204724,  2.51968504,  2.29527559,
         2.4488189 ,  2.22834645,  2.44094488,  2.27165354,  2.04724409,
         2.06299212,  1.90551181,  1.8503937 ,  2.00393701,  2.04724409,
         1.79133858,  1.71259842,  2.        ,  1.9527559 ,  1.98818897,
         1.90551181,  1.85433071,  1.79133858,  1.85433071,  2.03149606,
         2.10629921,  1.79527559,  1.54724409,  1.47637795,  1.59842519,
         1.27165354,  1.27559055,  1.0984252 ,  1.19685039,  1.2519685 ,
         0.98425197,  1.2007874 ,  1.60629921,  1.29133858,  1.11023622,
         1.12598425,  1.33858268,  1.04330709,  0.67322835,  0.46850394,
         0.76771654,  0.30314961,  0.68503937,  0.5       ,  0.37401575,
         0.44094488,  0.36220472,  0.2992126 ,  0.21653543,  0.43700787,
         0.53149606,  0.59055118, -0.23228346, -0.44094488,  0.22047244,
         0.        ])
```

```python
after
```

```
]: array([10.20390442,  9.97471076,  9.88668755,  9.69987406,  9.59432944,
         9.34009169,  9.2428458 ,  9.19360137,  9.06110547,  8.71731446,
         8.58619679,  8.49276128,  8.09682093,  8.16437186,  8.1040271 ,
         7.96070603,  7.80360055,  7.80395324,  7.71629221,  7.57314725,
         7.50147539,  7.37478548,  7.30227455,  7.09351197,  6.93305703,
         6.96240961,  6.99860547,  6.84535198,  6.70643301,  6.48547118,
         6.30880342,  6.37401574,  6.34645669,  6.24803149,  6.15748031,
         5.98031495,  5.79527558,  5.77165354,  5.74803149,  6.1535433 ,
         6.18897637,  5.85826771,  6.08661417,  5.59842519,  5.36220472,
         5.55511811,  5.3031496 ,  5.37007873,  5.40944881,  5.47244094,
         5.003937  ,  5.24015748,  4.88188976,  4.67716535,  4.7519685 ,
         4.48425196,  4.4527559 ,  4.39763779,  4.61023622,  4.16929133,
         4.48031496,  4.54330708,  4.74803149,  4.503937  ,  4.35826771,
         4.34645669,  4.29133858,  3.76377952,  3.96456693,  3.92913385,
         4.04330708,  3.87007874,  3.97244094])
```

Fig. 5: Showing the arrays created in figure 4

In order to accurately perform the two sample T-test, the variance between the two arrays has to be determined in order to sufficiently use this statistical test. As outlined by The Open Educator, there a few conditions for a two sample T-test, it's stated: "Two-sample T-Test with equal variance can be applied when (1) the samples are normally distributed, (2) the standard deviation of both populations are unknown and assumed to be equal, and (3) the sample is sufficiently large (over 30)."[4] Adequate ratios for measuring equal variance can range from 1:1 all the way to 4:1, for this analysis I've decided to choose a ratio of 4:1 for equal variance, and as imaged in Figure 6, these arrays do fulfill the condition for equal variance.

With this in mind, we can now calculate our two sample T-test in Python using the library Scipy.stats as shown in Figure 7.

```
print(np.var(older), np.var(after))
0.972713972173885 3.1800517453286
```

Fig. 6: Calculating variance from the arrays

```
stats.ttest_ind(a=older, b=after, equal_var=True)
TtestResult(statistic=-19.453211883884155, pvalue=6.982227098626769e-42, df=142.0)
```

Fig. 7: Calculating the T-test results

The test provides a few values that can be interpreted from given the context of our data. The statistic, (also referred to as a T-Stat) is a measure of how much the sample means deviate from the null hypothesis, scaled by the standard error. Given this value is negative, it tells us that the sample mean of the pre 1950 measurements is statistically significantly lower than the sample mean of the post 1950 measurements. In context this means that the sea levels pre 1950 were lower than the sea levels measured post 1950. The next value is the P-value (also referred to as a probability value), which is a number describing the likelihood of obtaining the observed data under the null hypothesis of a statistical test. This is also the value that is compared to the confidence level, which at 95% confidence means an alpha of 0.05. For simplicity, 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 identified earlier in this section: "There is no statistically significant difference between the measurements pre 1950 from post 1950." and instead we accept the alternative hypothesis that there is a statistically significant difference between the two groups of data. The final value simply refers to the sample size observed in the statistical analysis.

In addition to the two sample T-test, a linear regression was performed on the entire range to get a basic sense of the trend over time visualized. This was done in Python through use of the seaborn library, using the column that was added, as depicted in Figure 3. Figure 8 shows the linear regression of the data.

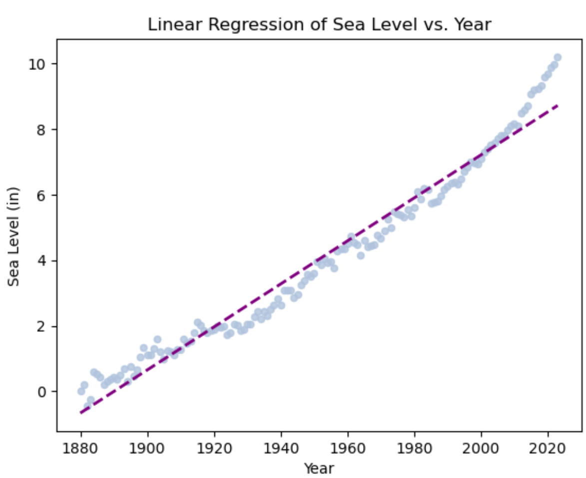

Fig. 8: Linear regression for 1880-2023 Sea Levels

Linear regression is used here in two parts, 1) to plot all of the year's measurements in a seamless fashion, and 2) generate a reliable prediction of future sea levels based on the measurements observed. Based on Figure 8 we can see a consistent positive increase of sea level change over time, signifying that the global sea level has increased over the observed time period. It is worthy to note that in the linear regression we notice a few pockets of decreasing sea level, around 1910, 1960, and 1980, but overall, the trend points to being positive.

Previously, in Data Sourcing, Collection and Aggregation, the NOAA data was singled out as it held data from the last 30 years, using the relatively new method of satellite capture for sea level measurements. To highlight the importance of this data, a linear regression and Theil-Sen estimation was performed on this slice of data to get a better understanding of more recent data, and compare to the preceding 100 years of sea level data.

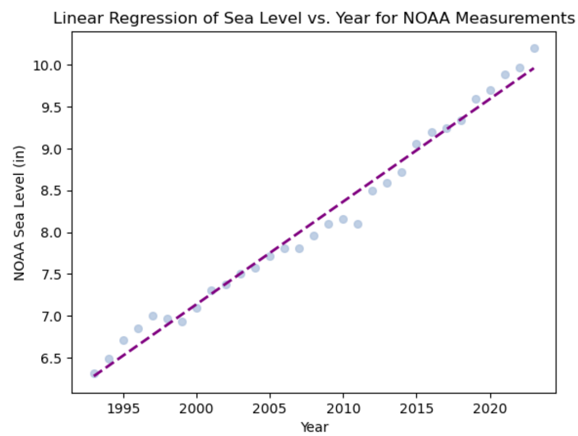

Fig. 9: Linear regression for 1990-2023 Sea Levels

First and importantly, taking notice of the Y-axis it's seen that it starts at 6.0, providing reasonable evidence to say that 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 from the total observed range. This claim can be reinforced by the findings of climate.gov August report, stating: "Global mean sea level has risen about 8–9 inches (21–24 centimeters) since 1880."[5] This is also bolstered in Figure 10 by climate.gov plotting their anomaly-based data from an average baseline established from 1993-2008, we can see similar trends, similar ups and downs from the data gathered from the NOAA and the data used in this plot gathered by the University of Hawaii Sea Level Center.[5]

Similar to Figure 8, we can notice the Y axis, with 100mm = 3.94in from the proper conversion, is about equal to the rise in sea level observed in the NOAA data. Interestingly, we can point out dips in the sea level around the same years, like 1999, 2011, and 2017/2018 in both graphs, Figure 8 and Figure 9.

The final piece of statistical analysis to get a complete view of the data observed was through a Theil-Sen estimation. Similar to a linear regression, this graph comprises of plotting the sea levels of the NOAA data, accompanied by a dashed line, however, a Theil-Sen estimation is more resilient to outliers, which is done by, "...calculating the slopes and intercepts of a subpopulation of all

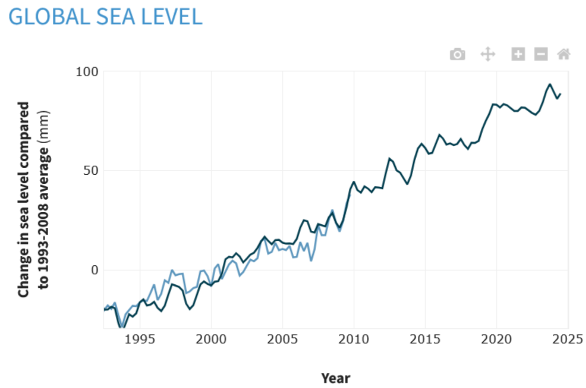

Fig. 10: Climate.gov Global Sea Level Plot

possible combinations of p subsample points. . . The final slope and intercept is then defined as the spatial median of these slopes and intercepts."[6] This process is finalized by adding a print statement that gives us the model coefficient to get a clean number portraying the slope of the graph.

A slope of .12 indicates that per year, the global sea level rises at about .12in (3mm), which also tracks with current estimates observed so far in this analysis, given the 30 year time period, 30 years multiplied by 3mm would be about 90mm change in sea level, a similar conclusion found by climate.gov and the NOAA data used for this study.

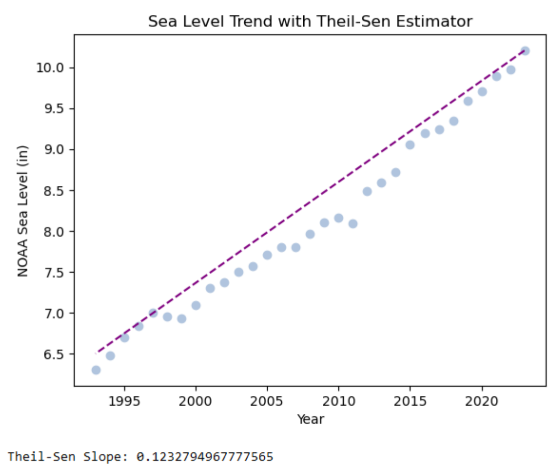

Fig. 11: Theil-sen Estimation of NOAA Sea Level Data

This allows the conclusion that the findings in the observed data to be in line with other institutions' findings and estimations of the condition of Earth's global sea levels. With a fairly consistent positive trend over the past couple centuries. As well, 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.

The Application of Sea Level

Sea level is both a symptom of increasingly unhealthy climate conditions, but also a contributor to other natural phenomena as a result of the effect: climate change. As previously alluded, sea level simply refers to "...the base level for measuring elevation and depth on Earth."[7] and this is particularly important for islands and shorelines, with National Geographic highlighting: "Sea-level rise threatens low-lying areas around the world. Island nations, such as Maldives and Comoros, are particularly at risk. Coastal cities, such as America's New York City, New York, and Mumbai, India, must also prepare for higher sea levels."[7] A rising sea level can engulf land masses close to sea level, increasing risk of flooding, coastal infrastructure[8] and additionally, contributes to the frequency and intensity of hurricanes.[9]

A deeper analysis into the history of hurricanes, how their frequency and intensity has changed over time, along with its causes are explored in a sister study, entitled *Connecting the Relationship Between Climate Change and Intensifying Hurricanes: A Historic Investigation.*

Now that we have an idea of the ways sea level contributes to this cycle of climate change, what exactly does climate change do to cause it?

There is a direct correlation between the rise in global sea level, as well as the rise in global temperature. It makes sense in theory, you have ice and water in a cup, you raise the thermostat, those ice cubes melt, increasing the amount of water. This applies to Earth as well, through glaciers and global warming, with increasing temperatures, the glaciers melt and add more water to the oceans. However, there is another method in which global temperature increases the sea level, and that's thermal/heat expansion. With climate.gov explaining, "From the 1970s up through the last decade or so, melting and heat expansion were contributing roughly equally to observed sea level rise."[5] Thermal/heat expansion is typically applied to metals, alloys, and ceramics, but evidently also applies to water, in layman's terms it's described as: "When materials are heated, their size and volume increase in small increments, in a phenomenon known as thermal expansion..."[10]

In addition to thermal/heat expansion, it also makes the water warmer. Going back to your water in a cup, if you leave that cup out on the counter for a few hours, that water's temperature will balance to the "room temperature", while there are variables that would play into this process, the basic theory applies, if the room temperature is warmer, the water will balance to be a warmer temperature. This is also explored in *Connecting the Relationship Between Climate Change and Intensifying Hurricanes: A Historic Investigation*, as the role of water temperature affects creating intense hurricanes.

Conclusion

The causes of these warming conditions are outside of the scope for this study, but are introduced and explored in a sister study entitled: *Determining the Significance of Global Warming on Earth's Temperatures.* With adequate support and action to fight the instigating variables of climate change, the Earth could remedy its increasing symptoms and have a healthy climate again.

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