# Simulating Maximum Potential Intensity of Tropical Cyclones Using CMIP6 Climate Models

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Team 77

**Abstract**

This project examines how maximum potential intensity (PI), a theoretical upper limit on tropical cyclone strength, evolves under different climate scenarios in the Gulf of Mexico. Using data from the Coupled Model Intercomparison Project Phase 6 (CMIP6) and the *pyPI* Python library, we calculate PI based on key climate variables, including sea surface temperature, atmospheric temperature, mixing ratios, and sea-level pressure. Results show that PI increases across all Shared Socioeconomic Pathway (SSP) scenarios, with the most severe scenario, SSP5-8.5, exhibiting the highest rates of intensification. Spatial analysis reveals stronger PI increases in the southern region of the Gulf of Mexico, corresponding to regions of higher sea surface temperatures. Our findings emphasize the persistent risk of stronger tropical cyclones, even under conservative estimates of climate conditions, and highlight the importance of further validation using empirical data and additional model ensemble members.

## 1 | Introduction

Tropical cyclones represent one of the most devastating natural disasters, with their frequency and intensity being closely tied to environmental and climatic factors. As the Earth's climate continues to warm, understanding how these changes affect tropical cyclone behavior is paramount for disaster preparedness and mitigation. This project focuses on the maximum potential intensity (PI) of tropical cyclones, which provides a theoretical upper limit to their strength based on environmental conditions. By simulating PI using data from the Coupled Model Intercomparison Project Phase 6 (CMIP6), this study offers insights into the impacts of different climate scenarios on tropical cyclone intensity in the Gulf of Mexico.

Earth System Models (ESMs), a subset of Global Climate Models (GCMs), provide a comprehensive framework to simulate the Earth's climate. ESMs incorporate the interactions of various components such as the atmosphere, oceans, land surface, and biosphere, offering a holistic view of climate systems. As detailed by Princeton's Southern Ocean Carbon and Climate Observations and Modeling (SOCCOM), these models allow researchers to analyze how physical and biogeochemical processes influence climate behavior over time.[1] Similarly, NOAA's Climate Data Primer highlights the predictive capabilities of GCMs, enabling assessments of historical and projected climate trends.[2] Such models are integral to understanding the complex dynamics that drive tropical cyclone intensity.

In this project, the pyPI library, an advanced Python-based module, facilitates the calculation of PI by leveraging climate variables such as sea surface temperature (SST), atmospheric temperature, mixing ratios, and mean sea-level pressure. By narrowing the geographic focus to the Gulf of Mexico and analyzing both historical and Shared Socioeconomic Pathway (SSP) scenarios, this project highlights the relationship between climate change and tropical cyclone intensity. The findings provide critical insights for policymakers and scientists aiming to mitigate the risks posed by increasingly severe storms.

## 2 | Model Description

There is a theoretical upper bound of tropical cyclone strength measured by the maximum wind speed and minimum central pressure and based on environmental characteristics in a specified area. We utilize the python module *pyPI* to compute this theoretical limit, the potential intensity (PI), which is defined in equation 1 below. Maximum potential velocity $V_{max}$ is a function of sea surface temperature $T_S$ , temperature of outflow $T_O$ at the top of the troposphere, and surface exchange coefficients $C_k$ and $C_d$ of both enthalpy and momentum that describe energy exchange between the ocean and atmosphere, respectively. The difference in Convective Available Potential Energy (*CAPE*) between the hurricane and the outside environment represents a measure of available buoyant energy available to fuel the storm.[3] Lastly, these values are calculated at the Radius of Maximum Wind (*RMW*) as hurricanes have a defined distance from the center or 'eye' of the storm where wind speeds are highest, typically near the eye of the storm.

$$(V_{max})^2 = \frac{T_s}{T_0}\frac{C_k}{C_D}(CAPE^* - CAPE_{env})|_{RMW} \qquad \textit{(Equation 1)}$$

In addition to PI, the minimum central pressure of the tropical cyclone system $p_m$ can be found with equation 2, given the gas constant of dry air $R_d$ , surface environmental virtual temperature $T_u$ , mean sea-level pressures $p_{msl}$ , and environmental *CAPE* evaluated at *RMW*.

$$R_d T_\upsilon log(\frac{p_{msl}}{p_m}) = \frac{1}{2}(V_{max})^2 + CAPE|_{RMW} \qquad \textit{(Equation 2)}$$

As follows, *CAPE* can be calculated by vertically integrating buoyant energy between the level at which the parcel is initially lifted (*j=0*) and the level of neutral buoyancy (*LNB*). The level of free convection (*LFC*) separates negative areas (NA), vertical regions which inhibit convection, from positive areas (PA), vertical regions which cause the parcel to rise. The buoyant energy of both negative and positive areas is determined by each level's density temperature differences $T_\rho$ - $T_{\rho,\ env}$ . For the complete mathematical derivation of PI, please refer to the complete *pyPI* paper.[4]

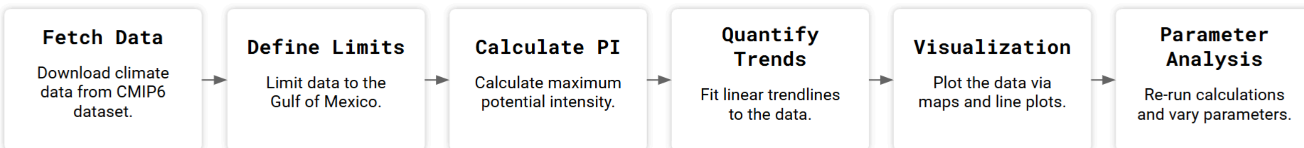
$$CAPE = PA - NA \qquad \textit{(Equation 3)}$$

$$NA \equiv - \int_{p_{j=LFC}}^{p_{j=0}} R_d(T_\rho - T_{\rho,\,env})\, d\, log(p) \qquad \textit{(Equation 4)}$$

$$PA \equiv + \int_{p_{j=LNB}}^{p_{j=LFC}} R_d(T_\rho - T_{\rho,\,env})\, d\, log(p) \qquad \textit{(Equation 5)}$$

Lastly, the pyPI module includes five adjustable parameters that influence the calculation of PI. First, the CKCD parameter represents the ratio of exchange coefficients for enthalpy $C_k$ and momentum $C_D$. This ratio, which defaults to 0.9, describes the energy and momentum exchange between the ocean and atmosphere, with higher values correlating with higher PI. Second, the ascent_flag parameter determines the behavior of air parcels during ascent in the CAPE calculation. When set to 0, the default value, it assumes reversible adiabatic ascent, where all condensed water is retained, increasing heat capacity and altering buoyancy. When set to 1, it assumes pseudoadiabatic ascent, where condensed water falls out of the parcel, which leads to greater PI due to higher buoyancy. Third, the diss_flag parameter, which defaults to 1, controls whether dissipative heating is included. When included, the leading factor in the calculation becomes $(C_k / C_D)(T_s / T_0)$ where $(T_s / T_0) > 1$, resulting in higher PI. If dissipative heating is excluded (diss_flag = 0), the leading factor becomes reduced to $(C_k / C_D)$. Including dissipative heating aligns with more recent studies and typically enhances the calculated maximum PI.[4] Fourth, V_reduc parameter represents the percent reduction in gradient wind, with a default value of 0.8. This parameter multiplicatively scales the calculated maximum potential wind speed to better match near-surface winds observed in real storms, as studies often use this factor for more accurate comparisons.[5] Fifth and finally, the ptop parameter sets the upper-level pressure boundary, defaulting to 50 hectopascals. This boundary determines the minimum pressure level considered in the calculation. A higher ptop value reduces the number of atmospheric levels included, speeding up computations but potentially omitting low-altitude outflow temperature data. Thus, using the pyPI module allows this project to explore how changes in environmental and physical processes over time influence the PI of tropical cyclones.

*Model Pipeline (Figure 2.1)*




## 3 | Analysis

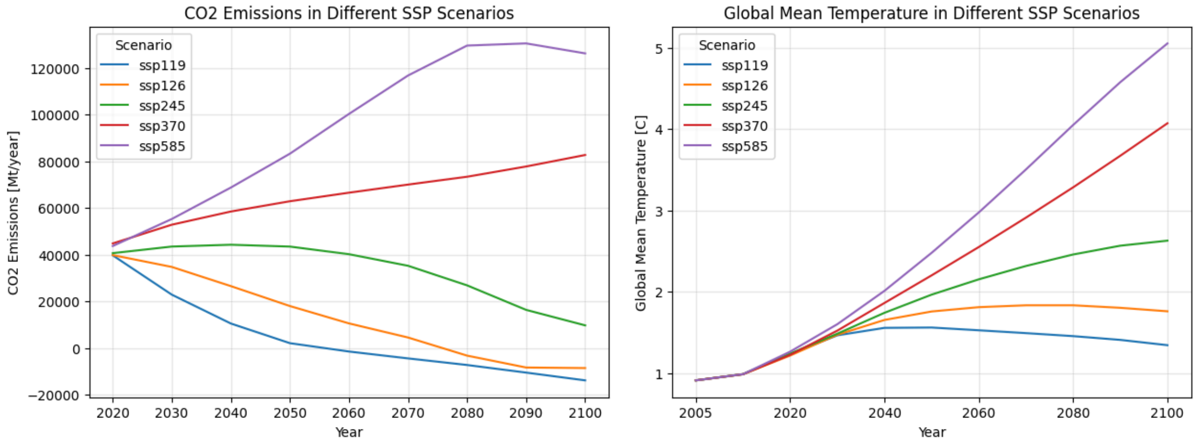
For our analysis of tropical cyclone maximum intensity, we opted to examine the GISS-E2-1-G model derived from ModelE created by the NASA Goddard Institute for Space Studies (NASA GISS). This is a coupled atmospheric and oceanic climate model that simulates global climate conditions in a resolution of 2° latitude by 2.5° longitude. The version we use in our analysis produces mean monthly data of environmental climate variables. Furthermore, each climate model includes several ensemble members that vary in how they handle physical interactions and initialize the ocean and atmosphere. We chose the ensemble member r1i1p3f1 for this analysis. This corresponds to the dataset from the first run of the model, first initialization method applied, third version of the model's physical parameterizations, and the first set of external forcings used. For additional information on the NASA GISS model's methods, please refer to the ModelE CMIP6 website.[6]

We limit the scope of our analysis to the Gulf of Mexico, allowing for a more detailed examination of the region's unique tropical cyclone behavior. We believe this analysis can enhance our understanding of tropical cyclone vulnerabilities in regions near the Gulf of Mexico. Furthermore, we focus on the official Atlantic hurricane season, which spans June 1st to November 30th.[7] This allows us to capture the peak period for extreme tropical cyclone events, enabling more accurate modeling of their characteristics.

*SSP Scenarios (Table 3.1)*[8]

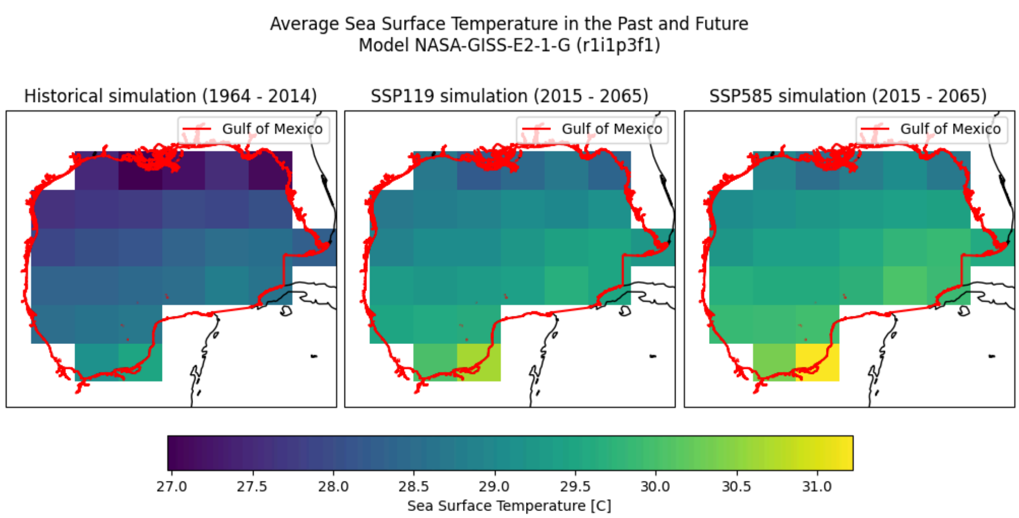
| SSP Scenario | Carbon Emissions | Warming |
|---|---|---|
| SSP1-1.9 : Sustainability | Immediate Rapid Decrease | 1.5°C by 2050 |
| SSP1-2.6 : Middle of the road | Immediate Decrease | 1.8°C by 2100 |
| SSP2-4.5 : Regional rivalry | Decrease by 2050 | 2.7°C by 2100 |
| SSP3-7.0 : Inequality | Maintained Increase | 3.6°C by 2100 |
| SSP5-8.5 : Fossil-Fueled Development | Rapid Increase | 4.4°C by 2100 |

*Plot of SSP Scenarios (Figure 3.2)*[9]



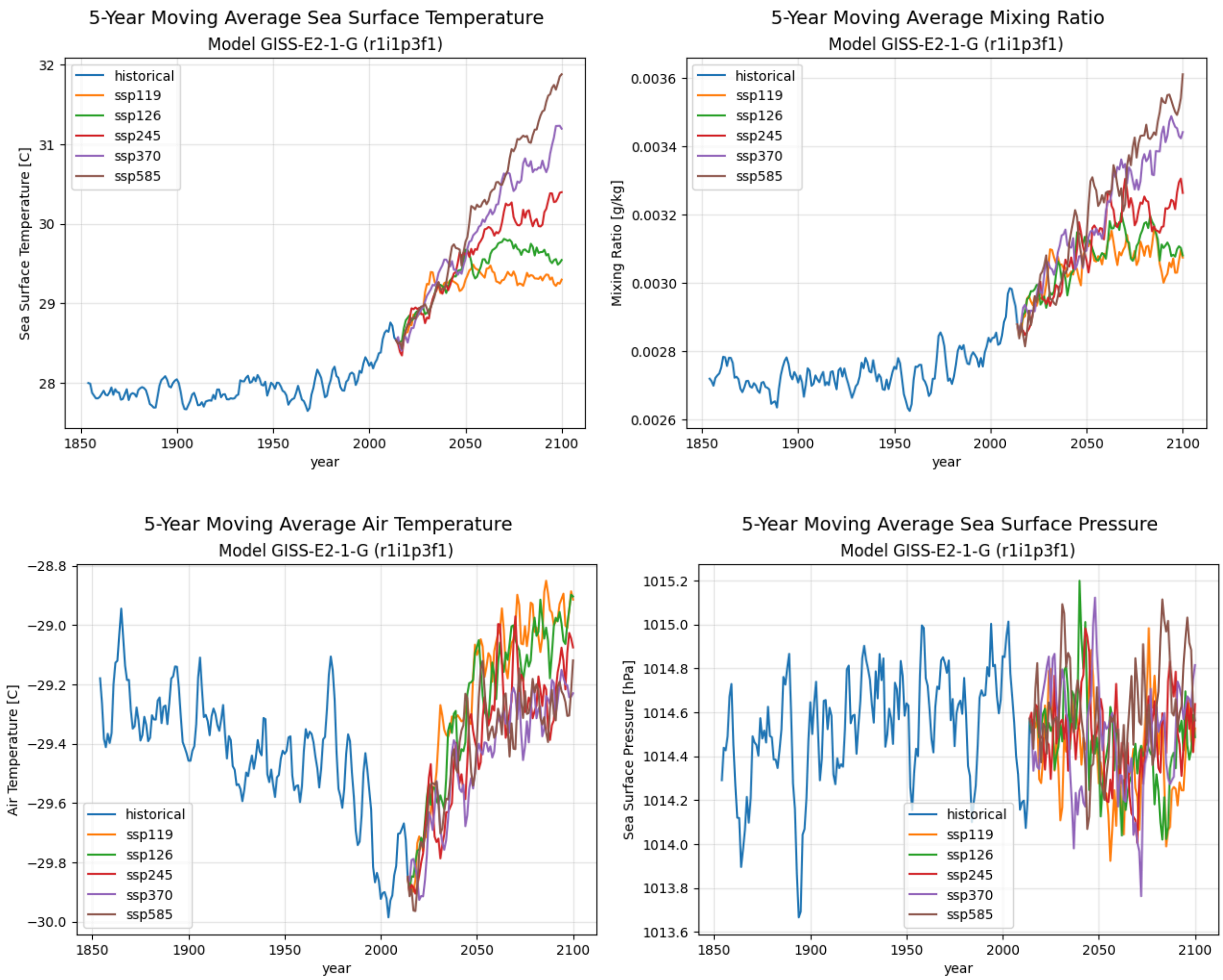

Using ensemble member r1i1p3f1 of the GISS-E2-1-G model, we examine six different scenarios of climate in the Gulf of Mexico. The historical scenario includes mean monthly data from January 1850 to December 2014, while the remaining five are potential future scenarios, called Shared Socioeconomic Pathways (SSP), from the Intergovernmental Panel on Climate Change's (IPCC) Sixth Assessment Report.[8] Each projection reflects different emissions levels, leading to varying degrees of warming, as shown in table 3.1 and figure 3.2. The most conservative of these estimates is SSP1-1.9 where emissions decrease rapidly, while SSP5-8.5 shows rapid increases in emissions. We analyze monthly mean climate data from January 2015 to December 2100 for the five SSP scenarios in the NASA-GISS model to determine how the climate might change in the Gulf of Mexico.

*Map of Sea Surface Temperature (Figure 3.3)*




First, we examine the spatial distribution of mean sea surface temperature by mapping the historical simulation data from 1964 to 2014 next to simulated data from 2015 to 2065 in the most conservative SSP scenario, SSP1-1.9, and the most extreme SSP scenario, SSP5-8.5. Our findings indicate that sea surface temperature increases over the next 50 years relative to the past 50 years. This aligns with our existing knowledge of the climate system: higher concentrations of carbon dioxide in the atmosphere lead to greater global warming. Furthermore, the maps reveal that sea surface temperature increases are more pronounced in the southern portion of the Gulf of Mexico, with the gridpoint furthest to the south exhibiting the largest change increase. We suspect this anomaly may be due to the relatively coarse resolution of the climate model's grid. Additional analysis of the data is needed to determine exactly why this is the case.

*Plot of Environmental Variables (Figure 3.4)*




Next, we take the spatial mean of the various environmental variables' monthly mean and analyze how they change over time. In the four plots above, we examine the four variables needed to calculate PI: sea surface temperature, mixing ratio, air temperature, and sea surface pressure. We take the 5-year moving average to smooth out variability in these measures and identify long term trends.

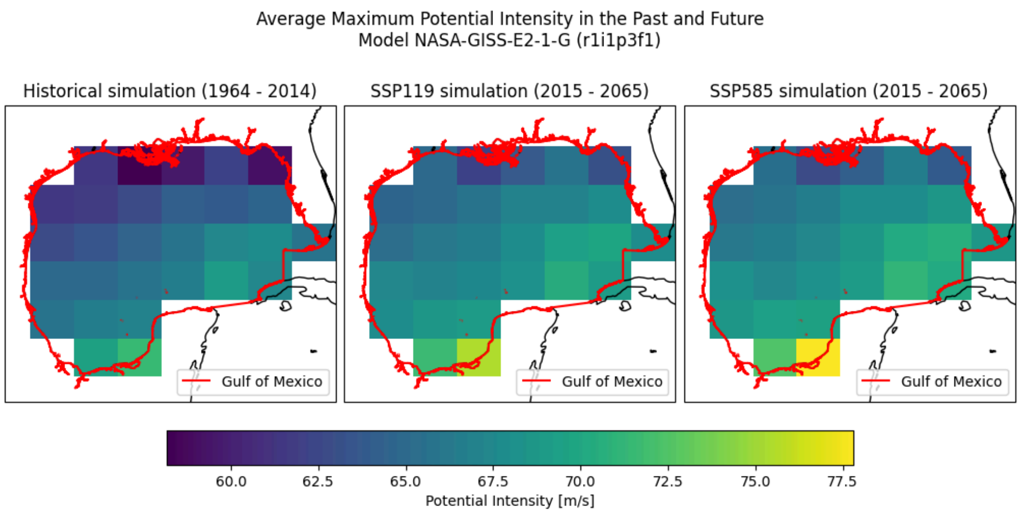
In all SSP scenarios, mean sea surface temperature from 2015 to 2100 in the Gulf of Mexico are projected to increase to levels above 1850 to 2014. Sea surface warming from 2015 to 2050 are comparable across the five SSP scenarios, increasing by 1°C to 1.5°C. However, from 2050 onward, sea surface temperature diverges in the different SSP scenarios. As expected, mean sea surface temperature is highest in SSP5-8.5, increasing to 32°C in 2100. Meanwhile, mean sea surface temperature plateaus at around 29.3°C in SSP1-1.9. We can see that mixing ratios, which measures the amount of water present in the air, closely follow mean sea surface temperature. This is expected, as warmer air can hold more moisture, increasing its mixing ratio.

Interestingly, we observe a downward trend in mean atmospheric temperature from 1850 to 2014, suggesting that the atmosphere above the Gulf of Mexico has cooled by about

1°C. Similar to sea surface temperature, we find that mean atmospheric temperature increases in all five SSP projections relative to the 1850 to 2014 period. Surprisingly, we find that the scenario with the lowest carbon emissions, SSP1-1.9, seems to have higher atmospheric temperatures compared to other scenarios with higher emissions. However, it is worth noting the difference in the mean atmospheric temperature across the five SSP scenarios is small in magnitude and subject to significant variability. We discuss this further in the discussion section.

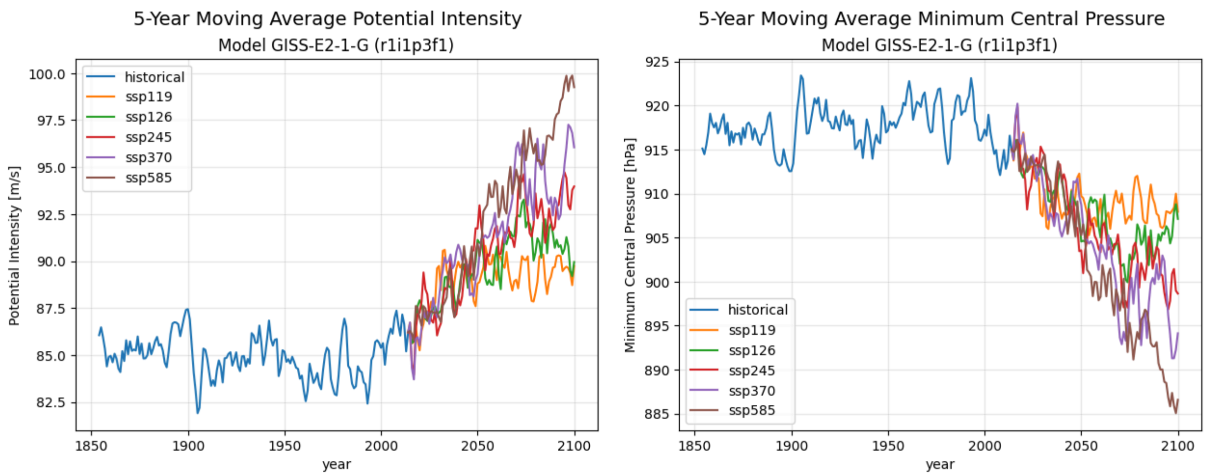
On the other hand, there does not seem to be any long-term trends in mean sea-level pressure. A significant amount of variability in pressure still exists, even after taking the 5-year moving average. Investigating further, we find that the variance in mean sea-level pressure is driven by monthly trends. Pressure seems to increase from June to July, decrease slightly from July to October, and increase again in November. Please see figure 8.1 in the appendix for more details.

*Map of Maximum Potential Intensity (Figure 3.5)*




Finally, we utilize the *pyPI* module to calculate PI and minimum central pressure, applying the default parameter values. Similar to the behavior of sea surface temperature, PI in all five SSP scenarios increases across all five SSP scenarios in the next 50 years compared to the past 50 years. This pattern is particularly pronounced in the Southern region of the Gulf of Mexico, where the Southernmost gridpoint exhibits the largest increase in PI . These results suggest that PI is strongly influenced by sea surface temperature. This conclusion is supported by equation 1, which shows sea surface temperature as the numerator in the first term ($T_S / T_0$) which defines PI ($V_{max}$).

*Plot of Potential Intensity Variables (Figure 3.6)*




We take the 5-year moving average of the spatial mean to examine long term trends in PI and minimum central pressure. Figure 3.6 shows both variables in the historical simulation and the five SSP scenarios. Even after taking the 5-year moving average, there seems to be significant variability in PI and minimum central pressure in the climate simulations. Despite this, we find a clear upward trend in all five SSP scenarios, where PI from 2015 to 2100 in the Gulf of Mexico is projected to increase to levels above 1850 to 2014. On the other hand, estimated minimum central pressure is projected to decrease, mirroring the plot for PI. This is expected, since minimum central pressure is inversely proportional with PI as described in equation 2.

*Maximum Potential Intensity Trend Statistics (Table 3.7)*

| **Scenario** | **Intercept** | **Slope** | **MSE** | **RMSE** |
|---|---|---|---|---|
| Historical | 85.25047 | - 0.00055 | 117.02672 | 10.81789 |
| SSP1-1.9 | 88.17886 | 0.00346 | 107.73301 | 10.37945 |
| SSP1-2.6 | 87.68689 | 0.00821 | 121.46527 | 11.02113 |
| SSP2-4.5 | 86.95981 | 0.01453 | 115.24041 | 10.73501 |
| SSP3-7.0 | 86.75737 | 0.01880 | 117.21355 | 10.82652 |
| SSP5-8.5 | 85.79639 | 0.02678 | 124.84942 | 11.17360 |

To quantify the magnitude of PI increase, we can interpret the six simulations as random walks with different constant drift terms. We fit a linear trendline to the monthly mean data from each simulation and report the results in table 3.7. As expected, we find that the slope of the trendline is positive in all five SSP scenarios, with the slope increasing as carbon emissions increase. This means that a future with higher carbon emissions will increase the PI of tropical cyclones faster compared to a scenario with lower carbon emissions. The fit of the trendline is comparable across all six scenarios, as the root mean squared errors are between 10.38 and 11.17. Furthermore, since root mean squared error measures the variance of the residuals, its similarity across the six scenarios suggests that the variation around the “drift” or slope seems to be constant. Our findings are also confirmed by an analysis of the residuals of PI, shown in table 8.3 in the appendix. This implies that higher emissions will increase the average PI, but not the variability in PI values.

We examine the sensitivity of the model’s parameters by re-calculating PI values when *ascent_flag=1*, causing all air parcels to follow only pseudoadiabatic ascent. This means the model assumes that all condensed liquid water falls out of the air parcel as it ascends. Modeling air parcels this way increased PI by 21 meters per second and decreased minimum central pressure by 52 hectopascals. We did not observe any significant differences in temporal or spatial trends in PI or minimum central pressure as a result of this parameter's change, as shown in figure 8.4 and 8.5 in the appendix. We believe this behavior is consistent with climate physics, since air parcels that lose more water are less dense and therefore more buoyant, increasing the *PA* term in the *CAPE* calculation.

## 4 | Discussion

The analysis of PI in the Gulf of Mexico using CMIP6 data connects theoretical expectations with observed trends, demonstrating alignment with the model's parameterization and assumptions. PI is projected to increase across all five SSP scenarios, with the most aggressive warming scenario (SSP5-8.5) showing the highest increase in intensity. This is consistent with expectations, as higher carbon emissions lead to greater oceanic heat content and warmer air, enabling the atmosphere to hold more moisture. Sea surface temperatures exhibit a clear upward trend, with the divergence between scenarios becoming evident after 2050, reflecting the compounded impacts of long-term carbon emissions.

Notably, atmospheric temperature trends reveal an intriguing anomaly. Historical data indicated a decline from the 1970s to the 2000s, but all SSP scenarios project increasing temperatures moving forward. Surprisingly, SSP1-1.9, the scenario with the lowest emissions, shows slightly higher atmospheric temperatures compared to higher-emission scenarios. This unexpected result may be due to aerosol cooling effects or internal variability in the climate models. Statistical tests and additional analysis are needed to determine whether this behavior reflects a genuine trend or is an artifact of model assumptions. Meanwhile, mean sea-level pressure demonstrates minimal long-term trends but exhibits notable month-to-month variability, potentially influenced by regional meteorological conditions.

The study's findings provide several new insights. First, the consistent increase in PI across all SSP scenarios highlights that even conservative mitigation pathways (e.g., SSP1-1.9) are insufficient to prevent rising cyclone intensity, showing the persistent risks posed by climate change. Second, the observed relationship between PI and SST, as well as mixing ratios, reinforces the fundamental drivers of tropical cyclone intensity under warming scenarios. These insights contribute to a growing body of evidence linking anthropogenic emissions to increasingly severe tropical cyclone behavior.

Nonetheless, the analysis is not without limitations. The geographic focus on the Gulf of Mexico restricts generalizability to other regions with distinct climatic conditions. Sparse grid resolution in the CMIP6 dataset introduces uncertainty in spatial and temporal trends, and the reliance on simulated data—particularly for pre-satellite-era observations—limits empirical validation. Furthermore, actual tropical cyclone intensities are often below PI values, due to external meteorological factors such as vertical wind shear. Addressing these gaps will require integrating empirical datasets like HURDAT2 or IBTrACS to validate trends and extending the analysis to include broader geographic regions, such as the entire North Atlantic storm basin.

Future research should prioritize these areas for improvement. Expanding the analysis to multiple CMIP6 models and ensemble members would provide a range of estimates and improve the robustness of predictions. Incorporating statistical tests to evaluate anomalies, like the counterintuitive trend in atmospheric temperature, would refine the conclusions drawn from the data. Additionally, exploring alternative parameterizations within the pyPI library could offer a nuanced understanding of model sensitivities. By addressing these challenges, future studies can build on the foundation established here to enhance the predictive power and applicability of PI analyses.

The consistent increase in PI across scenarios emphasizes the heightened risk of severe tropical cyclones in a warming world. By contextualizing these results within broader climatic trends and limitations, this study provides thoughtful commentary on the implications of climate change for cyclone behavior and disaster management.

## 5 | Conclusion

This project was motivated by the need to understand how climate change affects the potential intensity (PI) of tropical cyclones, a key metric for assessing storm severity. Using CMIP6 climate model data, the study simulated PI in the Gulf of Mexico, focusing on the relationship between environmental variables such as sea surface temperatures, atmospheric temperatures, mixing ratios, and mean sea-level pressures. The pyPI library facilitated these calculations, allowing for both historical and future scenario analyses under various Shared Socioeconomic Pathways (SSPs).

The results indicate that PI is projected to increase across all SSP scenarios, driven primarily by rising sea surface temperatures and mixing ratios. This finding emphasizes the persistent risk of more intense tropical cyclones, even under conservative climate mitigation efforts. Notably, the analysis also revealed unexpected atmospheric temperature trends and highlighted the importance of further statistical testing and validation.

Future work should address the study's limitations by expanding the geographic focus to include the broader North Atlantic basin and integrating empirical data from observational datasets such as HURDAT2 and IBTrACS. Refining parameterization within the pyPI library and exploring other climate models or ensemble members would improve the robustness and generalizability of the findings. By incorporating these enhancements, the methodology could be expanded to provide more comprehensive insights into tropical cyclone behavior and inform strategies for climate adaptation.

This project demonstrates the value of combining advanced climate modeling tools with focused regional analyses to understand the dynamics of tropical cyclones. As climate change continues to reshape global weather patterns, such research is essential for advancing our knowledge and preparing for the challenges ahead.

## 6 | Attribution of Effort

Max:

- Project report: Analysis, risk assessment, and library introduction. Implemented core library functionality, class method and tests, focusing on data preprocessing and statistical modeling. Enhanced documentation for library usability and clarity, attempted to setup github actions test pipeline and sphinx documentation.

Abbie:

- Project report: Abstract, introduction, discussion, conclusion, and intensity function development. Contributed to ensuring coherence in the project report and refining calculations for the intensity function.

Kent:

- Project report: Model description and assistance with raster data using ArcGIS. Developed key sections on data handling and testing the library to ensure data reliability.

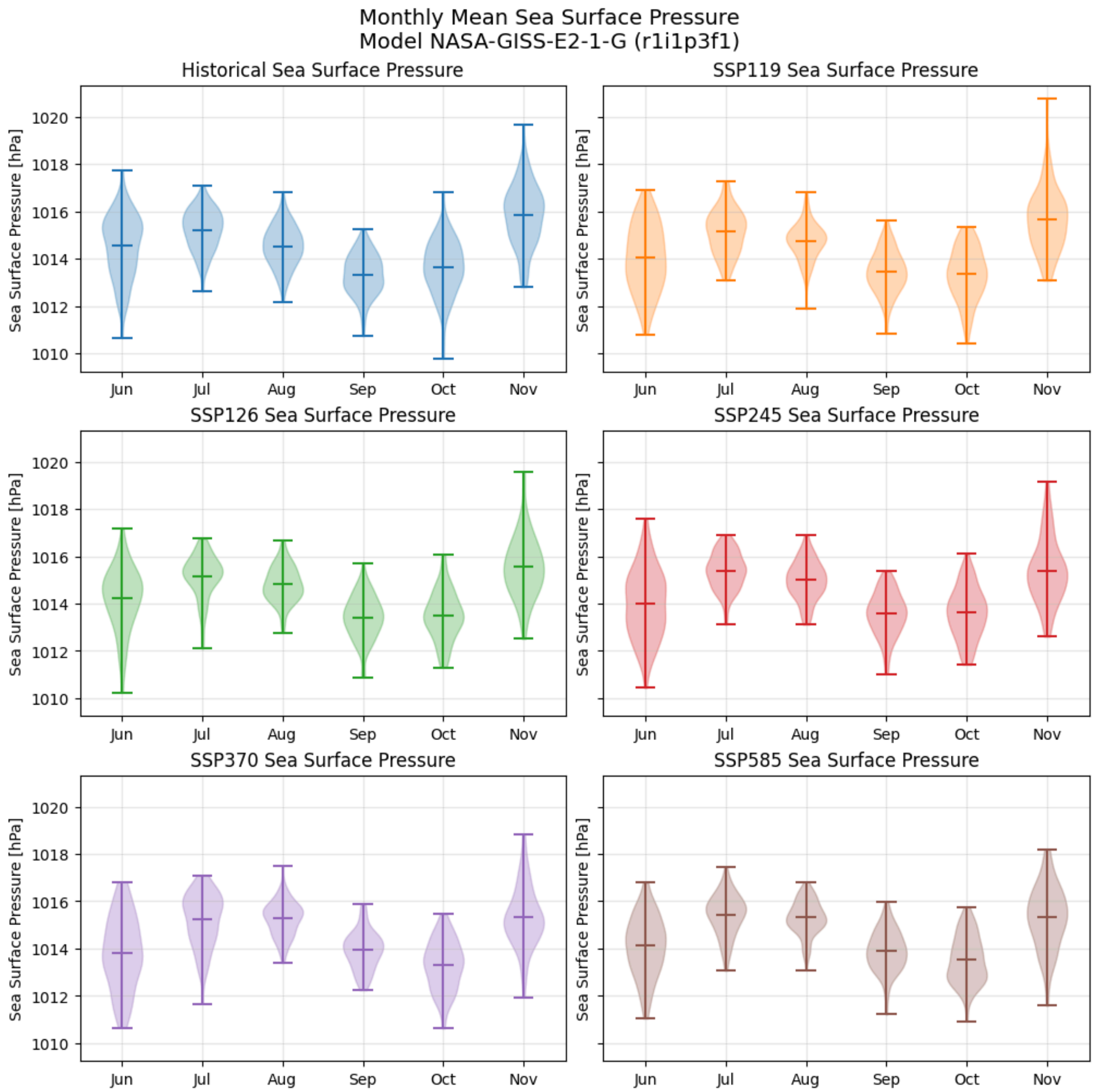
## 7 | Risk

We believe that our group took significant risk throughout the different stages of the project. Initially, we analyzed empirical data on tropical cyclones in the North Atlantic using an extreme value framework. However, we discovered that the data's quality was questionable, especially for tropical cyclones before satellite measurements. Even with these data challenges, we were able to analyze data from 1974 to 2023, doing our best to use extreme value theory to contextualize the trends we saw in tropical cyclone intensity.

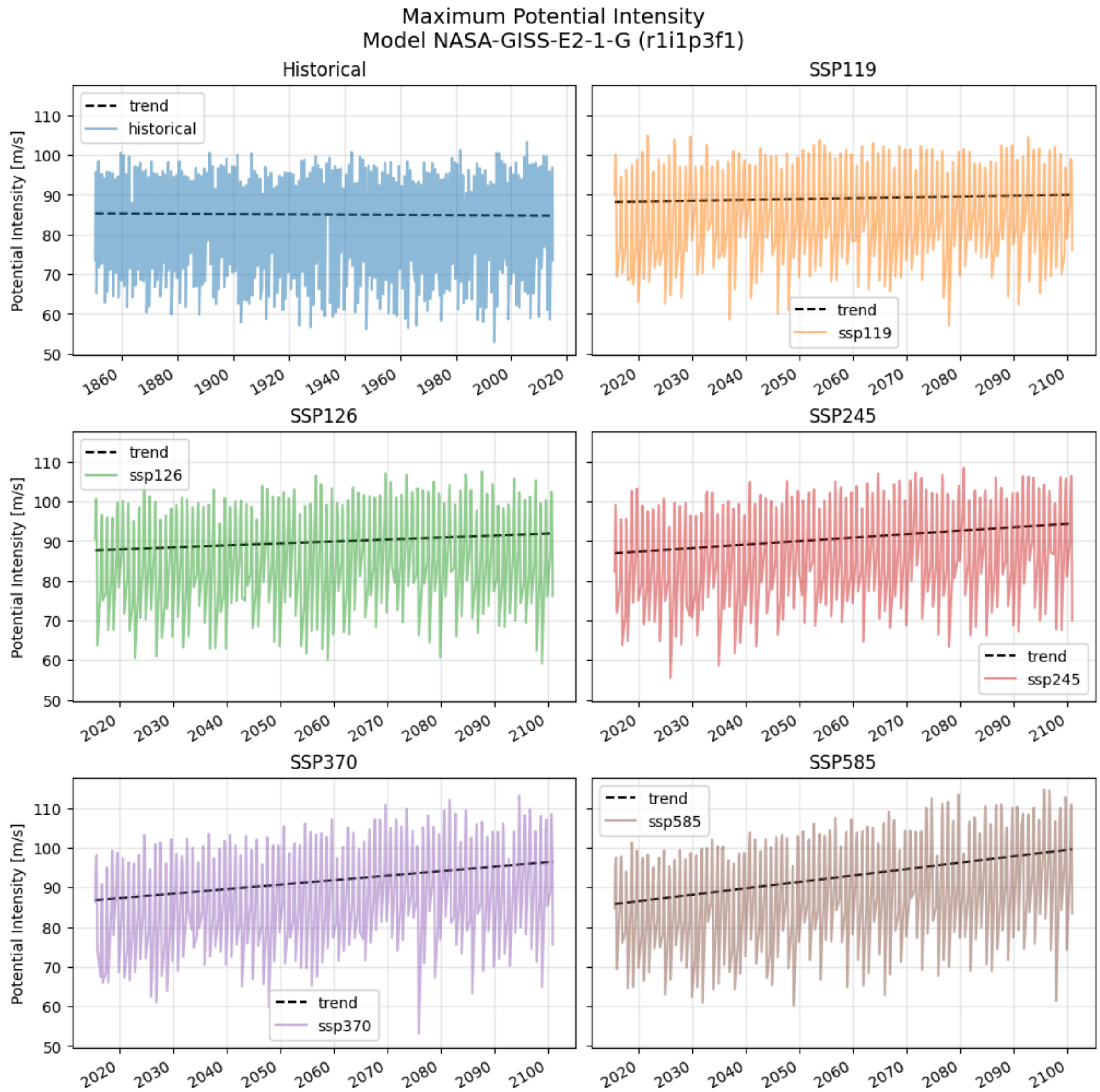
The issues in data quality pushed us to examine high quality data from climate model simulations to analyze past and future climate conditions. This posed a significant risk since none of the group members had experience working with climate modeling data. Changing the direction of our project also meant that most of our codebase on extreme values would not be applicable to the final project. We also needed to become familiar with a large amount of domain-specific knowledge on climate modeling to be able utilize the simulation data for our analysis. Zeyuan Hu and Alp Mehmet Sunol provided great advice and help at this stage, pointing us to theories and resources that improved our work.

Our team learned a great deal about tropical cyclone modeling and climate models. We combed through existing literature to see how scientists are quantifying the effects of climate change on tropical cyclones. We took another risk when we decided to apply maximum potential intensity (PI) theory to analyze how tropical cyclones change over time. The formulation of the model utilizes concepts in thermodynamics and climate science we were unfamiliar with. Thankfully, the pyPI python module allowed us to calculate PI without having to write the calculations ourselves. However, significant work was still needed to understand the parameters and inner workings of the module. Despite these challenges, we were able to conduct an analysis of PI in the Gulf of Mexico for five future projections of the climate and conduct statistical analyses to quantify the trends we observed.

*Plot of Mean Sea Level Pressure (Figure 8.1)*



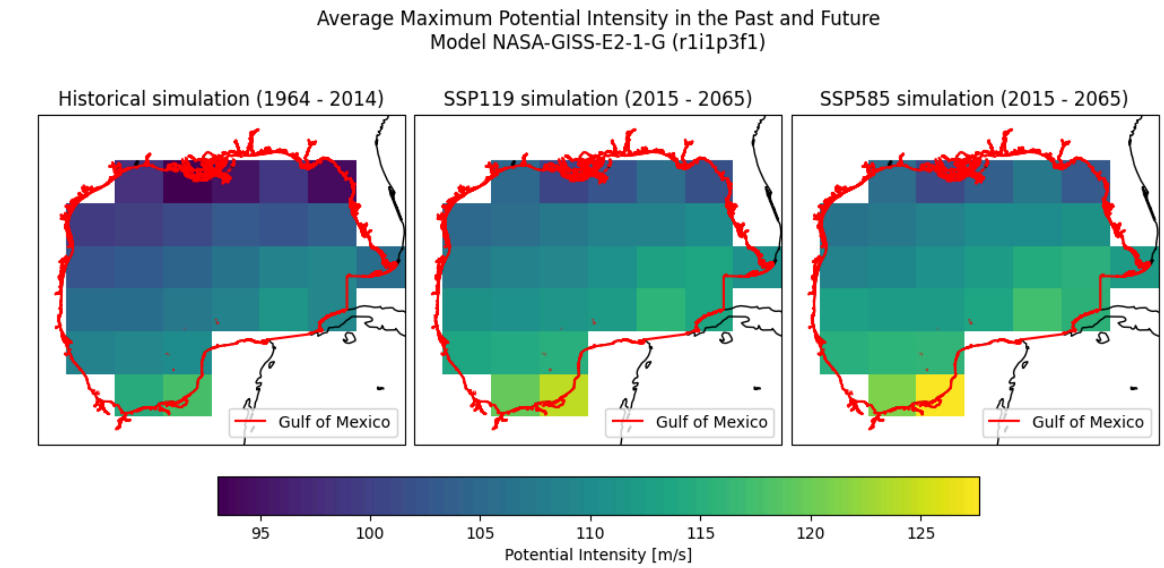
*Plot of Maximum Potential Intensity with Trendlines (Figure 8.2)*



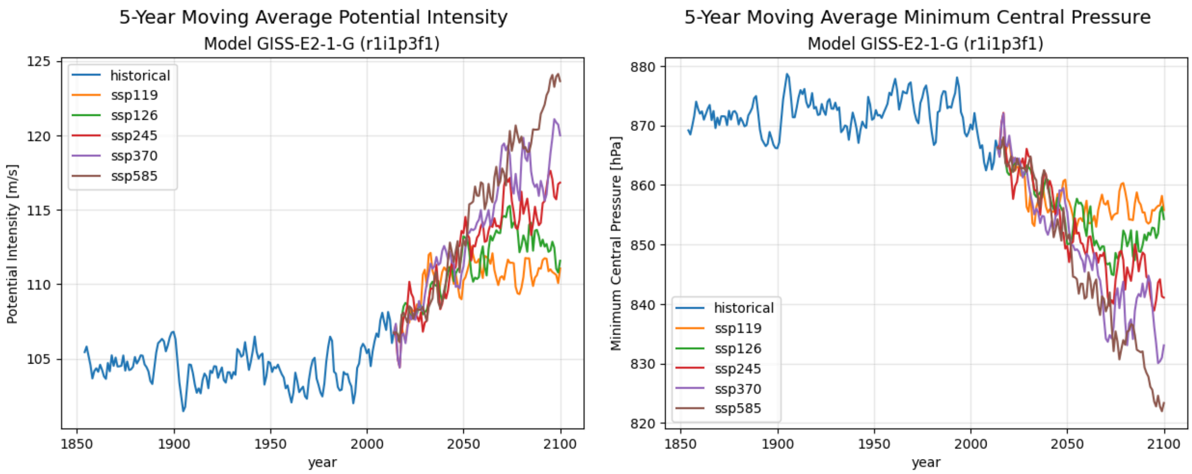

*Maximum Potential Intensity Trend Residuals Statistics (Table 8.3)*

| Scenario | Mean of Residuals | Standard Deviation of Residuals |
|---|---|---|
| Historical | - 1.71463e-14 | 10.82336 |
| SSP1-1.9 | - 2.55713e-14 | 10.38952 |
| SSP1-2.6 | - 2.10684e-14 | 11.03182 |
| SSP2-4.5 | - 2.53647e-14 | 10.74543 |
| SSP3-7.0 | - 1.49131e-14 | 10.83703 |
| SSP5-8.5 | - 3.70005e-14 | 11.18445 |

*Map of Maximum Potential Intensity with Pseudoadiabatic Ascent (Figure 8.4)*




*Plot of Potential Intensity Variables with Pseudoadiabatic Ascent (Figure 8.5)*




*Maximum Potential Intensity Trend Statistics with Pseudoadiabatic Ascent (Table 8.6)*

| **Scenario** | **Intercept** | **Slope** | **MSE** | **RMSE** |
|---|---|---|---|---|
| Historical | 104.35909 | 0.00036 | 126.27961 | 11.23742 |
| SSP1-1.9 | 109.29959 | 0.00435 | 118.87967 | 10.90320 |
| SSP1-2.6 | 108.75849 | 0.01029 | 134.31625 | 11.58949 |
| SSP2-4.5 | 107.74723 | 0.01912 | 128.65834 | 11.34277 |
| SSP3-7.0 | 107.39367 | 0.02566 | 129.99854 | 11.40169 |
| SSP5-8.5 | 106.28236 | 0.03492 | 136.03753 | 11.66351 |

## 9 | References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## 10 | LLM Attribution

1. For each of the methods and classes in the python module below, please write a docstring in the style of Google: {copy+paste the module}
2. Write some assert statements within the test_fetch_data() function for pytest to ensure correct output and included variables.
3. Test initialization and set_data function for PIAnalysis.
4. How do I quit running a pytest in terminal if taking too long?
5. Write a test for this function using the same dummy datasets as test_set_data.
6. Write test_calculate_mean() for the calculate_mean() method.
7. Write test_convert_variables() for the convert_variables() method.
    a. Many additional assert statements were added for the tests in 6. and 7. as GPT 4o did not provide comprehensive testing that addressed sensical values for parameters like *vmax* for instance.