SeeRise: Visualizing Emulated Sea Level Rise on Coastal Regions

Zoe Ludena
zludena@ucsd.edu

Eric Pham
erpham@ucsd.edu

Ylesia Wu
xw001@ucsd.edu

Duncan Watson-Parris
dwatsonparris@ucsd.edu

Abstract

The advent of sea level rise can have devastating consequences on coastal areas all around the world. Low-lying regions—such as Florida, a state particularly susceptible to sea level rise due to its low-lying topography and extensive coastline—are a major focal point when it comes to modeling sea level rise as they are most vulnerable to changes. Using the method described by "A Semi-Empirical Approach to Projecting Future Sea-Level Rise" (Rahmstorf 2007), which regresses the rate of sea level rise on surface air temperature anomaly, our team coupled this model with emulators from "ClimateBench v1.0: A Benchmark for Data-Driven Climate Projections" (Watson-Parris 2022) to create a predictor capable of simulating sea level rise in any future emission scenario, not just the ones prescribed by SSPs. This impact is then visualized using high-resolution topography data to assess the potential transformation of Florida's coastal landscape, which can aid policymakers in developing mitigation and adaptation strategies.

Website: `https://zoeludena.github.io/SeeRiseWebsite`
Code: `https://github.com/zoeludena/SeeRise`
App: `https://seerise-floridaapp.streamlit.app/`

1 Introduction

1.1 First Look

Sea level rise is a pressing global issue that comes alongside climate change. Coastal regions are projected to be or have already been impacted by the rising sea level. Beyond the land getting submerged, sea level rise can also lead to coastal erosion, saltwater intrusion, more frequent flooding, and change in coastal ecosystems. In our project, we focus on one of the most vulnerable regions facing sea level rise—Florida. Florida is especially impacted by sea level rise due to its low elevation, porous limestone foundation, and extensive coastline. Understanding the degree of sea level rise and its impact on the Florida coastline corresponding to different choices of human action is crucial for the local population, policymakers, and many other stakeholders.

1.2 Prior Work

Previous research has established a strong correlation between global temperature rise and sea level changes. "A Semi-Empirical Approach to Projecting Future Sea-Level Rise" (Rahmstorf 2007) introduced a semi-empirical approach to model sea level rise based on observed temperature trends. This method directly linked sea level changes to global mean temperature through historical data analysis. The study demonstrated that sea level rise is accelerating in response to increasing global temperatures, suggesting that traditional projections may underestimate future impacts. This approach provides a basis for our study, where we extend this model to evaluate the specific consequences of sea level rise in Florida. By integrating temperature-based projections with coastal visualization techniques, we build upon prior methodologies to assess localized risks and potential landscape transformations.

"ClimateBench v1.0: A Benchmark for Data-Driven Climate Projections" (Watson-Parris 2022) presents emulators that we recreated as part of this project. This paper is the first benchmarking framework that uses a set of baseline machine learning models on an Earth System Model to emulate the response of different climate variables. The emulators allow people to predict annual mean global distributions of temperature, diurnal temperature ranges, and precipitation given a wide range of emissions and concentrations of carbon dioxide, methane, sulfur dioxide, and black carbon—to explore the unexplored. The paper found that the three most accurate baseline models were neural networks, Gaussian processes, and random forests.

1.3 Description of Data

Climate Model Emulators

- Climate Model Emulator Input Data
  - "CO2" (Carbon Dioxide) (NOAA Climate.gov 2024). Carbon dioxide is one of Earth's most important greenhouse gases because it absorbs and radiates heat.

It is a stable molecule and can remain in the atmosphere for several thousand years.
  - "CH4" (Methane) (NASA Climate Change 2024). Methane is the second largest contributor to global warming after CO_2. Methane is a much more potent greenhouse gas, but has a much shorter half-life of only 8-9 years.
  - "SO2" (Sulfur Dioxide) (NASA Earth Observatory 2017). Sulfur dioxide can react with the atmosphere to form aerosol particles which helps make clouds. It negatively affects air quality (it is a critical air pollutant) because it mainly comes from burning coal (coal-fired power plants). It can also react with water vapor to form acid rain.
  - "BC" (Black Carbon) (Office of Environmental Health Hazard Assessment OEHHA). Black Carbon absorbs light and contributes to climate change by releasing heat energy into the atmosphere. It is considered a short-lived pollutant. It can cause snow, glaciers, and ice to darken and melt, leading to greater warming effects than CO_2 even with its short lifespan.
- Climate Model Emulator Output Data
  - "TAS" (Surface Air Temperature). Average monthly surface air temperature two meters above the ground. Measured in Kelvin.

The input and output data used for training and validation of the emulators are stored in binary `.nc` (NetCDF) files, which are essentially multidimensional data structures with "indexes". In our case, the data files are indexed along "lat" (latitude), "lon" (longitude), and "time" (year).

Sea Level Rise Model

- Sea Level Rise Model Input Data
  - Temperature anomaly. Difference between the average yearly surface air temperature two meters above the ground and that in the year 1900, measured in Kelvin.
- Sea Level Rise Model Output Data
  - Sea Level Change. Difference between global average sea levels of two consecutive years, measured in millimeter (mm).

To evaluate performance of the sea level rise model, we used data from "The Causes of Sea-Level Rise Since 1900" (Thomas Frederikse, et al 2020) and NASA's Sea Level Projection Tool (NASA 2021). The datasets from both of these sources are stored as Excel files.

The first dataset, `global_basin_timeseries.xlsx`, contains historical sea level time series across different ocean basins:

- Observed GMSL [mean]: The observed global average sea level (GMSL).
- Baseline Value (GMSL at 1900): The observed global average sea level in the year 1900. This value serves as the baseline and is subtracted from sea levels in later years to compute anomalies.
- GMSL Anomaly: The deviation of an observed mean sea level from the 1900 baseline, highlighting long-term sea level changes.

The second dataset, which is used to create the transformed datasets for training the sea level rise models, is the `ipcc_ar6_sea_level_projection_global.xlsx` file. It includes global sea level rise projections, at a decadal level, based on IPCC AR6 scenarios:

- `scenario`: Specifies the climate scenario being analyzed.
- `quantile`: Defines the confidence levels used for projections:
  - 5th percentile: Lower bound of projections, represents a conservative estimate of sea level rise.
  - 17th percentile: Middle-lower estimate of projected sea level rise.
  - 50th percentile: Median estimate of projected sea level rise.
  - 83rd percentile: Middle-upper estimate of projected sea level rise.
  - 95th percentile: Upper bound of projections, representing a high-end estimate.
- `confidence`: Level of confidence in the projections, either "medium" or "low".
- Years: Different years containing projected sea level rise.

2 Methods

2.1 Preparing the Data

Shared Socioeconomic Pathways (SSPs) look at different ways the world might evolve with different levels of climate mitigation and policy. The underlying factors—population, technological, and economic growth—could lead to different future emissions and warming outcomes (Brief 2023).

- SSP 126 "Taking the Green Road": There is an emphasis on human well-being, driven by an increasing commitment to achieve development goals. There is lower material growth and lower resource and energy intensity.
- SSP 245 "Middle of the Road": Social, economic, and technological trends do not shift much from historical patterns. Environmental systems experience some degradation and the intensity of resource and energy use declines.
- SSP 370 "A Rocky Road": policies shift to become increasingly oriented toward national and regional security issues. Countries focus on achieving their personal goals within their regions. Consumption is material-intensive and there is a low priority for addressing environmental concerns.
- SSP 585 "Taking the Highway": World places faith in competitive markets, innovation, and participatory societies to produce technological progress to create a sustainable future. Push for economic and social development is coupled with the exploitation of fossil fuel resources.

Our emulators are fitted to historical data and three different SSPs: SSP 126, SSP 370, and SSP 585. The emulators are then validated using SSP 245.

The emulators take in a combination of greenhouse gas emissions as inputs: normalized carbon dioxide, normalized methane, principal component black carbon, and principal component sulfur dioxide.

We performed Empirical Orthogonal Function (EOF) decomposition on Black Carbon (BC)

Table 1: Greenhouse Gas Values in 2025 (SSP 245)

Component	Value
CH_4	0.474023
pseudo_pcs, BC_0	1.747441
pseudo_pcs, BC_1	1.498689
pseudo_pcs, BC_2	−0.807297
pseudo_pcs, BC_3	3.507481
pseudo_pcs, BC_4	1.282007
pseudo_pcs, SO2_0	1.087772
pseudo_pcs, SO2_1	1.462824
pseudo_pcs, SO2_2	1.427859
pseudo_pcs, SO2_3	1.940259
pseudo_pcs, SO2_4	−1.740802

and Sulfur Dioxide (SO_2). Methane is normalized where the maximum amount of methane is 0.8. Principal component time series are extracted to create five BC and SO_2 columns, each corresponding to one EOF mode's time series. The unit for the principal component BC and SO_2 is Tg/year (teragrams per year).

Data for Interactive Visualization

To produce data for our interactive visualization of sea level rise, we fixed the methane, sulfur dioxide, and black carbon inputs for our emulators to be SSP 245's year 2025 levels (Table 1). Fixing the other greenhouse gases at a constant level allows us to better see the effect of CO_2, which is the most well known and prominent greenhouse gas. Setting the constant values at 2025 values is an intuitive choice because it is currently the year 2025, and we want to base our future predictions on the current situation.

Given a final CO_2 concentration in 2100, we interpolated the trajectory of atmospheric CO_2 concentration by linearly increasing/decreasing the carbon dioxide amount from 2015 to 2100, assuming equal step every year, to predict the yearly surface air temperatures. Linear interpolation was chosen because it does not assume an overly complicated model and is applicable given any valid 2100 CO_2 concentration. The predicted series of temperatures was then used as an input for our sea level model.

2.2 Climate Model Emulators

Pattern Scaling

The Pattern Scaling (PS) model's performance is among the best relative to the other emulators in ClimateBench, even though it is only based on a series of linear regressions. This model is limited by its inability to capture nonlinear relationships. If nonlinear relationships are present in different climate model runs, then we can expect the error for pattern scaling models to be a bit worse than what was observed before. Our PS model for the sea level rise prediction pipeline uses cumulative CO_2 to compute air surface temperature (TAS), which is then averaged and used to calculate the rate of sea level rise.

Gaussian Process Emulator

Climate systems are governed by complex, smooth, and highly nonlinear relationships, making Gaussian Process (GP) emulators well-suited for predicting future climate scenarios. Building on our previous research in "Utilizing Emulators to Explore the Climate Model Parameter Space," we chose to utilize the original GP model from ClimateBench as a foundation for our work. This approach leverages the flexibility and uncertainty quantification capabilities of GPs to improve climate predictions.

Random Forest Emulator

Random Forest (RF) is an ensemble method that combines multiple decision trees to improve predictive performance. While decision trees capture non-linear relationships well, they tend to overfit. Random Forest mitigates this by averaging predictions, reducing variance, and enhancing robustness. This makes it ideal for climate model emulation, where multiple target variables require separate models. Hyperparameter tuning was performed using random search of the training data without replacement to improve the original model's performance on our specific task.

CNN-LSTM Emulator

Neural networks excel at climate prediction because of their ability to model complex, nonlinear relationships between atmospheric variables. Their deep architectures allow them to learn patterns from large-scale climate data, capturing intricate dependencies that traditional models may overlook. The adaptability also allows them to generalize well across different climate scenarios, making CNNs valuable for long-term forecasting and extreme weather prediction. We decided to use the original CNN-LSTM model from ClimateBench.

2.3 Sea Level Rise Projection

Using the model described by Rahmstorf, we produced a linear fit for change in sea level, regressed on temperature anomaly (temperature difference from the 1900 baseline). We took the TAS variable from each of the emulator output files, coupling it with predicted sea level rise in the NOR-ESM2 model for each SSP, to train the sea level model.

Mathematically, the model equation is of the form:

$$\frac{dH}{dt} = a(T - T_0)$$

$\frac{dH}{dt}$ is change in sea level per year, a is a proportionality constant, and $T - T_0$ is temperature anomaly relative to a baseline. We then integrate the rate of sea level rise $\frac{dH}{dt}$ to get the total sea level rise at the final year of recorded temperature:

$$H(t) = \int_{t_0}^{t} \frac{dH}{dt} dt$$

Programmatically, we use `np.cumsum()` to add up all the yearly changes to obtain the total sea level rise at a final year. Depending on the source of the training sea level rise data, some data was transformed by using `np.diff()` to convert total sea level rise into the rate of change of sea level.

To confirm the validity of our approach, we compared visually and quantitatively the predicted sea level rise against both historical satellite data and other projections of sea level rise. The reason for comparing against historical data was to ensure that the Rahmstorf method is an appropriate way of modeling future sea level rise, but the model trained on historical data only was not used for prediction or visualization.

In order to train the models used for the prediction, the NASA projected sea level rise data was modified slightly by adding up the changes from 2015 to 2100 to be made consistent with the rest of our data (NASA 2021). This data is at a decadal level, so we inferred yearly rate of increase by dividing the rate of increase. We then trained a prediction model for each quantile of data included in the data set (5th, 17th, 50th, 83rd, 95th). These 5 separate models represent the median along with the 66th and 90th confidence intervals, giving us the median projections alongside an uncertainty spread. Among the 5 models, the median projection model was used the most, especially for visualizing sea level rise on elevation data, but the other 4 were used to create visualizations of the uncertainty of future sea level rise.

3 Results

3.1 Predicted Sea Level Rise

Table 2: Prediction Error Comparison

Emulator	**Predicted (mm)**	**NASA Predicted - Emulator Predicted (mm)**
Pattern Scaling	513.6	22.8
Gaussian Process	511.6	24.8
Random Forest	511.3	25.1
CNN-LSTM	417.0	119.4

For this paper, we compare our median predictions to the expected sea level rise under SSP 245. According to NASA projections, the expected cumulative rise in sea level under SSP 245 between 2015 and 2100 will be 536.4 mm (± about 158 mm for the 66% confidence interval) (NASA 2021)—about the width a large pizza box.

Since our sea level rise model requires a trajectory of TAS, thus a trajectory of CO_2 concentrations for predicting TAS using the emulators, we took the 2100 CO_2 concentration under SSP 245, around 4520 Gigatons, to linearly interpolate the trajectory from 2015 to 2100.

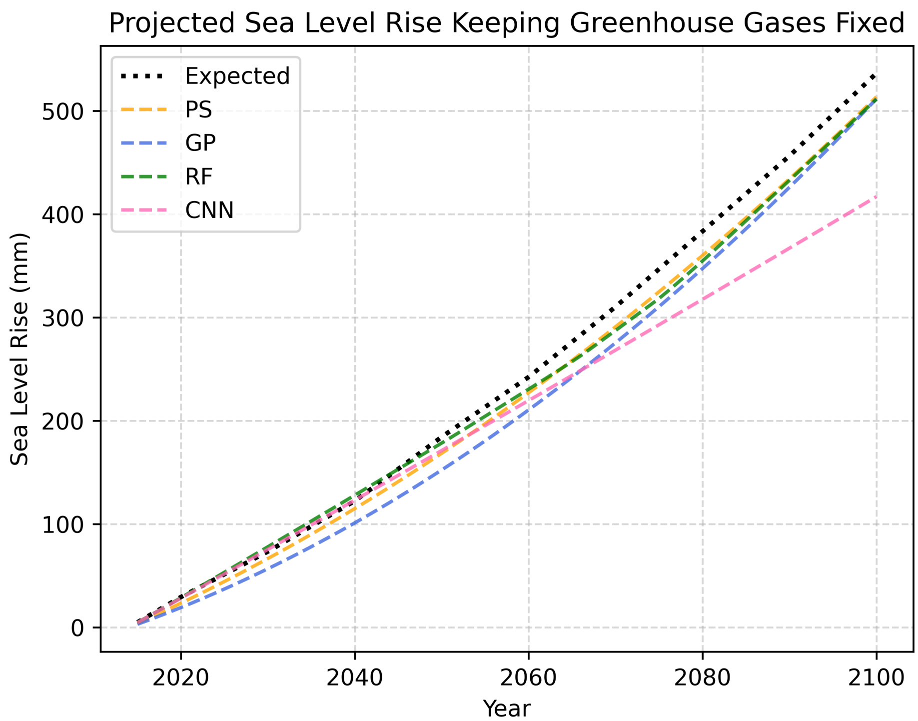


Figure 1: Sea Level Rise Predictions for emulators, calculated while keeping greenhouse gases at 2025 values, compared to NASA's expected sea level rise.

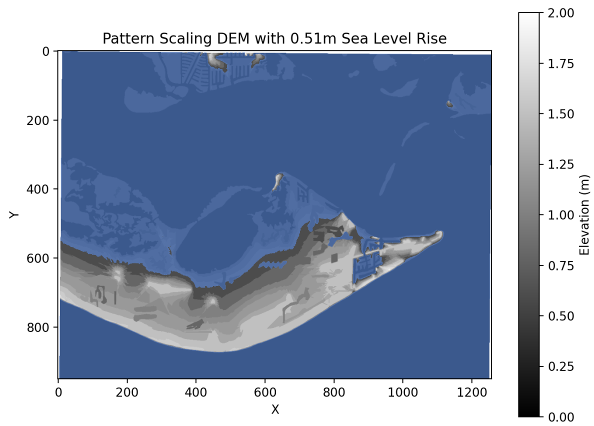
As we can see from Figure 1, the Pattern Scaling, Gaussian Process, and Random Forest emulators perform about equally well when compared to the expected sea level rise. Looking at Table 2, they are under-predicting by about the size of a peanut (20 mm) or an inch (25 mm). The CNN-LSTM model performs the worst. The measurement is off from the expected value by about a standard playing card's length (120 mm).

3.2 Florida Sea Level Rise

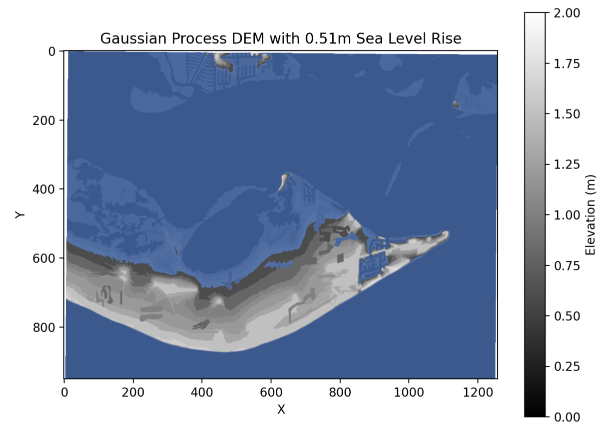
As stated earlier, Florida is a state particularly susceptible to sea level rise due to its low-lying topography and extensive coastline. To visualize the rise in sea level and its impact on Florida, we made use of digital elevation models (DEM). DEMs are a representation of the bare ground topographic surface of the Earth, excluding trees, buildings, and any other surface objects. To generate DEMs, LiDAR data (essentially 3D scans of the Earth's surface) is taken and processed using algorithms, supplemented with other data sources, to construct the true elevation of the land surface.

For visualizing the topography of Florida, corresponding to different sea level rise amounts, we chose the following coastal locations: Sanibel Island, Miami, Fort Myers Beach, the space in between Audubon and Merritt Island, and Everglades City. Given an emission scenario and the temperature projections, we took the median of predicted sea level rise in the year 2100 and determined how much of the land would be submerged. For this paper, we focus on SSP 245 and use the concentration of carbon dioxide in 2100, which is about 4520 Gigatons, as the input.

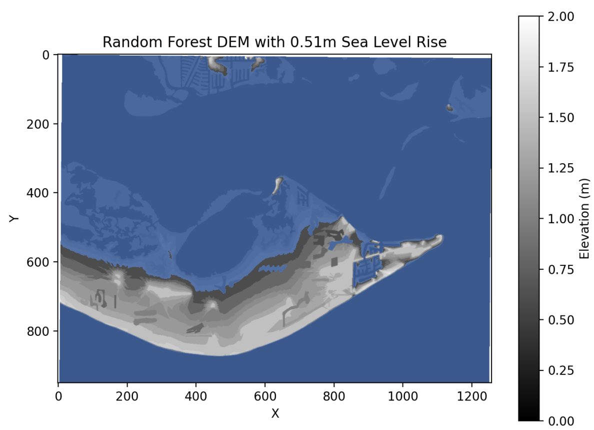
For seeing sea level rise under this and other scenarios through interactive visualizations, visit our web application, SeeRise. For your convenience, we have figures of how Sanibel Island is predicted to look in 2100 with 4520 gigatons of atmospheric CO_2 in Figure 2.



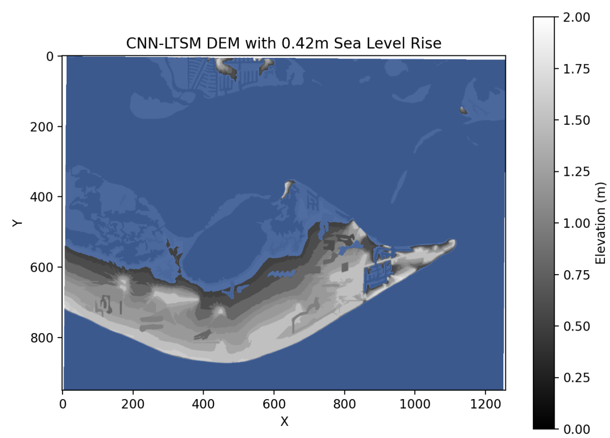
(a) Pattern Scaling



(b) Gaussian Process



(c) Random Forest



(d) CNN-LSTM

Figure 2: Median predictions of sea level rise with 4520 Gigatons of CO_2 in 2100 for Sanibel Island, FL. As we can see the Pattern Scaling, Gaussian Process, and Random Forest emulators produce identical graphs.

4 Discussion

Similar to past work, our sea level rise model using Rahmstorf's approach is prone to over-predicting when evaluated against the true expected projections. The model assumes a near-linear relationship between temperature and sea level rise rate, based on 20th-century observations. However, it is important to note that real-world ice sheet dynamics may not respond linearly to temperature changes, which can affect the true rate of sea level rise in the future.

On the other hand, our model suffers from under-prediction when only changing CO_2 year to year and keeping the other greenhouse gases constant. Future work can be done on scaling all other greenhouse gases input appropriately, which would likely produce more accurate temperature values and sea level rise predictions.

5 Conclusion

Inspired by the issue of sea level rise due to global warming, we worked on modeling projected sea level rise for the future up until 2100, and made use of climate model emulators as a first step for temperature inputs into the sea level projection model. The sea level rise projection model follows a semi-empirical differential equation approach from Rahmstorf, in which we fitted a linear model and obtained a rate of sea level change, then integrated to get the total sea level rise. We also explored the impact of sea level rise on one particularly vulnerable region, Florida, by utilizing DEM data and visualizing the change in local topography and coastline following different amounts of sea level rise.

Overall, our work demonstrated the effectiveness of using machine learning and statistical models alongside the Rahmstorf differential equation approach to achieve fairly sound results in predicting temperature and sea level rise. The interactive visualizations were created in the hope to make understanding the impacts of sea level rise more intuitive and accessible for potential audiences and to raise further awareness of the issue of global warming and sea level rise.

References

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Appendices

A.1 Additional Figures

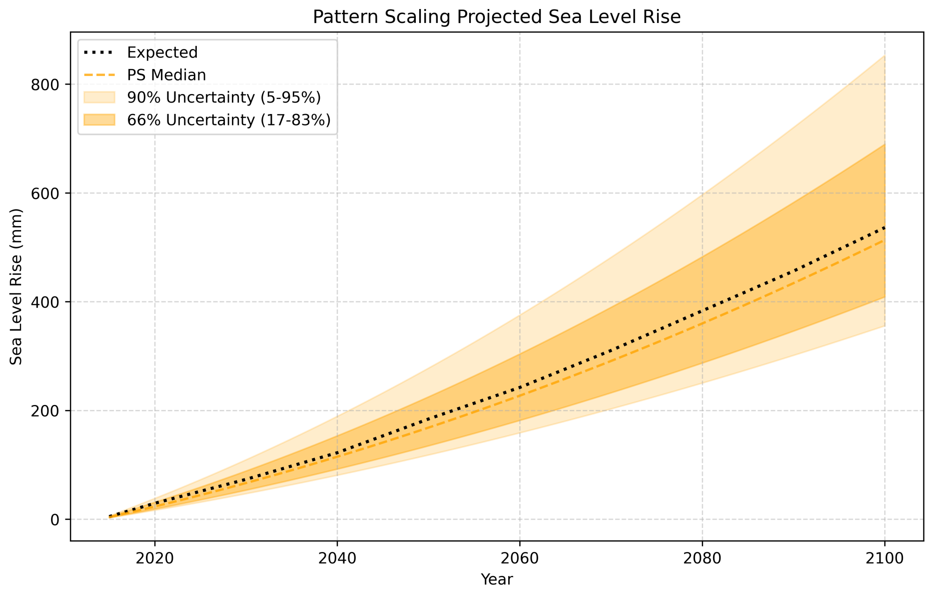

Figure A 1: Pattern Scaling sea level rise uncertainty compared to modified NASA's expected sea level rise (2015-2100).

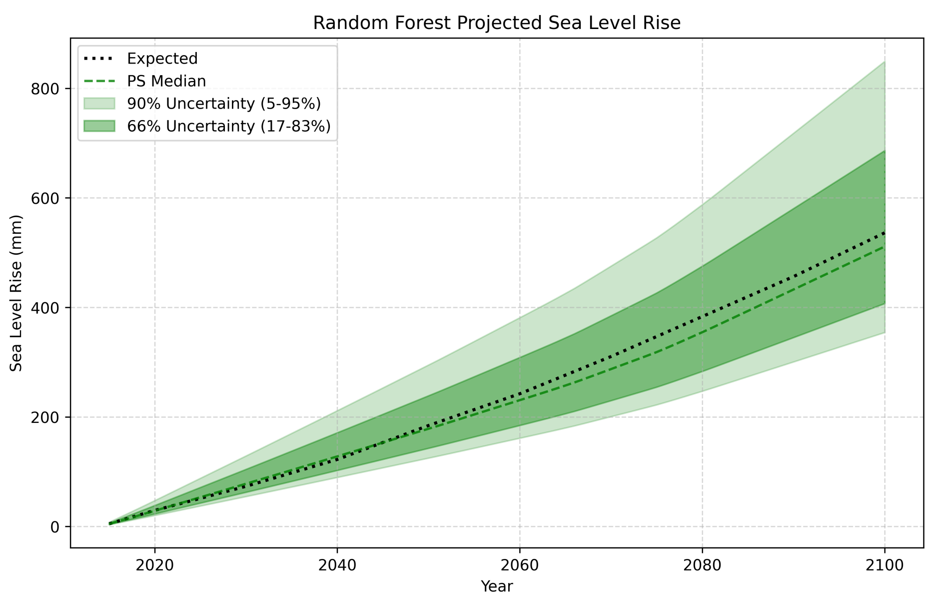

Figure A 2: Random Forest sea level rise uncertainty compared to modified NASA's expected sea level rise (2015-2100).

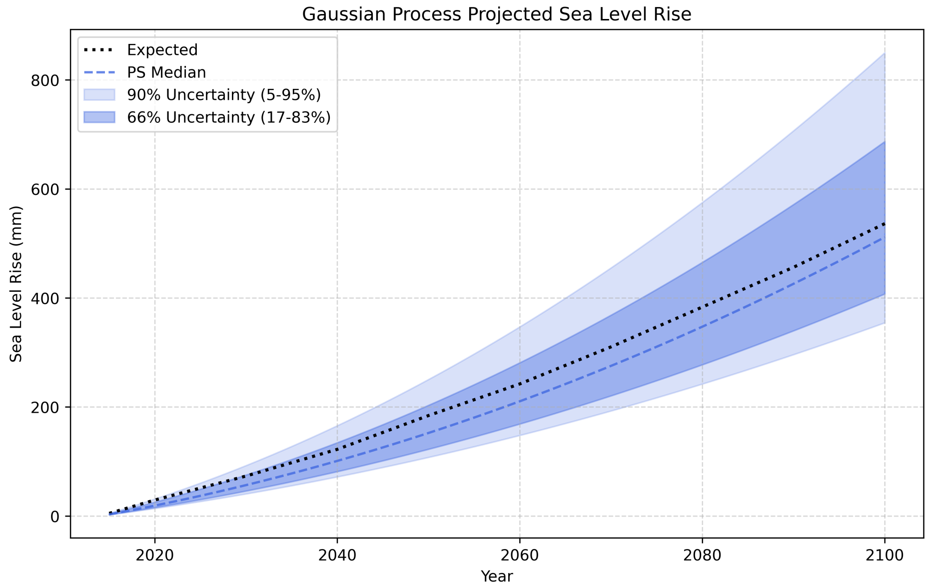

Figure A 3: Gaussian Process sea level rise uncertainty compared to modified NASA's expected sea level rise (2015-2100).

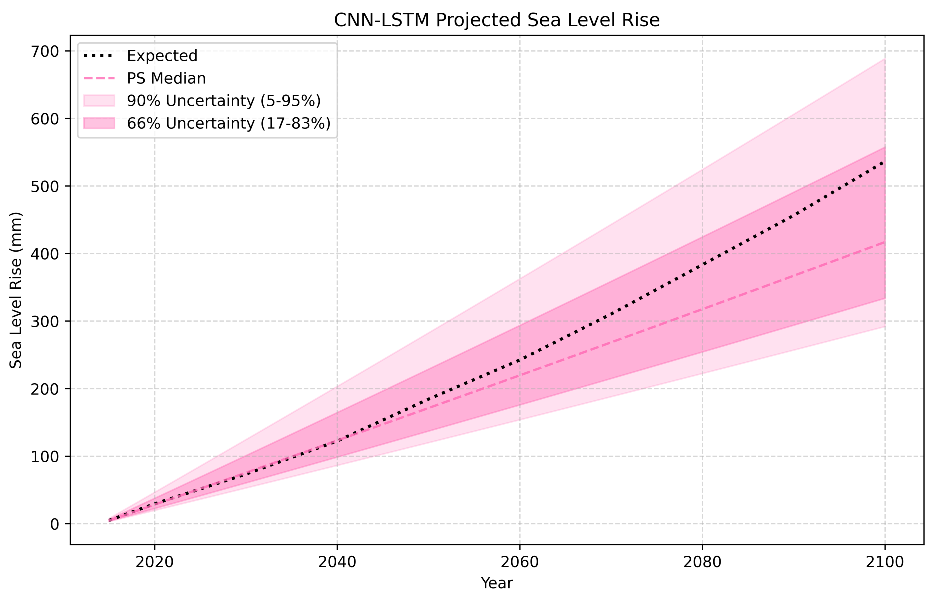

Figure A 4: CNN-LSTM sea level rise uncertainty compared to modified NASA's expected sea level rise (2015-2100).

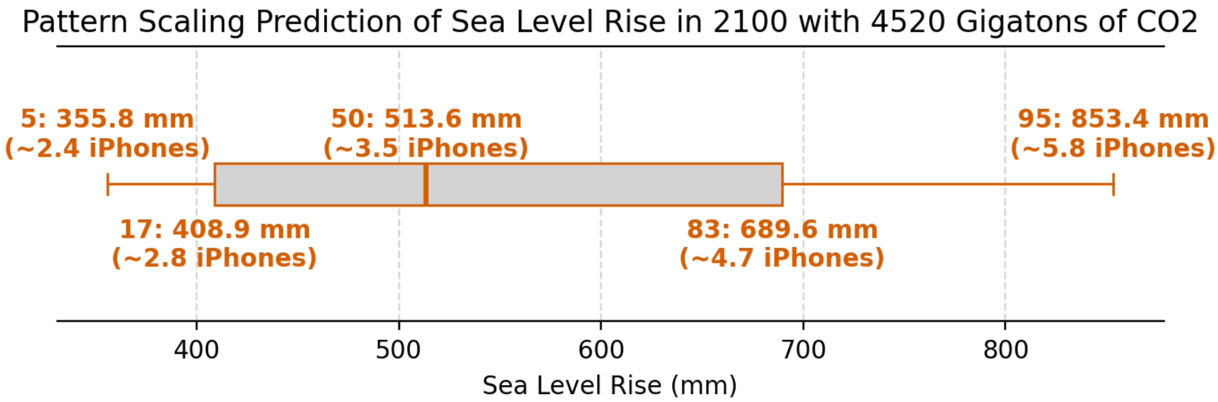

Figure A 5: Pattern Scaling's quartiles of sea level rise with 4520 Gigatons of carbon dioxide.

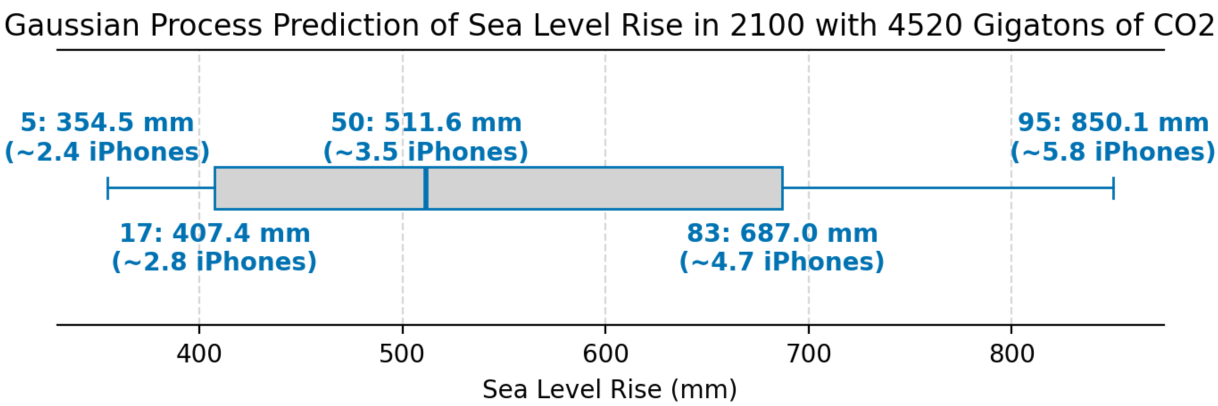

Figure A 6: Gaussian Process's quartiles of sea level rise with 4520 Gigatons of carbon dioxide.

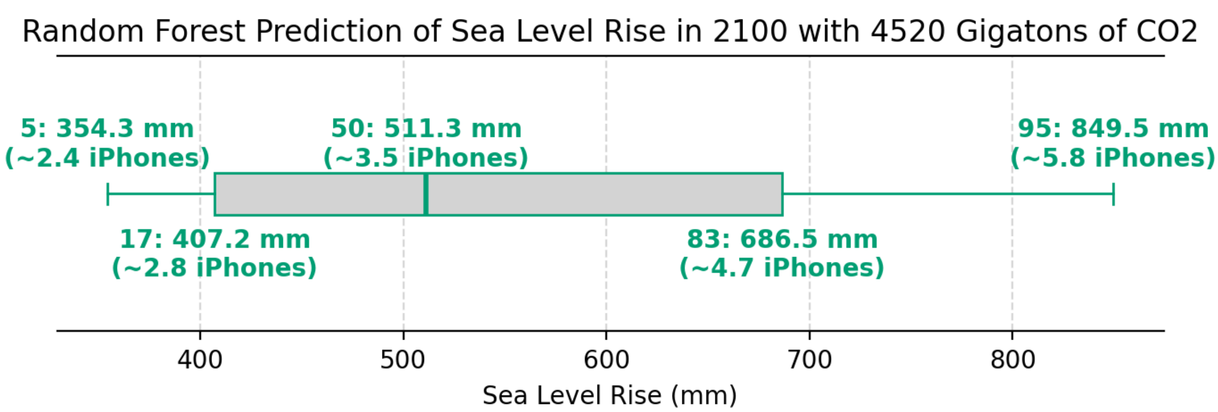

Figure A 7: Random Forest's quartiles of sea level rise with 4520 Gigatons of carbon dioxide.

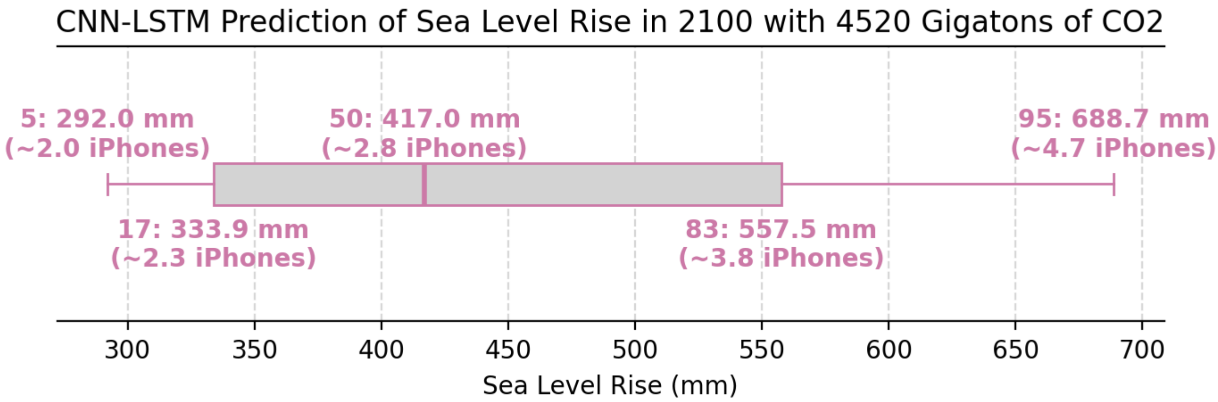

Figure A 8: Random Forest's quartiles of sea level rise with 4520 Gigatons of carbon dioxide.

A.2 Contributions

Zoe Ludena:

- Re-created the Gaussian Process Emulator from the ClimateBench (Watson-Parris 2022).
- Re-created the CNN-LSTM Emulator from the ClimateBench (Watson-Parris 2022).
  - Attempted finding hyper parameters, but was unsuccessful in producing something as good or better than original.
- Created the SeeRise website.
  - Created Figures (and content), Team (Zoe and Duncan's profiles), and App pages (embedded application).
- Created the SeeRise application.
  - Developed the front end, interactive components, and static figures.
  - Wrote commentary and explanations.
  - Added to DEM visualization.
  - Input datasets for Guassian Process and CNN-LSTM emulators for sea level rise.
- Added figures and writing to the poster.
- Edited and wrote Q2 Report.

Ylesia Wu:

- Re-created the Random Forest Emulator from the ClimateBench (Watson-Parris 2022).
  - Hyper parameter tuning : Improved the model compared to the original in terms of range of temperature predicted.
- Explored directly predicting sea level rise from TAS and year.
- Explored other interpolation methods for the trajectory of CO_2 concentrations.
- Created first draft of the poster.
  - Implemented poster requirements.
  - Organized content.
- Input datasets for Random Forest emulator for sea level rise for the SeeRise application
- Added personal bio to SeeRise website.
- Edited and wrote Q2 Report.

Eric Pham:

- Refactored the Pattern Scaling Emulator from the ClimateBench (Watson-Parris 2022) to take in cumulative CO2 emission as input.
- Found DEM data source. Developed code to create DEM visualizations on the SeeRise application. Also added/edited commentary and explanations on SeeRise application.
- Implemented pipeline to re-create Rahmstorf's paper (Rahmstorf 2007).
  - Using Rahmstorf's 2007 semi-empirical model of sea level rise, created regres-

sion models trained on different quantile projections from NASA.
  - Also trained on historical data to ensure that the Rahmstorf method is an appropriate way of approximating sea level rise.
- Modified NASA's expected value to match the years we used (2015-2100). Preprocessed The NASA data sets for a usable format for the Rahmstorf model files.
- Added personal bio to SeeRise website.
- Input datasets for Pattern Scaling emulator for sea level rise for the SeeRise application.
- Added writing to the poster.
- Edited and wrote Q2 Report.