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 especially 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 the "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

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 links 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. His 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) is the paper we are trying to recreate in Fall 2024. 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. This allows 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. This allows the baseline models to explore the unexplored. The paper found the most accurate three baseline models were neural networks, gaussian processes, and random forests.

1.3 Description of Data

There are two classes of data files that we need for the emulators. After preprocessing, both will be provided to the various models as input for training, validation, and ultimately testing. Both of these data files are binary .nc (NetCDF) files, which are essentially multi-dimensional data structures with “indexes”. In this case, both of the data files are indexed along “lat” (latitude), “lon” (longitude), and “time”.

- Climate Model Input Data
  - “CO2” (Carbon Dioxide) (NOAA Climate.gov 2024). 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). Second largest contributor to climate warming after CO2. 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 (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). Absorbs light and contributes to climate change by releasing heat energy into the atmosphere. It is considered a short-lived pollutant. They can cause greater warming effects than CO2 even with its short lifespan. Are causing snow, glaciers, and ice to darken and melt.
- Climate Model Output Data
  - “tas” (Surface Air Temperature). Average monthly surface air temperature two meters above the ground. Measured in Kelvin.
- Sea Level Rise Model Input Data
  - Temperature anomaly. Difference between 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 two consecutive global average sea levels, measured in milimeters (mm).

To compare how our emulators produced Sea Level Rise, 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), both provided as Excel files.

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

- Observed GMSL [mean]: The globally averaged mean sea level (GMSL) observations over time.
- Baseline Value (GMSL at 1900): The mean sea level in the year 1900 is subtracted to compute anomalies.
- GMSL Anomaly: The deviation of the observed mean sea level from the 1900 baseline, highlighting long-term sea level changes.

The second dataset, `ipcc_ar6_sea_level_projection_global.xlsx`, includes global sea level rise projections based on IPCC AR6 scenarios:

- Scenario: Specifies the climate scenario being analyzed.

- Quantile: Defines the confidence interval levels used for projections:
  - 5th percentile: Lower bound of projections, represents a conservative estimate of sea level rise.
  - 50th percentile: median estimate of projected sea level rise.
  - 95th percentile: Upper bound of projections, representing a high-end estimate.
- confidence: Level of confidence in the projections, it keeps confidence with "medium" and "high" estimates.
- Years: Represents different years containing projected sea level rise.

These datasets allowed for direct comparison between past observations and future projections.

2 Methods

2.1 Climate Model Emulators

Our first objective was to tune the hyperparameter for each emulator model. The emulators are fitted to historical data and each SSP, excluding SSP 245 which is used for validation. The emulators take in any combination of greenhouse gas emissions as input, but in order to assure ourselves that the outputs are sensible, we used the prescribed emissions for the SSP scenarios for training and validation. The emulators are used to predict surface air temperature based on difference emission inputs, and we later use the predicted temperature as the input to our sea level model.

Pattern Scaling

The pattern scaling model's performance is among the best relative to the other emulators in the 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.

In the Rahmstorf paper they use linear regression trained on historical temperature and the difference between the predicted temperature and the average. This makes our pattern scaling emulator a fantastic one-to-one comparison.

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 (TODO), 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 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.

The features for our random forest model consist of the first five principal components of SO2 and BC, CO2, and CH4. `max_features` was changed from `'auto'` to `'sqrt'` to accommodate a different version of `rf_model` while achieving a similar result. The rest of the hyperparameters are tuned using random search of the training data without replacement. The final values for the hyperparameters are `'n_estimators': 250, 'min_samples_split': 5, 'min_samples_leaf': 7, 'max_depth': 5.`

CNN-LTSM Emulator

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

2.2 Sea Level Rise Projection

Using the model described by Rahmstorf 2007, we then produce a linear fit for change in sea level height, regressed on temperature anomaly (temperature difference from a baseline). We take our temperature air surface variable from each of the emulator output files and then use it to train the model on predicted sea level rise in the NOR-ESM2 model for each SSP scenario.

Mathematically, the model equation is of the form:

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

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

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

Programmatically, this means using `np.cumsum()` to add up all the changes to obtain the year-over-year sea level rise. Additionally, depending on the source of the training sea level rise data, the data may need to be transformed by using `np.diff()` to turn total height into the rate of change of height.

Finally, as a simple sanity check, we compare visually and quantitatively the predicted sea level rise against both historical satellite data and other projections of sea level rise (NASA).

3 Results

4 Conclusion

References

NASA. 2021. "IPCC AR6 Sea Level Projection Data - Global Projections." [Link]

NASA Climate Change. 2024. "Vital Signs of the Planet: Methane." [Link]

NASA Earth Observatory. 2017. "The Ups and Downs of Sulfur Dioxide in North America." [Link]

NOAA Climate.gov. 2024. "Climate Change: Atmospheric Carbon Dioxide." [Link]

Office of Environmental Health Hazard Assessment (OEHHA). 2022. "Atmospheric Black Carbon Concentrations." [Link]

Rahmstorf, Stefan. 2007. "A Semi-Empirical Approach to Projecting Future Sea-Level Rise." [Link]

Thomas Frederikse, et al. 2020. "Global and Basin-Specific Sea Level Time Series Data Supplement for "The Causes of Sea-Level Rise Since 1900"." [Link]

Watson-Parris, Duncan. 2022. "ClimateBench v1.0: A Benchmark for Data-Driven Climate Projections." *Journal of Advances in Modeling Earth Systems* 14 (10), p. e2021MS002954. [Link]

Appendices

A.1 Additional Figures

A.2 Contributions