Quantifying the Economic Impacts of Potential Sea-Level Rise

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Abstract

Anthropogenic climate change is an undeniable issue in today's society, altering Earth's landscape. One of these impacts is rising sea levels: as global warming causes Earth's oceans to expand, they may damage coastal infrastructure and force people to relocate, among other consequences. Previous predictions of sea level rise come from Earth System Models (ESMs), which are complex and computationally intensive. Consequently, they can model sea-level rise only for a limited number of emission scenarios, or Shared Socioeconomic Pathways (SSPs). Our model aims to explore the full range of sea-level rise scenarios by emulating these ESMs, providing fast, efficient approximations. To do this, we processed the NorESM2-LM output data for sea-level rise and used the Building Blocks for Relevant Ice and Climate Knowledge (BRICK) model framework to develop a sea-level rise predictor. Moreover, limited studies reference the socioeconomic impacts of sea-level rise. Our study attempts quantify the impacts of sea level rise on population and GDP. This model is an adaptation of the Python Coastal Impact and Adaptation Model (PYCIAM). Its input is predictions generated by the model using the BRICK framework, and its outputs are damage costs and population relocation due to sea-level rise.

Website: https://ritvikmohindru.github.io/sea-level-rise/
Code: https://github.com/Nolancchu/DSC180B-B05-1-Capstone

Contents

1 Introduction

Human greenhouse gas (GHG) emissions have been accelerating global sea level rise, although their impacts are currently minimal. Global sea levels have risen approximately 0.2 m since 1900, with a significant portion occurring recently: annual sea-level rise has increased from 1.3 mm yr between 1901-1971 to 3.7 mm yr between 2006-2018. Anthropogenic sea-level rise results from two key factors. First, global warming causes the thermal expansion of oceans, as warmer water occupies more volume. Moreover, it causes glaciers and polar ice to melt, adding even more water to the oceans IPCC (2023). Sea-level rise could have dramatic consequences for humans. The most immediate would be relocating coastal populations, and to some degree, mortalities. Orchestrating mass migrations to the extent of relocating cities will be extremely difficult if sea levels rise to such a degree. According to a study by A.G. Cosby, population density increases closer to the coast, and this trend is accelerating Cosby et al. (2024). Furthermore, roughly 40% of the world's population lives within 100 km of the coast. Sea-level rise leaves these vast populations vulnerable to losing their homes and way of life. Second, sea-level rise has economic implications for infrastructure, tourism, and other coastal industries, impacting stakeholders such as businessmen and other financially invested parties. It is a reasonable assumption that eliminating GHG emissions will stop any sea-level rise and its detrimental impacts on mankind. However, limiting global warming from here on out does not necessarily mean climate components with longer timescales of response will not continue to change. As mentioned in the 2023 UN Intergovernmental Panel on Climate Change (IPCC) Synthesis Report, ”Sea level rise is unavoidable for centuries to millennia due to continuing deep ocean warming and ice sheet melt, and sea levels will remain elevated for thousands of years”(18). Not all hope is lost, as reduced GHG emissions should limit sea level rise and its acceleration. In 2015, nearly every country came together to adopt the Paris Agreement, aiming to limit global warming to 2°C below pre-industrial levels IPCC (2023). Consequently, it should be possible to control the impacts of sea-level rise. Because of its detrimental impacts on coastal communities and its variability across different SSPs, we hope to quantify the potential for sea-level rise in the near future and its socioeconomic repercussions in capital losses and population relocation. These figures provide government officials and policymakers with accurate estimates of sea level rise impacts to base new adaptation strategies, laws, and resource allocations as required. Based on our results, sea levels will rise approximately by 0.6 meters by the end of the century if we continue to emit GHGs at our current rate.

Historically, predictions of climate change variables such as sea-level rise have relied on ESMs. The problem with this literature is that it is far too complex and time-consuming to implement, especially when it becomes necessary to model various different scenarios of GHG emissions. Our proposed solution involves emulating ESMs to generate temperature predictions, which can be used to predict regional sea level rise. Furthermore, this can be used to predict population displacement and economic costs. These outputs typically vary widely, so our study also provides a good estimate that verifies these results.

2 Methodology

2.1 Data

The ClimateBench dataset, where we obtained the input variables for predicting sea level rise is derived from various ESM simulations. Our project uses training data are simulations performed by the Norwegian Earth System Model (NorESM2-LM) as part of the Coupled Model Intercomparison Project (CMIP6) under various SSPs. For our project, SSP245 is used as the test dataset, while the rest of the simulations make up the training data. This historical and scenario-based data have input variables of annual global carbon dioxide (CO_2) and methane (CH_4) emissions, in addition to gridded sulfur dioxide (SO_2) and black carbon (BC) aerosol emissions with a 2° spatial resolution. The first step is to generate the output variable of temperature, which is in an xarray format, containing the dimensions of time, latitude, and longitude. This data is stored in .nc files, which were converted to .csv files (1 for each SSP). These are used as inputs for the BRICK framework to create a model that produces accurate values for sea level rise based on the emulated values for temperature. This results in the regional sea level rise, which file as well. Next, to predict the economic damages and population impacts, we incorporate the pyCIAM framework, which estimates coastal inundation damages, capital losses, and population relocation under different adaptation strategies and sea-level scenarios.

2.2 Initial Surface Air Temperature (TAS) Data Collection

The first step of our project was to generate surface air temperature projection data for each considered year (2015-2100) along each pathway. In quarter one of the capstone, we already generated this data for each pathway using a random forest regression model taking in global mean emissions of Carbon Dioxide, Sulfur Dioxide, Methane, and Black Carbon. We then converted this data, which was stored in .nc files, into .csv files for future ease of access and use.

2.3 Generating Regional Sea Level Rise (RSLR) Data

Several models exist for estimating regional sea level rise based on a variety of inputs, but we decided on using the Building blocks for Relevant Ice and Climate Knowledge (BRICK) model due to it's compatibility/ease of use with our available hardware, and it's malleability to taking in our input data.

The BRICK framework operates by breaking down global sea level rise into four major physical components: thermosteric expansion (TE), glaciers and small ice caps (GSIC), the Greenland Ice Sheet (GIS), and the Antarctic Ice Sheet (AIS). Each component responds differently to global temperature changes and contributes differently to regional sea level patterns. Our implementation uses specialized BRICK subroutines: brick_te_F.R for thermosteric expansion, GSIC_magiccF.R for glaciers, simpleF.R for Greenland, and daisanto_fastdynF.R for Antarctica with fast ice dynamics to model each component's global contribution to sea level rise based on our generated surface air temperature projections.

To translate these global sea level components into spatially-resolved regional patterns, we utilize sea level fingerprints stored in the NetCDF file FINGERPRINTS_SLANGEN_Bakker.nc. These fingerprints represent the geographically varying gravitational, rotational, and deformational effects that occur when mass is redistributed from ice sheets and glaciers to the oceans. For instance, regions near melting ice sheets actually experience sea level drop due to reduced gravitational attraction, while far-field regions see amplified rise. Thermosteric expansion, by contrast, is assumed spatially uniform with a fingerprint value of 1 everywhere.

Our script processes each used SSP scenario (SSP1-2.6, SSP2-4.5, SSP3-7.0, and SSP5-8.5) independently in a loop. For each scenario, we read the corresponding surface air temperature projection CSV file, feed the temperature time series into each BRICK component model to compute global sea level contributions, and then apply the appropriate fingerprints to generate a three-dimensional array of regional sea level rise (longitude $\times$ latitude $\times$ time). The AIS component requires special handling: we use the combined DAIS-ANTO model which accounts for both slow thermodynamic processes and fast ice dynamics, feeding it not only temperature but also the cumulative sea level rise from the other three components. Finally, we write the resulting regional sea level rise data to NetCDF files (one per SSP scenario) containing annual projections from 2015 to 2100 across a global grid, providing the spatially-explicit sea level projections needed for subsequent socioeconomic impact analysis.

2.4 Modeling Economic Costs Using RSLR Data

The assessment of global coastal impact is conducted using the Data-Spatial Climate Impact Model (DSCIM) platform. This open-sourced framework integrates spatial data with economic modeling to quantify the physical and socioeconomic consequences of sea level rise. This framework consists of three components: SLIIDERS, sea level projection, and the pyCIAM model.

The dataset SLIIDERS, Sea Level Impacts Input Dataset by Elevation, Region, and Scenario, consists of two different segments: physical variables and socioeconomic variables. The physical variables of the dataset consists of partitions of global coastlines and their local physical attributes (inundation areas by erosion, extreme sea level heights, wetland areas, erosion characteristics). Socioeconomic variables consists of present and projected values of population, GDP, physical capital, and construction costs of each of the coast partitions. In addition to the SLIIDERS dataset, the pyCIAM model needs sea level data in order to make its predictions. To supplement this, we use our sea level projections from the BRICK model. To combine the two, we mapped the corresponding SSP and longitude and latitude coordinates to each coast coordinate. For the coordinates with a missing SLR, we imputed using the nearest coordinate with an SLR.

The core computational engine, pyCIAM (Python-based Coastal Impacts and Adaptation

Model), processes the inputs to determine the most economically viable response for each coastal segment. The model outputs six different costs as outputs: cost of permanent inundation, ESL-related damages to capital, mortality, expenditures on protection, relocation costs, and wetland loss. The model simulates the costs in periods of time (around 40-50 years), in which protection or retreat costs are updated based on the maximum projected sea level in that period of time. Based on the sea level rise there are three different adaptation plans: reactive retreat, protection, and proactive retreat. Reactive retreat is when a portion of land falls below mean sea level, meaning that people and mobile capital are relocated to unaffected inland regions, and that immobile capital is abandoned. Protection is an adaptation plan where infrastructure is put up in order to protect the coastline, the height of the infrastructure maintains a linear relationship with sea level rise. Lastly, proactive retreat is when people and mobile capital relocated to a safe area based on future maximum sea level rise in the planning period.

2.5 Evaluation Metrics

The BRICK model was evaluated against NASA's decade-by-decade projections for global sea level rise which they obtained from a model in the IPCC AR6 NASA (2021). The evaluation metrics used were Mean Bias Error (MBE) and Root-Mean Squared Error (RMSE). While RMSE is a standard metric used to determine overall error size, MBE provides both direction and magnitude of error, thus making it useful to determine if the BRICK model overestimated or underestimated SLR.

$$\text{MBE} = \frac{1}{n}\sum_{i=1}^{n}(\text{BRICK} - \text{NASA})$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{BRICK} - \text{NASA})^2}$$

The time interval used was from 2030-2100. For the BRICK model, this meant calculating the weighted global mean increase in SLR from 2020 for each decade, the data coming from the multi-dimensional arrays stored in the NetCDF file. These metrics were calculated in centimeters as the numbers were too small to grasp a clear understanding in meters.

3 Results

3.1 Sea Level Rise

Projected sea level changes between 2015 and 2100 demonstrate a clear positive correlation with increasing radiative forcing scenarios (Table 1). Under the low-emission SSP1-2.6 scenario, the mean projected sea level rise is 4.3897 meters. This value increases progressively across the intermediate scenarios, reaching a mean of 5.3108 meters under the high-emission SSP5-8.5 pathway. Notably, the variance within each SSP is substantial; for instance, SSP5-8.5 exhibits a range between a minimum of -19.9770 meters and a maximum of 7.0941 meters, reflecting significant regional uncertainty in geodetic and oceanographic responses.

Table 1: Sea Level Rise (2015-2100) By SSPs (feet)

SSP	Min	Max	Mean
SSP1-2.6	-17.4427	5.8989	4.3897
SSP2-4.5	-18.2438	6.2789	4.6842
SSP3-7.0	-18.8659	6.5743	4.9119
SSP5-8.5	-19.9770	7.0941	5.3108

Although they differ in intensity, the change in sea level on a spatial level remains consistent among each of the different SSPs. For reference, Table 1 visualizes the change in sea level on a global map. From the figure it can be observed that the areas that are the most affected is the coast of Antarctica, experiencing sea level loss around -10 meters due to loss of ice-sheet mass. Everywhere else around the world seems to have experience uniform sea level increase of around 5.5 meters.

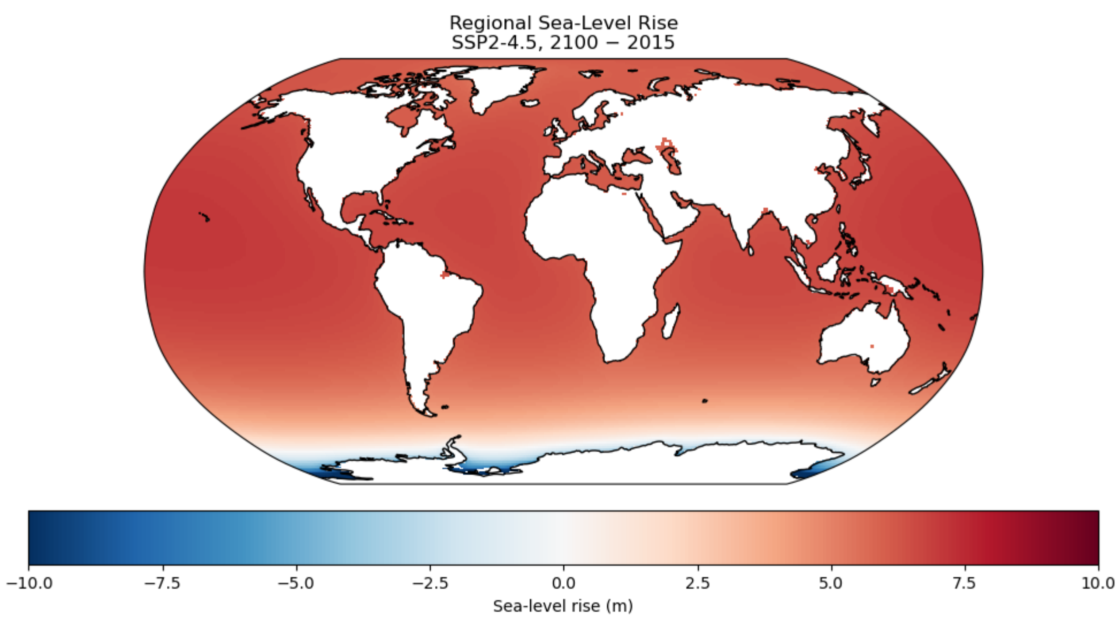

Figure 1: Map showing changes in sea level for SSP2-4.5

3.2 Projected Costs of Sea Level Rise

The economic impact of the rise of sea level is highly dependent on the approach simulated by the pyCIAM model (Table 2. The two adaptation scenarios that are the most economically taxing are the no-adaptation and retreat scenarios, with retreat having a cost of $9.824 trillion under SSP1-2.6 to $13.517 trillion under SSP5-8.5. Protection yields the most cost-effective approach among the other individual adaptation strategies with protection costing $3.784 trillion dollars for SSP1-2.6 to $4.238 trillion for SSP5-8.5. The results show how planning ahead of time and building infrastructure on average yields a more cost-effective approach then relocating.

Table 2: Differences Between SSPs and Their Adaptation Strategies (Trillion $)

SSP	No Adaptation	Protect (100Years)	Retreat (1Month)	Optimal
SSP1-2.6	9.824	3.784	9.924	0.838
SSP2-4.5	9.135	4.313	9.929	0.908
SSP3-7.0	7.991	4.622	8.634	0.763
SSP5-8.5	13.517	4.238	13.687	1.187

The economic implications of sea-level rise (SLR) are further elucidated by the cost-type breakdown presented in Table 3. This analysis contrasts the Optimal Adaptation strategy with a No Adaptation scenario across all four Shared Socioeconomic Pathways (SSPs). In the absence of adaptation measures, the most significant economic burden is consistently attributed to Storm Population, which represents the valuation of mortality risks associated with SLR-induced surge events. The second largest expenditure is Storm Capital, representing the total value of stationary infrastructure lost to inundation and storm damage. These two variables account for the vast majority of the trillions of dollars in damage projected under high-emission scenarios like SSP5-8.5. Conversely, the fiscal profile of the Optimal scenario shifts toward proactive investment rather than reactive loss. By investing in protection, the costs associated with mortality (Storm Pop.) and stationary infrastructure loss (Storm Capital) are reduced to the lowest expenditure categories in the model.

Table 3: Optimal Adaptation CostBreakdown for SSPs (Trillion $)

Scenario	**SSP1-2.6**		**SSP2-4.5**		**SSP3-7.0**		**SSP5-8.5**	
Cost Type	Opt.	No Ad.	Opt.	No Ad.	Opt.	No Ad.	Opt.	No Ad.
Wetland	0.050	0.048	0.048	0.047	0.032	0.031	0.080	0.077
Inundation	0.116	1.199	0.120	0.897	0.085	0.612	0.173	1.914
Relocation	0.175	2.197	0.195	2.023	0.140	1.438	0.282	3.888
Protection	0.393	0.000	0.426	0.000	0.404	0.000	0.509	0.000
Storm Capital	0.044	2.715	0.049	2.271	0.039	1.759	0.057	3.254
Storm Pop.	0.061	3.664	0.071	3.898	0.064	4.152	0.086	4.384
Total	**0.839**	**9.824**	**0.909**	**9.136**	**0.763**	**7.992**	**1.187**	**13.518**

One thing to note is that SSP3-7.0, around the board, contains the lowest costs while having a higher sea level rise than even SSP2-4.5. A factor that leads to this can be due to the fact that SSP3-7.0 is characterized as "Regional Rivalry", in which there is slow economic growth. Slow economic growth may help to contextualize the costs because it can be attributed to lower value of capital, meaning that the price of relocation and lost in capital is less than the other SSPs. This is backed by Table 3, in which for the no adaptation scenario SSP3-7.0 contains the lowest costs for storm capital, relocation, and inundation; despite having higher costs related to mortality then the other SSPs.

3.3 Model Evaluation

Through evaluating the BRICK model against NASA's SLR projections obtained from the IPCC AR6, it was determined that the BRICK model constantly underestimates SLR. This is particularly the case when emissions are greater, as higher SSPs correlate to a greater difference in SLR estimates.

Table 4: Evaluation of BRICK global sea-level rise projections relative to NASA AR6 projections using Mean Bias Error (MBE) and Root Mean Squared Error (RMSE).

Scenario	Bias (cm)	RMSE (cm)
SSP1-2.6	-0.793	1.724
SSP2-4.5	-4.157	4.487
SSP3-7.0	-7.661	9.035
SSP5-8.5	-9.965	11.610

Since all the values for MBE are constantly negative, it means that on a decade-to-decade basis, the values for sea level rise are underestimated in the BRICK model compared to NASA/IPCC's model. Additionally, the RMSE increases as emissions increase, indicating that the BRICK model is less sensitive to higher emissions and underestimations increase as emissions increase. Lastly, since the values for RMSE are high (1.724 cm, 4.487 cm, 9.035 cm, and 11.61 cm for SSP1, 2, 3, and 5 respectively), it can be concluded that the BRICK model was not accurate in predicting sea level rise. Overall, the BRICK model underperformed as it under-estimated its predictions for sea level rise and that trend increased for scenarios predicting increased emissions.

4 Discussion

4.1 Comparison To pyCIAM

These results are broadly consistent with findings from the pyCIAM literature Depsky et al. (2023). Similar to the pyCIAM paper, projected sea-level rise increases with higher radiative forcing, with mean values rising from 4.39 m under SSP1-2.6 to 5.31 m under SSP5-8.5. The analysis also reflects pyCIAM's conclusion that proactive coastal protection and mixed adaptation strategies significantly reduce economic damages compared to no adaptation. In this study, optimal adaptation costs range from $0.763–$1.187 trillion, far below the $7–13 trillion projected under no adaptation.

One notable outcome, also discussed in pyCIAM, is that SSP3-7.0 produces the lowest total economic costs despite having higher sea-level rise than SSP2-4.5. This occurs because SSP3-7.0 assumes slower economic growth and lower capital accumulation, meaning fewer high-value assets are exposed in coastal areas. As a result, the economic impact of sea-level rise depends not only on the magnitude of physical change but also on socioeconomic development patterns, reinforcing a key conclusion of the pyCIAM framework.

4.2 Model Limitations

The pyCIAM model shares several limitations with its predecessor CIAM. First, adaptation choices are restricted to a small set of predefined options: four protection heights, five proactive retreat heights, and one reactive retreat action. Coastal segments must select a single strategy for the entire model period and cannot switch strategies over time or combine retreat and protection, limiting the model's ability to represent more flexible, dynamic adaptation pathways.

Second, the model assumes perfect foresight, meaning coastal segments choose adaptation strategies based on full knowledge of future sea-level rise and socioeconomic conditions. While useful for optimization, this assumption is unrealistic in practice.

Third, several economic and behavioral factors are simplified or omitted. Policies such as insurance subsidies, permitting barriers, or political constraints, which may discourage proactive retreat—are not represented. Additionally, many cost parameters rely on limited empirical data at the global scale.

The model also simplifies physical coastal processes. Existing coastal protection infrastructure is not explicitly represented due to limited global data, and flooding is estimated using a simplified "bathtub" approach that ignores fine-scale hydrodynamic processes and sub grid spatial variation. Important processes such as erosion, salinization, changing storm surge dynamics, and accommodation strategies (e.g., building elevation or infrastructure hardening) are not included.

Finally, the model operates at relatively coarse spatial resolution (approximately 50 km coastal segments) due to limitations in available global datasets. While this allows global scale analysis, it limits the ability to capture localized coastal dynamics and adaptation decisions.

5 Conclusion

This study examined the physical and socioeconomic impacts of sea-level rise under multiple Shared Socioeconomic Pathways (SSPs) by combining machine learning climate emulation, the BRICK sea-level model, and the pyCIAM coastal impact model. Our results indicate that projected sea-level rise increases consistently with higher radiative forcing scenarios, with mean increases ranging from approximately 4.39 meters under SSP1-2.6 to 5.31 meters under SSP5-8.5 between 2015 and 2100. While the magnitude of sea-level rise varies across scenarios, spatial patterns remain broadly consistent, with far-field regions experiencing amplified rise and areas near Antarctica showing relative decreases due to gravitational effects associated with ice-sheet mass loss.

The economic consequences of sea-level rise are strongly influenced by adaptation strategies. Across all SSP scenarios, the absence of adaptation results in the largest economic losses, with global damages reaching between $7 and $13 trillion by the end of the century. In contrast, proactive coastal protection significantly reduces these costs, and the optimal adaptation strategy, which combines protection and retreat where appropriate, produces the lowest overall expenditures, reducing global costs to below $1.2 trillion. These results highlight the importance of early and coordinated adaptation planning in minimizing long-term damages.

An important finding of this study is that SSP3-7.0, despite producing greater sea-level rise than SSP2-4.5, results in the lowest overall economic costs. This outcome reflects the socioeconomic assumptions of the SSP3-7.0 pathway, which features slower economic growth and lower capital accumulation. As a result, fewer high-value assets are located in vulnerable coastal areas, reducing total economic exposure to sea-level rise. This reinforces the conclusion that the economic impacts of climate change depend not only on the magnitude of environmental change but also on patterns of human development and infrastructure investment.

Overall, this analysis demonstrates the value of integrating climate emulation, physical sea-level modeling, and economic impact assessment to evaluate future coastal risks. While uncertainties remain in both climate projections and socioeconomic assumptions, the results emphasize that proactive adaptation strategies can substantially reduce the economic and human consequences of rising seas. Future work could improve these estimates by incorporating higher-resolution coastal data, more dynamic adaptation pathways, and additional adaptation measures such as infrastructure hardening and accommodation strategies.

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A Additional Figures

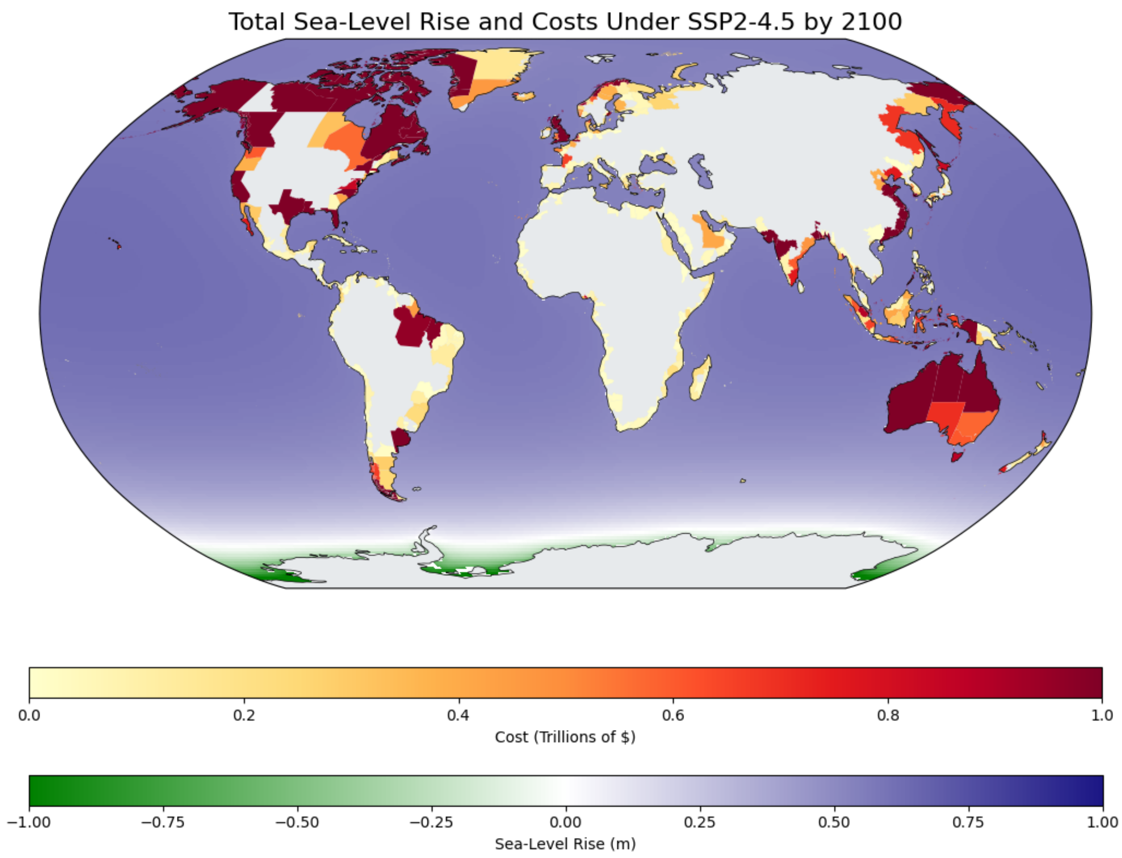

Figure 2: Map Showing Changes In Sea Level and Economic Costs per Region for SSP2-4.5

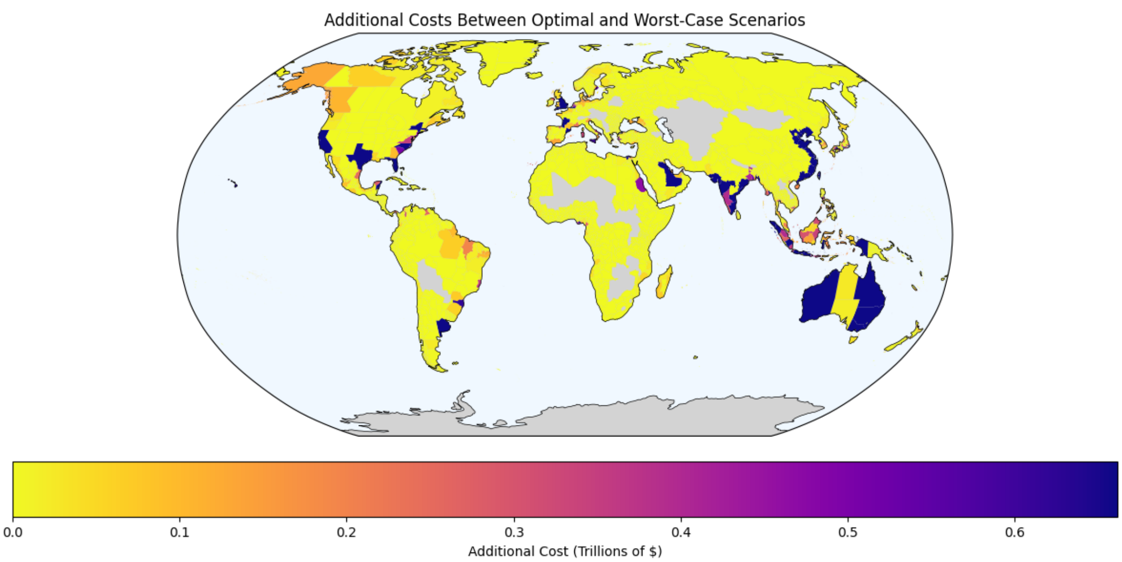

Figure 3: Map Showing Changes In Sea Level and Economic Costs per Region for SSP2-4.5