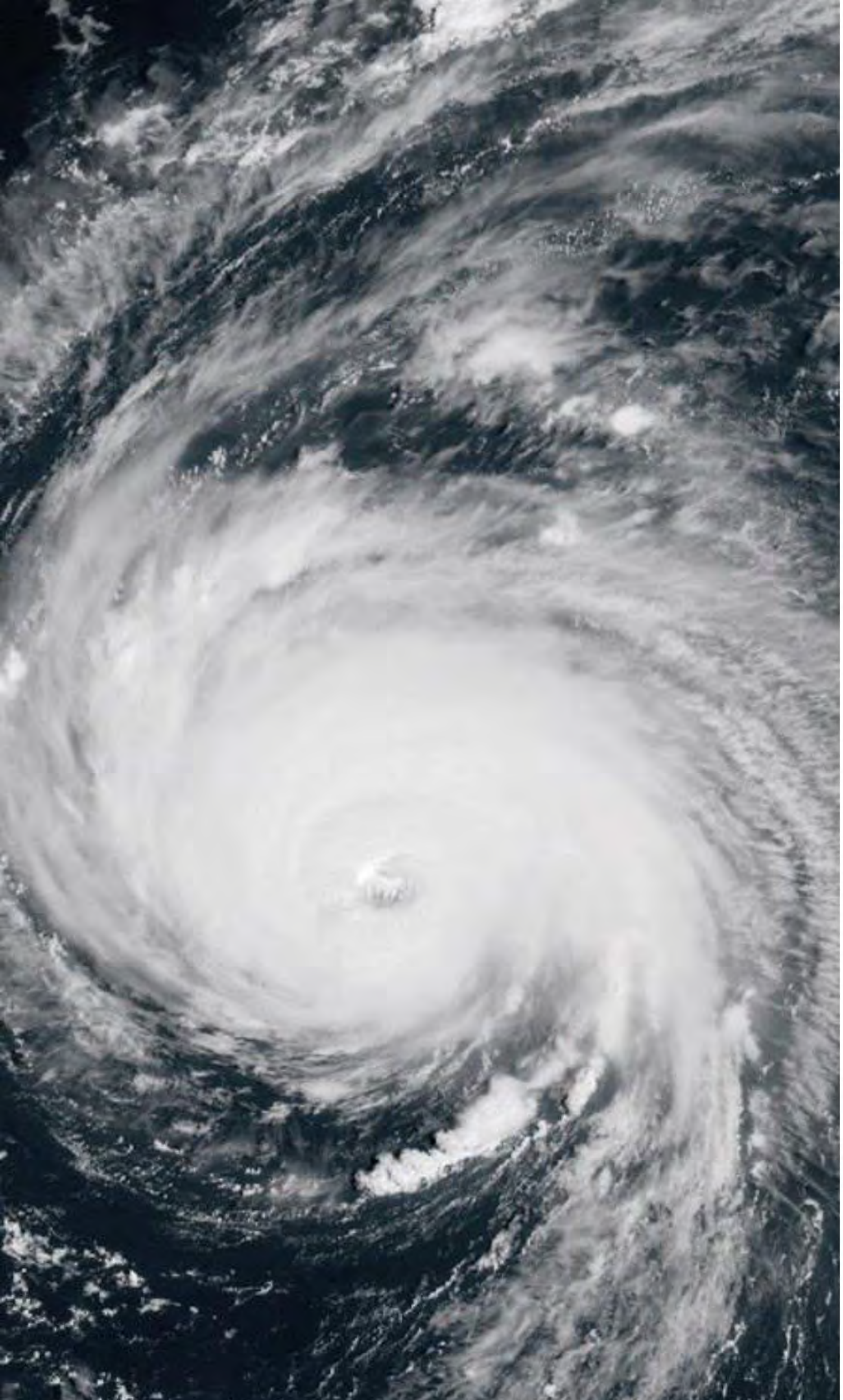

Team Go Comets

Storslysia Relocation Social Insurance Program

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SOA Case Competition 2023

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Objectives and Executive Summary

Storslysia is a country vulnerable to the perils of climate change. An increase in climate-related hazard events has plagued the country and compelled them to enlist Team Go Comets' help. Using housing and demographic data, historical hazard data, economic data, and projected emissions data, Team Go Comets developed a social insurance program to encourage and facilitate the relocation of Storslysia's population to safer regions within the country.

Our social insurance program for relocation will help Storslysia manage its exposure to displacement risk arising from catastrophic climate-related events. Our program will:

1. Encourage proactive movement of the population
2. Reduce Storslysia's climate catastrophe-related displacement costs
3. Maintain a budget of less than 10% of Storslysia's gross domestic product (GDP) each year with a high degree of certainty

We have found that implementing our program will reduce the expected losses associated with climate disasters by 20%. More importantly, an estimated 1,713,838 out of 6,953,424 citizens will relocate out of dangerous regions over the duration of our program, and consequently fatalities, injuries, and displacement due to climate disasters will be reduced.

We recommend that additional funds be put into spreading public awareness of the climate situation in Storslysia to supplement the relocation incentives in our model. To monitor the success of our program, the portions of Storslysia's population in designated dangerous regions and the number of fatalities and injuries caused by climate catastrophes can be observed to have a statistically significant decline over both our short-term timeframe of 10 years, and our long-term timeframe of 130 years.

Section 1: Program Design

All citizens of Storslysia will be covered by the social relocation insurance program. Thus, we recognize that certain requirements need to be fulfilled for a filed claim to be approved.

The objective of the insurance program is two-fold: encouraging relocation from regions susceptible to increased climate catastrophes and providing air for catastrophic climate-related displacement. Therefore, to be eligible for the full benefits of our program, we will require residency within a designated safe region by a set timeframe of 10 years. Designated safe regions, regions 1 and 3, were determined by our economic and hazard rate metrics.

- The hazard rate metric determined which regions were more prone to catastrophic events, further detailed in Appendix B1.
- The economic metric helped determine the economic capacity of each region, further detailed in Appendix B2.

Additionally, to incentivize relocation within the first 10 years, any citizen voluntarily relocating out of a designated dangerous region to a designated safe region will be eligible for stipend.

- All relocation unrelated to catastrophic climate-related displacement within the initial 10-year period will be considered as voluntary relocation.
- All relocation after the initial 10-year period will be considered as involuntary relocation.

Our program will also only provide financial aid to claims filed due to catastrophic climate-related events. Specifically for our policy, we define a catastrophic climate-related event as one causing widespread damage to insured property, including any incidents of injury or fatality to the insured. Such events include coastal storms, drought, flood, fog, hail, extreme heat, hurricane, landslide, lightning, severe storm, tornado, wildfire, wind, and winter storm.

Coverage

The program's coverage benefits will alter after the set timeframe of 10 years. For the initial 10 years of the program, full financial reimbursement for all financial aid claims in all regions will be provided at an initial limited budget. After the 10 years, the full financial reimbursement for financial aid claims up to 10% of Storslysia's GDP will only be provided to citizens residing in designated safe regions.

Applicants with approved voluntary relocation claims will receive compensation for relocation costs in the form of a relocation stipend along with temporary housing for 2 months.

- Relocation stipend is equivalent to 1 month living expense of region 1 or 3.

Applicants with approved financial aid claims will receive either compensation for property damage, injury, and fatality, temporary housing for two months, or both depending on eligibility.

- Property damage is defined as all external and internal damage to residential property caused by a catastrophic event.
- Injury benefits include all medical fees and related costs to the injury/injuries caused directly by the catastrophe event.
- Fatality benefits include a year's worth of salary compensation in the form of a single lump sum or monthly annuities. This benefit will be provided in addition to a pre-existing life insurance policy benefit.

Incentives

As mentioned earlier, the program's coverage benefits will be the main incentive for relocation. For the timeframe of 10 years, citizens of Storslysia will be motivated by the opportunity to avoid future expenses:

- Relocation within the first 10 years will result in additional relocation stipend.
- Relocation out of designated dangerous regions will ensure that the likelihood of being affected by a catastrophic climate-related event is minimized.
- Relocation to a designated safe region will ensure that they receive full financial aid in the case that they are affected by a catastrophic climate-related event.

After the 10 years, as full financial reimbursement for financial aid claims up to 10% of Storslysia's GDP will only be provided for the designated safe regions, this will serve as a longstanding incentive for people to continue relocating to designated safe regions.

Other suggestions to Storslysia's government is for continued education of Storslysia's population regarding the country's climate situation. Increased public awareness will help supplement our model's relocation incentives.

Short- and Long-Term Timeframes

For our program, we have designated 10 years and 130 years for our short- and long-term timeframes for evaluation, respectively. Ten years was chosen as the short-term timeframe to embody the impact of relocation on the program's costs as the majority of voluntary relocation is expected to occur within this timeframe. Our model returns that approximately 857,147 citizens will relocate during the short-term timeframe. Further analysis of the relocation data is detailed in Appendix D3.

For the long-term timeframe we have chosen 130 years, as over the period we will observe the effects of climate change on our program. Specifically, we have modeled for different climate change scenarios to monitor the impact each scenario has on our relocation program, further detailed in Appendix D1. Our model will provide estimates for the number of housing to be provided during the 130 years along with the number of people who have relocated after the initial 10 year period which will be considered as involuntary relocation. Our model shows that approximately 1,713,838 citizens will relocate during the long-term timeframe. The analysis of the economic impact is detailed in Appendix D1.

Section 2: Data and Data Limitations

Storslysia's task force gave data to our consulting group to aid in the creation of a social insurance product. The data that was provided includes: hazard events, historic census and economic data, historic inflation and interest rates and analysis of Shared Socioeconomic Pathways (SSP). SSPs are different global socioeconomic projections dependent on the world's greenhouse gas emission levels.

- We estimated the missing transportation and warehousing receipts/revenue for 2017 by using a multivariate regression on the sum of region population for 2019-2021 and the sum of GDP for 2019-2020 to get a value of 1,605,298 (in thousands of Storslysia currency)
- We estimated the inflation factor in 2003 by using a Monte Carlo simulation 1000 times of the 4 years around the year to fix the value. We fixed the improper values before we did any regression analysis to avoid outliers.
- We had one loss event that was an outlier, a hurricane in 1989. We decided to keep this loss event as we treat all loss events as independent, therefore a similar event may occur in the future.

In order to complete our models, we needed to have a strong basis for population growth and annual healthcare spending per capita. External data from Macrotrends and Our World in Data were obtained and used for our calculations. The applications of these data on our program are described in Appendices A5, C1, and C5, respectively.

The way that the value of the insurance product would be measured would be through estimating the number of losses that would be prevented by our insurance product, and the profitability of the main insurance part of our product. There are two categories of loss mitigation: losses avoided through preemptively moving people away from loss heavy regions and those mitigated through the more typical insurance function. These measurables give Storslysia the tools to observe the performance of this insurance.

Some of the models we developed would need to be regularly updated to ensure they are running as accurately as possible for loss modeling. Long term predictions can be very inaccurate, and updating will increase the quality of the short-term estimates through more relevant data and long-term through additional years to model with.

Section 3: Assumptions

Several assumptions were made in the program development process. Assumptions are an inherent part of any development process, as they allow developers to make certain predictions and estimations based on the available information. By identifying and documenting these assumptions, we ensure they are taken into consideration throughout program implementation, that any potential risks or uncertainties are properly addressed, and that any future updates or modifications to the program may consider these assumptions. Assumptions were partitioned into three categories: climate, economic, and social assumptions.

Climate Assumptions

The most impactful assumption on the outcome of our program regards climate change. The effect of climate change on natural disasters in the future depends on a multitude of uncontrollable variables, such as legislation, public opinion, international conflict, and industrial development. The SSPs give us potential outcomes for how we treat climate change in the coming decades. To ensure the capability of our program to remain within the cost constraints, we chose to simulate our program for all SSPs to see how the pathways affect the costs of our program, and guarantee we meet the relocation and financial goals for the harshest scenario.

Economic Assumptions

Inflation rate is critical to projecting our costs and benefits through time. After observing that regressions and time series do not fit the inflation data well, we assumed a constant inflation rate equal to the average of the inflation rates from 1960 to 2021.

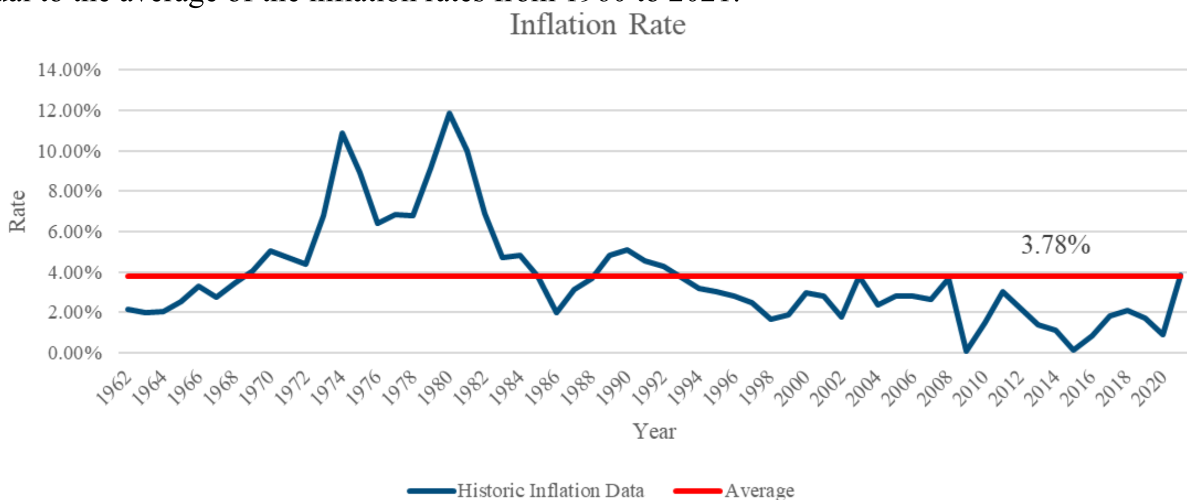


Figure 1: This graph shows inflation rate from 1962 to 2021. The blue line representing inflation is unpredictable and does not follow a coherent pattern.

When simulating hazard events in the future, we group benefits from injury, fatality, and property damage. This is because there is a limited number of nonzero injuries and fatalities data, making the data less credible, and the trend of injuries and fatalities is negative, meaning they will have a negligible effect on costs toward the end of the program's timeframe.

Social Assumptions

Data pertaining to relocation rates in anticipation of rising climate-catastrophe frequency is extremely limited. To circumvent this, we created several scenarios to model the worst-, middle-, and best-case scenarios for ultimate relocation rates estimated from real-world evacuations due to and in advance of natural disasters. The annual relocation rates were taken from a logistic model to take herd movement into account. This process is described in more detail in Appendix A6.

We assumed Storslysia's population would grow at a rate similar to developed countries, meaning a slow and steady rise. This process is described in more detail in Appendix A5.

Section 4: Risk and Risk Mitigation Considerations

The costs associated with displacement risk due to increasing climate catastrophes are contingent on several severe risks that may significantly affect our results. We performed a risk analysis to illustrate the significance of key risks below.

Risk Matrix

Figure 2: This graph shows several key risks and their associated severity and likelihood, with 5 indicating a high severity or likelihood.

1. Extreme Climate Change: The handling of climate change in the present has an observable impact on the frequency of hazard events and thus the costs of our program. To mitigate the effect of poor handling of climate change, this potential was fully incorporated into and addressed in our model.
2. Poor Relocation: A less-than-expected relocation rate from the population will result in increased injuries, fatalities, and property damage from natural disasters. Though several features of the program incentivize relocation, it is recommended that the government of Storslysia publicize the importance of voluntary relocation and the risks associated with immobility.
3. Excessively Catastrophic Events: An exceptionally impactful disaster may disrupt program implementation, cause extreme inflation, or result in severe damage to infrastructure and people. Though the occurrence of such a catastrophic event cannot be

controlled, the likelihood and severity of this risk can be reduced by mitigating the potential of the previous two risks.

Section 5: Pricing/Costs

Future Loss Cost Simulation

The simulation model utilized to estimate future loss cost is outlined in Appendix A. It involves several factors, including the frequency and severity of hazard events, the trending of frequency and severity, the projected population count, and relocation rates. The simulation is run 1,000,000 times to provide a reliable estimate of future loss under each Shared Social Pathways (SSP) scenario.

Economic Cost Improvement

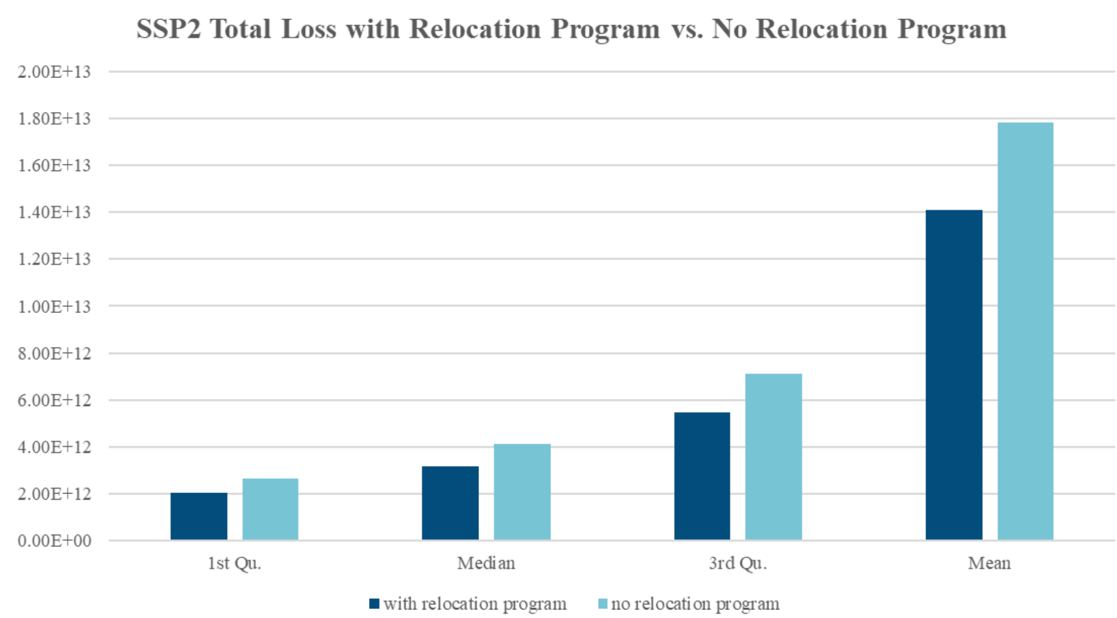


Figure 3: This figure compares the SSP2 total losses incurred with our program and without. The dark blue bars representing expected costs with our program are noticeably shorter than the light blue bars representing expected costs without our program.

Our relocation plan is expected to reduce total future economic costs of injury, fatality, and property damage from 2021 to 2150 by 21.02%, or up to 24.42% under the mid-case scenario of SSP2. The average loss cost improvement by our program is Ᵽ3.746 trillion, representing the difference between the total loss under no relocation and the sum of total loss under relocation with the cost of the program. To obtain further details, please refer to Appendix D1.

Capital Requirement

In order to ensure the financial stability of the program, it is imperative to determine the necessary economic capital with a high degree of certainty. The short-term costs of the program will involve covering temporary housing and hazard assistance for all six regions for the first 10 years, at a rate of up to 2.5% of the country's GDP per year while we accumulate the budget for the relocation stipend. During the first 10 years, a relocation stipend of Ᵽ3645.71 will be paid to individuals who relocate to regions 1 or 3. From year 11 to year 130, temporary housing and hazard assistance will be provided up to 10% of the country's GDP.

Under the model simulation, the total cost of the program will average 3.17% of Storlysia's annual GDP every year under the mid-case scenario SSP2, while the worst-case scenario under SSP5 could cost as much as 7.96%. To obtain further details, please refer to Appendix D2.

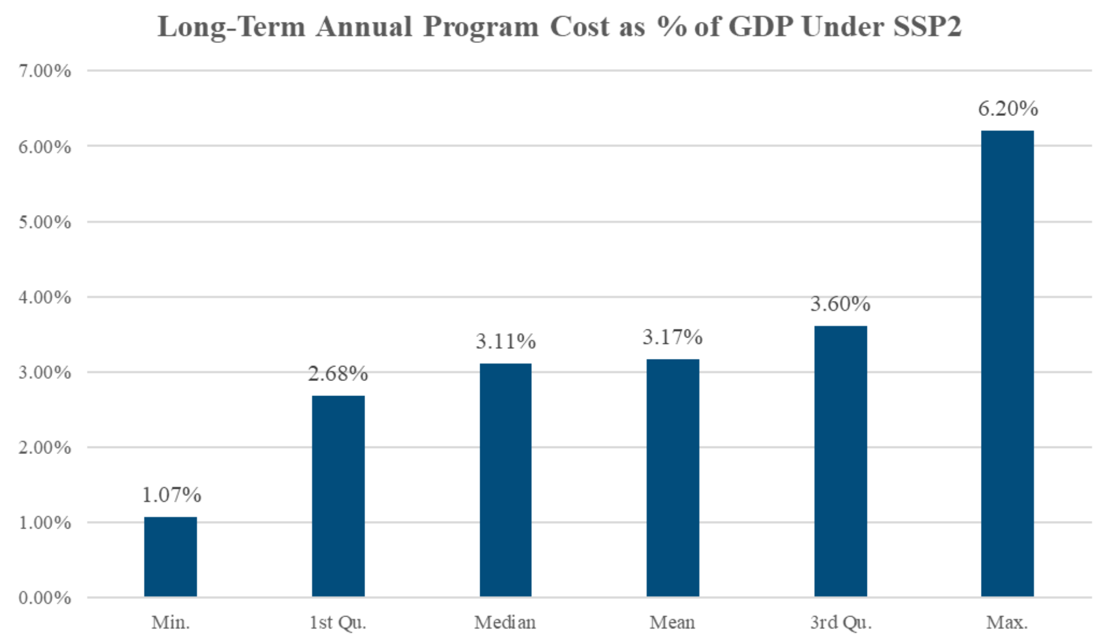


Figure 4: This graph shows that the long-term annual program costs are always under 10% of Storslysia's GDP.

Conclusion

Extensive research and development suggests that the financial assistance and support provided by our program will reduce the expected costs associated with climate disasters by 20%, and relocate an estimated 1,713,838 out of 6,953,424 citizens out of dangerous regions over the duration of our program. Our program is affordable, comprehensive, and easily implemented. It addresses all climate concerns and poses little risk to the government of Storslysia.

Appendix A: Future Loss Cost Model

$$F_x \sim NegativeBinomial(size = n_x, mu = \mu_x)$$

$$p_x \sim Bernoulli(p = Pr[HazardLoss_i > 0])$$

$$NonZeroLoss_x \sim Gamma(shape = a_x, rate = \theta_x)$$

$$Severity_{i,x,t,n} = p_x * e^{NonZeroLoss_x}$$

$$SingleLoss_{i,x,t,n} = Severity_{i,x,t,n} * (1 + SevTrend_x)^t$$

$$PopAdjFactor_{x,t,n} = \frac{(Population_{t,n} * RegionPop\%_{x,t,n})}{(Population_0 * RegionPop\%_{x,0})}$$

$$LossInYearT_{x,t,n} = \left(\sum_{i=1}^{F_x} SingleLoss_{i,x,t,n}\right) * FreqTrendFactor_t * PopAdjFactor_{x,t,n}$$

$$TotalLoss_n = \sum_{t=1}^{130} \sum_{x=1}^{6} LossInYearT_{x,t,n}$$

Figure 5: Formulas used in the future loss cost model

Notation

F_x – frequency distribution for the number of hazard events of a region in a given year

p_x – Bernoulli variable with p% chance that the hazard loss will be greater than zero

$HazardLoss_i$ – loss from property damage, injury and fatality, detail described in Appendix C

$NonZeroLoss_x$ – severity distribution of each region when the hazard loss is greater than zero

$Severity_{i,x,t,n}$ – severity of a given hazard for a region in year t

$SevTrend_x$ – selected severity trend for a region

$SingleLoss_{i,x,t,n}$ – trended severity of a given hazard for a region in year t

$Population_{t,n}$ – Storslysia's projected future population in year t

$Population_0$ – Storslysia's initial population in 2021

$RegionPop\%_{x,t,n}$ – a region's population expressed as a percentage of the total population in a given year t

$RegionPop\%_{x,0}$ – a region's population expressed as a percentage of the total population in 2021

$PopAdjFactor_{x,t,n}$ – adjustment factor for cumulative population gain or loss for a region in a given year t

$FreqTrendFactor_t$ – frequency trend for each SSP scenarios, given in the case material as the Risk Amplification Factor

$LossInYearT_{x,t,n}$ – total loss for a region in a given year t

$TotalLoss_n$ – total loss cost for a single simulation

Sub Notation

i represents a hazard event in a year, with values from 1 to F_x.

x represents a region number, with values from 1 to 6 for each region.

n represents the n-th simulation, with a total of 1,000,000 simulations.

t represents the year in each simulation, with values from 1 to 130, representing years 2021 to 2150.

Model Description

The Future Loss Cost Model follows a set of procedures to simulate the total future HazardLoss from 2021 to 2150. As part of these procedures, the model determines the component of each individual hazard event's loss using the formula outlined in Appendix C. This formula provides a systematic approach for calculating the loss associated with each event, taking into account the relevant parameters from property damage, number of injury and number of fatality from an event. By using this formula, we can accurately model the total future loss cost for the program, which is essential for ensuring that we can effectively manage the associated risks.

F_x

The model generates the number of hazard events for each year by using randomly generated negative binomial values. These values are based on the size and mu parameters of each region and are detailed in Appendix A1. This approach allows us to accurately simulate the frequency of hazard events for each region over time.

p_x / $NonZeroLoss_x$ / $Severity_{i,x,t,n}$

For each hazard event generated by the model, there is a probability of (1-p)% that the hazard loss will be zero. On the other hand, there is a probability of p% that the *$Severity_{i,x,t,n}$* of a given hazard event will be generated using the *$NonZeroLoss_x$* distribution. This distribution follows a gamma distribution with shape and rate parameters specific to the region. These parameters are detailed in Appendix A3, and the probabilities for zero loss severity are discussed in Appendix A2. By using those procedures, we can accurately model the $Severity_{i,x,t,n}$ of each hazard event each region may face.

$SingleLoss_{i,x,t,n}$ / $SevTrend_x$

Once $Severity_{i,x,t,n}$ has been determined, a severity trend ($SevTrend_x$) is applied to calculate the amount for a $SingleLoss_{i,x,t,n}$. This trend is detailed in Appendix A4. By applying this trend to the severity, we can accurately model the impact of trends on hazard losses over time. This is crucial for assessing the program's long-term risk and ensuring that we can adequately manage the associated costs.

$PopAdjFactor_{x,t,n}$

To account for changes in population over time, the model incorporates a population adjustment factor ($PopAdjFactor_{x,t,n}$). It is calculated as the product of Storslysia's future population at a given time t, as detailed in Appendix A5, and the percent of population in a region at that same time t, accounting for relocation as described in Appendix A6. This factor is then divided by the initial population in the region to accurately estimate the potential financial impact of hazard events over time with relocation. By using this adjustment factor, the model can provide a more precise evaluation of the long-term financial risks associated with a region increasing or decreasing its population.

$LossInYearT_{x,t,n}$ / $FreqTrendFactor_t$

To calculate the total loss for a region in a given year ($LossInYearT_{x,t,n}$), the model adds up all $SingleLoss_{i,x,t,n}$ for each hazard event that occurred in that region during the year. The $LossInYearT_{x,t,n}$ amount for each region in a given year is then multiplied by the frequency trend factor ($FreqTrendFactor_t$), also known as the Risk Amplification Factor. This factor is specific to each SSP scenario and can be found in the case material "Frequency Projection Model of Minor, Medium, and Major Hazard Events Per Year, as a Function of SSP Scenario". Additionally, it applies the $PopAdjFactor_{x,t,n}$ to account for differences in population size across regions. By using this formula for $LossInYearT_{x,t,n}$, we can accurately estimate the total loss for each region in a given year.

$TotalLoss_n$

In summary, the total future loss cost ($TotalLoss_n$) for a single simulation is calculated by summing up the total loss for all regions over a 130-year time period. This calculation takes into account the severity and frequency trends of hazard events, as well as changes in population and relocation patterns as described in the various appendices of the model documentation.

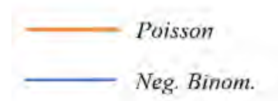
SSP Scenarios

To simulate each SSP scenario, we have run all four sets of the frequency trend factors for all simulations. This enables us to accurately model the impact of different scenarios on the program's outcomes.

A1: Hazard Frequency by Region

To determine the frequency model (F_x) that best fits the data, we compared the Poisson distribution and Negative Binomial Distribution for all six regions using the goodness-of-fit technique on estimated parameters using MLE.

After careful consideration, we selected the Negative Binomial distribution as the preferred frequency model.



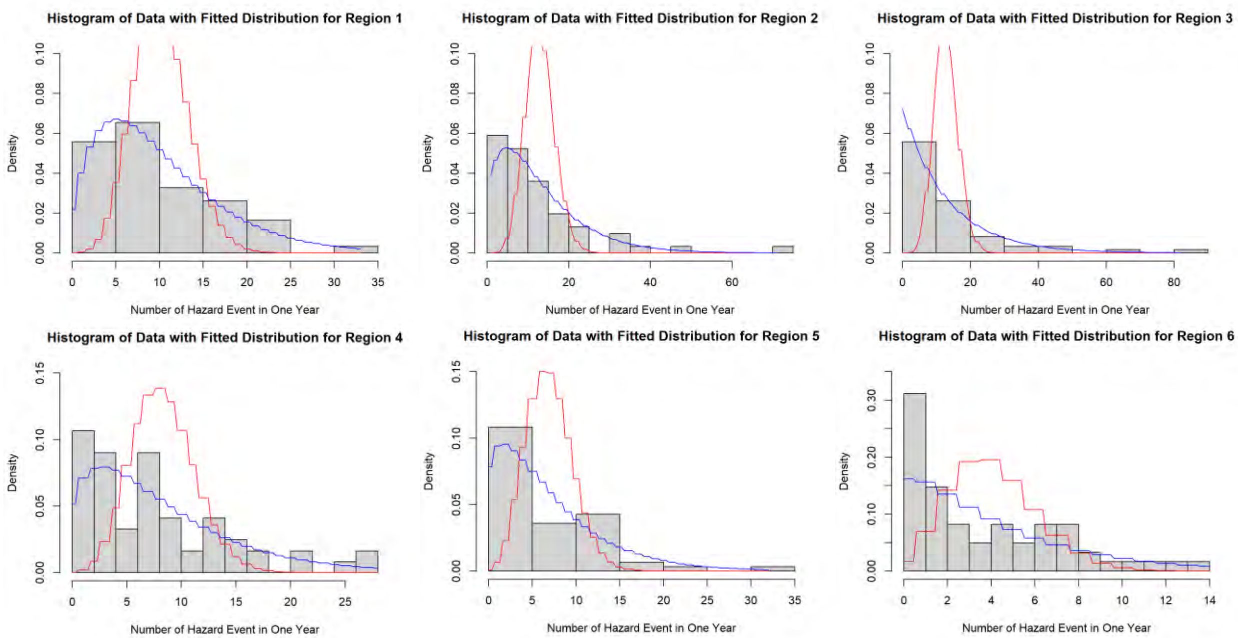


Figure 6: Histograms of hazard frequency data with overlayed Poisson density curves in red and Negative Binomial density curves in blue. These illustrate that a Negative Binomial distribution best fits the data.

$$f_x(u) = \frac{\Gamma(u+n)}{\Gamma(n)u!} p^n (1-p)^u$$

Above shows the density function of Negative Binomial Distribution with size parameter n and probability parameter p. The table below displays each region's parameters for its Negative Binomial Distribution.

Region	1	2	3	4	5	6
Size Parameter	2.225	1.686	1.002	1.637	1.449	1.266
P Parameter	10.131	12.902	12.803	8.328	6.951	4.066

Figure 7: Size and probability parameters for Negative Binomial distributions fitted with maximum likelihood to each region's hazard frequency data.

A2: Probability of Zero Loss Hazard Event

The concept of p% refers to the probability of a hazard event resulting in no loss. It is a measure of the likelihood that an event will cause no hazard loss.

This probability is treated separately from the probabilities of non-zero losses to improve the accuracy of estimating the severity of such losses. The chart below shows the probabilities of a hazard event causing zero loss in each region.

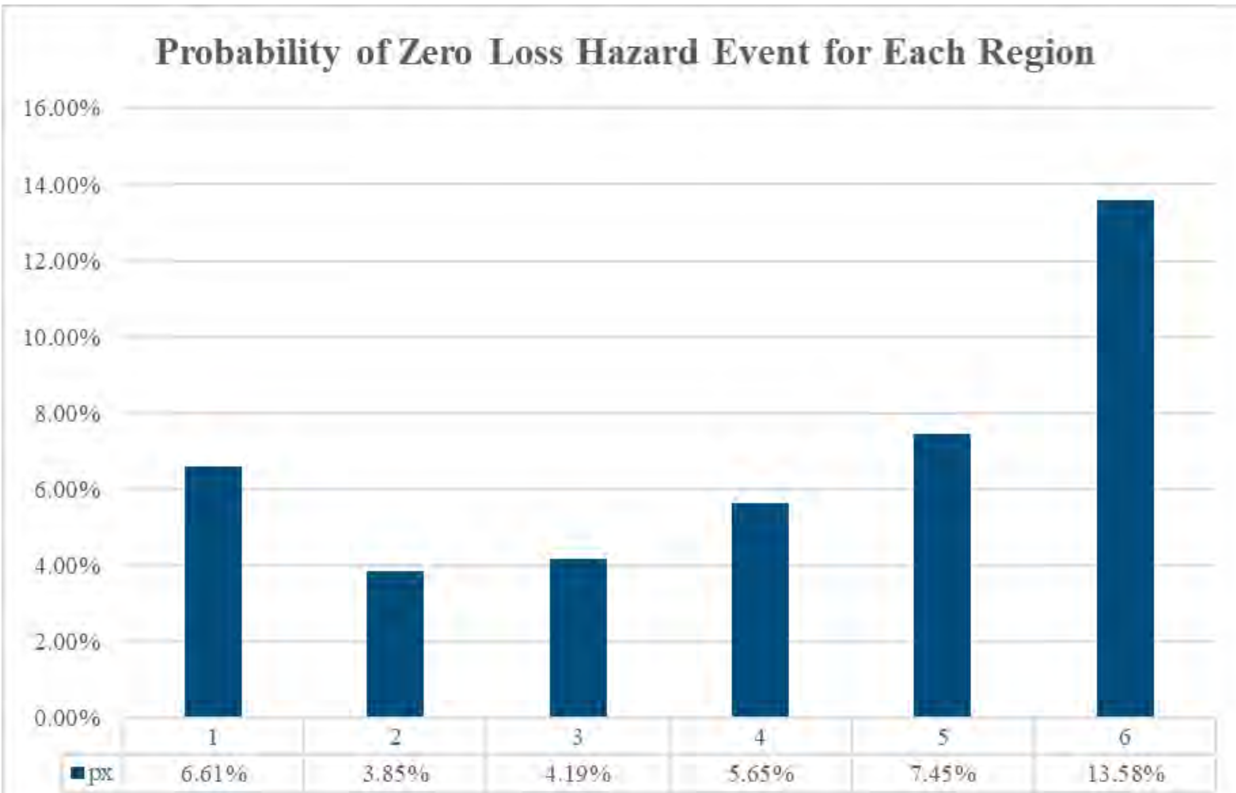


Figure 8: Each region's probability of a random hazard event causing zero loss.

By taking into account the probability of zero loss hazard events, severity models can better evaluate the potential risks and impacts of different levels of hazards in different regions.

A3: Severity Distribution of Nonzero Loss Hazard Event

To determine the severity distribution of non-zero loss hazard for each region, we first combine the injury, fatality, and property damage losses using the formula introduced in Appendix C. Any zero loss data will be treated according to the method described in Appendix A2.

Next, we apply a log transformation to the data to facilitate visualization and model fitting. The transformed data will be brought back to its original scale in the future loss cost model from Appendix A by raising it to the power of e.

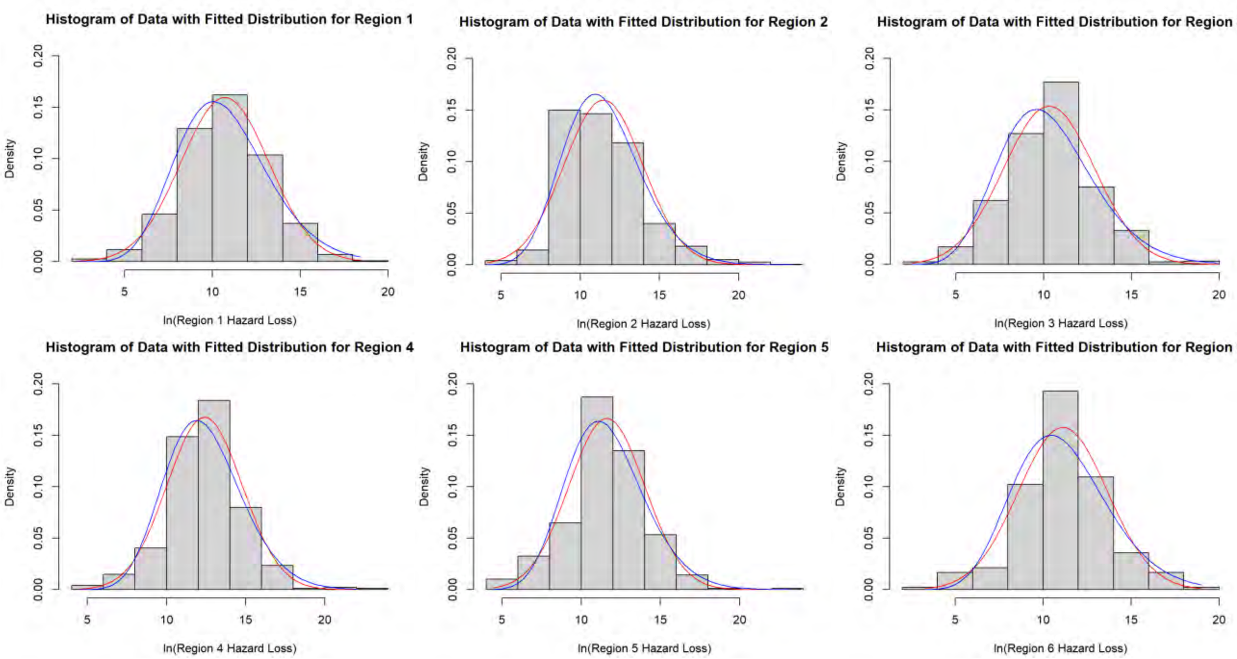


Figure 9: Histograms of log-transformed nonzero hazard loss data with overlayed Normal density curves in red and Gamma density curves in blue. These illustrate that a Gamma distribution best fits the log-transformed data.

We fit both Normal (red line) and Gamma distributions (blue line) to all six regions using the MLE method, ultimately choosing the Gamma distribution as our severity model. While both distributions showed similar fits for five of the regions, Region 2 displayed a clear skewness in the density of the log-transformed hazard loss. Additionally, we found that the Normal distribution had a light tail that did not provide enough density for extreme events, leading us to select the Gamma distribution fitting for all regions.

The table below shows the shape and rate parameters of the Gamma distribution for each region.

Region	**1**	**2**	**3**	**4**	**5**	**6**
Shape Parameter	16.556	21.699	14.260	25.245	21.826	16.651
Rate Parameter	1.546	1.895	1.383	2.036	1.881	1.497

Figure 10: Shape and rate parameters for Gamma distributions fitted with maximum likelihood to each region's log-transformed nonzero hazard loss data

A4: Hazard Loss Severity Trend

Severity trends are a crucial component of predicting future loss costs, as they reflect the appreciation of loss costs over time. To reduce volatility, the hazard loss for each region is grouped by year and a ten-year rolling average method is employed. The methodology used to define hazard loss is outlined in Appendix C, and this analysis specifically focuses on the trending of hazard loss. To ensure consistency across all regions, hazard loss in this case is scaled by housing units. Overall, this approach provides an adjustment for hazard loss over time and is an important consideration when estimating future losses.

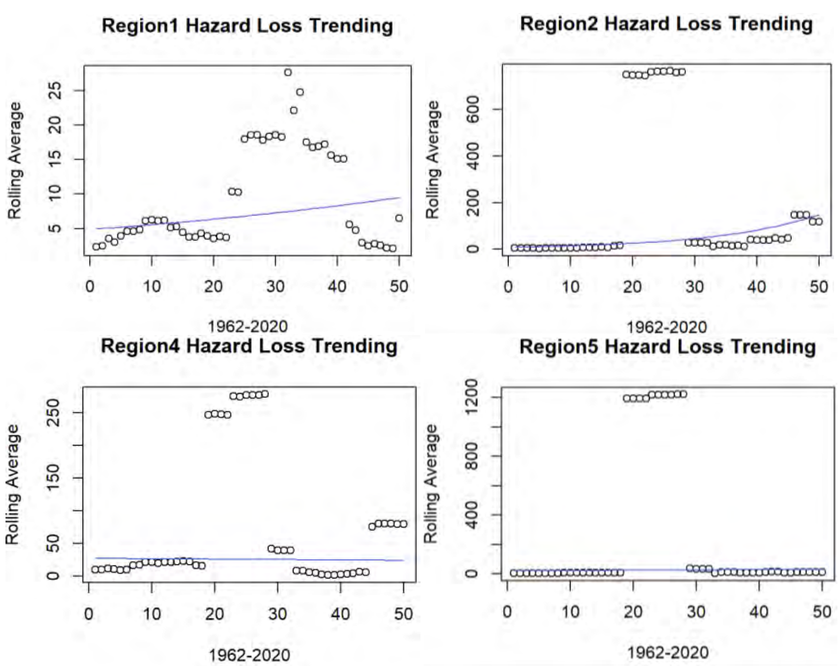
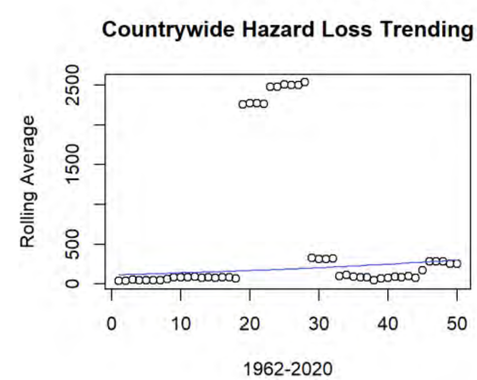


Figure 11: Plots of regional hazard loss data with trend lines fitted with exponential regression.



Trend Rate Regression

After collecting all the rolling averages, an exponential regression was performed for each region by plotting the hazard loss per housing unit against year t. The resulting plots are shown above, displaying the fitted exponential trend for all years for each of the six regions as well as the countrywide trend.

Trend Rate Selection

The severity trending rate selected in the model was adjusted for some regions.

- For region 1, the hazard data was found to be too volatile and had some spikes at the last point, so the countrywide severity trending rate was used instead.
- For regions 4 and 6, the indicated trend factors were both less than one. As the trend rate becomes negative, the future trended value at the end of 130 years would be unreasonably low. Thus, a trending ratio of 1.000 was chosen for no trend.

Region	**1**	**2**	**3**	**4**	**5**	**6**	**Countrywide**
Indicated Trend	1.01339	1.06023	1.03183	0.99760	1.00718	0.98222	1.01963
Selected Trend	1.01963	1.06023	1.03183	1.00000	1.00718	1.00000	
Difference	0.62%	0.00%	0.00%	0.24%	0.00%	1.78%	

Figure 12: Table showing the indicated and selected severity trend by region. Countrywide trend is used for region 1 that has volatile loss experience; negative trend rate in region 4 and 6 is adjusted to no trend.

A5: Population Growth Model

Population size projections for Storslysia were needed for our model. Due to the limited data provided, we decided to use population size data provided by Our World in Data to come up with estimates for Storslysia's future population sizes. Population predictions are complicated as they utilize metrics such as fertility, mortality, and migration trends. Our population size projections will be based purely on population size data analyzed.

Analyzing Storslysia's economic data that was provided, we assumed that Storslysia fit into the category of a developed country, as Storslysia's GDP per capita rivaled that of countries listed as developed countries by the United Nations Development Programme in 2021. The 66 countries were listed as developed in 2021 and we created 3 sets:

1. All 66 countries
2. 41 countries with population size greater than 5 million in 2021
3. 29 countries with population size greater than 5 million in 1950.

The different sets were created to monitor the effects of countries with small population sizes on the population growth rate, as smaller population sizes are less predictable when performing growth rate projections. Population size data from 1950 to 2021 for these 66 countries was then collected from Our World in Data and organized in two ways.

For the first method, the population size data for each set was taken as is, and a yearly total of the population size of all countries was calculated. The growth rate for each year was taken by dividing the total population size of the current year by the total population size of the previous year. This was then plotted onto a scatterplot, and we used logarithmic regression to project future population size values.

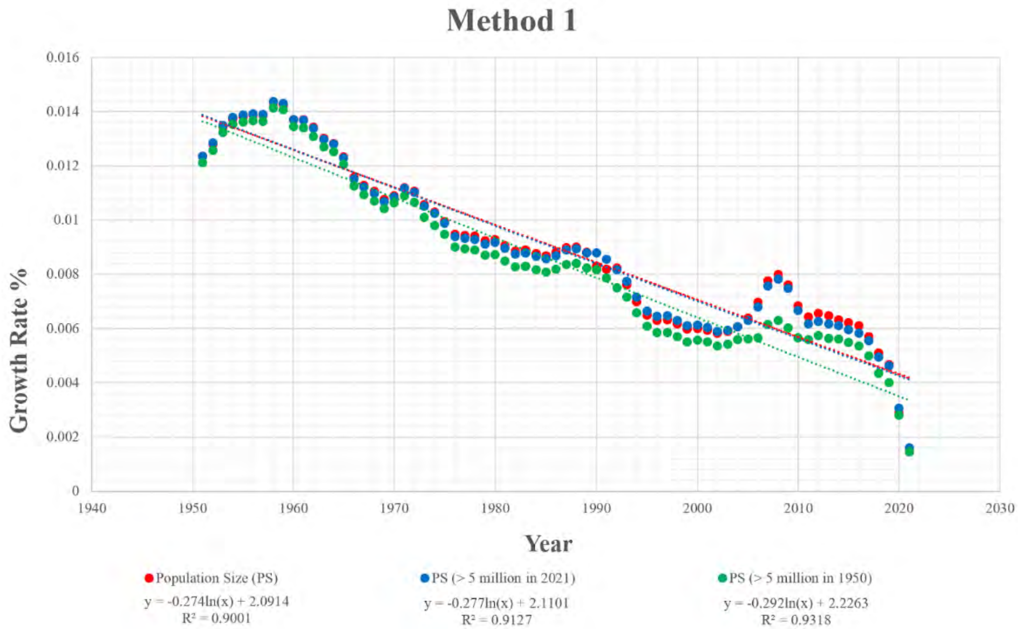


Figure 13: Scatterplot of population growth rate calculated using method 1 fitted with a logarithmic regression line.

For the second method, the population size data for each set was taken and the yearly growth rate for each country was calculated by taking the current year's population size and dividing by the previous year's population size. The average growth rate of all the countries listed was calculated for each year. This was then plotted onto a scatterplot and we used logarithmic regression to project future population size values.

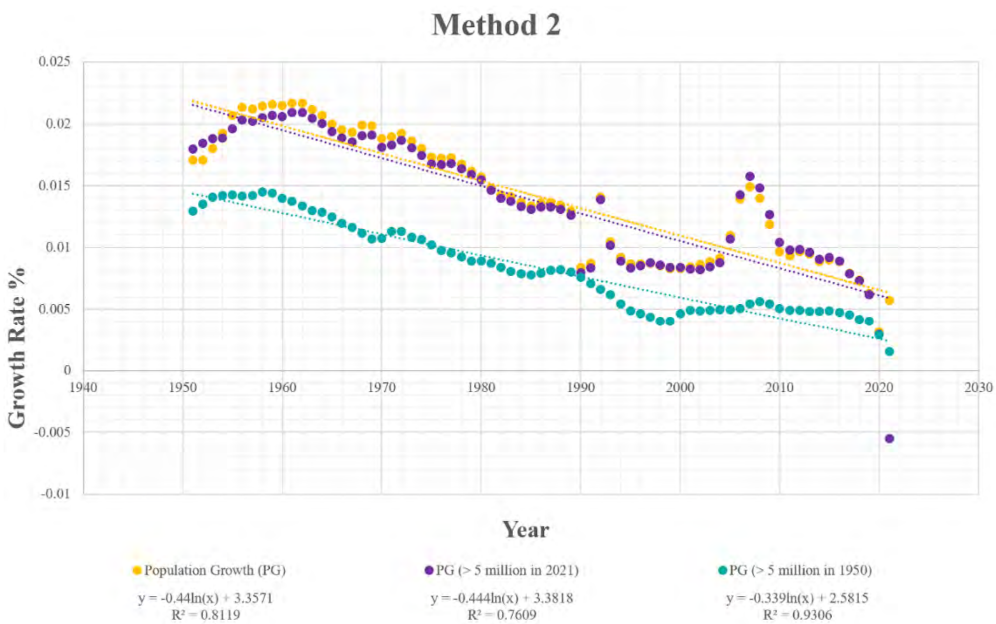


Figure 14: Scatterplot of population growth rate calculated using method 2 fitted with a logarithmic regression line.

The six logarithmic regression scenarios were then used to project the population sizes for Storslysia used for our future loss cost simulation model.

Scenario	2022	2023	2024	2025	2026	2027	2028	2029	2030
Population Size (PS)	18,484,891	18,588,771	18,690,717	18,790,693	18,888,662	18,984,587	19,078,434	19,170,168	19,259,755
PS (> 5 million in 2021)	18,408,884	18,436,179	18,460,990	18,483,309	18,503,127	18,520,438	18,535,234	18,547,511	18,557,265
PS (> 5 million in 1950)	18,446,053	18,510,571	18,572,643	18,632,245	18,689,351	18,743,940	18,795,989	18,845,477	18,892,383
Population Growth (PG)	18,524,115	18,666,228	18,805,373	18,941,468	19,074,432	19,204,189	19,330,661	19,453,773	19,573,451
PG (> 5 million in 2021)	18,418,484	18,453,892	18,485,320	18,512,746	18,536,156	18,555,534	18,570,868	18,582,151	18,589,375
PG (> 5 million in 1950)	18,399,065	18,415,952	18,429,769	18,440,511	18,448,172	18,452,751	18,454,245	18,452,655	18,447,984

Figure 15: Sample of annual population sizes for all scenarios projected from the trend lines obtained from methods 1 and 2.

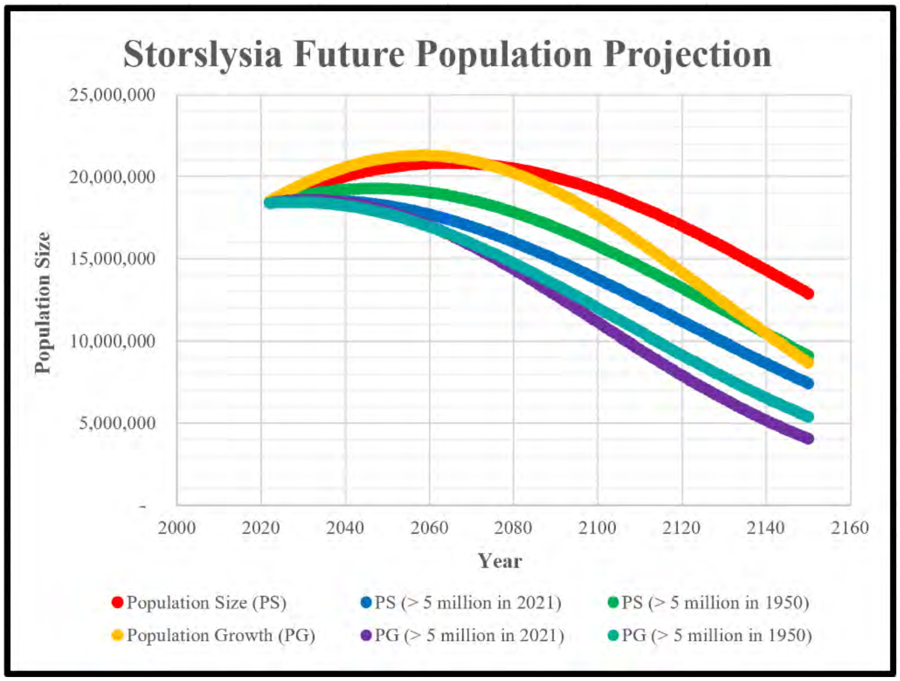


Figure 16: Projected population sizes for Storslysia up to year 2150.

A6: Relocation Rate Projections

To model relocation rates through time, a logistic function was implemented. This was to characterize not only the mass herd movement within the short-term timeframe, but also relatively small movement throughout the long-term timeframe due to involuntary relocation.

First, ultimate relocation rates were determined. These are the percentages of the portion of the country's population in each of the designated dangerous regions (regions 2, 4, 5, and 6) we expect to relocate to the designated safe regions (regions 1 and 3). The hazard safety of each region is explained in detail in Appendix B1. Using data from evacuation rates during hurricanes for those not within critical evacuation zones and relocation rates following natural disasters, we determined several cases for relocation. For region 4, the region most susceptible to losses due to climate catastrophes, we extrapolated ultimate relocation rates to be a random percentage between 15% and 40%. Ultimate relocation rates for regions 2, 5, and 6 were calculated as those for region 4 rescaled by the relative hazard score between region 1 and region 4. In other words, we expect that as the losses due to hazard events in a region decrease, the relocation rates decrease.

Next, we determined intermediary cumulative relocation rates by fitting a logistic function to three points: zero percent relocation at the present, the ultimate relocation rate at the end of our long-term timeframe in 130 years, and a random percentage between 0.001% and 99.999% of the ultimate relocation rate at the end of our short-term timeframe in 10 years. The random percentage of ultimate relocation by the end of our short-term timeframe allows us to account for different mobilization speeds from the citizens of Storslysia in our predictive model.

	Region 2	Region 4	Region 5	Region 6
Maximum Relocation Rate	0.370634	0.400000	0.273482	0.399191
Minimum Relocation Rate	0.138988	0.150000	0.102556	0.149697

Figure 17: Maximum and minimum ultimate relocation rates for designated dangerous regions.

Last, the annual relocation rate was determined by dividing the current year's cumulative relocation rate by the previous year's cumulative relocation rate for a randomly simulated case. The populations in region 2, 4, 5, and 6 used this method to compute outbound relocation, and those relocated citizens were partitioned randomly between regions 1 and 3.

Appendix B: Region Comparison Metrics

B1: Hazard Safety Scores

Based on the severity of hazard events at the minor, medium, and major levels, each region is assigned a hazard event score.

To determine the score, the severity of events at each level is evaluated against corresponding percentiles (50th, 90th, and 99.5th) using hazard loss data from Appendix C. The resulting severity ratio at each percentile is compared to the countrywide severity ratio at the same percentile, providing a measure of the region's dangerousness at each level.

Region	1	2	3	4	5	6	Countrywide
Minor Event Severity Ratio	0.760	1.101	0.519	3.570	1.879	4.905	1
Medium Event Severity Ratio	0.591	1.340	0.487	3.527	1.323	3.567	1
Major Event Severity Ratio	0.211	4.438	0.520	2.322	0.433	0.853	1

Figure 18: Minor, medium, and major hazard event severity ratios for each region. A higher ratio indicates the region more prone to disasters.

To assess the overall safety of a region, we calculate the average of three ratios and scale the result to a 100-point scale for clarity. A higher score indicates a safer region. In this case, we found that regions 1 and 3 are much safer than the others, as they have lower severity levels across all three metrics compared to the countrywide average.

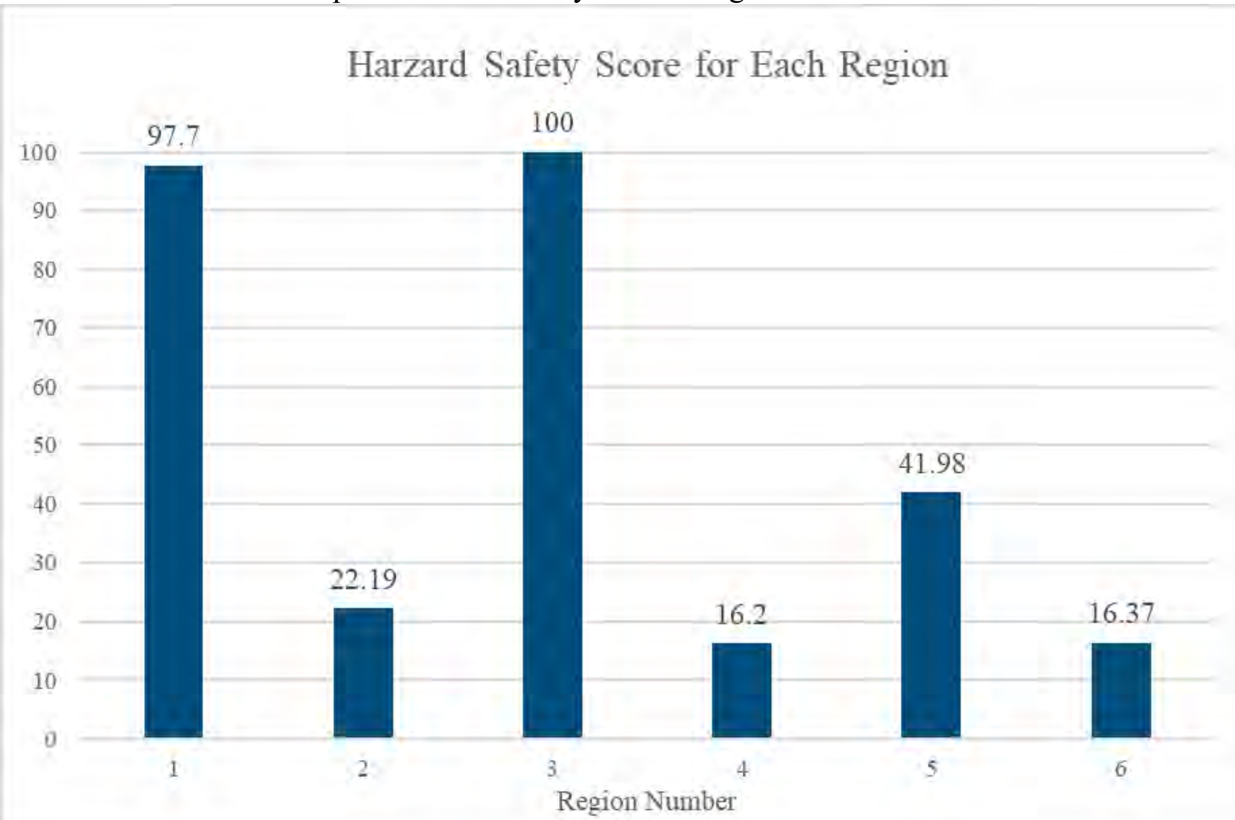


Figure 19: Bar chart of each region's hazard safety score. We can observe that regions 1 and 3 are the safest, while regions 2, 4, 5, and 6 are comparatively more dangerous.

B2: Economic Capability Scores

To compare the economic capacity of each region, we developed an economic metric. This was accomplished by first calculating total living expenses by summing the total transportation, warehousing, health care, social assistance, accommodations, food, and retail.

	Total accommodation and food services sales, 2017 (₱1,000)	Total health care and social assistance receipts/revenue, 2017 (₱1,000)	Total transportation and warehousing receipts/revenue, 2017 (₱1,000)	Total Living Expenses, 2017 (₱1,000)
Region 1	22342094	51556220	13500228	208043088
Region 2	36406400	26864638	2862506	170795058
Region 3	17508375	70145543	3929251	178494517
Region 4	2774258	6658061	2234577	27814884
Region 5	2611585	9541905	2307892	32061921
Region 6	151132	697773	1605298.21	4696135.21

Figure 20: Table of 2017 assorted living expenses and their total in thousands of ₱.

Next, we estimated the regional population in 2017 using a linear regression of 2019-2021 data.

	Census, July 1, 2019	Census, July 1, 2020	Census, July 1, 2021	Estimated Census, July 1 2017
Region 1	5414700	6306408	6406008	4555410
Region 2	3231492	4212348	4386948	2210412
Region 3	4614048	4993764	5019684	4267378
Region 4	1110012	1010676	995544	1210446
Region 5	1289472	1266672	1257096	1319644
Region 6	323820	307884	313836	330156

Figure 21: Table of 2019-2021 population data and projected 2017 population data.

Then, we divided the total living expenses by the estimated census for 2017 to calculate the individual living expenses in 2017. Last, we rescaled these values by dividing the minimum of the individual living expenses by each value to get an economic capability metric between zero and one, where zero is the worst and one is the best.

We immediately observe that the regions determined to be safest by the hazard safety scores are less affordable than regions 4, 5, and 6. Providing some stipend to people that elect to relocate to regions 1 or 3 will incentivize relocation.

	Total Living Expense	Estimated Census, July 1 2017	Individual Living Expenses	Economic Metric
Region 1	208043088000	4555410	45669.45	0.311455194
Region 2	170795058000	2210412	77268.43	0.184085393
Region 3	178494517000	4267378	41827.68	0.34006163
Region 4	27814884000	1210446	22979.04	0.618998455
Region 5	32061921000	1319644	24295.89	0.585448431
Region 6	4696135210	330156	14223.99	1

Figure 22: Table of various numbers used to calculate the economic metric.

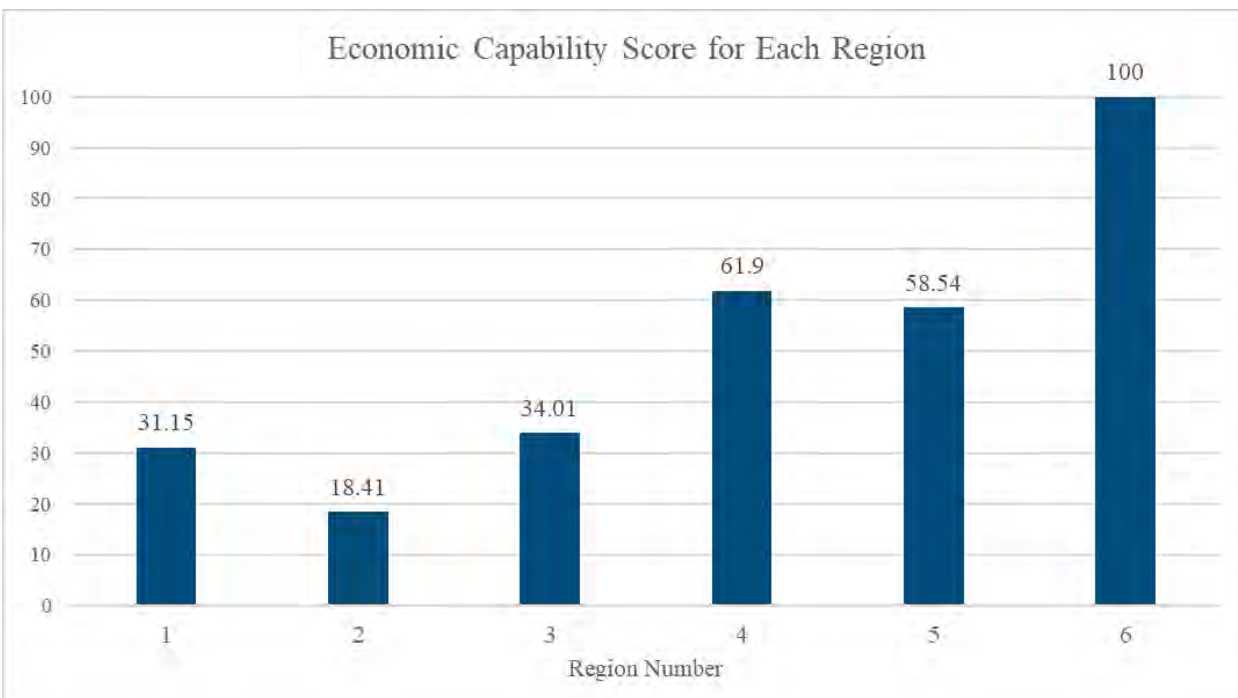


Figure 23: Bar chart of each region's economic capability score.

Appendix C: Hazard Loss Calculation

The hazard loss is composed of components from property damage, injury, and fatality. We group property damage with the expected loss cost from injury and fatality because over 90% of hazards have zero injuries and fatalities, making them difficult to model with low credulity issues. Additionally, the trend for injury and fatality for more than half of the regions is negative, meaning the future trended value at the end of 130 years would be unreasonably low. Thus, losses were combined at an aggregate base for analysis.

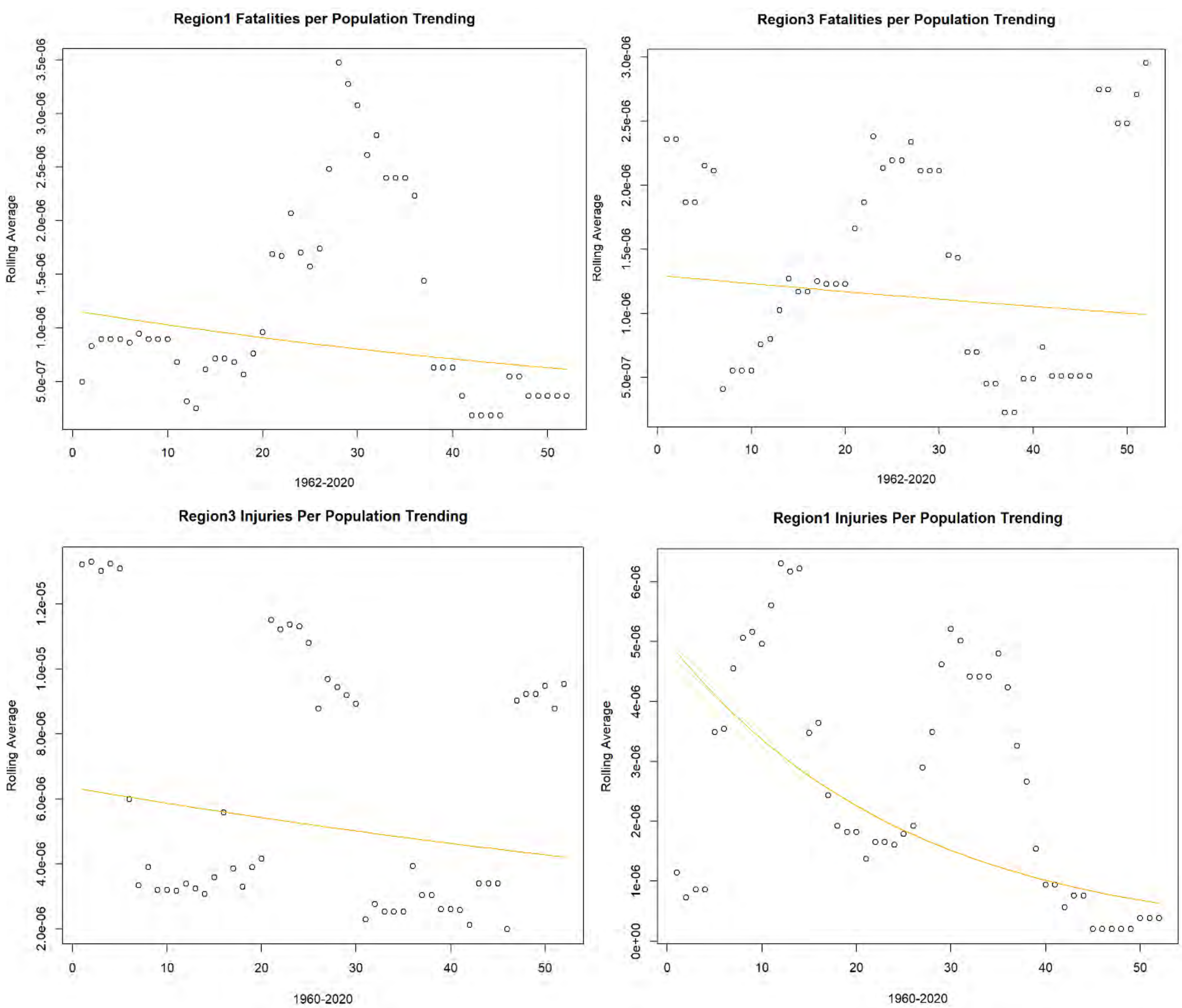


Figure 24: Scatterplots of fatalities and injuries per population with trend lines for regions 1 and 3. We can observe that the trend rate for each of these graphs is negative, meaning the trended values after 130 years would be unreasonably low.

To calculate property damage, we first adjust it for historical inflation after properly treating errors in the given inflation data. Next, we derive the expected loss cost from injury and fatality for each historical hazard event using Appendix C1 and C2, and multiply it by the number of injuries and fatalities from each event. The Hazard Loss is then the sum of inflation-adjusted property damage and the loss cost from injury and fatality.

$$HazardLoss_i = PropDmg_i + 7321.81 * Injury_i + 40532.63603 * Fatality_i$$

Notation

$PropDmg_i$ - inflation adjusted property damage caused by a hazard event

$Injury_i$ – number of fatalities caused by a hazard event

$Fatality_i$ – number of fatalities caused by a hazard event

$HazardLoss_i$ – Sum of inflation adjusted property damage and expected lost cost arise from injury and fatality caused by a hazard event

C1: Fatality Benefit Calculation

Our relocation insurance program recognizes that provision of life and health insurance is not our primary objective. However, as a social insurance, we believe that we have an obligation to provide a limited degree of fatality benefit. The fatality benefits were obtained by taking the provided 2020 per capita income (PCI) data for Storyslysia for each of the 6 regions and multiplying it by the percentage of the population for each region in relation to the full population size of Storslysia. This results in the weighted average of the PCI for each region, which we then combined to obtain the total PCI.

Region	Population Size (2020)	Population %	Per Capita Income (in Ꝑ, 2020)	Per Capita Income x Population %
1	6,306,408.00000	34.84636	45,482.00000	15,848.82192
2	4,212,348.00000	23.27553	38,381.00000	8,933.38181
3	4,993,764.00000	27.59328	40,937.00000	11,295.86243
4	1,010,676.00000	5.58454	28,186.00000	1,574.05813
5	1,266,672.00000	6.99906	32,418.00000	2,268.95434
6	307,884.00000	1.70123	35,948.00000	611.55739
Total	18,097,752.00000	100.00000	221,352.00000	40,532.63603

Figure 25: Table of various numbers used to calculate the total per capita income in Storslysia.

C2: Injury Benefit Calculation

Due to insufficient population size and healthcare spending data, we analyzed data of countries with comparatively similar GDP per capita sizes to Storslysia to obtain an estimated healthcare spending metric for Storslysia.

Storslysia's GDP per capita for 2020 was calculated by taking the GDP for 2020, converting to USD ($) and dividing by the total population size.

Region	2020 Population Size	GDP, 2020 (Ꝑ1,000)
1	6,306,408	531,771,287
2	4,212,348	222,153,795
3	4,993,764	417,708,522
4	1,010,676	45,815,957
5	1,266,672	69,643,447
6	307,884	9,845,914
Total	**18,097,752**	**1,296,938,922**

GDP, 2020	1,296,938,922,000
GDP Per Capita in (in Ꝑ)	71,662.98
GDP Per Capita (in $)	54,249.04

Figure 26: Storslysia's regional population and GDP and total GDP and GDP per capita.

Countries with GDP per capita ranging from over and under 30% of Storslysia were considered, resulting in a total of 25 countries. Of note, we excluded countries with populations less than 5 million because we found their GDP per capita too erratic and volatile to short term population variations. Additionally, Hong Kong was omitted due to the lack of healthcare spending data.

Country	GDP per Capita (in $, 2020)	Population Size (2021)
Norway	67,330	5,408,320
United States	63,028	331,893,745
Denmark	61,063	5,856,733
Singapore	60,729	5,453,566
Storslysia	54,249	18,379,116
Netherlands	52,396	17,533,405
Sweden	52,300	10,415,811
Australia	51,680	25,739,256
Finland	50,124	5,541,696
Austria	48,589	8,956,279
Germany	46,253	83,129,285
Belgium	45,189	11,587,882
Israel	44,178	9,364,000
Canada	43,258	38,246,108
New Zealand	41,597	5,122,600
United Kingdom	41,098	67,326,569
Japan	39,918	125,681,583
France	39,037	67,499,343

Legend	
GDP+30%	70,524
GDP+20%	65,099
GDP+10%	59,674
Storslysia GDP	54,249
GDP-10%	48,824
GDP-20%	43,399
GDP-30%	37,974

Figure 27: List of countries with GDP per capita similar to Storslysia.

For each of the remaining 17 countries, population size, GDP, and healthcare spending per capita data from 2015 to 2019 were obtained from Macrotrends. We could only calculate until 2019 as healthcare spending was only provided until 2019.

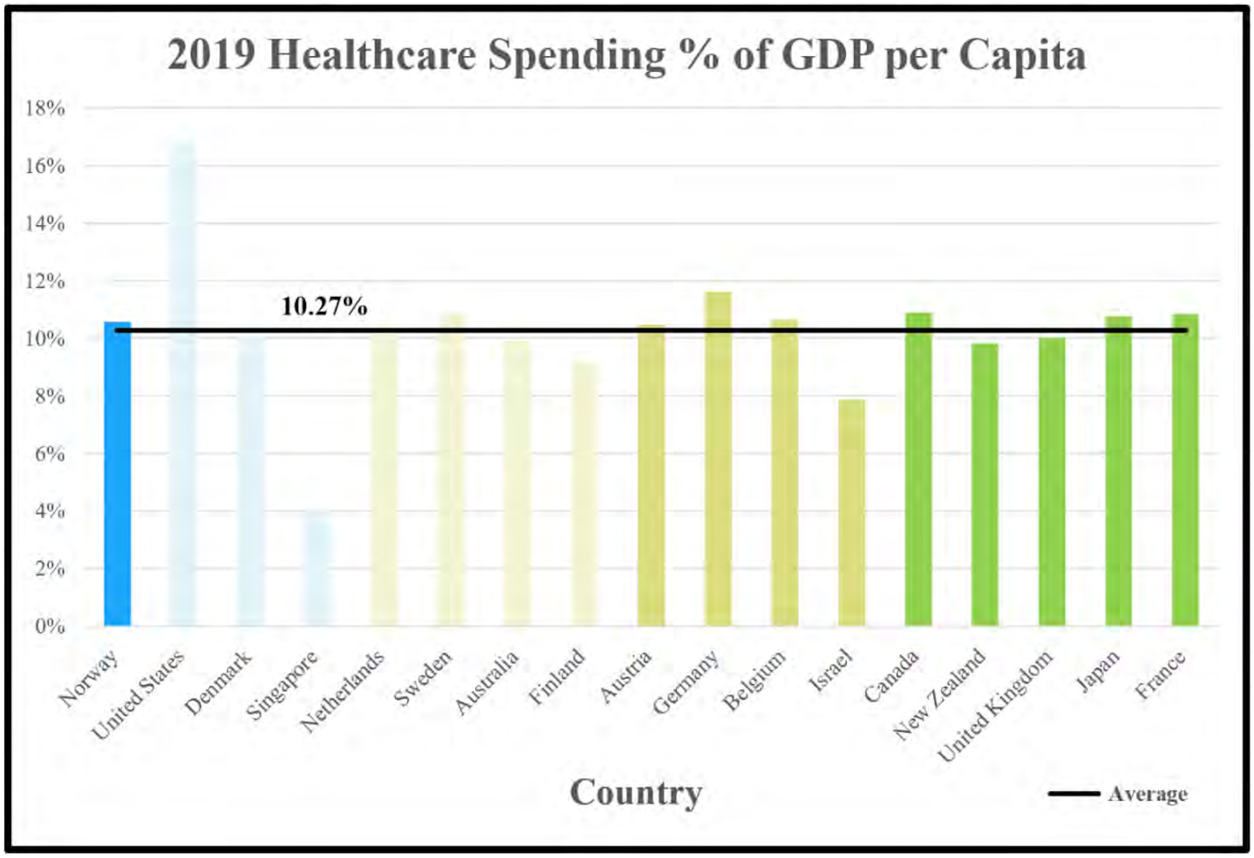


Figure 28: Bar chart showing 2019 data for ratio of healthcare spending to GDP per capita from countries with a similar GDP per capita to Storslysia, with a black line drawn at the average of 10.27%.

The average of the percentages for each year was obtained and linear regression was performed to calculate the percentage of healthcare spending per capita for 2020. The estimated healthcare spending per capita value was calculated by then multiplying the 2020 GDP per capita with the healthcare spending per capita value that was obtained. The healthcare spending per capita value was then converted back to Storslysian currency (Ƥ).

Year	Average % of GDP
2015	10.12
2016	10.29
2017	10.20
2018	10.16
2019	10.27
Avg. for 2020 from Linear Regression	10.22
Healthcare Spending per Capita (in $)	5,542.62
Healthcare Spending per Capita (in Ᵽ)	7,321.81

Figure 29: Table of average healthcare spending to GDP per capita ratios for 2015-2019 and projected 2020 average calculated using linear regression. The bottom two values give the estimated healthcare spending per capita in USD and Storslysia currency.

Appendix D: Long-Term Predictions

To support the efficacy of our model, we have made several long-term predictions demonstrating that we have accomplished our objectives.

D1: Future Loss Cost Improvement of All SSP Scenarios

To calculate the improvement, we subtracted the total hazard loss without the relocation program from the sum of the relocation stipend and the total hazard loss with the program. This provides an accurate assessment of the economic cost savings achieved through the implementation of the relocation program.

The more severe the climate scenario, the greater the total future losses due to property damage, injury loss, and fatality loss. Therefore, there is greater economic savings by implementing measures to mitigate these losses.

Below are comprehensive tables that detail the economic benefits of the relocation program over a 130-year period under each SSP scenario. The tables show both the actual dollar amount and the percentage of improvement achieved by implementing the program.

	Min.	1st Qu.	Median	Mean	3rd Qu.
SSP1	Ᵽ89 Billion	Ᵽ463 Billion	Ᵽ715 Billion	Ᵽ2,758 Billion	Ᵽ1,228 Billion
SSP2	Ᵽ118 Billion	Ᵽ625 Billion	Ᵽ968 Billion	Ᵽ3.746 Billion	Ᵽ1,661 Billion
SSP3	Ᵽ293 Billion	Ᵽ1,365 Billion	Ᵽ2,138 Billion	Ᵽ8,260 Billion	Ᵽ3,718 Billion
SSP5	Ᵽ1,175 Billion	Ᵽ5,748 Billion	Ᵽ9,152 Billion	Ᵽ35,300 Billion	Ᵽ16,230 Billion

Figure 30: Table of loss cost dollar improvement by SSP scenarios for our relocation program.

	Min.	1st Qu.	Median	Mean	3rd Qu.
SSP1	24.59%	23.34%	23.29%	20.93%	23.30%
SSP2	24.42%	23.48%	23.41%	21.00%	23.36%
SSP3	29.87%	23.88%	23.75%	21.45%	23.68%
SSP5	31.81%	24.25%	24.09%	21.94%	24.04%

Figure 31: Table of loss cost percentage improvement by SSP scenarios under our program.

D2: Capital Requirement of Relocation Program Under All SSP Scenarios

The capital requirements for the relocation program are designed to ensure that the country becomes debt-free with a high level of certainty. The program's policy only covers up to 10% of the country's GDP based on requirements, which helps to keep the hazard assistance program under our budget.

Relocation stipend payments will also be within the 10% GDP budget for the first nine years, but may exceed the budget in the tenth year. However, the program only pays out 2.5% of GDP, and not much relocation payment is expected during the first nine years, which encourages the government to save budget for any excess payments required in the tenth year.

The table below shows the long-term cost of the program as a percentage of Storslysia's GDP under various SSP scenarios.

	Min.	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max.**
SSP1	0.96%	2.51%	2.94%	2.99%	3.43%	5.92%
SSP2	1.07%	2.68%	3.11%	3.17%	3.60%	6.20%
SSP3	1.33%	3.07%	3.51%	3.57%	4.02%	6.86%
SSP5	2.15%	4.10%	4.57%	4.62%	5.10%	7.97%

Figure 32: Table of long-term annual capital requirement as a percentage of Storslysia's GDP by SSP scenarios. The program cost under all SSP scenarios is within the budget of 10% of Storslysia's GDP.

D3: Estimated Relocation

As we have designated each region as either safe (regions 1 and 3) or dangerous (regions 2, 4, 5, 6) through our hazard safety and economic capability scores detailed in Appendices B1 and B2, respectively, the successfulness of our relocation program can be measured by the number of people who relocate from designated safe regions to designated dangerous regions.

We can see from our model simulation report that the expected number of people who will relocate voluntarily within the first 10-year period from designated dangerous regions to designated safe regions is 857,147.

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
4,727	556,478	817,757	857,147	1,117,854	2,267,101

Figure 33: Summary statistics for simulated number of citizens relocating within the first ten years of our program.

This is significant as the population size of the designated dangerous regions combined is 6,953,424.

Region 2	Region 4	Region 5	Region 6	Total
4,386,948	995,544	1,257,096	313,836	6,953,424

Figure 34: Table of population sizes of designated dangerous regions.

Thus, 12.327% of the population will relocate to the designated safe regions within 10 years. The economic implications of the relocation can be seen in Appendix D1.

Expected Number of People Relocating	857147
Total Population Size for Regions 2, 4, 5, 6	6,953,424
Relocation Percentage of Total Population Size	12.33%

Figure 35: Table showing the ratio of the expected number of people relocating to the total population size of designated dangerous regions. This statistic shows we satisfied our goal of mobilizing Storslysia's citizens and relocating them to safer regions.

We can also see that after the initial 10 years, the expected number of people who relocate involuntarily over next 120 years will be 1,713,838, which will also play a significant role in preventing potential losses. The economic implications of the relocations over the long-term can is detailed in Appendix D1

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
953,199	1,459,968	1,713,813	1,713,838	1,967,582	2,472,060

Figure 36: Summary statistics for simulated number of citizens relocation within the full duration of our program.

Of note, there is a wide range regarding the possible number of people relocating to regions 1 and 3 during and after the initial 10 years. This is due to our relocation rate projections accounting for the different rates at which people will be relocating, which is further detailed in Appendix A6.

Appendix E: R Code for Future Loss Cost Model

```
set.seed(1)
for (num_sim in 1:1000000) {
  ### Relocation rate
  ### r variables for logistic function
  r2 <- runif(1, min = 0.1389877698, max = 0.3706340529)
  r4 <- runif(1, min = 0.15, max = 0.4)
  r5 <- runif(1, min = 0.1025559321, max = 0.2734824856)
  r6 <- runif(1, min = 0.1496966927, max = 0.3991911806)

  ### p variables for logisitic function
  p2 <- runif(1, min = 0.00001, max = 0.99999)
  p4 <- runif(1, min = 0.00001, max = 0.99999)
  p5 <- runif(1, min = 0.00001, max = 0.99999)
  p6 <- runif(1, min = 0.00001, max = 0.99999)

 reloc_rate$p2[num_sim] <- p2
 reloc_rate$p4[num_sim] <- p4
 reloc_rate$p5[num_sim] <- p5
 reloc_rate$p6[num_sim] <- p6


  ### number of years into future
  x <- 1:130
  s <- 10

  ### Split between population gained by region 1 or 3 every year
  split <- runif(130)

  ### parameter c for each region for a run
  c2 <- parm_c(r2)
  c4 <- parm_c(r4)
  c5 <- parm_c(r5)
  c6 <- parm_c(r6)

  ### parameter b for each region for a run
  b2 <- parm_b(p2, s, c2)
  b4 <- parm_b(p4, s, c4)
  b5 <- parm_b(p5, s, c5)
  b6 <- parm_b(p6, s, c6)

  ### curves for each region
  region2_relocation_rate <- logist(b2, c2, r2, x)
  region4_relocation_rate <- logist(b4, c4, r4, x)
  region5_relocation_rate <- logist(b5, c5, r5, x)
  region6_relocation_rate <- logist(b6, c6, r6, x)


  ### New population count by year
  region2_relocation <- data.frame(year = ssp_factor$Year, reloc =
region2_relocation_rate * population[2])
  region4_relocation <- data.frame(year = ssp_factor$Year, reloc =
region4_relocation_rate * population[4])
  region5_relocation <- data.frame(year = ssp_factor$Year, reloc =
region5_relocation_rate * population[5])
  region6_relocation <- data.frame(year = ssp_factor$Year, reloc =
region6_relocation_rate * population[6])

  ### calculate population change
  for (i in 2:130) {
    region2_relocation$chg[i] <- region2_relocation$reloc[i] -
region2_relocation$reloc[i-1]
    region4_relocation$chg[i] <- region4_relocation$reloc[i] -
region4_relocation$reloc[i-1]
    region5_relocation$chg[i] <- region5_relocation$reloc[i] -
region5_relocation$reloc[i-1]
    region6_relocation$chg[i] <- region6_relocation$reloc[i] -
region6_relocation$reloc[i-1]
  }

  ### find population split between region 1 and 3
  reloc_pop <- -region2_relocation$chg - region4_relocation$chg -
region5_relocation$chg - region6_relocation$chg
  reloc_pop[1] <- 0

  ### find incremental population increase for region 1 and 3
  pop_split_region1 <- split * reloc_pop * 1
  pop_split_region3 <- (1-split) * reloc_pop

  ### find cumulative population increase for region 1 and 3
  cum_pop_region1 <- 0
  cum_pop_region3 <- 0
  for (i in 1:130) {
    cum_pop_region1[i] <- sum(pop_split_region1[1:i])
    cum_pop_region3[i] <- sum(pop_split_region3[1:i])
  }

  ### regional population count
  region1_relocation <- data.frame(year = ssp_factor$Year, reloc =
cum_pop_region1 + population[1])
  region3_relocation <- data.frame(year = ssp_factor$Year, reloc =
cum_pop_region3 + population[3])

  ### population distribution
  total_pop <- region1_relocation$reloc + region2_relocation$reloc +
region3_relocation$reloc +
    region4_relocation$reloc + region5_relocation$reloc +
region6_relocation$reloc
  region1_percent <- region1_relocation$reloc / total_pop
  region2_percent <- region2_relocation$reloc / total_pop
  region3_percent <- region3_relocation$reloc / total_pop
  region4_percent <- region4_relocation$reloc / total_pop
  region5_percent <- region5_relocation$reloc / total_pop
  region6_percent <- region6_relocation$reloc / total_pop

  ### region 1 loss cost
  r1_freq <- rnbinom(130, mu = freq_table$parm_mu[1], size =
freq_table$parm_size[1])
  r1_loss_by_year <- rep(0,2)
  for (i in 1:130) {
    zero_count <- 0
    zero_loss_generate <- runif(r1_freq[i], min = 0, max = 1)
    for (j in zero_loss_generate) {
      if(j < r1_total_zero){
        zero_count <- zero_count + 1
      }
    }
    r1_loss_by_year[i] <- sum(exp(rgamma(r1_freq[i] - zero_count, shape =
sev_table$parm_shape[1], rate = sev_table$parm_rate[1])))
  }

  ### region 2 loss cost
  r2_freq <- rnbinom(130, mu = freq_table$parm_mu[2], size =
freq_table$parm_size[2])
  r2_loss_by_year <- rep(0,130)
  for (i in 1:130) {
    zero_count <- 0
    zero_loss_generate <- runif(r2_freq[i], min = 0, max = 1)
    for (j in zero_loss_generate) {
      if(j < r2_total_zero){
        zero_count <- zero_count + 1
      }
    }
    r2_loss_by_year[i] <- sum(exp(rgamma(r2_freq[i] - zero_count, shape =
sev_table$parm_shape[2], rate = sev_table$parm_rate[2])))
  }

  ### region 3 loss cost
  r3_freq <- rnbinom(130, mu = freq_table$parm_mu[3], size =
freq_table$parm_size[3])
  r3_loss_by_year <- rep(0,2)
  for (i in 1:130) {
    zero_count <- 0
    zero_loss_generate <- runif(r3_freq[i], min = 0, max = 1)
    for (j in zero_loss_generate) {
      if(j < r3_total_zero){
        zero_count <- zero_count + 1
      }
    }
    r3_loss_by_year[i] <- sum(exp(rgamma(r3_freq[i] - zero_count, shape =
sev_table$parm_shape[3], rate = sev_table$parm_rate[3])))
  }
```

```
  ### region 4 loss cost
  r4_freq <- rnbinom(130, mu = freq_table$parm_mu[4], size =
freq_table$parm_size[4])
  r4_loss_by_year <- rep(0,130)
  for (i in 1:130) {
    zero_count <- 0
    zero_loss_generate <- runif(r4_freq[i], min = 0, max = 1)
    for (j in zero_loss_generate) {
      if(j < r4_total_zero){
        zero_count <- zero_count + 1
      }
    }
    r4_loss_by_year[i] <- sum(exp(rgamma(r4_freq[i] - zero_count, shape =
sev_table$parm_shape[4], rate = sev_table$parm_rate[4])))
  }

  ### region 5 loss cost
  r5_freq <- rnbinom(130, mu = freq_table$parm_mu[5], size =
freq_table$parm_size[5])
  r5_loss_by_year <- rep(0,130)
  for (i in 1:130) {
    zero_count <- 0
    zero_loss_generate <- runif(r5_freq[i], min = 0, max = 1)
    for (j in zero_loss_generate) {
      if(j < r5_total_zero){
        zero_count <- zero_count + 1
      }
    }
    r5_loss_by_year[i] <- sum(exp(rgamma(r5_freq[i] - zero_count, shape =
sev_table$parm_shape[1], rate = sev_table$parm_rate[5])))
  }

  ### region 6 loss cost
  r6_freq <- rnbinom(130, mu = freq_table$parm_mu[6], size =
freq_table$parm_size[6])
  r6_loss_by_year <- rep(0,130)
  for (i in 1:130) {
    zero_count <- 0
    zero_loss_generate <- runif(r6_freq[i], min = 0, max = 1)
    for (j in zero_loss_generate) {
      if(j < r6_total_zero){
        zero_count <- zero_count + 1
      }
    }
    r6_loss_by_year[i] <- sum(exp(rgamma(r6_freq[i] - zero_count, shape =
sev_table$parm_shape[6], rate = sev_table$parm_rate[6])))
  }


  ### Population change
  pop_scenario <- runif(1, min = 0, max = 1)
  if (pop_scenario <= 1/6) {
    select_pop <- proj_population$X1
  } else if(pop_scenario <= 2/6) {
    select_pop <- proj_population$X2
  } else if (pop_scenario <= 3/6) {
    select_pop <- proj_population$X3
  } else if(pop_scenario <= 4/6){
    select_pop <- proj_population$X4
  } else if(pop_scenario <= 5/6){
    select_pop <- proj_population$X5
  } else{
    select_pop <- proj_population$X6
  }


  ### population change by region
  pop_adj_r1 <- select_pop * region1_percent / population[1]
  pop_adj_r2 <- select_pop * region2_percent / population[2]
  pop_adj_r3 <- select_pop * region3_percent / population[3]
  pop_adj_r4 <- select_pop * region4_percent / population[4]
  pop_adj_r5 <- select_pop * region5_percent / population[5]
  pop_adj_r6 <- select_pop * region6_percent / population[6]

  ### pop no change
  pop_nochg_r1 <- population[1]/sum(population) * select_pop /
population[1]
  pop_nochg_r2 <- population[2]/sum(population) * select_pop /
population[2]
  pop_nochg_r3 <- population[3]/sum(population) * select_pop /
population[3]
  pop_nochg_r4 <- population[4]/sum(population) * select_pop /
population[4]
  pop_nochg_r5 <- population[5]/sum(population) * select_pop /
population[5]
  pop_nochg_r6 <- population[6]/sum(population) * select_pop /
population[6]

  ### Vol moving
  popchg_r1 <- pop_nochg_r1 * population[1] - pop_adj_r1 * population[1]
  popchg_r2 <- pop_nochg_r2 * population[2] - pop_adj_r2 * population[2]
  popchg_r3 <- pop_nochg_r3 * population[3] - pop_adj_r3 * population[3]
  popchg_r4 <- pop_nochg_r4 * population[4] - pop_adj_r4 * population[4]
  popchg_r5 <- pop_nochg_r5 * population[5] - pop_adj_r5 * population[5]
  popchg_r6 <- pop_nochg_r6 * population[6] - pop_adj_r6 * population[6]

  Total_pop_chg[num_sim] <- sum(popchg_r2, popchg_r4, popchg_r5,
popchg_r6)

  ### Result under different SSP scenario
  ### SSP1
  r1_ssp1_total_loss <- r1_loss_by_year * pop_adj_r1 * ssp_factor$SSP1 *
sev_trend_by_year$r1
  r2_ssp1_total_loss <- r2_loss_by_year * pop_adj_r2 * ssp_factor$SSP1 *
sev_trend_by_year$r2
  r3_ssp1_total_loss <- r3_loss_by_year * pop_adj_r3 * ssp_factor$SSP1 *
sev_trend_by_year$r3
  r4_ssp1_total_loss <- r4_loss_by_year * pop_adj_r4 * ssp_factor$SSP1 *
sev_trend_by_year$r4
  r5_ssp1_total_loss <- r5_loss_by_year * pop_adj_r5 * ssp_factor$SSP1 *
sev_trend_by_year$r5
  r6_ssp1_total_loss <- r6_loss_by_year * pop_adj_r6 * ssp_factor$SSP1 *
sev_trend_by_year$r6

  SSP1_total_loss[num_sim] <- sum(r1_ssp1_total_loss, r2_ssp1_total_loss,
r3_ssp1_total_loss,
                    r4_ssp1_total_loss, r5_ssp1_total_loss,
r6_ssp1_total_loss)

  r1_ssp1_control <- r1_loss_by_year * pop_nochg_r1 * ssp_factor$SSP1 *
sev_trend_by_year$r1
  r2_ssp1_control <- r2_loss_by_year * pop_nochg_r2 * ssp_factor$SSP1 *
sev_trend_by_year$r2
  r3_ssp1_control <- r3_loss_by_year * pop_nochg_r3 * ssp_factor$SSP1 *
sev_trend_by_year$r3
  r4_ssp1_control <- r4_loss_by_year * pop_nochg_r4 * ssp_factor$SSP1 *
sev_trend_by_year$r4
  r5_ssp1_control <- r5_loss_by_year * pop_nochg_r5 * ssp_factor$SSP1 *
sev_trend_by_year$r5
  r6_ssp1_control <- r6_loss_by_year * pop_nochg_r6 * ssp_factor$SSP1 *
sev_trend_by_year$r6

  SSP1_control[num_sim] <- sum(r1_ssp1_control, r2_ssp1_control,
r3_ssp1_control,
                    r4_ssp1_control, r5_ssp1_control, r6_ssp1_control)


  ### Calculate Running balance & Budget under SSP1

  reloc_expense <- reloc_pop[1:10] * 3645.713879

  for (i in 1:10) {
    ### Loss for the first 10 years is capped at 2.5% of GDP for all regions
    ssp1_loss_paid_by_year[i] <- min((r1_ssp1_total_loss[i] +
r2_ssp1_total_loss[i] + r3_ssp1_total_loss[i] +
                    r4_ssp1_total_loss[i] + r5_ssp1_total_loss[i] +
r6_ssp1_total_loss[i]), 0.25 * plan_payment[i])
    ssp1_loss_paid_by_year_cv[i] <- ssp1_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i

    ### amount of budget left off from loss payment
    ssp1_budget_by_year[i] <- plan_payment[i] - ssp1_loss_paid_by_year[i]

    ### amount of relocation expense each year
    ssp1_relexp_by_year[i] <- reloc_expense[i]
    ssp1_relexp_by_year_cv[i] <- ssp1_relexp_by_year[i] * (1 +
proj_inflation)** -i
```

```
    ### amount of budget left off from loss and relocation expense
    ssp1_total_budget_by_year[i] <- ssp1_budget_by_year[i] -
ssp1_relexp_by_year[i]
  }

  for (i in 11:130) {
    ssp1_loss_paid_by_year[i] <- min((r1_ssp1_total_loss[i] +
r3_ssp1_total_loss[i]), plan_payment[i])
    ssp1_total_budget_by_year[i] <- plan_payment[i] -
ssp1_loss_paid_by_year[i]
    ssp1_loss_paid_by_year_cv[i] <- ssp1_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i
  }


  ### General Summary
  ### total relocation loss amount paid in one simulation
  Reloc_paid[num_sim] <- sum(reloc_expense)

  ### Number of people relocated
  Num_reloc[num_sim] <- sum(reloc_pop)
  Num_reloc_paid[num_sim] <- sum(reloc_pop[1:10])

  ### SSP1 run summary
  ssp1_loss_paid[num_sim] <- sum(ssp1_loss_paid_by_year)
  ssp1_CV_loss_paid[num_sim] <- sum(ssp1_loss_paid_by_year_cv)
  ssp1_CV_program_cost[num_sim]  <- sum(ssp1_loss_paid_by_year_cv,
ssp1_relexp_by_year_cv)



  ### SSP2
  r1_ssp2_total_loss <- r1_loss_by_year * pop_adj_r1 * ssp_factor$SSP2 *
sev_trend_by_year$r1
  r2_ssp2_total_loss <- r2_loss_by_year * pop_adj_r2 * ssp_factor$SSP2 *
sev_trend_by_year$r2
  r3_ssp2_total_loss <- r3_loss_by_year * pop_adj_r3 * ssp_factor$SSP2 *
sev_trend_by_year$r3
  r4_ssp2_total_loss <- r4_loss_by_year * pop_adj_r4 * ssp_factor$SSP2 *
sev_trend_by_year$r4
  r5_ssp2_total_loss <- r5_loss_by_year * pop_adj_r5 * ssp_factor$SSP2 *
sev_trend_by_year$r5
  r6_ssp2_total_loss <- r6_loss_by_year * pop_adj_r6 * ssp_factor$SSP2 *
sev_trend_by_year$r6

  SSP2_total_loss[num_sim] <- sum(r1_ssp2_total_loss, r2_ssp2_total_loss,
r3_ssp2_total_loss,
                                r4_ssp2_total_loss, r5_ssp2_total_loss,
r6_ssp2_total_loss)

  r1_ssp2_control <- r1_loss_by_year * pop_nochg_r1 * ssp_factor$SSP2 *
sev_trend_by_year$r1
  r2_ssp2_control <- r2_loss_by_year * pop_nochg_r2 * ssp_factor$SSP2 *
sev_trend_by_year$r2
  r3_ssp2_control <- r3_loss_by_year * pop_nochg_r3 * ssp_factor$SSP2 *
sev_trend_by_year$r3
  r4_ssp2_control <- r4_loss_by_year * pop_nochg_r4 * ssp_factor$SSP2 *
sev_trend_by_year$r4
  r5_ssp2_control <- r5_loss_by_year * pop_nochg_r5 * ssp_factor$SSP2 *
sev_trend_by_year$r5
  r6_ssp2_control <- r6_loss_by_year * pop_nochg_r6 * ssp_factor$SSP2 *
sev_trend_by_year$r6

  SSP2_control[num_sim] <- sum(r1_ssp2_control, r2_ssp2_control,
r3_ssp2_control,
                               r4_ssp2_control, r5_ssp2_control, r6_ssp2_control)

  ### Calculate Running balance & budget under SSP2
  for (i in 1:10) {
    ### Loss for the first 10 years is capped at 2.5% of GDP for all regions
    ssp2_loss_paid_by_year[i] <- min((r1_ssp2_total_loss[i] +
r2_ssp2_total_loss[i] + r3_ssp2_total_loss[i] +
                                      r4_ssp2_total_loss[i] + r5_ssp2_total_loss[i] +
r6_ssp2_total_loss[i]), 0.25 * plan_payment[i])
    ssp2_loss_paid_by_year_cv[i] <- ssp2_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i

    ### amount of budget left off from loss payment
    ssp2_budget_by_year[i] <- plan_payment[i] - ssp2_loss_paid_by_year[i]

    ### amount of relocation expense each year
    ssp2_relexp_by_year[i] <- reloc_expense[i]
    ssp2_relexp_by_year_cv[i] <- ssp2_relexp_by_year[i] * (1 +
proj_inflation)** -i

    ### amount of budget left off from loss and relocation expense
    ssp2_total_budget_by_year[i] <- ssp2_budget_by_year[i] -
ssp2_relexp_by_year[i]
  }

  for (i in 11:130) {
    ssp2_loss_paid_by_year[i] <- min((r1_ssp2_total_loss[i] +
r3_ssp2_total_loss[i]), plan_payment[i])
    ssp2_total_budget_by_year[i] <- plan_payment[i] -
ssp2_loss_paid_by_year[i]
    ssp2_loss_paid_by_year_cv[i] <- ssp2_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i
  }



  ### SSP2 run summary
  ssp2_loss_paid[num_sim] <- sum(ssp2_loss_paid_by_year)
  ssp2_CV_loss_paid[num_sim] <- sum(ssp2_loss_paid_by_year_cv)
  ssp2_CV_program_cost[num_sim]  <- sum(ssp2_loss_paid_by_year_cv,
ssp2_relexp_by_year_cv)


  ### SSP3
  r1_ssp3_total_loss <- r1_loss_by_year * pop_adj_r1 * ssp_factor$SSP3 *
sev_trend_by_year$r1
  r2_ssp3_total_loss <- r2_loss_by_year * pop_adj_r2 * ssp_factor$SSP3 *
sev_trend_by_year$r2
  r3_ssp3_total_loss <- r3_loss_by_year * pop_adj_r3 * ssp_factor$SSP3 *
sev_trend_by_year$r3
  r4_ssp3_total_loss <- r4_loss_by_year * pop_adj_r4 * ssp_factor$SSP3 *
sev_trend_by_year$r4
  r5_ssp3_total_loss <- r5_loss_by_year * pop_adj_r5 * ssp_factor$SSP3 *
sev_trend_by_year$r5
  r6_ssp3_total_loss <- r6_loss_by_year * pop_adj_r6 * ssp_factor$SSP3 *
sev_trend_by_year$r6

  SSP3_total_loss[num_sim] <- sum(r1_ssp3_total_loss, r2_ssp3_total_loss,
r3_ssp3_total_loss,
                                r4_ssp3_total_loss, r5_ssp3_total_loss,
r6_ssp3_total_loss)

  r1_ssp3_control <- r1_loss_by_year * pop_nochg_r1 * ssp_factor$SSP3 *
sev_trend_by_year$r1
  r2_ssp3_control <- r2_loss_by_year * pop_nochg_r2 * ssp_factor$SSP3 *
sev_trend_by_year$r2
  r3_ssp3_control <- r3_loss_by_year * pop_nochg_r3 * ssp_factor$SSP3 *
sev_trend_by_year$r3
  r4_ssp3_control <- r4_loss_by_year * pop_nochg_r4 * ssp_factor$SSP3 *
sev_trend_by_year$r4
  r5_ssp3_control <- r5_loss_by_year * pop_nochg_r5 * ssp_factor$SSP3 *
sev_trend_by_year$r5
  r6_ssp3_control <- r6_loss_by_year * pop_nochg_r6 * ssp_factor$SSP3 *
sev_trend_by_year$r6

  SSP3_control[num_sim] <- sum(r1_ssp3_control, r2_ssp3_control,
r3_ssp3_control,
                               r4_ssp3_control, r5_ssp3_control, r6_ssp3_control)

  ### Calculate Running balance & Budget under SSP3
  for (i in 1:10) {
    ### Loss for the first 10 years is capped at 2.5% of GDP for all regions
    ssp3_loss_paid_by_year[i] <- min((r1_ssp3_total_loss[i] +
r2_ssp3_total_loss[i] + r3_ssp3_total_loss[i] +
                                      r4_ssp3_total_loss[i] + r5_ssp3_total_loss[i] +
r6_ssp3_total_loss[i]), 0.25 * plan_payment[i])
    ssp3_loss_paid_by_year_cv[i] <- ssp3_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i

    ### amount of budget left off from loss payment
    ssp3_budget_by_year[i] <- plan_payment[i] - ssp3_loss_paid_by_year[i]

    ### amount of relocation expense each year
```

```
    ssp3_relexp_by_year[i] <- reloc_expense[i]
    ssp3_relexp_by_year_cv[i] <- ssp3_relexp_by_year[i] * (1 +
proj_inflation)** -i

    ### amount of budget left off from loss and relocation expense
    ssp3_total_budget_by_year[i] <- ssp3_budget_by_year[i] -
ssp3_relexp_by_year[i]
  }

  for (i in 11:130) {
    ssp3_loss_paid_by_year[i] <- min((r1_ssp3_total_loss[i] +
r3_ssp3_total_loss[i]), plan_payment[i])
    ssp3_total_budget_by_year[i] <- plan_payment[i] -
ssp3_loss_paid_by_year[i]
    ssp3_loss_paid_by_year_cv[i] <- ssp3_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i
  }



  ### SSP3 run summary
  ssp3_loss_paid[num_sim] <- sum(ssp3_loss_paid_by_year)
  ssp3_CV_loss_paid[num_sim] <- sum(ssp3_loss_paid_by_year_cv)
  ssp3_CV_program_cost[num_sim]  <- sum(ssp3_loss_paid_by_year_cv,
ssp3_relexp_by_year_cv)


  ### SSP5
  r1_ssp5_total_loss <- r1_loss_by_year * pop_adj_r1 * ssp_factor$SSP5 *
sev_trend_by_year$r1
  r2_ssp5_total_loss <- r2_loss_by_year * pop_adj_r2 * ssp_factor$SSP5 *
sev_trend_by_year$r2
  r3_ssp5_total_loss <- r3_loss_by_year * pop_adj_r3 * ssp_factor$SSP5 *
sev_trend_by_year$r3
  r4_ssp5_total_loss <- r4_loss_by_year * pop_adj_r4 * ssp_factor$SSP5 *
sev_trend_by_year$r4
  r5_ssp5_total_loss <- r5_loss_by_year * pop_adj_r5 * ssp_factor$SSP5 *
sev_trend_by_year$r5
  r6_ssp5_total_loss <- r6_loss_by_year * pop_adj_r6 * ssp_factor$SSP5 *
sev_trend_by_year$r6

  SSP5_total_loss[num_sim] <- sum(r1_ssp5_total_loss, r2_ssp5_total_loss,
r3_ssp5_total_loss,
                                  r4_ssp5_total_loss, r5_ssp5_total_loss,
r6_ssp5_total_loss)

  r1_ssp5_control <- r1_loss_by_year * pop_nochg_r1 * ssp_factor$SSP5 *
sev_trend_by_year$r1
  r2_ssp5_control <- r2_loss_by_year * pop_nochg_r2 * ssp_factor$SSP5 *
sev_trend_by_year$r2
  r3_ssp5_control <- r3_loss_by_year * pop_nochg_r3 * ssp_factor$SSP5 *
sev_trend_by_year$r3
  r4_ssp5_control <- r4_loss_by_year * pop_nochg_r4 * ssp_factor$SSP5 *
sev_trend_by_year$r4
  r5_ssp5_control <- r5_loss_by_year * pop_nochg_r5 * ssp_factor$SSP5 *
sev_trend_by_year$r5
  r6_ssp5_control <- r6_loss_by_year * pop_nochg_r6 * ssp_factor$SSP5 *
sev_trend_by_year$r6

  SSP5_control[num_sim] <- sum(r1_ssp5_control, r2_ssp5_control,
r3_ssp5_control,
                               r4_ssp5_control, r5_ssp5_control, r6_ssp5_control)

  ### Calculate Running balance & Budget under SSP5
  for (i in 1:10) {
    ### Loss for the first 10 years is capped at 2.5% of GDP for all regions
    ssp5_loss_paid_by_year[i] <- min((r1_ssp5_total_loss[i] +
r2_ssp5_total_loss[i] + r3_ssp5_total_loss[i] +
                                        r4_ssp5_total_loss[i] + r5_ssp5_total_loss[i] +
r6_ssp5_total_loss[i]), 0.25 * plan_payment[i])
    ssp5_loss_paid_by_year_cv[i] <- ssp5_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i

    ### amount of budget left off from loss payment
    ssp5_budget_by_year[i] <- plan_payment[i] - ssp5_loss_paid_by_year[i]

    ### amount of relocation expense each year
    ssp5_relexp_by_year[i] <- reloc_expense[i]
    ssp5_relexp_by_year_cv[i] <- ssp5_relexp_by_year[i] * (1 +
proj_inflation)** -i

    ### amount of budget left off from loss and relocation expense
    ssp5_total_budget_by_year[i] <- ssp5_budget_by_year[i] -
ssp5_relexp_by_year[i]
  }

  for (i in 11:130) {
    ssp5_loss_paid_by_year[i] <- min((r1_ssp5_total_loss[i] +
r3_ssp5_total_loss[i]), plan_payment[i])
    ssp5_total_budget_by_year[i] <- plan_payment[i] -
ssp5_loss_paid_by_year[i]
    ssp5_loss_paid_by_year_cv[i] <- ssp5_loss_paid_by_year[i] * (1 +
proj_inflation) ** -i
  }



  ### SSP5 run summary
  ssp5_loss_paid[num_sim] <- sum(ssp5_loss_paid_by_year)
  ssp5_CV_loss_paid[num_sim] <- sum(ssp5_loss_paid_by_year_cv)
  ssp5_CV_program_cost[num_sim]  <- sum(ssp5_loss_paid_by_year_cv,
ssp5_relexp_by_year_cv)

}
```

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