SOA Research Institute

Relocation Social Insurance Program Report: Storslysia

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EXECUTIVE SUMMARY

This report proposes a social insurance program designed to relieve the economic costs associated with climate-related catastrophes in Storslysia. The primary objective of the program is to mitigate the financial consequences for residents residing in high-risk areas facing displacement. The program covers costs arising from climate-related hazards such as temporary housing and household contents, but further assists Storslysia manage displacement risk through a buyback scheme aimed towards high-risk, low value properties. By implementing the program, the program will reduce economic costs associated with climate catastrophe-related events by approximately 16.58% in the short-term and 28.75% in the long-term. Furthermore, the proposed social insurance program will continue to lower costs even if the climate situation deteriorates as represented by Shared Socioeconomic Pathways (SSP) scenarios. Hence, with 95% confidence, the program costs do not exceed 10% of Storslysia's annual GDP in all four SSP scenarios. However, risks such as increasingly correlated hazard events pose threats to the program meaning ongoing monitoring is recommended.

SECTION 1: PROGRAM SYNOPSIS

1.1 OBJECTIVES

The proposed social insurance program is designed to provide citizens with financial protection and support from climate-related events. The program aims to reduce the costs associated with displacement and support the overall resilience of affected communities and individuals. More detailed outlines of the objectives are as below:

1. Mitigating Displacement Risk
The program will reduce displacement risk by incentivising proactive relocation, offering a buyback scheme to houses of low-income policyholders living in high-risk regions, enabling them to relocate before or after a severe or catastrophic climate-related event. This helps reduce costs associated with emergency displacement, improving the overall effectiveness of the program.

2. Financial Protection for Policyholders
The program provides policyholders with financial protection against the costs associated with voluntary, proactive relocation as well as involuntary displacement following a catastrophic event by covering temporary housing costs in high-risk areas.

3. Financial Sustainability for Storslysia
The program is constructed to be financially sustainable over the long-term by establishing appropriate premium levels, deductibles, and coverage limits that align with the expected costs of claims and ensure solvency.

4. Alleviating Climate Risk Pressure
The program is designed to relieve financial pressures of voluntary and involuntary relocation of citizens affected by catastrophic climate-related events, reducing economic and psychological burdens to Storslysia's population.

1.2 PROGRAM METRICS

The program's success will be assessed using the following five metrics:

1. Policyholder Uptake: The number of policyholders who have enrolled in the program, broken down by geographic region and demographics such as property value.
***2. Claims Frequency and Severity**:* The number and cost of claims made by policyholders under the program, broken down by voluntary and involuntary relocation.
3. Relocation Rates: The number and percentage of policyholders who have relocated proactively, broken down by geographic region and demographics.
4. Customer Satisfaction: Feedback from policyholders on their satisfaction with the program, including its coverage and customer service.
***5. Financial Sustainability**:* The program's financial performance, including premiums with relocation exceed 10% of Storslysia's GDP annually.

To track initial program uptake and document claims experience, these metrics may be reported on a monthly or quarterly basis. In the long-term, these metrics may be reported on an annual or biennial basis to evaluate the program's ongoing success in meeting its objectives.

SECTION 2: PROGRAM DESIGN

2.1 REQUIREMENTS

To file a claim within this program, policyholders must satisfy certain requirements including:

- Documentation of the damage, such as taking photos or videos of the damage, or providing a detailed inventory of the items that were lost or damaged.
- Notification to insurance program of the damage details.
- Proof of ownership, which may include receipts, invoices, or other documentation that shows when the property was purchased.
- Proof of displacement for those claiming relocation fees, where policyholders need to provide proof of temporary living arrangements, such as receipts for hotel stays or rental agreements.
- Compliance with policy terms, where policyholders must pay premiums on time and provide accurate information when applying for the policy and making any claims.

2.2 COVERAGE AND FEATURES

This insurance program will cover the following areas:

- ***Proactive Relocation**:* Financial assistance for individuals or families who voluntarily relocate to a safer area prior to a catastrophic event. This will involve offering to buyback houses, with limitations described below.
- ***Involuntary Displacement**:* Coverage for involuntary displacement following a hazard event will include financial assistance to cover the costs of temporary housing and property damage.
- ***Limitations of Coverage:*** The program has a deductible of $1,000 and limit of $600,000. Additionally, temporary housing costs following a hazard event will only be covered by the program for 6 months. The buyback scheme will only be offered to houses valued below Ᵽ300K in Storslysia that are at risk of severe or catastrophic hazard events. Refer to Appendix A for further detail.
- ***Voluntary Relocation Incentives**:* Through the buyback scheme, policyholders will be incentivised to relocate to lower-risk areas in order to reduce the likelihood of displacement and pay reduced premiums.

2.3 QUALITATIVE/QUANTITATIVE JUSTIFICATION FOR PROGRAM

Economic costs as defined under the program include property damage, labour and material costs, business interruption costs, temporary housing costs and contents coverage costs. The social insurance program is necessary to reduce the burden of such costs for both the government and the citizens of Storslysia, and to implement preventative measures as the climate situation worsens as depicted in the SSP scenarios. The proposed program will reduce economic costs by approximately 16.58% in the short-term and 28.75% in the long-term, which will be validated in Section 3.

2.4 SHORT-TERM & LONG-TERM PROGRAM EVALUATION TIME FRAME

A short-term time frame of 10 years (2020-30) was selected to obtain sufficient data points to evaluate program success using the aforementioned metrics. Over the short-term, ongoing monitoring and adjustments to the insurance program can be made.

The long-term time frame of 50 years (2020-70) was selected to account for climate factors that shift over multiple decades. This includes temperature, sea level, and other variables that impact risks like coastal erosion. Additionally, it often takes time for the effects of government climate policies to be realised. Time frames of over 50 years were deemed impractical and unmanageable as they are often superseded in priority by shorter-term events.

SECTION 3: PRICING & COSTS

The program aims to generate sufficient reserves to cover claims incurred from hazard events, which are modelled as below.

3.1 DAMAGE MODEL

3.1.1 FITTING A PROPERTY DAMAGE DISTRIBUTION

Property damage was modelled by considering the occurrence of climate-related catastrophes. As hazard events like floods, bushfires and hurricanes are low frequency but high impact, a statistical approach known as Extreme Value Analysis (EVA) was conducted to capture information at the tails, where the rarest and most extreme events occur (see Appendix B). There are three extreme value distributions (EVDs) commonly used, namely the Gumbel, Weibull and Fréchet distributions.

Each distribution was accordingly fitted to the property damage data and compared using statistical tests including AIC, BIC, and Log-Likelihood to determine the best model. The results of the analysis indicate that the Fréchet distribution provides the best fit for the dataset, as evidenced by its superior performance across all statistical tests and goodness-of-fit plots (see Appendix C).

Table 1: Results of statistical tests for extreme value distributions

Distribution	AIC	BIC	Log-Likelihood	Final Selection
Gumbel	7743.014	7749.4	-3869.507	✗
Weibull	4835.001	4841.387	-2415.50	✗
Fréchet	4821.952	4831.53	-2407.976	✓

Known to have the best performance in capturing heavy right tails, the Fréchet distribution is commonly used in studies to model extreme phenomena in fields such as meteorology, hydrology, and finance (RAL 2022). With a shape parameter (α), scale parameter (σ), and location parameter (μ), the parameter estimates are shown in Appendix D and the probability density function is shown below:

$$f(x;\alpha,\sigma,\mu) = \left(\frac{\alpha}{\sigma}\right) \times \left(\frac{x-\mu}{\sigma}\right)^{-1-\alpha} \times \exp\left(-\left(\frac{x-\mu}{\sigma}\right)^{-\alpha}\right) \quad \text{(Glen 2021)}$$

3.1.2 CALCULATING RETURN PERIOD

With a distribution fitted to the data, return periods of 2, 5, 10 and 100 years were set as benchmarks for quantifying the damages of Minor, Moderate, Severe and Catastrophic events. The return period is defined as the time between disasters of a particular scale occurring, meaning that a 1-in-100-year hazard event was set to be catastrophic in terms of severity. With the Fréchet distribution, the damage level that corresponded to a given quantile was calculated, where quantiles were set as $1 - \frac{1}{return\ period}$. For example, to obtain a damage estimate of a minor event, the 50% quantile of our fitted distribution was taken.

3.1.3 OBTAINING CONFIDENCE INTERVALS

To determine confidence intervals (CIs) for the predictions, percentile bootstrapping was chosen over other bootstrapping methods to generate more stable results, given there are many extreme data points. The dataset was resampled $B = 1000$ times with replacement, and from each resampled dataset, a hazard rate and severity value were calculated for each of the 6 regions. The 95% confidence interval was then constructed as follows by taking the interval between the 25th quantile value to the 975th quantile value from the 1000 estimates in the bootstrapped sample:

$$\left[\hat{\theta}_{lower}, \hat{\theta}_{upper}\right] = \left[\hat{\theta}^*_{\frac{\alpha}{2}\times B}, \hat{\theta}^*_{\left(1-\frac{\alpha}{2}\right)\times B}\right] \quad \text{(Data Flair 2021)}$$

3.1.4 PROJECTING DAMAGE ESTIMATES

After obtaining the return period and severity values for each region, the damage estimates were projected into the future by re-evaluating the likelihood of a disaster of each magnitude occurring. For example, if there was a certain disaster with a return period of 2 years, it would be expected to occur 0.5 times on average per year.

To achieve this, LOESS models were fit to the provided future atmospheric CO2 emissions to obtain annual estimates under each SSP model up until 2150 (see Appendix E). The Risk Adjustment Factor (RAF) was calculated as $RAF_{Year} = \left(\frac{CO2_{Year}}{CO2_{2020}}\right)^2$ and multiplied by these annual frequencies to account for the increasing intensity of hazard events with higher CO2 emissions. With a hypothetical RAF of 1.1, the disaster would now occur 0.55 times annually, and return every $\frac{1}{0.55} = 1.81$ years instead.

3.2 ECONOMIC COSTS WITH AND WITHOUT PROGRAM

3.2.1 ECONOMIC COST FACTORS

To compare the financial situation with insurance (WI) and without insurance (WOI), the annual economic cost of hazard events across Storslysia was calculated. The factors that contribute to these values are as follows.

Property Damage Inflated by Materials & Labour Cost

The properties in Storslysia were categorised into 6 groups according to property value as depicted in Appendix F. This categorisation was used to balance accuracy with simplicity in the modelling. Next, total annual property damage was divided proportionally between these household groups in each region. The number of households affected in each group was then estimated by dividing annual property damage by median damage (estimated with percentages in Appendix G for each household group) and subsequently the number of people affected was calculated using the persons per household data. Following natural disasters, demand for materials and labour for repair purposes skyrocket, amplifying property damage costs by a factor between 0-50%.

Temporary Housing Cost

In the aftermath of severe and catastrophic events, temporary disaster shelters provide a safe haven for displaced households until they can rebuild or find permanent housing. It was assumed that 50% of households affected by a severe event and 100% of households affected by a catastrophe would require temporary housing. Cost of temporary housing was then calculated on a region-by-region basis by assuming the average time spent in temporary housing was 6 months per person affected.

Business Interruption Cost

Following the occurrence of hazard events, it is common that the economy undergoes a recovery period. Loss of wages was used as a proxy for measuring the magnitude of these impacts. It was assumed that income would be interrupted for a fortnight, a month and four months respectively following a moderate, severe, or catastrophic event. The final cost was determined by multiplying the number of households affected with the corresponding median household income for each of the assumed business interruption periods.

Contents Coverage

Contents coverage provides financial protection for the personal belongings and contents inside a home in the event of climate-related hazards. The costs associated with replacing lost household goods were given to range from 40-75% of median homeowner costs calculated on an annual basis for an affected household in each region.

3.2.2 ECONOMIC COST PROJECTIONS

Figure 1 and Figure 2 compares the annual cost projection of WI and WOI models. The insurance program's buyback scheme gradually relocates high-risk households to lower-risk areas for the first three household groups, as described in the previous section. As such, WI projection reduces Storslysia's economic losses by minimising the costs outlined in Section 3.2.1 for households who participate in the relocation scheme. The annual percentage of participants is assumed to follow a sigmoid distribution, where the terminal percentage of relocation is 60% (see Appendix H).

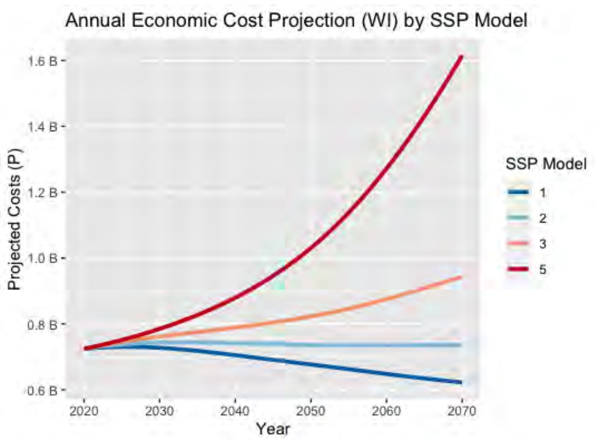


Figure 1: Cost projection with insurance

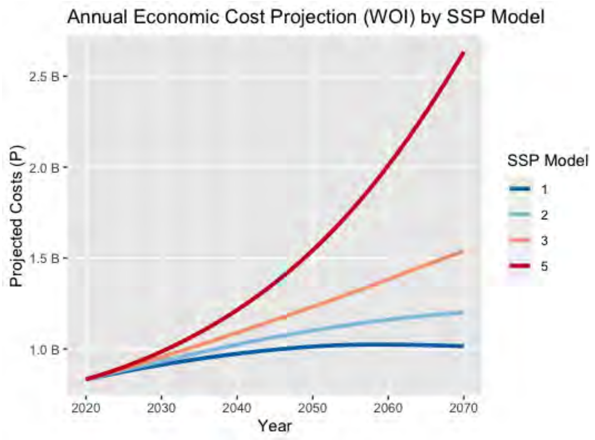


Figure 2: Cost projection without insurance

As mentioned in Section 2.3, these models demonstrate the program will reduce economic costs by approximately 16.58% in the short-term and 28.75% in the long-term. Under SSP1 and SSP2, the WI model is clearly following a different trajectory relative to the WOI model, indicative of the success of the insurance program in reducing costs under these climate scenarios. For SSP3 and SSP5, whilst the shape of the WI and WOI curves are similar overall, in the short-to-medium-term, the WI curve is more convex, suggesting successful reduction of costs in this timeframe.

3.3 PREMIUM SETTING

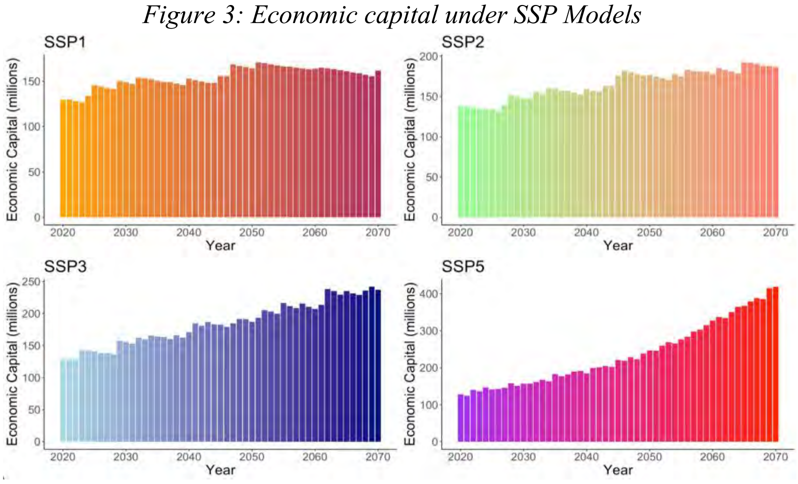
The policyholder premiums were set by first determining the number of policyholders in each region per year. Quadratic regression models were fit to the world population projections, and a constant percentage is taken as Storslysia's population share (see Appendix I). It is assumed that 50% of the population was insured and that there was one policyholder per household, with an average of 2.527 individuals per household.

The average annual premium per policyholder was determined by dividing the economic cost projections by the number of policyholders for each region. Within the six different household groups described previously, 30%, 50%, 100%, 150%, 200% and 300% of this amount was allocated respectively to factor in total property value insured. Finally, Appendix J presents the base premiums for the year 2020 under each SSP model.

3.4 ECONOMIC CAPITAL

The proposed insurance program evaluated economic capital for all four SSP models, covering years 2020 to 2070. Under the 95% confidence interval applied to projected economic costs, the following results in Figure 3 are also within a 95% confidence range. As observed, minor fluctuations occur within each model due to the unpredictability of weather events. Further analysis on trends is included in Appendix K.

Figure 3: Economic capital under SSP Models



The key takeaway is that economic capital remains positive in both short and long-term scenarios, indicating that the program is sustainable and can generate sufficient reserves to cushion unforeseen events in the future. Under the baseline model of SSP5, in the short-term, the program can recover accumulated reserves within one year up to an approximately $50 million event, which occurs with probability 4.31%. In the long-term, recoveries of up to approximately $600 million event can be made within one year, which occurs with 1.69% probability. See Figure 4 to the right for both these scenarios.

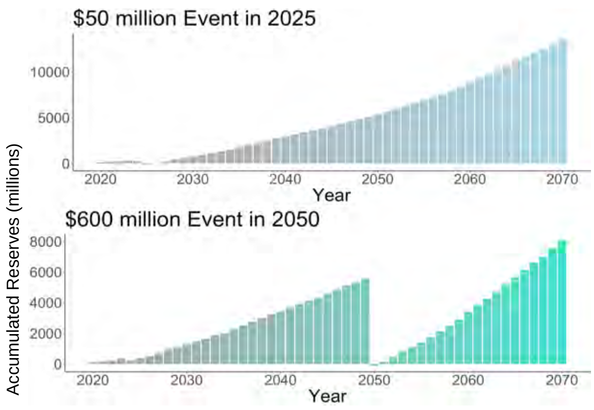


Figure 4: Reserves in unforeseen future events

3.5 COSTS OF VOLUNTARY VS EMERGENCY DISPLACEMENT

The program defines the following definitions:

- ***Voluntary Displacement Cost*** is calculated as the number of houses exposed to severe or catastrophic events multiplied by the median household value in each region which is inherently the buyback cost at pre-disaster market value.
- ***Involuntary Displacement Cost*** is the cost of temporary disaster accommodation for affected households in each region based on an average stay of 6 months.

Figure 5 depicts the cumulative program cost projection for both voluntary relocation and emergency displacement across all SSP scenarios. These results demonstrate that there are minimal cost savings between the two groups in the short-term. However, as time horizon increases, a large disparity in the costs accumulate, suggesting that a swift adoption of the buyback scheme in Storslysia will minimise long-term costs and promote the financial sustainability of the program. Additionally, the more intensive the SSP emission scenario is, the wider the disparity between the groups will be as time progresses. A region-by-region breakdown of costs is provided in Appendix L.

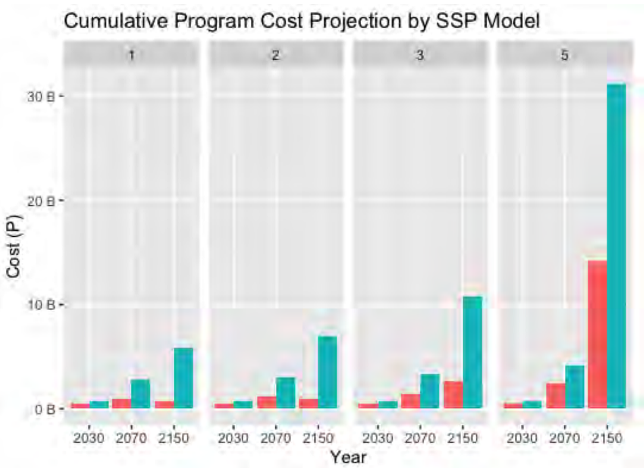


Figure 5: Costs of voluntary and involuntary relocation

SECTION 4: ASSUMPTIONS SUMMARY

Hazard Data Classification and Processing

The process of grouping correlated natural events was utilised to simplify hazard assessment and management. By identifying which hazards tended to occur simultaneously, the number of unique hazards was reduced from approximately 50 to 13 (refer to Appendix M for classifications). However, it is acknowledged that grouping events together results in some loss of detail and granularity. An outlier landslide event was excluded from the study and seasonality effects were assumed to be negligible for simplicity.

Aforementioned Assumptions

Table 2: Summary of assumptions previously mentioned

Assumptions	Rationale	Analysis
Storslysia's population and GDP is a constant percentage of the world population and GDP over time.	This provides a consistent framework for analysis and incorporates global population trends. Further, it considers the interaction of Storslysia with the global economy.	Changes in population and GDP trends will influence policyholder uptake.
The distribution of property value remains constant over time.	This enables a more accurate and equitable allocation of premiums paid by policyholders.	Shifts in wealth distribution will influence premium determination, and property damage sizes.
Return period linkage to severity classes.	Catastrophic hazard events are rarer in occurrence than minor events.	Climate risk change in non-linear ways may result in unexpected claims burdens.
Economic cost assumptions.	For ease of modelling, constant numbers were assumed for various economic factors. These estimates were informed from external research. **Refer to 3.2.**	Changes in economic factors are unlikely to remain constant over time, resulting in inaccuracies.

SECTION 5: RISKS & RISK MITIGATION CONSIDERATIONS

5.1 RISK ASSESSMENT

Both quantifiable and qualitative risks that may arise in the implementation and maintenance of the insurance program are assessed below. Quantifiable risks are those that can be numerically measured and are often associated with changes in financial losses or gains and can affect the results of modelling and analysis. On the other hand, qualitative risks are more subjective and stem from non-financial factors such as regulatory compliance, reputation, and policyholder satisfaction (Golnaraghi 2021).

Table 3: Quantifiable/qualitative risks and mitigation strategies

#	Risk	Type	Impact	Likelihood	Explanation/Mitigation
1	Non-Linear Changes in Climate Patterns	Quantifiable	5	3	Previous non-correlated events may occur in coincidence leading to unexpected and potentially catastrophic claim burdens. **Mitigation:** Scenario modelling, multi-criteria analysis and flexible decision paths to assess risks of all different outcomes and prepare an adaptable plan to account for each scenario (IPCC 2012).
2	Regional Disparity	Quantifiable	3	4	As premiums are reflections of an individual's property value and region, there may be vast disparity in the environmental hazards faced within a region. **Mitigation:** Incorporation of a more precise climate rating system to profile the risk of homeowners not limited to their region. An address-by-address level of granularity would greatly improve the accuracy of premium setting.
3	Public policy change/ Regulatory change or Market conditions	Qualitative	3	3	May affect the premiums invested in the market due to policies that affect certain asset classes in a fluctuating market. **Mitigation:** Frequent updates to asset allocation to offset these changes
4	Innovation	Qualitative	3	4	Unforeseen technical disruptions delaying business and services. (International Association of Insurance Supervisors 2018)

					Mitigation: Conducting thorough tests before scaling them for operational use as well as forming contingency plans for potential incidents.
5	Reputational Risk	Qualitative	2	2	Damaged brand image can affect longevity of financial performance and trust in government. **Mitigation:** Incorporation of a strong corporate governance and transparent communication with the wider public

5.2 SENSITIVITY ANALYSIS

Sensitivity analysis was performed by adjusting the following key assumptions Table 4. The proposed insurance program will remain financially sustainable within the following recommended ranges. Refer to Appendix N for an example of a worst-case scenario.

Table 4: Results of sensitivity analysis

#	Base Assumption	Explanation/Analysis	Recommended Range for Financial Viability
1	50% of the population is insured	Policyholder uptake may differ from year to year depending on the demand for insurance. Factors that might affect this include employment rates, income levels, government regulations, awareness, and social influence.	45% - 100%
2	Material and labour costs increase by 50%	Storslysia's laws limit price increases to 50%, and the program was designed under this assumption. However, changing regulations over time could result in further increases.	0% - 55%
3	The cost of replacing household goods is 75%	The cost of replacing household goods typically range from 40% to 75% of housing costs. The program was designed under worst case scenario assumptions of 75%. However, changes in the economy can influence this percentage to decrease or increase.	0% - 82.5%

5.3 FINANCIAL VIABILITY OF PROGRAM

To minimise costs to 10% of Storslysia's annual GDP, projections of future GDP were first made. Logistic regression models were fit to the world GDP projections, and a constant percentage was taken as Storslysia's GDP share (see Appendix O). Under 95% confidence intervals, the program costs lie well within 10% of Storslysia's annual GDP under all four SSP scenarios until 2070 (see Appendix P). The below graphs supplement this by depicting the economic costs from 2020 to 2070 associated WI and WOI with a 95% CI (see Figures 6 & 7).

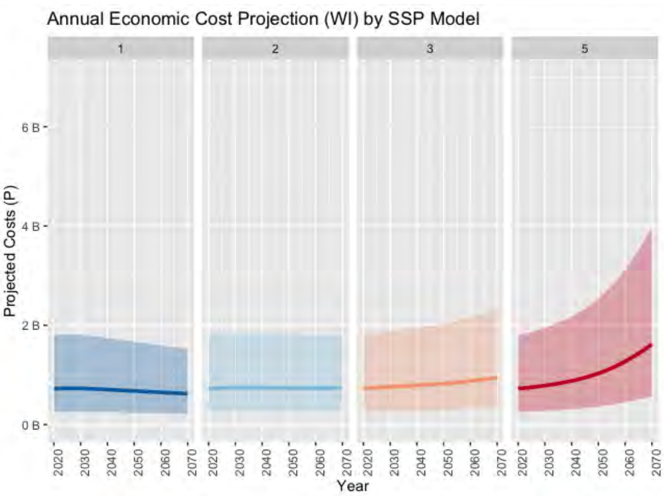


Figure 6: Costs with a 95% CI with insurance

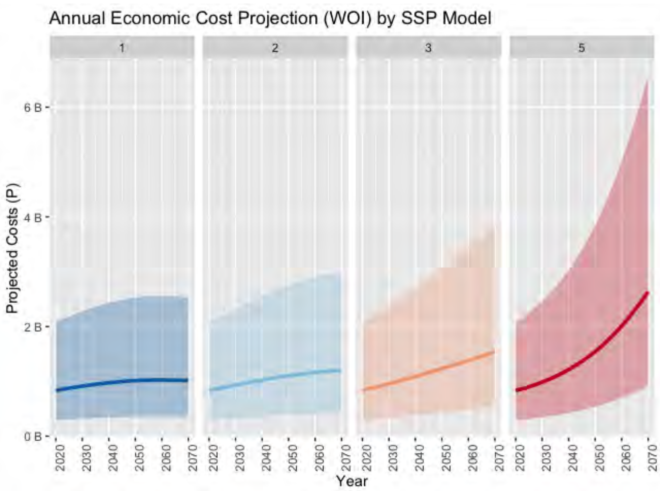


Figure 7: Costs with a 95% CI without insurance

SECTION 6: DATA & DATA LIMITATIONS

6.1 DATA SOURCES

The data provided by the task force was used to create this proposal, and no further external data sources were used. The datasets used included:

- Demographic and economic information of Storslysia up to 2022;
- Historical hazard events in Storslysia since the 1960s;
- Projections of world population, world GDP and SSP emissions until 2100-2150

6.2 DATA LIMITATIONS

Insufficiency in Data Reporting

Limited data points and frequency of data collection for the economic and demographic dataset hindered the accuracy of projections. Assumptions had to be set to produce economic cost projections due to overfitting of models fit on variables such as census data and building permit data. These assumptions decrease the reliability of long-term forecasts. Additionally, scarce historical data on hazard events for low-risk regions such as Region 6 increased the volatility of the damage model predictions.

Insufficiency in Data Breadth

The lack of certain data types limited the ability the program's modelling to effectively assess climate risk. An absence of data was found in the following areas:

- *Demographic data* – availability of information on annual births, deaths and migration allow for a more accurate population projection, while variables such as labour productivity could help with the GDP projection.
- *Historical hazard events* – collection of additional variables such as the size of the affected area or even a survey on the number of households affected would reduce the need for model assumptions.
- *Geographical data* – climate risk is affected by a large range of geographical factors including altitude, latitude and longitude, proximity to bodies of water, topography, and vegetation cover. Information on these factors at the region level would have aided with assessing the physical climate risk of areas.
- *Weather data* – a multitude of weather variables interact with the frequency and severity of climate events. Data such as the temperature, precipitation, humidity, and wind in each region could increase predictive accuracy of our models.

SECTION 7: FINAL RECOMMENDATIONS

Government-led Social Incentives

Additional incentives can be introduced to supplement the program, including assistance with housing, and accessing resources such as education, employment, and healthcare services. The government can also provide disaster preparedness training, increase awareness of climate risks, and community engagement activities to facilitate voluntary relocations.

Future-proofing Storslysia

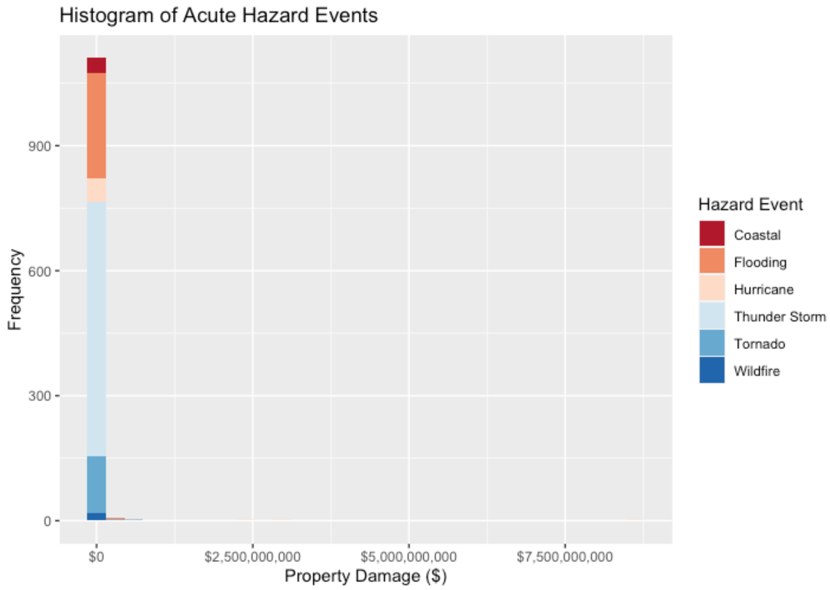
Finally, it is recommended that preventative measures be introduced alongside the insurance program in the near future to guard the country against future climate risk. Strategies include the cessation of issuing building permits in high-risk areas and the fortification of buildings in vulnerable areas for higher resilience against weather damage.

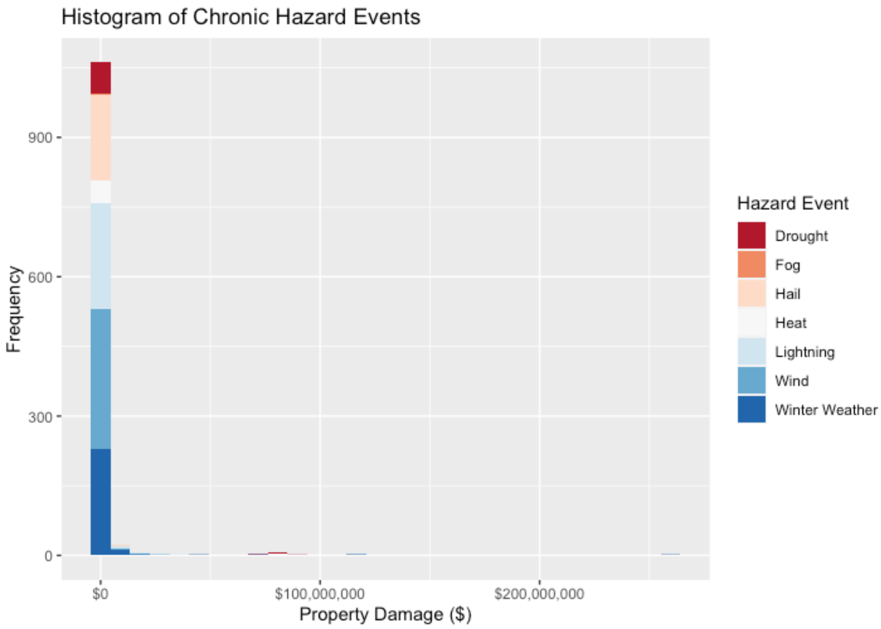
SECTION 8: APPENDICES

APPENDIX A: LIMIT AND DEDUCTIBLE

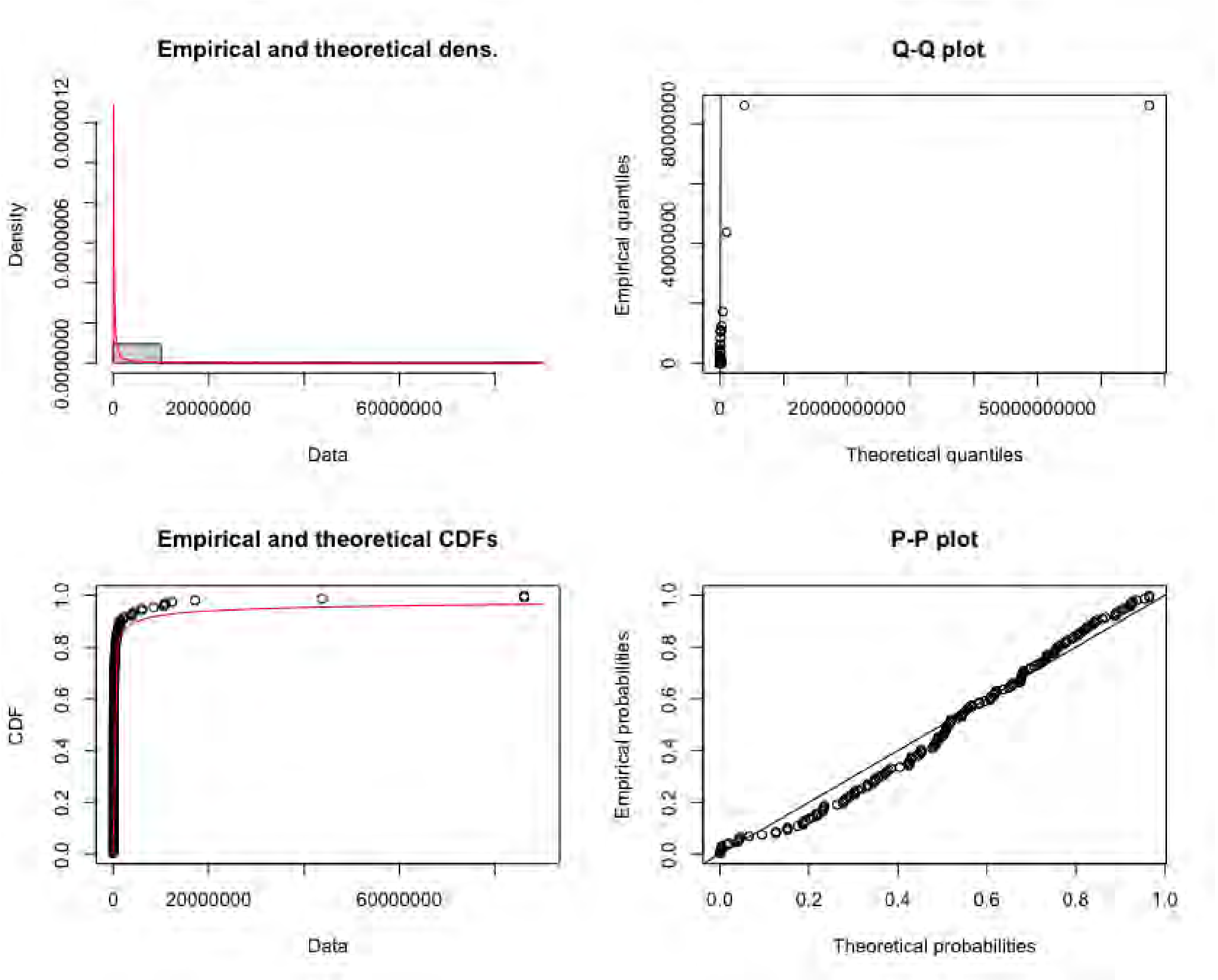
Limits and deductibles were selected based on minor-to-catastrophic hazard event simulations, although these are adjustable depending on funding sources of the insurance program.

APPENDIX B: HISTOGRAM OF ACUTE AND CHRONIC HAZARD EVENTS





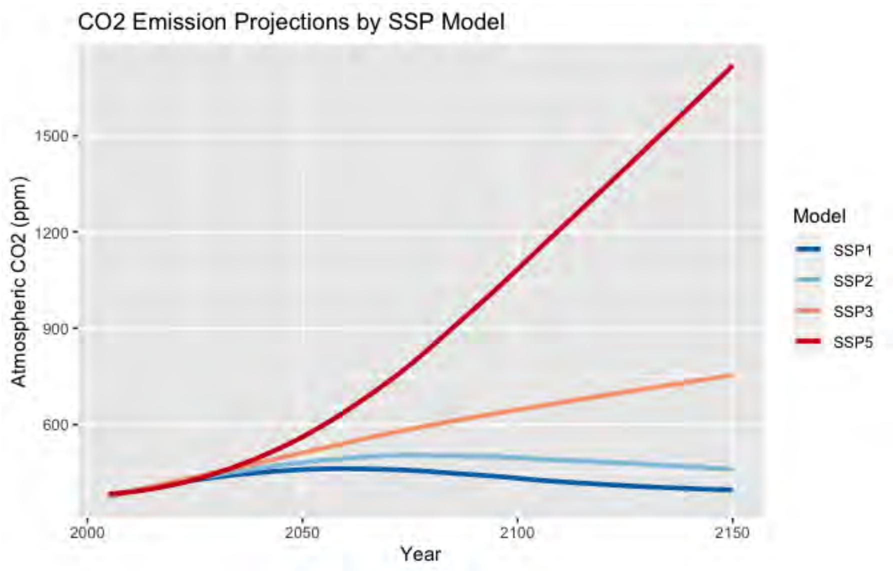
APPENDIX C: FRÉCHET GOODNESS-OF-FIT PLOTS



APPENDIX D: PARAMETER ESTIMATES

Parameter	Estimate
Location (μ)	0.0002431343
Scale (σ)	14504.2827892670
Shape (α)	0.3832517900

APPENDIX E: STORSLYSIA CO2 EMISSION PROJECTIONS



APPENDIX F: PROPERTY VALUE DISTRIBUTIONS

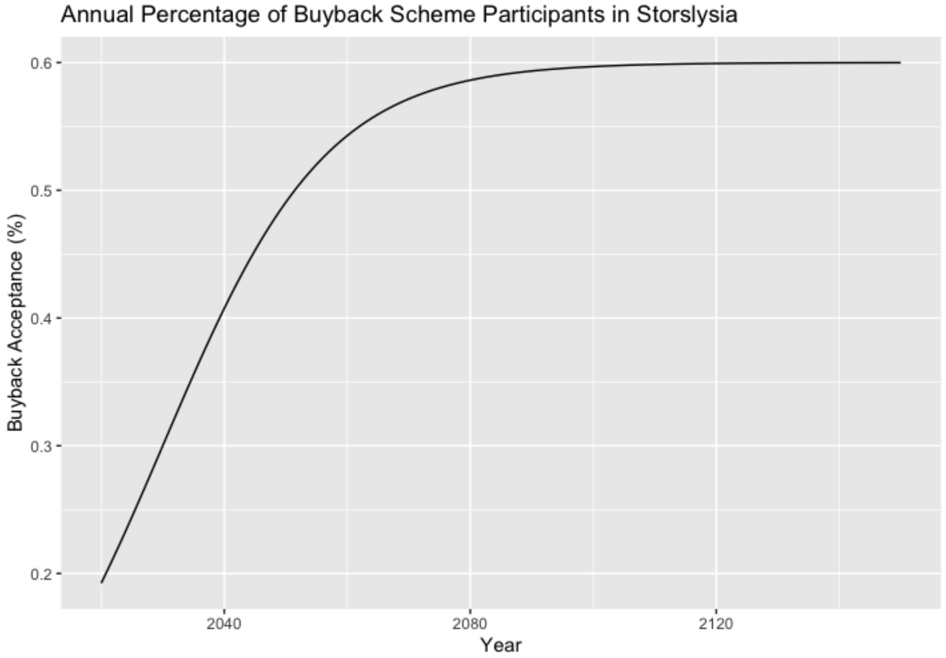
The properties in Storslysia were categorised into 6 groups according to their property value: <100K, 100-199K, 200-299K, 300-499K, 500-999K, >$1M.

Household Group	Region					
	1	2	3	4	5	6
1	8.89%	11.70%	9.79%	37.70%	23.93%	23.38%
2	22.99%	22.24%	32.84%	33.04%	37.58%	29.41%
3	18.96%	20.67%	18.14%	12.13%	18.71%	16.07%
4	34.43%	35.70%	29.02%	13.04%	16.79%	25.03%
5	11.01%	7.96%	8.60%	2.91%	2.29%	4.63%
6	3.72%	1.73%	1.61%	1.18%	0.70%	1.48%

APPENDIX G: ANNUAL PROPERTY DAMAGE BY MEDIAN DAMAGE

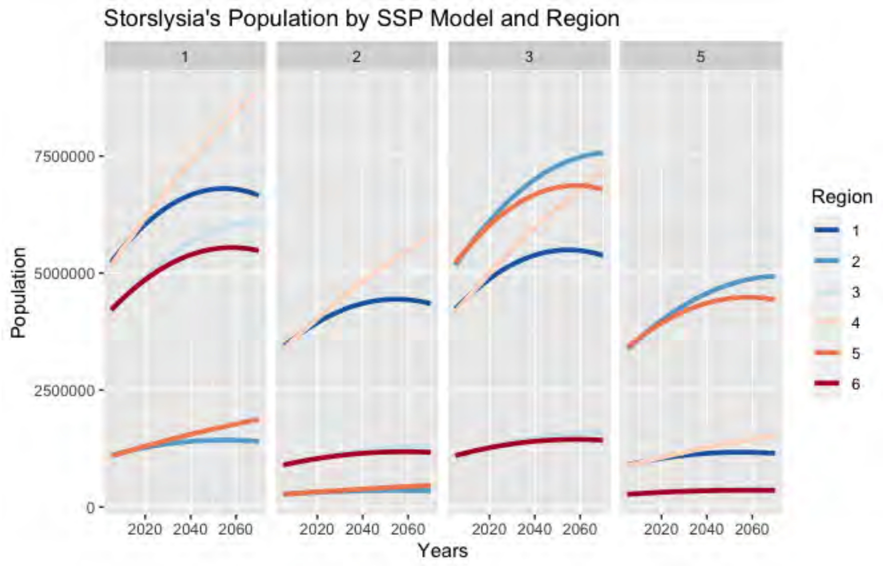
Return Period	Assumed Damage Percentage
2	0.5%
10	2.0%
50	15.0%
100	50.0%

APPENDIX H: ANNUAL PERCENTAGE OF PARTICIPANTS THAT PARTICIPATE IN BUYBACK SCHEME



A sigmoid distribution is a type of probability distribution that is often used to model events that have a cumulative effect over time. It is characterized by an S-shaped curve, with a slow initial phase, a rapid growth phase, and a saturation phase where the rate of adoption levels off. The adoption of a buyback scheme may follow a sigmoid distribution if it involves a gradual process of awareness, consideration, and decision-making among potential participants.

APPENDIX I: STORSLYSIA'S POPULATION PROJECTION



APPENDIX J: BASE PREMIUMS

Full premiums for 2020 to 2100, under four different models.

Model	Region	Household Groups					
		<100k	100-200k	200-300k	300-500k	500k-1M	>1M
SSP1	Region 1	45	75	150	225	300	450
	Region 2	120	200	400	600	800	1200
	Region 3	66	110	220	330	440	660
	Region 4	99	165	330	495	660	990
	Region 5	120	200	400	600	800	1200
	Region 6	513	855	1710	2565	3420	5130
SSP2	Region 1	48	80	160	240	320	480
	Region 2	129	215	430	645	860	1290
	Region 3	72	120	240	360	480	720
	Region 4	111	185	370	555	740	1110
	Region 5	129	215	430	645	860	1290
	Region 6	549	915	1830	2745	3660	5490
SSP3	Region 1	48	80	160	240	320	480
	Region 2	126	210	420	630	840	1260
	Region 3	69	115	230	345	460	690
	Region 4	108	180	360	540	720	1080
	Region 5	126	210	420	630	840	1260
	Region 6	543	905	1810	2715	3620	5430
SSP5	Region 1	48	80	160	240	320	480
	Region 2	129	215	430	645	860	1290

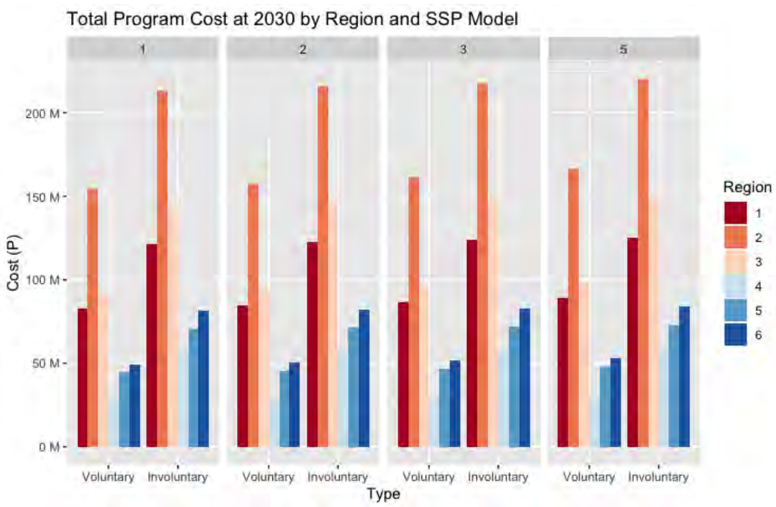
	Region 3	72	120	240	360	480	720
	Region 4	111	185	370	555	740	1110
	Region 5	132	220	440	660	880	1320
	Region 6	558	930	1860	2790	3720	5580

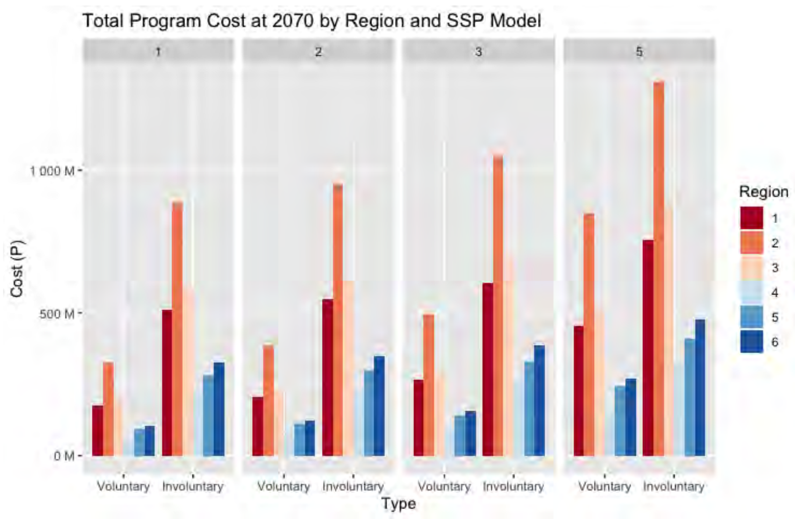
APPENDIX K: ECONOMIC CAPITAL FURTHER ANALYSIS

Further analysis of each model's projected economic capital reveals that the four emission scenarios influence the trends:

- Under ***SSP5***, emissions increase exponentially which amplify the severity of future hazard events. As a result, economic capital increases to adjust for the increased probability and size of future damages.
- Under ***SSP3***, emissions increase linearly which aligns with the pattern in projected economic capital. Closer inspection will reveal a cyclical trend in which economic capital rises dramatically following a period of gradual decline. This is likely attributed to the rare occurrence of catastrophic events which result in a significantly larger amount of claims payout.
- Under ***SSP2***, emissions are projected to increase at a slower rate and improve over time. This is reflected in the amount of economic capital held, as there is a decreasing trend observed from 2075 onwards. With fewer hazard events and reduced severity of damages, there is reduced need to hold large amounts of capital.
- Under ***SSP1***, emissions are similarly projected to improve over time. Trends in economic capital remain significantly more constant in comparison to the other three models. A decline is observed at a much earlier stage, from 2050 onwards. Much like the SSP2 model, reduced frequency and severity of hazard events will correspond to a decreased demand for economic capital.

APPENDIX L: VOLUNTARY VS INVOLUNTARY COSTS BY REGION



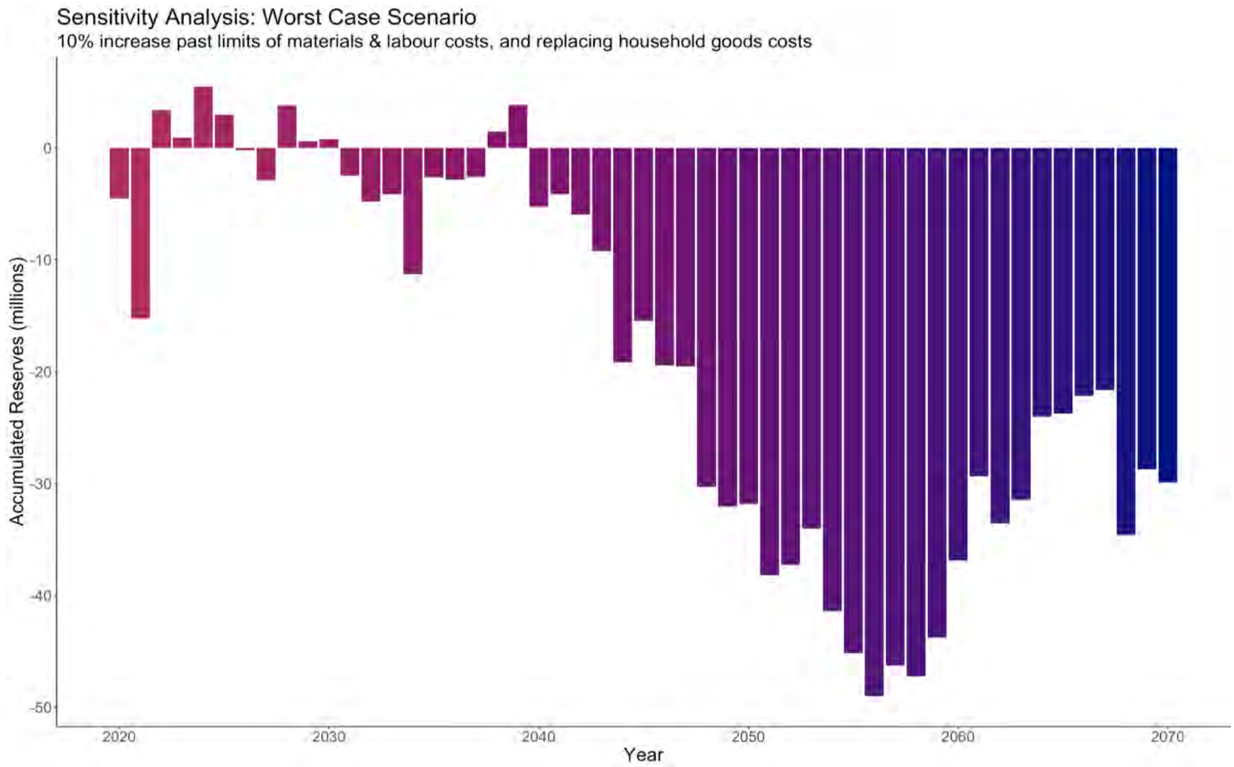


APPENDIX M: HAZARD EVENT CLASSIFICATIONS

- Hurricane and tropical storms always occur simultaneously and hence were classified 'hurricane'
- Severe storms occurred simultaneously with thunderstorm, and hence were classified as 'thunderstorm'
- Property damage designation was completed with the following method:
  - When multiple chronic events occurred simultaneously, property damage was evenly split
  - If both chronic and acute events occurred together, the acute event was assigned 100% of property damage

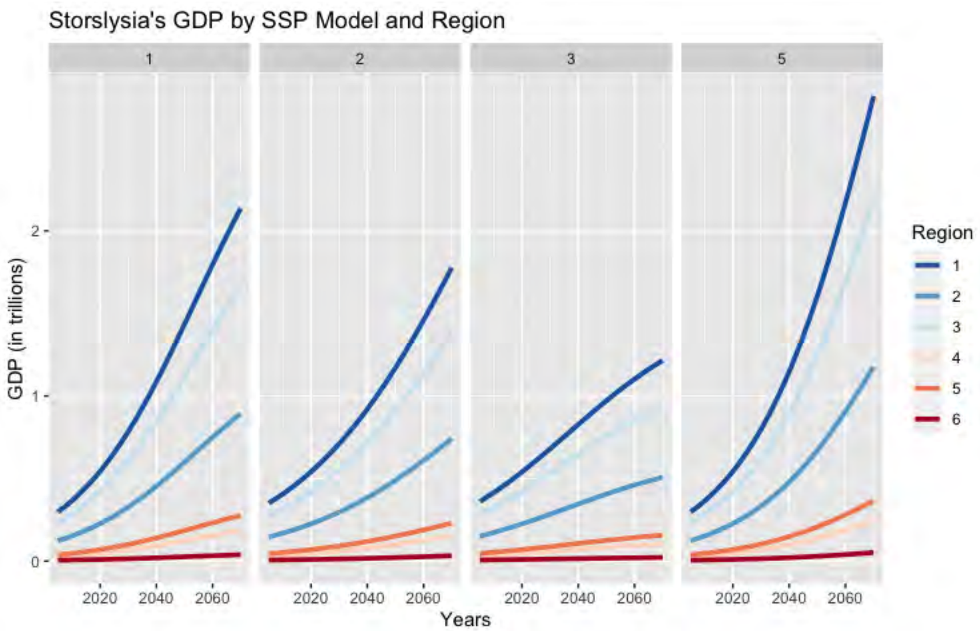
Acute	Chronic
Flooding	Winter Weather
Coastal	Heat
Hurricane	Drought
Tornado	Fog
Thunderstorm	Hail
Wildfire	Wind
	Lightning

APPENDIX N: WORST-CASE SCENARIO PROJECTION



A worst-case scenario was modelled with a 10% increase past the limits of materials & labour costs, and the cost of replacing household goods (to 55% and 82.5% respectively). The resulting accumulated reserves are plotted above.

APPENDIX O: STORSLYSIA'S GDP PROJECTIONS



APPENDIX P: PROGRAM COSTS AS A PERCENTAGE OF GDP

Year	SSP1	SSP2	SSP3	SSP5
2020	0.0681%	0.0685%	0.0686%	0.0681%
2021	0.0663%	0.0674%	0.0679%	0.0664%
2022	0.0645%	0.0664%	0.0672%	0.0649%
2023	0.0627%	0.0654%	0.0665%	0.0634%
2024	0.0610%	0.0643%	0.0659%	0.0620%
2025	0.0593%	0.0633%	0.0653%	0.0606%
2026	0.0577%	0.0623%	0.0647%	0.0593%
2027	0.0562%	0.0613%	0.0641%	0.0581%
2028	0.0547%	0.0603%	0.0635%	0.0570%
2029	0.0532%	0.0593%	0.0630%	0.0559%
2030	0.0518%	0.0584%	0.0625%	0.0549%
2031	0.0504%	0.0574%	0.0620%	0.0539%
2032	0.0491%	0.0565%	0.0615%	0.0530%
2033	0.0478%	0.0555%	0.0611%	0.0521%
2034	0.0465%	0.0546%	0.0607%	0.0513%
2035	0.0453%	0.0537%	0.0603%	0.0505%
2036	0.0442%	0.0529%	0.0599%	0.0497%
2037	0.0430%	0.0520%	0.0595%	0.0490%
2038	0.0419%	0.0511%	0.0592%	0.0483%
2039	0.0409%	0.0503%	0.0589%	0.0477%
2040	0.0399%	0.0495%	0.0586%	0.0470%
2041	0.0389%	0.0487%	0.0583%	0.0465%
2042	0.0379%	0.0479%	0.0580%	0.0459%
2043	0.0370%	0.0471%	0.0578%	0.0454%
2044	0.0361%	0.0463%	0.0575%	0.0449%
2045	0.0353%	0.0455%	0.0573%	0.0445%
2046	0.0344%	0.0448%	0.0571%	0.0441%
2047	0.0336%	0.0440%	0.0569%	0.0437%
2048	0.0329%	0.0433%	0.0567%	0.0433%
2049	0.0321%	0.0425%	0.0566%	0.0430%
2050	0.0314%	0.0418%	0.0564%	0.0427%
2051	0.0307%	0.0411%	0.0563%	0.0424%
2052	0.0300%	0.0404%	0.0561%	0.0422%
2053	0.0294%	0.0398%	0.0560%	0.0420%

2054	0.0288%	0.0391%	0.0560%	0.0418%
2055	0.0281%	0.0384%	0.0559%	0.0416%
2056	0.0275%	0.0378%	0.0559%	0.0415%
2057	0.0270%	0.0372%	0.0558%	0.0414%
2058	0.0264%	0.0366%	0.0558%	0.0413%
2059	0.0259%	0.0360%	0.0558%	0.0412%
2060	0.0254%	0.0354%	0.0558%	0.0412%
2061	0.0249%	0.0348%	0.0558%	0.0412%
2062	0.0244%	0.0342%	0.0559%	0.0411%
2063	0.0239%	0.0337%	0.0559%	0.0411%
2064	0.0235%	0.0331%	0.0559%	0.0412%
2065	0.0230%	0.0326%	0.0560%	0.0412%
2066	0.0226%	0.0321%	0.0560%	0.0413%
2067	0.0222%	0.0315%	0.0561%	0.0413%
2068	0.0218%	0.0310%	0.0562%	0.0414%
2069	0.0215%	0.0305%	0.0562%	0.0415%
2070	0.0211%	0.0300%	0.0563%	0.0416%

APPENDIX Q: PROGRAM CODE

```
##################################################################################
## ACTL4001 Assignment - SOA Social Insurance Program
## Team: The Standard Deviants
## Members: Jennifer Lin, Rosy Liu, Kevin Shao, Jessica Zhao, Sharon Zhou
##################################################################################
##Importing libraries
library(readxl)
library(scales)
library(dplyr)
library(ggplot2)
library(data.table)
library(tidyr)
library(caret)
library(RColorBrewer)
library(reshape2)
##################################################################################

## HAZARD DATA CLEANING
hazard_data_raw <- read_excel("2023-student-research-hazard-event-data.xlsx", "Hazard Data",
"B13:I3379")

# Removing landslide hazard event
hazard_data <- hazard_data_raw[hazard_data_raw$`Hazard Event` != "Landslide", ]

# Categories for hazard events
```

```
acute <- list("Flooding", "Coastal", "Hurricane", "Tornado", "Thunder Storm", "Wildfire")
chronic <- list("Winter Weather", "Heat", "Drought", "Fog", "Hail", "Wind", "Lightning")

# Summarising and combining data
hazard_data <- hazard_data %>%
  group_by(Region, `Hazard Event`, Quarter, Year) %>%
  summarise("Duration" = sum(Duration),
        "Fatalities" = sum(Fatalities),
        "Injuries" = sum(Injuries),
        "Property Damage" = sum(`Property Damage`)) %>%
  mutate(`Hazard Event` = gsub("/ ", "/", `Hazard Event`),
        `Hazard Event` = gsub(" - ", "/", `Hazard Event`))

# Apply assumptions (hurricane = tropical storm, severe storm = thunder storm)
hazard_data <- hazard_data %>%
  mutate(`Hazard Event` = gsub("Tropical Storm", "Hurricane", `Hazard Event`),
        `Hazard Event` = gsub("Severe Storm", "Thunder Storm", `Hazard Event`),
        `Hazard Event` = gsub("Hurricane/Hurricane", "Hurricane", `Hazard Event`),
        `Hazard Event` = gsub("Thunder Storm/Thunder Storm", "Thunder Storm", `Hazard Event`))

# Group types of hazard events
hazard_data_group <- hazard_data %>%
  mutate(`Hazard Event` = ifelse(grepl("/", `Hazard Event`) & grepl(paste(acute, collapse = "|"),
`Hazard Event`), gsub(paste(chronic, collapse = "|"), "", `Hazard Event`), `Hazard Event`),
        `Hazard Event`= gsub("^/|^//|/$|//$", "", `Hazard Event`),
        `Hazard Event`= gsub("//", "/", `Hazard Event`),
        `Hazard Event` = strsplit(`Hazard Event`, "/"),
        Count = lengths(`Hazard Event`)) %>%
  unnest(`Hazard Event`) %>%
  mutate(Duration = round(Duration/Count, 2),
        Fatalities = round(Fatalities/Count, 0),
        Injuries = round(Injuries/Count, 0),
        `Property Damage` = round(`Property Damage`/Count, 0)) %>%
  select(-Count)

# Add column indicating if hazard event is acute or chronic physical risk
hazard_data_group <- hazard_data_group %>%
  mutate(Type = ifelse(grepl(paste(acute, collapse = "|"), `Hazard Event`), "Acute", "Chronic"))

## WORLD POPULATION PROJECTION

world_pop <- read_excel("Assignment/2023-student-research-emissions.xlsx",
                                sheet = "World Population",
                                col_types = c("numeric","numeric", "numeric", "numeric","numeric"),
skip = 1)

colnames(world_pop) <- c("Year", "SSP1", "SSP2", "SSP3", "SSP5")

#Quadratic regression pattern seen
ggplot(world_pop, aes(x=Year, y = SSP3)) + geom_point()

#Modelling with quadratic regression
model_1 <- lm(SSP1 ~ Year + I(Year^2), data = world_pop)
model_2 <- lm(SSP2 ~ Year + I(Year^2), data = world_pop)
model_3 <- lm(SSP3 ~ Year + I(Year^2), data = world_pop)
```

```
model_5 <- lm(SSP5 ~ Year + I(Year^2), data = world_pop)

new_years <- seq(2005, 2100, by = 1)

# use the model to predict population values for the new years
SSP1_pop <- 1000000000*predict(model_1, newdata = data.frame(Year = new_years, year_squared =
new_years^2))
SSP2_pop <- 1000000000*predict(model_2, newdata = data.frame(Year = new_years, year_squared =
new_years^2))
SSP3_pop <- 1000000000*predict(model_3, newdata = data.frame(Year = new_years, year_squared =
new_years^2))
SSP5_pop <- 1000000000*predict(model_5, newdata = data.frame(Year = new_years, year_squared =
new_years^2))

final_SSP1 <- as.data.frame(cbind(Years, SSP1_pop))
final_SSP1 <- final_SSP1 %>%
  mutate(Model = "SSP1") %>%
  rename(Population = SSP1_pop)

final_SSP2 <- as.data.frame(cbind(Years, SSP2_pop))
final_SSP2 <- final_SSP2 %>%
  mutate(Model = "SSP2") %>%
  rename(Population = SSP2_pop)

final_SSP3 <- as.data.frame(cbind(Years, SSP3_pop))
final_SSP3 <- final_SSP3 %>%
  mutate(Model = "SSP3") %>%
  rename(Population = SSP3_pop)

final_SSP5 <- as.data.frame(cbind(Years, SSP5_pop))
final_SSP5 <- final_SSP5 %>%
  mutate(Model = "SSP5") %>%
  rename(Population = SSP5_pop)

final <- rbind(final_SSP1, final_SSP2, final_SSP3, final_SSP5)

new_final <- rbind(final_SSP1[15:17,], final_SSP1[15:17,], final_SSP3[15:17,], final_SSP5[15:17,])

new_final_original <- cbind(Years, SSP1_pop, SSP2_pop, SSP3_pop, SSP5_pop )
final_original <- new_final_original[15:17,]

## STORSLYSIA POPULATION PROJECTION

demographic_data <- read_excel("Assignment/2023-student-research-eco-dem-data.xlsx",
                               sheet = "Demographic-Economic", skip = 7)

census_data <- demographic_data[1:3,]

census_data[,1] <- c(2021,2020,2019)

colnames(census_data)[1] <- "Year"

new_census <- census_data[order(census_data$Year),]

final_census <- cbind(new_census, final_original)
```

```
#Getting the population shares per region per model

final_census <- transform(final_census, SSP1_reg1_share = as.numeric(`Region 1`)/ SSP1_pop)
final_census <- transform(final_census, SSP1_reg2_share = as.numeric(Region.2)/ SSP1_pop)
final_census <- transform(final_census, SSP1_reg3_share = as.numeric(Region.3)/ SSP1_pop)
final_census <- transform(final_census, SSP1_reg4_share = as.numeric(Region.4)/ SSP1_pop)
final_census <- transform(final_census, SSP1_reg5_share = as.numeric(Region.5)/ SSP1_pop)
final_census <- transform(final_census, SSP1_reg6_share = as.numeric(Region.6)/ SSP1_pop)

final_census <- transform(final_census, SSP2_reg1_share = as.numeric(Region.1)/ SSP2_pop)
final_census <- transform(final_census, SSP2_reg2_share = as.numeric(Region.2)/ SSP2_pop)
final_census <- transform(final_census, SSP2_reg3_share = as.numeric(Region.3)/ SSP2_pop)
final_census <- transform(final_census, SSP2_reg4_share = as.numeric(Region.4)/ SSP2_pop)
final_census <- transform(final_census, SSP2_reg5_share = as.numeric(Region.5)/ SSP2_pop)
final_census <- transform(final_census, SSP2_reg6_share = as.numeric(Region.6)/ SSP2_pop)

final_census <- transform(final_census, SSP3_reg1_share = as.numeric(Region.1)/ SSP3_pop)
final_census <- transform(final_census, SSP3_reg2_share = as.numeric(Region.2)/ SSP3_pop)
final_census <- transform(final_census, SSP3_reg3_share = as.numeric(Region.3)/ SSP3_pop)
final_census <- transform(final_census, SSP3_reg4_share = as.numeric(Region.4)/ SSP3_pop)
final_census <- transform(final_census, SSP3_reg5_share = as.numeric(Region.5)/ SSP3_pop)
final_census <- transform(final_census, SSP3_reg6_share = as.numeric(Region.6)/ SSP3_pop)

final_census <- transform(final_census, SSP5_reg1_share = as.numeric(Region.1)/ SSP5_pop)
final_census <- transform(final_census, SSP5_reg2_share = as.numeric(Region.2)/ SSP5_pop)
final_census <- transform(final_census, SSP5_reg3_share = as.numeric(Region.3)/ SSP5_pop)
final_census <- transform(final_census, SSP5_reg4_share = as.numeric(Region.4)/ SSP5_pop)
final_census <- transform(final_census, SSP5_reg5_share = as.numeric(Region.5)/ SSP5_pop)
final_census <- transform(final_census, SSP5_reg6_share = as.numeric(Region.6)/ SSP5_pop)

#Taking the average for each case as the final percentage to be used
reg_shares <-colMeans(final_census[,13:36])

reg1_project <- final %>%
  mutate(Storslysia_Population = case_when(
    Model == "SSP1" ~ reg_shares[1] * Population,
    Model == "SSP2" ~ reg_shares[7] * Population,
    Model == "SSP3" ~ reg_shares[13] * Population,
    Model == "SSP5" ~ reg_shares[19] * Population,
    )) %>%
  mutate(Region = 1) %>%
  dplyr::select(Years, Model, Region, Storslysia_Population)

reg2_project <- final %>%
  mutate(Storslysia_Population = case_when(
    Model == "SSP1" ~ reg_shares[2] * Population,
    Model == "SSP2" ~ reg_shares[8] * Population,
    Model == "SSP3" ~ reg_shares[14] * Population,
    Model == "SSP5" ~ reg_shares[20] * Population,
  )) %>%
  mutate(Region = 2) %>%
  dplyr::select(Years, Model, Region, Storslysia_Population)

reg3_project <- final %>%
```

```
  mutate(Storslysia_Population = case_when(
    Model == "SSP1" ~ reg_shares[3] * Population,
    Model == "SSP2" ~ reg_shares[9] * Population,
    Model == "SSP3" ~ reg_shares[15] * Population,
    Model == "SSP5" ~ reg_shares[21] * Population,
  )) %>%
  mutate(Region = 3) %>%
  dplyr::select(Years, Model, Region, Storslysia_Population)

reg4_project <- final %>%
  mutate(Storslysia_Population = case_when(
    Model == "SSP1" ~ reg_shares[4] * Population,
    Model == "SSP2" ~ reg_shares[10] * Population,
    Model == "SSP3" ~ reg_shares[16] * Population,
    Model == "SSP5" ~ reg_shares[22] * Population,
  )) %>%
  mutate(Region = 4) %>%
  dplyr::select(Years, Model, Region, Storslysia_Population)

reg5_project <- final %>%
  mutate(Storslysia_Population = case_when(
    Model == "SSP1" ~ reg_shares[5] * Population,
    Model == "SSP2" ~ reg_shares[11] * Population,
    Model == "SSP3" ~ reg_shares[17] * Population,
    Model == "SSP5" ~ reg_shares[23] * Population,
  )) %>%
  mutate(Region = 5) %>%
  dplyr::select(Years, Model, Region, Storslysia_Population)

reg6_project <- final %>%
  mutate(Storslysia_Population = case_when(
    Model == "SSP1" ~ reg_shares[6] * Population,
    Model == "SSP2" ~ reg_shares[12] * Population,
    Model == "SSP3" ~ reg_shares[18] * Population,
    Model == "SSP5" ~ reg_shares[24] * Population,
  )) %>%
  mutate(Region = 6) %>%
  dplyr::select(Years, Model, Region, Storslysia_Population)

all_project <- rbind(reg1_project, reg2_project, reg3_project, reg4_project, reg5_project,reg6_project)

all_project <- as.data.table(all_project)

ggplot(all_project, aes(x=Years, y = Storslysia_Population, color = Region)) +geom_point()+
  facet_grid(. ~ `Model`)

ggplot(population_gdp, aes(x=Years, y = Population, color = Region)) + geom_point() +
  facet_grid(.~`SSP Model`)
###################################################################################
## WORLD GDP PROJECTION

world_gdp <- read_excel("Assignment/2023-student-research-emissions.xlsx",
                  sheet = "World GDP",
                  col_types = c("numeric","numeric", "numeric", "numeric","numeric"), skip = 1)
```

```
colnames(world_gdp) <- c("Year", "SSP1", "SSP2", "SSP3", "SSP5")

#Logistic growth pattern seen
ggplot(world_gdp, aes(x=Year, y = SSP1)) + geom_point()

#Create non-linear regression model with logistic growth
model_1 <- nls(SSP1 ~ SSlogis(Year, phi1, phi2, phi3), data = world_gdp)

#Plot graph
alpha <- coef(model_1)  #extracting coefficients
plot(SSP1 ~ Year, data = world_gdp, main = "Logistic Growth Model of Australian Population",
    xlab = "Year", ylab = "Population", xlim = c(2005, 2100))  # Census data
curve(alpha[1]/(1 + exp(-(x - alpha[2])/alpha[3])), add = T, col = "blue")  # Fitted model

model_2 <- nls(SSP2 ~ SSlogis(Year, phi1, phi2, phi3), data = world_gdp)
model_3 <- nls(SSP3 ~ SSlogis(Year, phi1, phi2, phi3), data = world_gdp)
model_5 <- nls(SSP5 ~ SSlogis(Year, phi1, phi2, phi3), data = world_gdp)

exchange_rate = 1.321

SSP1_gdp <- exchange_rate * predict(model_1, newdata = data.frame(Year = new_years, year_squared
= new_years^2))
SSP2_gdp <- exchange_rate * predict(model_2, newdata = data.frame(Year = new_years, year_squared
= new_years^2))
SSP3_gdp <- exchange_rate * predict(model_3, newdata = data.frame(Year = new_years, year_squared
= new_years^2))
SSP5_gdp <- exchange_rate * predict(model_5, newdata = data.frame(Year = new_years, year_squared
= new_years^2))

final_SSP1_gdp <- as.data.frame(cbind(Years, SSP1_gdp))
final_SSP1_gdp <- final_SSP1_gdp %>%
  mutate(Model = "SSP1") %>%
  rename(GDP = SSP1_gdp)

final_SSP2_gdp <- as.data.frame(cbind(Years, SSP2_gdp))
final_SSP2_gdp <- final_SSP2_gdp %>%
  mutate(Model = "SSP2") %>%
  rename(GDP = SSP2_gdp)

final_SSP3_gdp <- as.data.frame(cbind(Years, SSP3_gdp))
final_SSP3_gdp <- final_SSP3_gdp %>%
  mutate(Model = "SSP3") %>%
  rename(GDP = SSP3_gdp)

final_SSP5_gdp <- as.data.frame(cbind(Years, SSP5_gdp))
final_SSP5_gdp <- final_SSP5_gdp %>%
  mutate(Model = "SSP5") %>%
  rename(GDP = SSP5_gdp)

final <- rbind(final_SSP1_gdp, final_SSP2_gdp, final_SSP3_gdp, final_SSP5_gdp)

new_final_gdp <- rbind(final_SSP1_gdp[15:16,], final_SSP1_gdp[15:16,], final_SSP3_gdp[15:16,],
final_SSP5_gdp[15:16,])

new_final_original_gdp <- cbind(Years, SSP1_gdp, SSP2_gdp, SSP3_gdp, SSP5_gdp)
```

```
final_original_gdp <- new_final_original_gdp[15:16,]

## STORSLYSIA'S GDP PROJECTION

gdp_data <- demographic_data[28:29,]
gdp_data <- mutate_all(gdp_data, function(x) as.numeric(as.character(x)))

gdp_data[,1] <- c(2020,2019)
gdp_data$`Region 1` <- gdp_data$`Region 1`/1000000000
gdp_data$`Region 2` <- gdp_data$`Region 2`/1000000000
gdp_data$`Region 3` <- gdp_data$`Region 3`/1000000000
gdp_data$`Region 4` <- gdp_data$`Region 4`/1000000000
gdp_data$`Region 5` <- gdp_data$`Region 5`/1000000000
gdp_data$`Region 6` <- gdp_data$`Region 6`/1000000000

colnames(gdp_data)[1] <- "Years"
new_gdp <- gdp_data[order(gdp_data$Years),]

final_gdp <- cbind(new_gdp, final_original_gdp)

final_gdp <- transform(final_gdp, SSP1_reg1_share = as.numeric(`Region 1`)/ SSP1_gdp)
final_gdp <- transform(final_gdp, SSP1_reg2_share = as.numeric(Region.2)/ SSP1_gdp)
final_gdp <- transform(final_gdp, SSP1_reg3_share = as.numeric(Region.3)/ SSP1_gdp)
final_gdp <- transform(final_gdp, SSP1_reg4_share = as.numeric(Region.4)/ SSP1_gdp)
final_gdp <- transform(final_gdp, SSP1_reg5_share = as.numeric(Region.5)/ SSP1_gdp)
final_gdp <- transform(final_gdp, SSP1_reg6_share = as.numeric(Region.6)/ SSP1_gdp)

final_gdp <- transform(final_gdp, SSP2_reg1_share = as.numeric(Region.1)/ SSP2_gdp)
final_gdp <- transform(final_gdp, SSP2_reg2_share = as.numeric(Region.2)/ SSP2_gdp)
final_gdp <- transform(final_gdp, SSP2_reg3_share = as.numeric(Region.3)/ SSP2_gdp)
final_gdp <- transform(final_gdp, SSP2_reg4_share = as.numeric(Region.4)/ SSP2_gdp)
final_gdp <- transform(final_gdp, SSP2_reg5_share = as.numeric(Region.5)/ SSP2_gdp)
final_gdp <- transform(final_gdp, SSP2_reg6_share = as.numeric(Region.6)/ SSP2_gdp)

final_gdp <- transform(final_gdp, SSP3_reg1_share = as.numeric(Region.1)/ SSP3_gdp)
final_gdp <- transform(final_gdp, SSP3_reg2_share = as.numeric(Region.2)/ SSP3_gdp)
final_gdp <- transform(final_gdp, SSP3_reg3_share = as.numeric(Region.3)/ SSP3_gdp)
final_gdp <- transform(final_gdp, SSP3_reg4_share = as.numeric(Region.4)/ SSP3_gdp)
final_gdp <- transform(final_gdp, SSP3_reg5_share = as.numeric(Region.5)/ SSP3_gdp)
final_gdp <- transform(final_gdp, SSP3_reg6_share = as.numeric(Region.6)/ SSP3_gdp)

final_gdp <- transform(final_gdp, SSP5_reg1_share = as.numeric(Region.1)/ SSP5_gdp)
final_gdp <- transform(final_gdp, SSP5_reg2_share = as.numeric(Region.2)/ SSP5_gdp)
final_gdp <- transform(final_gdp, SSP5_reg3_share = as.numeric(Region.3)/ SSP5_gdp)
final_gdp <- transform(final_gdp, SSP5_reg4_share = as.numeric(Region.4)/ SSP5_gdp)
final_gdp <- transform(final_gdp, SSP5_reg5_share = as.numeric(Region.5)/ SSP5_gdp)
final_gdp <- transform(final_gdp, SSP5_reg6_share = as.numeric(Region.6)/ SSP5_gdp)

reg_shares_gdp <-colMeans(final_gdp[,13:36])

reg1_project <- final %>%
  mutate(Storslysia_GDP = case_when(
    Model == "SSP1" ~ reg_shares_gdp[1] * GDP,
    Model == "SSP2" ~ reg_shares_gdp[7] * GDP,
    Model == "SSP3" ~ reg_shares_gdp[13] * GDP,
```

```
    Model == "SSP5" ~ reg_shares_gdp[19] * GDP,
  )) %>%
  mutate(Region = 1) %>%
  dplyr::select(Years, Model, Region, Storslysia_GDP)

reg2_project <- final %>%
  mutate(Storslysia_GDP = case_when(
    Model == "SSP1" ~ reg_shares_gdp[2] * GDP,
    Model == "SSP2" ~ reg_shares_gdp[8] * GDP,
    Model == "SSP3" ~ reg_shares_gdp[14] * GDP,
    Model == "SSP5" ~ reg_shares_gdp[20] * GDP,
  )) %>%
  mutate(Region = 2) %>%
  dplyr::select(Years, Model, Region, Storslysia_GDP)

reg3_project <- final %>%
  mutate(Storslysia_GDP = case_when(
    Model == "SSP1" ~ reg_shares_gdp[3] * GDP,
    Model == "SSP2" ~ reg_shares_gdp[9] * GDP,
    Model == "SSP3" ~ reg_shares_gdp[15] * GDP,
    Model == "SSP5" ~ reg_shares_gdp[21] * GDP,
  )) %>%
  mutate(Region = 3) %>%
  dplyr::select(Years, Model, Region, Storslysia_GDP)

reg4_project <- final %>%
  mutate(Storslysia_GDP = case_when(
    Model == "SSP1" ~ reg_shares_gdp[4] * GDP,
    Model == "SSP2" ~ reg_shares_gdp[10] * GDP,
    Model == "SSP3" ~ reg_shares_gdp[16] * GDP,
    Model == "SSP5" ~ reg_shares_gdp[22] * GDP,
  )) %>%
  mutate(Region = 4) %>%
  dplyr::select(Years, Model, Region, Storslysia_GDP)

reg5_project <- final %>%
  mutate(Storslysia_GDP = case_when(
    Model == "SSP1" ~ reg_shares_gdp[5] * GDP,
    Model == "SSP2" ~ reg_shares_gdp[11] * GDP,
    Model == "SSP3" ~ reg_shares_gdp[17] * GDP,
    Model == "SSP5" ~ reg_shares_gdp[23] * GDP,
  )) %>%
  mutate(Region = 5) %>%
  dplyr::select(Years, Model, Region, Storslysia_GDP)

reg6_project <- final %>%
  mutate(Storslysia_GDP = case_when(
    Model == "SSP1" ~ reg_shares_gdp[6] * GDP,
    Model == "SSP2" ~ reg_shares_gdp[12] * GDP,
    Model == "SSP3" ~ reg_shares_gdp[18] * GDP,
    Model == "SSP5" ~ reg_shares_gdp[24] * GDP,
  )) %>%
  mutate(Region = 6) %>%
  dplyr::select(Years, Model, Region, Storslysia_GDP)
```

```
all_project_gdp <- rbind(reg1_project, reg2_project, reg3_project, reg4_project,
reg5_project,reg6_project)

population_gdp$`SSP Model` <- as.factor(population_gdp$`SSP Model`)
population_gdp$`Region` <- as.factor(population_gdp$`Region`)

cut_population_gdp <- population_gdp %>%
  filter(Years <= 2070)

ggplot(cut_population_gdp, aes(x=Years, y=Population)) +
  geom_line(aes(colour = Region), size = 1.3) + facet_grid(.~ `SSP Model`) +
  labs(y="Population", title = "Storslysia's Population by SSP Model and Region") +
  scale_colour_brewer(palette = "RdBu", direction = -1)

ggplot(cut_population_gdp, aes(x=Years, y=`GDP (in trillions)`)) +
  geom_line(aes(colour = Region), size = 1.3) + facet_grid(.~ `SSP Model`) +
  labs(y="GDP (in trillions)", title = "Storslysia's GDP by SSP Model and Region") +
  scale_colour_brewer(palette = "RdBu", direction = -1)

#fwrite(all_project_gdp, "all_project_gdp.csv")

all_project_gdp <- as.data.table(all_project_gdp)

ggplot(all_project_gdp, aes(x=Years, y = Storslysia_GDP, color = Region)) +geom_point()+
  facet_grid(. ~ `Model`)
##########################################################################################

## DAMAGE MODEL

hazard_data_cleaned <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx")

acute_data <- hazard_data_cleaned %>%
  filter(`Type` == "Acute")

chronic_data <- hazard_data_cleaned %>%
  filter(`Type` == "Chronic")

ggplot(chronic_data, aes(x = `Property Damage`, fill = `Hazard Event`)) +
  geom_histogram() + scale_fill_brewer(palette = "RdBu") +
  labs(title = "Histogram of Chronic Hazard Events", y = "Frequency", x = "Property Damage ($)")+
  scale_x_continuous(labels = dollar_format())

## CO2 EMISSIONS PROJECTION

co2 <- read_excel("Assignment/2023-student-research-emissions.xlsx",
                  sheet = "CO2",  skip = 1)

colnames(co2) <- c("Year", "SSP1", "SSP2", "SSP3", "SSP5")

p1 <- ggplot(co2, aes(x=Year, y=SSP1)) +geom_point() +geom_smooth(method = "loess", span = 1)

p2 <- ggplot(co2, aes(x=Year, y=SSP2)) +geom_point() +geom_smooth(method = "loess", span = 1)

p3 <- ggplot(co2, aes(x=Year, y=SSP3)) +geom_point() +geom_smooth(method = "loess", span = 1)
```

```
p4 <- ggplot(co2, aes(x=Year, y=SSP5)) +geom_point() +geom_smooth(method = "loess", span = 1)

#Creating a LOESS model to interpolate CO2 values

loess_1 <- loess(SSP1 ~ Year, data = co2)

newdata <- data.frame(Year = seq(2005,2150,by=1))
CO2 <- predict(loess_1, newdata = newdata)

SSP1_CO2 <- cbind(newdata, CO2)

SSP1_CO2 <- SSP1_CO2 %>%
  mutate(Model = "SSP1")

#Visualising results

loess_2 <- loess(SSP2 ~ Year, data = co2)
CO2 <- predict(loess_2, newdata = newdata)

SSP2_CO2 <- cbind(newdata, CO2)

SSP2_CO2 <- SSP2_CO2 %>%
  mutate(Model = "SSP2")

loess_3 <- loess(SSP3 ~ Year, data = co2)
CO2 <- predict(loess_3, newdata = newdata)

SSP3_CO2 <- cbind(newdata, CO2)

SSP3_CO2 <- SSP3_CO2 %>%
  mutate(Model = "SSP3")

loess_5 <- loess(SSP5 ~ Year, data = co2)
CO2 <- predict(loess_5, newdata = newdata)

SSP5_CO2 <- cbind(newdata, CO2)

SSP5_CO2 <- SSP5_CO2 %>%
  mutate(Model = "SSP5")

final_CO2<-rbind(SSP1_CO2, SSP2_CO2, SSP3_CO2, SSP5_CO2)

ggplot(final_CO2, aes(x=Year, y=CO2, colour = Model)) + geom_line(size = 1.3) +
  labs(y="Atmospheric CO2 (ppm)", title = "CO2 Emission Projections by SSP Model") +
  scale_colour_brewer(palette = "RdBu", direction = -1)

count_data <- acute_data %>%
  group_by(Year, Quarter, Region, `Hazard Event`) %>%
  summarise(Frequency = n())

flood_count <- count_data %>%
  filter(`Hazard Event` =="Flooding")
```

```
## DAMAGE MODEL v3 - USING EXTREME VALUE ANALYSIS & DISTRIBUTIONS
```

```
library(extRemes)
library(evd)
library(fitdistrplus)

non_zero_hazard <- hazard_data_cleaned$`Property Damage`[hazard_data_cleaned$`Property
Damage`!=0]

non_zero_hazard <- sort(non_zero_hazard, decreasing = T)

ggplot(non_zero_hazard, aes(`Property Damage`))+
  histogram()

###GUMBEL (for comparison only)

fit <- fevd(non_zero_hazard, type = "Gumbel")
summary(fit)
plot(fit)

rl <- return.level(fit, return.periods = c(2, 5, 10, 20, 50, 100))
rp <- qevd(1 - 1/rl, fit$results$par[[1]],  fit$results$par[[2]])

library(boot)

set.seed(123)

boot_rp <- function(data, index) {
  fit <- fevd(data[index], type = "Gumbel")
  rl <- return.level(fit, return.periods = c(2, 5, 10, 20, 50, 100))
  rp <- qevd(1 - 1/rl, fit$results$par[[1]],  fit$results$par[[2]])
  return(rp)
}
boot_results <- boot(non_zero_hazard, boot_rp, R = 1000)

# Calculate the confidence intervals for the return period estimates
ci <- boot.ci(boot_results, type = "basic", conf = 0.95)
rp <- apply(boot_results$t, 2, quantile, probs = c(0.5, 0.025, 0.975))

lower_ci <- apply(boot_results, 2, quantile, probs = 0.025)
upper_ci <- apply(boot_results, 2, quantile, probs = 0.975)

boot_results <- boot(non_zero_hazard, boot_rp, R = 1000)

quantile(boot_results$t, probs = c(.025, .975), type = 6)

boot_ci <- boot.ci(boot_results, type = "perc", conf = 0.95)

plot(boot_results$t, type = "l", xlab = "Bootstrap Samples", ylab = "Return Period", main =
"Bootstrapped Return Periods")
lines(c(1, length(boot_results$t)), rep(rp[1], 2), lty = 2, col = "red")
lines(c(1, length(boot_results$t)), rep(rp[2], 2), lty = 2, col = "blue")
legend("topright", legend = c("2-year", "5-year", "Bootstrapped CI"), lty = c(2, 2, 1), col = c("red",
"blue", "black"))
abline(h = boot_ci[1,], lty = 1)
abline(h = boot_ci[2,], lty = 1)
```

```
##WEIBULL

fit <- fitdist(non_zero_hazard, "weibull")

rp <- c(2, 5, 10, 25, 50, 100)

quantiles <- qweibull(1 - 1/rp, shape = fit$estimate["shape"],
                      scale = fit$estimate["scale"])

return_periods <- 1/(1 - pweibull(quantiles, shape = fit$estimate["shape"],
                                  scale = fit$estimate["scale"]))
lower_ci <- 1/(1 - pweibull(qweibull(1 - 0.025, shape = fit$estimate["shape"],
                                     scale = fit$estimate["scale"]),
                            shape = fit$estimate["shape"],
                            scale = fit$estimate["scale"]))
upper_ci <- 1/(1 - pweibull(qweibull(1 - 0.975, shape = fit$estimate["shape"],
                                     scale = fit$estimate["scale"]),
                            shape = fit$estimate["shape"],
                            scale = fit$estimate["scale"]))

results <- data.frame(Return_Period = return_periods, Quantile = quantiles,
                      Lower_CI = lower_ci, Upper_CI = upper_ci)

print(results)


### FINAL WEIBULL MODEL !!!

acute_region_fit <- function(region){
  non_zero_hazard <- sort(hazard_data_cleaned$`Property Damage`[hazard_data_cleaned$`Property
Damage`!=0 & hazard_data_cleaned$Region == region & hazard_data_cleaned$Type == "Acute"],
decreasing = T)

  fit <- fitdist(non_zero_hazard, "weibull")
  rp <- c(2, 10, 50, 100)

  quantiles <- qweibull(1 - 1/rp, shape = fit$estimate["shape"],
                        scale = fit$estimate["scale"])

  return_periods <- 1/(1 - pweibull(quantiles, shape = fit$estimate["shape"],
                                    scale = fit$estimate["scale"]))

  boot_rp <- function(data, index, rp) {
    fit <- fitdist(data[index], "weibull")
    quantiles <- qweibull(1 - 1/rp, shape = fit$estimate["shape"],
                          scale = fit$estimate["scale"])
    return(quantiles)
  }

  boot_results <- boot(data = non_zero_hazard, statistic = boot_rp,
                       R = 1000, rp = rp)

  lower_ci <- c()
  upper_ci <- c()
```

```
  for (i in 1:4) {
    lower_ci[i] <- boot.ci(boot_results, type = "perc", index = i)$perc[1,4]
    upper_ci[i] <- boot.ci(boot_results, type = "perc", index = i)$perc[1,5]
  }

  results <- data.frame(Return_Period = return_periods, Quantile = quantiles,
                        Lower_CI = lower_ci, Upper_CI = upper_ci)

  results <- results %>%
    mutate(`Annual Cost` = Quantile/Return_Period) %>%
    mutate(`Lower CI` = Lower_CI/Return_Period) %>%
    mutate(`Upper CI` = Upper_CI/Return_Period) %>%
    mutate(Region = region) %>%
    mutate(Year = 2020)

  return(results)

}

chronic_region_fit <- function(region){
  non_zero_hazard <- sort(hazard_data_cleaned$`Property Damage`[hazard_data_cleaned$`Property
Damage`!=0 & hazard_data_cleaned$Region == region & hazard_data_cleaned$Type == "Chronic"],
decreasing = T)

  fit <- fitdist(non_zero_hazard, "weibull")
  rp <- c(2, 10, 50, 100)

  quantiles <- qweibull(1 - 1/rp, shape = fit$estimate["shape"],
                        scale = fit$estimate["scale"])

  return_periods <- 1/(1 - pweibull(quantiles, shape = fit$estimate["shape"],
                                    scale = fit$estimate["scale"]))

  boot_rp <- function(data, index, rp) {
    fit <- fitdist(data[index], "weibull")
    quantiles <- qweibull(1 - 1/rp, shape = fit$estimate["shape"],
                          scale = fit$estimate["scale"])
    return(quantiles)
  }

  boot_results <- boot(data = non_zero_hazard, statistic = boot_rp,
                       R = 1000, rp = rp)

  lower_ci <- c()
  upper_ci <- c()

  for (i in 1:4) {
    lower_ci[i] <- boot.ci(boot_results, type = "perc", index = i)$perc[1,4]
    upper_ci[i] <- boot.ci(boot_results, type = "perc", index = i)$perc[1,5]
  }

  results <- data.frame(Return_Period = return_periods, Quantile = quantiles,
                        Lower_CI = lower_ci, Upper_CI = upper_ci)

  results <- results %>%
```

```
    mutate(`Annual Cost` = Quantile/Return_Period) %>%
    mutate(`Lower CI` = Lower_CI/Return_Period) %>%
    mutate(`Upper CI` = Upper_CI/Return_Period) %>%
    mutate(Region = region) %>%
    mutate(Year = 2020)

  return(results)

}

final_results <- data.frame()

for (j in 1:6) {
  results <- acute_region_fit(j)
  final_results <- rbind(final_results,results)
}

final_results2 <- data.frame()

for (j in 1:6) {
  results <- chronic_region_fit(j)
  final_results2 <- rbind(final_results2,results)
}


graphing <- final_results %>%
  dplyr::select(Year, Region, Return_Period, `Annual Cost`, `Lower CI`, `Upper CI`)

graphing$Region <- as.character(final_results$Region)
graphing$Return_Period <- as.character(round(graphing$Return_Period,0))

ggplot(graphing, aes(x = factor(`Return_Period`, level = c("2","10", "50","100")), y = `Annual Cost`,
color= Region)) +
  geom_point(position=position_dodge(width=0.5)) +
  geom_errorbar(aes(ymin = `Lower CI`, ymax = `Upper CI`), width = 0.2,
position=position_dodge(width=0.5)) +
  xlab("Return Period") +
  ylab("Annual Cost") +
  ggtitle("Annual Cost for All Hazard Events")

##

graphing2 <- final_results2 %>%
  dplyr::select(Year, Region, Return_Period, `Annual Cost`, `Lower CI`, `Upper CI`)

graphing2$Region <- as.character(final_results$Region)
graphing2$Return_Period <- as.character(round(graphing2$Return_Period,0))

ggplot(graphing2, aes(x = factor(`Return_Period`, level = c("2","10", "50","100")), y = `Annual Cost`,
color= Region)) +
  geom_point(position=position_dodge(width=0.5)) +
  geom_errorbar(aes(ymin = `Lower CI`, ymax = `Upper CI`), width = 0.2,
position=position_dodge(width=0.5)) +
  xlab("Return Period") +
  ylab("Annual Cost") +
```

```
  ggtitle("Annual Cost for Chronic Hazard Events")


#Projecting into the future

rp_factors <- read_excel("Assignment/2023-student-research-emissions.xlsx", sheet = "Return Period
Factors 2")

projecting <- final_results %>%
  dplyr::select(Year, Region, Return_Period, Quantile, Lower_CI, Upper_CI) %>%
  rename(`Return Period` = Return_Period)

n_replicates <- 4
replicated_df <- do.call(rbind, replicate(n_replicates, projecting, simplify = FALSE))
replicated_df$`SSP Model`<- rep(c(1, 2, 3, 5), each = nrow(projecting))
replicated_df <- replicated_df[,-1]

#Rounding error with return factor 100
replicated_df$`Return Period` <- round(replicated_df$`Return Period`,0)
rp_factors$`Return Period` <- round(rp_factors$`Return Period`,0)

check <- merge(rp_factors, replicated_df, by = c("Return Period", "SSP Model"))

final_check <- check %>%
  mutate(`Annual Cost` = Quantile/`Return Period Factor`) %>%
  mutate(`Lower CI` = `Lower_CI`/`Return Period Factor`) %>%
  mutate(`Upper CI` = `Upper_CI`/`Return Period Factor`) %>%
  dplyr::select(Year, Region, `SSP Model`, `Return Period`, `Annual Cost`, `Lower CI`, `Upper
CI`) %>%
  rename(`Return_Period` = `Return Period`)

final_final <- rbind(final_check, replicated_df)

region_1 <- final_final %>%
  filter(Region == 1) %>%
  filter(`SSP Model` ==1)

ggplot(region_1, aes(x = Year, y = `Annual Cost`, color= `Return_Period`)) +
  geom_point(position=position_dodge(width=0.5)) +

  geom_errorbar(aes(ymin = `Lower CI`, ymax = `Upper CI`), width = 0.2,
position=position_dodge(width=0.5)) +
  xlab("Return Period") +
  ylab("Annual Cost") +
  ggtitle("Annual Cost for Hazard Events")

household_value <- read_excel("Assignment/2023-student-research-eco-dem-data.xlsx",
                              sheet = "Sheet1")

household1 <- hazard_data_cleaned %>%
  group_by(Year, Region,`Type`) %>%
  summarise(`Property Damage` = sum(`Property Damage`)) %>%
  group_by(Year, Region,`Type`) %>%
  summarise(`Property Damage` = sum(`Property Damage`)) %>%
  group_by(Region,`Type`) %>%
```

```
  summarise(`Average Annual Property Damage` = mean(`Property Damage`))

household2 <- merge(household1, household_value, by = "Region")

household2 <- household2 %>%
  mutate(`Percentage Affected` = `Average Annual Property Damage`/`Total Household Value`)

final_final_SSP5 <- final_check %>%
  filter(`SSP Model`==1)

write_xlsx(final_final_SSP1, "test.xlsx")

##GEV (for comparison only)

boot_rp <- function(data, i) {
  fit <- fevd(non_zero_hazard, type = "GEV")
  rl <- c(2, 5, 10, 25, 50, 100)
  q <- qevd(1 - 1/rl, loc = fit$results$par[[1]], scale = fit$results$par[[2]], shape = fit$results$par[[3]])
  return(q)
}

boot_results <- boot(non_zero_hazard, boot_rp, R = 1000)

q_ci <- boot.ci(boot_results, type = "basic")

lower_ci <- q_ci$basic[, "lower"]
upper_ci <- q_ci$basic[, "upper"]

##FINAL FRECHET MODEL

library(VGAM)

region_fit <- function(region){
  non_zero_hazard <- sort(hazard_data_cleaned$`Property Damage`[hazard_data_cleaned$`Property
Damage`!=0 & hazard_data_cleaned$Region == region], decreasing = T)

  fit <- fitdist(non_zero_hazard, "frechet", method = "mle", lower = c(0, 0, 0), start =
list(location=1,scale=1, shape=1))
  rp <- c(2, 10, 50, 100)

  quantiles <- qfrechet(1 - 1/rp, location = fit$estimate["location"], shape = fit$estimate["shape"],
                    scale = fit$estimate["scale"], lower.tail = TRUE)

  return_periods <- 1/(1 - pfrechet(quantiles, location = fit$estimate["location"], shape =
fit$estimate["shape"],
                              scale = fit$estimate["scale"], lower.tail = TRUE))

  boot_rp <- function(data, index, rp) {
    fit <- fitdist(data[index], "frechet", method = "mle", lower = c(0, 0, 0), start = list(location=1,scale=1,
shape=1))
    quantiles <- qfrechet(1 - 1/rp, location = fit$estimate["location"], shape = fit$estimate["shape"],
                      scale = fit$estimate["scale"], lower.tail = TRUE)
    return(quantiles)
  }
```

```
  boot_results <- boot(data = non_zero_hazard, statistic = boot_rp,
                       R = 500, rp = rp)

  lower_ci <- c()
  upper_ci <- c()

  for (i in 1:4) {
    lower_ci[i] <- boot.ci(boot_results, type = "perc", index = i)$perc[1,4]
    upper_ci[i] <- boot.ci(boot_results, type = "perc", index = i)$perc[1,5]
  }

  results <- data.frame(Return_Period = return_periods, Quantile = quantiles,
                        Lower_CI = lower_ci, Upper_CI = upper_ci)

  results <- results %>%
    mutate(`Annual Cost` = Quantile/Return_Period) %>%
    mutate(`Lower CI` = Lower_CI/Return_Period) %>%
    mutate(`Upper CI` = Upper_CI/Return_Period) %>%
    mutate(Region = 6) %>%
    mutate(Year = 2020)

  return(results)

}

final_results <- data.frame()

for (j in 1:6) {
  results <- region_fit(j)
  final_results <- rbind(final_results,results)
  out <- paste0("Code finished running for Region ", j, ".")  # Some output
  print(out)
}


View(final_check)

##Household Groupings

household_groups <- read_excel("Assignment/2023-student-research-eco-dem-data.xlsx",
                               sheet = "Household Groups")

n_replicates <- 4
replicated_results <- do.call(rbind, replicate(n_replicates, graphing, simplify = FALSE))
replicated_results$`Household Group`<- rep(c(1, 2, 3, 4), each = nrow(graphing))

merged_household_groups <- merge(replicated_results, household_groups, by = c("Region",
"Household Group"))

housing_test <- graphing %>%
  mutate(Percentage = case_when(Return_Period == "2" ~ 0.05,
                                Return_Period == "10" ~  0.25,
                                Return_Period == "50" ~ 0.75,
                                Return_Period == "100" ~ 1))
```

```
housing_test2 <- merge(housing_test, household_value, by = "Region")

housing_test2 <- housing_test2%>%
  mutate(households_affected = `Annual Cost`/(`Median Value`*Percentage))


## Cumulative sum of number of high-risk houses relocated
#SSP1
hazard_data_cleaned_ssp1 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx",
                                       sheet = "Projection - SSP1")
hazard_data_cleaned_ssp1 <- hazard_data_cleaned_ssp1[-18865,]
hazard_data_cleaned_ssp1 <- hazard_data_cleaned_ssp1[-18865, c(1:4, 8, 24)]

hazard_data_cleaned_ssp1_sum <- hazard_data_cleaned_ssp1 %>%
  group_by(Year, Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(sum = cumsum(`Number of High-Risk Houses Relocated`)) %>%
  ungroup() %>%
  group_by(Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(cumulative_sum = cumsum(`Number of High-Risk Houses Relocated`))

write_xlsx(hazard_data_cleaned_ssp1_sum,
"/Users/sharonzhou/Desktop/hazard_data_cleaned_ssp1.xlsx")

#SSP2
hazard_data_cleaned_ssp2 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx",
                                       sheet = "Projection - SSP2")

hazard_data_cleaned_ssp2 <- hazard_data_cleaned_ssp2[-18865, c(1:4, 8, 24)]

hazard_data_cleaned_ssp2_sum <- hazard_data_cleaned_ssp2 %>%
  group_by(Year, Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(sum = cumsum(`Number of High-Risk Houses Relocated`)) %>%
  ungroup() %>%
  group_by(Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(cumulative_sum = cumsum(`Number of High-Risk Houses Relocated`))

write_xlsx(hazard_data_cleaned_ssp2_sum,
"/Users/sharonzhou/Desktop/hazard_data_cleaned_ssp2.xlsx")

#SSP3
hazard_data_cleaned_ssp3 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx",
                                       sheet = "Projection - SSP3")

hazard_data_cleaned_ssp3 <- hazard_data_cleaned_ssp3[-18865, c(1:4, 8, 24)]

hazard_data_cleaned_ssp3_sum <- hazard_data_cleaned_ssp3 %>%
  group_by(Year, Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(sum = cumsum(`Number of High-Risk Houses Relocated`)) %>%
  ungroup() %>%
  group_by(Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(cumulative_sum = cumsum(`Number of High-Risk Houses Relocated`))

write_xlsx(hazard_data_cleaned_ssp3_sum,
"/Users/sharonzhou/Desktop/hazard_data_cleaned_ssp3.xlsx")
```

```
#SSP5
hazard_data_cleaned_ssp5 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx",
                                       sheet = "Projection - SSP5")

hazard_data_cleaned_ssp5 <- hazard_data_cleaned_ssp5[-18865, c(1:4, 8, 24)]

hazard_data_cleaned_ssp5_sum <- hazard_data_cleaned_ssp5 %>%
  group_by(Year, Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(sum = cumsum(`Number of High-Risk Houses Relocated`)) %>%
  ungroup() %>%
  group_by(Region, `SSP Model`, Return_Period, `Household Group`) %>%
  mutate(cumulative_sum = cumsum(`Number of High-Risk Houses Relocated`))

write_xlsx(hazard_data_cleaned_ssp5_sum,
"/Users/sharonzhou/Desktop/hazard_data_cleaned_ssp5.xlsx")

## Tidying stuff
a1 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx", sheet = "Projection - SSP1")
a1 <- head(a1, -1)
a1 <- a1 %>%
  select('Year', 'Region', 'SSP Model', 'Return_Period', 'Household Group',
         'Total Projected Annual Cost (WOI)', 'Total Projected Annual Cost (WI)')
a2 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx", sheet = "Projection - SSP2")
a2 <- head(a2, -1)
a2 <- a2 %>%
  select('Year', 'Region', 'SSP Model', 'Return_Period', 'Household Group',
         'Total Projected Annual Cost (WOI)', 'Total Projected Annual Cost (WI)')
a3 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx", sheet = "Projection - SSP3")
a3 <- head(a3, -1)
a3 <- a3 %>%
  select('Year', 'Region', 'SSP Model', 'Return_Period', 'Household Group',
         'Total Projected Annual Cost (WOI)', 'Total Projected Annual Cost (WI)')
a5 <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx", sheet = "Projection - SSP5")
a5 <- head(a5, -1)
a5 <- a5 %>%
  select('Year', 'Region', 'SSP Model', 'Return_Period', 'Household Group',
         'Total Projected Annual Cost (WOI)', 'Total Projected Annual Cost (WI)')
all <- rbind(a1, a2, a3, a5)

write_xlsx(all, "/Users/sharonzhou/Desktop/all.xlsx")

initial_graphing <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx",
                               sheet = "Graphing")

final_graphing <- initial_graphing %>%
  group_by(Year, `SSP Model`) %>%
  summarise_at(c("Total Projected Annual Cost (WI)",
                 "Total Projected Annual Cost (WOI)",
                 "Lower Annual Cost (WI)",
                 "Lower Annual Cost (WOI)",
                 "Upper Annual Cost (WI)",
                 "Upper Annual Cost (WOI)"),sum) %>%
  filter(Year <= 2070)

final_graphing$`SSP Model` <- as.factor(final_graphing$`SSP Model`)
```

```
#Graph without confidence intervals (without insurance)

ggplot(final_graphing, aes(x=Year, y=`Total Projected Annual Cost (WOI)`, color = `SSP Model`,
                    fill = `SSP Model`, group = `SSP Model`)) +
  geom_line(size = 1.3) +
  scale_fill_brewer(palette = "RdBu", direction = -1) +
  scale_colour_brewer(palette = "RdBu", direction = -1) +
  labs(title = "Annual Economic Cost Projection (WOI) by SSP Model",
       y= "Projected Costs (P)") +
  scale_y_continuous(labels = unit_format(unit = "B", scale = 1e-9))

#Graph without confidence intervals (with insurance)

ggplot(final_graphing, aes(x=Year, y=`Total Projected Annual Cost (WI)`, color = `SSP Model`,
                    fill = `SSP Model`, group = `SSP Model`)) +
  geom_line(size = 1.3) +
  scale_fill_brewer(palette = "RdBu", direction = -1) +
  scale_colour_brewer(palette = "RdBu", direction = -1) +
  labs(title = "Annual Economic Cost Projection (WI) by SSP Model",
       y= "Projected Costs (P)") +
  scale_y_continuous(labels = unit_format(unit = "B", scale = 1e-9))

#Graph with confidence intervals (without insurance)

ggplot(final_graphing, aes(x=Year, y=`Total Projected Annual Cost (WOI)`, color = `SSP Model`,
                   fill = `SSP Model`, group = `SSP Model`)) +
  facet_grid(.~`SSP Model`) +
  geom_line(size = 1.3) +
  geom_ribbon(aes(ymin = `Lower Annual Cost (WOI)`, ymax = `Upper Annual Cost (WOI)`),
            alpha=.3, linetype=0) +
  scale_fill_brewer(palette = "RdBu", direction = -1) +
  scale_colour_brewer(palette = "RdBu", direction = -1) +
  labs(title = "Annual Economic Cost Projection (WOI) by SSP Model", y= "Projected Costs (P)") +
  scale_y_continuous(labels = unit_format(unit = "B", scale = 1e-9)) +
  theme(axis.text.x = element_text(angle = 90))

#Graph with confidence intervals (with insurance)

ggplot(final_graphing, aes(x=Year, y=`Total Projected Annual Cost (WI)`, color = `SSP Model`,
                    fill = `SSP Model`, group = `SSP Model`)) +
  facet_grid(.~`SSP Model`) +
  geom_line(size = 1.3) +
  geom_ribbon(aes(ymin = `Lower Annual Cost (WI)`, ymax = `Upper Annual Cost (WI)`),
            alpha=.3, linetype=0) +
  scale_fill_brewer(palette = "RdBu", direction = -1) +
  scale_colour_brewer(palette = "RdBu", direction = -1) +
  labs(title = "Annual Economic Cost Projection (WI) by SSP Model", y= "Projected Costs (P)") +
  scale_y_continuous(labels = unit_format(unit = "B", scale = 1e-9), limits=c(0, 7000000000))+
  theme(axis.text.x = element_text(angle = 90))

#Voluntary and involuntary cost constrast

voluntary_involuntary_cost <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx",
                       sheet = "Voluntary Involuntary Costs")
```

```
voluntary_involuntary_cost$Year <- as.factor(voluntary_involuntary_cost$Year)
voluntary_involuntary_cost$Region <- as.factor(voluntary_involuntary_cost$Region)
voluntary_involuntary_cost$`SSP Model` <- as.factor(voluntary_involuntary_cost$`SSP Model`)

voluntary_involuntary_cost_long<-reshape2::melt(voluntary_involuntary_cost, id = c("SSP Model",
"Year", "Region"))

voluntary_involuntary_cost_long2 <- voluntary_involuntary_cost_long %>%
  group_by(Year, `SSP Model`, variable) %>%
  rename(Type = variable) %>%
  summarise(sum = sum(value))

#Graph of voluntary and involuntary costs over all regions

ggplot(voluntary_involuntary_cost_long2, aes(x=Year, y=sum,
                         fill = Type)) +
  facet_grid(.~`SSP Model`) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Cumulative Program Cost Projection by SSP Model",
       y = "Cost (P)") +
  scale_y_continuous(labels = unit_format(unit = "B", scale = 1e-9))

#Graph of voluntary and involuntary costs by region (short-term)

voluntary_involuntary_cost_short <- voluntary_involuntary_cost_long %>%
  rename(Type = variable) %>%
  filter(Year == 2030)

ggplot(voluntary_involuntary_cost_short, aes(x=Type, y=value,
                                    fill = Region)) +
  facet_grid(.~`SSP Model`) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Total Program Cost at 2030 by Region and SSP Model",
       y = "Cost (P)") +
  scale_y_continuous(labels = unit_format(unit = "M", scale = 1e-6))+
  scale_fill_brewer(palette = "RdBu") +
  scale_colour_brewer(palette = "RdBu")

#Graph of voluntary and involuntary costs by region (long-term)

voluntary_involuntary_cost_longterm <- voluntary_involuntary_cost_long %>%
  rename(Type = variable) %>%
  filter(Year == 2070)

ggplot(voluntary_involuntary_cost_longterm, aes(x=Type, y=value,
                                    fill = Region)) +
  facet_grid(.~`SSP Model`) +
  geom_bar(stat = "identity", position = "dodge") +
  labs(title = "Total Program Cost at 2070 by Region and SSP Model",
       y = "Cost (P)") +
  scale_y_continuous(labels = unit_format(unit = "M", scale = 1e-6))+
  scale_fill_brewer(palette = "RdBu") +
  scale_colour_brewer(palette = "RdBu")
```

```
#Sigmoid graph

sigmoid <- read_excel("Assignment/Data/hazard_data_cleaned.xlsx",
                      sheet = "Sigmoid")

sigmoid_processed <- sigmoid %>%
  select(Year, `Relocation percentage`)

ggplot(sigmoid_processed, aes(x=Year, y=`Relocation percentage`)) +
  geom_line(size = 1.3) + labs(title = "Annual Percentage of Buyback Scheme Participants in
Storslysia",
           y= "Buyback Acceptance (%)")
```

SECTION 9: REFERENCES

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