

# 2023 SOA Research Case Study

## Relocation Social Insurance

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# Contents

<b>1. Executive Summary .....</b>	<b>3</b>
<b>2. Purpose and Objectives .....</b>	<b>3</b>
<b>2.1 Purpose and Objective .....</b>	<b>3</b>
<b>3. Program Design.....</b>	<b>4</b>
<b>3.1 Buyback Scheme – Voluntary Relocation .....</b>	<b>4</b>
<b>3.3 Hazard Insurance Coverage .....</b>	<b>4</b>
<b>3.4 Requirements of Claimants .....</b>	<b>5</b>
<b>3.5 Other Features .....</b>	<b>5</b>
<b>3.6 Evaluation Timeframes .....</b>	<b>5</b>
<b>4. Assumptions .....</b>	<b>6</b>
<b>5. Pricing &amp; Costs .....</b>	<b>7</b>
<b>5.1 Methodology.....</b>	<b>7</b>
<b>5.2 Costs without the Program .....</b>	<b>7</b>
<b>5.3 Costs of the Program .....</b>	<b>8</b>
<b>5.3.1 Buyback Scheme .....</b>	<b>8</b>
<b>5.3.2 Emergency Hazard Insurance .....</b>	<b>8</b>
<b>6. Risk and Risk Mitigation Considerations .....</b>	<b>10</b>
<b>6.1 Quantitative Risks &amp; Sensitivity Analysis.....</b>	<b>10</b>
<b>7. Data and Data Limitations.....</b>	<b>12</b>
<b>8. Appendix .....</b>	<b>13</b>
Appendix A – Loss Normalisation .....	13
Appendix B – Detailed Information on Climate Hazard Model .....	13
Appendix C – Buyback Valuation Methodology .....	14
Appendix D – Admin Expense and Temporary Housing Calculations .....	14
Appendix E – Yearly Breakdown of Costs of the Program.....	15
Appendix F – Pricing of Proposed Funding System for the Program .....	15
Appendix G – Calculation of Risk Margins.....	16
Appendix H – Detailed Information on Post Relocation Issues.....	16
Appendix - Additional data used .....	18
<b>9. References .....</b>	<b>28</b>

## **1. Executive Summary**

In order to manage the financial and social risks of permanent displacement associated with catastrophe-related accidents, ensuring resilience to natural disasters will be essential to how Storslysia adapts to its rapidly changing climate environment. This report, through analysis of Storslysia's historical catastrophe data, explores how Storslysia can effectively manage its worsening climate situation by implementing a social insurance program addressing both voluntary relocation costs through a buyback scheme and involuntary costs through a hazard insurance program. The report provides comprehensive detail on the design of the program as well as the calculation of revenue and costs associated with the program. Moreover, due to the highly volatile nature of catastrophes and climate risk, the report also investigates further risks through a sensitivity analysis where several factors effecting the frequency and severity of catastrophes aggravate at a higher level than expected.

## **2. Purpose and Objectives**

### **2.1 Purpose and Objective**

Natural disasters are an inescapable fact of life for those living in Storslysia. Because of this, an effective natural disaster insurance scheme is of utmost importance. Currently, there is a lack of protection against natural disaster, which necessitates government intervention. The newly proposed Social Insurance Program seeks to determine the most effective model for Storslysia's population providing a social insurance scheme covering both involuntary and voluntary displacement. Coverage is countrywide and addresses voluntary, proactive relocation as well as involuntary displacement following a catastrophic event.

The primary objective of the program is to manage Storslysia's exposure to financial impacts caused by catastrophic climate related events. Whilst complete prevention of climate catastrophes may not be possible, the program's main objective remains to minimise the impact of the damages to citizens. Sufficient claims reserving must be kept ensuring feasibility of the program. Analysis of change in expected liabilities and expected vs actual cost analysis, as more experience develops will be some of the key metrics that will need to be closely monitored and investigated frequently to ensure the financial sustainability of the program.

To report on these metrics, the program will publish annual reports highlighting the number of citizens receiving financial assistance, the amount of compensation provided, and the program's effectiveness in helping citizens recover from the financial impacts of these events. Additionally, the program will periodically review its metrics to ensure that they are still relevant and aligned with the objectives. The program will continually seek feedback from citizens, and industry partners to identify areas for improvement and to ensure that the program is meeting its objectives.

### **3. Program Design**

The program aims to address Storslysia's exposure to displacement risk through two key components. The first focuses on actions targeted at proactive voluntary relocation facilitated by a voluntary buyback scheme. The second component comprises of a hazard insurance program addressing involuntary displacement for those directly affected by climate catastrophes. Claim payouts for this hazard insurance program are designed to alleviate financial pressures associated with property damage, replacement accommodation and other costs.

#### **3.1 Buyback Scheme – Voluntary Relocation**

The first step of the plan aims to address voluntary relocation as a preventative measure through a buyback scheme. Individuals positioned in areas within each region that are deemed very high risk and in imminent danger will be offered a one-off option for their property to be purchased at pre-disaster affected prices by the Storslysia government through a buyback to aid in relocations to safer environments. The payment will be a lump sum to purchase their existing property, where the price will be agreed upon by both the government administrators and the property owners. Note that only properties in areas identified as high risk will be permitted to undertake the buyback program. Individuals will not be allowed to relocate existing high risk locations and instead must relocate to areas that are deemed safer. Individuals will be given a timeframe of 1 year to apply for the buy-back scheme and allowed sufficient time to organise movement as needed.

#### **3.2 Incentives and Considerations of the Buyback Scheme**

The voluntary buyback scheme offers households living in extreme risk areas the incentive to relocate to a safer area as they will be given the opportunity to sell their property at the market value pre-disaster. Typically, post natural disaster many properties in disaster impacted areas become unsellable or extremely low in value, leaving homeowners stuck with no options. Thus, this program will enable these people to retain their asset value and use the funds to move elsewhere. Similar programs have been run in Australia with great success (e.g., Queensland's Voluntary Home Buyback). The voluntary buyback scheme also offers policyholders a lengthy time window of 1 year to prepare for relocation. In contrast, forced relocation often results in various other challenges outside of obtaining new property such as employment which has shown to have various negative effects on individual's mental wellbeing. (Refer to Appendix H).

However, due to the costs and issues associated with relocations, the nature of these buybacks should be a one off as opposed to an ongoing system. Only those identified areas as extremely high risk will be eligible to sell their property to the government. Further iterations of buybacks should only be considered in the event of a very severe catastrophe or as a result of a thorough reassessment of catastrophe risk.

#### **3.3 Hazard Insurance Coverage**

The second component that is planned to address the ongoing costs of climate related loss is the hazard insurance program. The program is intended to help cover the costs associated with

repairing or rebuilding damaged property, as well as covering the costs of temporary housing or relocation expenses in the case of natural disaster. Importantly, the claims will only be covered if the Storslysian government has defined the event as a climate catastrophe. However, it's important to note that the program also has some limitations. The program may not cover damages that were caused by human error, negligence, or intentional actions, such as arson or vandalism. The program also will not cover damages for vehicles, bodily injuries, or personal belongings. It is therefore recommended that individuals also obtain private insurance to supplement their coverage.

### **3.4 Requirements of Claimants**

For individuals seeking to claim benefits from this social insurance program, there are several requirements that must be met. Firstly, claimants must reside in the affected region of the climate catastrophe and must provide evidence showcasing damage directly linked to this event. Finally, claimants must submit their claim within a specified time frame and comply with any additional requirements or requests for information from the program administrators. If a payout is made to repair or rebuild, claimants will be required to show that they have taken steps to prevent similar damages, if possible, in the future. By meeting these requirements, claimants can access the benefits provided by the program to help recover from the financial impacts of climate-related damages to their property.

### **3.5 Other Features**

The program will boast a simple and quick claim process for individuals to receive some compensation for their property damage as soon as possible. Much similar to the Australian Governments flood payments, citizens will have easy access to the claim process via a mobile app, and by answering a few quick questions will get access to compensation. The app and online tools will allow for a more streamlined claims process, individuals can focus on rebuilding their lives without worrying about complicated procedures.

Additionally, the program will implement additional education or workshops on how to prepare for and respond to climate catastrophes. The program will include initiatives to educate the public on emergency preparedness, evacuation plans, and disaster response strategies. By raising awareness and providing guidance, individuals can be better equipped to handle climate catastrophes and minimize their impact.

### **3.6 Evaluation Timeframes**

There needed to be a reliable estimate of the program's effectiveness and impact over both the short and long term. Five years is a reasonable amount of time to assess the initial outcomes of the program and the buyback scheme and make any adjustments based on the events and data gathered. Twenty years, on the other hand, provides a longer-term perspective on the programs performance and enables trend identification or patterns which may have emerged.

Secondly, the choice of five and twenty years aligns with typical timelines of climate change impacts. The frequency of climate-related catastrophes such as cyclones, floods, wildfires can

drastically change over a short period of time. By evaluating the program at five and twenty years, we can assess whether our insurance program is keeping up with the evolving nature of climate change impacts and adjusting accordingly. Lastly, conducting evaluations at five and twenty years also allows us to demonstrate our commitment to transparency and accountability to our stakeholders, including policyholders, investors, and regulators.

## 4. Assumptions

Modelling Assumptions	Rationale
Natural disaster frequency and severity will follow the same distribution as historical data over the next 5- 20 years.	The impacts of climate change are likely to impact the severity and frequency of natural disasters in the much longer term than relevant for policy analysis (i.e 50 - 100 years later). We have performed sensitivity analysis in the case this is not true.
Storslysia GDP as a percentage of Global GDP stays constant	Only 2 years of GDP was provided, assumption was required to project GDP.
Storslysia population as a percentage of Global population stays constant.	Only 3 years of population was provided, assumption was required to project population.
Storslysia GDP is forecasted using a linear regression model with population as a regressor	Based on historical data, a relative linear relationship between GDP and population was seen. Thus, the national GDP was forecasted using the estimated population figures.
More recent years of injuries and fatalities were given a higher weighting	Accidents that have occurred more recently are likely to be better predictors of future accidents
Accidents resulting in fatalities were given a higher weighting compared to injuries	Accidents resulting in death are likely to be more disastrous than accidents resulting in injuries
Program Assumptions	Rationale
Existing property insurance excludes coverage for extreme catastrophe damage	Many countries tend to exclude climate disaster coverage in insurance policies. No data provided about existing insurance coverage in Storslysia
Populations identified as eligible for the buyback program will accept and undertake voluntary relocation.	These populations are typically at extreme risk and are willing to reduce their climate risk given the opportunity. Past cases and studies have also shown a very high acceptance of voluntary buybacks.
Those populations identified as high risk for the buyback program correspond to historical extreme property damage costs.	Historical extreme property damage costs can be indicative of high severity or frequency of climate catastrophes affecting these populations.
10% cost of capital applied over 20 year horizon for program	Information on financial performance of government was not provided and thus a historical similar programs Cost of Capital was used.

## 5. Pricing & Costs

### 5.1 Methodology

Due to the relatively infrequent nature of natural hazards, historical data for the extreme events is relatively scarce. As such, a probabilistic approach is typically the most appropriate way to handle natural hazard phenomena.

Given Storslysia's historical data for the last 60 years, property damage costs were first normalised to 2020 values with inflation, population, and GDP (See Appendix A). Taking the logarithm of property damage costs, an appropriate distribution was fitted to the historical property damage. For each region, Monte Carlo simulation was then used to project hazards and the associated property damage cost (Appendix B).

### 5.2 Costs without the Program

Under the assumption that hazards will develop under the same frequency and severity as historical events, the mean total cost of property damage over all 6 Regions for 5 years is **¥6,505,385,068**. Over the long term (20 years) the total costs will be **¥45,688,293,287**. Within each region, the "normalised" total property damage and key statistics are shown in Table 1 along with the uncertainty.

	<b>5 years</b>				
	No of Events	Total Damage Cost over the period	Std Dev	VaR	TVaR
<b>Region 1</b>	51	504,956,825	362,854,591	1,179,998,832	1,637,727,023
<b>Region 2</b>	68	4,199,746,359	15,432,913,091	16,339,354,914	49,833,255,271
<b>Region 3</b>	65	1,090,027,141	7,511,563,529	2,255,231,645	12,923,916,658
<b>Region 4</b>	42	274,596,296	353,831,148	785,515,820	1,279,912,989
<b>Region 5</b>	35	296,949,909	690,660,677	905,291,032	2,213,253,366
<b>Region 6</b>	21	139,108,538	192,463,254	423,990,459	768,256,391
<b>Total Storslysia</b>	280	6,505,385,068			
	<b>20 years</b>				
	No of Events	Total Damage Cost over the period	Std Dev	VaR	TVaR
<b>Region 1</b>	205	2,010,669,426	778,940,508	3,468,393,732	4,273,805,375
<b>Region 2</b>	263	36,858,907,283	312,734,004,934	78,893,787,439	538,917,608,510
<b>Region 3</b>	257	3,751,914,952	13,965,982,498	7,725,935,665	30,926,395,387
<b>Region 4</b>	168	1,083,585,868	628,022,733	2,158,460,384	3,038,194,533
<b>Region 5</b>	141	1,427,835,892	4,485,713,401	3,145,110,694	9,378,163,245
<b>Region 6</b>	82	555,379,866	382,028,983	1,200,339,381	1,739,074,810
<b>Total Storslysia</b>	1,116	45,688,293,287			

Table 1 Cost of Climate Catastrophe without Program.

It is evident that Region 2 will have the highest property damage cost in the next few years (up to 80% of total damage). This is due to the significant higher population and house prices skewing more to the higher ends. The occurrence of natural disaster catastrophes is also the highest in region 2 with many coastal disasters, hail, and flooding.



It is notable that volatility for damage estimates for each region is quite high for most regions. This is because climate disasters are extremely volatile and unpredictable, making volatility a key risk in climate forecasting and modelling. We have considered this volatility in our program.

### 5.3 Costs of the Program

#### 5.3.1 Buyback Scheme

Sufficient reserves must be established to be able to repurchase properties for the buyback program. The reserves were estimated by assessing the percentage of houses considered as “very high-risk” for each region with historical data (See Appendix C). The grand total of reserves required for all of Storslysia is **¥4,090,476,539**. Note that this is the cost of all the at-risk properties, under the assumption that everyone will accept the buyback.

Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	Total
440,879,170	1,899,479,015	658,770,612	175,219,043	777,465,776	138,662,922	4,090,476,539

Table 2: Buyback scheme cost to fund by region.

#### 5.3.2 Emergency Hazard Insurance

Since the buyback program will be a one-off initiative proposed to be completed over the next year, costs specified hereafter will address the ongoing hazard insurance program unless specified.

##### 5.3.2.1 Property Damage Costs

With the buyback program implemented, high risk individuals have been relocated to safer areas and no longer vulnerable to extremely large damages from climate disasters. As such, within each region the distribution for property damage will shift left, as well as a reduction in standard deviation. In Figure 1, the red histogram represents log of property damage prior to the buyback, and the blue histogram represents the log of property damage post buyback. With the new distribution, new costs for Storslysia were simulated.

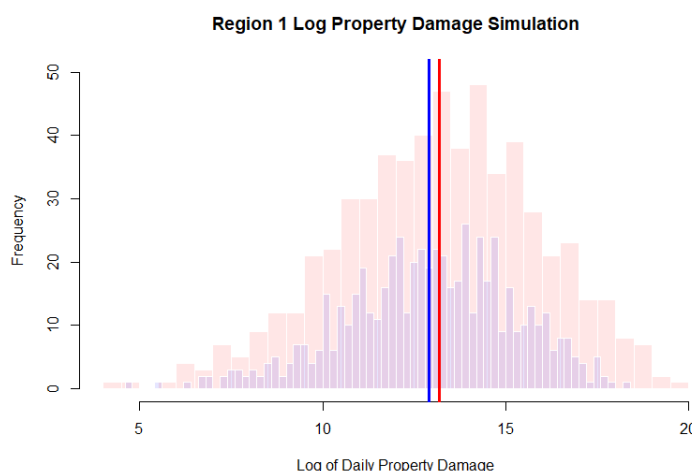


Figure 1: Modelled Impact of Buyback Program

We have also considered admin, handling, and temporary housing costs for those who require additional assistance while property damage is being repaired or retrofitted post disaster (See Appendix D). The summary of the program costs is summarised in Table 3.

Considering only the cost of the climate damage as compared to without the program, it is evident that estimated value of property damage is significantly lower, up to 70% lower (3.24 billion with the program compared to 6.51 billion without program). Further, the volatility associated with the climate cost estimates has also reduced by around 3 folds, demonstrating the benefit of the



buyback initiative. However, we acknowledge the volatility is still quite high given the unpredictable nature of climate disasters. This is a key risk that would need to be managed, which we have proposed a funding strategy for in section 5.3.2.3. Alternatively, the government may look into reinsurance or catastrophe bonds in order to mitigate such uncertainty and risks.

	5 years						
	Climate Damage over the period	Admin Costs	Temporary Housing	Total Cost	Std	VaR	TVaR
Region 1	357,734,972	7,154,699	7,956,995	372,846,666	226,334,583	774,893,951	1,042,917,605
Region 2	1,835,752,591	36,715,052	29,785,522	1,902,253,165	6,654,271,386	6,373,555,831	21,928,853,932
Region 3	482,274,482	9,645,490	12,495,846	504,415,818	1,489,488,175	1,329,329,510	3,677,165,704
Region 4	158,349,382	3,166,988	5,646,840	167,163,210	150,036,527	407,019,882	600,518,582
Region 5	187,888,374	3,757,767	5,633,518	197,279,659	368,025,618	546,939,909	1,203,957,106
Region 6	92,210,994	1,844,220	2,658,188	96,713,402	104,704,701	254,514,873	446,181,246
Total	3,114,210,795	62,284,216	64,176,908	3,240,671,919			
	20 years						
Region 1	1,423,300,686	28,466,014	38,569,552	1,490,336,252	477,855,425	2,322,245,935	2,763,137,666
Region 2	9,435,356,168	188,707,123	206,422,039	9,830,485,330	51,808,689,152	24,873,441,904	96,836,557,386
Region 3	2,035,525,528	40,710,511	64,729,829	2,140,965,868	3,000,722,522	4,930,681,880	10,137,755,719
Region 4	627,993,322	12,559,866	27,178,979	667,732,167	278,236,079	1,139,321,034	1,460,322,018
Region 5	805,396,420	16,107,928	29,736,928	851,241,276	1,459,624,733	1,861,229,548	3,854,080,053
Region 6	371,385,445	7,427,709	13,099,994	391,913,148	204,831,922	735,561,713	979,444,756
Total	14,698,957,569	293,979,151	379,737,322	15,372,674,042			

Table 3: Costs under the program

### 5.3.2.2 Breakdown of Insurance Costs

As required by the program, the total costs of the program remain well within the limit of 10% of GDP over the next 20 years. The uncertainty range shows that there is a 95% confidence that the program costs will not exceed 5% of GDP in any given year. Note the higher value in the year 2021, which includes the additional cost of the buyback program (Appendix E).

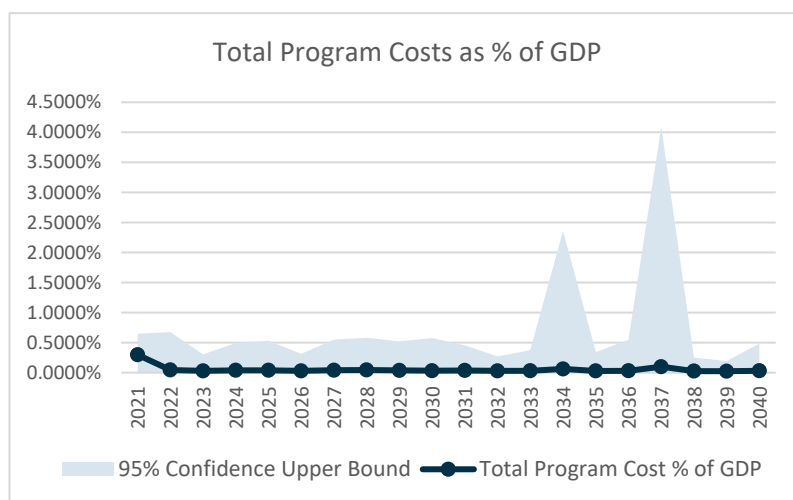


Figure 2: Program cost represented as % of GDP with 95% confidence interval

### 5.3.2.3 Revenue

Our team has proposed a potential funding system that could be used for this program, inspired by the Spanish “Consortio charge”. This system would require the working population to pay a fixed yearly surcharge based on region of residence, which is enough to cover the central estimate of climate property damage over that region. The government should then cover for anything

that deviates above the central estimate (given high volatility). For example, a value that could be up to the 95th percentile of the damage cost. (Appendix F)

#### 5.3.2.4 Capital Required

The capital required for the next 20 years will be **₪20,489,807,973** to cover for the whole of Storslysia. Assuming a constant risk-free rate over the next 20 years and 10% cost of capital, this converts to a risk margin **₪ 8,278,917,968** required today. This capital requirement was chosen with a 95% certainty that it will be sufficient to cover property damage over the next 20 years. See Appendix G for more detailed calculation.

	Estimated Total Cost	95 <sup>th</sup> Percentile Damage Cost	Capital Required <sup>(a)</sup>
<b>Region 1</b>	1,490,336,252	2,322,245,935	831,909,683
<b>Region 2</b>	9,830,485,330	24,873,441,904	15,042,956,574
<b>Region 3</b>	2,140,965,868	4,930,681,880	2,789,716,012
<b>Region 4</b>	667,732,166	1,139,321,034	471,588,867
<b>Region 5</b>	851,241,276	1,861,229,548	1,009,988,272
<b>Region 6</b>	391,913,148	735,561,713	343,648,565
<b>Total</b>	13,214,605,623		20,489,807,973 <sup>(b)</sup>

Table 4 Capital Required for Each Region

Notes:

- (a) 95% percentile damage Cost – Estimated Total Cost
- (b) Sum of capital required for all regions

## 6. Risk and Risk Mitigation Considerations

### 6.1 Quantitative Risks & Sensitivity Analysis

#### SPCC Scenarios and Impact on Costs

A key assumption made was that natural disaster frequency and severity will follow the same distribution as historical data over the foreseeable 20-year period. However, a risk is that climate change could potentially have a much larger impact on frequency and severity of hazards in Storslysia than predicted. Scenario analysis has been performed under the 4 potential emission scenarios and how it could impact costs of hazard insurance, under the assumption that increasing carbon emissions directly impacts the frequency of natural hazards.

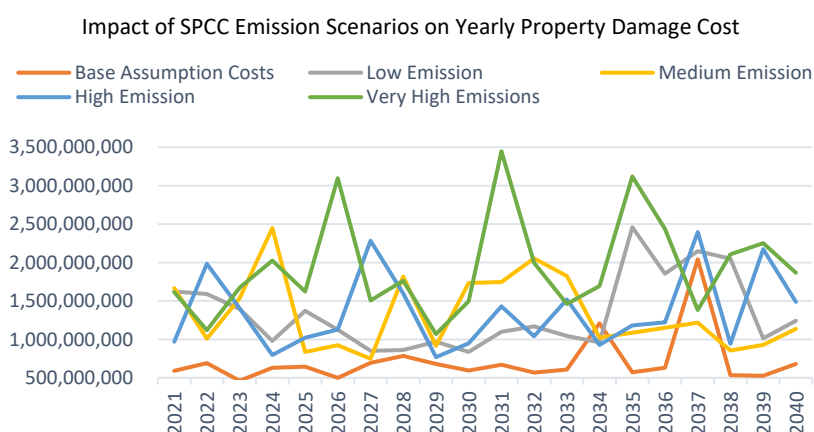


Figure 3: Impact of SPCC Emission Scenarios on Yearly Damage Costs

Table 5: Total Costs per Emission Scenarios

	no. events per year	total cost over 20 years
Base	56	14,698,957,570
Low Emissions	68	26,661,533,359
Medium Emissions	71	26,961,776,703
High Emissions	75	28,232,560,495
Very High Emissions	86	38,755,745,238

The impact of higher emissions leads to more frequent events is that property Damage Costs are much higher and more frequent. As such, the volatility of the natural disasters also increases, as we notice that the very high emissions case has larger peaks and troughs compared to the base assumption case.

Academic research has not yet been able to quantify the direct impact of climate change on the frequency and severity of natural disasters. As such, it will be a key component of the program to continuously monitor the development of natural disasters and adjust data and assumptions as necessary.

#### **Variations in Inflation and GDP Predictions and their Impact on Cost**

Since the accuracy of the claim costs prediction heavily relies on the accuracy of inflation, GDP and population forecasts, sensitivity analysis for each was conducted to gain a holistic view on potential financial impacts if the actual figures do not align with expectation.

Inflation	-10%	-5%	0%	+5%	+10%	GDP	-5%	-2.5%	0%	+2.5%	+5%
2021	-0.37%	-0.18%	0.00%	0.18%	0.37%	2021	-5.00%	-2.50%	0.00%	2.50%	5.00%
2025	-0.97%	-0.48%	0.00%	0.49%	0.97%	2025	-22.62%	-11.89%	0.00%	13.14%	27.63%
2030	-1.69%	-0.85%	0.00%	0.85%	1.71%	2030	-40.13%	-22.37%	0.00%	28.01%	62.89%
2040	-2.98%	-1.50%	0.00%	1.52%	3.06%	2040	-64.15%	-39.73%	0.00%	63.86%	165.33%

Figure 4: Variations in Inflation and GDP

Figure 4 suggests that if the inflation over the next five years is 5% higher than the forecast every year, then the claim costs in 2025 would increase by 0.49%. On the other hand, the future values of claim costs are calculated based on a linear function of GDP and population. Thus, as GDP and population figures vary from the predictions, the impact on claim costs is scaled by the compounded variation between the realised and the base line figures. For instance, if GDP is always 2.5% higher than the estimation, then the claims costs in 2025 would increase by 13.14%.

The analyses imply it is unfavourable if the actual prints of those economic figures are higher than expected as claim costs would be inflated. The desired result is when actual GDP figures are within 2.5% of base line estimation so the claim costs are manageable in the long run. However, given the negative relationship between economic growth and inflation (Andrés and Hernando), it is not too concerning as the impact of higher inflation is likely to be offset by lower-than-expected GDP growth.

## **6.2 Qualitative Risks and Mitigations**

Risk	Mitigation
1 The model assumes that all policyholders that are eligible for voluntary buyback program will take the offer. However, if certain households refuse to undertake the buyback and relocate, then there would be a significant impact on claim costs as there will be more claims with high severity.	Conduct community outreach and education programs to help raise awareness about the buyback scheme and explain the benefits. Hold extra reserves in the case that certain properties cannot be convinced.

2	Program costs from natural disasters may deviate highly from estimates as climate hazards are extremely volatile.	Have high reserves and capital in the case of an extreme event. Undertake reinsurance with a climate reinsurer or introduce a natural disaster pool.  Monitor disasters frequently and update models when disaster occurs.
3	Model risks – claim values may deviate from expectation due to model risk, caused by improper fitting or lack of granularity.	Update model when more experience is obtained for specific hazards. Constantly monitor claims experience and update models and assumptions with experience.
4	Political changes and uncertainty may impact the success of the program. For example, changes in legislations may result in difficulty implementing the program.	Highlight the benefits of the program to government personnel and the wider population.

## 7. Data and Data Limitations

Limitations with the data mainly consisted of the lack of granularity of the data as well as a lack of data in general in some areas. More granular data at a claims or accident level rather than an aggregated level would allow for more accurate risk assessments as well as more thorough analysis within each region. For example, further breakdown on the location of homes damaged such as GNAFs or LGA's as opposed to just region numbers, or a further breakdown of damage costs would allow for more sophisticated models to be built for both voluntary and involuntary displacement costs.

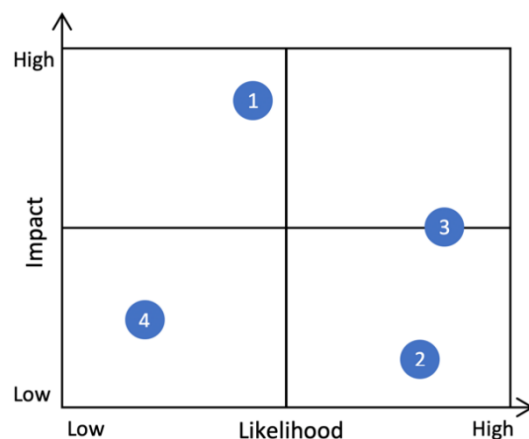


Figure 5: Risk Matrix

Further the lack of hazard specific data such as water levels for floods or severity of hurricanes and tropical storms resulted in less sophisticated models predicting accident frequency and severity. Once again, more granular data on the hazards would allow for more accurate models specific to the hazard to be developed.

There is also no data provided regarding the existing insurance market in Storslysia, particularly around home and content insurance and whether or not coverage for natural disaster already exists. If such data was provided, programs could be proposed to work in conjunction with private insurers for more effective insurance options.

The data provided also lacked long term information on population and GDP, with only 3 years of information being provided. This very short-term outlook made it very difficult to make realistic projections over a 20-year period. To address this, simplifying assumptions had to be made which may not be very accurate.

## 8. Appendix

### Appendix A – Loss Normalisation

Normalisation adjusts for the fact that if a hazard event of equal strength was to happen in the present, it will typically cause more damage than it had in past years because of wealth accumulation over time.

Normalisation adjusts nominal economic loss from past disasters upwards by multiplying past damage with a factor for inflation, for population growth and for growth in wealth per capita (GDP), thus in effect estimating the damage a past hazard event would have caused had it hit the same, but nowadays wealthier, area today. Loss normalisation therefore provides a more accurate measure of the economic loss value of a hazard in the future. All Property damage losses were normalised to 2020 for analysis.

$$\text{Normalised Damage}_t^{2020} = \text{Damage}_t \cdot \frac{CPI_{2020}}{CPI_t} \cdot \frac{GDP_{2020}}{GDP_t} \cdot \frac{CPI_{2020}}{CPI_t} \cdot \frac{Population_{2020}}{Population_t}$$

### Appendix B – Detailed Information on Climate Hazard Model

#### Simulation Methodology

1. Estimate the probability of a climate hazard occurring in one day (p) using historical data of event frequency and event duration.
2. Fit an appropriate distribution to the historical property damage data, after considering the impact of voluntary buyback. We have assumed that voluntary buyback will reduce extreme claims as those at-risk properties have been relocated.
3. Simulate n years. For each day, a hazard will or will not occur. This is generated using a Bernoulli with probability p. If the hazard occurs, the amount of property damage of that hazard is estimated using the severity distribution.
4. Repeated every day for N years.
5. Repeated for 1000 iterations.
6. The result is averaged in a Monte Carlo process.

	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
<b>Distribution</b>	Weibull	Gamma	Normal	Weibull	Normal	Weibull
<b>Parameters before program</b>	Shape =5.57	Shape =20.57	mean=11.99	Shape =4.87	mean=12.509	Shape =5.14
	Scale =14.34	Rate =1.63	SD=2.95	Scale =13.53	SD=2.66	Scale =13.77
<b>Parameters after program</b>	Shape =5.84	Shape =22.70	mean=11.90	Shape =5.23	mean=12.409	Shape =5.42
	Scale =14.22	Rate =1.82	SD=2.84	Scale =13.39	SD=2.51	Scale =13.63

### Appendix C – Buyback Valuation Methodology

First assessing the percentage of houses in very high-risk areas for each region by scoring on historical data of the number of injuries and fatalities. Accident years closer to recent years were weighted higher as opposed to accident years further in the past, and accidents resulting in fatalities were also given higher weightings. Reserves were also calculated on assumptions that all eligible policyholders would undertake the buyback. Costs in relation to voluntary buybacks are summarized below.

Region	Injuries	Fatalities	Exposure (%)	Population	Median Cost of Home	Reserve (Exposure * Population * Median House Cost)
1	874	375	0.089	4,175,553	260,765	440,879,170
2	2259	638	0.411	2,510,677	248,083	1,899,479,015
3	2063	484	0.225	3,542,607	221,267	658,770,612
4	924	242	0.433	844,305	121,135	175,219,043
5	4169	133	1.344	984,692	158,255	777,465,776
6	425	66	0.771	247,041	175,164	138,662,922
					Total	4,090,476,539

### Appendix D – Admin Expense and Temporary Housing Calculations

Admin, Handling, and other expenses for the program was calculated as a fixed percentage of property damage costs, based on similar figures for admin expenses for social insurance policies in other countries such as the USA.

Source: <https://www.ssa.gov/oact/STATS/admin.html>

Temporary housing calculations was calculated based on the proportion of estimated region damage to region median house price. This proportion is then used as an exposure benchmark for the number of people effected by catastrophe. A certain amount of people is then determined based on the region population which is multiplied by the temporary housing cost with disaster value for each region. It is believed that the temporary housing cost is an increased proxy of relocation cost after disaster.

Note, inflation was also considered in all expenses.

## Appendix E – Yearly Breakdown of Costs of the Program

Year	Projected GDP	Program Costs	Admin Costs	Temporary Housing Cost	Total	Std Dev	Total Program Cost % of GDP
2021	1,584,254,119,338	590,858,565	11,817,171	9,584,160	602,675,736	2,833,122,386	0.038%
2022	1,620,633,091,992	691,192,460	13,823,849	11,794,759	705,016,309	5,208,128,491	0.044%
2023	1,655,114,846,768	462,370,476	9,247,410	8,796,323	471,617,885	2,324,282,497	0.028%
2024	1,689,848,131,357	631,236,259	12,624,725	11,437,426	643,860,984	3,929,847,861	0.038%
2025	1,724,920,198,380	646,342,042	12,926,841	12,184,305	659,268,883	4,331,874,210	0.038%
2026	1,760,345,973,972	500,445,766	10,008,915	10,379,935	510,454,681	2,548,874,606	0.029%
2027	1,796,129,521,361	695,441,533	13,908,831	13,873,168	709,350,363	4,662,647,005	0.039%
2028	1,832,274,515,568	784,689,804	15,693,796	16,274,226	800,383,600	5,026,795,029	0.044%
2029	1,868,784,610,383	681,455,274	13,629,105	15,079,128	695,084,380	4,602,674,633	0.037%
2030	1,905,663,494,016	595,897,686	11,917,954	13,773,620	607,815,639	5,296,855,351	0.032%
2031	1,942,914,891,624	669,847,239	13,396,945	16,523,439	683,244,184	4,141,853,230	0.035%
2032	1,980,542,565,976	569,160,061	11,383,201	15,255,779	580,543,262	2,421,994,514	0.029%
2033	2,018,550,317,845	607,764,329	12,155,287	15,968,933	619,919,615	3,529,083,550	0.031%
2034	2,056,941,986,401	1,210,604,159	24,212,083	29,417,103	1,234,816,242	24,097,097,695	0.060%
2035	2,095,721,449,588	573,686,975	11,473,740	17,321,422	585,160,715	3,343,745,057	0.028%
2036	2,134,892,624,525	630,435,475	12,608,709	18,352,351	643,044,184	5,611,881,672	0.030%
2037	2,174,459,467,896	2,042,647,859	40,852,957	53,518,945	2,083,500,816	44,271,731,639	0.096%
2038	2,214,425,976,351	536,059,133	10,721,183	17,534,281	546,780,316	2,560,028,068	0.025%
2039	2,254,796,186,911	526,510,454	10,530,209	18,238,404	537,040,663	1,923,225,385	0.024%
2040	2,295,574,177,376	680,926,576	13,618,532	23,879,335	694,545,107	5,283,334,511	0.030%

## Appendix F – Pricing of Proposed Funding System for the Program

There will be continual yearly funding coming in from the levy system. This requires the working class (ages 18 – 65) population to pay a fixed cost based off which region they reside in. Thus, individuals in different regions will be paying different fixed cost that reflects the central estimate of property damage yearly. A break down for each region is presented.

Region 2 is estimated to have to highest property damage yearly due to its higher property density and relatively higher. This huge damage cost is spread to the population and thus the amount paid is not too high. At an income perspective, the population in region also earns a relatively higher income compared to the rest of Storslysia.

Region	Yearly Damage	Population	Cost per person
1	3725840.631	3888446.856	0.95818222
2	24576213.33	2483012.568	9.89774021
3	5352414.67	3252755.232	1.64550182
4	1669330.417	569451.168	2.93147246
5	2128103.19	739172.448	2.87903479
6	979782.8711	196775.172	4.97919967
Storslysia	37696737.23	11129613.44	3.38706617

The government should then cover for anything that deviates above the central estimate. For example, a value that could be up to the 95<sup>th</sup> percentile of the damage cost.



## Appendix G – Calculation of Risk Margins

$$\text{Risk Margin} = \text{Capital}_0 - \sum_{t=0}^n \frac{(\text{Capital}_t - \text{Capital}_{t+1}) + \text{Capital}_t \times r_f}{(1 + \text{CoC})^t}$$

Where a Cost of Capital rate of 10% is assumed and a risk-free rate of 2% assumed. Table below is a yearly break down for the Risk margin calculation

Year	Capital release	Interest rate	Net Cash Flow	Discounted Net Cash Flow at CoC
2021	1024490399	409796159.5	1434286558	1303896871
2022	1024490399	409796159.5	1434286558	1185360792
2023	1024490399	409796159.5	1434286558	1077600720
2024	1024490399	409796159.5	1434286558	979637018
2025	1024490399	409796159.5	1434286558	890579107.3
2026	1024490399	409796159.5	1434286558	809617370.3
2027	1024490399	409796159.5	1434286558	736015791.2
2028	1024490399	409796159.5	1434286558	669105264.7
2029	1024490399	409796159.5	1434286558	608277513.4
2030	1024490399	409796159.5	1434286558	552979557.6
2031	1024490399	409796159.5	1434286558	502708688.7
2032	1024490399	409796159.5	1434286558	457007898.8
2033	1024490399	409796159.5	1434286558	415461726.2
2034	1024490399	409796159.5	1434286558	377692478.4
2035	1024490399	409796159.5	1434286558	343356798.5
2036	1024490399	409796159.5	1434286558	312142544.1
2037	1024490399	409796159.5	1434286558	283765949.2
2038	1024490399	409796159.5	1434286558	257969044.7
2039	1024490399	409796159.5	1434286558	234517313.4
2040	1024490399	409796159.5	1434286558	213197557.6

Buyer's investment over the next 20 years resulted in a total of 12,210,890,005. This deducted from the capital will result in a risk margin of 8,278,917,968.

## Appendix H – Detailed Information on Post Relocation Issues

Studies have shown a significant component of frictional unemployment occurs as a direct result of involuntary relocation. This is an issue that Storslysia could address as a part of its relocation scheme. Suggested assistance may come in the form of unemployment benefits or other forms of financial aid. Studies have also shown relocations cause a significant impact on mental well beings of those forced to relocate. 'The Contemporary refugee crisis' saw about one

third of displaced persons experiencing high rates of depression, anxiety, and social separation as a direct result of relocation which often leads to significantly lower quality of life in later life. Treatment for these affected individuals have shown to help, however generally do not have a huge benefit.

A research paper by the WHO also showed “significantly heightened risk of developing depression, anxiety, suicidal ideation and substance use problems” amongst children who were forced to leave their homes. It also showed significant increases of the presence of racial abuse and social disassociation amongst individuals relocating to new foreign locations.

## Appendix - Additional data used

### Appendix - R Code

```
library(fitdistrplus)
library(actuar)
library(DescTools)
library(dplyr)
library(data.table)
library(writexl)
library(readxl)
library(ggplot2)
library(yarr)
library(moments)
historical_data<-read_excel("normalised_data.xlsx")

historical_data$log_property_loss_inflation_normalised<-
ifelse(historical_data$property_loss_inflation_normalised==0,0,log(historical
_data$property_loss_inflation_normalised))
historical_data$log_property_loss_inflation_pop_normalised<-
ifelse(historical_data$property_loss_inflation_pop_normalised==0,0,log(histor
ical_data$property_loss_inflation_pop_normalised))
historical_data$log_property_loss_inflation_pop_gdp_normalised<-
ifelse(historical_data$property_loss_inflation_pop_gdp_normalised==0,0,log(hi
storical_data$property_loss_inflation_pop_gdp_normalised))
historical_data$log_property_loss_original<-
ifelse(historical_data$property_loss_original==0,0,log(historical_data$proper
ty_loss_original))

historical_data<-setDT(historical_data)

data_region1<-historical_data[region==1&property_loss_original>0,]
data_region2<-historical_data[region==2&property_loss_original>0,]
data_region3<-historical_data[region==3&property_loss_original>0,]
data_region4<-historical_data[region==4&property_loss_original>0,]
data_region5<-historical_data[region==5&property_loss_original>0,]
data_region6<-historical_data[region==6&property_loss_original>0,]

#Fitting the Log Property Damage

goodness_fit_region1<-list()

region1_logN <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised, "lnorm")
goodness_fit_region1[["region1_logN"]] <- gofstat(region1_logN)

region1_t <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised, "t",
start=list(df=1))
goodness_fit_region1[["region1_t"]] <- gofstat(region1_t)
```

```

region1_N <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised, "norm")
goodness_fit_region1[["region1_N"]] <- gofstat(region1_N)

region1_weibull <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised,
"weibull")
goodness_fit_region1[["region1_weibull"]] <- gofstat(region1_weibull)

region1_cauchy <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised,
"cauchy")
goodness_fit_region1[["region1_cauchy"]] <- gofstat(region1_cauchy)

region1_exp <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised, "exp")
goodness_fit_region1[["region1_exp"]] <- gofstat(region1_exp)

region1_gamma <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised, "gamma")
goodness_fit_region1[["region1_gamma"]] <- gofstat(region1_gamma)

region1_logistic <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised, "logis")
goodness_fit_region1[["region1_logistic"]] <- gofstat(region1_logistic)

region1_pareto <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised,
"pareto", start=list(shape = 1, scale = 50))
goodness_fit_region1[["region1_pareto"]] <- gofstat(region1_pareto)

region1_gompertz <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised, distr =
dGompertz, start=list(shape = 0.5, rate = 0.5))
goodness_fit_region1[["region1_gompertz"]] <- gofstat(region1_gompertz)

region1_gumbel <-
fitdist(data_region1$log_property_loss_inflation_pop_gdp_normalised,
"gumbel", start=list(alpha = 1, scale = 1))
goodness_fit_region1[["region1_gumbel"]] <- gofstat(region1_gumbel)

goodness_fit_region1

#loop
set.seed(10)

# define number of years and days
num_years <- 60
num_days <- num_years * 360

```

```

# define damage distribution parameters
#the daily probability of the hazard occurring for the next n years will be
the number of hazards in the last 10 years divided by the total days in the
last n years
p_hazard<-as.numeric(count(historical_data[region==1&year>2020-
num_years,]))/(num_years*360)

num_iterations <- 1000
output_df <- data.frame(matrix(NA, nrow = num_days, ncol = num_iterations))
colnames(output_df) <- paste0("Iteration_", 1:num_iterations)

for (i in 1:num_iterations) {
  # initialize loss amount vector for this iteration
  loss_amounts <- rep(NA, num_days)

  # simulate daily hazard occurrence and loss amount
  for (j in 1:num_days) {
    # simulate hazard occurrence for this day
    hazard<- rbinom(1, 1, p_hazard)
    # Generate loss amount from Weibull distribution
    if (hazard == 1) {
      loss <- rweibull(1, shape = region1_weibull$estimate[1], scale =
region1_weibull$estimate[2])}
      # Check if loss exceeds cutoff, and if so, generate loss from lognormal
distribution
      else{loss <- 0}
      #   if (loss > cutoff) {
      #     loss <- rgamma(1, shape = gamma_shape_ext, rate = gamma_rate_ext)
      #   }
      # } else {
      #   # If no hazard occurs, set loss to 0
      #   # store loss amount for this day in the current iteration's column of
output dataframe
      loss_amounts[j] <- loss
    }
    # store loss amounts for this iteration in the output dataframe
    output_df[, i] <- loss_amounts
  }
}

#clean the output dataset by removing the effect of logging the Property
Damage
output_df_clean <- matrix(0, nrow = nrow(output_df), ncol = ncol(output_df))
# Define a function that takes the exponent of each cell, or returns 0 if the
cell is 0
exponent_or_zero <- function(x) {
  if (x == 0) {
    return(0)
  } else {

```

```

    return(exp(x))
  }
}

# Apply the function to each cell of the dataframe
output_df_clean <- apply(output_df, MARGIN = c(1, 2), FUN = exponent_or_zero)

#Count of Number of Disasters in n years.
mean(colSums(output_df_clean != 0))
#Average Property Damage Size
mean(colSums(output_df_clean)/colSums(output_df_clean != 0)) #check to ensure
the avg property damage is reasonable

#total projected cost for n years
cost<-mean(colSums(output_df_clean))
cost

#Count Number of Events
n_rows<-20*360
counts <- apply(output_df_clean[1:n_rows, ], 2, function(x) sum(x != 0))
mean(counts)

#Aggregates the Simulations by Quarter
agg_output_qtr_reg1<- matrix(0, nrow = 240, ncol = 1000)

# iterate through each column of the original matrix and calculate the sum of
every 365 rows
for (i in 1:1000) {
  agg_output_qtr_reg1[, i] <- apply(matrix(output_df_clean[, i], nrow = 90),
2, sum)
}

#Check that the col sums are the same and that the aggregation has worked
correctly
check<-as.data.frame(colSums(output_df_clean)-colSums(agg_output_qtr_reg1))
agg_output_qtr_reg1<-as.data.frame(agg_output_qtr_reg1)

#Adding Year and Quarter Cols
# add a new column for quarters
Quarter <- rep(1:4, times=60)
agg_output_qtr_reg1 <- cbind(Quarter, agg_output_qtr_reg1)

# add a new column for years
Year <- rep(2021:(2021+59), each = 4)
agg_output_qtr_reg1 <- cbind(Year, agg_output_qtr_reg1)

#Aggregates the Simulations by Year
agg_output_yr_reg1<- matrix(0, nrow = 60, ncol = 1000)

# iterate through each column of the original matrix and calculate the sum of

```

```

every 365 rows
for (i in 1:1000) {
  agg_output_yr_reg1[, i] <- apply(matrix(output_df_clean[, i], nrow = 360),
2, sum)
}
agg_output_yr_reg1<-as.data.frame(agg_output_yr_reg1)

# add a new column for years
Year_2 <- rep(2021:(2021+59))
agg_output_yr_reg1 <- cbind(Year_2, agg_output_yr_reg1)

#output yearly dataset

write_xlsx(agg_output_yr_reg1,"simulation_region1_yearly.xlsx")

#Figures for the report
ggplot(agg_output_yr_reg1[Year_2<2040,], aes(x=Year_2, y= V1)) +
  geom_bar(stat = "identity")+
  xlab("Year")+
  ylab("Property Damage")+
  ggtitle("Example Simulation of Yearly Loss for Region1")

ggplot(output_df[which(output_df$Iteration_2>0),], aes(x=Iteration_2)) +
  geom_histogram()

output_df[Iteration_1!=0]

#plot two histograms in same graph
output_df<-setDT(output_df)

hist(output_df[output_df$Iteration_1>0,Iteration_1],
col=transparent('red',0.9), main='Region 1 Log Property Damage Simulation',
breaks=50,
  border = F, xlab="Log of Daily Property Damage", ylim=c(0,50))
hist(output_df[output_df$Iteration_5>0,Iteration_5],
col=transparent('blue',0.9),add=TRUE, breaks=50,border = F)
hist(output_df[output_df$Iteration_10>0,Iteration_10],
col=transparent('pink',0.9),add=TRUE, breaks=50,border = F)
hist(output_df[output_df$Iteration_30>0,Iteration_30],
col=transparent('purple',0.9),add=TRUE, breaks=50,border = F)
hist(output_df[output_df$Iteration_100>0,Iteration_100],
col=transparent('yellow',0.9),add=TRUE, breaks=50,border = F)
hist(output_df[output_df$Iteration_100>0,Iteration_250],
col=transparent('darkgreen',0.9),add=TRUE, breaks=50,border = F)
hist(output_df[output_df$Iteration_100>0,Iteration_400],
col=transparent('darkblue',0.9),add=TRUE, breaks=50,border = F)
hist(output_df[output_df$Iteration_1000>0,Iteration_1000],
col=transparent('orange',0.9),add=TRUE, breaks=50,border = F)

```



```
#####Impact of Voluntary
Relocation#####
#find the cutoff for highest % of values.
percent<-0.01
cutoff <-
as.numeric(quantile(historical_data[region==1,property_loss_inflation_pop_gdp
_normalised], 1-percent))
cut_historical_data_reg1<-
historical_data[property_loss_inflation_pop_gdp_normalised<cutoff&region==1&p
roperty_loss_inflation_pop_gdp_normalised>0,]

region1_weibull_cut <-
fitdist(cut_historical_data_reg1$log_property_loss_inflation_pop_gdp_normalis
ed, "weibull")
goodness_fit_region1_cut[["region1_weibull"]] <- gofstat(region1_weibull_cut)

#loop
set.seed(10)

# define number of years and days
num_years <- 60
num_days <- num_years * 360

# define damage distribution parameters
#the daily probability of the hazard occurring for the next n years will be
the number of hazards in the last 10 years divided by the total days in the
last n years
p_hazard<-as.numeric(count(historical_data[region==1&year>2020-
num_years,]))/(num_years*360)

num_iterations <- 1000
output_df_cut <- data.frame(matrix(NA, nrow = num_days, ncol =
num_iterations))
colnames(output_df_cut) <- paste0("Iteration_", 1:num_iterations)

for (i in 1:num_iterations) {
  # initialize loss amount vector for this iteration
  loss_amounts <- rep(NA, num_days)

  # simulate daily hazard occurrence and loss amount
  for (j in 1:num_days) {
    # simulate hazard occurrence for this day
    hazard<- rbinom(1, 1, p_hazard)
    # Generate loss amount from Weibull distribution
    if (hazard == 1) {
      loss <- rweibull(1, shape = region1_weibull_cut$estimate[1], scale =
region1_weibull_cut$estimate[2])
    }
    # Check if loss exceeds cutoff, and if so, generate loss from lognormal
distribution
  }
}
```

```

    else{loss <- 0}
    loss_amounts[j] <- loss
  }
  # store loss amounts for this iteration in the output dataframe
  output_df_cut[, i] <- loss_amounts
}

#clean the output dataset by removing the effect of logging the Property
Damage
output_df_cut_clean <- matrix(0, nrow = nrow(output_df_cut), ncol =
ncol(output_df_cut))
# Define a function that takes the exponent of each cell, or returns 0 if the
cell is 0
exponent_or_zero <- function(x) {
  if (x == 0) {
    return(0)
  } else {
    return(exp(x))
  }
}

# Apply the function to each cell of the dataframe
output_df_cut_clean <- apply(output_df_cut, MARGIN = c(1, 2), FUN =
exponent_or_zero)
output_df_cut_clean <- as.data.frame(output_df_cut_clean)
#Count of Number of Disasters in n years.
mean(colSums(output_df_cut_clean != 0))

#Average Property Damage Size
mean(colSums(output_df_cut_clean)/colSums(output_df_cut_clean != 0)) #check
to ensure the avg property damage is reasonable

#total projected cost for n years
mean(colSums(output_df_cut_clean))

#Count Number of Events
n_rows<-20*360
counts <- apply(output_df_cut_clean[1:n_rows, ], 2, function(x) sum(x != 0))
mean(counts)

total_damage <- apply(output_df_cut_clean[1:n_rows, ], 2, FUN=sum)
mean(total_damage)

#COMPARISON
output_df_cut<-setDT(output_df_cut)

hist(output_df[output_df$Iteration_1>0,Iteration_1],
col=transparent('red',0.9), main='Region 1 Log Property Damage Simulation',
breaks=50,

```

```

border = F, xlab="Log of Daily Property Damage", ylim=c(0,50))
hist(output_df_cut[output_df_cut$Iteration_1>0,Iteration_1],
col=transparent('blue',0.9), breaks=50,border = F, add=T)
abline(v = mean(output_df[output_df$Iteration_1>0,Iteration_1]),col =
"red",lwd = 3)
abline(v = mean(output_df_cut[output_df_cut$Iteration_1>0,Iteration_1]),col =
"blue",lwd = 3)

#Yearly cost
#Aggregates the Simulations by Year
agg_output_cut_yr_reg1<- matrix(0, nrow = 60, ncol = 1000)

# iterate through each column of the original matrix and calculate the sum of
every 365 rows
for (i in 1:1000) {
  agg_output_cut_yr_reg1[, i] <- apply(matrix(output_df_cut_clean[, i], nrow
= 360), 2, sum)
}
agg_output_cut_yr_reg1<-as.data.frame(agg_output_cut_yr_reg1)

# add a new column for years
Year_2 <- rep(2021:(2021+59))
agg_output_cut_yr_reg1 <- cbind(Year_2, agg_output_cut_yr_reg1)

write_xlsx(agg_output_cut_yr_reg1,"simulation_region1_yearly_cut.xlsx")

#####IPCC Scenario
Analysis#####
ssp_factors<-read_excel("C:/Users/miche/OneDrive/Desktop/Uni
2023/ACTL4001/Assignment/ssp_factors.xlsx")

num_years <- 20
num_days <- num_years * 360

p_hazard<-as.data.frame(matrix(0, nrow = nrow(ssp_factors), ncol =
ncol(ssp_factors)))

for (i in 1:nrow(p_hazard)) {
  for (j in 1:ncol(p_hazard)) {
    # Calculate p_hazard for this cell using the formula
    p_hazard[i, j] <- as.numeric(count(historical_data[region == 1&year
>2020-num_years, ]))*as.numeric(ssp_factors[i,j])/(num_years * 360)
  }
}
colnames(p_hazard)<-c("low","medium","high","vhigh")

#Loop
set.seed(10)

```

```

num_iterations <- 1000
ssp_scenario<-"vhigh"
assign(paste0("output_df_",ssp_scenario),data.frame(matrix(NA, nrow =
num_days, ncol = num_iterations)))

for (i in 1:num_iterations) {
  # initialize loss amount vector for this iteration
  loss_amounts <- rep(NA, num_days)

  # simulate daily hazard occurrence and loss amount
  for (j in 1:num_days) {
    # determine the year index for the current day
    year_index <- ceiling(j / 3600)

    # simulate hazard occurrence for this day using the appropriate p_hazard
    value for the current year
    hazard <- rbinom(1, 1, p_hazard[year_index,ssp_scenario])

    # generate loss amount from Weibull distribution if hazard occurs,
    otherwise set loss to 0
    loss <- ifelse(hazard == 1, rweibull(1, shape =
region1_weibull_cut$estimate[1], scale = region1_weibull_cut$estimate[2]), 0)

    # store loss amount for this day in the current iteration's column of
    output dataframe
    loss_amounts[j] <- loss
  }

  # store loss amounts for this iteration in the output dataframe
  output_df_vhigh[, i]<- loss_amounts
}

#clean the output dataset by removing the effect of logging the Property
Damage
output_df_vhigh_clean <- matrix(0, nrow = nrow(output_df_vhigh), ncol =
ncol(output_df_vhigh))
# Define a function that takes the exponent of each cell, or returns 0 if the
cell is 0

# Apply the function to each cell of the dataframe
output_df_vhigh_clean <- apply(output_df_vhigh, MARGIN = c(1, 2), FUN =
exponent_or_zero)

#Yearly cost
#Aggregates the Simulations by Year
agg_output_cut_yr_reg1_vhigh<- matrix(0, nrow = 20, ncol = 1000)

# iterate through each column of the original matrix and calculate the sum of
every 365 rows
for (i in 1:1000) {

```

```
    agg_output_cut_yr_reg1_vhigh[, i] <- apply(matrix(output_df_vhigh_clean[,
i], nrow = 360), 2, sum)
}
agg_output_cut_yr_reg1_vhigh<-as.data.frame(agg_output_cut_yr_reg1_vhigh)

# add a new column for years
Year_2 <- rep(2021:(2021+19))
agg_output_cut_yr_reg1_vhigh <- cbind(Year_2, agg_output_cut_yr_reg1_vhigh)

write_xlsx(agg_output_cut_yr_reg1_vhigh,"simulation_region1_yearly_vhigh.xlsx
")
```

## 9. References

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