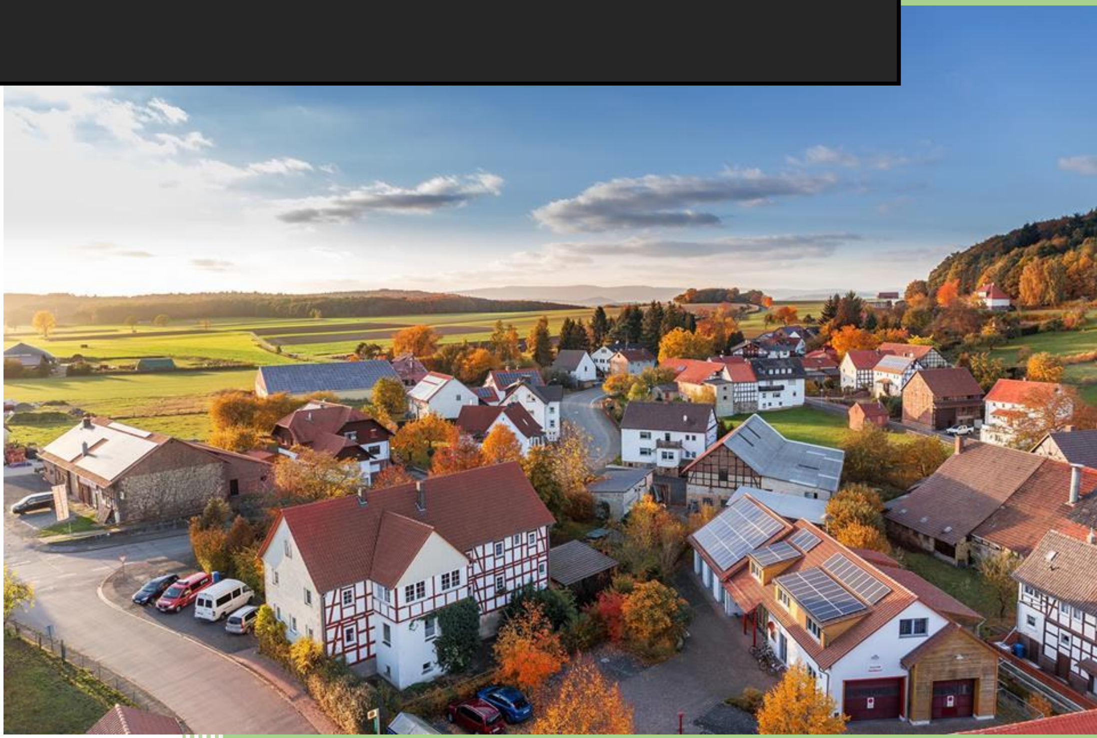
Relocation Social Insurance Case Study

2023 Student Research Case Study Challenge



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1. Objectives and Executive Summary

MAIVE Consulting has been tasked with designing a social insurance program for relocation. With climate change becoming an increasing problem around the globe, Storslysia is threatened by the impact of climate-related catastrophes. The aim of our firm is to help Storslysia manage its exposure to displacement risk due to catastrophic weather events. MAIVE Consulting will utilise the actuarial control cycle as a framework to understand the business environment and form appropriate solutions.

MAIVE Consulting has outlined three core principles that its proposition should adhere to. In turn, they are that the benefit payable:

1. Should be strictly greater for proactive relocation than for reactive relocation, to ensure incentivisation of the former as reactive relocation involves higher costs;
2. Will scale based on the wealth of each household, in the social interests of Storslysia's society, and;
3. Will vary based on the risk inherent to each household at a region level, to both minimise the extent of cross-subsidies and to target the strength of the financial incentive to relocate at a risk-level.

MAIVE Consulting recommends that the proposed social insurance program offers a catastrophic relief payment, carefully discerning who is eligible to claim and how much each claimant can receive in alignment with the above core principles. Monitoring this social program on a regular cycle and adjusting assumptions based on the economic and social environment will increase the likelihood of success.

This program aims to support residents when relocating to a new area. To do this, the program will offer financial support to cover logistical costs of relocating, such as transportation and accommodation, as well as managing psychological impacts. Further, this program aims to cover any losses faced because of a catastrophic event, or potential catastrophic event, including damaged items, and property damage.

To monitor the success of the proposed program, we will collect these key metrics:

Key Metric	Reason
Total payout amount	To ensure that costs do not exceed 10% of GDP
Claims per region	To identify high risk areas
Frequency and severity of proactive and reactive relocators	To compare reactive with proactive relocators and identify if program incentives are successful. Ensure cover provided is appropriate.
Frequency and severity of climate disasters	To identify if assumptions/cover is appropriate.
Proportion of relocators to total population	To identify if cover is appropriate for resident's preferences.

These metrics will be reported monthly over the first year, quarterly over the next 2 years, biannually over the following 5 years, and annually thereafter for a period of 20 years.

2. Program Design

A citizen of Storslysia will be eligible to file a claim under the scheme by default. The citizen can then elect either a proactive or reactive cover.

Each cover will provide a catastrophic relief payment, as well as the following extras: transport fees – Ꝕ1,600 for an individual, an extra Ꝕ250 for each additional individual;[1] coverage for tools of trade, not including home office equipment – a maximum of Ꝕ2,600;[2] 15% of short-term bills for the first 3 months after relocating;[3] provision of temporary accommodation – Ꝕ1,925 per person for the first 3 months; and two Ꝕ50 vouchers per adult – redeemable at select businesses, including but not limited to restaurants, furniture storage, furniture removal;[4] and a free subscription to a mental health program (valued Ꝕ1000 per person). The aim is to rehabilitate and promote the wellbeing of each citizen. Gasparri et al has indicated that climate change-induced extreme weather events can affect mental health, particularly for low-income populations.[5]

The catastrophic relief payment, unlike the above extras, vary between the proactive and reactive covers. For reactive claims, the payment is calculated as the minimum of the actual property damages and the property's base value – defined as the maximum payout for both home and contents damages. The base value decreases at an increasing rate as a *percentage* of property value which serves as a proxy for the wealth of the household and ensures the benefits of the social program are fair. On the other hand, to further incentivise proactive relocation over reactive relocation, the catastrophic relief payment under this kind of claim attracts an additional payout loading on the base value, called the *risk loading factor* (RLF). The RLF encapsulates MAIVE Consulting's best actuarial view of the climate-related risk faced by households in each region and is a strictly positive multiplicative factor. The RLF is the mechanism through which the program is able to enforce larger payouts for proactive relocation, as well as targeting the size of the incentive at the risk-level with information on both the initial wealth of households and their exposure to climate risk. The method used to compute the RLF's is outlined in Appendix A.3.1.

This program will be monitored monthly over the short-term period of the first year. This frequency will ensure that, as the program is introduced into practice, any initial inefficiencies can immediately be adjusted to improve program performance. The regularity of monitoring will then shift to a quarterly review over the next 2 years, before transitioning to biannually over the following 5 years, and finally annually thereafter for a period of 20 years. Consistent monitoring over the long term will allow unforeseen risks to be identified and mitigated. To realise this, the following aspects of the program will be monitored in both the short-term and long-term:

- Program efficiency – including, which catastrophic events are occurring most frequently, which areas are such events prevalent, whether the scale of such events increasing such that previously unaffected areas are now affected, as well as whether

[1] These figures were sourced from external data. In particular, the relocation fees of $3000 AUD provided to individuals moving to a capital city under the Australian Federal Government Job Seeker incentive. See: 'Job Seeker Government Relocation Funding', *Muval* (Web Page) <https://www.muval.com.au/blog/job-seeker-relocation-funding-support>.

[2] This figure was based on the coverage of the Australian General Insurer GIO, which provided a maximum value of $5000 AUD, consistent with other Australian insurers. See further: GIO, *Home and Contents Insurance: Product Disclosure Statement* (Report, 2020).

[3] This would help ease the financial stress following a relocation.

[4] This feature was inspired by the $50AUD vouchers offered by the Australian NSW Government to boost economic activity during COVID-19. See further: NSW Government, 'NSW Vouchers for People', *Vouchers and Support* (Web Page, 2023) <https://www.nsw.gov.au/money-and-taxes/vouchers-and-support/voucher-for-people>.

[5] Giulia Gasparri et al, 'Integrating Youth Perspectives: Adopting a Human Rights and Public Health Approach to Climate Action' (2022) 19 (8) *International Journal of Environmental Research and Public Health* 4840, 4844.

the mental health program is seeing a decrease in developments of health disorders such as anxiety and depression across the nation.

- Program impact – including, whether proactive or reactive relocation is elected more often, how often residents are claiming the vouchers, which stores have the vouchers been claimed at – for example, if the majority vouchers have been claimed to buy furniture, the program could strengthen its partnership with those types of businesses to provide a greater selection of stores where citizens can shop for their new furniture.

3. Pricing & Costs

3.1 Outline of Pricing Methodology

To ascertain the cost of each relocation, the initial step was to forecast, using the emissions data provided, the GDP and the Census. For the former, the worldwide GDP growth rates were calculated. Storslysia was assumed to have the same GDP growth rate as the world. Those rates were then used to forecast the GDP per decade. The Census was calculated by first determining the proportion of each region against the world, using 2020 data. Assuming that the proportion remains constant, that figure was multiplied against the forecasted world population to calculate the census per region for each decade. See Appendix A.1.

A historical analysis was then performed using the 1960-2020 catastrophic loss data to determine the displacement for each peril per region. The propensity of displacement $d_{j,k}$ for region j and peril k refers to the conditional probability that a catastrophic event will lead to relocation. An event will be defined as such provided certain conditions are met. See Appendix A.2.

The conditional distribution of these propensities was then mapped by the number of displacement event per region per peril divided by total number of events for that peril. Known parametric probability distributions were employed to characterise these losses – which were first inflated to present value. The Gamma, Lognormal and Pareto distributions were considered. However, the Weibull distribution was the most appropriate as it is long-tailed and its shape is similar to property damage values when plotted on a histogram. It also passed the Chi-Squared test, and gave the best performance on KS, CVM and AD tests.

This fitting then paved the way for the sampling of future losses from the chosen distribution. Estimation uncertainty could also be quantified; this provides less ambiguity than using the first moment as a proxy for future losses.

To predict the future claims costs, the risk loading factor $r_{j,k}$ was defined as the present value of the predicted inflated future claims for region j and peril k. This value is used in our model to scale the payouts based on risk. The explicit procedure for estimating this factor has been included under Appendix A.3.

This factor was used to model the total claims process which was broken up into two parts, those attributable to proactive relocation and reactive relocation, because of the different payout structures. The total claims process in the decade commenced year i was calculated by summing across all regions and all perils, where a flat proportion of people were assume to uptake proactive relocation in each accident decade. See Appendix A.3.2.

On this basis, the entire claims arrival process will be modelled through time to quantifiably assess the program feasibility. Going forward, we performed 100 simulations with and without our program model to understand the economic costs associated.

3.2 Projected Economic Costs

With this program in place, expenses were projected according to the SSP1, SSP2, SSP3 and SSP5 scenarios[6] as shown in Figure 1. SSP1 and SSP2 represent the most positive scenarios for both human development and environmental action with low to medium emissions.

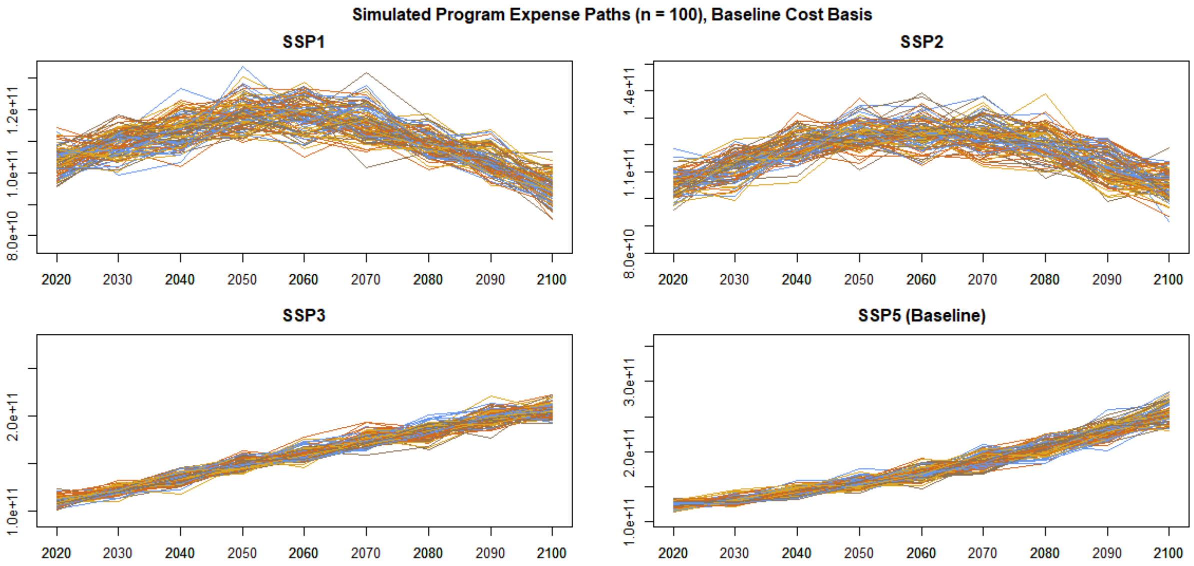

Figure 1: Simulated Expense Paths with the program at different emission scenarios

It is expected that the economic costs increase and peak at, on average, Ᵽ120 billon in 2060 and decrease afterwards due to improved sustainable action resulting in a lower risk of catastrophic events, reducing claims to relocate. By 2100, economic costs will be lower than 2020 values at, on average, Ᵽ95 billion for SSP1 and Ᵽ105 billion for SSP2. This is largely because the effects of discounting are lower in earlier years, and much stronger in later years.

In contrast, SSP3 represents a scenario where economic development and environmental concerns are low, which leads to strong environmental degradation in some regions. In this high emission scenario, we expect an increase in economic costs at a linear rate. As climate change worsens, more regions become unsafe due to increasing natural disasters and consequently, the need to relocate increases. By 2100, economic costs will reach on average Ᵽ205 billion.

Lastly, SSP5 represents a scenario with high growth in human development but is achieved through large amounts of fossil fuels, resulting in large negative effects to the environment and very high emissions. From our projections, economic costs are expected to increase at an exponential rate. By 2100, the economic costs will reach on average Ᵽ256 billion with the increased risk of natural disasters.

Projected costs without the program were identified, that is, the cost of all residents reactively relocating and graphed results in Figure 2.

[6] The SSP scenarios is based on the SOA Emissions Data. See Appendix A.1.3.

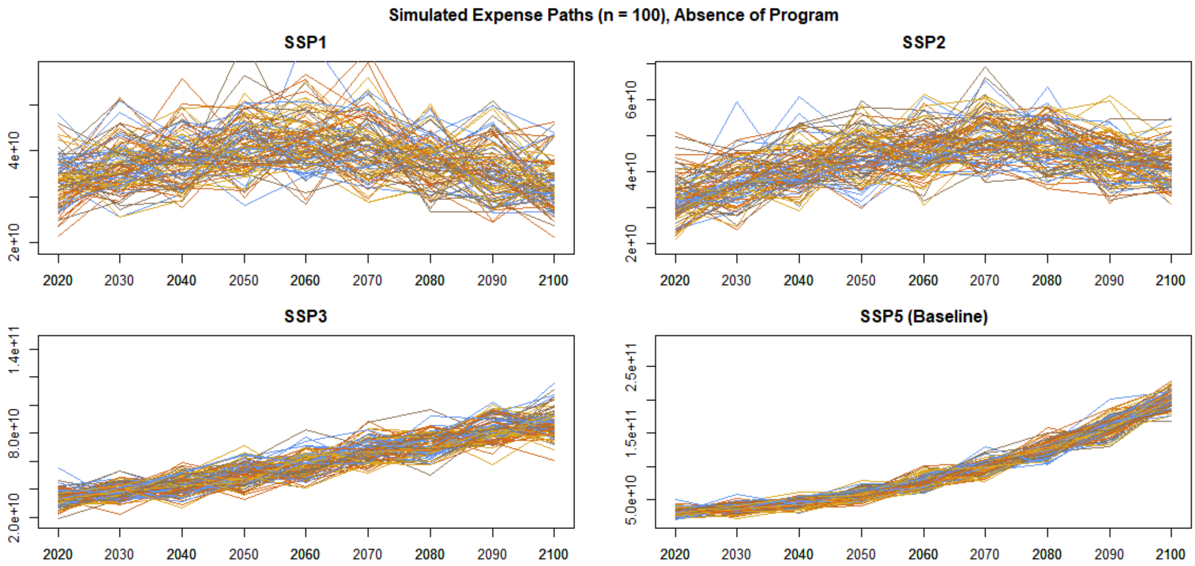

Figure 2: Simulated Expense Paths without the program at different emission scenarios

From the above observations, the general trend is similar for all scenarios as for with the program, however there is a large increase in the variance of the expense results. Without the program, standard deviations in earlier years are 5 times as large than with the program. When comparing the SSP5 scenario projections, we can observe that our program does well to smooth the experience claims and increases certainty, which offers support for mitigating risks. Without the program, by 2100 in the SSP5 scenario, costs will reach, on average, to Ꝑ313 billion, Ꝑ57 billion higher than with the program.

3.3 Economic Capital Needed

From the 100 simulations we conducted, it is expected that the total costs of our program will not exceed 10% of forecasted GDP. Even in the worst case SSP5 scenario, our projected economic costs will only be 9.57% of Storslysia's GDP.

In the SSP5 scenario, the total economic capital needed in 2020 is Ꝑ124 billion. This will increase by roughly 6% in 2030 and roughly 10% every 10 years after. In 2100, the economic capital needed is Ꝑ256 billion. However, this is well covered by GDP growth that we expect to increase to roughly Ꝑ13.1 trillion.

3.4 Proactive and Reactive relocation costs

Using our baseline assumptions, we performed 300 simulations on the total proactive and reactive costs from 2020 to 2100, discounted to the present value under our program. We have summarised these below.

	Mean	**Standard Error**
Proactive	Ꝑ29.8 trillion	Ꝑ17.2 trillion
Reactive	Ꝑ11.1 trillion	Ꝑ6.4 trillion

It can be observed that the costs associated with proactive relocation is higher under our program. This is an expected outcome as our program shifts the payouts to proactive payouts and are strictly higher than reactive payouts. This is to incentivise proactive relocation and ensure that the economy and lives are saved.

4. Assumptions

The below summarises the key model assumptions. See Appendix E for further details.

Categorising 'Catastrophic' Weather Events

In this scheme, relocation only occurs in anticipation of, or following the occurrence of a 'catastrophic' weather event. There is no existing definition of 'catastrophic' provided in the data. In 2021, 432 natural disasters occurred worldwide ranging from drought, earthquake, flood, landslide, storm, wildfire.[7] On average, the number of deaths, per continent was 4.857. Hence, for this scheme, it has been assumed that past weather events which have led to *more than 5 deaths* are 'catastrophic' event(s). In addition, a total of 101.8 million people were affected by such disasters.[8] The world population in 2021 was 7.89 billion.[9] On average, per continent, the number of citizens affected by a disaster was 15.5. Under this scheme, it has been assumed that historical weather events which have led to *more than 16 people* being injured should be considered 'catastrophic'.

Maximum Payout for Reactive Relocation

Property value is assumed to be a proxy for a citizen's net worth. The payout is a floating percentage of that value. Citizens whose houses are valued in the lowest property bracket (less than Ꝑ50K), and thus are assumed to be most in need of capital,[10] will receive a lump sum that is equivalent to their property value. The percentage will then decrease at an increasing rate. For the same reason, the percentage of contents recoverable via compensation decreases as wealth increases. The following base amount cap[11] has thus been imposed on the basis that the more well off a citizen is, the less dependent that citizen will be on government funding:

Property Value	*<Ꝑ50K*	*Ꝑ50K-Ꝑ99K*	*Ꝑ100K-Ꝑ149K*	*Ꝑ150K-Ꝑ199K*	*Ꝑ200K-Ꝑ249K*
Cap (Ꝑ)	87,500	172,083	253,750	249,375	245,000
Property Value	*Ꝑ250K-Ꝑ299K*	*Ꝑ300K-Ꝑ399K*	*Ꝑ400K-Ꝑ499K*	*Ꝑ500K-Ꝑ749K*	*Ꝑ750K-Ꝑ999K*
Cap (Ꝑ)	240,625	315,000	309,167	303,333	297,500
Property Value	*Ꝑ1M-Ꝑ1.499K*	*Ꝑ1.5M-Ꝑ1.99M*	*>=Ꝑ2M*		
Cap (Ꝑ)	291,666	285,833	280,000		

However, should a citizen suffer more, their payout will be the total amount of damage caused to their property by the actual catastrophic event. Notably, in some instances, the Cap is greater than the upper threshold of the property value. At first, this may be considered as a matter of moral hazard however it is important to note the Cap accounts for contents loading.

Currency; Number of people per household

The sources from which quantitative justifications were derived have used either AUD or USD. The exchange rate between US$ and Ꝑ have been assumed to be 1.321 (1 US$ = 1.321Ꝑ). In addition, based on the provided 2016-2020 data, it has been assumed that each household holds 2.5 citizens.

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[7] OCHA Services, *2021 Disasters in Numbers* (Report, 22 April 2022).
[8] Ibid.
[9] *World Bank*, 'Population: Total', *Data* (Web Page) <https://data.worldbank.org/indicator/SP.POP.TOTL>.
[10] ACOSS and UNSW Sydney, *Poverty in Australia 2020* (Report, 2020).
[11] NSW Government, 'Home Building Compensation Reform Discussion Paper', *State Insurance Regulatory Authority* (Web Page) <https://www.sira.nsw.gov.au/consultations/home-building-compensation-reform/publications/home-building-compensation-reform>.

Timing of events
Due to the need for otherwise heavy (and imprecise) interpolation, it is assumed that the claims only occur at the end of every 10 years and as such, the costs of claims will only be discounted at the end of every 10 years. The present value will thus appear cheaper. The performance of the scheme may thus be overstated. The corollary of this assumption is that the scheme can only fail every 10 years. However, in practice, claims can occur at the end of each day, month or year. This means an actual program can fail much more often.

Property Value Distribution; Displacement propensities of perils
The distribution of property values has been assumed to stay the same. This is because no further data has been given on this distribution across different years.

The displacement propensities of each peril have been assumed to be constant for the next hundred years. This is because it is futile to predict any change in the propensities as the rate of these extreme weather events are dependent on climate change – which, by definition, is inherently unexpected and unpredictable. In practice, were a program like this to be implemented, new data would be inputted more regularly – for example, every 5 years – as part of the monitoring cycle. The availability of new statistics will then be the basis upon which these propensities can be updated.

Percentage of Region affected by a catastrophic event(s)
No data was given in relation to the percentage of each region that was affected by past events. In accordance with the Emergency Event Database ('EED') rankings of extreme weather events, it has been assumed that the more fatal a particular type of natural disaster, the greater the proportion of a region that may likely be affected. As such, we have assumed that 3% of a given region would be exposed to a given peril. No assumptions were made as to differentiate how each region may be affected because no information was given relating to each region's geographical features.

GDP Growth
The investment returns on the remainder of the capital have been assumed to be included in the forecasted GDP. Now, GDP is typically estimated each quarter or each year.[12] However, the data provided only accounts for GDP every 10 years. As a result, the GDP forecasting has been made on a 10-year basis. This means that there is a lack of review and monitoring between each 10-year period, during which GDP data should usually be updated. This may lead to an overstatement of the reserves as GDP is not as frequently updated.

Baseline Assumptions
The baseline inputs used for the model involved a 5% interest rate to discount the future claims cost to 2020 and a 3% inflation rate to inflate the cost. These assumptions were performed using data and projections from the SSP5 Scenario as this is the most extreme case that would overestimate costs.

[12] US Department of Commerce, 'Gross Domestic Product', *Bureau of Economic Analysis* (Web Page) <https://www.bea.gov/resources/learning-center/what-to-know-gdp#:~:text=BEA%20estimates%20the%20nation's%20GDP,statistics%20are%20released%20every%20month.>.

5. Risk and Risk Mitigation Strategies

5.1 Risks Identified

The main risks that the program experiences are related to the financial, operational and strategic aspect that can directly and indirectly affect the total claims cost. In Appendix D, these are expressed using Risk Categorisation and Definition (RCD) Tool.

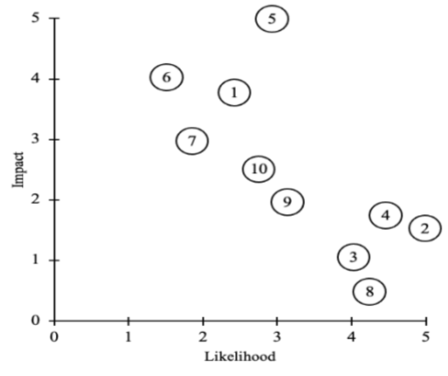
The main financial risk involves changes in inflation. The inflation rate increases the cost of living, making it difficult for individuals to meet their needs as the purchasing power has decreased. This affects the housing value and cost of services, but on top this, the calculation of the present value of future total claims costs as these values are inflated much more.

Additionally, the operational risk that also strains the financial risk is natural disaster. There may be regions that experience a higher impacted disaster that can increase the cost of reactive relocation as there is larger property damage. The intensity and frequency of these catastrophic events increases the claim costs which adds to the financial risk.

Furthermore, despite the incentives for individuals to proactively relocate, there is a strategic risk that individuals may not wish to relocate. This could be because of personal preferences or even an operational risk of a population increase in a particular region due to proactive or active relocation. On top of this, there is also a moral hazard risk as residents may proactively relocate and receive an unfair payout.

Figure 3 below is a risk heatmap that compares and prioritises potential risks. Climate change will have the largest impact to the social insurance programs. This cannot be prevented from occurring, however the impact of such risk on the social insurance program can be mitigated. This is a similar approach to how other risks identified will be managed. However, there is an aim to avoid risk 10 by implementing strict eligibility requirements that ensure fair payouts.

Figure 3: Risk Map for Relocation Social Insurance



1: Economic recession
2: Interest rate changes
3: Decreased currency value
4: Increase in inflation
5: Climate change/extreme weather
6: Insufficient land to relocate residents
7: Sudden population increases
8: Changes in tax costs
9: Changes in resident preferences
10: Moral hazard

See Appendix D for more detail.

5.2 Sensitivity Analysis

The sensitivity analysis examines the present value of the nominal claims cost for each decade as of 2020. The tabulated values include the standard deviations as data limitations have added a degree of uncertainty to the predicted values. These sensitivity changes are compared against the base model assumptions mentioned in Section 4.

Sensitivity analysis was performed across the four SSP Scenarios using the base model assumptions. The most favourable situation would be under SSP1 as there is low challenges to mitigation and adaptation, meaning that there is constant improvement to the overall economy. In this scenario, the nominal claims costs decrease, on average, by 1% each year, with a decreasing proportion of Storslysia's GDP being used. On the other hand, under the most unfavourable situation being SSP5, with high challenges to mitigation and low challenges to adaptation, the nominal claims cost is increasing, on average, by 9% each year, which can be calculated in Table 15 in Appendix B. However, Table 16 in Appendix B captures the proportion of Storslysia's GDP being used as claims costs and demonstrates that even in the most unfavourable situation, the cost to Storslysia's GDP is well below 10% in 2020, and continues to decrease, reinforcing that the scheme will not lead to ruin. As such, these scenario testing will be conducted under the most unfavourable scenario, SSP5, to ensure that claims cost does not exceed 10% of Storslysia's GDP.

A financial risk that may occur are the changes in inflation rate that affect the future claims costs. Stress testing was performed on the inflation rate with the results tabulated in Table 17, Appendix C.1, and shows that an increase in inflation leads to an increase in claims cost. A 4% increase in inflation to the baseline increases the claims costs by, on average, 0.235% in present value terms. This demonstrates that even at the extremity of 7% inflation, the program does not lead to ruin. Additionally, given this analysis has been performed under the most unfavourable baseline scenario SSP5, under all other more favourable scenarios, the program will not lead to ruin, as highlighted in Table 18, Appendix C.1.

Another large driver of the expected claims experience of the scheme is the frequency of catastrophic events. Further sensitivity analysis was performed on this metric by simulating the claims experience under 0.5x, 2x and 4x multipliers on the frequency of events under the baseline SSP5 scenario, with results tabulated in Table 19 in Appendix C.2. The favourable situation of half the number of events reduces the claims cost by, on average 19%, whereas the unfavourable situation with a factor of 4x increases the claims cost by, on average 113%. Table 20 in Appendix C.2 demonstrates that under this extremity, the program does lead to ruin in the decade commenced 2020 – highlighting the need for ongoing monitoring of the frequency assumptions relative to actual experience is required to ensure sufficient capital is injected into the scheme. It should be noted the 4x frequency multiplier is well covered by GDP growth as the scheme continues into the future.

5.3 Risk Mitigation Strategies

Several strategies have been identified that aim to target the above risks and balance financial stability, social equity, and ethical standards over the long term.

Financial risks:

- Perform a valuation each year to ensure that costs associated with the adjusted benefits and the risk of a proactive or reactive relocation do not exceed 10% of Storslysia's GDP and that there is adequate reserves to cover these payouts. At each valuation, adjust assumptions in the calculation of our costs to any economic or policy changes.

Operational risks:

- Monitor the adequacy of benefits such as changing circumstances e.g. worsening climate change or unexpected population increases, and adjust benefits accordingly.
- Manage land available (Risk 4) for relocation by partnering with city planners.
- Forecast future extreme weather occurrences at different risk-levelled scenarios. Use this forecast to inform how much funding we require to avoid ruin.
- Manage tax risk by keeping up to date with tax laws and adjusting benefits.

Strategy risks:

- Manage unexpected resident preference by keeping up to date with local culture and adjust incentives for proactive relocation accordingly.
- Manage moral hazard (Risk 10) by ensuring out eligibility criteria is up to date, and screening claimants carefully to ensure they receive a justified amount.

6. Data and Data Limitations

6.1 Data Limitations

Below lists the main data limitations identified, see Appendix F for additional limitations.

Exposure

As there is no explicit data surrounding the exposure to catastrophic events, assumptions have been made to attempt to match the number of households exposed to certain risks. As a result of the mismatch between claims and exposure, there is heightened uncertainty in projections.

Hazard Events & Compound Climate Events

Historical loss data contains 51 unique combinations of natural perils. Such an extensive list with little loss data impacts accuracy. Thus, perils were grouped to aggregate data, with 10 unique perils identified as per Table 9 in Appendix A.2.2. Hence, compound climate events are not explicitly accounted for. Due to such complex relationships, perils are treated in isolation.

Limited Data: Region Characteristics

Geographical and topological characteristics of the regions was limited, which rendered it impossible to model the climate risk at a granular level. As a consequence, the distribution of peril sizes was fit at the country level, which presents a cross-subsidy risk as pricing is at the region/risk level. The level of ongoing cross-subsidisation should be monitored on an ongoing basis to assess whether the current pricing framework is performant, and there is scope for improvements in the pricing's sophistication by improving the quality of this data.

Scheme Eligibility - Proactive Relocation: High Risk Region & Length of Residence

To obtain proactive relocation support, initial scheme design required a citizen to live in a 'high risk' region. However limited data resulted in difficulties to define this. There were also challenges with initial criteria that an individual must have resided in such household for a minimum of 1 year. Data did not account for this, hence automatic eligibility would be more feasible, with citizens given the choice to elect between the two covers.

Scheme Eligibility - Reactive Relocation: Length of Residence

To obtain reactive relocation support, initial scheme design required a citizen to hold their property for more than 2-weeks before a catastrophe was identified. This is to deter deliberate purchases to claim a payout. However, with limited data, this was not integrated in the model.

Age Criteria

Initial plans for a citizen to receive reactive relocation support included an eligibility requirement. For example, if the legal title holder is less than 67 years old, that citizen would be eligible provided that the damage to their property exceeded a certain amount. That amount would be lower for those older than 67. However, as data was not available, the differentiation of coverage between age groups was not carried out.

6.2 External Data

This report identified external data sources used to inform assumptions and model inputs.

Glossary

Terminology	Definition
Property Value	The market value of the claimant's property assessed at the time of the catastrophic event.
Catastrophic event	A catastrophic event is exhaustively defined to include: Winter Weather, Severe Storm, Thunder Storm, Wind, Lightning, Hail, Flooding, Heat, Hurricane, Tropical Storm, Drought, Tornado, Coastal, Wildfire, Fog, and Landslide.

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Appendix

A: Pricing Methodology

A.1: Preliminaries

A.1.1: Emissions Scenarios

Table 1: Emissions Scenarios	
Scenario	**Definition**
SSP1 – Low Challenges to mitigation and adaptation	"The world shifts gradually, but pervasively, toward a more sustainable path, emphasizing more inclusive development that respects perceived environmental boundaries. Management of the global commons slowly improves, educational and health investments accelerate the demographic transition, and the emphasis on economic growth shifts toward a broader emphasis on human well-being. Driven by an increasing commitment to achieving development goals, inequality is reduced both across and within countries. Consumption is oriented toward low material growth and lower resource and energy intensity."
SSP2 – Medium challenges to mitigation and adaptation	"The world follows a path in which social, economic, and technological trends do not shift markedly from historical patterns. Development and income growth proceeds unevenly, with some countries making relatively good progress while others fall short of expectations. Global and national institutions work toward but make slow progress in achieving sustainable development goals. Environmental systems experience degradation, although there are some improvements and overall the intensity of resource and energy use declines. Global population growth is moderate and levels off in the second half of the century. Income inequality persists or improves only slowly and challenges to reducing vulnerability to societal and environmental changes remain."
SSP3 – High Challenges to mitigation and adaptation	"A resurgent nationalism, concerns about competitiveness and security, and regional conflicts push countries to increasingly focus on domestic or, at most, regional issues. Policies shift over time to become increasingly oriented toward national and regional security issues. Countries focus on achieving energy and food security goals within their own regions at the expense of broader-based development. Investments in education and technological development decline. Economic development is slow, consumption is material-intensive, and inequalities persist or worsen over time. Population growth is low in industrialized and high in developing countries. A low international priority for addressing environmental concerns leads to strong environmental degradation in some regions."
SSP4 – Low challenges to mitigation, high challenges to adaptation	"Highly unequal investments in human capital, combined with increasing disparities in economic opportunity and political power, lead to increasing inequalities and stratification both across and within countries. Over time, a gap widens between an internationally-connected society that contributes to knowledge- and capital-intensive sectors of the global economy, and a fragmented collection of lower-income, poorly educated societies that work in a labor-intensive, low-tech economy. Social cohesion degrades and conflict and unrest become increasingly common. Technology development is high in the high-tech economy and sectors. The globally connected energy sector diversifies, with investments in both carbon-intensive fuels like coal and unconventional oil, but also low-carbon energy

	sources. Environmental policies focus on local issues around middle and high-income areas.”
SSP5 – High challenges to mitigation, low challenges to adaptation	“This world places increasing faith in competitive markets, innovation and participatory societies to produce rapid technological progress and development of human capital as the path to sustainable development. Global markets are increasingly integrated. There are also strong investments in health, education, and institutions to enhance human and social capital. At the same time, the push for economic and social development is coupled with the exploitation of abundant fossil fuel resources and the adoption of resource and energy-intensive lifestyles around the world. All these factors lead to rapid growth of the global economy, while global population peaks and declines in the 21st century. Local environmental problems like air pollution are successfully managed. There is faith in the ability to effectively manage social and ecological systems, including by geo-engineering if necessary.”

A.1.2: GDP Forecasting

The GDP forecasting was calculated using research emissions data, with a primary focus on SSP5-Baseline scenario. This scenario represents the most extreme situation, which will allow for overestimation of claims costs. Calculating the Worldwide GDP growth rates across the 10-year interval, assuming that Storslysia would have the same growth rate as the worldwide, this was used to forecast the GDP for each decade.
This can be mathematically expressed as:

$$GDP_{SSP,i} = \left(GDP_{SSP,i-10}\right)\left(1 + GR_{SSP,i}\right), \text{ with } GR_{SSP,i+10} = \frac{GDP_{SSP,i} - GDP_{SSP,i-10}}{GDP_{SSP,i-10}}$$

where:

- $GDP_{SSP,i}$ refers to the GDP of a particular SSP scenario, for the 10-year interval year i
- $GDP_{SSP,i-10}$ refers to the previous GDP of a particular SSP scenario for the previous decade $i - 10$
- $GR_{SSP,i}$ refers to the growth rate of a particular SSP scenario for the 10-year year i

Predicted GDP growth rates below:

	Table 2: GDP Growth Rates			
	SSP1–2.6	**SSP2–3.4**	**SSP3–6.0**	**SSP5-Baseline**
2020	0.0%	0.0%	0.0%	0.0%
2030	53.1%	41.3%	33.7%	62.7%
2040	43.2%	29.7%	17.8%	56.9%
2050	30.5%	24.2%	11.8%	40.2%
2060	22.3%	21.0%	9.3%	31.1%
2070	17.7%	19.9%	8.9%	26.7%
2080	13.4%	18.0%	8.5%	22.3%
2090	10.4%	16.6%	8.5%	19.1%
2100	7.7%	15.7%	8.9%	16.9%

Predicted GDP for each SSP Scenario below:

	Table 3: GDP (Ψ1,000)			
	SSP1–2.6	**SSP2–3.4**	**SSP3–6.0**	**SSP5-Baseline**
2020	1,296,938,922	1,296,938,922	1,296,938,922	1,296,938,922
2030	1,985,149,587	1,831,945,458	1,734,089,895	2,110,230,356
2040	2,843,024,626	2,376,823,910	2,042,212,756	3,311,712,537
2050	3,710,452,838	2,951,189,902	2,283,624,488	4,641,743,129
2060	4,538,267,222	3,572,094,923	2,495,475,599	6,087,594,567
2070	5,340,733,850	4,284,539,525	2,717,446,563	7,710,359,165
2080	6,055,693,403	5,057,497,686	2,947,406,883	9,426,034,991
2090	6,685,693,394	5,896,225,882	3,196,941,127	11,229,531,019
2100	7,201,692,174	6,819,698,703	3,482,560,633	13,122,120,006

A.1.3: Inflation and Discounting Forecasts

Due to the long-term nature of the program's time horizon, speculating on exact figures to inflate and discount by is futile. We instead opted to choose a set of baseline assumptions, relying on stress testing to assess the sensitivity of our model to variations in these baseline assumptions. The baseline assumptions are discussed in Section 4.

A.1.4: Census Forecasting

The Census forecasting was calculated using research emissions data, with a primary focus on SSP5-Baseline scenario. This scenario represents the most extreme situation, which will allow for overestimation of claims costs. Calculating the proportion of each region against the world population using 2020 data, assuming a constant proportion, this was multiplied against the world population to calculate the census for each decade for each region.
This can be mathematically expressed as:

$$C_{i,SSP} = WP_{SSP,i} * \ Proportion, where\ proportion = \frac{POP_{2020,j}}{WP_{2020,SSP5}}$$

Where:

- $C_{SSP,i}$ refers to the census for a particular SSP scenario in year i
- $WP_{SSP,i}$ refers to the predicted world population for a particular SSP scenario in year i
- $POP_{2020,j}$ refers to the population in year 2020 for region j
- $WP_{2020,SSP5}$ refers to the world population for SSP5 Scenario in Year 2020

Forecasted Population for each Region for each SSP Scenario:

Table 4: Scenario: SSP1– 2.6						
	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Global Dist.	0.084%	0.056%	0.066%	0.013%	0.017%	0.004%
2020	6,306,408	4,212,348	4,993,764	1,010,676	1,266,672	307,884
2030	6,732,404	4,496,891	5,331,091	1,078,947	1,352,235	328,681
2040	7,008,048	4,681,007	5,549,362	1,123,122	1,407,600	342,139
2050	7,124,988	4,759,116	5,641,961	1,141,863	1,431,088	347,848
2060	7,091,577	4,736,799	5,615,504	1,136,509	1,424,377	346,217
2070	6,932,872	4,630,793	5,489,833	1,111,074	1,392,500	338,469
2080	6,657,228	4,446,677	5,271,563	1,066,899	1,337,136	325,011
2090	6,272,997	4,190,031	4,967,307	1,005,321	1,259,961	306,253
2100	5,813,589	3,883,171	4,603,523	931,696	1,167,687	283,824

Table 5: Scenario: SSP2–3.4						
	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Global Dist.	0.084%	0.056%	0.066%	0.013%	0.017%	0.004%
2020	6,306,408	4,212,348	4,993,764	1,010,676	1,266,672	307,884
2030	6,899,461	4,496,891	5,331,091	1,078,947	1,352,235	328,681
2040	7,008,048	4,681,007	5,549,362	1,123,122	1,407,600	342,139
2050	7,124,988	4,759,116	5,641,961	1,141,863	1,431,088	347,848
2060	7,091,577	4,736,799	5,615,504	1,136,509	1,424,377	346,217
2070	6,932,872	4,630,793	5,489,833	1,111,074	1,392,500	338,469
2080	6,657,228	4,446,677	5,271,563	1,066,899	1,337,136	325,011
2090	6,272,997	4,190,031	4,967,307	1,005,321	1,259,961	306,253
2100	5,813,589	3,883,171	4,603,523	931,696	1,167,687	283,824

Table 6: Scenario: SSP3–6.0						
	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Global Dist.	0.084%	0.056%	0.066%	0.013%	0.017%	0.004%
2020	6,306,408	4,212,348	4,993,764	1,010,676	1,266,672	307,884
2030	7,148,400	4,765,600	5,616,600	1,106,300	1,446,700	340,400
2040	7,778,400	5,185,600	6,111,600	1,203,800	1,574,200	370,400
2050	8,366,400	5,577,600	6,573,600	1,294,800	1,693,200	398,400
2060	8,878,800	5,919,200	6,976,200	1,374,100	1,796,900	422,800
2070	9,340,800	6,227,200	7,339,200	1,445,600	1,890,400	444,800
2080	9,769,200	6,512,800	7,675,800	1,511,900	1,977,100	465,200
2090	10,189,200	6,792,800	8,005,800	1,576,900	2,062,100	485,200
2100	10,600,800	7,067,200	8,329,200	1,640,600	2,145,400	504,800

Table 7: Scenario: SSP5–Baseline						
	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Global Dist.	0.084%	0.056%	0.066%	0.013%	0.017%	0.004%
2020	6,306,408	4,212,348	4,993,764	1,010,676	1,266,672	307,884
2030	6,762,000	4,508,000	5,313,000	1,046,500	1,368,500	322,000
2040	7,056,000	4,704,000	5,544,000	1,092,000	1,428,000	336,000
2050	7,207,200	4,804,800	5,662,800	1,115,400	1,458,600	343,200
2060	7,215,600	4,810,400	5,669,400	1,116,700	1,460,300	343,600
2070	7,106,400	4,737,600	5,583,600	1,099,800	1,438,200	338,400
2080	6,888,000	4,592,000	5,412,000	1,066,000	1,394,000	328,000
2090	6,577,200	4,384,800	5,167,800	1,017,900	1,331,100	313,200
2100	6,199,200	4,132,800	4,870,800	959,400	1,254,600	295,200

A.2: Historical Input Analysis

A.2.1: Calculation of Displacement Propensities

A long-run historical analysis was performed using catastrophic loss data from 1960 to 2020 to determine the propensity of displacement for each region j and peril k. We define the propensity of displacement $d_{j,k}$ for region j and peril k to be the conditional probability of a catastrophic event to trigger displacements. For an event to be defined as such, we stipulate it must meet at least one of the following conditions:

1. at least two fatalities were observed to have arisen from the event,
2. at least ten injuries were observed to have arisen from the event, or
3. the total regional damage arising from the event exceeds $30,000,000.

After classifying each historical loss event as either a displacement event or not, the conditional distribution of displacement propensities was determined via

$$d_{j,k} = \frac{s_{j,k}}{n_j} \tag{B.1}$$

where $s_{j,k}$ denotes the number of displacement events occurring over the time horizon in region j and for peril k, and n_j denotes the total number of events observed over the time horizon in region j.

Using B.1, the resultant propensity table for all regions and perils is as follows:

Table 8: Propensity Table						
	Region 1	*Region 2*	*Region 3*	*Region 4*	*Region 5*	*Region 6*
Coastal	0%	0%	0%	0%	7%	0%
Drought	9%	8%	5%	10%	7%	33%
Flooding	9%	7%	11%	7%	0%	0%
Hail	20%	7%	5%	10%	20%	0%
Lightning	7%	5%	14%	0%	0%	8%
Other	5%	1%	2%	0%	0%	0%
Severe Storm	25%	37%	38%	21%	60%	8%
Tornado	5%	12%	11%	10%	0%	8%
Wind	9%	7%	4%	14%	7%	17%
Winter Weather	11%	17%	11%	28%	0%	25%

A.2.2: Estimation of Conditional Property Damage

Long-run historical analysis was also performed to characterise historical losses by known parametric probability distributions. This method enabled the sampling of future losses from this distribution, as well as the quantification of estimation uncertainty (as opposed to employing the first moment as a proxy for future losses).

Prior to fitting any parametric distributions, the loss data was cleaned, property damage was inflated to present value, and the perils were mapped to a smaller number of sub classes. The raw data provided 51 unique or combined perils which necessitated this mapping, else the additional granularity would thin the amount of data available and reduce the confidence of the parameter estimates. A total of 10 peril sub-classes were ultimately mapped, which may be viewed in Table 9.

A number of distributions were then considered for fitting the pre-processed loss data. Namely, the Weibull, Gamma, Log-Normal and Mixed-Exponential distributions were tested against a battery of goodness of fit tests. We found that, based on performance in the Kolmogorov-Smirnov, Anderson-Darling, Cramer von Mises and Chi-Square goodness of fit tests, the Weibull distribution was the most appropriate to model the size of future losses. The fitted Weibull parameters are documented in Table 10 below.

Table 9: Peril mappings to sub-classes			
Peril	Mapped Sub-Class	Peril	Mapped Sub-Class
Severe Storm/Thunder Storm/ Wind	Severe Storm	Hurricane/Tropical Storm/ Severe Storm/Thunder Storm	Other
Flooding	Flooding	Coastal/ Flooding	Other
Winter Weather	Winter Weather	Flooding/ Lightning/ Wind	Other
Hail	Hail	Coastal/ Hurricane/Tropical Storm/ Severe Storm/Thunder Storm/ Wind	Other
Wind	Wind	Coastal/ Severe Storm/Thunder Storm	Other
Lightning	Lightning	Landslide	Other
Tornado	Tornado	Hail/ Tornado/ Wind	Other
Severe Storm/Thunder Storm	Severe Storm	Lightning/ Tornado/ Wind	Other
Drought	Drought	Flooding/ Hail	Other
Hurricane/Tropical Storm	Tornado	Flooding/ Hail/ Wind	Other
Hail/ Lightning/ Wind	Wind	Fog	Other
Lightning/ Wind	Wind	Severe Storm/Thunder Storm - Wind	Severe Storm
Hail/ Severe Storm/Thunder Storm/ Wind	Severe Storm	Lightning/ Severe Storm/Thunder Storm	Severe Storm
Flooding/ Severe Storm/Thunder Storm	Severe Storm	Hail/ Severe Storm/Thunder Storm	Severe Storm
Heat	Drought	Severe Storm/Thunder Storm/ Wind/ Winter Weather	Other
Hail/ Lightning/ Severe Storm/Thunder Storm/ Wind	Severe Storm	Flooding/ Lightning/ Severe Storm/Thunder Storm	Other
Hail/ Wind	Wind	Hail/ Severe Storm/Thunder Storm/ Wind/ Winter Weather	Other
Lightning/ Severe Storm/Thunder Storm/ Wind	Severe Storm	Coastal/ Flooding/ Severe Storm/Thunder Storm/ Wind	Other
Coastal	Coastal	Flooding/ Lightning	Other
Drought/ Heat	Drought	Severe Storm/Thunder Storm/ Winter Weather	Other
Wildfire	Drought	Coastal/ Wind	Other
Flooding/ Wind	Wind	Hail/ Lightning	Other
Wind/ Winter Weather	Winter Weather	Hail/ Tornado	Other
Flooding/ Severe Storm/Thunder Storm/ Wind	Severe Storm	Coastal/ Hurricane/Tropical Storm/ Wind	Other
Severe Storm/Thunder Storm - Wind	Severe Storm	Coastal/ Severe Storm/Thunder Storm/ Wind	Other
Tornado/ Wind	Other	Hail/ Lightning/ Severe Storm/Thunder Storm	Other
Hail/ Severe Storm/Thunder Storm	Severe Storm	Tornado/ Wind	Other

Table 10: Fitted Weibull Distributional Parameters		
Peril	Shape	Scale
Coastal	0.941	1012.372
Drought	0.508	3095.655
Flooding	0.458	1670.258
Hail	0.381	2114.817
Lightning	0.416	2305.909
Other	0.468	1737.591
Severe Storm	0.423	1540.399
Tornado	0.586	1501.124
Wind	0.340	2027.951
Winter Weather	0.476	3632.196

A.3: Prediction of Future Claims Costs

A.3.1: Determination of Risk Loading Factors (RLF's)

The risk loading factor $r_{j,k}$ is defined as the present value of predicted inflated future claims for region j and peril k. Mathematically formulated, this is expressed as:

$$
\begin{aligned}
r_{j,k} &= \mathbb{E}\left[X_{i,j,k}^{R}\right]v^{i}u^{i} + \mathbb{E}\left[X_{i+1,j,k}^{R}\right]v^{i+1}u^{i+1} + \cdots + \mathbb{E}\left[X_{n,j,k}^{R}\right]v^{n}u^{n} \\
&= \sum_{i=1}^{n} \mathbb{E}\left[X_{i,j,k}^{R}\right]v^{i}u^{i} \qquad \text{(C.1)}
\end{aligned}
$$

where:

- $X_{i,j,k}^{R}$ is the claims random variable due to reactive relocation in year i, region j, and peril k,
- v is the discounting factor,
- u is the inflation factor, and
- n is the furthest year into which the claims cost is forecast.

We now develop an explicit expression for $\mathbb{E}\left[X_{i,j,k}^{R}\right]$ so that (C.1) may be determined numerically. To do so, we decompose $\mathbb{E}\left[X_{i,j,k}^{R}\right]$ into three constituent components:

$$
\begin{aligned}
\mathbb{E}\left[X_{i,j,k}^{R}\right] &= \{\text{num of peril } k\} * \{\text{num exposed households}\} * \{\text{benefit to household}\} \\
&= \mathbb{E}[N_i] * d_{j,k} * \left[\left(\sum_{v=1}^{V} n_{i,j} * p_{v,j} * \mathbb{E}[\min\{a_v, D_k\}]\right) + n_{i,j} * b^{lump}\right] \\
&= c_i * e_i * d_{j,k} * n_{i,j} * \left[\left(\sum_{v=1}^{V} p_{v,j} * \mathbb{E}[\min\{a_v, D_k\}]\right) + b^{lump}\right] \qquad \text{(C.2)}
\end{aligned}
$$

where:

- N_i is the count random variable for the number of catastrophic events occurring in the decade commenced i,
- c_i is the number of natural disasters forecast to occur in the decade commenced i, and
- e_i is the probability that one such event converts to a displacement event in the decade commenced i.
- $d_{j,k}$ is the propensity for such an event to be of peril k in the region j as developed in (B.1),
- $n_{i,j}$ is the number of households exposed to risk in the decade commenced i in region j,
- $p_{v,j}$ is the proportion of households in region j with property value v,
- a_v is the base benefit assigned to properties with value v,
- D_k is the damage random variable sampled from the distribution of peril k, and,
- b^{lump} is the total lump benefit payable to an exposed household, as defined in the policy terms (Section 2 of this report).

As was developed in Appendix A.2, $D_k \sim$ Weibull. In the case of N_i, the choice was made to model the number of catastrophic events in the decade commenced year i as a

Binomial$(n = c_i, p = e_i)$ random variable to reflect the inherent uncertainty in the central estimates provided of future emissions scenarios.

The number of forecasted natural disasters is taken as the sum for each decade under each SSP scenario (as taken from the provided data), and the quantity $\hat{e_i}$ is estimated discretely from these forecasts as:

$$\hat{e_i} = \frac{0.5 * \widehat{c_i^{medium}} + \widehat{c_i^{high}}}{\hat{c_i}} \tag{C.4}$$

Determining the final component of equation (C.2), $\mathbb{E}[\min\{a_v, D_k\}]$, necessitated that a numerical approach be taken due to the presence of the min function. The Law of Large Numbers was relied upon for this estimation via Monte Carlo simulation.

On this basis, an explicit formula for the risk loading factor, $r_{j,k}$, was obtained as:

$$\widehat{r_{j,k}} = \sum_{i=1}^{n} \left\{ c_i * e_i * d_{j,k} * n_{i,j} * \left[\left(\sum_{v=1}^{V} p_{v,j} * \mathbb{E}[\widehat{\min\{a_v}, D_k\}] \right) + b^{lump} \right] v^i u^i \right\} \tag{C.5}$$

noting that the true value of $r_{j,k}$ may only be estimated on the given data. The estimated risk loading factors under each of the four SSP's are tabulated below.

Table 11: SSP1 Risk Loading Factor

	Region 1	*Region 2*	*Region 3*	*Region 4*	*Region 5*	*Region 6*
Coastal	5.8079	7.5743	7.7699	4.0702	10.8708	2.4414
Drought	2.7235	2.2392	2.9521	2.0311	1.0000	1.0000
Flooding	3.1890	3.9372	2.9029	5.0949	1.0000	5.1787
Hail	4.6793	2.1508	1.9709	2.5234	4.2355	1.0000
Lightning	2.6656	2.1764	1.6700	3.1117	2.0768	3.9008
Other	2.2283	1.9274	3.5661	1.0000	1.0000	2.3915
Severe Storm	1.8682	3.0777	2.9356	2.5149	1.0000	2.4892
Tornado	2.6276	2.3844	1.9513	2.5404	2.0607	6.4614
Wind	1.0000	1.0000	1.0000	1.0000	2.1050	1.0000
Winter Weather	1.8053	1.2403	1.3166	1.0000	1.0000	1.0000

Table 12: SSP2 Risk Loading Factor						
	Region 1	*Region 2*	*Region 3*	*Region 4*	*Region 5*	*Region 6*
Coastal	5.8046	7.7939	8.1230	4.3578	12.1591	2.5241
Drought	2.7464	2.3133	3.0950	2.0324	1.0000	1.0000
Flooding	3.2216	4.2589	3.0644	5.4777	1.0000	5.6573
Hail	5.0069	2.2700	2.0279	2.6923	4.5768	1.0000
Lightning	2.8944	2.2238	1.6896	3.2936	2.2094	4.0048
Other	2.3325	2.0114	3.6790	1.0000	1.0000	2.4850
Severe Storm	1.8573	3.1867	3.0175	2.6416	1.0000	2.4601
Tornado	2.7137	2.5082	2.0228	2.6932	2.1975	6.9797
Wind	1.0000	1.0000	1.0000	1.0000	2.1693	1.0000
Winter Weather	1.8931	1.2707	1.3642	1.0000	1.0000	1.0000

Table 13: SSP3 Risk Loading Factor						
	Region 1	*Region 2*	*Region 3*	*Region 4*	*Region 5*	*Region 6*
Coastal	6.3429	8.7690	8.8876	4.7343	12.4534	2.6395
Drought	2.9719	2.3885	3.2774	2.2202	1.0000	1.0000
Flooding	3.4554	4.6438	3.3008	5.9231	1.0000	6.2850
Hail	5.4074	2.4153	2.1194	2.7989	4.9054	1.0000
Lightning	2.9582	2.3631	1.7560	3.4813	2.2429	4.3179
Other	2.5315	2.1295	4.0783	1.0000	1.0000	2.6626
Severe Storm	1.9866	3.5365	3.2218	2.7868	1.0000	2.6637
Tornado	2.9841	2.7282	2.1728	2.8659	2.3403	7.8234
Wind	1.0000	1.0000	1.0000	1.0000	2.2875	1.0000
Winter Weather	1.9609	1.2843	1.3979	1.0000	1.0000	1.0000

Table 14: SSP5 Risk Loading Factor						
	Region 1	*Region 2*	*Region 3*	*Region 4*	*Region 5*	*Region 6*
Coastal	8.2266	11.5422	11.4354	5.9297	16.4874	3.2576
Drought	3.6523	2.8934	4.0787	2.6857	1.0000	1.0000
Flooding	4.4864	5.9022	3.9514	7.4098	1.0000	7.4888
Hail	7.1474	2.8782	2.5170	3.4370	5.9384	1.0000
Lightning	3.6950	2.9180	2.0176	4.3044	2.7519	5.2844
Other	2.9883	2.4999	5.0976	1.0000	1.0000	3.2252
Severe Storm	2.2752	4.4532	4.1751	3.4274	1.0000	3.1723
Tornado	3.6909	3.3105	2.5607	3.4950	2.7835	9.9867
Wind	1.0000	1.0000	1.0000	1.0000	2.7400	1.0000
Winter Weather	2.3464	1.3824	1.5110	1.0000	1.0000	1.0000

A.3.2: Claims Process

Since an explicit procedure for estimating $r_{j,k}$ has been outlined, it is now possible to model the claims process of the scheme through time. Denote the claims process in the decade commenced year i as S_i. The claims process may be broken into two parts: those attributable to proactive relocation, and reactive relocation, via (C.6) below:

$$\begin{aligned} S_i &= \sum_{j=1}^{J} \sum_{k=1}^{K} X_{i,j,k} \\ &= \sum_{j=1}^{J} \sum_{k=1}^{K} \left[\alpha x_{i,j,k}^{P} + (1-\alpha) X_{i,j,k}^{R}\right] \end{aligned} \tag{C.6}$$

where $\alpha\%$ is a flat proportion of people assumed to uptake proactive relocation in each accident decade. The proactive cost component, $x_{i,j,k}^{P}$ is computed as

$$x_{i,j,k}^{P} = n_{i,j} * \left[\sum_{v=1}^{V} \left(p_{v,j} * \widehat{r_{j,k}} * a_v\right) + b^{lump}\right] \tag{C.7}$$

where the definitions in (C.7) are consistent with those previously outlined above. For modelling the reactive cost component, the expectation is removed from equation (C.2) to restore randomness in the cost forecasts, explicitly:

$$X_{i,j,k}^{R} = N_i * d_{j,k} * n_{i,j} * \left[\left(\sum_{v=1}^{V} p_{v,j} * \min\{a_v, D_k\}\right) + b^{lump}\right] \tag{C.8}$$

On this basis the entire claims arrival process may be modelled through time to quantifiably assess the program feasibility.

A.4: Capital Forecasting and Ruin Analysis

Define the ruin probability of the program, ψ_{100} to be the probability that the program's costs exceed 10% of Storlysia's GDP at some point in the 100-year time horizon. Due to the complexity of the program's cost structure, we adopted a Monte Carlo approach to estimating ψ_{100}.

To obtain the Monte Carlo estimate of ψ_{100}, the form

$$\psi_{100} = \mathbb{E}\left[\psi_{100} | \mathcal{F}_{S_{100}}\right] \tag{D.1}$$

of the probability of ruin was assumed where $\mathcal{F}_{S_{100}}$ is the filtration of the claims process at time $t = 100$. The Monte Carlo replacement of the theoretical mean with its simulated mean was then made to obtain the estimator $\widehat{\psi_{100,m}}$:

$$\mathbb{E}\left[\psi_{100} | \mathcal{F}_{S_{100}}\right] = \widehat{\psi_{100,m}} = \frac{1}{R} \sum_{i=1}^{R} \psi_{100,m}^{i}, \tag{D.2}$$

where R is the number of simulated estimates each of m replicates. Each of the R simulations were computed as

$$\psi_{100,m}^{i} = \frac{1}{m}\sum_{i=1}^{m} \mathbb{I}_{\left\{ \min\limits_{t<100} \{ 0.1*GDP_t - S_t\} < 0 \right\}}, \tag{D.3}$$

that is, $\psi_{100,m}^{i}$ is equal to the discrete probability of the number of ruins out of m 100-year periods. On this basis, by simulating the claims process S_t as many times as is desired, the quantity ψ_{100} may be estimated under various SSP scenarios and assumption settings.

B. Scenario Testing Results

Table 15: Nominal Claims Cost for each SSP Scenario

Year	SSP1-2.6		SSP2-3.4		SSP3-6.0		SSP5-Baseline	
	Claims Cost (₱)	SD (%)	Claims Cost (₱)	SD (%)	Claims Cost (₱)	SD (%)	Claims Cost (₱)	SD (%)
2020	1.036E+11	3.89	1.057E+11	3.87	1.091E+11	3.88	1.241E+11	3.54
2030	1.094E+11	3.77	1.121E+11	4.16	1.223E+11	3.41	1.313E+11	3.59
2040	1.134E+11	4.20	1.197E+11	3.93	1.344E+11	3.87	1.435E+11	3.52
2050	1.188E+11	4.00	1.239E+11	3.84	1.490E+11	3.37	1.552E+11	4.19
2060	1.183E+11	4.37	1.244E+11	4.35	1.602E+11	3.77	1.701E+11	4.67
2070	1.158E+11	4.44	1.235E+11	4.62	1.742E+11	3.65	1.863E+11	4.75
2080	1.094E+11	3.26	1.205E+11	4.50	1.831E+11	3.46	2.059E+11	4.38
2090	1.037E+11	3.77	1.118E+11	4.97	1.979E+11	3.47	2.297E+11	4.30
2100	9.475E+10	4.35	1.049E+11	4.68	2.054E+11	3.36	2.556E+11	4.57

Table 16: Proportion of Claims Cost against GDP for each SSP Scenario

Year	SSP1	SSP2	SSP3	SSP5
2020	7.98%	8.15%	8.41%	9.57%
2030	5.51%	6.12%	7.05%	6.22%
2040	3.99%	5.04%	6.58%	4.33%
2050	3.20%	4.20%	6.52%	3.34%
2060	2.61%	3.48%	6.42%	2.79%
2070	2.17%	2.88%	6.41%	2.42%
2080	1.81%	2.38%	6.21%	2.18%
2090	1.55%	1.90%	6.19%	2.05%
2100	1.32%	1.54%	5.90%	1.95%

C. Sensitivity Analysis Results

C.1: Inflation Rate Change Testing

Table 17: Nominal Claims Cost for changes in Inflation Rate

Inflation Rate	**3% (Baseline)**		**1%**		**5%**		**7%**	
Year	Claims Cost (Ᵽ)	SD (%)	Claims Cost (Ᵽ)	SD (%)	Claims Cost (Ᵽ)	SD (%)	Claims Cost (Ᵽ)	SD (%)
2020	1.241E+11	3.54	1.244E+11	3.37	1.241E+11	3.87	1.247E+11	3.58
2030	1.313E+11	3.59	1.319E+11	3.28	1.324E+11	3.54	1.326E+11	3.33
2040	1.435E+11	3.52	1.429E+11	3.28	1.433E+11	3.71	1.436E+11	3.73
2050	1.552E+11	4.19	1.547E+11	3.61	1.543E+11	3.88	1.539E+11	4.27
2060	1.701E+11	4.67	1.710E+11	4.03	1.706E+11	3.84	1.702E+11	4.23
2070	1.863E+11	4.75	1.865E+11	4.55	1.872E+11	4.02	1.870E+11	3.93
2080	2.059E+11	4.38	2.072E+11	4.06	2.057E+11	4.11	2.070E+11	4.19
2090	2.297E+11	4.30	2.284E+11	4.90	2.294E+11	4.18	2.304E+11	3.85
2100	2.556E+11	4.57	2.576E+11	4.59	2.536E+11	3.92	2.557E+11	4.28

Table 18: Proportion of Claims Cost against GDP for changes in Inflation Rate

Inflation Rate	**3% (Baseline)**	**1%**	**5%**	**7%**
2020	9.57%	9.59%	9.57%	9.61%
2030	7.17%	6.64%	7.63%	6.29%
2040	6.04%	5.03%	7.02%	4.34%
2050	5.26%	4.17%	6.76%	3.32%
2060	4.76%	3.77%	6.84%	2.80%
2070	4.35%	3.49%	6.89%	2.43%
2080	4.07%	3.42%	6.98%	2.20%
2090	3.89%	3.42%	7.17%	2.05%
2100	3.75%	3.58%	7.28%	1.95%

C.2: Catastrophic Event Frequency Testing

Table 19: Nominal Claims Cost for changes in Frequency of Hazard Events

Factors	**1 (Baseline)**		**0.5**		**2**		**4**	
	Claims Cost (Ᵽ)	SD (%)	Claims Cost (Ᵽ)	SD (%)	Claims Cost (Ᵽ)	SD (%)	Claims Cost (Ᵽ)	SD (%)
2020	1.241E+11	3.54	1.122E+11	2.70	1.473E+11	4.41	1.952E+11	3.66
2030	1.313E+11	3.59	1.174E+11	2.81	1.618E+11	3.93	2.183E+11	4.13
2040	1.435E+11	3.52	1.249E+11	2.74	1.788E+11	3.55	2.512E+11	3.96
2050	1.552E+11	4.19	1.336E+11	3.19	2.009E+11	3.83	2.926E+11	3.84
2060	1.701E+11	4.67	1.406E+11	3.54	2.276E+11	3.94	3.439E+11	4.01
2070	1.863E+11	4.75	1.471E+11	3.51	2.633E+11	4.60	4.119E+11	3.86
2080	2.059E+11	4.38	1.550E+11	3.60	3.044E+11	4.33	5.075E+11	3.17
2090	2.297E+11	4.30	1.634E+11	4.40	3.574E+11	4.12	6.217E+11	3.05
2100	2.556E+11	4.57	1.739E+11	3.85	4.161E+11	4.13	7.403E+11	3.52

Table 20: Proportion of Claims Cost against GDP for changes in Frequency of Hazard Events

Factors	1 (Baseline)	0.5	2	4
2020	10%	9%	11%	15%
2030	6%	6%	8%	10%
2040	4%	4%	5%	8%
2050	3%	3%	4%	6%
2060	3%	2%	4%	6%
2070	2%	2%	3%	5%
2080	2%	2%	3%	5%
2090	2%	1%	3%	6%
2100	2%	1%	3%	6%

D. Risks Identified using Risk Categorisation and Definition (RCD) Tool

Table 21: RCD Tool

No.	Risk Category	Risk Subcategory	Risk	Definition
1	Financial	Market	Economic Recession	Coverage amount may need to decrease.
2	Financial	Market	Interest rate changes	Cost calculations need to be adjusted
3	Financial	Market	Decreased currency value	Reduced purchasing power for resources.
4	Financial	Market	Increase in Inflation	Cost of living may increase, making it more difficult to meet their needs. • Increased housing value • Increased cost of services
5	Operational	Disasters	Climate change/Extreme Weather	• Regions may experience higher impacting disasters. Increased difficulty of finding a safe location to relocate. • Risk of reactive relocation, physical asset damage and costs will increase. • Climate change may lead to extreme weather events ○ Of greater intensity ○ Of greater frequency ○ Which now affect previously unaffected locations
6	Operational	Resources	Insufficient land to relocate residents	Insufficient land may require residents to move further, increasing costs to relocate residents.
7	Operational	Resources	Sudden population increases	Number of residents to cover for relocation increases, increasing costs.
8	Operational	Government	Changes in tax costs	This may impact changes in our stamp duty cover. Taxes may increase so much that it is too costly offer that benefit.
9	Strategic	Strategy	Changes in resident preferences	Residents may not want to proactively move even with the incentives.
10	Strategic	Strategy	Moral Hazard	Residents may take advantage of the social program and receive an unfair payout.

E. Elaboration on Assumptions

E.1: Categorising ‘Catastrophic’ Weather Events

The data provided concerned the historical occurrence of weather events in general. For the purposes of this scheme, reactive relocation is only necessary if a ‘catastrophic’ weather event has occurred. Proactive relocation refers to the response citizens in anticipation of a ‘catastrophic’ weather event that may occur in the future. That is, the threshold for relocation is a weather event achieving a magnitude that can be deemed ‘catastrophic’. However, no definition of ‘catastrophic’ has been provided in the data.

In 2021, 10,492 died due to a natural disaster.[13] This total was spread across 5 continents – the Americas, Europe, Asia, Africa and Oceania.[14] In 2021, a total of 432 disasters occurred – ranging from drought, earthquake, flood, landslide, storm, wildfire.[15] This means that, on average, the number of deaths, per continent, caused by an event that could be considered an event of dire severity – that is, a disaster event – was 4.857. Hence, for this scheme, it has been assumed that past weather events which have led to *more than 5 deaths* are disaster events or ‘catastrophic’ event(s). The figure has been rounded up to ensure that death indirectly caused by the weather event are not counted. For example, freak accidents due to slipping or falling down the stairs because a flood has made the house unnaturally wet. In contrast, a death that could be seen as being directly caused by a catastrophic event is dying due to drowning in the floodwaters.

Further, a total of 101.8 million people were affected by such disasters.[16] The world population in 2021 was 7.89 billion.[17] This means that the average number, per continent, of citizens affected by a disaster was 15.5. Under this scheme, it has been assumed that historical weather events which have led to *more than 16 people* being injured should be considered ‘catastrophic’.

E.2: Percentage of Region affected by a catastrophic event(s)

The area size affected by a catastrophic event is dependent on the type of disaster and its intensity. For example, tornados and flash floods are short-lived and thus often affect a relatively small area.[18] In comparison, droughts can develop slowly and affect most of a country. However, no data was given in relation to the percentage of each region that was affected by past events.

Based on the Emergency Event Database (‘EED’), in 2021, the most extreme weather events – from most to least fatal – are as follows: Earthquake, Flood, Heat, Winter Storm, Landslide.

As a result, it has been assumed that the more fatal a particular type of natural disaster, the greater the proportion of a region that may likely be affected.

However, there are obviously flaws with this assumption. First, the 2021 EED data has been calculated based off the exact magnitude of events that have happened. Future events may

[13] OCHA Services, *2021 Disasters in Numbers* (Report, 22 April 2022).
[14] Ibid.
[15] Ibid.
[16] Ibid.
[17] *World Bank*, ‘Population: Total’, *Data* (Web Page) <https://data.worldbank.org/indicator/SP.POP.TOTL>.
[18] World Meteorological Organisation, ‘Natural Hazards and Disaster Risk Reduction’, *Focus Areas* (Web Page) <https://public.wmo.int/en/our-mandate/focus-areas/natural-hazards-and-disaster-risk-reduction>.

prove to be more fatal if it turns out to be higher in magnitude. For example, droughts and floods had the greatest impact radius from 1928 to 1990 but have since been less severe.[19]

Further, in practice, the portion of a region that is affected, is contingent upon its topography. No information was provided in relation to the geographical features of each region. Hence, no assumptions could be made as to the varying extent to which each specific region may be affected.

In addition, the rising temperatures associated with climate change may intensify the unpredictability of weather events.[20] This means areas or regions that were previously unaffected may be affected in the future.[21] This presents another limitation as the forecasting of catastrophic events has been based on past events and the areas that have been historically affected.

Further, climate change may cause extreme weather events, such as heat waves and large storms, to occur more frequently.[22] However, another limitation is that this scheme has not mathematically incorporated such increases in prevalence. This is because the exact rate of that increase is largely unknown and based on conjecture.

[19] Hannah Ritchie, Pablo Rosado and Max Roser, 'Natural Disasters', *Our World in Data* (Web Page) <https://ourworldindata.org/natural-disasters#number-of-deaths-by-type-of-natural-disaster>.
[20] Josie Garthwaite, 'Climate of Chaos: Stanford Researchers Shsow Why Heat May Make Weather Less Predictable', *Stanford: News* (Web Page, 14 December 2021) <https://news.stanford.edu/2021/12/14/warming-makes-weather-less-predictable/>.
[21] Tessa Satherley and Daniel May, 'Natural Disasters and Climate Risk', *Parliament of Australia* (Web Page) <https://www.aph.gov.au/About_Parliament/Parliamentary_departments/Parliamentary_Library/pubs/BriefingBook47p/NaturalDisastersClimateRisk>.
[22] Ibid.

F. Additional Data Limitations

F.1: Population Growth

Historical data relating to inflation, interest rates and population were provided. However anticipated growth rates were not available. Ultimately, projections were made based on the worldwide population growth rates. As such, the projections are not based on specific Storslysia growth and there needs to be consideration regarding such figures.

F.2: Inflation & Interest Rates

Limited data regarding inflation and interest rates has resulted in the assumption that these rates will remain as 3% and 5% respectively in the future. As such, market volatility is not apparent in the model.