RELOCATION SOCIAL INSURANCE SCHEME

FACTUARIAL | University of New South Wales
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1. Executive Summary

Weather events have the potential to displace many families and businesses through damage incurred on property. In order to avoid the costs associated with continuous property damage as weather events are projected to increase in both frequency and severity, relocation efforts provide a long-term solution in which climate risk is effectively removed from households.

The primary objective of the proposed program is to reduce displacement risk, increase the safety of residents, provide long-term solutions from property damage costs, reduce financial burden for property owners and reduce the risk of natural hazards sustained by property. To assess the program's success, the number of households successfully relocated, reduction in property damages and reduction in loss and life will be monitored quarterly and annually.

The proposed insurance scheme outlines a voluntary, proactive relocation scheme as well as involuntary, reactive relocation following a hazard event. Under proactive relocation, households will be able to claim the market value of their existing household and be eligible for additional features involving insurance deductive waivers, subsidised removalist costs, and discounts on improved safety features. Under involuntary relocation, households can claim the market value of their existing property inclusive of property damage sustained during the event.

The proposed program aims to mitigate the risk of natural hazards for high-risk households by offering proactive relocation for the first 25 years. The primary source of costs comes from proactive relocation as it is a priority to quickly reduce the number of houses exposed to severe weather events under the emission scenarios. The program requires Ꝑ715 million in capital to ensure solvency, which can decrease substantially to Ꝑ3 million once proactive relocation is ceased 2050 onwards under the full implementation plan. To mitigate the sudden change in capital holdings, payouts could be distributed over 20 years as an annuity to smooth cost distribution. The economic costs without the program vary under the four emission scenarios with the most notable being under a very high emission scenario.

It is within the government's best interest to implement an insurance program relocating households out of natural peril prone areas to help Storslysia in managing its exposure from cataclysmic events and prepare for the financial responsibility involved in mass displacement.

2. Introduction and Background

Natural disasters can have devastating consequences on human lives, property, and infrastructure. The damage sustained from extreme weather events including but not limited to droughts, bushfires, hail, storms, tornadoes, cyclones have potential to destroy buildings and displace families and businesses. As the frequency and severity of extreme weather events are projected to increase, the cost of property repairs and home insurance will become exceptionally high, leaving many people uninsured, underinsured, and unprotected. This calls to action a long-term solution to effectively and efficiently mitigate climate risk to individuals in Storslysia.

This report considers five Shared Socioeconomic Pathways (SSP) as outlined by the Intergovernmental Panel on Climate Change (IPPC) in which property damage, frequency, population, and GDP are modelled under *(Appendix, A)*. The frequency and severity of natural hazards are then modelled under these emission assumptions. The SSPs are combined with radiative forcing per square metre which measures the change in energy flux imposed by climate change to create four key emission scenarios (SSP1-2.6, SSP2-3.4, SSP3-6.0 and SSP5-Baseline). The forcing figures can encapsulate changes in "solar energy output, volcanic emissions, deliberate land modification, anthropogenic emissions of greenhouse gases, aerosols, and their precursors" (Sorteberg, n.d.).

An analysis of weather events in Storslysia from 1960 to 2020 revealed regions 2, 3 and 4 as having faced higher annual average property damages incurred by hazard events. Between 2010 and 2020, the frequency of disasters trends upwards across all regions, with the impacts being the most significant in regions 2 and 3, and noticeable in regions 4 and 5. This increase is driven by the significant increase in frequency of minor and medium hazards in the past decade. *(Appendix, B)*

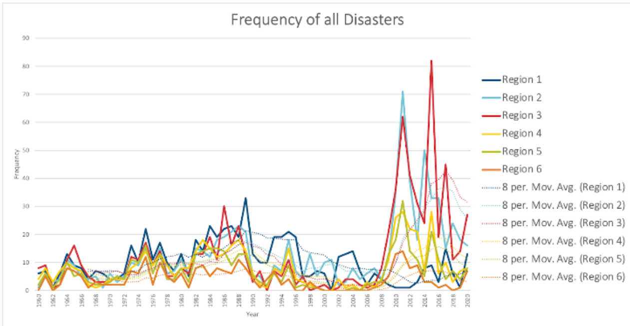


Figure 1 - Historical Frequency

Households in natural peril prone areas face higher risk of sustaining property damage in the event of a hazard. This places financial burden on homeowners to continuously cover the cost of repairs and may also force homeowners to pay extremely high premiums for home and content insurance. Insurance companies may additionally opt out of covering houses within high-risk areas which further exacerbates the burden for high-risk households. Therefore, relocation is considered a final resort in which climate risk is effectively removed altogether. The report covers a proposed insurance scheme aimed at removing climate risk on property by relocating high-risk households in Storslysia to lower risk areas.

3. Objectives

The proposed social insurance program is designed to assist the citizens of Storslysia for relocation in order to manage displacement risk arising from cataclysmic weather events. The coverage proposed covers voluntary, proactive relocation as well as involuntary, reactionary relocation with primary focus on moving households out of natural peril prone areas.

The main objectives of our proposed program design:

- Effectively reduce displacement risk arising from relocations by offering government and insurance support in social, economic, and psychological factors.
- Provide long term solutions - by remove climate risk from high-risk households it reduces continually incurred insurance losses from severe weather events.
- Reduce financial burdens on homeowners from property damages incurred by severe weather events and rising home insurance premiums.
- Reduce the risk of natural hazards, reduce the risk posed to people, property, and infrastructure by moving communities away from high-risk areas.
- Ensuring social equity, needs and interest of all members, including low-income residents and marginalised populations. Ensuring the scheme is fair and accessible.

Key metrics to be reported and used to monitor the proposed program's success:

- Number of households relocated successfully from high-risk areas to low-risk areas. Reported quarterly.
- Reduction in property damage costs following a hazard event. Reported quarterly.

- Cost savings, comparing relocation costs under the relocation program with post-disaster recovery costs. Reported quarterly.
- Reduction in loss of life and injuries by displacing individuals from high risk to low-risk areas. Reported annually.
- Economic benefits, increase to GDP. Reported annually.
- Greenhouse gas emissions, through the subsidisation and additional incentives to use renewable energy sources and low-carbon materials. Reported annually.

It is recommended to report on these key metrics on a regular basis, quarterly or annually to ensure the program is being tracked and assessed in meeting its objectives. Regular reporting also allows for continual adjustments to be made to promote efficacy and longevity.

4. Program Design

The program provides the framework for a relocation scheme. Proactive relocation is claimed before a weather event occurs with additional incentives to encourage citizens to voluntarily relocate before a disaster. Involuntary relocation, however, can only be filed post disaster with reduced government payouts. The social insurance program implements a buy-back scheme in which the government purchases a homeowner's current property and provides them with the funds to relocate to a lower risk area, removing a high-risk house from the property market.

4. 1 Proactive relocation

Under a proactive program, citizens will be compensated for their land and house value at market prices and will be eligible for additional incentives outlined in Section 4.4. Under this program, temporary housing is not provided. Proof of acquiring a new property in a low-risk region must be provided in order to be accepted with the transfer of funds contingent upon the purchase of the new property. To be approved, households must satisfy two criteria's; the household must be from a high-risk region (Regions 2, 3 and 4) and must also be within the top 0.01% of the predictive factor *(Appendix, G).* Only offered for the first 25 years of program.

4.2 Involuntary relocation

Under involuntary relocation, citizens will only be able to claim their land, household contents and remaining value of their house (market value - property damage) after an event. Temporary housing costs will be further subsidised for a month in the event property damage exceeds 20% of property value for the event being claimed under to allow time to acquire a new property. For claims to be awarded, households must now satisfy three criteria's; the household must be within a high-risk region, be in the top 5% of the risk rating and must be within the top 0.01% of property damage sustained during the weather event. Assuming this criteria, an estimated 120-200 houses will be eligible for involuntary relocation per hazard event.

4.3 Limitations of coverage

However, relocation under the proposed programs do not cover the full relocation cost to the consumer in the event a purchased property is worth more than their existing one as the government will only purchase the market value of their existing property. The difference in property prices is solely on homeowners. Furthermore, the damage sustained to existing property and household contents are not covered under involuntary relocation schemes. The costs associated with removalist, property acquisition and real estate fees are also not provided under the government buy-back scheme.

4.4 Incentives for proactive relocation

Incentives to encourage voluntary, proactive relocation rather than involuntary relocation:

- Deductible waivers: Reduce out-of-pocket insurance expenses for homeowners in the event of damage.
- Improved home safety features: Offer discounts to technologies such as security systems, smoke detectors, house alarms and natural peril resistant measures such as improved roofing, reinforced glass for windows and fire-resistant materials.
- Moving services: Assist in the relocation process by providing removalists, trucks, and other features. Potentially cover moving expenses for lower property value distribution.
- Green incentives: Discounts or free sustainable upgrades to technology such as solar panels, and rainwater tanks.
- Community and council agreements can also be made in which residents are encouraged to move to their regions and in turn offered discounts on relocation costs or housing. Reduced strata rates for apartments, council fees for housing and priority in buying houses can further incentivise people to relocate to safer regions.

4.5 Additional key features

Citizens from a low socio-economic background will receive additional benefits to assist in covering costs associated with relocation to ensure equity and accessibility. Under proactive relocation, an additional Ꝓ50,000 above market value will be provided for property value of Ꝓ0. This benefit will decrease linearly to Ꝓ0 for property value up to Ꝓ150,000 such that for every Ꝓ30,000 increase in property value, the additional payout will reduce by Ꝓ10,000.

Those with lower than median incomes will also be allowed to take out government-backed loans for their new property which would reduce market borrowing rates. Furthermore, a reduction in house deposits may be offered to citizens with low income to assist in their purchase of a new home in a safer region. All these benefits, however, call upon an additional criterion to distinguish which residents would be eligible for the supplementary assistance.

Under the very high emission scenario, frequency and severity are both expected to increase exponentially which further increases the risk of incurring cataclysmic weather events. Whilst the government initiates relocation insurance schemes, action can be taken to reduce CO2 emissions in parallel. A consideration includes using bought-back land as location for renewable energy plants such as wind farms, solar panels, and hydropower dams to reduce the reliance on fossil fuels. Governments can also prioritise sustainable transportation practices by building bike lanes and sidewalks and investing in public transport infrastructure to reduce the number of cars on the road. Reduction in waste can be encouraged by compost and recycling schemes with an abolishment of single use plastic. Homeowners can also be encouraged to be environmentally conscious by being offered discounts on eco-friendly upgrades including updating insulations and investing in energy efficient appliances.

4.6 Qualitative justifications

A) The buy-back program is available under both involuntary and proactive relocation schemes for households exposed to higher risk. For proactive relocation, homeowners can claim the market value of their property in exchange for their ownership of the house in a low-risk region. For involuntary relocation however, homeowners can only claim the market value of their home minus the property damage that was incurred due to the disaster. This provides the incentive to relocate voluntarily before a weather event to receive the full market value of their property.

B) Temporary housing will be provided for renters and homeowners who relocate involuntarily to a low-risk region and sustain property damage greater 20% of their property value in an event. Temporary housing will be provided for one month only after the disaster to provide sufficient time for individuals to find another property.

C) The additional assistance provided to households from a low socio-economic background has been established to support relocation of individuals with low property value and low income. By reducing house deposits and offering government backed loans, it will assist individuals with low incomes in acquiring funds to purchase a new home. It will ensure the social insurance scheme is equitable, accessible, and fair without exacerbating financial inequality between demographics and regions.

4.7 Quantitative justifications

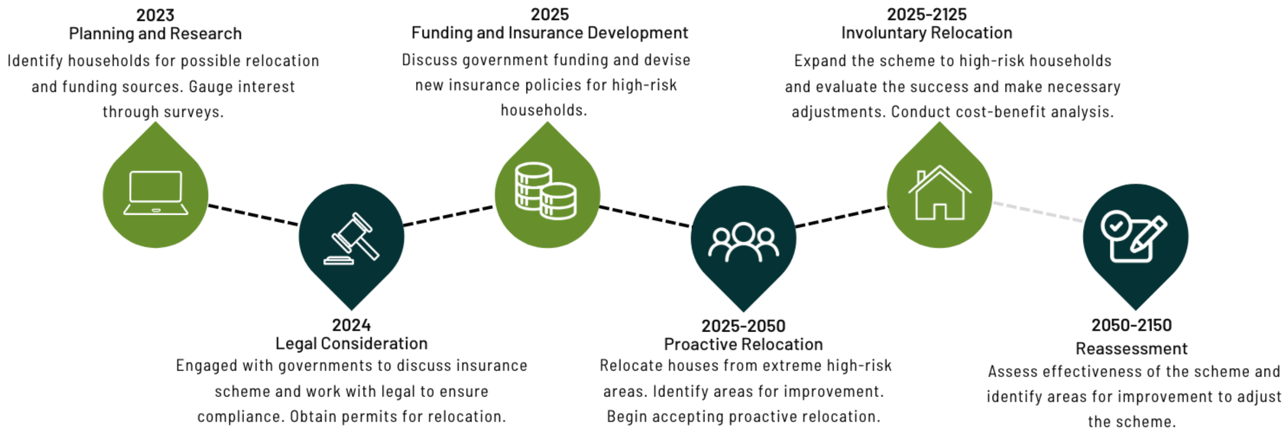
4.7.1 *Market value of property will be provided under proactive relocation with adjusted property value offered under involuntary relocation.*
Under the buy-back government scheme, the idea is to relocate households to lower risk areas in order to avoid paying continually incurred property damage. With a one-off lump sum payment to facilitate relocation, costs with recovery efforts will be substantially minimised.

4.7.2 *Temporary housing is provided under involuntary relocations for the first month.*
This program feature was designed to assist victims of natural disasters as they readjust and seek accommodation. As temporary housing costs are insignificant, sensitivity analyses show that adjusting the amount of time that temporary housing is subsidised is immaterial to the costs of the program.

4.7.3 *Property value below Ᵽ150,000 will be eligible for higher payouts in the form of market value under involuntary relocation and above market value under proactive relocation.*
This is to assist in the purchase of a new home where the market value of their existing property is insufficient to purchase a home in a new region given higher house prices. The combination of low median household income, high poverty rate, and low property value *(Appendix, J)* suggest that region 4 is the poorest out of the six regions and combined with being a high-risk region, region 4 will require the most assistance. Therefore, the threshold for Ᵽ150,000 allows for 50% of region 4's population to claim the additional funds.

4.7.4 *The Ᵽ50,000 benefit will decrease linearly to Ᵽ0 for property values up to Ᵽ150,000 i.e. for every Ᵽ30,000 increase in property value, the additional payout will reduce by Ᵽ10,000.*
This program feature aims to assist those of low socio-economic status so that they are not excluded from the relocation benefits due to financial hardships. This specific method maintains the wealth distribution of citizens to ensure fairness to those whose properties lie above the Ᵽ150,000 threshold.

4.8 Timeline



5. Pricing and Costs

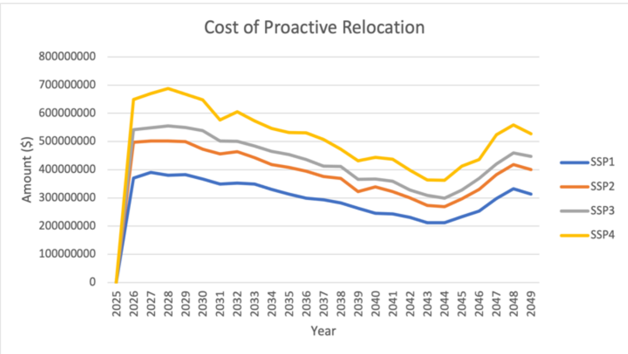


Figure 2 - Proactive Relocation Costs

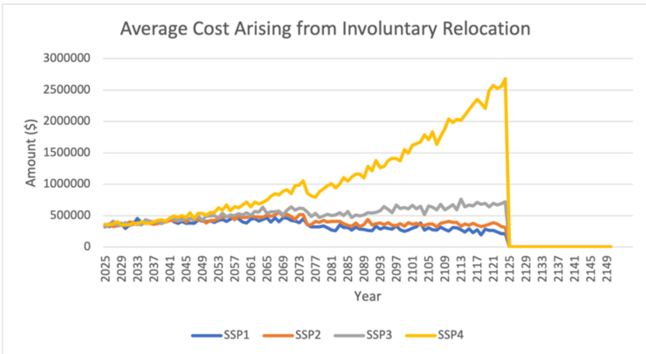


Figure 3 - Involuntary Relocation Costs

The source of program costs primarily come from the proactive relocation feature of the scheme. The scheme heavily prioritises and encourages proactive relocation within the 25 years it is being offered and thus, with so many houses being bought back, costs to the government will initially be high. Thus, proactive relocation is the dominant source of expenditure throughout the program's first 25 years as observed in the figures below. Involuntary costs decrease over time for the SSP1 and SSP2 emission scenarios, but for higher emissions scenarios, we see a growth over time, especially for SSP4. This justifies the large costs incurred for proactive relocation as it is more beneficial to quickly reduce the number of houses exposed, than allow them to be impacted by the severe natural disasters of the high emission scenarios.

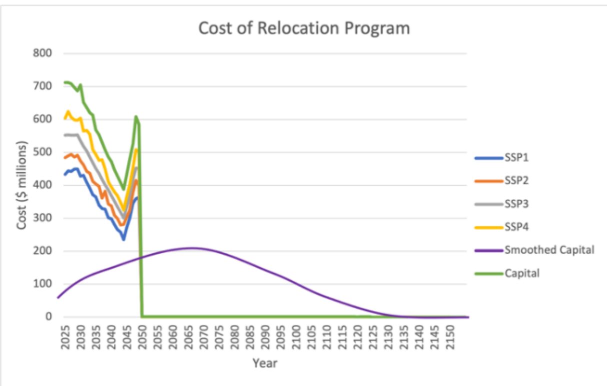


Figure 4 - Capital Requirements

Thus, it is recommended to initially hold Ᵽ715 million in capital to ensure the risk of insolvency is below 0.01% for all emission scenarios. Once proactive relocation is no longer offered, from 2050 onwards, capital holdings can decrease dramatically to 3 million. The program will no longer see high levels of activity beyond 2050 as most high-risk homes have already been relocated to maximise economic benefit. *(Appendix, K)*

However, this capital structure may not be ideal for implementation - a possible strategy to mitigate this sudden change in capital holdings would be to offer the payout as an annuity over several years (20 years) to smooth out the distribution of costs.

The economic costs without the program varies under the four emission scenarios with the most notable being under a very high emission scenario in which cost rise exponentially. These figures exceed the cost with the program as recovery efforts and continuous property damages are sustained to households in high-risk areas. It is therefore in the governments best interest to implement the proposed scheme to reduce the cost post-disaster and eliminate climate risk from high-risk households.

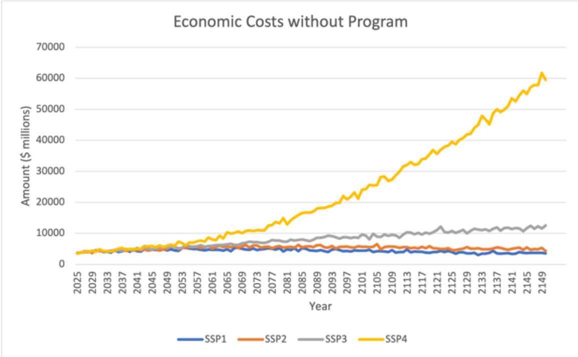


Figure 5 - Economic Costs without Program

6. Assumptions

A. Damage proportion caused by houses by each class of event is assumed to follow log-normal distribution with mean of 0 and normal deviation added to simulate randomness. Distribution is right skewed and non-negative which largely conforms to claim expectations. Standard deviation fitted so projects would fall within historical expectations.
B. Property damage proportions for each type of event falls within the following ranges: Major: 0-70%, Minor: 0-10%, Medium: 0-30%. These ranges appeared to be the most appropriate under our classifications of events.
C. Natural disasters occurring across multiple regions are considered as different and independent events. The modelling approach projects disasters in each region individually.
D. Stamp duty, administration fees, taxes or real estate commission are not included in total costs of relocation. There is a lack of data to account for these costs within the model.
E. Population size of each region will grow proportionally to the projected world population. No other information provided on Storslysia's population growth.
F. Storslysia GDP will grow proportionally to the projected increase in global GDP. No other information provided on Storslysia's GDP growth.
G. Citizens will relocate to a house of equal value to their existing property. Most citizens will purchase property of comparable value so any deviation in cost will likely even out.
H. No government intervention to build new houses. Invisible Hand Principle: supply for houses will meet demand as construction companies identify opportunities of business.
I. All housing costs (including property value) will rise with projected inflation. Governments will likely implement policies to prevent abnormally inflated property prices in safe regions.
J. Citizens relocating will be completed beginning of the following year to simplify the model.

7. Risk and Risk Mitigation Strategies

7.1 Qualitative risk

7.1.1 *Issues with accessibility to workplaces and employment transition upon relocation.*

Government can offer payments for individuals over the age of 18 and those actively seeking new employment after relocation. These payments will be available for one year or until the individual is able to find employment. New regulations can also be enforced for a hybrid working environment within workplaces to assist the citizens in adjusting to new workplaces.

7.1.2 *Desertion of high-risk areas upon relocation*
Utilise empty land for sustainable activities such as tree plantations, solar farms, and wind farms to help control the emission levels apart from having a use in those empty areas. Land can also be used for community gardens to encourage more social interactions and community bonding.

7.1.3 *Emotional distress and anxiety due to sudden relocation.*
Implement counselling and support programs to console and assist families. Promote and organise community events to elevate a sense of belonging and inclusivity.

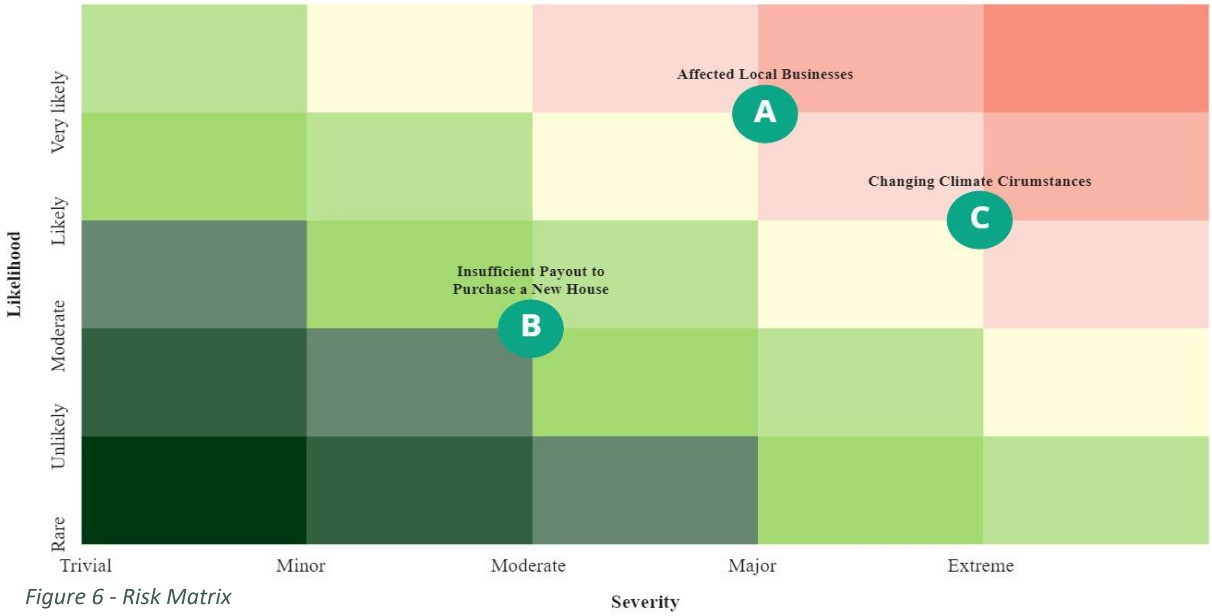


Figure 6 - Risk Matrix

7.2 Quantifiable risks

7.2.1 *Local businesses will be affected as customers relocate out of high-risk regions.*
Possible mitigation includes providing financial assistance such as cash-back deals, vouchers, and increased marketing of small businesses. Further assistance may also be provided to small business to relocate to low-risk regions to promote sales. Approximately Ᵽ89mil, Ᵽ18mil and Ᵽ12mil decline in sales are expected in regions 2, 3 and 4 respectively. *(Appendix, L)*

7.2.2 *The government pay-out is insufficient to purchase a new property in a low-risk region due to a lower value property market in certain regions.*
Property values in low-risk regions will be significantly higher than areas of high-risk as market prices encapsulate climate risk to property and land. Therefore, pay-outs may be insufficient to purchase new property. Approximately, Ᵽ32,061 difference between average property value and the minimum threshold of Ᵽ150,000. *(Appendix, M)*

7.2.3 *Climate circumstances may worsen and result in larger severities and frequencies of natural disasters.*
Under increasing emission scenarios, frequency and severity increase which poses greater risk to property and land. Mitigation therefore includes using bought-back land as renewable energy farms, encourage upgrades to eco-friendly appliances and invest in sustainable infrastructure.

7.3 Sensitivity analysis

Standard deviation: Adjusting the change in standard deviation used in log normal model.
Impact: Change in the average proportion of damages incurred on each house after an event.

Minor	+10%	-13.16%
	-10%	+26.23%
Medium	+10%	-8.52%
	-10%	+13.76%
Major	+10%	-7.41%
	-10%	+12.35%

Truncation: Adjusting the limits imposed on possible damage proportions.
Impact: Changes in the average proportion damages incurred on each house after an event.

Minor	+10%	+10.53%
	-10%	-18.35%
Medium	+10%	+16.86%
	-10%	-8.75%
Major	+10%	+14.81%
	-10%	-9.87%

Frequency: Adjusting the inputs into the frequency model (number of events in 2020).
Impact: For all SSP scenarios and classification of events, any change in inputs to frequency will result in a proportional change in projected frequencies.
Example: increasing the expected number of minor events in 2020 by 10% would reflect a 10% increase in the frequency of minor events across all years and SSP scenarios.

7.3 Degree of certainty program exceeding 10% of GDP

Costs of relocation with the program in place lie well below the 10% GDP limit and falls more after the initial 25 years of proactive relocation as costs cease and economic benefits are reaped. For each emission scenario, there is a 99% certainty that the economic costs arising from relocation will remain lower than the following percentages of GDP:

SSP1	SSP2	SSP3	SSP4
2.07%	2.47%	2.68%	2.71%

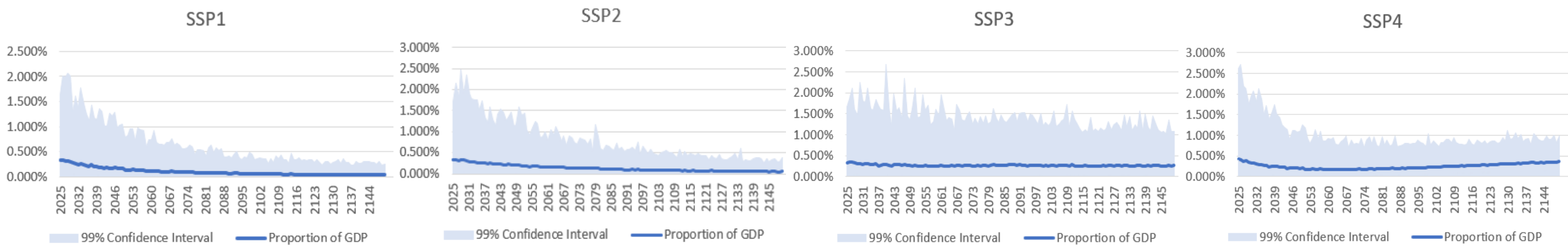


Figure 7 - Cost as proportion of GDP with confidence intervals

7.5 Degree of certainty of cost-saving with and without program

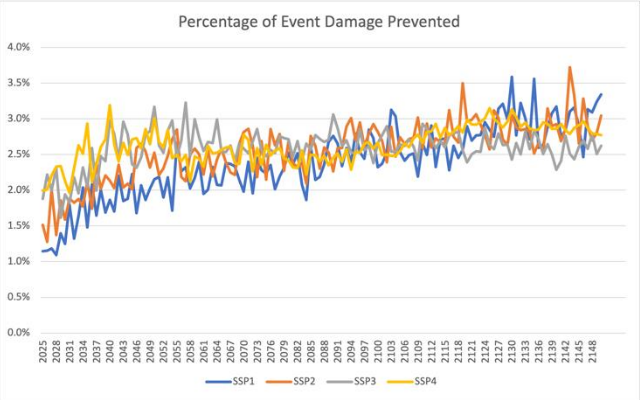


Figure 8 - Prevented Damage

In the first 25 years of the program of proactive relocation, the cost of the scheme will outweigh the economic benefits. However, after the end of this period, costs significantly drop and the probability of a loss (annual economic benefit – annual cost) falls to almost 0 - with 98.4% confidence that the annual cost will not outweigh the economic benefit for the years 2045 and beyond. The benefit of this scheme is distributed across all future years as cost savings accumulate with time. As this insurance scheme works as a preventative measure, the initial expenses will be large as the government is investing in long-term economic health.

Total damage (Ᵽ) prevented over full 130 years of relocation implementation:

SSP1	SPP2	SPP3	SSP4
9,167,221,700	11,202,851,070	18,596,544,424	65,807,543,960

8. Data and Data Limitations

A. No claim data provided per household, only aggregated data per region. Therefore, damage severity to each household was simulated which may not reflect actual experience.
B. No housing availability data within each region and therefore, unable to determine how many people can move to each region, amount of available housing, capacity to build new property and the insufficient data describing infrastructure to support a growing population.
C. Due to a lack of data regarding relocation period length, simplifying assumptions were made that relocation will be concluded in the following year.
D. Unable to account for the impact of private home and contents insurance due to lack of data of coverage, premium prices, and proportion of households with insurance. Home and contents insurance has the potential to impact the insurance scheme. After an event occurs, individuals would now have the option to repair property from insurance and then claim proactive relocation, receiving a higher government pay out than involuntary relocation.

9. Conclusion

The proposed social insurance scheme provides the framework for involuntary and proactive relocation in which market value compensation is offered for households moving out of high-risk regions. The program provides substantial cost saving measures and requires Ᵽ715 million in capital to ensure solvency, dropping to Ᵽ3 million once proactive relocation has ceased. Given these cost-reduction measures and a reduction in climate risk on property and land, the social insurance scheme is heavily recommended for implementation in Storslysia.

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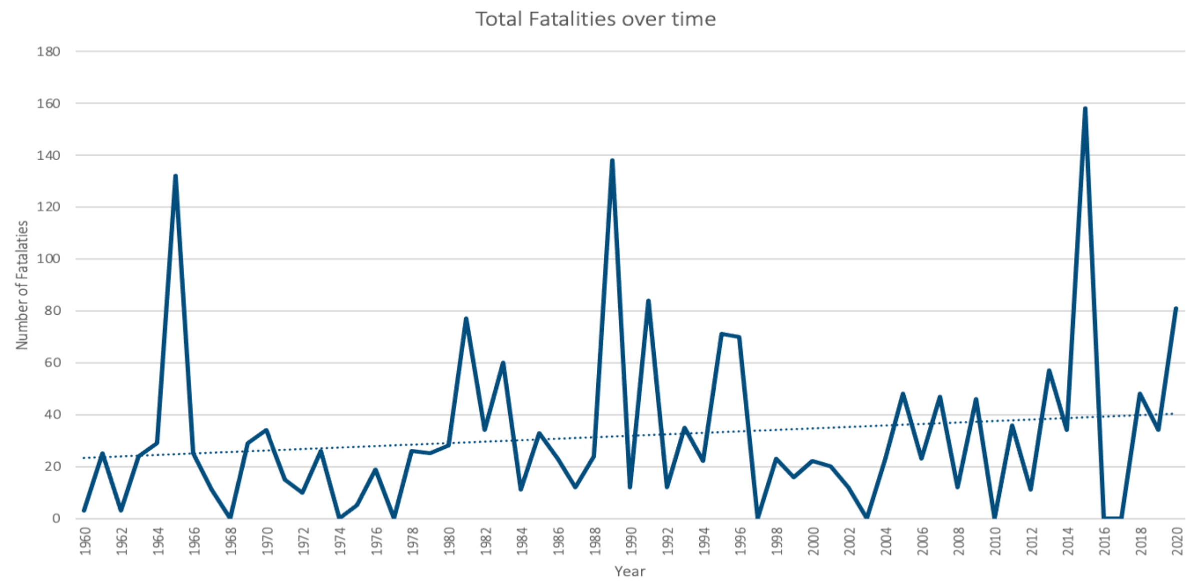
Appendix

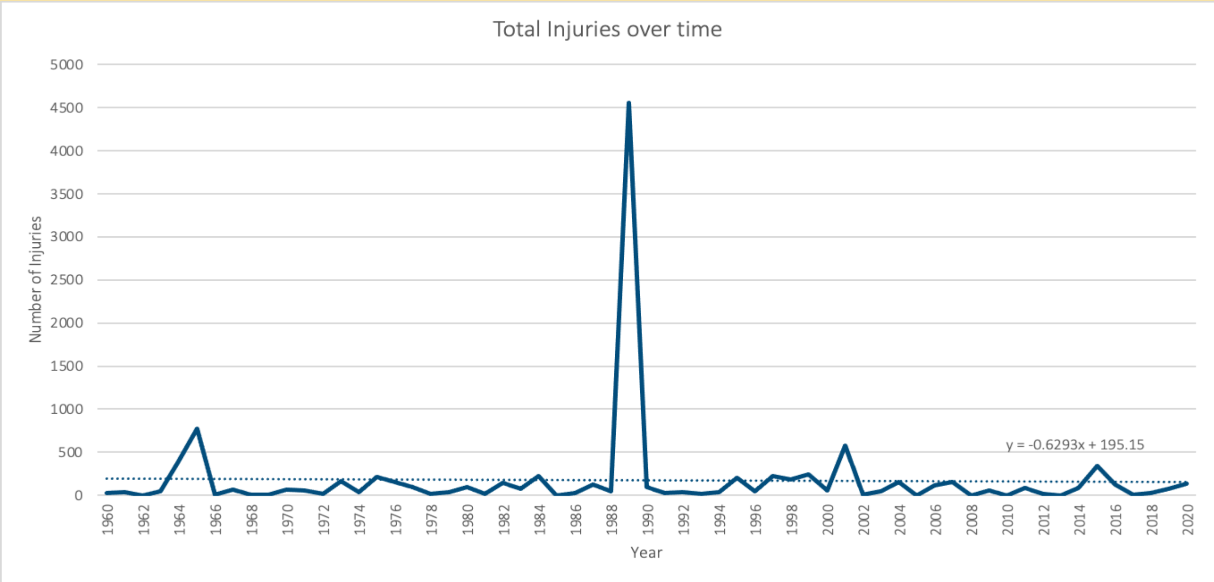
A. Shared socio-economic pathways (SSP)

Under SSP1, human development and environmental action are both positive with continual improvements in education, health, reduction in poverty and an elimination of global inequality. SSP5 similarly assumes these human developments but they are now achieved under a heavy reliance on fossil fuels. This then poses major environmental implications. Pessimistic approaches on human development are assumed under SSP3 and SSP4 with high levels of nationalism and a continuation of global inequality. SSP2 is the average of these scenarios in which development progresses, but not as slowly as SSP3 and SSP4 yet the progress perpetuates inequality.

B. Exploratory analysis

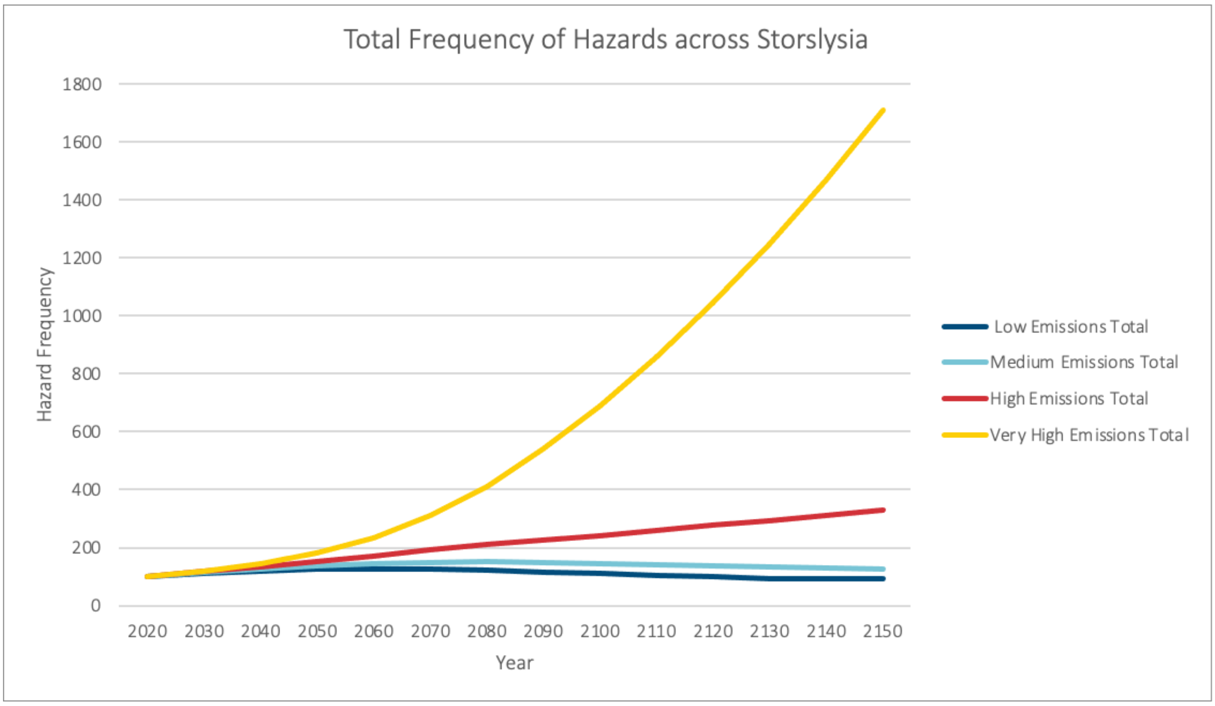


An analysis into total fatalities over time cause by natural events revealed quite volatile trends with deaths ranging from 0 to 160. The most notable peaks occurred in 1965, 1989 and 2015 brought on by weather events. In 1965, spike is death was attributed to a landslide in region 3. In 1989, spike in deaths across regions 2, 3 4, and 5 due to winter weather, severe storms/thunderstorms/wind, hurricane/tropical storms. Increase in deaths in 2015 due to costal floodings in region 3. A general upward linear trends can be seen in which total death is increasing with time across all regions.



Total injuries cause by natural events remains fairly small (less than 200 injuries) with a significant increase in 1990 of over 4,500 injuries caused by flooding. The general trend reveals a constant linear relationship in which injuries have not been increasing with time, deeming it an area not of concern.

C. Frequency projections (2020-2150)



A frequency projection was conducted for Storslysia for 2150, where under high and very high emissions scenarios, the frequency of hazards are projected to increase significantly. This increase follows a shallow but upward linear trend for the high emissions scenario but follows an exponentially increasing trend for the very high emissions scenario.

D. Population projections (2020-2100)

Using simulated world population figures, incremental growth was used to project population within Storslysia following the same assumption as shown below:

Incremental Growth	SSP1–2.6	SSP2–3.4	SSP3–6.0	SSP5– Baseline
2005	-	-	-	-
2010	1.05972	1.05692	1.06009	1.05837
2020	1.09538	1.10771	1.11919	1.09579
2030	1.06332	1.08541	1.10519	1.06623
2040	1.04094	1.06416	1.08813	1.04348
2050	1.01669	1.04323	1.07559	1.02143
2060	0.99531	1.02290	1.06124	1.00117
2070	0.97762	1.00853	1.05203	0.98487
2080	0.96024	0.99471	1.04586	0.96927
2090	0.94228	0.98300	1.04299	0.95488
2100	0.92676	0.97622	1.04040	0.94253

SSP1	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2021	6,302,060.22	4,191,550.09	4,989,663.80	997,197.77	1,260,905.99	295,677.81	18,037,055.68
2030	6,701,135.27	4,456,978.06	5,305,631.96	1,060,344.86	1,340,752.28	314,401.47	19,179,243.90
2040	6,975,499.37	4,639,459.80	5,522,860.06	1,103,758.48	1,395,646.60	327,273.99	19,964,498.31
2050	7,091,896.26	4,716,876.29	5,615,017.44	1,122,176.38	1,418,935.10	332,735.06	20,297,636.54
2060	7,058,640.01	4,694,757.29	5,588,686.76	1,116,914.12	1,412,281.25	331,174.75	20,202,454.19
2070	6,900,672.80	4,589,692.05	5,463,616.03	1,091,918.40	1,380,675.42	323,763.30	19,750,338.01
2080	6,626,308.70	4,407,210.32	5,246,387.93	1,048,504.78	1,325,781.10	310,890.78	18,965,083.61
2090	6,243,861.77	4,152,841.84	4,943,585.11	987,988.82	1,249,261.74	292,947.28	17,870,486.56
2100	5,786,588.28	3,848,705.62	4,581,538.26	915,632.78	1,157,771.20	271,493.08	16,561,729.23

SSP2	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2021	6,302,060.22	4,191,550.09	4,989,663.80	997,197.77	1,260,905.99	295,677.81	18,037,055.68
2030	6,840,343.94	4,549,566.85	5,415,850.59	1,082,372.35	1,368,604.92	320,932.81	19,577,671.47
2040	7,279,252.21	4,841,488.21	5,763,356.74	1,151,822.39	1,456,420.98	341,525.35	20,833,865.89
2050	7,593,941.16	5,050,790.32	6,012,512.10	1,201,616.76	1,519,383.43	356,289.82	21,734,533.59
2060	7,767,848.21	5,166,457.27	6,150,203.21	1,229,134.70	1,554,178.47	364,449.13	22,232,271.00
2070	7,834,098.51	5,210,520.87	6,202,656.97	1,239,617.73	1,567,433.73	367,557.44	22,421,885.25
2080	7,792,692.07	5,182,981.12	6,169,873.37	1,233,065.84	1,559,149.19	365,614.74	22,303,376.34
2090	7,660,191.46	5,094,853.92	6,064,965.85	1,212,099.79	1,532,638.69	359,398.13	21,924,147.84
2100	7,478,003.13	4,973,679.02	5,920,718.02	1,183,271.47	1,496,186.74	350,850.28	21,402,708.65

SSP3	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2021	6,302,060.22	4,191,550.09	4,989,663.80	997,197.77	1,260,905.99	295,677.81	18,037,055.68
2030	6,965,004.22	4,632,479.39	5,514,550.51	1,102,097.80	1,393,546.75	326,781.58	19,934,460.24
2040	7,578,841.25	5,040,747.25	6,000,556.73	1,199,227.45	1,516,362.27	355,581.37	21,691,316.31
2050	8,151,755.82	5,421,797.26	6,454,162.53	1,289,881.79	1,630,990.09	382,461.17	23,331,048.65
2060	8,651,009.94	5,753,855.12	6,849,447.58	1,368,880.58	1,730,880.04	405,884.99	24,759,958.25
2070	9,101,157.10	6,053,251.56	7,205,852.14	1,440,108.99	1,820,944.75	427,004.84	26,048,319.37
2080	9,518,566.28	6,330,873.71	7,536,336.36	1,506,157.15	1,904,459.31	446,588.69	27,242,981.50
2090	9,927,790.97	6,603,052.28	7,860,340.51	1,570,910.25	1,986,336.32	465,788.55	28,414,218.88
2100	10,328,831.17	6,869,787.29	8,177,864.57	1,634,368.29	2,066,575.79	484,604.41	29,562,031.52

SSP4	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2021	6,302,060.22	4,191,550.09	4,989,663.80	997,197.77	1,260,905.99	295,677.81	18,037,055.68
2030	6,719,415.20	4,469,136.19	5,320,105.11	1,063,237.36	1,344,409.70	315,259.12	19,231,562.68
2040	7,011,563.69	4,663,446.46	5,551,414.03	1,109,465.07	1,402,862.29	328,966.04	20,067,717.58
2050	7,161,811.48	4,763,377.45	5,670,372.90	1,133,239.32	1,432,923.63	336,015.31	20,497,740.10
2060	7,170,158.58	4,768,929.18	5,676,981.73	1,134,560.11	1,434,593.70	336,406.94	20,521,630.24
2070	7,061,646.29	4,696,756.79	5,591,066.99	1,117,389.82	1,412,882.74	331,315.80	20,211,058.42
2080	6,844,621.70	4,552,412.02	5,419,237.50	1,083,049.23	1,369,460.81	321,133.52	19,589,914.78
2090	6,535,779.01	4,346,998.31	5,174,710.93	1,034,179.94	1,307,668.07	306,643.34	18,705,979.60
2100	6,160,159.53	4,097,170.82	4,877,313.75	974,744.31	1,232,514.73	289,020.16	17,630,923.30

E. World GDP projections (2020-2100)

Using simulated world GDP figures, incremental growth was used to GDP (Ꝕ1000) within Storslysia following the same assumption as shown below:

Incremental Growth	SSP1–2.6	SSP2–3.4	SSP3–6.0	SSP5– Baseline
2005	-	-	-	-
2010	1.19248	1.19441	1.18418	1.19192
2020	1.48729	1.49822	1.50285	1.50807
2030	1.53064	1.41251	1.33706	1.62709
2040	1.43215	1.29743	1.17769	1.56936
2050	1.30511	1.24165	1.11821	1.40161
2060	1.22310	1.21039	1.09277	1.31149
2070	1.17682	1.19945	1.08895	1.26657
2080	1.13387	1.18041	1.08462	1.22252
2090	1.10403	1.16584	1.08466	1.19133
2100	1.07718	1.15662	1.08934	1.16854

SSP1	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2020	531,771,287	222,153,795	417,708,522	45,815,957	69,643,447	9,845,914	1,296,938,922
2030	813,951,631	340,037,998	639,362,337	70,127,842	106,599,207	15,070,573	1,985,149,587
2040	1,165,697,812	486,984,159	915,660,402	100,433,329	152,665,659	21,583,265	2,843,024,626
2050	1,521,360,989	635,566,691	1,195,035,282	131,076,294	199,245,100	28,168,481	3,710,452,838
2060	1,860,781,692	777,363,736	1,461,651,633	160,319,852	243,697,346	34,452,963	4,538,267,222
2070	2,189,809,300	914,818,942	1,720,104,166	188,667,969	286,788,459	40,545,014	5,340,733,850
2080	2,482,957,231	1,037,284,985	1,950,373,066	213,924,792	325,180,589	45,972,740	6,055,693,403
2090	2,741,270,017	1,145,198,231	2,153,278,816	236,180,313	359,010,533	50,755,484	6,685,693,394
2100	2,952,839,992	1,233,584,111	2,319,467,897	254,408,603	386,718,803	54,672,769	7,201,692,174

SSP2	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2020	531,771,287	222,153,795	417,708,522	45,815,957	69,643,447	9,845,914	1,296,938,922
2030	751,134,828	313,795,530	590,019,481	64,715,719	98,372,402	13,907,500	1,831,945,458
2040	974,546,055	407,128,233	765,509,914	83,964,218	127,631,461	18,044,029	2,376,823,910
2050	1,210,047,771	505,511,883	950,497,476	104,254,400	158,473,953	22,404,418	2,951,189,902
2060	1,464,631,435	611,867,244	1,150,473,986	126,188,631	191,815,512	27,118,115	3,572,094,923
2070	1,756,748,185	733,902,499	1,379,932,888	151,356,610	230,072,593	32,526,750	4,284,539,525
2080	2,073,676,723	866,303,174	1,628,881,552	178,662,304	271,579,152	38,394,782	5,057,497,686
2090	2,417,572,310	1,009,969,655	1,899,012,943	208,291,406	316,617,450	44,762,118	5,896,225,882
2100	2,796,214,914	1,168,152,117	2,196,438,257	240,914,215	366,206,393	51,772,806	6,819,698,703

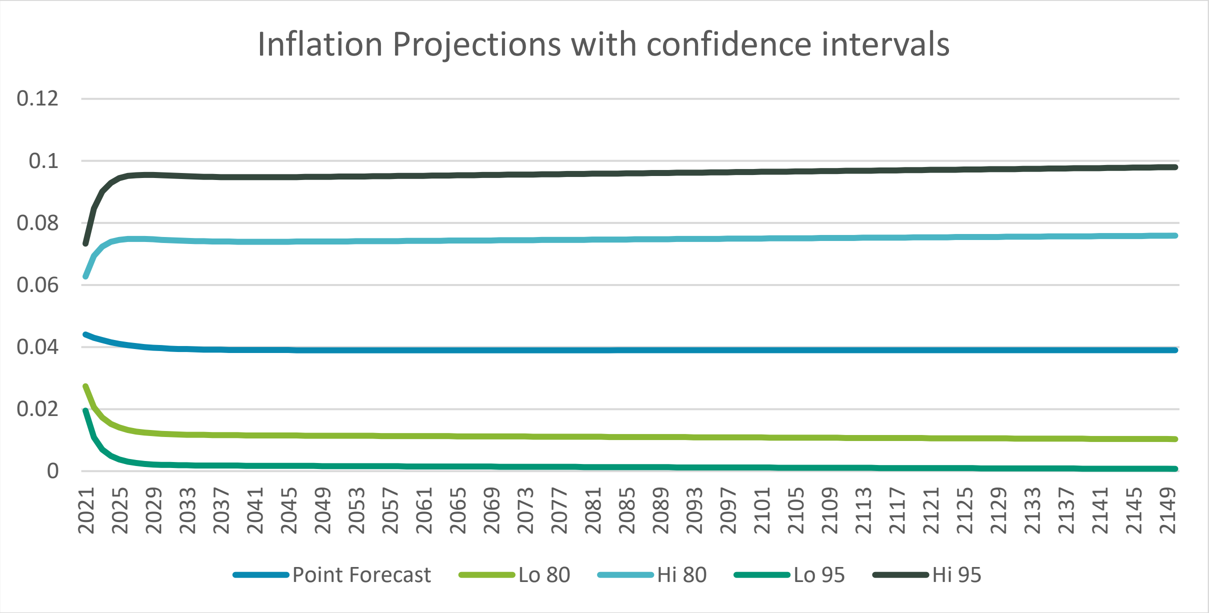
SSP3	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2020	531,771,287	222,153,795	417,708,522	45,815,957	69,643,447	9,845,914	1,296,938,922
2030	711,012,061	297,033,765	558,502,883	61,258,851	93,117,722	13,164,614	1,734,089,895
2040	837,348,689	349,812,398	657,740,822	72,143,669	109,663,403	15,503,776	2,042,212,756
2050	936,332,400	391,164,023	735,492,931	80,671,834	122,626,809	17,336,491	2,283,624,488
2060	1,023,195,656	427,452,184	803,724,375	88,155,734	134,002,858	18,944,792	2,495,475,599
2070	1,114,208,257	465,473,783	875,215,145	95,997,130	145,922,327	20,629,919	2,717,446,563
2080	1,208,496,657	504,863,886	949,279,069	104,120,761	158,270,811	22,375,699	2,947,406,883
2090	1,310,810,763	547,606,824	1,029,647,218	112,935,864	171,670,382	24,270,077	3,196,941,127
2100	1,427,920,559	596,530,837	1,121,637,442	123,025,723	187,007,671	26,438,402	3,482,560,633

SSP4	Region 1	Region 2	Region 3	Region 4	Region 5	Region 6	TOTAL
2020	531,771,287	222,153,795	417,708,522	45,815,957	69,643,447	9,845,914	1,296,938,922
2030	865,237,285	361,463,191	679,647,428	74,546,474	113,315,834	16,020,143	2,110,230,356
2040	1,357,869,371	567,266,118	1,066,611,947	116,990,304	177,833,414	25,141,382	3,311,712,537

2050	1,903,208,914	795,088,214	1,494,978,390	163,975,265	249,253,828	35,238,517	4,641,743,129
2060	2,496,037,356	1,042,749,364	1,960,647,557	215,051,739	326,893,628	46,214,923	6,087,594,567
2070	3,161,403,785	1,320,714,122	2,483,295,610	272,377,888	414,033,368	58,534,394	7,710,359,165
2080	3,864,865,703	1,614,593,725	3,035,867,825	332,986,239	506,162,285	71,559,214	9,426,034,991
2090	4,604,335,687	1,923,516,127	3,616,724,524	396,696,947	603,007,000	85,250,735	11,229,531,019
2100	5,380,335,593	2,247,699,339	4,226,275,625	463,554,972	704,635,857	99,618,620	13,122,120,006

F. Inflation projections (2020-2150)

TBATS model was implemented to project inflation, using exponential smoothing state models to project time series data.



Year	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2021	0.04404	0.027367	0.062724	0.019508	0.073323
2030	0.039645	0.012022	0.074585	0.002041	0.095354
2040	0.039047	0.011547	0.073951	0.001741	0.09472
2050	0.038983	0.01141	0.074028	0.001633	0.094889
2060	0.038976	0.011295	0.074207	0.001533	0.095188
2070	0.038975	0.011181	0.074397	0.001434	0.0955
2080	0.038975	0.011069	0.074587	0.001339	0.095812
2090	0.038975	0.010958	0.074777	0.001245	0.096123
2100	0.038975	0.010848	0.074966	0.001154	0.096433
2110	0.038975	0.010739	0.075154	0.001066	0.096742
2120	0.038975	0.01063	0.075342	0.00098	0.09705
2130	0.038975	0.010522	0.075528	0.000896	0.097356
2140	0.038975	0.010415	0.075714	0.000815	0.097662
2150	0.038975	0.010309	0.075899	0.000736	0.097966

G. Predictive factor - Risk rating criteria

Households are assessed using a predictive factor that acts as a measure of their exposure to natural disaster damage. The predictive factor is the product sum of projected frequency and severity of each class of natural disaster

$$\textit{Predictive Factor} = \textit{Minor Frequency} \times \textit{Minor Severity} + \textit{Medium Frequency} \times \textit{Medium Severity} + \textit{Major Frequency} \times \textit{Major Severity}$$

Under the risk rating, regions 2, 3 and 4 have been deemed areas of high-risk given higher frequency and property damage whilst regions 1, 5, and 6 are of lower risk.

H. Modelling approach

1. *Defined minor, medium, and major events*

To categorise events into minor, medium and major events, a classification variable was designed to measure the severity of an event. The variable took the weighted sum of property damage, fatality and injuries sustained per event.
Events were then classified by the following:
- Minor = Variable < 5
- Medium = 5 < Variable < 100
- Medium = Variable > 100

2. *Simulated a data set of houses that follow the provided property value distributions and household population data*
3. *Simulated average damage proportion of a household for each of the three types of events*
   This value was simulated under a log-normal distribution and was consistent for a given household across every year where an event occurs.
4. *Created a predictive factor to measure a household's exposure to natural disasters* (See Appendix)
5. *Simulate damages caused by projected events*
   To calculate damages of each event, the average damage proportion calculated in step 3 was introduced to some randomised normal deviation for each household to simulate randomness.
6. *Adjust for proactive and involuntary relocation*
   Houses were moved to regions according to the scheme and datasets are updated to reflect the changes in households per region.

I. Modelling limitations

Events are simulated in minor, medium and major order and therefore, are not reflective of actual experiences in which events occur in random severity. Many simulations is required to increase accuracy however, due to long computing time, this was unfeasible. Input assumptions also require testing for the simulation to be accurate. Furthermore, the complexity of property damage sustained in natural weather events calls for the input of a multitude of factors such as building type, infrastructure materials, and preparation efforts. The simplicity of the model fails to take this into account and hence, may be a poor reflection of real-life experiences.

Program costs are projected without the inputs of inflation and interest rates. Therefore, the present real values of the cost incurred to the government may vary significantly with changing market conditions. Population figures may vary significantly from the forecasted amounts and hence, the demand for the relocation program may vary as populations fluctuate.

J. Low socio-economic background

Median property value:

Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Ᵽ250-299K	Ᵽ250-299K	Ᵽ200-249K	Ᵽ100-149K	Ᵽ150-199K	Ᵽ150-199K

Median household income:

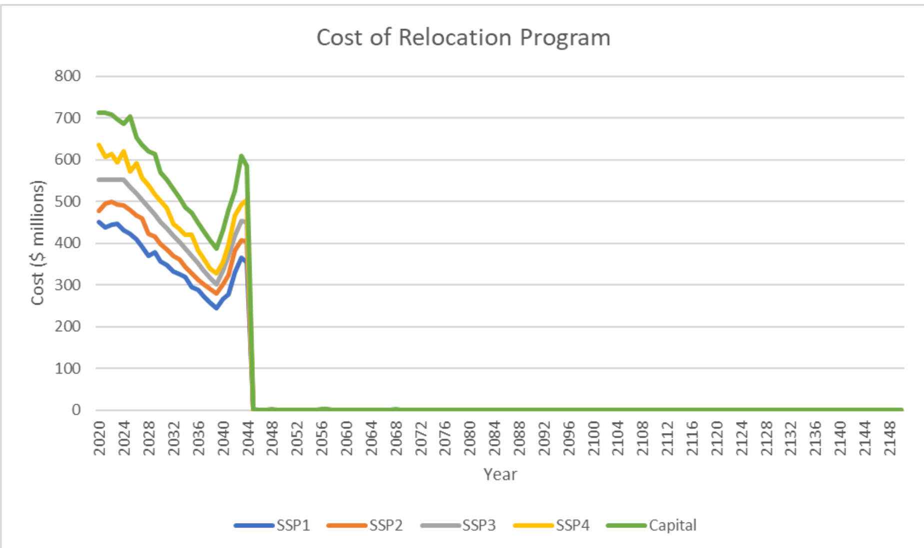
Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
Ᵽ82,459	Ᵽ68,123	Ᵽ71,916	Ᵽ48,615	Ᵽ61,518	Ᵽ69,340

Percentage of people in poverty:

Region 1	Region 2	Region 3	Region 4	Region 5	Region 6
12.1%	12.8%	16.0%	19.1%	20.5%	16.8%

According to the given data, region 4 has the lowest median household income of Ᵽ48,615 and a high poverty rate of 19.1%. In comparison, the other regions have higher median household incomes ranging from Ᵽ61,518 to Ᵽ82,459, and lower poverty rates ranging from 12.1% to 16.8%, barring region 5 with a percentage of 20.5%. Additionally, Region 4 has the lowest median property value of Ᵽ100-149K, which is significantly lower than the median property values of the other regions that range from Ᵽ150-299K.

K. Costs of relocation program with capital requirements



L. Local businesses in decline

Region	2	3	4
Average number of people moving out (simulated)	1,400	400	300
Households (2016-2020)	1,634,628	1,865,736	403,548
Proportion of People Moving in Year 2020	0.000856464	0.000214393	0.000743406
Retail Sales	104,661,514,000	86,911,348,000	16,147,988,000
Expected Decline in Sales	89,638,816.66	18,633,150.24	12,004,510.99

Severity	₱120,276,477.89
Probability	100%

M. Difference in government payouts and property values

To examine the risk ‘The government pay-out is insufficient to purchase a new property in a low-risk region due to a lower value property market in certain regions’ the difference in government payouts and property values was examined. The following analysis compares home values to a minimum threshold of ₱150,000:

Region 2

Proportion of Household < 150,000	18.63%
Number of Households < 150,000	304531.1964

Average Property Value	Number of households	Total Sum Property Value
25,000	103,471.9524	2,586,798,810
75,000	87,779.5236	6,583,464,270
125,000	113,279.7204	14,159,965,050

Average Property Value	76,610.30596
₱150,000 – Average Property Value	73,389.69404

Region 3

Proportion of Household < 150,000	21.02%
Number of Households < 150,000	392,177.7072

Average Property Value	Number of households	Total Sum Property Value
25,000	66,420.2016	1,660,505,040
75,000	116,235.3528	8,717,651,460
125,000	209,522.1528	26,190,269,100

Average Property Value	93,244.52902
₱150,000 – Average Property Value	56,755.47098

Region 4

Proportion of Household < 150,000	53.48%
Number of Households < 150,000	215,817.4704

Average Property Value	Number of households	Total Sum Property Value
25,000	75,947.7336	1,898,693,340
75,000	76,189.8624	5,714,239,680
125,000	63,679.8744	7,959,984,300

Average Property Value	72,157.81601
₱150,000 – Average Property Value	77,842.18399

Distribution of total people relocating from high-risk regions

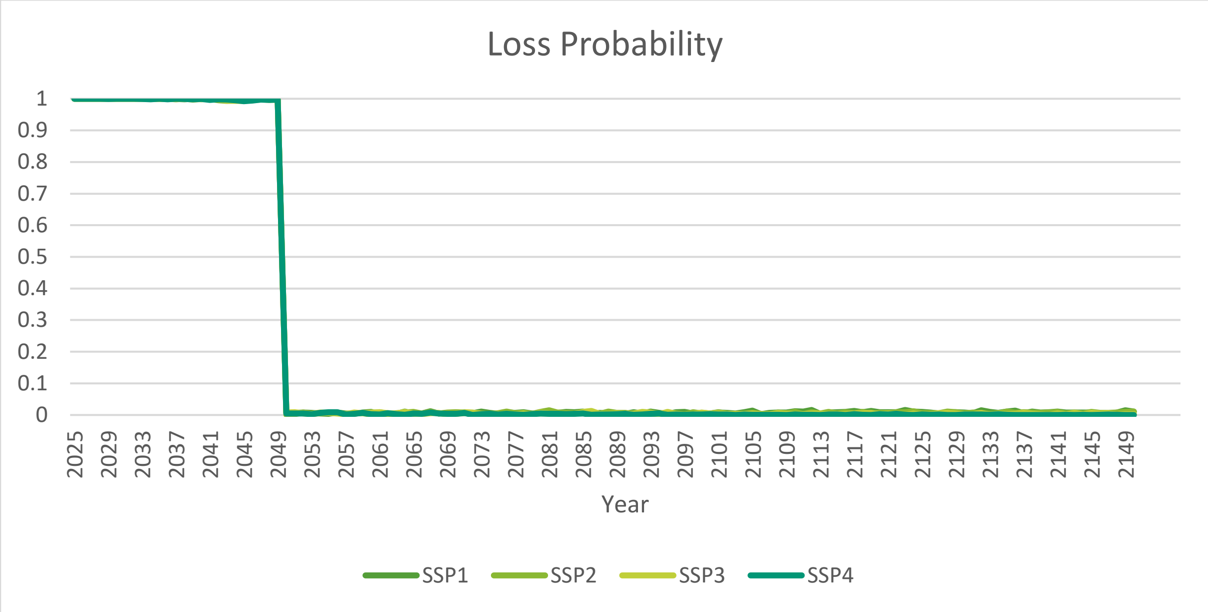
Region 2	0.666666667
Region 3	0.19047619
Region 4	0.142857143

Assuming total of 2,100 people are relocating out of regions 2, 3 and 4

Total expected difference = ₱67,330,000
Difference per household = ₱32,061.90

N. Loss Probability

Refers to the probability that the cost of our program in that year is greater than the economic benefit in that year



O. Technical Code

```
#install.packages("EnvStats")
setwd("~/University/2023/T1/ACTL4001/Assignment")
setwd("C:/Users/benba/OneDrive/Documents/R Code")
setwd("~/R/4001")
setwd("~/R")
install.packages ("extraDist")
library(tidyverse)
library(dplyr)
library(readxl)
library(truncnorm)
library(EnvStats)
library(data.table)
library(ggplot2)
library(forecast)
library(randomForest)
library(extraDist)
library(actuar)
library(tidyr)
library(zoo)
library(pacman)
library(purrr)
library(furrr)
library(future)

hazardEventData <- read_excel("2023-student-research-hazard-event-data (2).xlsx", range =
"B13:I3379")
```

```
demographicEconomic <- read_excel("2023-student-research-eco-dem-data.xlsx", sheet =
"Demographic-Economic", range = "B8:H51")
inflationInterest <- read_excel("2023-student-research-eco-dem-data.xlsx", sheet = "Inflation-
Interest", range = "B8:F68")
base_data <- read_excel("base-data.xlsx")
base_data <- base_data %>% mutate(bound =
c(50000,100000,150000,200000,250000,300000,400000,500000,750000,1000000,1500000,2000000,
20000000),
                    cum1= cumsum(base_data[,2]),
                    cum2= cumsum(base_data[,3]),
                    cum3= cumsum(base_data[,4]),
                    cum4= cumsum(base_data[,5]),
                    cum5= cumsum(base_data[,6]),
                    cum6= cumsum(base_data[,7])
)
#######BOUNDARIES#######
upperbound <-
c(50000,100000,150000,200000,250000,300000,400000,500000,750000,1000000,1500000,2000000,
20000000)
lowerbound <-
c(0,50000,100000,150000,200000,250000,300000,400000,500000,750000,1000000,1500000,200000
0)
mu<- c(40000,
    75000,
    125000,
    175000,
    225000,
    275000,
    350000,
    450000,
    625000,
    875000,
    1250000,
    1750000,
    5000000)
sdinput <- c(30000,
        20000,
        20000,
        20000,
        20000,
        20000,
        50000,
        50000,
        100000,
        100000,
        200000,
        200000,
        1000000)
boundTable <- data.table(bucket = as.factor(c(1:13)),
               upper=upperbound,
               lower=lowerbound,
```

```
                    mu=mu,
                    sd=sdinput
)

#### make predictions about freq and sev of each household #######

###function to design each region
houses <- function(region) {
  households <- select(inputs[input=="Housing Units"], paste0(region))[[1,1]]
  r1<- data.frame(rv=sort(runif(households),decreasing=FALSE))
  r1 <- r1 %>% mutate(
    bucket = cut(r1$rv, unname(c(0,unlist(base_data$cum1))),
                 labels=c(1,2,3,4,5,6,7,8,9,10,11,12,13),
                 include.lowest = TRUE)) %>%
    as.data.table()

  r1 <- r1[boundTable, on = "bucket"]
  r1[, capprice :=rtruncnorm(1,
                             mean=mu,
                             sd=sdinput,
                             a=lowerbound,
                             b=upperbound
  )
  ]
  return(r1)
}

pred <- function(region, emissions, r1=houses(region)) {
  households <- nrow(r1)
  min_freq <- select(freq_interpolate[Year==2020 & Region==region &
Emissions==paste0(emissions)], Minor)
  med_freq <- select(freq_interpolate[Year==2020 & Region==region &
Emissions==paste0(emissions)], Medium)
  maj_freq <- select(freq_interpolate[Year==2020 & Region==region &
Emissions==paste0(emissions)], Major)

  r1 <- as.data.table(r1)
  r1[, maj_damage_prop:=rlnormTrunc(households,
                                   meanlog=0,
                                   sdlog=10000,
                                   min=0,
                                   max=0.65
  )
  ]

  r1[, med_damage_prop:=rlnormTrunc(households,
                                   meanlog=0,
                                   sdlog=50000,
                                   min=0,
                                   max=0.20
  )
```

```
  ]
  r1[, min_damage_prop:=rlnormTrunc(households,
                                  meanlog=0,
                                  sdlog=100000,
                                  min=0,
                                  max=0.05
  )
  ]
  r1[,min_freq:= rtruncnorm(households,
                           mean=min_freq,
                           sd=min_freq/3,
                           a=med_freq,
                           b=min_freq*1.5)]
  r1[,med_freq:= rtruncnorm(households,
                           mean=med_freq,
                           sd=med_freq/3,
                           a=maj_freq,
                           b=min_freq)]
  r1[,maj_freq:= rtruncnorm(households,
                           mean=maj_freq,
                           sd=maj_freq/3,
                           a=0.01,
                           b=med_freq)]
  r1[, pred_fact
:=min_freq*min_damage_prop+med_freq*med_damage_prop+maj_freq*maj_damage_prop]
  r1 <- r1[, c("rv", "bucket","upper","lower","mu","sd", "min_freq","med_freq","maj_freq"):=NULL]
  return(r1)
}

### voluntary
vol <- function(dataset, movement_percentile, prob_move) {
  threshold <- max(quantile(dataset$pred_fact, probs=(1-movement_percentile)))
  r_ordered <- dataset[pred_fact>= threshold]
  r_remain <- dataset[pred_fact< threshold]
  r_remain <- r_remain[,relocate:=FALSE]
  r_ordered<- r_ordered[,rand :=runif(nrow(r_ordered))]
  r_ordered <- r_ordered[, relocate := (rand<prob_move)]
  r_remain2 <- r_ordered[relocate==FALSE]
  r_remain2 <- r_remain2[,rand:=NULL]

  return(list(relocated=r_ordered,
              cost=sum(r_ordered[relocate==TRUE]$capprice),
              remaining=rbind(r_remain, r_ordered[relocate==FALSE][, rand:=NULL])))
}

### event modeller ###
event_deviation <- data.table(event = c("maj", "med", "min"), mean=c(-0.2, -0.1, -0.01), sd=c(0.005,
0.00005, 0.0001), max=c(0.65, 0.2, 0.05), min=c(0,0,0),
                              scalefactormean=c(0.8, 0.7, 0.6), scalefactorsd = c(0.2,0.1,0.05))

in_between <- Vectorize(function(x,a,b) {
```

```
  if(x<a) {
    return(a)
  } else if (x> b) {
    return(b)
  } else {
    return(x) }
})

##Event Simulator with contents damage
event_model <- function(dataset, event_type) {
  r_event <- dataset[,dev :=rnorm(nrow(dataset),
                                  mean=rtruncnorm(1, mean=event_deviation[event == event_type]$mean,
sd=event_deviation[event == event_type]$sd*10, a=-Inf, b=0.001),
                                  sd=rnorm(1, mean=event_deviation[event == event_type]$sd, sd=0.00001)
  )]
  inp_col_name <- paste0(event_type,"_damage_prop")
  max <- event_deviation[event==event_type]$max
  min <- event_deviation[event==event_type]$min
  scale_factor <- rtruncnorm(1, mean=event_deviation[event == event_type]$scalefactormean,
sd=event_deviation[event == event_type]$scalefactorsd,
                             a=0, b=1.3)

  r_event[, damage_prop_actual:= in_between(eval(parse(text=inp_col_name))+ dev, min, max)]
  r_event[, event_damage := damage_prop_actual*capprice*scale_factor]
  r_event[, contents_prop := rtruncnorm(nrow(dataset),
                                        a=0.45,
                                        b=0.7,
                                        mean=0.55,
                                        sd=0.1)]

r_event[,contents_cost:=contents_prop*event_damage][,home_contents_cost:=event_damage+content
s_cost]
  return(r_event)
}

## Involuntary Relocation ##
invol <- function(region, dataset, risk_percentile=0, movement_percentile=0) {
  persons_per_household <- select(inputs[input=="Persons per Household, 2016-2020"],
paste0(region))[[1,1]]
  temp_cost <- select(inputs[input=="Temporary housing cost with disaster (per person per month)"],
paste0(region))[[1,1]]
  med_rent <- select(inputs[input=="Median Rent"], paste0(region))[[1,1]]
  med_housing_cost <- select(inputs[input=="Median Monthly Homeowner Housing Costs"],
paste0(region))[[1,1]]

  threshold = quantile(dataset$pred_fact, probs=(1-risk_percentile))
  r_event<- dataset[, high_risk:= (pred_fact>= threshold)]
  # simulate persons per household
  r_event<-r_event[, persons := rztpois(nrow(r_event), persons_per_household)]
```

```
  r_event_high_risk <- r_event[high_risk==TRUE]
  threshold2 = max(0.15, quantile(r_event_high_risk$damage_prop_actual, probs=(1-
movement_percentile)))
  r_event_relocate <- r_event_high_risk[damage_prop_actual>= threshold2]
  r_event_relocate <- r_event_relocate[, temp_housing_cost := 28/31*temp_cost*persons][,
rent_length:=rztpois(nrow(r_event_relocate), 2)][, rent_cost:=
rent_length*(med_rent+med_housing_cost)]
  r_event_relocate <- r_event_relocate[, total_cost_gov :=  capprice-event_damage +
temp_housing_cost][, total_cost := temp_housing_cost + contents_cost]

  r_remain1 <- r_event[high_risk==FALSE]
  r_remain2 <- r_event_high_risk[damage_prop_actual< threshold2]
  r_remain_tot <- rbind(r_remain1, r_remain2)
  r_remain_tot <- r_remain_tot[, displaced := damage_prop_actual>=0.2][, days :=
displaced*rztpois(1, damage_prop_actual*20)][ , displacement_cost := days*temp_cost/31*persons]
  r_remain_tot <- r_remain_tot[,total_cost:= displacement_cost+ home_contents_cost]

  return(list(relocate <- r_event_relocate,
              remain <- r_remain_tot,
              cost_gov <- sum(r_event_relocate$total_cost_gov),
              total_cost <- (sum(r_event_relocate$total_cost) + sum(r_remain_tot$total_cost))))
}

##### REGION SIMULATION TO CREATE HOUSEHOLDS
inputs <- read_excel("INPUTs per region.xlsx") %>% as.data.table()
freq <- read_excel("freq proj.xlsx")
freq_interpolate <- freq %>% group_by(Region, Emissions) %>%
  complete(Year=2020:2150) %>%
  mutate(Minor= na.approx(Minor),
         Medium=na.approx(Medium),
         Major=na.approx(Major)) %>%
  as.data.table()

##### NO PROGRAM
no_prog <- function(region, region_dataset, start_year=2020, end_year=2150, emissions) {
  output <- data.table(Year=numeric(), Event= character(), Cost = numeric())
  year=start_year
  while (year <=end_year){
    print(year)
    min_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Minor)[[1,1]]
    med_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Medium)[[1,1]]
    maj_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Major)[[1,1]]
    min_events <- rpois(1, min_freq)
    med_events <- rpois(1, med_freq)
    maj_events <- rpois(1, maj_freq)
    min_counter <- 1
    med_counter <- 1
    maj_counter <- 1
```

```
    print("min")
    print(min_events)
    while(min_counter <= min_events) {
      print(min_counter)
      event_data <- event_model(region_dataset, "min")
      event_costs <- invol(region, event_data, 0,0)
      output <- rbind(output, list(year, "Min", event_costs[[4]]))
      min_counter <- min_counter+1
    }
    print("med")
    print(med_events)
    while(med_counter <=med_events) {
      print(med_counter)
      event_data <- event_model(region_dataset, "med")
      event_costs <- invol(region, event_data, 0,0)
      output <- rbind(output, list(year, "Med", event_costs[[4]]))
      med_counter <- med_counter+1
    }

    print("maj")
    print(maj_events)
    while(maj_counter <=maj_events) {
      print(maj_counter)
      event_data <- event_model(region_dataset, "maj")
      event_costs <- invol(region, event_data, 0,0)
      output <- rbind(output, list(year, "Maj", event_costs[[4]]))
      maj_counter <- maj_counter+1
    }
    year=year+1

  }
  return(output)
}

# set up parallel processing
no_cores <- availableCores() - 1
plan(multicore, workers = no_cores)

### WITH PROGRAM RELOCATION TO OTHER AREAS 2/3/4
prog_risk <- function(region, region_dataset, start_year=2020, end_year =2150, emissions) {
  output <- data.table(Year=numeric(), Event= character(), Gov_Cost = numeric(), Total_cost
=numeric(), houses_relocate= numeric(), houses=list())
  year=start_year
  remaining_houses <- region_dataset
  vol_relocation_costs <-0
  print(nrow(remaining_houses))
  while (year <=end_year){
    print(year)
    min_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Minor)[[1,1]]
```

```
  med_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Medium)[[1,1]]
  maj_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Major)[[1,1]]

  ## VOLUNTARY RELOCATION
  vol <- vol(remaining_houses, 0.0001, 0.9)
  vol_relocation_costs <-vol_relocation_costs+ vol[[2]]
  remaining_houses <- vol[[3]]
  output <- rbind(output, list(year, "VOLUNTARY", vol[[2]], 0, 1, vol[[1]]$capprice))
  print(nrow(remaining_houses))

  min_events <- rpois(1, min_freq)
  med_events <- rpois(1, med_freq)
  maj_events <- rpois(1, maj_freq)
  min_counter <- 1
  med_counter <- 1
  maj_counter <- 1

  print("min")
  print(min_events)
  while(min_counter <= min_events) {
    print(min_counter)
    print(nrow(remaining_houses))
    event_data <- event_model(remaining_houses, "min")
    event_costs <- invol(region, event_data, 0.05,0.001)
    remaining_houses <- event_costs[[2]]
    output <- rbind(output, list(year, "Min", event_costs[[3]], event_costs[[4]], 1,
event_costs[[1]]$capprice))
    min_counter <- min_counter+1
  }
  print("med")
  print(med_events)
  while(med_counter <=med_events) {
    print(med_counter)
    print(nrow(remaining_houses))
    event_data <- event_model(remaining_houses, "med")
    event_costs <- invol(region, event_data, 0.05,0.001)
    remaining_houses <- event_costs[[2]]
    output <- rbind(output, list(year, "Med", event_costs[[3]], event_costs[[4]], 1,
event_costs[[1]]$capprice))
    med_counter <- med_counter+1
  }
  print("maj")
  print(maj_events)
  while(maj_counter <=maj_events) {
    print(maj_counter)
    print(nrow(remaining_houses))
    event_data <- event_model(remaining_houses, "maj")
    event_costs <- invol(region, event_data, 0.05,0.001)
    remaining_houses <- event_costs[[2]]
```

```
      output <- rbind(output, list(year, "Med", event_costs[[3]], event_costs[[4]], 1,
event_costs[[1]]$capprice))
      maj_counter <- maj_counter+1
    }
    year=year+1
  }
  return(output)
}

### WITH PROGRAM RELOCATED TO 1/5/6
prog_safe <- function(region, region_dataset, start_year=2020, end_year =2150, emissions,
new_houses) {
  output <- data.table(Year=numeric(), Event= character(), Gov_Cost = numeric(), Total_cost
=numeric(), houses= numeric())
  year=start_year
  total_houses <- region_dataset
  while (year <=end_year){
    print(year)
    min_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Minor)[[1,1]]
    med_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Medium)[[1,1]]
    maj_freq <- select(freq_interpolate[Year==year & Region==region &
Emissions==paste0(emissions)], Major)[[1,1]]

    total_houses<-rbind(total_houses, new_houses[Year==year-1][, Year:=NULL], fill=TRUE)%>%
as.data.table()

    print(nrow(total_houses))
    min_events <- rpois(1, min_freq)
    med_events <- rpois(1, med_freq)
    maj_events <- rpois(1, maj_freq)
    min_counter <- 1
    med_counter <- 1
    maj_counter <- 1

    print("min")
    print(min_events)
    while(min_counter <= min_events) {
      print(min_counter)
      print(nrow(total_houses))
      event_data <- event_model(total_houses, "min")
      event_costs <- invol(region, event_data)
      output <- rbind(output, list(year, "Min", event_costs[[3]], event_costs[[4]],
nrow(event_costs[[2]])))
      min_counter <- min_counter+1
    }
    print("med")
    print(med_events)
    while(med_counter <=med_events) {
      print(med_counter)
```

```
      print(nrow(total_houses))
      event_data <- event_model(total_houses, "med")
      event_costs <- invol(region, event_data)
      output <- rbind(output, list(year, "Med", event_costs[[3]], event_costs[[4]],
nrow(event_costs[[2]])))
      med_counter <- med_counter+1
    }
    print("maj")
    print(maj_events)
    while(maj_counter <=maj_events) {
      print(maj_counter)
      print(nrow(total_houses))
      event_data <- event_model(total_houses, "maj")
      event_costs <- invol(region, event_data)
      output <- rbind(output, list(year, "Med", event_costs[[3]], event_costs[[4]],
nrow(event_costs[[2]])))
      maj_counter <- maj_counter+1
    }
    year=year+1
  }
  return(output)
}

####### TEST CODE #####
emissions="Low"
start_year=2020
end_year=2021

FINAL_SIM <- function(start_year = 2020, end_year = 2150, emissions) {
  r1 <- pred(1, emissions)
  r2 <- pred(2, emissions)
  r3 <- pred(3, emissions)
  r4 <- pred(4, emissions)
  r5 <- pred(5, emissions)
  r6 <- pred(6, emissions)

  print("Houses and predictions made")

  r1_noprog <- no_prog(1, r1, start_year, end_year, emissions)[, region:=1]
  r2_noprog <- no_prog(2, r2, start_year, end_year, emissions)[, region:=2]
  r3_noprog <- no_prog(3, r3, start_year, end_year, emissions)[, region:=3]
  r4_noprog <- no_prog(4, r4, start_year, end_year, emissions)[, region:=4]
  r5_noprog <- no_prog(5, r5, start_year, end_year, emissions)[, region:=5]
  r6_noprog <- no_prog(6, r6, start_year, end_year, emissions)[, region:=6]

  print("No program done")

  r2_prog <- prog_risk(2, r2, start_year, end_year, emissions)
  r3_prog <- prog_risk(3, r3, start_year, end_year, emissions)
  r4_prog <- prog_risk(4, r4, start_year, end_year, emissions)
```

```
  print("Risky areas done")

  combined_risk <- rbind(r2_prog, r3_prog, r4_prog)
  combined_risk <- combined_risk[,rv:= runif(nrow(combined_risk))][, region:= cut(rv,
breaks=c(0,0.33,0.66,1), labels=c(1,5,6))] %>%
    group_by(Year, region)%>% as.data.table()
  combined_risk <- combined_risk[(houses!="NULL")]

  print("Identified risky areas")

  relocated_1 <- pred(1, paste0(emissions), data.table(Year=combined_risk[region==1]$Year,
capprice=as.numeric(combined_risk[region==1]$houses)))
  relocated_5 <- pred(5, paste0(emissions),
data.table(Year=combined_risk[region==1]$Year,capprice=as.numeric(combined_risk[region==5]$ho
uses)))
  relocated_6 <- pred(6, paste0(emissions),
data.table(Year=combined_risk[region==1]$Year,capprice=as.numeric(combined_risk[region==6]$ho
uses)))
  print("Found new houses")
  r1_safe <- prog_safe(1, r1, start_year, end_year, emissions, relocated_1)[, region:=1]
  r5_safe <- prog_safe(5, r5, start_year, end_year, emissions, relocated_5)[, region:=5]
  r6_safe <- prog_safe(6, r6, start_year, end_year, emissions, relocated_6)[, region:=6]
  print("SImulated safe areas")
  r2_prog <- r2_prog[, c("houses_relocate", "houses"):=NULL]
  r2_prog <- r2_prog[!duplicated(r2_prog), ][, region:=2]
  r3_prog <- r3_prog[, c("houses_relocate", "houses"):=NULL]
  r3_prog <- r3_prog[!duplicated(r3_prog), ][, region:=3]
  r4_prog <- r4_prog[, c("houses_relocate", "houses"):=NULL]
  r4_prog <- r4_prog[!duplicated(r4_prog), ][, region:=4]

  NO_PROG_FINAL <- rbind(r1_noprog, r2_noprog, r3_noprog, r4_noprog, r5_noprog, r6_noprog,
fill=TRUE)
  PROG_FINAL <- rbind(r1_safe, r2_prog, r3_prog, r4_prog, r5_safe, r6_safe, fill=TRUE)

  return(list(
    NO_PROG_FINAL,
    PROG_FINAL,
    combined_risk
  ))
}

test <- FINAL_SIM(2020,2150, "Low")
test_med <- FINAL_SIM(2020,2150, "Medium")
test_high <- FINAL_SIM(2020,2150, "High")
test_very_high <- FINAL_SIM(2020,2150, "Very High")
test[[2]]
region=1
region_dataset=r1
new_houses=relocated_1
```

```
######INFLATION PROJECTIONS#######
training_data <- inflationInterest%>%
  select(Year, Inflation)%>%
  filter(Inflation>-3)


inflation_ts <- ts(training_data$Inflation, frequency = 1, start=c(1962,1))
inflation_ts
inflation_plot<- ggplot(data=training_data, aes(x=Year, y=Inflation)) +geom_line()
inflation_plot

inflation_model<-auto.arima(y=inflation_ts)
print(inflation_model)


inflation_forecast<- forecast(inflation_model, h=100)
print(inflation_forecast)


######USING RANDOMFOREST TO FORECAST INFLATION######

summary(inflationInterest)
inflation_df <- as.data.frame(inflationInterest)


inflation_rf <- randomForest(Inflation~Year, data=inflation_df, ntree=500)

inflation_rf
future_years<- data.frame(Year=seq(2023,2100, by=1))

inflation_rf_predict<- predict(inflation_rf, newdata=future_years)
summary(inflation_rf_predict)
view(inflation_rf_predict)
view(future_years)

######USING TBATS TO FORECAST INFLATION#######

inflation_tbats<- tbats(inflation_ts)

forecast_tbats<-forecast(inflation_tbats, h=100)

forecast_tbats


###### USING ETS ######

ETS_fit <- model(ETS(inflation_ts))

forecast_ETS <- forecast(ETS_fit)
```