2023 SOA STUDENT RESEARCH CASE STUDY CHALLENGE

Team: ClimateDynamics

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To appear in EPTCS.

1 Executive summary

1.1 Objective

We aim to develop a social insurance program which can provide nationwide coverage against displacement due to natural perils in anticipation to the increasing frequency and severity of catastrophic climate events.

The product is designed to be accessible to all, tailored to meet the diverse geographical risks presented by Storslysia's six regions. In our design we focus on accurately forecasting future events so that Storslysia's residents may be relocated promptly, minimising potential costs associated with accommodation, lost of personal effects and psychological pressure. Based on our results, we have found that the relocation program could substantially reduce the economic cost of property damages over the long-term horizon. Additionally, we are 90.69% confident that the program cost will not exceed 10% of the national GDP in any given year by weighting different climate and macro-economic scenarios.

1.2 Monitoring Metrics

Alongside relevant laws and regulations concerning social values, short-term monthly evaluations such as weather patterns/ changes throughout observable periods can be assessed and compared across previous data.

Long-term annual assessment can also be conducted to measure the alignments and deviations towards the annual economic figures and UN Climate Change Conference objectives. Results from sensitivity analysis can also be another performance indicator to regulate the projected relocation outcome.

2 Program Design

2.1 Claim Requirement

For a citizen of Storslysia to submit a valid claim they must meet the following requirements:

- The claim must be lodged within 6 months of the event which caused the loss.
- Policyholders cannot claim for a natural event which occurs within 72 hours of policy inception.
- The damage must not be a direct result of negligence to maintain the property or improper installation of pipes/circuitry/heaters etc.
- Any information disclosed must be full and truthful. This includes information about the extent of the damage, prior claims history and any other relevant facts. [1]

2.2 Claim Coverage

The social will cover 50% of cost for new property, rest will come from owner or private insurance as wekk as support for temporary housing. This ensure basic living for households, and low income households can receive up to 1.5x the coverage. Below is list of claim coverage, note that the amount is per household unless specified otherwise.

Coverage Item	**Coverage Amount**	**Other Conditions**
New Housing	50% (up to 150k)	Limits by region, based on mean price
Temporary Housing	up to 1000 / month	This is per person
Living support	up to 3,000	For low-income households [2]
Moving Cost	up to 6,000	For low-income households

Table 1: Claims Coverage

2.3 Voluntary Relocation

Cost reduction benefits resulting from planned relocation can be categorised into two types:

Relocation priorities and options: Geographical incentives are provided to affected parties to encourage voluntary relocation, as a wider range of relocation alternatives and faster processing time are offered. This in turn lowers the urgency and need for transport and emergency aid, thus reducing unnecessary costs associated with involuntary relocation.

Cost Reduction and Additional Benefits: Households opting for voluntary relocation will have 80% coverage and limits for new housing, be provided with financial support in the form of free moving costs (of 4000φ under Section 4.3.2) and additional relocation expenses coverage (of 2000φ under Section 4.3.2) as well as supplementary support such as property/goods relocation services.

Through provision of these benefits we hope to incentivise a greater proportion of individuals at risk to act early to not only reduce costs but also to maintain public safety.

2.4 Other features/requirements

2.5 Program Timeframes

The model monitoring process will involve monthly reporting focusing on relocation costs and actions whereby every month there will be assessment of program progress and market conditions. Voluntary relocation options may be reduced if there is a labour shortage. Model performance will be reviewed annually and the parameters will be calibrated in line with the current years' economic and climate data. In the case that actual experience deviates greatly from forecasts we may rebuild the economic and hazard models entirely to better predict aggregate cost. The past program costs and coverage will need to be analysed, inflation and GDP increase will also need to be reflected in coverage amounts and excess limits.

In the long run, every ten years the model will undergo a major overhaul. As climate events become increasingly unpredictable globally, new findings will be used to rebuild the technical cost model. Emerging technologies will also help to improve costs and efficiency. Detailed list is as below:

[1]Adjusters may decline the claim on the grounds of insufficient or false information.

[2]Defined as households earning less than 50% of median income

Time frame	Actions	Other Changes
1 Month	Monitor property and construction market Monitor current year's program costs Adjust relocation schedules	National Economic Figures Property/Industry Reports
1 Year	Annual assessment of program costs/coverage Update Hazard Model Update Economic Model Update program coverage limits/amount	National Economic Figures Legal and Policy Change World Economic Outlook Climate Change Report
10 Years	Review program coverage/past results Update/Rebuild Economic Model Update/Rebuild Hazard Model	Major Climate Events Tech Improvement

Table 2: Program Timeframe

3 Pricing/Costs

3.1 Economic Modelling

Time series models have been built from the provided data and used to make future predictions. These predictions can then be used to adjust other economic figures including GDP, property value, prices of goods and services (Refer to Appendix 7.1). Subsequently, adjusted the GDP and population growth forecasts under the 4 different emission scenarios to form a more accurate prediction moving forward (Refer to Appendix 7.9).

3.1.1 Inflation and interest rate

ARIMA(1,1,0) is chosen to model future inflation rates as it has the lowest validation MSE. We can observe the fit in the graph below where the ARIMA curve is shown in light brown. Out of the proposed models it outlines a stable, conservative estimate of future experience. Further information on the model selection process can be viewed in Appendix 7.2. We follow a similar procedure as above to forecast one-year interest rates, and find that ARIMA(1,1,0) still outperforms other models with the lowest validation MSE.

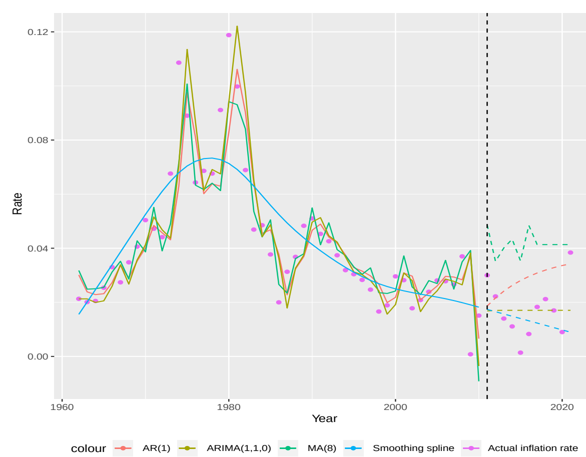

Figure 1: Validation of inflation rate forecasts

Note that the interest rate estimates have been bounded by 0 due to expected government intervention to prevent negative interest rates. The AR(1) and smoothing spline trajectories serve as upper and lower bounds, respectively, to test the extent to which future differences may impact aggregate cost. Full projections of inflation rates and interest rates in Appendix 7.2.

3.1.2 GDP Growth/Property Value

Due to lack of historical GDP data, GDP growth is simulated using the 1 year risk free rate. The optimal projection for 1 year rate is applied to region specific GDP per capita, adjusted using GDP forecasts under 4 emission scenarios. The GDP per capita in combination with population projection with give total GDP which will be used to evaluate the cost. Similarly for property value, inflation is used to project future property price growth and then adjusted for the 4 emission scenarios.

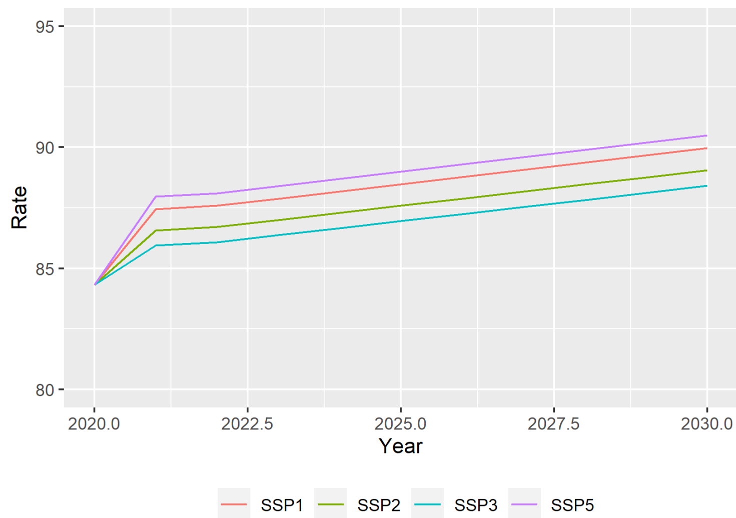

Figure 2: GDP per capita Forecasts for Region 1

3.2 Hazard and damage modelling

Frequency and severity of hazard loss have been modelled separately in our analysis. We have taken a standard approach and used Poisson regression to model hazard frequency since the count of hazard events is a discrete random variable. In particular we chose a Poisson GAM as it outperformed the Poisson GLM with regards to AIC and BIC metrics.

For severity model we chose to model the damage ratio (the ratio of property damage to exposure) instead of the absolute value of property damage, as dollar value of property damage could be heavily influenced by the market value of the property rather than the inherent severity of the peril [5]. It's derived by dividing the property damage by the total housing value in each region, which serves as a proxy for exposure. To model the damage we fit a zero adjusted Beta distribution as the damage ratio varies between 0 and 1 and the distribution is highly non-symmetric. The zero adjustment was used to account for the presence of a non-negligible proportion of zero damage instances recorded. For a more detailed discussion of the severity model, see 7.5.

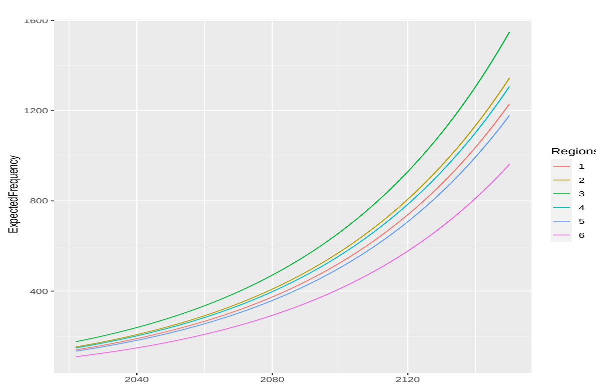

Figure 3: Projected hazard events count

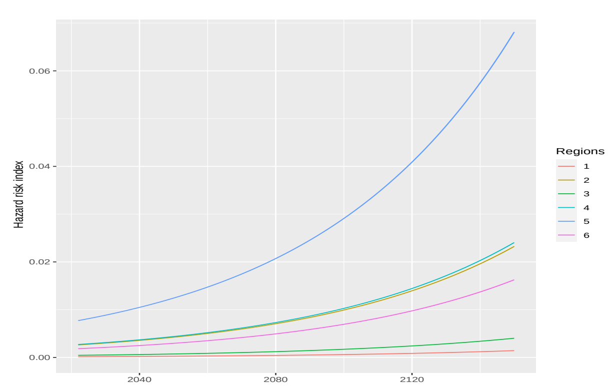

Figure 4: Projected climate risk index

The fitted frequency and damage models specified above are used to generate projections for future hazard events count and damage ratio. The projected events counts are shown in Figure 3, where Region 3 has the highest projected events count. To more comprehensively evaluate the risk in each region, we have developed a climate risk index, defined as the product of predicted events count and the damage ratio (i.e., Climate risk Index $= \hat{N}_t \cdot \hat{d}$), that factors both frequency and severity into risk evaluation. Based on the climate risk index, Region 5 has the highest risk in all projected years.

3.3 Pricing and Cost

Based on the results in the above section (i.e., Section 3.2), Region 5 is deemed to have the highest risk, whereas Region 1 is regarded as the region with the lowest risk. Therefore, our program seeks to relocate residents in Region 5 to Region 1.

To calculate the potential impact on economic cost from the relocation program, we assume all the residents from Region 5 are successfully relocated to Region 1. The increase in the exposure in Region 1 will be the construction cost of building new houses to accommodate immigrants from Region 5, which could be approximated as: $\tilde{E}_5 = H_5 \cdot \bar{V}_1$, where H_i is the number of households in region i and $\bar{V}_i$ as the mean housing value in region i. We further assume the climate risk in Region 1 stays the same after relocation (i.e., the expected frequency $\hat{N}_1$ and the expected damage ratio $\hat{d}_1$ stay the same), then the new total property damage in Region 1 after relocation will be: $\tilde{D}_1 = (E_1 + \tilde{E}_5) * \hat{d}_1 * \hat{N}_1$, and the new total property damage in Region 5 will be zero (i.e., $\tilde{D}_5 = 0$) as we assume all the residents in Region 5 will move to Region 1.

The projected property damage with and without relocation are shown in Figure 5, under the baseline inflation scenario. The difference between the projected property damage becomes more significant in later projected years, which might be explained by the quadratic growth of hazards frequency and the accumulation effects of inflation rates.

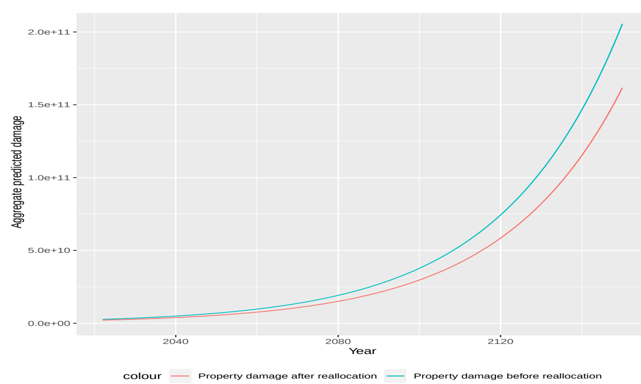

Figure 5: Property damage before/after relocation

Additionally, we have also calculated the present value of expected cost saving from the reduction in projected property damage after the relocation during the next **10-year** horizon. The results are illustrated in Table 3. The present value of the total expected cost saving is φ **6,566,773,052.43**.

3.3.1 Economic capital

Value at risk (VaR) is a widely used risk metric that estimates the potential loss of a portfolio of assets, given a certain level of confidence. In this case, we are using the VaR of annual aggregate property damage to estimate the economic capital needed for the program to remain solvent with a high degree of certainty.

To compute the VaR, we first calculated the annual property damage experienced by the whole nation. We assumed that the annual property damage followed the same distribution, and collected

Year	Projected damage (before)	Projected damage (after)	Discount factor	PV of cost saving
2022	2,677,851,746.54	2,105,867,694.83	0.99666	570,075,831.01
2023	2,770,223,396.34	2,178,508,935.50	0.99334	587,772,958.17
2024	2,865,781,377.00	2,253,655,912.82	0.99002	606,019,465.41
2025	2,964,635,600.01	2,331,395,061.37	0.98672	624,832,407.41
2026	3,066,899,768.20	2,411,815,797.29	0.98343	644,229,368.24
2027	3,172,691,506.56	2,495,010,621.08	0.98015	664,228,477.89
2028	3,282,132,497.50	2,581,075,224.03	0.97688	684,848,429.12
2029	3,395,348,620.84	2,670,108,598.26	0.97362	706,108,495.02
2030	3,512,470,098.58	2,762,213,150.60	0.97037	728,028,546.96
2031	3,633,631,644.69	2,857,494,820.36	0.96713	750,629,073.19
Total				**6,566,773,052.43**

Table 3: Projected cost saving from reduced property damage due to relocation

61 samples from 1960 to 2020. Based on these samples, we calculated the empirical cumulative distribution function and derived the VaR with 95% and 99.5% confidence levels respectively based on Solvency II capital requirement [2], which are presented in Table 4.

Confidence Level	**Economic Capital (φ)**
95%	701,469,488
99.5%	12,788,671,531

Table 4: Economic capital needed with 95% and 99.5% degree of certainty

3.3.2 Relocation Costs

The costs associated with relocation are listed below, note these figures are for 2020, the cost will be updated annually based on inflation and respective rates for the coming year. (Region 1 values are used as example, refer to Appendix 7.8 for full table) The amount of costs that can be saved from voluntary relocation is more than 3 times of median household income.

Related Items	**Cost(φ)**	**Estimation Method**	**Avoidable?**
New Property Cost	371,828	Property value distribution	No
- Additional Construction	111,939	50% of construction costs [3]	Yes
Replacing Household Goods	124,272	60% of housing costs	Yes
Temporary Housing	44,064	Refer to Appendix 7.7	Yes
Moving Costs	4,000	Industrial averages for USA states	No
- Additional Moving Costs	2,000	50% of normal costs	Yes
Avoidable Total	**282,275**		

Table 5: Relocation Costs (2020) for Region 1

[3]Cost estimated using industrial averages for USA states [1]

To factor the initial investment in relocation cost into program cost consideration, we have projected the Net Present Value (NPV) of the relocation project up to the year 2150 as shown in Figure 6, where the cost saving from reducing property damage is entered as positive cash flow and the initial investment in relocation is treated as negative cash flow. As per the figure, the relocation program is expected to break-even at 2088. Although the payback period of the project is relatively long due to the large initial relocation investment, the cost saving is substantial in the long term due to the quadratic increasing trend of hazards frequency.

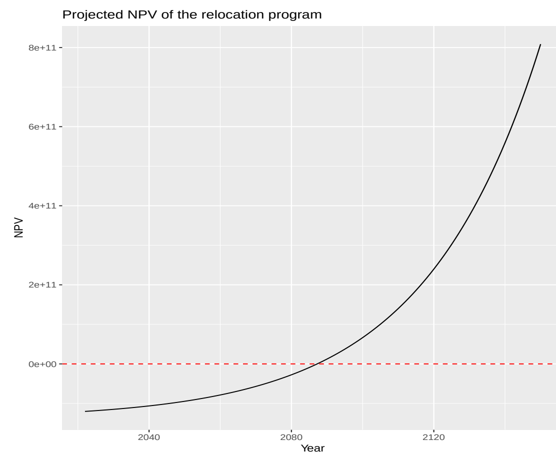

Figure 6: Projected NPV for relocation program

4 Assumptions

4.1 Economic Projection

Due to incompleteness of information, assumptions are made to create forecasts for some of Storslysia's economic figures.

- Property prices increase/decrease according to inflation rate
- GDP growth follows same pattern as the bank's 1-year lending rate
- Regional housing prices are calculated under per capita proportional basis

These figures are subjective to various social economic factors including global economy and government intervention etc, and in long term can lead to large difference with real figures.

4.2 Emission Scenarios

We have made assumption that Storslysia's economy will be affected similar to the global GDP growth forecast under the 4 different emission scenarios. The model predictions are adjusted to reflect emission scenarios individually and calculated the weighted outcome after assigning a weight to each scenario. Different areas in the world will be affected by climate change differently, for example for a coastal region will be heavily impacted by rising sea level (flooding or even permanent inundation) from high emission [8]. If Storslysia is a island country or large amount of economic activities based in coastal region, it won't likely to have highest GDP growth in SSP5-baselines emission scenarios (Refer to Appendix 9.4 for Emission Scenarios' Forecasts).

4.3 Timeliness of Quantitative Analysis

The quantitative models are strongly influenced by the past trend and we have assumed a similar long term trend (Refer to Figure 1 for historical inflation and interest rates) . However macroeconomic related forecasts (GDP, inflation etc.) are heavily affected by various drivers including global trade, commodity prices and government monetary policies, and should not be relied on long term [6]. This means that the long time frame (10years) prediction of the model will have high uncertainties, and the model should be constantly adjusted each year to stay accurate and up to date.

4.4 Calculation of the impact of relocation

We assume all the residents in the high risk region (i.e., Region 5) will be relocated to the low risk region (i.e., Region 1) under our relocation program due to data limitation. However, there could be various barriers to successful relocation. For instance, relocation might be challenging for those people whose income earnings are dependent on the local community [3]. Additionally, cultural difference could also be another challenge [3]. The relocation assumption could be further adjusted if historical migration rates between different regions are provided.

5 Risk and Risk Mitigation

5.1 Qualitative Risks

- **Availability of new properties**: The availability of new properties can be affected by many factors including limited labour, resources, build permits issued (Region 3 permits issued is only 0.32% of properties), which will be a great issue in events of major hazard events. Voluntary relocation is a big part of mitigation, distributing relocation evenly in advance to ease the peak demand, and government can initiate development projects to build relocation properties in mass.
- **Disruption of Work**: Hazard events can cause damage to commercial properties and affect business activities as well, causing people to lose their job temporarily or permanently. In the program plan there will be loss of income help to households with income below a threshold, to help households in poverty or lost income for the duration of relocation.

5.2 Quantifiable Risks

There are multiple quantifiable risks which are ranked from most severe to least:

1. **Catastrophic Hazard Events**: Large flooding and earthquakes can cause thousands of households to force to relocate. Such events are very hard to forecast but becoming more common with climate change. We have modelled the worst scenario and tested the sustainability of program under stress, and there is a very large increase in severity of damage (details in Section 5.3)
2. **Macro-economic variables**: The inflation rate and interest rates could deviate from the baseline assumptions due to policy changes or external shock to the system. To assess the risk from changing macro-economic environment, we have projected the program cost under the high-inflation scenario, the baseline inflation scenario, and a low inflation scenario, with details shown in Section 5.3

5.3 Sensitivity Analysis and degree of certainty

To assess the sensitivity of our projected program cost, we have performed a scenario analysis of the program cost under different climate change and macroeconomic scenarios. The projections of program cost under the SSP 1 scenario (i.e., the most optimistic scenario regarding to CO2 emission), the SSP 2 scenario (i.e., the medium pathway), and the SSP 5 scenario (i.e., the most pessimistic scenario regarding to CO2 emission), are shown in Figure 7, Figure 8 and Figure 9, respectively. Under the SSP 1 scenario, the projected program cost under the baseline inflation scenario does not surpass the 10% of national GDP (marked by the red line) in any given year. As for the SSP 2 emission scenario, the projected program cost only reaches the 10% of GDP at the end of the year 2150. However, under the high emission scenario (i.e., SSP 5), the program cost is expected to surpass the 10% of GDP in the middle of the forecasting horizon. This result highlights the view that the increasing damage caused by the high CO2 emission cannot be justified by the fast economic growth.

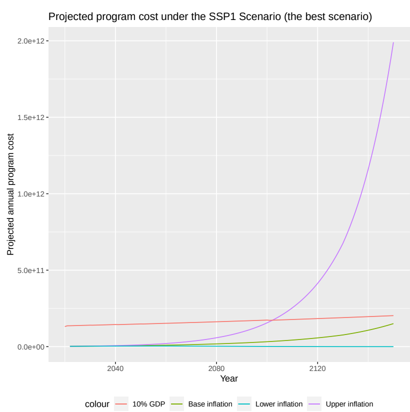

Figure 7: Projected cost under SSP1 (best scenario)

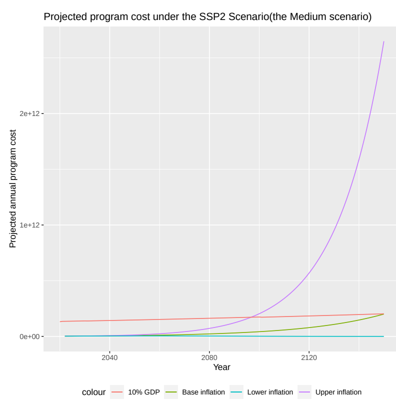

Figure 8: Projected cost under SSP2 (medium scenario)

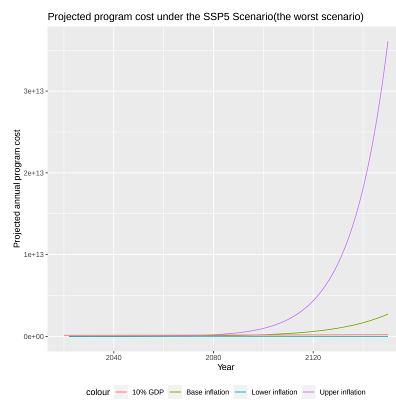

Figure 9: Projected cost under SSP5 (worst scenario)

Climate scenario	Inflation scenario	Proportion exceeding 10% GDP	Confidence level
	Lower	0.00%	100.00%
SSP1	Base	0.00%	100.00%
	Upper	37.21%	62.79%
	Lower	0.00%	100.00%
SSP2	Base	0.00%	100.00%
	Upper	41.86%	58.14%
	Lower	0.00%	100.00%
SSP3	Base	20.93%	79.07%
	Upper	48.06%	51.94%
	Lower	0.00%	100.00%
SSP5	Base	41.09%	58.91%
	Upper	56.59%	43.41%

Table 6: Degree of certainty under climate scenarios

Table 6 shows the proportion of times that the projected program cost will exceed the 10% of national GDP under each combination of climate and macro-economic scenarios. Our confidence level that the 10% of GDP constraint will not be surpassed is then one minus the exceeding proportion. As per Table 6, our confidence level decreases when either the inflation rate or CO2 emission is high.

The weights of each scenario are shown in Table 11 in Appendix 7.11, where those weights are determined judgmentally to reflect our perceptions of future environment. By applying the scenario weights to the results shown in Table 6, our weighted confidence level that the program cost will not exceed 10% of national GDP is $\mathbf{90.69\%}$.

6 Data Limitations and Improvements

6.1 Economic Modelling

And as only only GDP figures from 2019-2021 are present, the 1 year lending rate are used to predict GDP growth. Having access to historical GDP can help improve the prediction accuracy. And similarly there is no access to historical property prices and construction costs, whilst inflation can be a decent method to estimate price change, they do not always align, for example investment can drive land and property prices up much faster than inflation. Having access to historical data for key affected sectors will improve accuracy of model prediction.

6.1.1 Cost Estimation through Other Sources

There are various costs/figures that are estimated through other sources, the estimation are done individually for the 6 regions and come from USA states with comparable GDP per-capita, that the currency has been converted to Storslysia currency when comparing and using the numbers. The list of estimated costs include

- Construction cost of dwellings
- Time taken to construct dwellings
- Lifespan of household goods
- Cost of moving home

For data estimated from other sources, these might not be a very accurate reflection of Storslysia, and can lead to large errors over long time. To gain these numbers and improve on accuracy of predictions, will require research into Storslysia's government or private reports and studies, and if not available yet then arrange studies and surveys into these figures.

6.2 Hazard and damage Modelling

In this project, we only have access to regional level hazard information. Given that high resolution data is not available, our estimation of property damage could carry substantial uncertainty. For instance, the elevation and structures of individual property could cause significant variation in the actual damage ratio among different properties for flooding events [4]. If damage data with finer resolution is collected in future, we could incorporate more granular information into our modelling to reduce the uncertainty involved.

7 Appendix

7.1 Inflation and Interest Rates

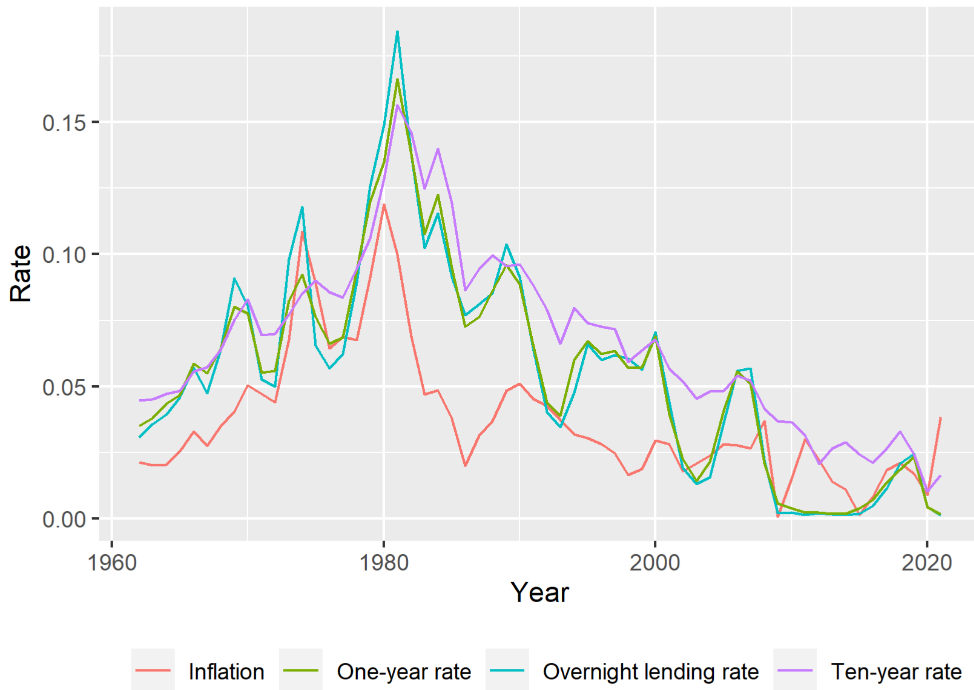

Figure 10: Plot of Inflation and Interest Rates

7.2 Macro-economic models validation

To investigate potential time-series candidate models to generate projections for inflation rate and interest rate, the plots of Autocorrelation Function (ACF) and Partial Auto-correlation function (PACF) are generated in Figure 11 and Figure 12 shown in the Appendix, respectively. Based on the plot, there seems to be a cut-off after lag 1 in the PACF plot, and a geometric decay in the ACF plot. Therefore, one potential candidate is the Auto-Regression model with order 1 (i.e., AR(1)). To take account into the non-stationary characteristics of the original time-series of inflation rates, we have also explored the Auto-regressive Integrated Moving Average model with a differencing order 1 and AR oder 1 (i.e., ARIMA(1,1,0)). To capture the general trend of inflation rates by smoothing-out short-term fluctuations, we have also fitted a smoothing spline to the inflation rates.

To validate our candidate models, we have allocated the historical data before the year 2011 to the training period and the historical data after the year 2011 to the validation period. The candidate models are firstly fitted on the training data and generate predictions in the validation period, with the results shown in Figure 1. The black dashed line marked the cut-off between training and validation period. As per the figure, the Moving Average model severely deviates from the validation data points and therefore is excluded from our consideration. The AR(1) model tends to slightly over-estimate the inflation rates, whereas the smoothing spline tends to under-estimate the observations. The ARIMA model seems to have an unbiased estimation. Indeed, the ARIMA model has the lowest validation Mean-Squared Error (MSE) as per Table 7. Therefore, the projection from the ARIMA model is selected as our best estimation of the future inflation rates.

The projections of inflation rates and interest rates under each candidate model are shown in Figure 14 and Figure 15, respectively. The projections from the ARIMA model can be used as our **base scenario**. To take into model uncertainty, the projections from the AR(1) model will be used as the **high inflation and interest scenario**, which assumes the surge in inflation rate and the interest rate in the recent years will continue in the future. The projections from the smoothing spline will be used as the **low inflation and interest scenario**, which assumes the general decreasing trend of inflation and interest since 1990 will continue in our forecasting horizon.

Model	Validation MSE
AR(1)	0.0002519
MA(6)	0.0006895
ARIMA(1,1,0)	0.0001006
Smoothing Spline	0.0001298

Table 7: Validation MSE for inflation rates forecasts

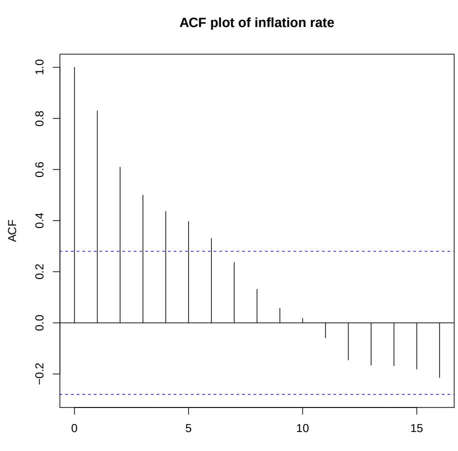

Figure 11: Autocorrelation Function (ACF) of inflation rates

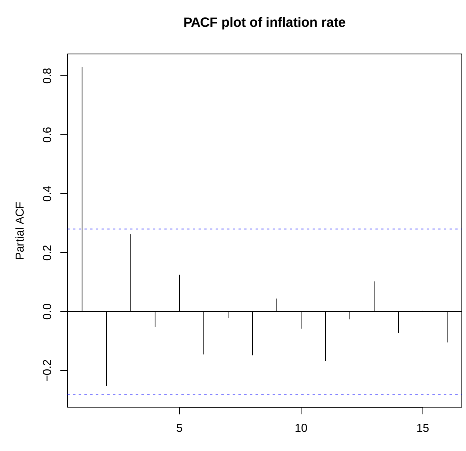

Figure 12: Partial Auto-correlation function (PACF) of inflation rates

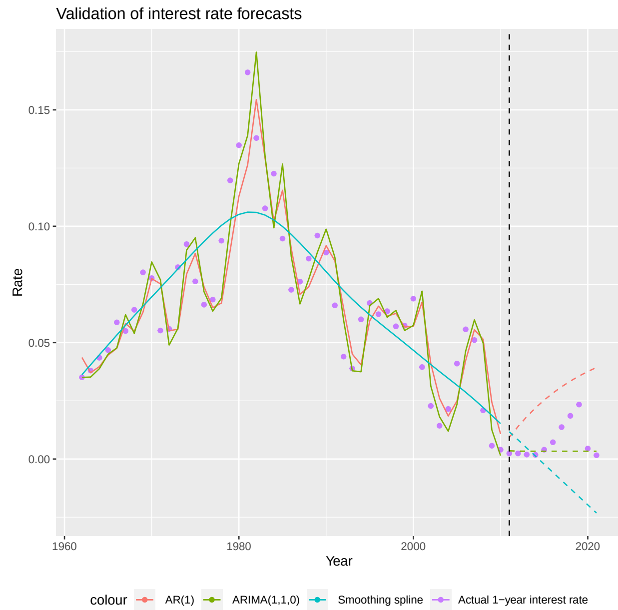

Figure 13: Validation of interest rate forecasts

Projections of interest rate and inflation rates over the full time horizon:

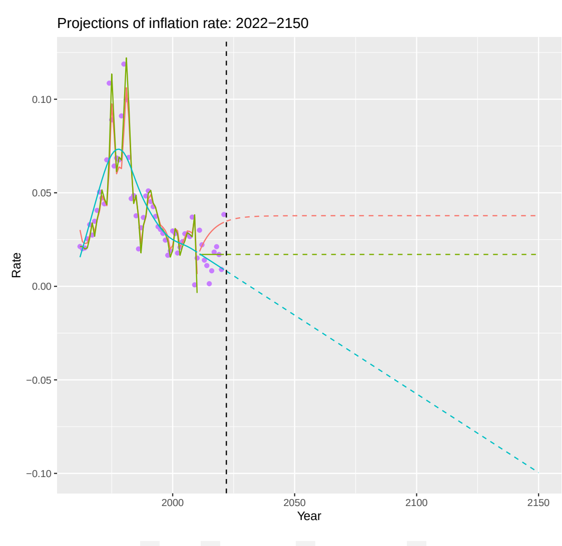

Figure 14: Inflation rates projections

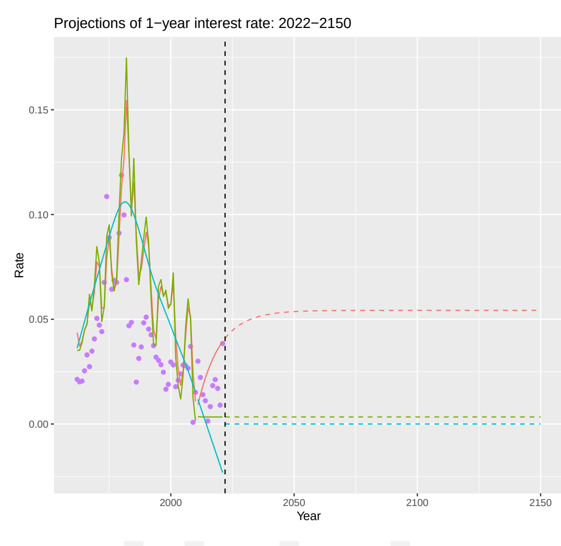

Figure 15: Interest rates projections

7.3 EDA of hazard events count and damage ratio

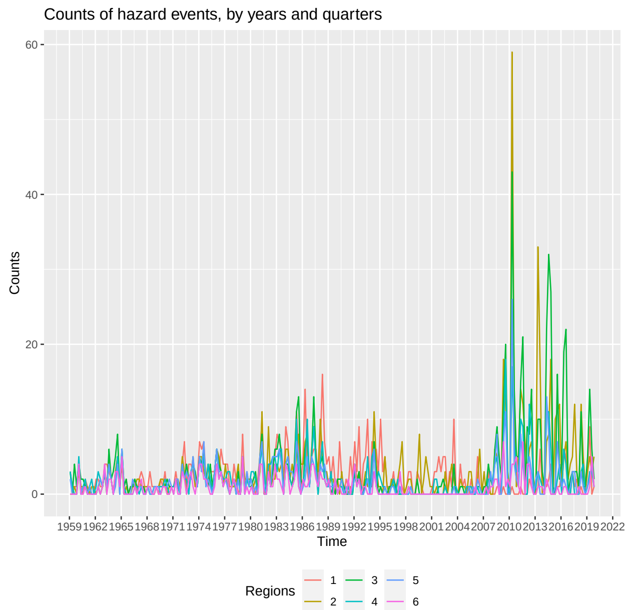

Figure 16: Plot of hazard events counts by year and region

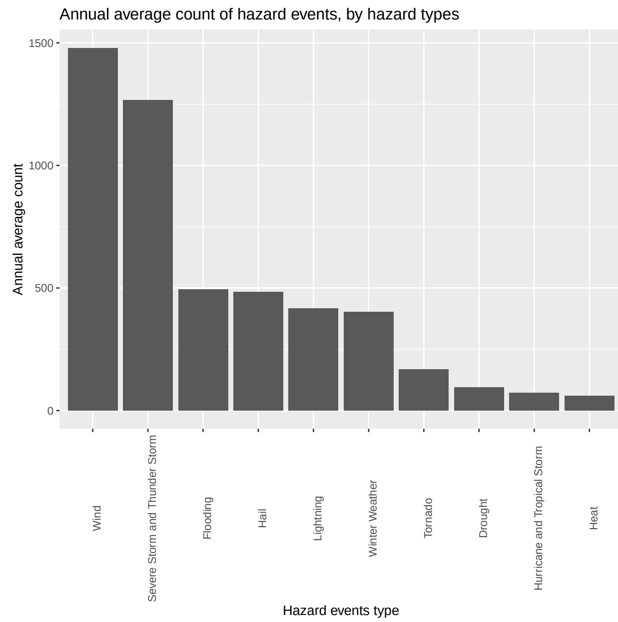

Figure 17: Plot of hazard events counts by hazard events types

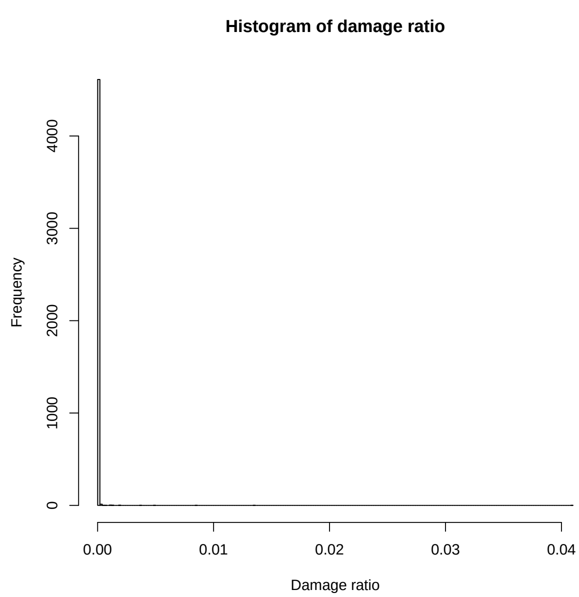

Figure 18: Histogram of damage ratio

7.4 Development and formulation of frequency model

Since the count of hazard events is a discrete random variable, we use Poisson regression to model the hazard events frequency. Since the hazard events count seem to vary with both regions, calendar years and event types as shown in Figure 17 and Figure 16, we built a Poisson GLM to model the hazard events count Y_i as a function of the above covariates. To capture potential non-linear relationship between the hazard event count and its covariates, we have also explored a more flexible GAM approach, where a smooth function is applied to the calendar year variable. The detailed formulation of the GLM and the GAM models are given below. The link function for the Poisson GLM for the hazard events count can be specified as:

$$\eta_{GLM}(Y_i) = Year_i + Quarter_i + Type_i + Region_i \tag{1}$$

and the link function for the Poisson GAM for the hazard events count can be specified as:

$$\eta_{GAM}(Y_i) = s(Year_i) + Quarter_i + Type_i + Region_i \tag{2}$$

The regression output for the Poisson GLM and the GAM are given in Appendix 7.5. For model evaluation, AIC and BIC are used as evaluation metrics as they could take into account both the goodness-of-fit and the model's complexity. As per Table 9, the Poisson GAM outperforms the GLM based on both AIC and BIC. Therefore, the Poisson GAM is selected to model the hazard events count.

Model	AIC	BIC
Poisson GLM	8547.482	8680.895
Poisson GAM	8396.522	8529.935

Table 8: Frequency model evaluation based on AIC and BIC

7.5 Development and formulation of severity model

For the damage model, we choose to model the damage ratio (i.e., the ratio of property damage to exposure) instead of the absolute value of property damage. This is because the dollar value of property damage could be heavily influenced by the housing value, which might not necessarily reflect the underlying risk. To derive the damage ratios, we divide the property damage by the total housing value in each region, which serves as a proxy for the exposure.

Since the damage ratio is bounded between 0 and 1, a natural candidate distribution is the Beta distribution. Another advantage of the Beta distribution is that it can capture the non-symmetrical distribution of damage ratio, which could be shown in Figure 18. However, the Beta distribution does not support zero values. Given the non-negligible proportion of zero damage value present in the data, we follow a two-steps estimation approach. In the first step, we fit a Logistic regression to estimate the probability that the damage has occurred, denoted as $\hat{p} = Pr(d > 0)$. The regression output could be found in Appendix 7.5. In the second step, we fit a Beta distribution to the damage ratio by regions on the subset of the data where the damage ratio is greater than zero, which seeks to estimate the conditional expectation of damage ratio $E[d|d > 0]$. Therefore, the final damage ratio could be estimated as: $\mathsf{E}[d] = \mathsf{E}[d|d > 0] \cdot \mathsf{Pr}(d > 0)$. The fitted frequency and damage models specified above are used to generate projections for future hazard events count and damage ratio. The projected events counts are shown in Figure 3, where Region 3 has the highest projected events count. To more comprehensively evaluate the risk in each region, we have developed a climate risk index, defined as the product of predicted events count and the damage ratio (i.e., Climate risk Index $= \hat{N}_t \cdot \hat{d}$), that factors both frequency and severity into risk evaluation. Based on the climate risk index, Region 5 has the highest risk in all projected years.

```
Call:
glm(formula = Count ~ as.character(Region) + as.character(Quarter) +
    Year + Hazard_Event, family = poisson(link = "log"), data = HAZARD_count_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3703  -0.7065  -0.2463   0.3327  10.0199

Coefficients:
                                      Estimate Std. Error z value Pr(>|z|)
(Intercept)                         -34.061050   1.732210 -19.663  < 2e-16 ***
as.character(Region)2                 0.088726   0.045377   1.955   0.0505 .
as.character(Region)3                 0.230149   0.044465   5.176 2.27e-07 ***
as.character(Region)4                 0.060709   0.048670   1.247   0.2123
as.character(Region)5                -0.042639   0.051053  -0.835   0.4036
as.character(Region)6                -0.245731   0.062177  -3.952 7.75e-05 ***
as.character(Quarter)2                0.409466   0.041318   9.910  < 2e-16 ***
as.character(Quarter)3                0.303835   0.043338   7.011 2.37e-12 ***
as.character(Quarter)4               -0.073649   0.055187  -1.335   0.1820
Year                                  0.017010   0.000866  19.641  < 2e-16 ***
Hazard_EventDrought                   0.196106   0.184558   1.063   0.2880
Hazard_EventFlooding                  0.633481   0.159601   3.969 7.21e-05 ***
Hazard_EventFog                       0.009440   1.012265   0.009   0.9926
Hazard_EventHail                      0.646230   0.159652   4.048 5.17e-05 ***
Hazard_EventHeat                      0.050743   0.199598   0.254   0.7993
Hazard_EventHurricane and Tropical Storm     0.115502   0.192614   0.600   0.5487
Hazard_EventLandslide                 0.406720   1.012944   0.402   0.6880
Hazard_EventLightning                 0.379281   0.160460   2.364   0.0181 *
Hazard_EventSevere Storm and Thunder Storm   0.767430   0.155250   4.943 7.69e-07 ***
Hazard_EventTornado                   0.116681   0.170859   0.683   0.4947
Hazard_EventWildfire                  0.109647   0.271172   0.404   0.6860
Hazard_EventWind                      0.803556   0.154947   5.186 2.15e-07 ***
Hazard_EventWinter Weather            0.739269   0.162526   4.549 5.40e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 3650.4  on 2441  degrees of freedom
Residual deviance: 2632.4  on 2419  degrees of freedom
AIC: 8547.5

Number of Fisher Scoring iterations: 5
```

Figure 19: Regression output summary for Poisson GLM: frequency predictions

```
Call:
glm(formula = Count ~ as.character(Region) + as.character(Quarter) +
    Year + Hazard_Event, family = poisson(link = "log"), data = HAZARD_count_data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-2.3703  -0.7065  -0.2463   0.3327  10.0199

Coefficients:
                                      Estimate Std. Error z value Pr(>|z|)
(Intercept)                         -34.061050   1.732210 -19.663  < 2e-16 ***
as.character(Region)2                 0.088726   0.045377   1.955   0.0505 .
as.character(Region)3                 0.230149   0.044465   5.176 2.27e-07 ***
as.character(Region)4                 0.060709   0.048670   1.247   0.2123
as.character(Region)5                -0.042639   0.051053  -0.835   0.4036
as.character(Region)6                -0.245731   0.062177  -3.952 7.75e-05 ***
as.character(Quarter)2                0.409466   0.041318   9.910  < 2e-16 ***
as.character(Quarter)3                0.303835   0.043338   7.011 2.37e-12 ***
as.character(Quarter)4               -0.073649   0.055187  -1.335   0.1820
Year                                  0.017010   0.000866  19.641  < 2e-16 ***
Hazard_EventDrought                   0.196106   0.184558   1.063   0.2880
Hazard_EventFlooding                  0.633481   0.159601   3.969 7.21e-05 ***
Hazard_EventFog                       0.009440   1.012265   0.009   0.9926
Hazard_EventHail                      0.646230   0.159652   4.048 5.17e-05 ***
Hazard_EventHeat                      0.050743   0.199598   0.254   0.7993
Hazard_EventHurricane and Tropical Storm     0.115502   0.192614   0.600   0.5487
Hazard_EventLandslide                 0.406720   1.012944   0.402   0.6880
Hazard_EventLightning                 0.379281   0.160460   2.364   0.0181 *
Hazard_EventSevere Storm and Thunder Storm   0.767430   0.155250   4.943 7.69e-07 ***
Hazard_EventTornado                   0.116681   0.170859   0.683   0.4947
Hazard_EventWildfire                  0.109647   0.271172   0.404   0.6860
Hazard_EventWind                      0.803556   0.154947   5.186 2.15e-07 ***
Hazard_EventWinter Weather            0.739269   0.162526   4.549 5.40e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 3650.4  on 2441  degrees of freedom
Residual deviance: 2632.4  on 2419  degrees of freedom
AIC: 8547.5

Number of Fisher Scoring iterations: 5
```

Figure 20: Regression output summary for Poisson GAM: frequency predictions

```
Call:
glm(formula = Damage_indicator ~ as.character(Region) + as.character(Quarter) +
    Hazard_Event, family = binomial(link = "logit"), data = HAZARD_data_withExp)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.4928   0.0767   0.2225   0.2920   1.8008

Coefficients:
                                           Estimate Std. Error z value Pr(>|z|)
(Intercept)                                 1.00595    0.43135   2.332 0.019695 *
as.character(Region)2                       0.11543    0.19978   0.578 0.563391
as.character(Region)3                      -0.01673    0.20150  -0.083 0.933838
as.character(Region)4                       0.04521    0.21567   0.210 0.833961
as.character(Region)5                       0.14169    0.22234   0.637 0.523946
as.character(Region)6                      -0.15685    0.24281  -0.646 0.518297
as.character(Quarter)2                     -2.46656    0.26962  -9.148  < 2e-16 ***
as.character(Quarter)3                     -1.91457    0.29214  -6.554 5.61e-11 ***
as.character(Quarter)4                      0.02759    0.26902   0.103 0.918312
Hazard_EventDrought                         1.51100    0.43516   3.472 0.000516 ***
Hazard_EventFlooding                       19.09668  278.20322   0.069 0.945274
Hazard_EventFog                            17.41710 6522.63862   0.003 0.997869
Hazard_EventHail                            3.93834    0.41973   9.383  < 2e-16 ***
Hazard_EventHeat                            0.16526    0.46603   0.355 0.722883
Hazard_EventHurricane and Tropical Storm    3.28254    0.56524   5.807 6.35e-09 ***
Hazard_EventLandslide                     -19.55529 6522.63862  -0.003 0.997608
Hazard_EventLightning                       3.02880    0.40315   7.513 5.78e-14 ***
Hazard_EventSevere Storm and Thunder Storm  4.61139    0.41463  11.122  < 2e-16 ***
Hazard_EventTornado                         3.55075    0.49705   7.144 9.09e-13 ***
Hazard_EventWildfire                       18.93469 1346.85050   0.014 0.988783
Hazard_EventWind                            4.94978    0.42393  11.676  < 2e-16 ***
Hazard_EventWinter Weather                  0.21626    0.40624   0.532 0.594483
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 2629.6  on 5006  degrees of freedom
Residual deviance: 1822.2  on 4985  degrees of freedom
AIC: 1866.2

Number of Fisher Scoring iterations: 17
```

Figure 21: Regression output summary for Logistic GLM: damage indicator prediction

7.6 Validation of frequency model

Model	AIC	BIC
Poisson GLM	8547.482	8680.895
Poisson GAM	8396.522	8529.935

Table 9: Frequency model evaluation based on AIC and BIC

7.7 Temporary Housing Calculation

One main component of cost avoidable with proactive relocation is temporary housing, for example for Region 1 it is calculated with following information:

1. Temporary housing cost: 1920 per person per month
2. Persons per household: 2.55
3. Time for new property construction: 9 months[7]

7.8 Relocation Cost Tables

	Relocation Costs (φ)				
Related Items	**Region 2**	**Region 3**	**Region 4**	**Region 5**	**Region 6**
New Property Cost	320,618	310,463	193,760	216,663	255,598
- Additional Construction Costs	70,011	111,041	60,179	72,989	42,453
Replacing Household Goods	118,368	124,632	106,128	103,536	106,992
Temporary Housing	40,988	42,793	36,878	35,978	39,424
Moving Costs	4,000	4,000	4,000	4,000	4,000
- Additional Moving Costs	2,000	2,000	2,000	2,000	2,000
Avoidable Total	231,367	280,466	205,184	214,502	190,869

Table 10: Relocation Costs (2020) for Region 2-5

7.9 Plot of Emission Scenarios

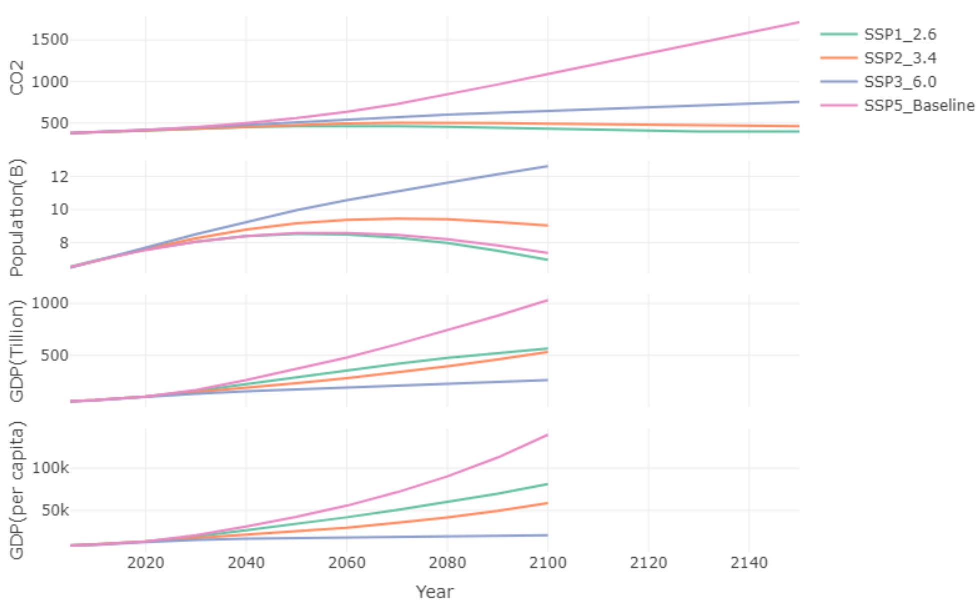

Figure 22: Plot of Emission Scenarios

7.10 Plot of Program cost under SSP3 scenario

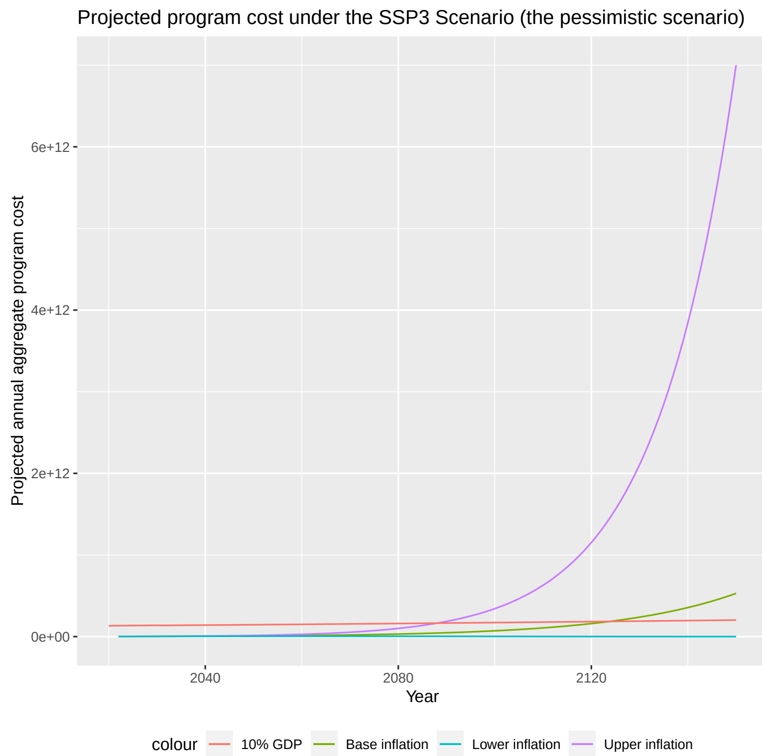

Figure 23: Projected program cost under the SSP3 scenario

7.11 Scenario weight for the sensitivity analysis

Climate scenario	Weight	Inflation scenario	Weight
SSP1	10%	Lower	10%
SSP2	70%	Baseline	80%
SSP3	10%	Upper	10%
SSP5	10%	NA	NA

Table 11: Scenario weights

7.12 R code

All the R code that generate the results in this report could be sourced from the github page: `https://github.com/xtrikil/ACTL5100_Project`

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