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Projecting the effect of climate change-induced increases in extreme rainfall on residential property damages: A case study from New Zealand

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Abstract

New Zealand's public insurer, the Earthquake Commission (EQC), provides residential insurance for some weather-related damage. Climate change and the expected increase in intensity and frequency of extreme weather-related events are likely to translate into higher damages and thus an additional financial liability for the EQC. We project future insured damages from extreme precipitation events associated with future projected climatic change. We first estimate the empirical relationship between extreme precipitation events and the EQC's weather-related insurance claims based on a complete dataset of all claims from 2000 to 2017. We then use this estimated relationship, together with climate projections based on future greenhouse gases concentration scenarios from six different dynamically downscaled Regional Climate Models, to predict the impact of future extreme precipitation events on EQC liabilities for different time horizons up to the year 2100. Our results show predicted adverse impacts that vary -increase or decrease over time and space. The percent change between projected and past damages—the climate change signal—ranges between an increase of 7% and 8% higher in the period 2020 to 2040, and between 9% and 25% higher in the period 2080 to 2100. We also provide detail caveats as to why these quantities might be mis-estimated. The projected increase in the public insurer's liabilities could also be used to inform private insurers, regulators, and policymakers who are assessing the future performance of both the public and private insurers that cover weather-related risks in the face of climatic change.

JEL codes

Q54

Keywords

Insurance, precipitation, climate change, extreme weather-events, loss projection

Summary haiku

Flood and landslip loss

will increase with climate change.

Costs will flow with rain.

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1 Introduction

Anthropogenic warming of the atmosphere as a result of greenhouse gas (GHG) emissions is expected to produce changes in the frequency and intensity of weather extremes (IPPC, 2012). In New Zealand, great efforts have been made to produce climate projection data that improve the understanding of potential impacts and implications of climate change on the environment, economy and society (Mullan et al, 2018). However, no study, in New Zealand or elsewhere, has used such projection data together with past detailed insurance claims data to project future monetary losses from damages caused by weather-related extreme precipitation events under different climate change scenarios.

New Zealand offers a convenient case study, as the national public insurer (the Earthquake Commission or EQC) provides residential insurance for weather risk. Specifically, it covers land damage resulting from floods and storms, and buildings, contents, and land damage that occur due to rainfall-induced landslides. These weather-related hazards have already cost the EQC NZ$450 million (using 2017 values) since the year 2000. The expectation that the frequency and intensity of extreme weather will be amplified by climate change ultimately implies additional liability for the EQC, and potentially poses a risk to the long-term sustainability of New Zealand's public insurance scheme.

A body of literature addresses projections of future losses from weather-related events. These studies differ in their approach, type of hazard, spatial scope, changes in hazard, and climate scenarios, as well as in how they consider future changes in exposure and vulnerability (Bouwer, 2013). In contrast with this previous literature, we use a risk modelling approach, coupled with an econometric analysis of past insurance claims data, to model the empirical relationship between weather-related insurance pay-outs (from damages to residential property) and extreme precipitation events (the hazard), while controlling for exposure and vulnerability risk factors. Previous papers (e.g. Pinto et al, 2007; Leckebusch et al, 2007, Klawa and Ulbrich, 2003) have generally used simple damage functions obtained from first principles and laboratory and field testing, but their models incorporate limited information of exposure and vulnerability risk factors. Unlike other papers, the individual damage records we use also allow us to exploit the time dimension in our data, as every claim can be linked with a time-specific weather event. The time-grid/cell structure of the data also permits us to isolate contemporaneous variation while controlling for exposure and vulnerability through the use of grid-cell fixed effects, and thus isolate the impact of the changes in the hazard (i.e., anthropogenic climate change). Furthermore, we can attach the geophysical characteristics of the building's surrounding -and underlying landscape thanks to the availability of geographic coordinates for each residential building.

We use outputs from six Regional Climate Model (RCM) simulations to assess the changes in hazard under the four main greenhouse gas (GHG) concentrations scenarios (Representative Concentration Pathways (RCP): 2.6, 4.5, 6.0, and 8.5). The main advantage of using downscaled RCM output is that it allows us to identify the climate change signal with spatial detail, since climate change impact on precipitation can be heterogenous across space.

Using inputs/risk factors with high spatial and temporal resolution allows us to project more precisely the future impact of climate change. We aim to answer two questions: What are the EQC's expected future liabilities, given future climate projections? And, how much more will the EQC have to pay in the future as consequence of anthropogenic induced climate change?

To address these questions, we start by identifying the empirical relationship between insurance claim pay-outs and the number of extreme precipitation events using a longitudinal geo-coded dataset of all insurance claims for the period 2000-2017. The historic extreme precipitation events are identified based on grid-cell threshold values of the 95th, 98th and 99th percentiles of the distribution of daily rainfall taken from observation-based gridded dataset. We calculate the number of extreme rainfall events based on the same percentile values for durations of up to five days of accumulated precipitation to consider the antecedent moisture conditions of the soil, and the persistent rainfall that might lead to an insurance claim.

The empirical historical relationship identified between insurance claims and extreme rainfall, identified in the damage regressions, is then applied to past and future climate projections data to identify the predicted change in EQC liabilities – i.e., the climate change signal. Our results reveal a moderate climate change signal, where the percent change in the expected annual losses relative to the baseline past ranges from 7.1% to 25.5% between 2020 and 2100, for the mean model ensemble, with considerable variability between the individual regional climate models. The impact of climate change on the levels of losses is heterogeneous across time and space. Some locations are predicted to experience increases in extreme precipitation events and thus in damages, while others are predicted to experience decreases in extreme events and damages.

The paper is organized as follows. Section 2 provides a short literature review to benchmark our methodological approach. Section 3 describes the data we use to estimate the relationship between extreme events and insurance; while Section 4 describes the results obtained from the regression models we estimate. Section 5 applies the estimated relationship (the regression coefficients) to future climate projections and quantifies the climate change signal. The last section provides some caveats and concluding remarks.

2 Literature Review

Projecting damages from future weather extreme events implies considering the changes in the weather-related hazards, but also scenarios of changing exposure and vulnerability. Changes in hazard should include the inherent natural variability and the contribution of anthropogenic activity. Changes in exposure mean the development of new residential areas or the concentration (densification) of existing ones. As for changes in vulnerability, projections should consider the effect that adaptation actions or mitigation policies have on the levels of risk. Bouwer (2013) summarizes some of the basic features of the studies that estimate future projected losses as a consequence of human-driven climatic change. These features include estimation method, hazard type, hazard (probability) change and climate scenarios, region (or spatial coverage), exposure (or socioeconomic scenario) and vulnerability (damage function estimations).

Estimation methods commonly used in research of projected damages include Integrated Assessment Models (e.g., Narita et al, 2009; Narita et al, 2010), Computable General Equilibrium Models (e.g., OECD, 2015), traditional risk models (e.g., Klawa and Ulbrich, 2003; Leckebusch et al, 2007; Pinto et al, 2007) and hybrid models (e.g., Dorland et al, 1999; Bender et al, 2010). Integrated Assessment Models describe the interactions between the economy and the biophysical system under analysis. Similarly, Computable General Equilibrium models describe the "relations between different economic actors and contain a full description of the economic system using multiple economic sectors" (OECD, 2015). They focus mostly on modelling the overall economy of a region or a country but are less detailed about the links to the bio-physical systems, while integrated assessment models contain only a more simplified description of the economy. Risk models include the conventional framework of risk as a determinant of hazard, exposure and vulnerability. Hybrid models combine conventional risk models with economic modelling.

The studies using these approaches mainly make projections of damages coming from tropical cyclones, extra-tropical cyclones, or river flooding. The changes in hazard in these studies are measured using factors and Global and Regional Climate Models (GCMs, RCMs) for different scenarios. Factors are numeric values that show changes in the probability of the hazard, where GCM and RCMs represent the climate and mainly differ in the spatial resolution and representation of processes, where higher resolution implies that local features of the climate are better resolved. Regarding the spatial scale, some of the studies cover single countries or regions (e.g., Schwierz et al, 2010), while others are global (e.g., Pielke, 2007).

Projections of changes in exposure over the future are rarely incorporated, but the studies that do include these consider mainly changes in value of assets or changes in population (e.g., Bouwer et al, 2010). Finally, vulnerability (damage) estimation uses loss models or empirical relationships, and generally "…involve a simple relationship described by a damage curve... or a loss model that specifies different damage categories" (Bower, 2013).

In this research, we project future damages by implementing a risk model in which damages are caused by extreme precipitation events (the hazard). We use several past and future climate models to quantify the change in hazard for four greenhouse gas concentration scenarios: a mitigation scenario (RCP 2.6), two stabilization scenarios (RCP 4.5 and RCP 6.0), and one scenario with high greenhouse gas concentration (RCP8.5).[1] Our analyses are performed for all the inhabited areas of New Zealand and assume no changes in exposure or vulnerability.

In New Zealand, the Ministry of Environment in collaboration with Crown Research Institutes has produced guidance documents for local government to address climate change impacts and their assessments [Mullan, 2008]. However, these guidance documents are rather prescriptive on what local governments can or should do, and typically only reference example case studies. NIWA (2015) provides an exposure analysis of the number of residential buildings located in low lying coastal areas and thus exposed to sea level rise (using the so-called bath-tub approach). However, the study does not make micro-based projections of future damages from rising seas as a result of climate change. In addition, Paulik et al (2019) produce an exposure analysis of residential buildings to pluvial and fluvial flooding events. However, the study does not explicitly incorporate the effects of climate change on flood risk. Neither of these studies account for vulnerability and focus exclusively on exposure. Fleming et al (2018), a precursor to this paper, describes the EQC's weather-related claims between 2000-2017 and the geophysical and socioeconomic context of individual residential buildings. Owen et al. (2019) analyses the impact of the EQC on the recovery of households after they lodge claims following extreme weather events, and Walsh et al. (2019) provides an analysis of flood management schemes on flood damages.

3 Data and summary statistics

We conduct our investigation using a longitudinal dataset of all individual weather-related insurance claims in New Zealand and extreme rainfall events aggregated at grid level. There are two possible physical processes underlying each insurance claim: a flood or storm, or a rainfall-induced landslip. Although we cannot differentiate between the two in the claim dataset, the set of covariates that we include are intended to capture the generating processes for both.

3.1 The EQC insurance scheme

In New Zealand, public natural hazard insurance is provided to residential property homeowners by the Earthquake Commission (EQC). In spite of its name, the EQC also insures some weather risk and currently provides insurance cover for buildings and for land. (Until July 2019, it also covered contents.) Specifically, it covers residential land damage caused by a storm or a flood, and both residential building and land damage caused by rainfall-induced landslips.

The land cover policy includes damages that occurred to the land underneath the building, the land underneath appurtenant structures, an 8-meter buffer around these, and underneath the main access point to the house. Other covers related to the land include damage to retaining walls, bridges, culverts. More details are available in the EQCover Guide (2016).

In order to access this insurance, homeowners need to have private fire insurance and pay a flat yearly premium as a compulsory addendum the private insurance. During the time we cover in this research (2000-2017), the EQC's cover for residential buildings provided the first NZ$ 100,000 of the replacement value for each insured dwelling. Damages above this amount were covered by private insurers. In contrast, the EQC land cover cap is set at the land’s assessed market value and is thus different across insured households (no premium is charged on land cover).

The insurance data contain a total of 15,196 weather-related settled (completed) claims between 2000-2017.[2] These claims amount to NZ$ 449,730,984 (in 2017 NZ$) where about 67% of the pay-outs are because of land damage, 32% for building damage, and 1% for contents damage. The shares of pay-outs per cover over time are shown in Figure 1a. We see that the land damage share has been trending upwards, which could be driven by increasing land prices, or changes in hazard, exposure or vulnerability.

The evolution over time of the EQC payouts in absolute values, shown in Figure 1b, demonstrates no increasing trend; rather, the series is dominated by specific extreme events, such as the Bay of Plenty and Waikato heavy flooding in 2005, the North Island 'weather bomb' in 2008; and the Tasman-Nelson heavy rain and flooding event in 2011. The seasonality of damages i.e. distribution of total losses per month is shown in Figure 1c. Larger losses tend to occur during autumn and winter (April to August). However, significant damages also occur even in peak summer (December-January). As indicated in Figure 1d, the distribution of total damages follows a negative exponential distribution: small compensation values are quite frequent and high or extreme compensation values are very rare.

Figure 1: Descriptive Information about the EQC Claims Data - 2000-2017

2 We remove claims whose status is reported as: Open, Re-open, Declined, Not-accepted, Withdrawn, Invalid, Field Work in Progress, Field Work Complete and Accepted. We keep only the insurance claims that report a total claim compensation value greater than zero.

Figure 1a: Annual share of damages per cover (land, building and contents)

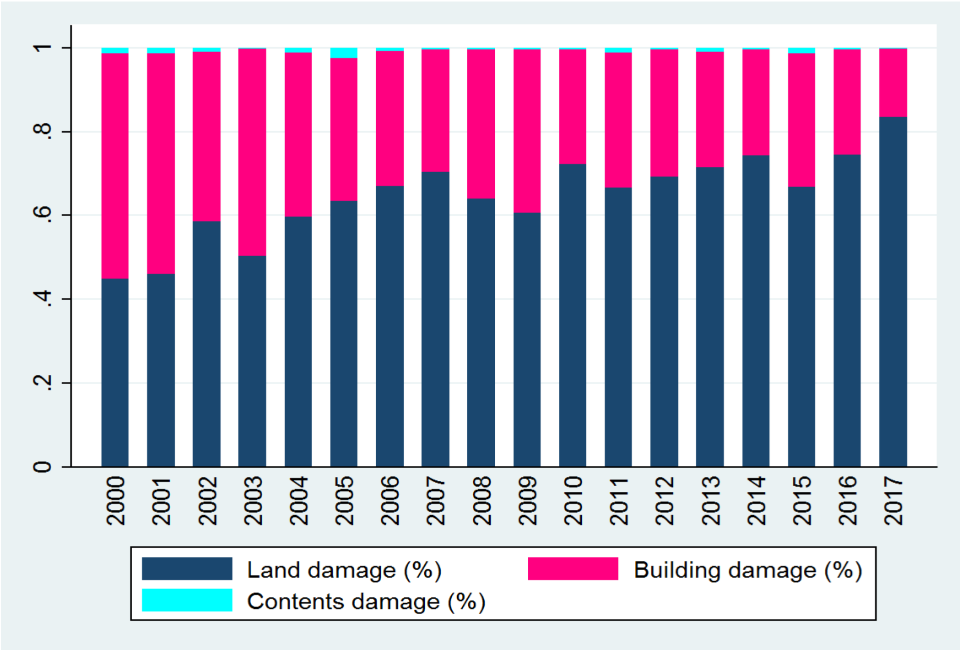


Figure 1b: Total value of claims paid out by the EQC per year and per coverage type (land, building and contents) as a result of weather-related insurance claims

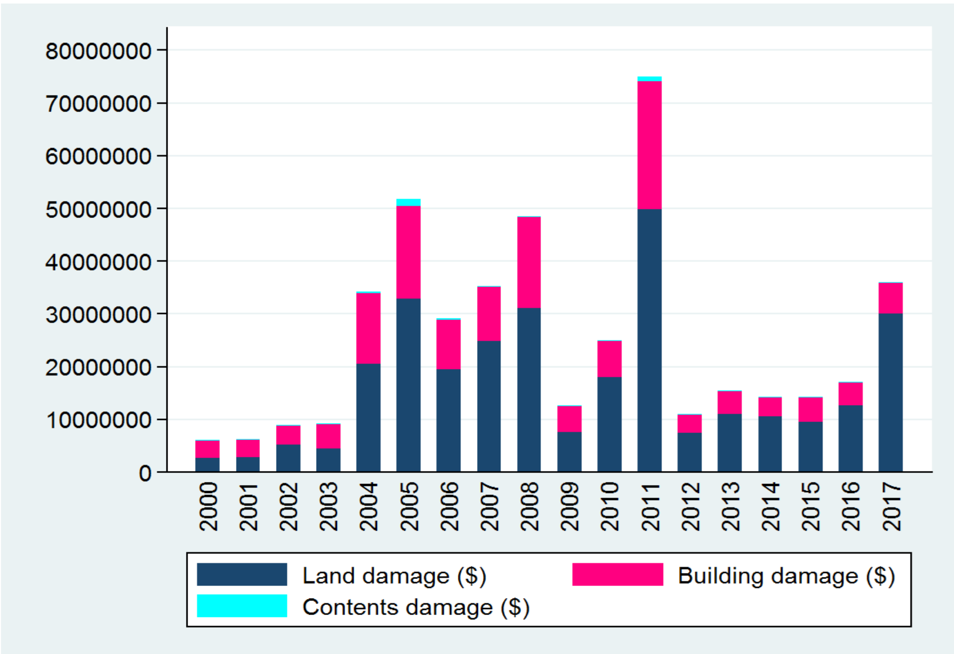


Figure 1c. Total damage for each month of the year aggregated for 2000-2017

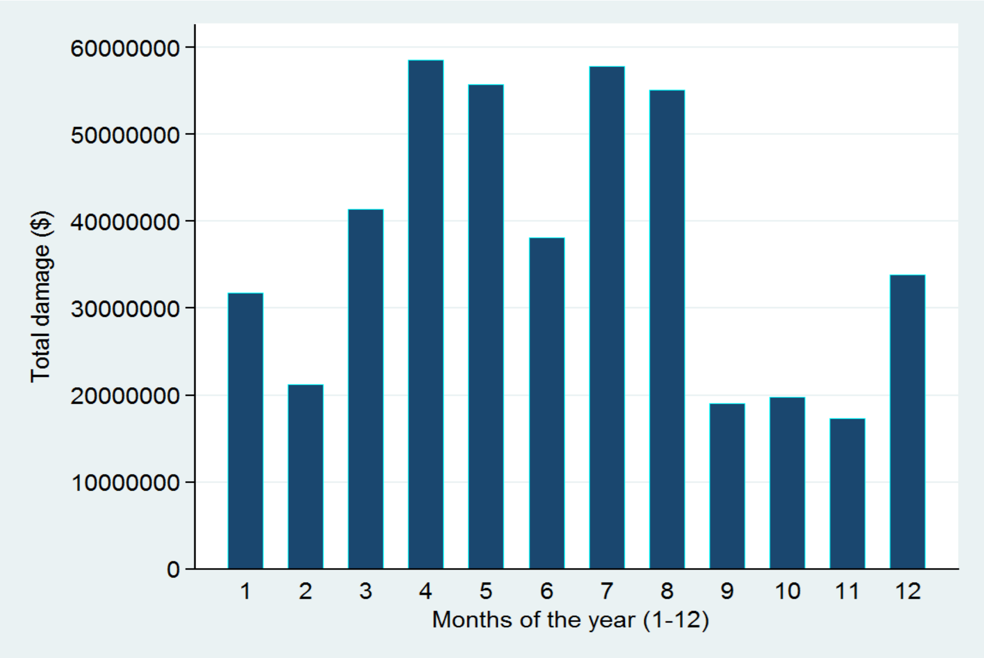
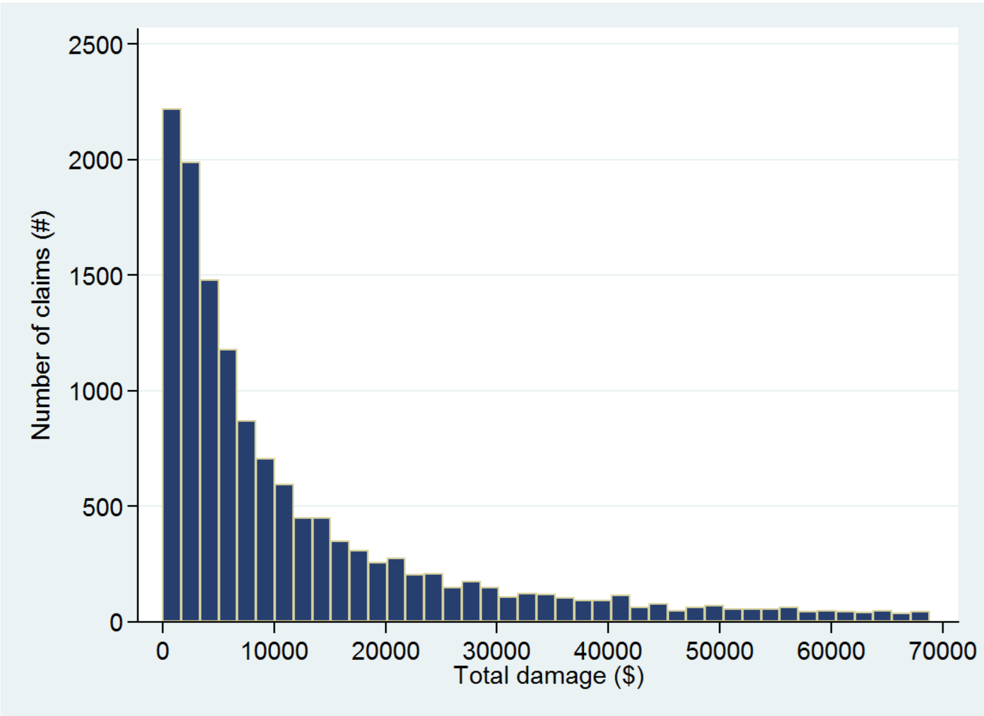


Figure 1d: Total number of insurance claims associated with each claim amount



Note: The graph only includes damages below the 90th percentile (68,857 NZ$) of the distribution and thus excludes the most extreme damages.

For our regressions, we drop from the sample any claim without a geospatial reference, which leaves us with 11,339 observations/records. We also drop 2,945 claims for which we precipitation information is not available. In summary, for the regressions described in the next section, we are left with 8,394 claims lodged to the EQC between 2000 and 2017 totalling NZ$180,404,945, which represent about 40% of the total payouts ever made by the EQC for weather-related risk. We do not have information about any over-cap private insurance claims that were paid in these instances. However, these are not required to estimate the relationship between extreme precipitation events and EQC liabilities.

We aggregate claims data to the grid cell by year level to match the geographic level at which precipitation data are available (Tait et al., 2006). Grid-cell/year is thus our unit of observation. We aggregate property-level claims to the grid cell-year-level in three ways such that we can capture the likelihood, frequency, and intensity of insurance claims that result from extreme precipitation (the hazard). Likelihood of a claim is measured using a binary variable for whether a claim was lodged because of land, building and/or contents damage in the grid-cell/year. Frequency is measured by the total number of claims in the grid-cell/year. Finally, intensity is measured by the total value of paid claims in real NZ$ from land, building and/or contents damage in the grid-cell/year. These three spatially explicit insurance claim measurements form our dependent variables.

3.2 Extreme precipitation (the hazard)

The precipitation data we use are an 18-year historic time-series (2000-2017) of observed daily precipitation, available for 5km by 5km grid cells (Tait et al., 2006). These data were produced by the National Institute of Water and Atmospheric Research (NIWA) and are known as the Virtual Climate Station Network (VCSN) data.

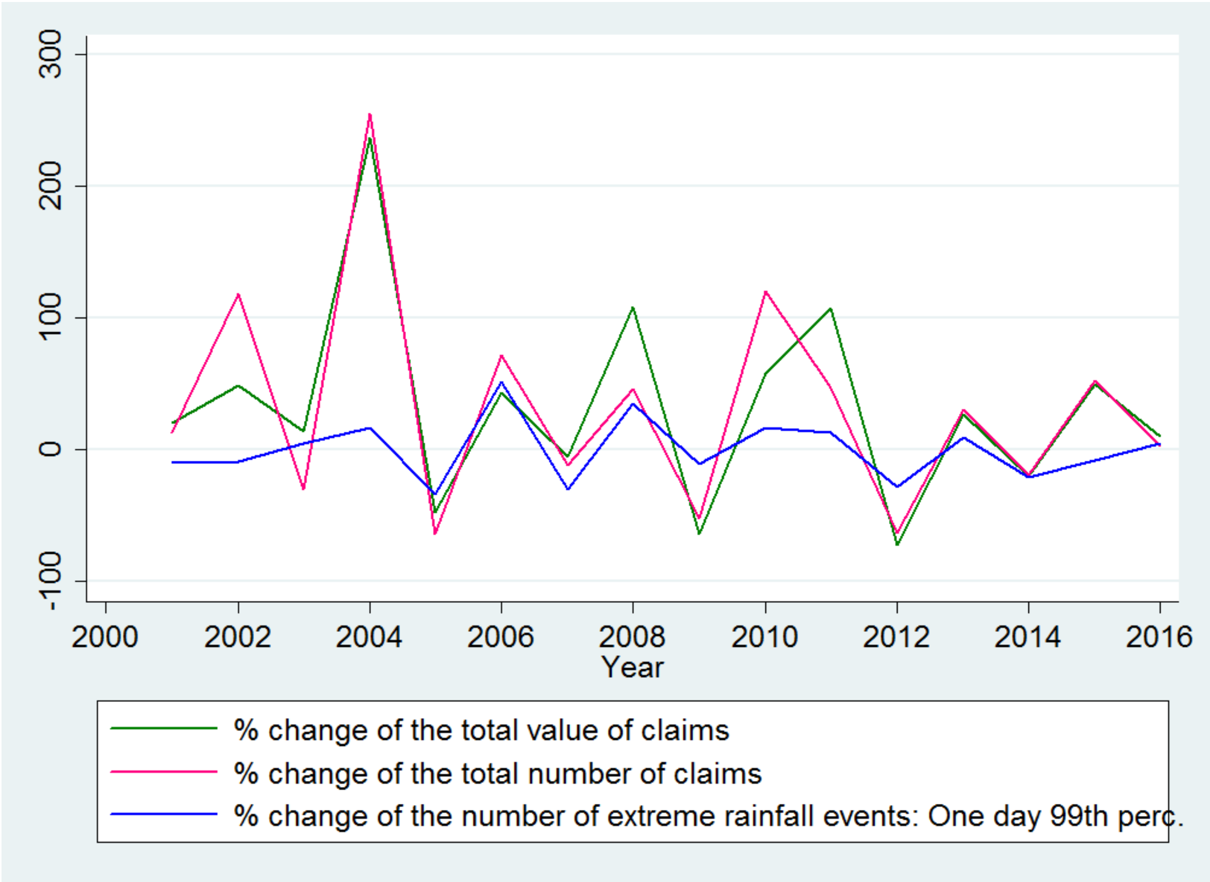
As defined by the Intergovernmental Panel on Climate Change, extreme weather is defined as "the occurrence of a value of a weather or climate variable above (or below) a threshold value near the upper (or lower) ends of the range of observed values of the variable" (IPCC, 2012, p. 557). We thus define extreme events based on the 95th, 98th, and 99th percentiles of the historical precipitation distribution for one day of accumulated precipitation. As in Griffiths (2007), the percentile thresholds are defined separately for each grid cell. In order to account also for the antecedent conditions that may lead to weather-related claims (for instance, a saturated soil or waterways), we also calculate the same thresholds for percentiles for up to five days of accumulated precipitation. Only wet days are considered in the percentile calculations, as in Carey-Smith et al. (2010), and we perform these calculations for inhabited grids only.[3] We

3 The dataset is composed of 11,231 grids out of which 55.5% have residential buildings within them. Extreme precipitation events occurring in uninhabited grids could affect adjacent grids with inhabited properties (and similarly extreme precipitation events in inhabited grid cells could affect adjacent

use these thresholds to construct, at the grid-cell/year level, the number of extreme events defined by three alternative percentile values (95th, 98th, and 99th percentiles) and five alternative durations (from one day up to five days).

In Figure 2 we examine the evolution of the percent changes of the number and value of insurance claims as well as the number of extreme events. We can see that at a national level the three time series show a positive correlation.

Figure 2: Percent change time series: Extreme events, number and value of claims.



3.3 Exposure and vulnerability variables

We use a large number of variables to capture the extent of exposure and vulnerability to extreme precipitation (the hazard) for each grid-cell/year observation(these variables are reported in Table 2)[4] We aggregate all our continuous control variables (e.g. slope, elevation) from the property level to the grid cell level by taking averages and convert indicator variables to percentages (e.g. percentage of properties located in areas with poor soil drainage). Building

inhabited grid cells). However, accounting for such effects is beyond the scope of this paper. The consequences of this simplification are discussed in the last section.

4 Our vulnerability and exposure measures come from cross-sectional data. Although the underlying features are inherently dynamic in nature, they are not measured regularly for operational, financial, or practical reasons. Bouwer (2006, 2013) highlights the issue of ignoring changes in exposure and vulnerability (which may be driven by changes in adaptation and mitigation policies) as one the main limitations of research that attempts to identify the impact of anthropogenic climate change through extreme events on monetary losses.

exposure is captured by: the number of residential properties; the total land area exposed[5]; the total value of assets in each grid-cell (building, land, contents, appurtenant, structures); and the total share of buildings in urban areas. We source the data from EQC (2017), CoreLogic (Quotable Value, 2017) and Land Information New Zealand (LINZ) (2017).

Furthermore, to capture building exposure, we consider the characteristics of the soil where properties are located. Specifically, we consider the soil flood return period, drainage, readily available water, and permeability. We consider each characteristic and the categories that are likely to be associated with damages (or amplify them) under extreme precipitation events. Thus, we calculate the share of residential buildings per grid that are located: on soils with flood return periods ranging from 'slight' to 'very severe'; on soils with 'very poor', 'poor' and 'imperfect' drainage; on soils with 'very high', 'high' and 'moderately high' profiles of readily available water; and on soils with a 'slow' rate of water movement through saturated soil.

We calculate inundation-related exposure variables such as the share of residential buildings per grid-cell that are located in pluvial and fluvial flood-prone areas and the share of properties located in storm surge areas with a 1% annual exceedance probability. The flood zones were collated by NIWA with data from Local Councils, while the storm surge maps were constructed by NIWA directly (NIWA, 2018). All the soil data were obtained from Landcare Research (LCR, 2002). We also measure the average distance of residential buildings from large rivers, small rivers, lakes, and the shoreline. The distances were calculated by the authors from data obtained directly from LINZ's spatial data infrastructure (LINZ, Topographic map series 1:50,000).

We develop a landslip susceptibility-exposure measure based on the slope of the terrain and the type of soil on which the property is located. Specifically, we create an indicator variable for any property located on terrain with a slope greater than five degrees, and located on any of the following types of soil: "very poor", "poor" or "imperfect" soil drainage; soil with a "slow" rate of water movement through saturated soil; soil with "very high", "high" or "moderately high" profile of readily available water; fluvial soil; and, soil with flood return periods ranging from slight (less than 1 in 60-year event) to very severe (greater than 1 in 5-year event). We define the slope threshold as five degrees based on Dellow (2011), who reports probabilities of landslip hazard for slopes greater than five degrees and a rainfall index between 0 and 25 millimetres. We aggregate this property-level measure to the grid-cell level by taking the

5 We approximate the land exposure (in km2) by using building outlines that are "a representation of the roof outline of a building, classified from aerial imagery using a combination of automated and manual processes to extract and refine a building roof outline" (LINZ, 2019). We spatially overlay the building outlines on the residential property dataset, and calculate an 8-metre buffer, because the EQC covers not only the land underneath the building but the surrounding land up to 8 meters. Because not all properties can be linked to an outline (presumably due to the 70-metre anonymization offset applied in the geolocation of the residential buildings), we calculate the average land exposed and multiply it by the number of properties within each grid. Due to the complexity of the cover offered by the EQC, it is not feasible to capture other related land exposures (retaining walls, access paths, etc.).

percentage of properties located on land with these characteristics and a slope greater than five degrees.[6]

To capture additional vulnerability, we use: the share of residential buildings that are constructed with materials that are vulnerable to water damage[7]; the share of residential buildings of "deficient condition"; the buildings' average floor height from the ground, and the average elevation (above sea level) and average slope on which houses are situated. Data on the building floor height, condition and construction materials come from the RiskScape asset inventory (NIWA and GNS, 2017). Topographic data are sourced from LINZ (2009). Finally, we calculate the share of residential buildings located in areas with no agricultural land use capability as a proxy for economic activity, sourced from LCR (2008).

3.4 Summary Statistics

Table 1 presents summary statistics at grid-cell/year level for the subsamples of observations with and without insurance claims during the study period (2000-2017). The mean number of extreme events in grids with claims is statistically significantly higher than the mean number in grids without claims for all percentiles and durations. However, since extreme events are constructed from percentile thresholds that are calculated separately for each grid, a relevant question is whether grids with claims have different rainfall thresholds to grids without claims. Thus, we examine the percentile threshold values for grid-year cells with and without claims. We find that grid cells with claims have significantly higher mean threshold values than do grid cells without claims for all percentile values and durations. That is, despite the fact an event in a grid cell with claims must have higher rainfall to be classified as extreme, such grid cells have higher numbers of extreme weather events.

The differences between the two samples are also observable in exposure and vulnerability measures at grid level, as shown in Table 2. For instance, the average number of properties exposed is about 22 times higher for grids with claims than grids without claims. Similarly, the mean amount of land exposed and the mean value of assets (building, land, appurtenant structures, and contents) are approximately 10 and 27 times higher, respectively, in grids with claims than in grids without claims. Similarly, the share of buildings located in

6 Results for a second alternative approach to measure landslip susceptibility, which we also examined, are not reported here. Specifically, we used the GNS landslip database (2019) to approximate landslip exposure hazard maps. We created buffers of varying diameters around all the landslides - represented as points that were triggered by intense precipitation. However, after consultation with GNS experts, we concluded that the buffers were not large enough to overcome the uncertainties associated with the geolocation of the hazards.

7 We use the RiskScape asset inventory to calculate measures of vulnerability associated with the construction materials. We calculate the percentage of timber and brick and masonry buildings within a grid. We include the brick masonry buildings since "houses in New Zealand normally have a timber frame and plasterboard wall linings in the inside, which makes them highly vulnerable to flooding". (NIWA, 2010). We also calculate the percentage of timber and brick and masonry buildings with a deficient quality.

urban areas is 8 times higher in grids with claims than in grids without claims. This is in line with the findings of prior studies where it is shown that damages from extreme weather events are strongly associated with exposure (Bouwer, 2018; Miller et al, 2009, Pielke et al 2008).

Regarding the inundation-vulnerability and landslip-vulnerability measures, the differences in means between grids with claims and grids without claims are statistically significant for all variables except average distance of residential buildings from lakes. For instance, the average percentage of properties in fluvial and pluvial flood prone areas in grids with claims is 3.3 percentage points higher than the average percentage of properties in grids without claims. The same is observed for the average percentage of properties located in 'very poor', 'poor' and 'imperfect' soil drainage (3.7 percentage points higher), the average percentage of properties located in soils with 'very high', 'high' and 'moderately high' profiles of readily available water (4.8 percentage points). All these differences are statistically significant. Finally, find statistically significant differences in means for four additional vulnerability-related measures: average elevation, average floor height, the share of buildings in deficient condition, and the share of buildings located in areas with agricultural land. In summary, we observe statistically significant differences for all hazard measures as well as for most of the exposure and vulnerability metrics we employ in our study.

Table 1: Descriptive statistics for insurance claims and extreme precipitation – per grid-cell/year.

	Grid-cells with claims (N=2,370)				**Grid-cells without claims (N=109,788)**			
	Mean	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Total paid, in 1,000 $NZ (adjusted for 2017)	76.1	264.6	0.00	9,147.9				
Total number of claims	3.54	9.99	1.00	238.00	-	-	-	-
Ratio of total paid to total value exposed	0.00	0.03	0.00	0.90	-	-	-	-
Ratio of total paid to total value exposed in 100k terms, in 2017 $NZ	305.79	3,252.18	0.00	90,028.88	-	-	-	-
Break down of total paid, per cover								
Total paid for land damage, in 1,000 $NZ (adjusted for 2017)	49.1	170.9	-7.3	5,847.6	-	-	-	-
Total paid for building damage, in 1,000 $NZ (adjusted for 2017)	26,518.01	140,966.00	-0.3	3,148.7	-	-	-	-
Total paid for contents damage, in 1,000 $NZ (adjusted for 2017)	474.18	4,582.56	-0.9	151.6	-	-	-	-
Percentile threshold values, for precipitation durations (1 to 5 days), in mm.								
95th percentile one day	36.39	9.46	17.10	65.70	33.15	12.31	16.30	191.40
98th percentile one day	52.67	14.46	23.00	92.90	47.10	17.70	22.20	268.60
99th percentile one day	66.46	18.93	29.50	122.20	58.91	22.22	27.30	318.90
95th percentile two days	49.44	13.14	23.25	92.10	45.40	18.24	19.30	282.00
98th percentile two days	71.35	20.05	30.80	133.70	63.91	25.64	28.30	372.20
99th percentile two days	89.22	26.00	39.70	170.30	79.59	31.77	36.40	460.50
95th percentile three days	59.48	15.96	27.80	114.80	54.77	22.95	21.70	346.20
98th percentile three days	84.08	23.73	38.65	161.80	76.02	31.31	31.70	450.60
99th percentile three days	103.35	29.76	46.30	201.60	93.41	38.32	41.00	578.20
95th percentile four days	68.13	18.30	32.10	133.50	62.87	26.98	23.60	402.60
98th percentile four days	94.68	26.57	44.10	179.20	86.17	36.33	35.70	533.90
99th percentile four days	115.07	32.94	50.80	218.60	104.69	43.62	42.70	674.90
95th percentile five days	76.15	20.65	36.30	151.40	70.36	30.82	25.40	453.70
98th percentile five days	103.70	28.87	48.60	197.90	95.04	40.59	36.70	606.20
99th percentile five days	125.22	35.40	55.30	235.70	114.88	48.46	45.00	721.10
Number of extreme precipitation events based on percentiles values and durations (1 to 5 days)								
95th percentile one day	39.24	133.99	0	3,570	6.17	3.05	0	23
98th percentile one day	11.84	40.62	0	1,190	2.47	1.82	0	12
99th percentile one day	6.86	27.10	0	952	1.24	1.23	0	8
95th percentile two days	39.24	133.99	0	3,570	8.85	4.36	0	30
98th percentile two days	18.13	66.36	0	1,904	3.50	2.65	0	18
99th percentile two days	10.58	39.71	0	1,044	1.75	1.80	0	12
95th percentile three days	48.69	162.81	0	4,522	10.81	5.58	0	37
98th percentile three days	23.18	85.06	0	2,380	4.26	3.37	0	23
99th percentile three days	13.33	51.23	0	1,392	2.12	2.31	0	16
95th percentile four days	56.79	187.74	0	4,998	12.32	6.60	0	40
98th percentile four days	26.84	99.29	0	2,610	4.86	4.05	0	26
99th percentile four days	15.99	62.48	0	1,666	2.43	2.78	0	19
95th percentile five days	63.24	214.18	0	5,950	13.48	7.50	0	45
98th percentile five days	30.48	119.18	0	3,306	5.33	4.62	0	31
99th percentile five days	18.47	76.36	0	2,088	2.67	3.21	0	22

Note: We distinguish between grids that have made weather-related claims and grids without any claim. We observe statistically significant differences for all hazard measures between the two sub-groups.

Table 2: Descriptive statistics for exposure – per grid-cell

	Grid cells with claims (n=791)				Grid cells without claims (n=5,440)			
Residential property exposure measures	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**
Total number of residential buildings exposed	1,262	3,107	2	25,604	57	327	1	9,761
Total area of res. land exposed (km2)	17	34	0	203	2	5	0	77
Total value of assets *	783	2,360	0	29,500	29	175	1	5,390
Land value (modelled) *	278	1,200	0	18,600	5	54	0	2,180
Building value (modelled) *	393	975	0	8,460	19	96	0	2,680
Appurtenant structure value (modelled) *	15	33	0	318	1	4	0	108
Contents value (modelled) *	98	243	0	2,060	5	25	0	718
Share of res. bldgs. located in urban areas	30	37	0	99	4	15	0	99
Inundation and landslip exposure measures								
Share of res. bldgs. in flood-prone areas	9	17	0	100	6	17	0	100
Share of res. bldgs. exposed to storm surge	2	9	0	100	1	8	0	100
Distance of res. bldgs. from big rivers (m)	4,419	3,987	60	29,819	5,117	4,570	4	43,212
Distance of res. bldgs. from small rivers (m)	295	260	26	2,519	354	817	0	12,064
Distance of res. bldgs. from lakes (m)	1,652	1,809	120	17,652	1,699	1,731	0	18,736
Distance of res. bldgs. from shoreline (m)	13,495	19,336	34	105,482	32,149	25,754	8	114,088
Share of res. bldgs. with landslip susceptibility	21	25	0	100	16	26	0	100
Share of res. bldgs. on soils with flood return periods from slight to very severe	17	26	0	100	18	30	0	100
Share of res. bldgs. on very poor to imperfect soil drainage	32	35	0	100	29	37	0	100
Share of res. bldgs. on soils with a 'slow' rate of water movement in saturated soil	6	16	0	100	6	18	0	100
Share of res. bldgs. on soils with very high to moderately high available water	33	37	0	100	28	39	0	100
Vulnerability measures								
Share of res. bldgs. with vulnerable materials	95	7	0	100	96	8	0	100
Share of res. bldgs. in deficient condition	22	12	0	100	21	17	0	100
Average elevation (above mean sea level)	99	111	2	741	214	185	1	2,336
Average slope	5	4	0	27	5	5	0	52
Average floor height (above ground)	1	0	0	1	1	0	0	2
Share of res. bldgs. located in areas with no agriculture	81	33	0	100	98	11	0	100

* Note: In Million 2017 NZ$. All the modelled values were constructed by the EQC.

4 Regression models

To estimate the historical relationship between extreme weather events and claims, we use the equations:

$$L_{it} = \frac{e^{\beta_1 Haz_{it} + \beta_2 Exp_i + \beta_3 Vul_i + \gamma_t + \epsilon_{it}}}{1 + e^{\beta_1 Haz_{it} + \beta_2 Exp_i + \beta_3 Vul_i + \gamma_t + \epsilon_{it}}} \quad [1]$$

$$F_{it} = e^{\beta_1 Haz_{it} + \beta_2 Exp_i + \beta_3 Vul_i + \gamma_t + \epsilon_{it}} \quad [2]$$

$$I_{it} = \beta_1 haz_{it} + \beta_2 exp_i + \beta_3 vul_i + \gamma_t + \varepsilon_{it} \quad [3]$$

where *i* denotes a grid-cell, t denotes year, and the dependent variable L_{it} is the likelihood, F_{it} is the frequency and I_{it} is the intensity of claims as described in the previous section (measured at the grid-cell/year). The terms haz_{it}, exp_i and vul_i are vectors of variables measuring hazard (at the grid-cell/year), exposure (at the grid-cell) and vulnerability (at the grid-cell), respectively. The variables contained in each vector are as described above. We use a logistic regression when looking at likelihood [1], a Poisson regression for frequency[2], and an OLS regression for intensity [3]. Depending on the model, the coefficients are expressed as incidence rate ratios (IRR), odds ratios (OR) or conventional coefficients, respectively. The regressions also include time fixed-effects.

We estimate a fixed-effects models rather than a random-effects models because we are interested in analysing the effect of variables that vary over time (given our interest in projecting climate change impacts). By using fixed-effects models, we remove the effect of observed and unobserved time-invariant characteristics. We use robust standard errors to allow for heteroskedasticity. All the estimations were produced using Stata/MP 13 and are presented in Table 3.[8]

4.1 Likelihood model for the probability of a claim

Column (1) of Table 3 presents the results of a series of logistic regressions in which the dependent variable is an indicator for whether a claim occurred in the grid-cell/year (L_{it}) and the main control variable of interest is the number of extreme weather events for the various percentile thresholds and durations. Each presented coefficient comes from a separate regression, run separately for each percentile thresholds and duration, and is expressed as an odds ratio. Exposure and vulnerability are controlled for with the grid-cell fixed effects.

The first coefficient presented in this column shows that a one-unit increase in the number of extreme events (as defined at the 95th percentile for one day of accumulated precipitation) is associated with a 21.3% increase in the likelihood (probability) of an insurance claim. Across the

8 We ran a series of Hausman tests for all percentiles and days of accumulated precipitation to confirm whether fixed-effects are preferable to random-effects. The results show a fixed-effects model is more appropriate for the logistic regression models, whereas for the Poisson regression and OLS regression the Hausman tests are inconclusive. Specifically, the models fitted do not meet the asymptotic assumptions of the test.

different definitions of extreme event, the estimated increase in the odds of an insurance claim from an additional extreme weather event range from 9.3% to 46.3%. In each case, the coefficient is statistically significant at the 0.01 level.

4.2 Frequency model for the number of claims

Column (2) of Table 3 presents results from a series of Poisson regressions in which the dependent variable is the number of claims in the grid cell and year (F_{it}). We opt for a Poisson model rather than a negative binomial one because the negative binomial fixed effect estimator is not a true fixed effects estimator (Wooldridge, 1999). The coefficients of the estimated model are expressed as incidence rate ratios (IRR). Our exposure variable, required for count models, is the number of properties per grid cell. The first-row coefficient shows that if the number of extreme events increases by one unit (as defined at the 95th percentile for one day of accumulated precipitation), its incidence rate ratio is expected to increase by a factor of 1.24 (a 24% increase in the incidence rate) while holding all other variables in the model constant. For the different definitions of extreme weather event, the IRR range from 1.09 to 1.41, and are all statistically significant at the 0.01 level.

4.3 Intensity model for the total value of claims

Column (3) of Table 3 presents results from a series of OLS regressions of the value of total payouts, adjusted for inflation to 2017 NZ$ values, on extreme weather counts. Using our first definition of extreme event, rainfall above the 95th percentile for one day of accumulated precipitation, we estimate that one additional extreme event in a grid cell and year is associated with a NZ$ 319 increase in pay-outs. As we vary our definition of extreme event in the subsequent rows of the table, the estimated coefficients range from NZ$ 132.4 to NZ$ 887.9; all are statistically significant at the 0.01 level.

An alternative model is to use as the dependent variable the ratio of the total pay-outs (for each grid-cell/year) to the total value of residential assets exposed (building, land, contents and appurtenant structures). As column (4) of Table 3 shows, with this ratio as the dependent variable, we find non-significant results for most models, except for the model with 95th percentile one day of accumulated precipitation (0.303), and the model 95th percentile two days accumulated precipitation (0.366). For the loss projection undertaken in the next section, we use the models where the dependent variable is the total payouts (column 3).

Table 3: Historical relationship between EQC insurance claims and extreme precipitation (also known as damage function)

	(1) Probability	(2)	(3)	(4)
Model type	Logit (Probability)	Poisson (Frequency)	OLS (Intensity)	OLS (Intensity)
Dependent variable	Indicator for at least one claim in grid/cell	Number of claims in grid/cell	Value of claims in grid/cell	Value of claims relative to exposed assets in grid/cell
Coefficient type	Odds Ratio (OR)	Incidence Rate Ratio (IRR)	OLS	OLS
95th percentile one day	1.213***	1.241***	319.0***	0.303***
	(0.0141)	(0.0237)	(72.46)	(0.0600)
98th percentile one day	1.404***	1.411***	538.1***	1.314
	(0.0238)	(0.0492)	(89.42)	(0.716)
99th percentile one day	1.597***	1.569***	887.9***	2.502
	(0.0364)	(0.0805)	(163.0)	(1.825)
95th percentile two days	1.157***	1.170***	250.5***	0.366**
	(0.00915)	(0.0138)	(45.32)	(0.132)
98th percentile two days	1.295***	1.275***	441.4***	1.253
	(0.0145)	(0.0368)	(70.27)	(0.800)
99th percentile two days	1.463***	1.376***	634.1***	1.803
	(0.0235)	(0.0500)	(90.74)	(1.150)
95th percentile three days	1.128***	1.127***	187.6***	0.484
	(0.00690)	(0.0126)	(32.72)	(0.290)
98th percentile three days	1.238***	1.221***	355.4***	1.000
	(0.0109)	(0.0248)	(52.28)	(0.630)
99th percentile three days	1.359***	1.260***	486.9***	1.454
	(0.0166)	(0.0322)	(69.25)	(0.890)
95th percentile four days	1.107***	1.105***	153.7***	0.359
	(0.00551)	(0.0104)	(24.15)	(0.197)
98th percentile four days	1.192***	1.172***	261.7***	0.836
	(0.00867)	(0.0198)	(39.57)	(0.545)
99th percentile four days	1.298***	1.255***	432.0***	1.266
	(0.0132)	(0.0231)	(63.26)	(0.738)
95th percentile five days	1.093***	1.090***	132.4***	0.284
	(0.00467)	(0.00988)	(21.54)	(0.147)
98th percentile five days	1.175***	1.152***	237.4***	0.651
	(0.00741)	(0.0144)	(37.76)	(0.379)
99th percentile five days	1.250***	1.239***	383.2***	1.134
	(0.0108)	(0.0167)	(57.04)	(0.679)
Year fixed-effects	Yes	Yes	Yes	Yes
Grid-cell fixed-effects	Yes	Yes	Yes	Yes
N	14,238	14,238	112,158	112,158

Note: This table presents the coefficients on extreme weather events from a series of regressions of claims on extreme events. Each coefficient in the table comes from a separate regression. The dependent variable and regression type vary by column, and the definition of extreme event differs by row. For the intensity models, the dependent variable is the total amount of pay-outs from damage for all the insurance covers (column 3), and the total amount of pay-outs from damage to all the insurance covers divided by the total value of assets exposed, divided by a hundred thousand (column 4). The stars *** denote statistical significance at the 1% level.

5 Applying the damage function to future climate projections

Our next step is to use the damage functions we estimated in Section 4 to project the value of insurance claims in the future, given the available predictions about the future impact of climate change on the occurrence of extreme precipitation events. To this end, we use a suite of six Coupled Model Intercomparison Project (CMIP-5) climate models

The six CMIP-5 models used in this study are: HadGEM2-ES from the UK; NorESM1-M from Norway; CESM1-CAMS, GFDL-CM3, and GISS-E2-R from the US; and BCC-CSM1.1 from China. The models are dynamically downscaled with NIWA's RCMs, and then further semi-empirically downscaled to the 5km horizontal grid of the Virtual Climate Station Network (VCSN) –further details are provided in Mullan (2018) and Sood (2014). The six different representations of the climate have been built-up to reflect the past climate (1971-2005) and project future climate under the different green-house-gas emissions scenarios (RCPs 2.6, 4.5, 6.0, 8.5) and periods (2006-2100).[9] Each model thus yields a different realization of possible future precipitation conditional on an emissions scenario.

5.1 Projecting losses

We project losses for up to the year 2100 by applying the historical relationship between extreme precipitation and weather-related claims that we estimated in Section 4, to the modelled past and future weather data. The projection is done for all RCP scenarios in 20-year time slices for all percentiles and days of accumulated precipitation, and for all climate models; altogether, this implies 360 projections for each 20-year time slice. We avoid making predictions for short time-spans (e.g. 5 years) because these will be too volatile and may be affected by cyclical phenomena such as the Southern Ocean oscillations (El Niño/La Niña). We count the future number of extreme precipitations as the number of times modelled future rainfall exceeds the percentile thresholds calculated from the modelled past data from the same simulation. This allows us to establish the appropriate benchmark against which we can calculate future climate change impact.[10]

We project future losses assuming no changes in exposure (e.g. number and value of residential property) or vulnerability (e.g. construction materials). The main constraint preventing us from considering different scenarios for changes in exposure and vulnerability is the detailed spatial resolution at which we operate. The 5km x 5km grid-cells we use are much

9 Some of these models predict the climate to 2120. However, we restrict our predictions to 2100.
10 The model simulations of the past rainfall produce 95th, 98th, and 99th percentiles thresholds of past extreme events that are considerably lower than the corresponding percentiles of the past observed rainfall. We therefore cannot use the thresholds calculated from past observed rainfall, but calculate new thresholds from the modelled data of the past. It is those thresholds that are then used to identify and count the number of projected future extreme events (given the percentile and duration thresholds we obtained from the modelled data).

smaller than administrative units or regions at which socioeconomic pathway scenarios are generally developed for. However, the study provides a detailed baseline of potential future losses that the EQC could face given no further growth of residential areas. As the country continues to economically grow and develop, the projected losses here are of course likely to be higher.

Given the 360 projections we produced per each 20-year, we present only a subset of these. In Table 4 we present the results of the projections for one of the climate models (GFDL-CM3(10)) and for only two durations (one and five days). In Table 5 we present results for all 6 climate models, but only for one duration (one day) and one percentile threshold (99%). All other results are available upon request.

Table 4: Projected Future Liabilities with the GDFL-CM3 for the changing hazard (in NZ$ Millions)

		One day of accumulated precipitation			**Five days of accumulated precipitation**		
		95th percentile	**98th percentile**	**99th percentile**	**95th percentile**	**98th percentile**	**99th percentile**
2020-2040	RCP 2.6	1620	1284	1182	628	616	623
	RCP 4.5	1600	1289	1199	621	606	611
	RCP 6.0	1640	1316	1217	646	633	641
	RCP 8.5	1523	1199	1099	563	556	558
2040-2060	RCP 2.6	1583	1271	1169	598	583	583
	RCP 4.5	1605	1296	1224	626	628	651
	RCP 6.0	1605	1296	1212	621	623	646
	RCP 8.5	1635	1326	1246	641	648	676
2060-2080	RCP 2.6	1685	1374	1286	673	678	705
	RCP 4.5	1583	1299	1222	601	593	601
	RCP 6.0	1633	1316	1241	631	616	631
	RCP 8.5	1720	1426	1359	698	701	725
2080-2100	RCP 2.6	1660	1326	1224	641	623	626
	RCP 4.5	1643	1354	1279	631	631	648
	RCP 6.0	1625	1336	1269	641	651	678
	RCP 8.5	1643	1396	1359	671	710	760

Note: Projected losses for 20-year aggregates for the percentiles 95th ,98th and 99th percentile values and one and five days of accumulated precipitation, and all Representative Concentration Pathways, using the GDFL-CM3 (NOAA-USA) climate model. These results assume no future changes in exposure or vulnerability. The projected liability figures were inflated by a correction factor of 2.50. The need for an adjustment rises as a result of the claims omitted from the regression analysis. The factor is calculated such that we add the value of the claims included and the value of the claims omitted and divide that over the value of the claims omitted.

Table 5: Projected Future Liabilities with all climate models for the changing hazard (in NZ$ Millions)

		One day of accumulated precipitation, 99th percentile					
	Climate models	**GFFL CM3(10) NOAA-USA**	**GISS-E2 R(14) NASA-USA**	**NorESM-M(9) NCC-Norway**	**HadGEM 2ES(2) MOHC-UK**	**CESM1 CAM5(1) NSF-USA**	**BCCCSM1.1(17) BCC-CHINA**
2020-2040	RCP 2.6	1181.9	1330.5	1342.4	1244.7	1191.6	1191.6
	RCP 4.5	1198.3	1334.4	1219	1193.6	1230.2	1230.2
	RCP 6.0	1215.5	1196.8	1353.9		1213	1213
	RCP 8.5	1099.9	1257.2	1347.2	1222.3	1234.2	1234.2
2040-2060	RCP 2.6	1169.7	1182.6	1343.2	1235.2	1306.8	1306.8
	RCP 4.5	1223	1367.4	1397	1203.6	1213.5	1213.5
	RCP 6.0	1211.8	1304.5	1292.3		1292.1	1292.1
	RCP 8.5	1245.5	1379.8	1321.7	1276.6	1299.8	1299.8
2060-2080	RCP 2.6	1285.3	1230.5	1365.9	1255.4	1361.1	1361.1
	RCP 4.5	1221	1252.7	1340.2	1308	1393	1393
	RCP 6.0	1240.5	1355.4	1432.7		1354.9	1354.9
	RCP 8.5	1359.1	1420.2	1485.8	1292.3	1467.6	1467.6
2080-2100	RCP 2.6	1223.3	1219.5	1291.8	1144.7	1337.9	1337.9
	RCP 4.5	1279.1	1306	1397	1144.2	1345.7	1345.7
	RCP 6.0	1268.9	1342.2	1299.8		1443.1	1443.1
	RCP 8.5	1359.1	1454.1	1473.1	1451.4	1463.8	1463.8

Note: Projected losses for 20-year aggregates for the 99th percentile value (p=99) and one day of accumulated precipitation (d=1), all Representative Concentration Pathways and all climate models. These results do not consider future changes in exposure or vulnerability. Results for the UK climate model and RCP 6.0 were dubious and thus not included in the table. The projected liability figures were inflated by a correction factor of 2.50. The need for an adjustment rises as a result of the claims omitted from the regression analysis. The factor is calculated such that we add the value of the claims included and the value of the claims omitted and divide that over the value of the claims omitted.

Several observations about the results presented in Table 4 and Table 5 are noteworthy. In Table 4, we observe that predicted liabilities are largest when we use the 95% percentile 1-day model and decrease as we increase the duration or the percentile threshold we use. Essentially, this is because there are more events for these lower thresholds (e.g., 95 percentile) than there are, in the modelled data, for the higher thresholds (e.g., 99 percentile, in terms of either duration or percentile threshold). When we compare across the climate models, in Table 5, we see that the differences across models are not very large, though some models do have a flatter profile across time than others (e.g., the Norwegian model). We also observe, as can be expected, the differences between the RCP scenarios are more pronounced later in the century than they are in the near future (2020-2040). We next use these results to estimate by how much anthropogenic climate change will likely change future EQC liabilities from extreme weather events.

5.2 Quantifying the climate change signal

To quantify the expected impact of climate change on damages, we compare the predicted damages using the past model of the climate for the years 1986 to 2005 with the losses based on future climate change projections (RCPs), for each of the periods 2020-2040, 2040-2060, 2060-2080, and 2080-2100. We repeat this for all percentile values, days of accumulated precipitation and climate models.

The climate change signal is calculated with the following:

$$CC\_Signal_{pd} = 100 * \sum_{i=1}^{6,231}(CFuture_{ipd} - CPast_{ipd}) / \sum_{i=1}^{6,231}(CPast_{ipd}) \qquad [4]$$

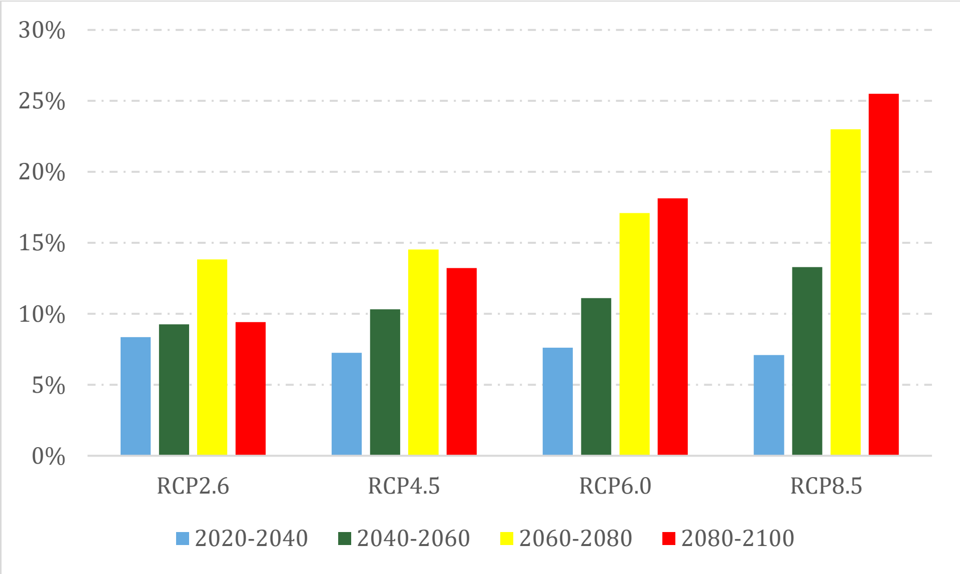
It is the percentage change of the sum, aggregated across inhabited grid-cells, of the future liabilities of the EQC, based on the modelled data, minus the past modelled liabilities, based on the same climate model. In an online appendix, we present the estimated impact of climate change in each 20-year period in the future relative to the 20-year period 1986-2005, for the 99th percentile of one day rainfall duration, all RPCs, and all climate models. We chose this duration because the time of concentration (TC) for most catchments in New Zealand is less than a day. This means that intensity rainfall duration (IRD) and the time for a drop of water to reach the coast occurs over sub-daily periods. Thus, one day of accumulated precipitation is more appropriate to use over any longer durations. We chose the 99th percentile because it is the most extreme metric within one day of precipitation.

These projections reveal only a modest climate change-driven increase in the value of EQC insurance claims that are projected in the future. Even towards the end of the century (2080-2100), we see that difference in losses relative to in the period 1986-2005 ranges, depending on the climate model, from: -0.53% to 18.73% for RCP 2.6; -0.58% to 21.43% for RCP 4.5; 4.02% to 25.38% for RCP 6.0; and -4.43% to 27.17% for RCP 8.5.[11]

These results can best be summarized by averaging across the different climate models for the same RPCs and time horizons; these summarised results are shown in Figure 3. The results from averaging climate change signal across the six different climate models appear consistent with our intuition. Overall, liabilities will increase more if future GHG emissions are higher (higher RCPs). The climate signal for the low emissions scenario (RCP 2.6) is lower, and actually decreases toward the end of the century, when GHG concentrations in the atmosphere are assumed to decrease (the same, but to a lesser extent, is observed in RCP 4.5). In contrast, the time profile of the highest-emissions RCP 8.5 is much steeper, with the climate signal more than doubling between 2020-2040 and 2080-2100.

11 Negative numbers indicate lower predicted future liabilities of the EQC than the predicted past liabilities, and reflect the prediction that some parts of New Zealand will become dryer and thus experience fewer claims related to extreme precipitation.

Figure 3: Increase in EQC liabilities due to climate change: average of all climate models (in %)



Note: These results are calculated for the average one day of accumulated precipitation and 99th percentile. The table averages results across six climate models, for each RCP and time horizon.

6 Caveats

In this work, we dealt with a range of issues arising from geospatial considerations of the EQC data, as well as the historical and projected precipitation data. Given this, some important caveats should be taken in consideration when using our results or for further use of the methodology we proposed here for estimating the future impacts of climate change.

First, because of partial records, 60% of the total damages between 2000-2017 were omitted from the regression analyses and thus from our projections. About 35% correspond to losses that could not be georeferenced. The remaining 25% correspond to claims without precipitation information, as the precipitations records are not spatially complete. It is not clear, however, whether this omission biases our results in a specific direction (and which direction it is).

Second, our data shows that the EQC paid for some landslip/flood claims in grids that did not experience any measured precipitation. This is most likely because the intense precipitation happened upstream, but the damages (claims) occurred downstream, or because these were dry landslips (triggered by other factors). In order to be able to identify claims that have been caused by precipitation upstream, we require a complete hydrological mapping of all the watersheds in New Zealand. Such a mapping is not available and is unlikely to be available in the next few years. We did not remove these 'zero precipitation' claims from the regressions, but as long as the occurrence of these events is orthogonal to the wet landslide events, this should not bias our results.

Third, because of the difference between past modelled precipitation and the past observed precipitation percentile threshold values, future damage assessment of extreme precipitation events may be inaccurately projected. The biases in the precipitation extremes in the climate model simulations, which mostly are due to internal variability of the climate system, may lead to potential overestimation or underestimation of future losses. In order to deal with randomness associated with occurrence of climate extremes, one should use the mean model ensemble rather than results from a single simulation, which is what we presented. Even though six simulations may not be sufficient to adequately assess the extremes with a probabilistic approach, the use of carefully selected multiple models allows us to determine the range of the ensemble as an estimate of variability. As long as improved higher-resolution validated datasets and more simulation data products are not available, we see no other way of overcoming this problem (see also Sood, 2014).

Fourth, the predictions we make about future climate change costs assume constant exposure and vulnerability over time. Population projections are generally produced for large regions or administrative areas, but our estimations and calculations are produced at 5km by 5km grid. We doubt any reliable modelling of the future distribution of population throughout New Zealand on grid basis is currently possible, so we do not attempt to account for that in our estimates. We also are not aware of any attempt to forecast future vulnerability for the housing stock. We therefore assume that vulnerability is constant over time. There are reasons to expect both increases and decreases in both exposure and vulnerability, so our *ceteris paribus* assumption is as plausible as any other.

Fifth, although the EQC dataset does not explicitly classify insurance claims as being caused by a flood or a rainfall-induced landslip, we deduce that more than 70% of the weather-related insurance claims are most likely related to landslips.[12] As discussed in Section 3, we create two approximations of landslip susceptibility: by combining slope and soil type and based on an adaptation of the algorithm developed by Dellow et al. (2011). These two measures approximate landslip hazard, though not as accurately as would be possible using actual landslip hazard maps. If rainfall-induced landslip hazard maps were to become available, future research could improve our estimates of the future potential liabilities of the EQC.

Sixth, our definition of extremes is based on a short time series (20 years) and only few simulations in a non-stationary system. The limited number of simulations imply that the climate signal of extremes is not statistically robust considering the levels of uncertainty. Conventionally, extreme events are defined as such when their return periods are low, and their

12 We differentiate between claims triggered by storm/floods from the claims triggered by landslips by examining the "claim status" variable the dataset, and, based on the EQC policy coverage, we identify floods/storm damages if: the land claims status is different from "N/A", and the building claims status is equal to "N/A", and the contents status is equal to "N/A". However, this algorithm is only an approximation and does not necessarily accurately identify the cause of the damage.

threshold value is high. For instance, an event with a 100-year return period would qualify as an extreme event; in contrast, our definition of extremes for the lowest percentile and day of accumulated precipitation renders a total of 18 extreme precipitation events in a given year. This issue can be addressed by using the modelled extreme precipitation with low return periods and examining the relationship with weather-related claim data. For such matter, we propose the use of the High Intensity Rainfall Design System (HIRDSv4) dataset, which provides a range of return periods and durations (daily and sub-daily), or the simulations from the weather@home initiative. We propose to take these challenges on in future research.

7 Concluding comments

In this paper, we project future liabilities of New Zealand's public insurer (the EQC) from extreme precipitation events. We calculate these future liabilities for four different Representative Concentration Pathways, for the output from six climate models, and using a range of definitions of 'extreme precipitation events'. We show that the climate signal (i.e. the percent difference between future and past liabilities for the EQC) will range - depending on the GHG emissions scenario- between 7% and 8% higher in the period 2020-2040 and between 9% and 25% higher in the period 2080 to 2100 as a result of climate change-induced increases in extreme precipitation events. The estimated climate change signal follows, approximately, the GHG concentration trajectories according to each RCP so that higher GHG concentrations are generally associated with larger increase in liabilities.

Our projections do not consider future changes in exposure or vulnerability, which means that we are estimating changes in future damages that are driven exclusively by changes in the hazard, due to climate change, given current conditions. New Zealand's population and the value of its residential building stock have grown steadily over the past few decades (RBNZ, 2019) and both are projected to continue to increase. This suggests that the future liabilities may be higher than our estimates. However, other scenarios in which either exposure (through better land-use planning) and vulnerability (through better construction standards) are reduced, thus causing the EQC liabilities to instead decrease, are also possible. Irrespective of that, however, we conclude that extreme weather events resulting from climate change will increase the EQC's liabilities. Whether this increase necessitates a policy change, for example in the amount of premiums the EQC collects annually, or in the types of risks it insures, are questions for future research.

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