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EQC and extreme weather events (part 2): Measuring the impact of insurance on New Zealand landslip, storm and flood recovery using nightlights

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The authors are solely responsible for the analysis and views expressed, and any errors or omissions are our own.

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Abstract

Climate change is predicted to make extreme weather events worse and more frequent in many places around the world. In New Zealand, the Earthquake Commission (EQC) was created to provide insurance for earthquakes. In some circumstances, however, homeowners affected by extreme weather events can also make claims to the EQC – for landslip, storm or flood events. In this paper, we explore the impact of this public natural hazard insurance on community recovery from weather-related events. We do this by using a proxy for short-term economic recovery: satellite imagery of average monthly night-time radiance. Linking these night-time light data to precipitation data records, we compare houses which experienced damage from extreme rainfall episodes to those that suffered no damage even though they experienced extreme rainfall. Using data from three recent intense storms, we find that households which experienced damage, and were paid in a timely manner by EQC, did not fare any worse than households that suffered no damage from these extreme events. This finding suggests that EQC insurance is serving its stated purpose by protecting households from the adverse impact of extreme weather events.

JEL codes

Q15; Q10; Q17; Q02

Keywords

climate change, extreme weather, public insurance, recovery, New Zealand

Summary haiku

Extremes will worsen.

Recent history shows us

Damage can be fixed.

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1 Introduction

We explore the recovery of households which have made claims to the public natural hazard insurer in New Zealand for landslip, storm or flood related losses. We investigate the relationship between claim payments and a novel proxy for short-term economic recovery: satellite imagery of average monthly night-time radiance. Our aim here is to use the method developed in (Nguyen & Noy, 2019) to investigate the economic effect of insurance payments after three major weather events. Put differently, we investigate how insurance claim payments, for residential property damaged from extreme weather events, affect the recovery process of the local economy.

By matching public insurer (the New Zealand Earthquake Commission) claim payments, Land Information New Zealand (LINZ) property information, socio-economic data from Statistics New Zealand (StatsNZ) Census, and night-light data from the USA National Oceanic and Atmospheric Administration (NOAA) we can connect changes in night-light to households. Using this linked data, we compare those properties which have been exposed to damaging extreme weather events but not made Earthquake Commission (EQC) claims, with those that did.

We identify properties that have experienced extreme weather events using National Institute for Weather and Atmosphere (NIWA) daily precipitation intensity data, supplemented by descriptions of events from NIWA's historic weather event catalogue. Using this rain data for the whole country, we build counterfactuals for properties which claim for losses following major weather events, using properties which experienced extreme weather (defined as meeting specified thresholds of mm/day of precipitation during the event). We focus on three weather events in June 2015, November 2016 and March 2017. These were chosen as those recent events which were most damaging to the private insurance industry according to the Insurance Council of New Zealand data; see Fleming, Noy, Pástor-Paz, & Owen (2018).

Our econometric methodology is based on a property level model of economic recovery (proxied by change in night-time light from the month of the event to two months later) regressed on damage (proxied by change in night-time light between the month of the event and the month prior) and a binary variable indicating the property made an EQC claim which was both successful and paid out within a three-month window. We also control for neighbourhood effects using census data pertaining to a) household income and b) owner-occupier status.

In the case of these three weather events, we find that households which experienced damage and were paid in a timely manner by the EQC did not fare any worse, on average, than households that suffered no damage. This finding suggests that EQC landslip storm and flood insurance is protecting households from the negative impacts of extreme weather events.

Our paper proceeds with a literature review in section 2, presentation of the New Zealand system for residential natural hazard insurance in section 3, discussion and presentation of our data in section 4, and methodology in section 5. Section 6 presents our empirical results, and section 7 concludes.

2 Literature review

Disasters occur at the intersection of a hazard (natural or manmade) with an exposed and vulnerable society. Disaster risk is a combination of the hazard profile, the exposure of people and assets, and the vulnerability of the exposed population. A disaster has immediate, short-term (usually classified as months to a few years) and long-term effects. Immediate damages are generally measured using mortality, morbidity, and damage to physical assets, and termed direct damages. “Response” is typically used to describe activities dealing with immediate direct damages from a disaster, whereas “recovery” is used to describing efforts to cope with the short- and long- term effects. Immediate damages can be measured at the single unit level, such as through information by household or firm. One can use this micro-information to study immediate response and recovery (see for example: Brookshire et al., 1997; Chang, 2010; De Alwis & Noy, 2019; or Sawada & Shimizutani, 2008)). Short term impacts are sometimes referred to as indirect losses, and refer to economic activity which did not occur due to the disaster (Noy, 2016).

In the empirical analysis of this paper we consider short-term economic losses, but these have historically been difficult to measure due to a lack of data availability. One can use an overall measure of the economy, such as that measured by national income, fiscal accounts or the balance of payments. These are usually only available at the annual, country-wide level. Global night-time light data, published by NOAA, offers an alternative data source available in higher frequency and spatial detail. Since 2012, night-light data is publicly available at monthly frequency. Platt, Brown, & Hughes (2016) investigate the use of a wide range of data to identify the speed and quality of recovery post-disasters, finding that remote sensing (night-light satellite imagery) seems to provide accurate and reliable information. Their analysis includes crowd-sourced geographic information, ground surveys, household surveys, official statistics and insurance data. Given that we can use these night-light data to measure both immediate damage and short-term recovery, we can investigate more deeply the determinants of the recovery process, and at a finer spatial level than previously possible. The particular aspect we focus in this paper is the role of insurance in recovery.

Financial risk transfer mechanisms are a key tool for households to prevent adverse economic consequences from natural hazard events, and as such, insurance has proven popular and useful for economic recovery of regions, communities and households (Mills, 2005). The potential role of insurance in mitigating disaster losses has been often discussed (see e.g.

Kunreuther & Lyster (2016) but the empirical literature on the effects of insurance on dynamics of recovery is surprisingly limited. Still, insurance is highlighted as an important part of international disaster risk reduction efforts (as specified in the United Nation's 2015 Sendai Framework for Disaster Risk Reduction (UNISDR, 2015).

In New Zealand, there has been significant research done investigating economic impact and recovery following earthquakes (e.g. Fabling, Grimes, & Timar, 2016, 2019; Wood, Noy, & Parker, 2016). To our knowledge, Nguyen & Noy (2019) and Poontirakul, Brown, Seville, Vargo, & Noy (2017) are the only examples of attempts to look into the role of insurance payments in post-catastrophe recovery. Nguyen & Noy (2019) utilise night-light data to explore the recovery of residential areas after the Canterbury earthquake series in 2010-2011 and Poontirakul et al. (2017) study commercial recovery using firm survey data. There has not been similar work investigating extreme weather events in New Zealand.

Elsewhere, von Peter, von Dahlen, & Saxena (2012) is the only other paper we know of that has empirically examined the role of insurance in recovery using aggregate national data. They find that the macroeconomic cost of natural catastrophes is driven primarily by uninsured losses and argue that sufficiently insured events are inconsequential in terms of foregone output.

In contrast, there has been work done using night-time light to investigate recovery post-earthquake, both in New Zealand and abroad. Wang et al. (2018) utilise night-time light to investigate the seismic economic loss from the Wenchuan Earthquake in 2008. The authors demonstrate the functional relationship between GDP and night-time light parameters based on pre-earthquake data, and then evaluate the indirect loss from the earthquake. Gillespie et al. (2014) investigate the efficacy of night-time light as a proxy for economic activity in Indonesia following an earthquake -triggered tsunami in 2004. They find significant relationships between night-time imagery brightness and per capita expenditures, and spending on both energy and food.

There have been a number of studies investigating the impact of cyclones, hurricanes or typhoons using remote sensing. Del Valle et al. (2018) investigate the short term economic impact of a tropical cyclone which hit Guangdong Province of Southern China. The authors proxy monthly economic activity using monthly night-time light radiance, in this case combined with wind speed. These authors found that there was only a significant impact on night-time light in the month of the cyclone strike. Similarly, Ishizawa, Miranda, & Strobl (2017) utilise night-timelight imagery to study the impact of tropical cyclones on local economic activity in the Dominican Republic. Rather than studying a particular event, this paper investigates the impact on night-time light from these "hurricane strikes" since 1992, finding the negative impacts of these storms lasted up to 15 months. Using quarterly gross domestic product, the authors conclude that these storms reduced GDP by around US $1.1billion. Mohan & Strobl (2017) also use night-time light to investigate the short-term economic impact of tropical Cyclone Pam, which struck the South Pacific Islands in March 2015. Using unaffected islands as a control group, their regression analysis suggests that initially the storm reduced economic activity in the affected islands of Vanuatu. Elliott, Strobl, & Sun (2015) explore the impact of typhoons in coastal China using night-time light imagery as a proxy for economic activity. This paper estimates that between 1992 and 2010 total net economic losses were around $US 28.34 billion.

Finally, Michaels et al. (2019) examine whether economic activity relocates away from areas that are at high risk of recurring shocks, in the context of floods, using spatially detailed inundation maps and night lights data spanning the globe's urban areas. This paper studies the impact of floods which displaced at least 100,000 people each. Their data spans over 1,800 cities in 40 countries, from 2003-2008. The authors find that low elevation areas are about 3-4 times more likely to be hit by these large floods than other areas, and yet they concentrate more economic activity per square km. In these cases, the low elevation areas also sustain more damage, though they recover rapidly, and economic activity tends not to move to safer areas. The authors do mention that in more recently populated urban areas, flooded areas show a larger and more persistent decline in economic activity.

3 New Zealand public natural hazard insurance

In New Zealand, public natural hazard insurance is provided through the Earthquake Commission (EQC). The EQC began on 1 January 1945 as the Earthquake and War Damage Commission. The scheme was reconstituted in 1994 as the EQC under the Earthquake Commission Act 1993 (see Owen (2017) for further historical discussion). The Act acknowledged the commission’s primary purpose to be residential natural hazard relief.

The EQC today insures residential homes, some residential land, and (until 2019) residential contents of all homeowners who have private fire insurance. It provides insurance against the following hazards: earthquakes, volcanic eruptions, natural landslips, hydrothermal activity, tsunami, or fire following one of these. It also insures residential land (under a dwelling, limited land around the dwelling, and access ways) for storm and flood damage. Excesses (deductibles) are very low, and there is no disincentive to claiming (unlike in a private system where premium prices are often linked to claim history). In this paper we explore the EQC’s cover for damage due to weather-related events (landslip, storm and flood).

4 Data

We make use of national property and claim information. The EQC’s data includes information on claim dates (event, claim lodging, claim decisions), payments, and type of claim (land, property). Property information includes a longitude latitude pair. We also use estimated average slope per property, as well as the distance to the nearest coast, nearest river and nearest lake, calculated from LINZ geographical and hydrological data. From Statistics New Zealand we make use of national mesh-block boundary data (specifically the 2016 boundaries) and 2013 household level census information. Further information on these datasets is detailed in Fleming et al. (2018).

We use daily precipitation observational data collected from NIWA. This data holds NIWA's Virtual Climate Station Network (VCSN) estimates of rainfall measured in mm/day at a resolution of around 5km. We also utilise monthly average night-time light satellite data, collected from NOAA's public repository. The Earth Observations Group (EOG) release average radiance composite images using night-time data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB). These span the globe from 75N latitude to 65S, produced in 15 arc-second geographic grids and available as a set of 6 geotiff tiles. The tiles are cut at the equator and each span 120 degrees of latitude. Each tile is a set of images containing average radiance values with the corresponding numbers of available observations, at a resolution of about 750m (NOAA, 2013). February 2012 is the earliest monthly average night-time light TIF available. In New Zealand, there had been three particularly damaging events since 2012 – see Table 1. We focus our attention on these. We restrict the dataset to properties which, according to NIWA's VCSN data, experienced daily rainfall higher than a threshold (50mm/day, 100mm/day or 150mm/day) in any of the first three days of the weather event. These data are geo-processed such that for each property in the country, we can access the average night-time light and rainfall time-series data for that property. We utilise the nearest lat-long grid point in the netcdf of rain, or the time series TIFs of night light, to achieve this.

Before investigating only claims from the three weather events we chose to focus on, we plot each property's rain from the ten days before and following each claim's "loss date", for the full sample of claims.

As shown in Figure 1, Landslip/Storm/Flood claims do tend to be made during an extreme rainfall event. To construct our counterfactuals of properties exposed, we utilise rainfall on the loss date and up to the two days prior or following (those days most likely to have been during the period of rain). Due to the differing nature of the rainfall events, we use slightly different thresholds to find counterfactuals for use in our major analysis. For events one and three, which were characterised by a short period of extreme rain, we investigate those properties which experienced at least 50mm of rainfall. However for event two, which was a heavier (but not as extreme) few days during a particularly rainy month, this threshold is too high to capture the damaged properties – a 30mm threshold is more appropriate. In alternate specifications, we compare claiming properties to those properties exposed to a minimum threshold of rainfall, with thresholds being 30mm, 50mm, 100mm or 150mm (see Appendix).

Figure 1: Distribution of rainfall nearest properties, across time

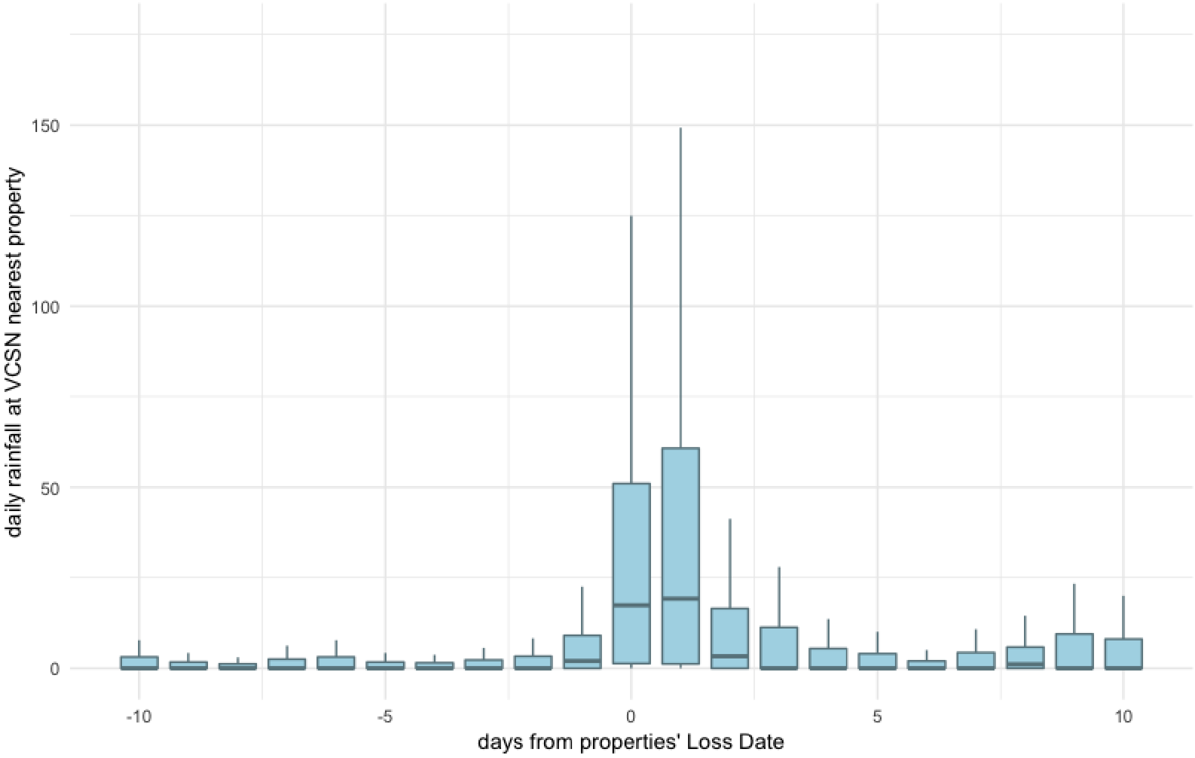
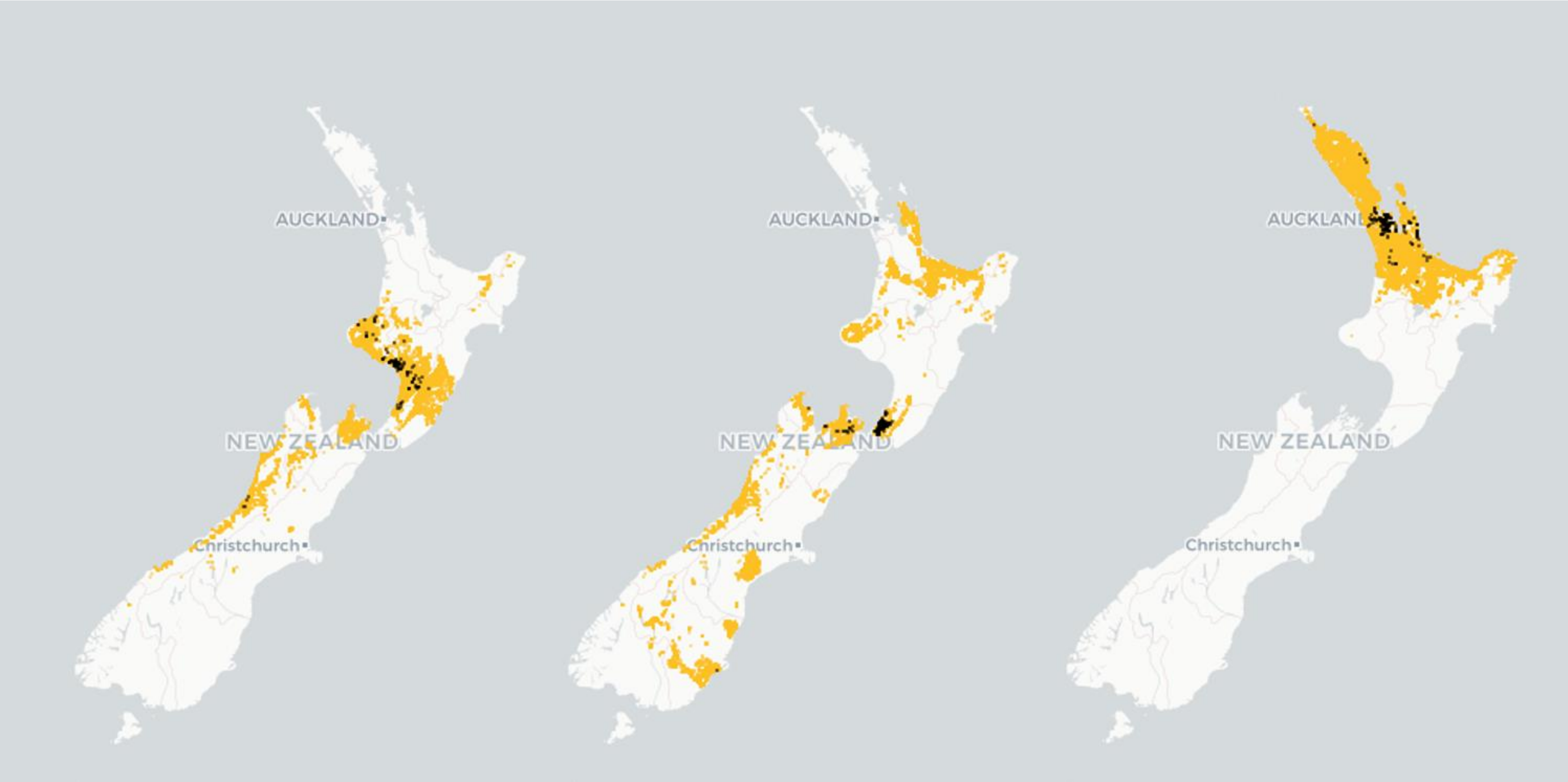


Table 1: Weather events analysed in this paper

	(1)	(2)	(3)	(4)	(5)
	Date of beginning of event	Event title	Event characteristics	Number of attributable EQC claims	Private insurance cost
event one	2015.06.20	June 2015 storm	New Zealand Storm *one week of intense rain in western areas of the South and North Islands*	~370	$41,500,000
event two	2016.11.10	November 2016 flooding	Lower North Island flooding/wind *no description*	~400	$9,100,000
event three	2017.03.07	March 2017 storm	North Island Heavy Rain and Flooding *seven days of heavy rain*	~270	$61,700,000

Note: This table contains information on the three weather events in New Zealand which we analyse in this paper. Column (1) contains date information in YYYY.MM.DD form for the first day of the weather event. Column (2) contains the title of the event, and Column (3) the name and characteristics reported in the NZ Historic Weather Events Catalogue (NIWA 2018a). Column (4) contains the number of EQC claims attributable to the event, for those claims which we can attribute to the event and have the necessary control variables to conduct our later analysis. This means these are an underestimate of the true EQC pay-out. Column (5) contains information from ICNZ (2018) for the amount paid by NZ private insurance following the full weather event. All dollar values expressed in NZ dollar values.

Figure 2: Locations of exposed properties and claimants



Note: This figure presents the location of properties exposed to the three weather events analysed in this paper. From left, these are: event one - the June 2015 storm, event two -the November 2016 flooding, and event three – the March 2017 storm. Yellow points represent all those properties exposed to at least a minimum of (50mm, 30mm and 50mm) precipitation during the event, and black points represent those properties which made EQC claims following the event.

Table 2: Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	event one 50mm			event two 30mm			event three 50mm		
	all	claimed	not claimed	all	claimed	not claimed	all	claimed	not claimed
night-time light recovery	0.247	0.632	0.246	0.764	1.088	0.763	0.021	0.120	0.021
	(1.786)	(1.198)	(1.787)	(3.687)	(4.749)	(3.685)	(4.151)	(0.658)	(4.152)
night-time light damage	-0.550	-0.204	-0.551	-1.531	-0.032	-1.533	-1.295	-0.296	-1.295
	(2.089)	(0.753)	(2.091)	(6.557)	(3.148)	(6.561)	(3.696)	(1.215)	(3.970)
slope (degrees)	1.579	4.725	1.571	4.777	12.935	4.766	2.943	7.890	2.942
	(3.208)	(7.261)	(3.187)	(5.803)	(7.297)	(5.793)	(3.472)	(6.553)	(3.469)
distance to river (km)	0.508	0.214	0.508	0.665	0.723	0.665	0.656	0.343	0.656
	(0.465)	(0.232)	(0.465)	(0.692)	(0.786)	(0.692)	(0.688)	(0.336)	(0.688)
distance to coast (km)	16.343	9.269	16.361	11.880	2.039	11.894	7.541	4.982	7.541
	(16.929)	(8.944)	(16.941)	(19.830)	(3.091)	(19.839)	(13.599)	(6.476)	(13.601)
distance to lake (km)	1.382	1.355	1.382	1.717	2.076	1.716	1.430	1.582	1.430
	(1.388)	(0.573)	(0.390)	(1.382)	(1.539)	(1.382)	(1.072)	(1.571)	(1.072)
median household income	56.147	54.965	56.150	71.283	99.308	71.245	72.417	71.523	72.417
(000s)	(21.781)	(19.912)	(21.785)	(30.022)	(29.539)	(30.005)	(29.183)	(31.599)	(29.182)
dwellings not owner occupied	0.309	0.274	0.309	0.329	0.261	0.329	0.369	0.281	0.369
(proportion)	(0.167)	(0.146	(0.167)	(0.199)	(0.160)	(0.199)	(0.197)	(0.125)	(0.197)
total properties exposed	146,311	373	145,938	296,901	401	296,500	749,152	272	748,880

Note: This table contains summary statistics from the three weather events used in our analysis. Event one is the June 2015 storm, event two the November 2016 flooding, and event three the March 2017 storm. *Night-time light damage* is the difference in average night-time light radiance from the month prior to and the month of the event, and *night-time light recovery* is the difference in night-time light from two months following and the month of the event.

5 Methodology

We estimate an econometric model of recovery defined by:

$$\mathrm{recovery}_{n,t} = \alpha + \beta_1 \mathrm{damage}_{n,t} + \beta_2 \mathrm{EQC}_{i,t} + \beta_3 \mathbf{X}_{1i} + \beta_4 \mathbf{X}_{2m} + \varepsilon$$

where *recovery* denotes the difference in a property's associated night-time light (NTL) from two months after the month of the event (once an EQC claim is likely to have been paid out) and the month of the event itself, that is: $\mathrm{recovery}_{n,t} = \mathrm{NTL}_{n,t+2} - \mathrm{NTL}_{n,t}$. We note the associated grid-cell area with subscript *n. damage* is the difference in the properties' average night-time radiance in the month of the loss and the month previous, that is $\mathrm{damage}_{n,t} = \mathrm{NTL}_{n,t} - \mathrm{NTL}_{n,t-1}$. Property-level variables are subscripted with *i*. EQC is a binary indicator for whether an EQC claim had been made against the property for that event. In different specifications this may be *claimed*, where the indicator is one if a property lodged a claim, *approved* indicating the property made a claim and it was not declined, and *paid*, indicating a claim was made, approved and paid within a 90-day window from the loss date**.** $\boldsymbol{X_1}$ is a vector of control variables relating to the property and $\boldsymbol{X_2}$ containing Census 2013 information for the corresponding meshblock (the smallest geographical unit for which statistical data is tabulated) subscripted *m*. Property level information includes the average slope of the land, and distance to water bodies (lake, river and coast). Meshblock-level information includes median household income and proportion of dwellings not owner-occupied.

One important empirical caveat to this work is that it makes the assumption that all households that experienced damage submitted claims to the EQC. Since we know that almost all houses in New Zealand are insured by the EQC (insurance penetration is around 98%), and since the excess/deductible is very small (NZD 200), we think that this assumption is reasonable. Therefore, for properties which faced these extreme weather events but did not make claims, we assume that their damages were not significant. Table 3: Properties in different samples below describes the number of properties with all the necessary control variables available, which fall into four categories: with or without claims, and experienced or did not experience over a minimum threshold of rainfall.

As shown in Table 2: Summary statistics, the night time light damage variable is consistently negative across the various specifications, indicating it does capture community damage somewhat. However, we do note that there is community level damage attributed to properties which did not make claims.

Table 3: Properties in different samples

		(1)	(2)	(3)	(4)	(5)	(6)
		event one 50mm		event two 30mm		event three 50mm	
		Yes	No	Yes	No	Yes	No
claimed	Yes	373	23	401	17	272	1
	No	145,938	1,378,509	296,500	1,227,926	748,880	775,690
total		146,311		296,901		543,258	

Note: This table contains the number of properties per event per subset of rain threshold and claim status. Event one is the June 2015 storm, event two the November 2016 flooding, and event three the March 2017 storm.

6 Results

Our primary regression results are displayed in Table 4. Our key EQC insurance indicator is a binary variable indicating either whether a property claimed, whether a property made a successful claim, or whether a payout was made during a three-month period following the event. We present regression results using each of these as our key EQC variable, for each of the three events. Columns 1-3 present results from event one - the June 2015 storm, Columns 4-6 from event two - the November 2016 flooding, and Columns 7-9 from event three - the March 2017 storm. The exposed property base for each is different: event one affected close to 150,000 homes, event two close to 300,000, and event three close to 750,000 (not all of which could be used in our regression analysis due to availability of other control variables).

In the regressions presented in Table 4 we also include several control variables: the slope of the land on which the property is located, its distances to various water bodies, and two mesh-block level control variables: average mesh-block household income, and the proportion of dwellings in the mesh-block not owned by their occupants. We also always include a control for the degree of damage (as described in the previous section).

In Table 4, we find statistically significant negative coefficients on the *night-time light damage* variable throughout most of our specifications. This is as expected and indicates recovery increases as the amount of previous damage increases. Other control variables have very consistent coefficient estimates associated with them for the different EQC controls, suggesting they are orthogonal to our main variable of interest. However, they do not appear consistently estimated across the three events, suggesting that the recovery process has been somewhat different across events.

The main coefficients of interest are our EQC insurance indicators (claim filed, claim approved, or claim paid within three months). These are positive, and mostly statistically significant, in particular for events one and three. These should be interpreted as supporting our hypothesis that insurance payments provide some degree of identifiable recovery for extreme-rain damaged properties. We note that our 'untreated' group is made of properties that did not submit insurance claims, and therefore likely suffered no damage also (these are not damaged but un-insured properties – note that in New Zealand residential insurance penetration is very high). As such, even a statistically-insignificant (i.e. close to zero) coefficient suggests that the insurance payments are able to counter-act the damage experienced in these properties.

We also present the results as applied to different thresholds defining extreme rainfall for each event: one where the properties included must have experienced at least 50mm/day (or 30mm for event two) during the first three days of the event, another smaller subsample using a threshold of 100mm/day, and 150mm/day. The results of these alternate specifications are presented in the Appendix (see Appendix Tables 3, 4 & 5). For these different definitions of the control group of exposed properties, similar patterns are found, with the EQC insurance coefficients ranging from statistically-insignificant to positive and significant.

Table 4: Regression results – primary specifications

	Dependent variable: Night-time light recovery								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	event one (50mm threshold)			event two (30mm threshold)			event three (50mm threshold)		
Night-time light damage	−0.516***	−0.516***	**−0.516******	-0.003**	-0.003**	**-0.003****	−0.638***	−0.638***	**−0.638******
	(0.002)	(0.002)	**(0.002)**	(0.001)	(0.001)	**(0.001)**	(0.001)	(0.001)	**(0.001)**
claimed	0.587***			0.323			0.521*		
	(0.073)			(0.179)			(0.235)		
approved		0.700***			0.335			0.527*	
		(0.085)			(0.199)			(0.280)	
closed in 90 days			**0.471******			**1.020**			**0.726**
			(0.108)			**(0.596)**			**(0.605)**
slope (degrees)	−0.016***	−0.016***	**−0.016******	-0.043***	-0.043***	**-0.043******	−0.032***	−0.032***	**−0.032******
	(0.001)	(0.001)	**(0.001)**	(0.010)	(0.010)	**(0.010)**	(0.002)	(0.002)	**(0.002)**
distance to river (km)	−0.238***	−0.238***	**−0.239******	0.370***	0.370***	**0.370******	−0.154***	−0.154***	**−0.154******
	(0.008)	(0.008)	**(0.008)**	(0.010	(0.010	**(0.010**	(0.008)	(0.008)	**(0.008)**
distance to lake (km)	0.022***	0.022***	**0.021******	0.184***	0.184***	**0.184******	0.148***	0.148***	**0.148******
	(0.003)	(0.003)	**(0.003)**	(0.005)	(0.005)	**(0.005)**	(0.005)	(0.005)	**(0.005)**
distance to coast (km)	0.002***	0.002***	**0.002******	-0.011***	-0.011***	**-0.011*****	0.024***	0.024***	**0.024******
	(0.0002)	(0.0002)	**(0.0002)**	(0.0003)	(0.0003)	**(0.0003)**	(0.0004)	(0.0004)	**(0.0004)**
median HH income (000s)	0.002***	0.002***	**0.002******	0.015***	0.015***	**0.015******	−0.010***	−0.010***	**−0.010******
	(0.0002)	(0.0002)	**(0.0002)**	(0.0003)	(0.0003)	**(0.0003)**	(0.0002)	(0.0002)	**(0.0002)**
prop. dwellings not owned	0.724***	0.724***	**0.724******	3.600***	3.600***	**3.600******	−3.586***	−3.587***	**−3.587******
	(0.025)	(0.025)	**(0.025)**	(0.036)	(0.036)	**(0.036)**	(0.030)	(0.030)	**(0.030)**
Constant	−0.266***	−0.266***	**−0.263******	-1.690***	-1.690***	**-1.690******	1.082***	1.082***	**1.082******
	(0.017)	(0.017)	**(0.017)**	(0.026)	(0.026)	**(0.026)**	(0.024)	(0.024)	**(0.024)**
Observations	146,311	146,311	**146,311**	296,901	296,901	**296,901**	543,258	543,258	**543,258**
Adjusted R^2	0.383	0.383	**0.383**	0.060	0.060	**0.060**	0.345	0.345	**0.345**

Note: *p<0.05; **p<0.01; ***p<0.001

This table contains regression results from our primary analysis. Event one is the June 2015 storm, event two the November 2016 flooding, and event three the March 2017 storm.

7 Conclusion

In this paper we study the role public insurance for floods and storms plays in community recovery, using three recent events in New Zealand as case studies. Our econometric methodology is a property level model where recovery and damage are measured by changes in night-time light (measured using satellite data), and where the key insurance variable is a binary variable indicating if the property owners made an insurance claim for that event, that was approved and paid within three months after the event.

We control for neighbourhood effects using census data pertaining to a) household income and b) owner-occupier status, and for property-level geospatial characteristics; but find that these controls are fully orthogonal to our interest in the role of insurance in recovery. In the case of these events - the June 2015 storm, November 2016 flooding, and the March 2017 storm - we compare claimants whose property was damaged and were paid for it, with undamaged properties. We find that the two groups experience similar levels of recovery. In other words, we find that households which experienced damage and were paid in a timely manner by the public insurer (the EQC) did not fare any worse, on average, than households that suffered no damage. This finding suggests that EQC landslip, storm, and flood insurance is indeed effective in protecting households from the negative impacts of extreme weather events.

Given the high penetration rate of insurance in New Zealand (likely around 98%), it is impossible to estimate what would have happened to the recovery had properties been uninsured. From a policy perspective, however, this may become an issue of some concern as climate change may end up changing the risk profile in some locations, thereby leading to private insurance withdrawal. As in the current scheme, the public insurance is conditional on the purchase of a private insurance policy, this may in the future leads to an increase in the number of uninsured properties in the highest risk locations. Our evidence suggests that these properties will find it more difficult to recover, but a better understanding of the implications of such insurance retreat are clearly necessary (Storey & Noy, 2017).

From an international perspective, there is also clearly need for more research on the role of insurance in disaster recovery, as the likely dynamics of insurance retreat that is caused by climatic change are surely a concern not only in New Zealand. In other locations, the pubic insurance might be only partial, might not be conditional on private insurance, or might be structured differently (in terms of premiums, excesses, etc.) so the exact details of the role of insurance systems in recovery may very well differ across different jurisdictions.

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Appendix

Appendix Table 1: Additional summary statistics – investigating alternate thresholds

		(1)	(2)	(3)	(4)	(5)	(6)
		rainfall threshold during event					
event one							
		>50mm		>100mm		>150mm	
		Y	*N*	*Y*	*N*	*Y*	*N*
claimed	*Y*	**373**	23	15	381	8	388
	N	**145,938**	1,378,509	16,315	1,508,132	7,847	1,516,600
event two							
		>30mm		>50mm		>100mm	
		Y	*N*	*Y*	*N*	*Y*	*N*
claimed	*Y*	**401**	17	33	385	13	405
	N	**296,500**	1,227,926	36,770	1,487,656	3,462	1,520,964
event three							
		>50mm		>100mm		>150mm	
		Y	*N*	*Y*	*N*	*Y*	*N*
claimed	*Y*	**272**	1	228	45	93	180
	N	**748,880**	775,690	244,132	1,280,438	7,501	1,517,069

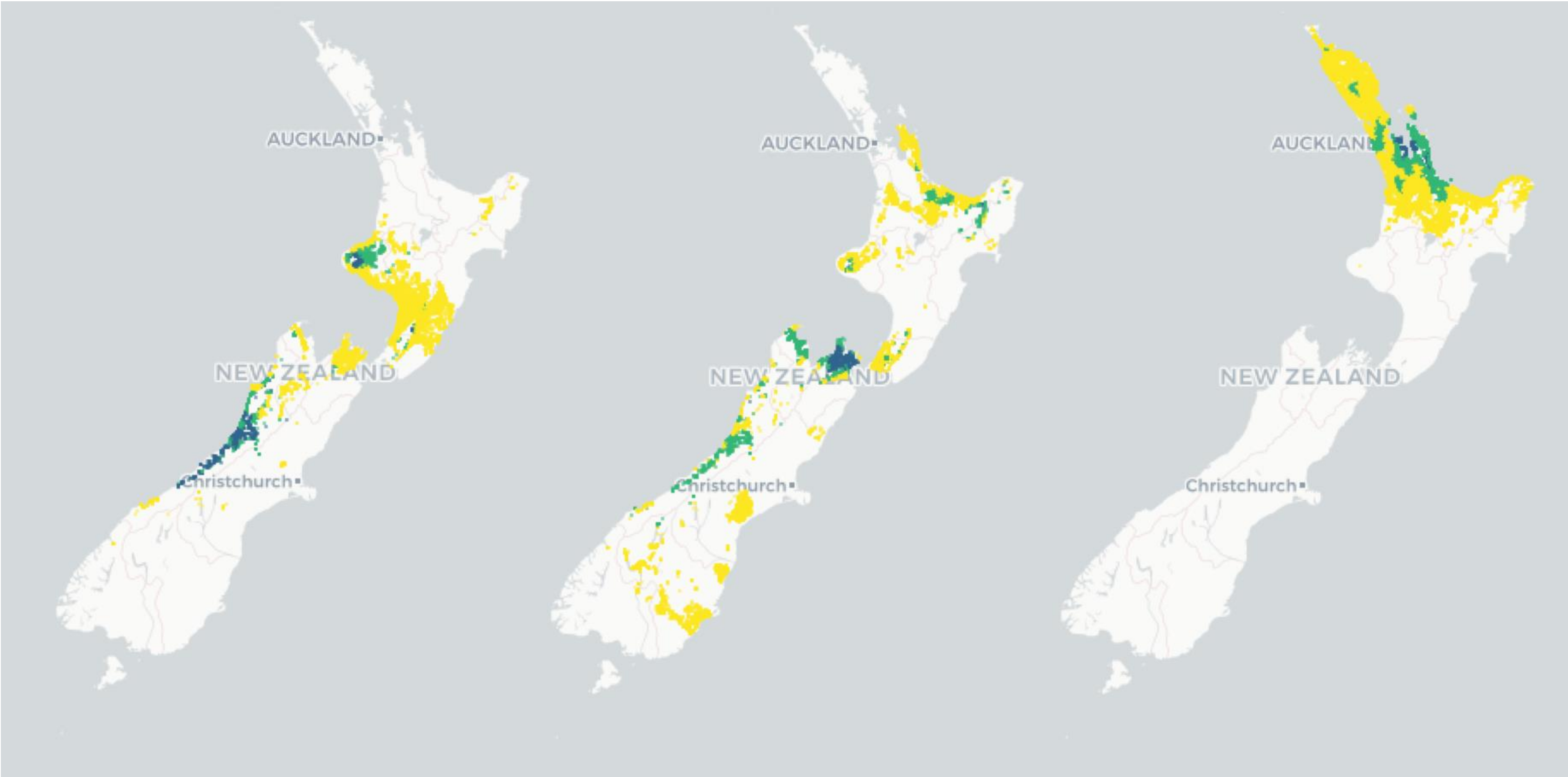
Note: This table contains the number of properties by rain threshold and claim status.

Appendix Table 2: Additional summary statistics – raw night-time light data

	event one 50mm threshold			event two 30mm threshold			event three 50mm threshold		
	all	claimed	not claimed	all	claimed	not claimed	all	claimed	not claimed
month prior to event	5.617	4.179	5.620	8.152	7.264	8.153	13.354	2.646	13.358
	(6.235)	(3.892)	(6.240)	(10.702)	(7.272)	(10.706)	(20.394)	(4.267)	(20.396)
month of event	5.067	3.976	5.070	6.621	7.233	6.620	12.059	2.350	12.063
	(5.263)	(3.674	(5.267)	(10.708)	(7.768)	(10.711)	(19.891)	(3.529)	(19.893)
one month after event	5.428	4.504	5.430	0.682	0.000	0.683	12.003	2.432	12.006
	(5.787)	(4.364)	(5.790)	(2.503)	(0.000)	(2.505)	(17.445)	(3.526)	(17.447)
two months after event	5.314	4.608	5.316	7.384	8.321	7.383	12.081	2.470	12.084
	(5.866)	(4.532)	(5.869)	(12.260)	(10.306)	(12.262)	(19.803)	(3.309)	(19.806)

Note: This table contains the means and standard deviations of the individual monthly night-time light data per event, the inputs to the damage and recovery variables.

Appendix Figure 1: Locations of exposed properties (more extreme rainfall thresholds)



Note: This figure presents the location of properties exposed to the three weather events analysed in this paper. From left, these are: event one - the June 2015 storm, event two -the November 2016 flooding, and event three – the March 2017 storm. Yellow points present all those properties exposed to precipitation during the event. Points represent properties exposed to at least 50mm, 100mm, or 150mm of rainfall for events one and three, and 30mm, 50mm or 150mm for event two. These are shown in yellow, teal and blue respectively. These datasets represent the three specifications analysed in the tables below.

Appendix Table 3: Additional regression results – event one (three thresholds of rain intensity)

	Dependent variable: night-time light recovery								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
sample	50mm threshold			100mm threshold			150mm threshold		
night-time light damage	−0.516***	−0.516***	**−0.516*****	−0.447***	−0.447***	**−0.447*****	−0.575***	−0.575***	**−0.575*****
	(0.002)	(0.002)	**(0.002)**	(0.005)	(0.005)	**(0.005)**	(0.006)	(0.006)	**(0.006)**
claimed	0.587***			−0.095			−0.182		
	(0.073)			(0.181)			(0.233)		
approved		0.700***			−0.088			−0.057	
		(0.085)			(0.287)			(0.466)	
closed in 90 days			**0.471*****			**−0.094**			**−0.212**
			(0.108)			**(0.234)**			**(0.249)**
slope (degrees)	−0.016***	−0.016***	**−0.016*****	0.011***	0.011***	**0.011*****	−0.0003	−0.0003	**−0.0003**
	(0.001)	(0.001)	**(0.001)**	(0.002)	(0.002)	**(0.002)**	(0.003)	(0.003)	**(0.003)**
distance to river (km)	−0.238***	−0.238***	**−0.239*****	0.055*	0.055*	**0.055***	0.037	0.037	**0.037**
	(0.008)	(0.008)	**(0.008)**	(0.022)	(0.022)	**(0.022)**	(0.028)	(0.028)	**(0.028)**
distance to lake (km)	0.022***	0.022***	**0.021*****	−0.010	−0.010	**−0.010**	0.012	0.012	**0.012**
	(0.003)	(0.003)	**(0.003)**	(0.006)	(0.006)	**(0.006)**	(0.009)	(0.009)	**(0.009)**
distance to coast (km)	0.002***	0.002***	**0.002*****	−0.002**	−0.002**	**−0.002****	−0.006***	−0.006***	**−0.006*****
	(0.0002)	(0.0002)	**(0.0002)**	(0.001)	(0.001)	**(0.001)**	(0.001)	(0.001)	**(0.001)**
median HH income (000s)	0.002***	0.002***	**0.002*****	−0.001**	−0.001**	**−0.001****	−0.001	−0.001	**−0.001**
	(0.0002)	(0.0002)	**(0.0002)**	(0.0003)	(0.0003)	**(0.0003)**	(0.0004)	(0.0004)	**(0.0004)**
prop. dwellings not owned	0.724***	0.724***	**0.724*****	0.260***	0.260***	**0.260*****	−0.087*	−0.087*	**−0.087***
	(0.025)	(0.025)	**(0.025)**	(0.038)	(0.038)	**(0.038)**	(0.052)	(0.052)	**(0.052)**
Constant	−0.266***	−0.266***	**−0.263*****	−0.157***	−0.158***	**−0.157*****	−0.089*	−0.089*	**−0.088***
	(0.017)	(0.017)	**(0.017)**	(0.027)	(0.027)	**(0.027)**	(0.038)	(0.038)	**(0.038)**
Observations	146,311	146,311	**146,311**	16,330	16,330	**16,330**	7,855	7,855	**7,855**
Adjusted R^2	0.383	0.383	**0.383**	0.364	0.364	**0.364**	0.526	0.526	**0.526**

Note: *p<0.05; **p<0.01; ***p<0.001

Appendix Table 4: Additional regression results – event two (three thresholds of rain intensity)

	Dependent variable: night-time light recovery								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	30mm threshold			50mm threshold			100mm threshold		
night-time light damage	-0.003**	-0.003**	**-0.003****	-0.084***	-0.084***	**-0.084*****	0.054	0.054	**0.053**
	(0.001)	(0.001)	**(0.001)**	(0.005)	(0.005)	**(0.005)**	(0.041)	(0.041)	**(0.041)**
claimed	0.323			1.214*			-0.483		
	(0.179)			(0.472)			(0.401)		
approved		0.335			1.441**			-0.544	
		(0.199)			(0.503)			(0.436)	
closed in 90 days			**1.020**			**-0.437**			**-0.339**
			(0.596)			**(1.352)**			**(1.020)**
slope (degrees)	-0.043***	-0.043***	**-0.043*****	-0.0061***	-0.0061***	**-0.0061*****	-0.005	-0.005	**-0.005**
	(0.010)	(0.010)	**(0.010)**	(0.003)	(0.003)	**(0.003)**	(0.004)	(0.004)	**(0.004)**
distance to river (km)	0.370***	0.370***	**0.370*****	1.407***	1.407***	**1.407*****	-0.722***	-0.722***	**-0.722*****
	(0.010	(0.010	**(0.010**	(0.043)	(0.043)	**(0.043)**	(0.127)	(0.127)	**(0.127)**
distance to lake (km)	0.184***	0.184***	**0.184*****	0.047***	0.047***	**0.047*****	0.076***	0.076***	**0.076*****
	(0.005)	(0.005)	**(0.005)**	(0.007)	(0.007)	**(0.007)**	(0.008)	(0.008)	**(0.008)**
distance to coast (km)	-0.011***	-0.011***	**-0.011*****	0.026***	0.026***	**0.026*****	-0.114***	-0.114***	**-0.114*****
	(0.0003)	(0.0003)	**(0.0003)**	(0.002)	(0.002)	**(0.002)**	(0.009)	(0.009)	**(0.009)**
median HH income (000s)	0.015***	0.015***	**0.015*****	-0.016***	-0.016***	**-0.016*****	0.008***	0.008***	**0.008*****
	(0.0003)	(0.0003)	**(0.0003)**	(0.001)	(0.001)	**(0.001)**	(0.002)	(0.002)	**(0.002)**
prop. dwellings not owned	3.600***	3.600***	**3.600*****	-0.058	-0.057	**-0.059**	1.399***	1.399***	**1.399*****
	(0.036)	(0.036)	**(0.036)**	(0.095)	(0.095)	**(0.095)**	(0.215)	(0.215)	**(0.215)**
Constant	-1.690***	-1.690***	**-1.690*****	1.238***	1.237***	**1.238*****	0.877***	0.878***	**0.873*****
	(0.026)	(0.026)	**(0.026)**	(0.070)	(0.070)	**(0.070)**	(0.134)	(0.134)	**(0.134)**
Observations	296,901	296,901	**296,901**	36,803	36,803	**36,803**	3,475	3,475	**3,475**
Adjusted R^2	0.060	0.060	**0.060**	0.089	0.089	**0.089**	0.114	0.114	**0.114**

Note: *p<0.05; **p<0.01; ***p<0.001

Appendix Table 5: Additional regression results – event three

	Dependent variable: night-time light recovery								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
sample		50mm threshold			100mm threshold			150mm threshold	
night-time light damage	**−0.638*****	**−0.638*****	**−0.638*****	**−0.508*****	**−0.508*****	**−0.508*****	**−0.066*****	**−0.066*****	**−0.066*****
	(0.001)	**(0.001)**	**(0.001)**	**(0.002)**	**(0.002)**	**(0.002)**	**(0.010)**	**(0.010)**	**(0.010)**
claimed	**0.521***			**0.027**			**0.022**		
	(0.235)			**(0.104)**			**(0.033)**		
approved		**0.527***			**0.014**			**0.023**	
		(0.280)			**(0.125)**			**(0.037)**	
closed in 90 days			**0.726**			**0.106**			**0.124**
			(0.605)			**(0.259)**			**(0.099)**
slope (degrees)	−0.032***	−0.032***	−0.032***	−0.019***	−0.019***	−0.019***	−0.0002	−0.0002	−0.0002
	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
distance to river (km)	−0.154***	−0.154***	−0.154***	−0.222***	−0.222***	−0.222***	0.065***	0.065***	0.065***
	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.007)	(0.015)	(0.015)	(0.015)
distance to lake (km)	0.148***	0.148***	0.148***	−0.050***	−0.050***	−0.050***	−0.004***	−0.004***	−0.004***
	(0.005)	(0.005)	(0.005)	(0.003)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
distance to coast (km)	0.024***	0.024***	0.024***	−0.014***	−0.014***	−0.014***	−0.009***	−0.009***	−0.009***
	(0.0004)	(0.0004)	(0.0004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
median HH income (000s)	−0.010***	−0.010***	−0.010***	−0.005***	−0.005***	−0.005***	−0.001***	−0.001***	−0.001***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
prop. dwellings not owned	−3.586***	−3.587***	−3.587***	0.859***	0.859***	0.859***	0.564***	0.564***	0.565***
	(0.030)	(0.030)	(0.030)	(0.033)	(0.033)	(0.033)	(0.041)	(0.041)	(0.041)
Constant	1.082***	1.082***	1.082***	0.575***	0.575***	0.575***	0.128***	0.128***	0.128***
	(0.024)	(0.024)	(0.024)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Observations	543,258	543,258	543,258	99,921	99,921	99,921	7,594	7,594	7,594
Adjusted R^2	0.345	0.345	0.345	0.340	0.340	0.340	0.043	0.043	0.043

Note: *p<0.05; **p<0.01; ***p<0.001

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