Linking temperature to catastrophe damages from hydrologic and meteorological extremes

Conrad Wasko[1,2], Ashish Sharma[1] and Alexander Pui[3]

[1] School of Civil and Environmental Engineering, University of New South Wales, Sydney, New South Wales, 2052, Australia

[2] Department of Infrastructure, University of Melbourne, Parkville, Victoria, 3010, Australia

[3] Swiss Re International Japan, Tokyo, Japan

Abstract

Increases in the magnitude of storm and flood related catastrophes due to climate change are predicted to increase associated economic losses. There exists, however, conflicting evidence for greater economic losses despite well acknowledged increases in the severity of observed extreme events in recent decades. Here, using a worldwide catastrophe insurance database from 1970 to 2015, we link the catastrophe economic loss from extreme storms and floods to local temperature. Although no statistically significant temporal trend is detected in standardised global catastrophe economic losses, we find a statistically significant positive association between economic losses expressed as a proportion of GDP and local temperature. The association between economic losses and temperature is greater as the event becomes more extreme, with the signal muted for flooding as compared to storms. Although local associations of economic loss with temperature cannot be directly linked to rising global temperatures as a result of climate change, the positive economic loss-temperature associations are consistent with observed extreme precipitation-temperature associations, and hence pertinent to the advancement of understanding future natural catastrophes.

1. Introduction

Storm related climate catastrophes result in major loss of life and widespread economic damage, with developing countries particularly exposed as they lack the financial and material resources to mitigate impacts (Razavi et al., 2020). Overall, the economic losses

from these catastrophes is expected to be exacerbated by climatic change (Arent et al., 2014; IPCC, 2012). This expectation is supported by evidence from dynamic downscaling of individual weather events and statistical downscaling of global climate models, both of which predict increased insurance losses can be expected as we head into the significantly warmer temperatures over the rest of this century (Held et al., 2013).

The contribution of climate change to economic loss potential from storm events is largely based on the assumption of increasing storm intensity driven via the Clausius-Clapeyron relation. Assuming constant relative humidity, this physical relationship dictates that as temperatures increase, so does the moisture holding capacity of the atmosphere, and hence extreme precipitation intensity should increase as a result (Trenberth, 2011; Trenberth et al., 2003). This in turn is predicted to lead to increased flood risk (Trenberth et al., 2003; Westra et al., 2014), particularly in urban settings (Fadhel et al., 2018; Hettiarachchi et al., 2018; Miller and Hutchins, 2017). Increases in precipitation intensity are likely to be coupled with changes in storm temporal pattern (Wasko and Sharma, 2015) as well as duration (Emmanuel et al., 2012; Webster, 2005) and areal extent (Prein et al., 2017). Storms may also invigorate due to increased latent heat release at higher (absolute) humidity intensifying upward motions (Lenderink and van Meijgaard, 2008; Trenberth et al., 2003), or change due to larger atmospheric changes such at the expansion of the Hadley Cell (Grise et al., 2018; Mathew and Kumar, 2019; Seidel et al., 2008; Staten et al., 2018) increasing the frequency of extreme precipitation events (Myhre et al., 2019). All these factors are predicted to lead to increased storm severity with climate change (Seneviratne et al., 2012).

Observed increases in extreme precipitation, flooding, and storm severity are abound in literature (Do et al., 2017; Donat et al., 2013; Emanuel, 2005; Martinez-Villalobos and Neelin, 2018; O'Gorman, 2015; Slater et al., 2021; Sun et al., 2021; Wasko and Nathan, 2019; Westra et al., 2013a). While historical changes in climate extremes have been attributed to anthropogenic climate change (Diffenbaugh et al., 2017; Kay et al., 2011; Min et al., 2011; Pall et al., 2011), the linking of economic losses to climatic change is more difficult (Bouwer, 2011; Hoeppe, 2016). Changes in economic losses have been associated with local climate variability (Pielke and Landsea, 1999; Welker and Faust, 2013), and the economic cost of hurricane Harvey has recently been attributed to climate change (Frame et

al., 2020), but debate remains on whether temporal trends in economic loss exist (Paprotny et al., 2018). Although a summary of historical studies finds more studies observe increases rather than decreases in economic loss (Bouwer, 2011), after appropriate normalisation for increases in economic growth, studies generally find little temporal trend and hence association with climate change (Arent et al., 2014). For example, normalised total annual losses from Hurricanes in the United States (Pielke et al., 2008; Weinkle et al., 2018) and Latin America and The Caribbean (Pielke et al., 2003) show no temporal trend. Likewise no climate change signal was identified in normalised annual aggregations of flood losses across Europe (Barredo, 2009).

Global normalised economic loss aggregations across various natural disaster types also display no statistically significant upward trend (Barthel and Neumayer, 2012; Neumayer and Barthel, 2011), with continental Australian studies showing similar results (Crompton and McAneney, 2008; McAneney et al., 2019). As global temperatures have been monotonically increasing and can be substituted for a temporal trend, there is likewise no link found between increasing global temperatures and increasing global economic losses (Miller et al., 2008). The two primary arguments for differing trends in economic loss are the method of normalisation of economic loss (Barthel and Neumayer, 2012; Kron et al., 2019) and the absence of consideration of changes in vulnerability (Mechler and Bouwer, 2015). For example, climate change signals may be obscured by increasing defences and resilience to climatic catastrophes (Nicholls, 2011) meaning increases in economic loss are not as large as they would have been had vulnerability-reducing measures not been implemented (Mechler and Bouwer, 2015). Here we suggest another possibility. As global warming does not always affect the global temperature uniformly (Neukom et al., 2019) it may be that higher global temperatures will not be associated with greater economic losses, but local temperatures will.

There is significant evidence that local temperature influences storm severity (Lenderink and van Meijgaard, 2008; Peleg et al., 2018). Changes in both tropical cyclones and local scale convective events have been correlated to increases in temperature (Lenderink and Attema, 2015; Webster, 2005). Increased lightning strikes have been linked to higher temperatures (Molnar et al., 2015) and a greater number of insurance claims (Mills, 2005).

Indeed, local temperature sensitivities have been shown to be the primary variable explaining rainfall variability across various temporal scales (Wasko and Sharma, 2017a; Westra et al., 2013b) with higher temperatures linked to greater flood event magnitude (Wasko and Sharma, 2017b). Local temperature increases have been successfully used as a predictor in non-stationary analysis of flood risk (Condon et al., 2015; Towler et al., 2010) and extreme rainfall (Agilan and Umamahesh, 2015; Mondal and Mujumdar, 2015), even being linked to indicators of water quality (Guo et al., 2021) and hence health outcomes (Jhajharia et al., 2013).

As discussed above, storm extremes are linked to higher temperatures from the increased moisture carrying capacity of a warmer atmosphere as specified by the Clausius Clapeyron relationship (Roderick et al., 2019; Trenberth, 2011). Assuming constant relative humidity, this increase in moisture carrying capacity can lead to larger downpours especially over short periods of time where local moisture contributes substantially (Fowler et al., 2021). While this physical link to temperature becomes weaker when the relationship is extended to other derived variables such as floods (Bennett et al., 2018; Sharma et al., 2018; Tramblay et al., 2019) and economic loss (Nicholls, 2011), a positive link with extreme precipitation is well established. Hence, here we seek to investigate, can a link between temperature and the economic loss resulting from extreme hydrologic and meteorological events be identified?

We analyse natural disasters on a per event basis, rather than a total or annual economic loss, to capture the event severity (in terms of economic loss). The normalised temporal trend on a per catastrophe basis is first analysed to see if economic losses have increased due to an increase in event severity. Next, because global temperature anomalies are not necessarily spatially uniform, the sensitivity of normalised economic loss to local temperature as a driver of storm intensification is investigated. The influence of storm severity and the originating storm mechanism on the relationship of normalised economic loss to local temperature are also investigated. Finally, the implications in the context of climate change are discussed.

2. Data

In this study we use the Sigma catastrophe database for the years 1970 to 2015 (SwissRe, 2016). Sigma represents a comprehensive database of significant catastrophe events collated from newspapers, direct and reinsurance periodicals, specialist publications and reports from (re)insurers. This data set provides information on 5024 natural catastrophes for which various statistics are reported including fatalities, economic loss, and insured loss. Here, we focus on the economic loss. The economic loss consists of both infrastructure damage (stock losses) and lost production due to economic interruption (flow losses). The total economic loss is reported as: A nominal loss in the local currency; the local loss in U.S. dollars; and the inflated loss in 2016 U.S. dollars. The nominal economic loss is converted to U.S. dollars using the end of year exchange rate and subsequently the U.S. dollar value is adjusted for inflation using the US consumer price index to give economic loss for the base year 2016. Consistent with insurance industry practice, catastrophes are classified on the type of catastrophe using peril terminology. These perils are storms, floods, hail, heat related catastrophes such as droughts and fires, cold related catastrophes such blizzards, earthquakes, or unclassified. Storm damages generally stem from events causing water ingress or wind driven rain damage whereas flood events are generally from riverine inundation such as over topping of riverbanks. Perils originating from blizzards can be classified as either cold related catastrophes or storms depending on the primary peril. A description of each event is also given providing the storm mechanism. For example, the Haiyan typhoon of 2013 in the Philippines is classified as a storm and described as “Haiyan typhoon”. Such data sets provide a quantitative link between the hydrologic sciences and economic loss (Gao et al., 2019).

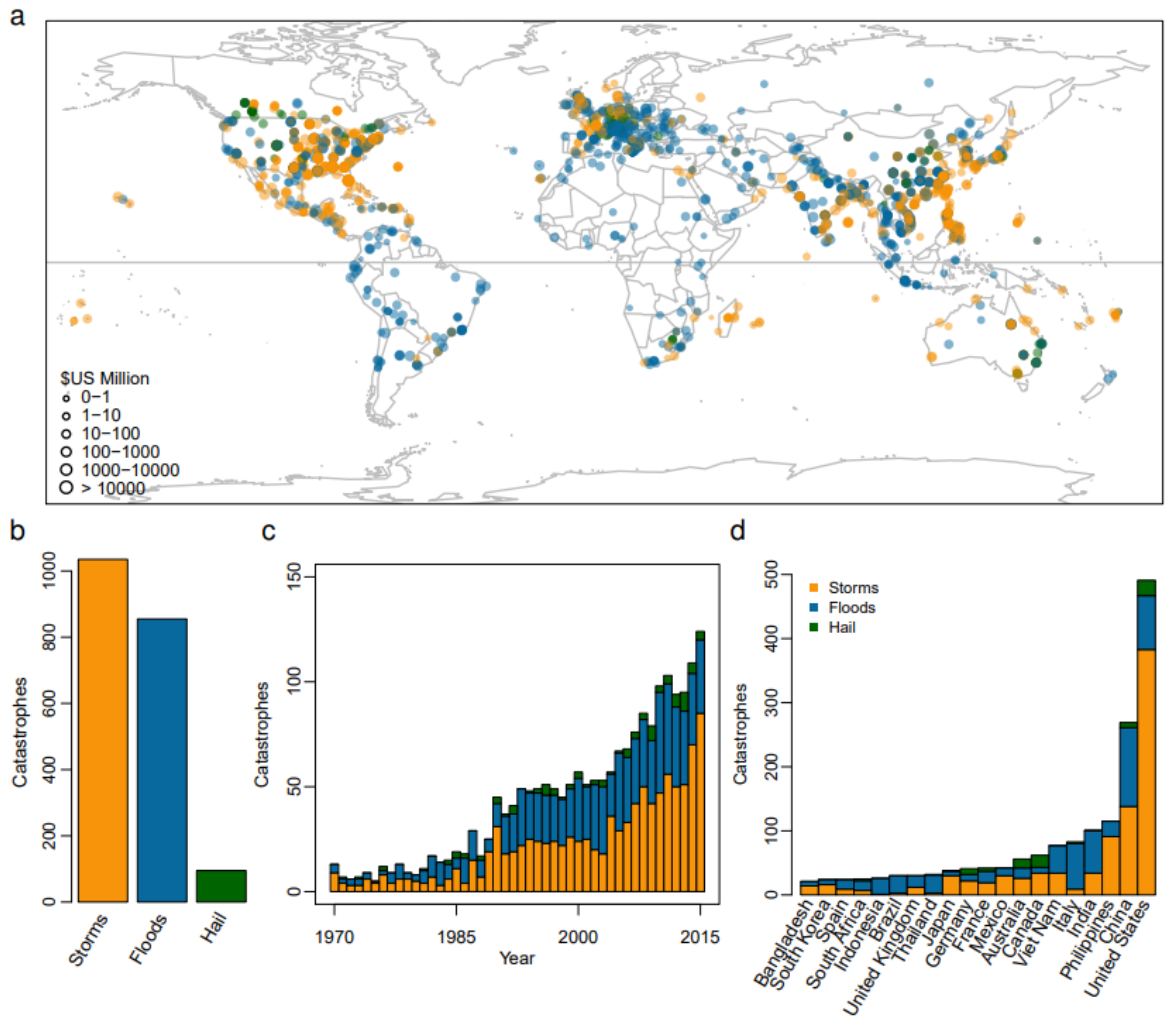


Figure 1. Economic loss data. (a) Inflated economic loss per catastrophe. The size of the circle indicates the size of the economic loss in 2016 US million dollars. The colour of the circle indicates the type of peril. (b) Histogram of catastrophe number. (c) Time series of catastrophe number. (d) Histogram of catastrophe country origin for countries with more than 20 recorded catastrophes.

Here we focus on the hydrologic storm related catastrophes, that is storms, floods, or hail events, a total of 1985 events. The location of each catastrophe is reported as a region, state, territory, or country. For this study the location description was mapped to geographical coordinates using an application programming interface. The location and economic loss of each catastrophe is presented in Figure 1a. Economic loss is highly non-linear with the largest 50% of events responsible for 97% of losses, and the largest 10% responsible for 75% of losses, after normalisation (Section 3.1). The automated matching of each catastrophe event to a set of coordinates was verified manually. The proportion of catastrophes classified as either storms or floods far exceeds those classified as hail (Figure

1b). The number of recorded events has increased in time (Figure 1c), with few recorded events prior to 1985. For countries with more than 20 recorded catastrophes, the number of catastrophes is summarised in Figure 1d. Most recorded events are in the Unites States, Europe, and China (Figure 1a, 1d).

3. Methods

3.1 Normalisation of individual catastrophes

We analyse economic loss on a per catastrophe basis to isolate possible increases in storm severity. The effect of normalisation on economic loss is discussed in detail in Neumayer and Barthel (2011). For spatial pooling, for a given catastrophe year (*t*), normalising by the country wealth is recommended (Neumayer and Barthel, 2011):

$$y_i = Normalised\ Economic\ Loss_i = \frac{Economic\ Loss_i^t}{Wealth^t} \quad (1)$$

This results in a sample of normalised economic loss y_i where $i = 1..n$ and n is the total number of events (as presented in Figure 1a). As long as the wealth is for the same year as the economic loss, the result is a dimensionless ratio of the actual loss to the potential loss (APLR) which can then be pooled spatially (Neumayer and Barthel, 2011). As discussed, economic loss consists of both losses to physical infrastructure (stock) and losses related to economic losses (flow). To accurately normalise a measure of wealth is required. A simplification is to use GDP as a wealth measure. Although GDP is a flow measure, it is typically highly correlated with wealth stock (Neumayer and Barthel, 2011) resulting in consistent normalisations (Paprotny et al., 2018). Here, the nominal Gross Domestic Product in U.S. dollars (UN, 2017) is used as an indicator of wealth consistent with standard practice (Munich RE, 2016) and previous studies (Neumayer and Barthel, 2011; Pielke and Landsea, 1999; Welker and Faust, 2013). Twelve catastrophes with a normalised economic loss (APLR) above 0.4 were removed. These catastrophes were for small nations where the normalised economic loss is improbably high (Neumayer and Barthel, 2011). Removal of these data points did not affect the results presented.

3.2 Analysis of temporal trend

For temporal analysis, the total normalised economic loss for each calendar year is divided by the number of catastrophes recorded to find the average normalised economic loss per catastrophe. The temporal trend of normalised economic loss per catastrophe per year was assessed using the non-parametric rank-based Kendall's Tau correlation (Kendall, 1975, 1938). Kendall's Tau is a rank-based (non-parametric) correlation measure which equals 1 if all pairs are concordant and -1 if all pairs are discordant (Equation 2).

$$\tau = \frac{N_c - N_d}{n(n-1)/2} \quad (2)$$

Where N_c and N_d are the number of concordant discordant pairs respectively and *n* is the number of observations, in this case years. The temporal trend was calculated with a varying start and end year ensuring that the minimum record length considered was 10 years. This allowed consideration of change points or bias due to an individual year or short period having a high normalised economic loss. Due to the possibility of serial autocorrelation it is prudent to use multiple trend tests (Zamani et al., 2017). The analysis was repeated using a modified Mann-Kendall test with bias corrected pre-whitening to remove the effect of any serial correlation (Hamed, 2009). As the results were consistent with those based on Kendall's Tau the results presented here focus on the use of Kendall's Tau.

3.3 Analysis of temperature associations

The Clausius-Clapeyron equation describes how the equilibrium vapour pressure (e_s) varies with Temperature (*T*):

$$\frac{\partial e_s}{\partial T} \simeq \frac{e_s L_v(T)}{R_v T^2} \quad (3)$$

where L_v is the latent heat of vapourisation and R_v is the gas constant. As temperature increases, the saturation vapour pressure increases exponentially translating to an increase between 5.7-6.7%/°C in the range 10-30°C (Wasko, 2021). Hence the intensity (and severity) of an extreme storm event can be linked to local temperature (Agilan and Umamahesh, 2017; Fowler et al., 2021; Lenderink and Attema, 2015).

Here, each standardised catastrophe event was matched to the local NCEP/NCAR Reanalysis 1 monthly temperature on a 2.5° grid (Kalnay et al., 1996; NCEP, 1994) based on the start time of the catastrophe. Monthly temperature was used as it has been shown be an effective predictor for non-stationary flood risk (Condon et al., 2015; Towler et al., 2010) and

extreme rainfall intensities (Agilan and Umamahesh, 2015; Cross et al., 2020; Wasko and Sharma, 2017a). The analysis was also performed using an observed 1.0° gridded dataset (Berkeley Earth, 2015; Rohde et al., 2013) with the results found to be almost identical. All the standardised catastrophe events (Equation 1), with their matched local temperature, were pooled and their sensitivity (association) to temperature was investigated using quantile regression (Koenker and Bassett, 1978; Wasko and Sharma, 2014). Quantile regression was implemented in the statistical software *R* using the package 'quantreg' (Koenker, 2021). Quantile regression allows the response with differing event rarity to be investigated and is less biased to outlying data. A quantile regression is fitted to the logarithm of economic loss.

Quantile regression is similar to linear regression and is expressed as per Equation (4) but a cost function *D* is used to minimize deviation from the quantile (q) of interest (Equation 5). That is, for a regression of the form where y_i is the normalised economic loss for each catastrophe and T_i is the local monthly temperature:

$$\log(y_i) = \beta_0^{(q)} + \beta_1^{(q)} T_i \tag{4}$$

The regression coefficients $\beta_0^{(q)}$ and $\beta_1^{(q)}$ are chosen to minimize a cost function *D*, defined as:

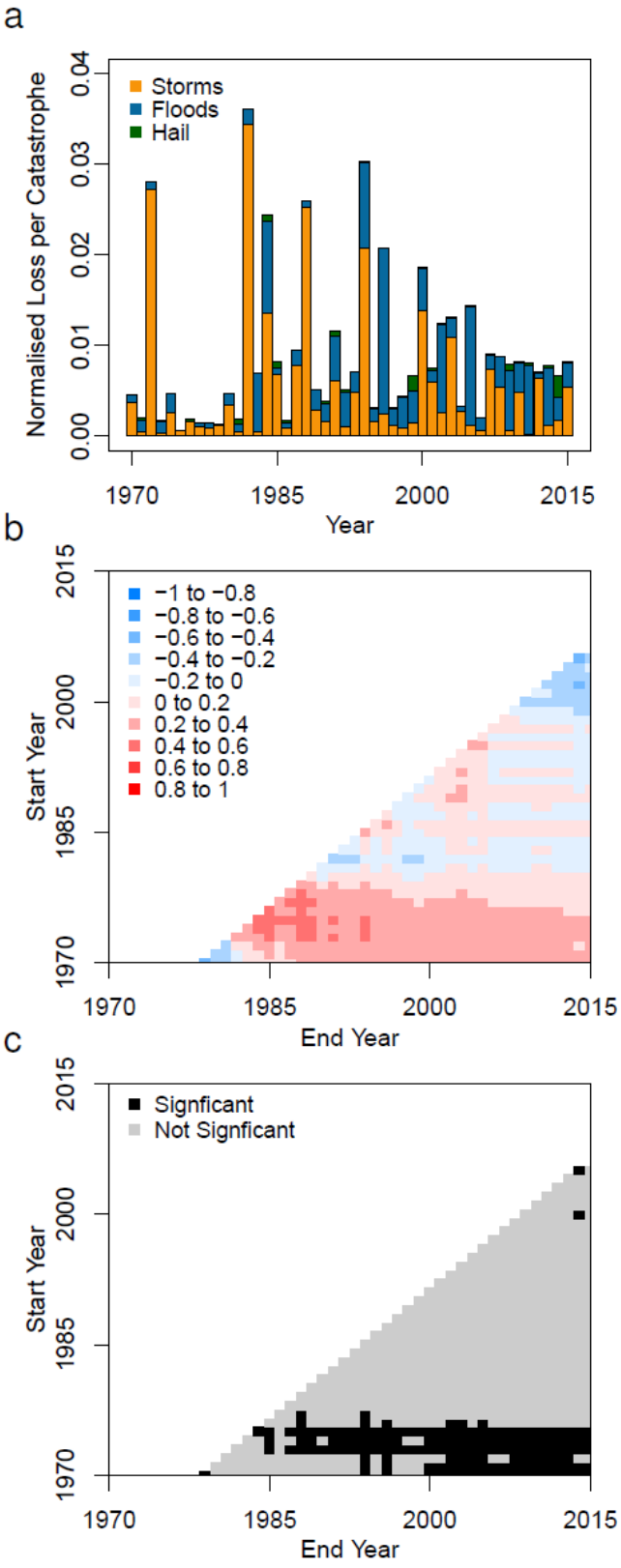
$$D\left(\beta_0^{(q)}, \beta_1^{(q)}\right) = q \sum_{y_i \geq \beta_0^{(q)} + \beta_1^{(q)} T_i} |y_i - \beta_0^{(q)} - \beta_1^{(q)} T_i| + (1-q) \sum_{y_i < \beta_0^{(q)} + \beta_1^{(q)} T_i} |y_i - \beta_0^{(q)} - \beta_1^{(q)} T_i| \tag{5}$$

For example, to regress for the 99th percentile, q is set equal to 0.99 and substituted into Equation (5) to calculate the regression coefficients $\beta_0^{(0.99)}$ and $\beta_1^{(0.99)}$. This substitution results in a large weight for the first summation term (points above the regression line) and a small weight for the second summation term (points below the regression line) resulting in regression coefficients being optimised to minimise the absolute difference of fitted values close to the first summation term, that is, the fitted regression line to the 99th percentile of all the data.

The sensitivity of the normalised economic loss (y) as a percentage change per degree in temperature is then calculated by:

$$\Delta \mathrm{y}\% = 100 \cdot (10^{\beta_1} - 1) \quad (6)$$

As China and the U.S. account for almost 40% of our catastrophe sample (Figure 1d), and have the two largest global Gross Domestic Products, the catastrophe data is split between these two countries and those remaining to prevent possible bias due to the uneven sample of events between countries. Individual quantiles were calculated using a $2\,^{\circ}\mathrm{C}$ moving temperature window to confirm the assumption of linearity between the logarithm of normalised economic loss and temperature. To analyse the possible impact of storm mechanism each event description was mined for key words. These were tornado/thunderstorm, hurricane, typhoon, and cyclone/tropical storm. Descriptions without these key words were classified as 'other' storms and include storms described as winter storms as well as storms without any additional description. The temperature range used for regression (to remove the influence of outliers) is indicated in each figure by the extents of the fitted regression.



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272 *Figure 2. Per catastrophe trend analysis (a) Economic loss per catastrophe per year standardised by*
273 *GDP. (b) Surface of Kendall's tau statistic for monotonic trend in Figure 2a. Kendall's tau has been*
274 *calculated on a time series from the start year to the end year with a minimum record length of 10*
275 *years. (c) Statistical significance of Kendall's tau presented in Figure 2b at the 95% level.*

4. Results

4.1 Temporal trend

A time series of the normalised economic loss per catastrophe per year is presented in Figure 2a. For simplicity, from here on, economic loss refers to the economic loss standardised by GDP. A surface of Kendall's tau statistic for monotonic trend is presented in Figure 2b. Statistical significance is presented in Figure 2c. The trend test is performed on a moving window of years, with a minimum of 10 years required for testing. Economic loss per catastrophe is seen to increase only if the data pre-1980 is included but there is minimal catastrophe data recorded before 1985 (Figure 1c). When data pre-1980 is omitted no statistically significant trends are obtained. These results are consistent with previous global studies that used annual aggregations (rather than the per event analysis performed here) that concluded there is little evidence for a temporal increase in catastrophe related economic loss (Miller et al., 2008; Neumayer and Barthel, 2011).

4.2 Sensitivity to temperature

The economic loss as a function of local temperature is presented in Figure 3a. The trend lines were fitted using quantile regression for the 99th percentile. To confirm linearity the points present the 99th percentile calculated empirically from the data using a moving temperature window. The economic loss for China and the U.S. exhibit a sensitivity of 14.8%/°C, with the rest of the world demonstrating a sensitivity of economic loss to temperature of 15.2%/°C. We note the analysis was also performed repeated using an observed gridded temperature product (Berkeley Earth, 2015; Rohde et al., 2013) and the results were found to be consistent with those presented in Figure 3a.

The most extreme percentiles have the greatest sensitivity to temperature with less extreme catastrophes less sensitive to higher temperature (Figure 3b). The median catastrophe economic loss sensitivity to temperature is 8.8%/°C for the U.S. and China, and 2.6%/°C for the rest of the world. Using panel regression gave similar results (not shown). Below the median there is evidence of a negative association between economic loss and temperature when the U.S. and China are excluded. The positive associations with temperature for both China and U.S. and the rest of the world are similar and within confidence limits for the most extreme percentiles. The sensitivities of economic loss with

temperature are consistent with observed increased storm severity with higher temperatures (Webster, 2005), with this association stronger the more extreme the event (Wasko and Sharma, 2017b).

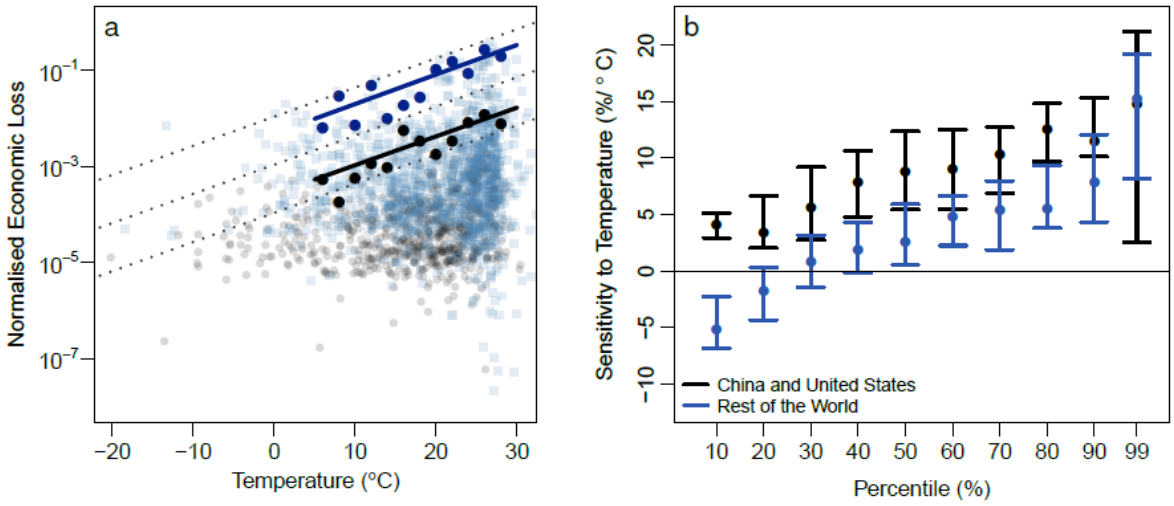


Figure 3. Relationship between economic loss, temperature, and percentile for global catastrophe data (a) Relationship between economic loss and temperature. Data is analysed between 5 and 30 °C to avoid influence of outlying data. Filled circles show the 99th percentile for moving 2 °C temperature bins. The straight lines are the quantile regression fitted to the logarithm of economic loss for the 99th percentile. Dotted guidelines show a sensitivity of 15% per °C. (b) Sensitivity of economic loss - temperature relationship to percentile. The whiskers are the 95% confidence interval of the fitted quantile regression for the target percentile.

4.3 Variability with peril

The 90th percentile sensitivity of economic loss to temperature for each individual peril (flood, storm, hail), using all the data presented in Figure 3a, is presented in Figure 4a. The sensitivities and their statistical significance are summarised in Table 1. There are few catastrophes classified as hail (Figure 1b) and hence the sensitivity of hail economic loss with temperature (5.8%/°C) is not statistically significant (Table 1). However, it appears that storm economic loss has a greater (more positive) sensitivity to temperature (15.8%/°C) than the economic loss from flooding (4.2%/°C). This is consistent with drier soil moisture

conditions at higher temperature reducing the sensitivity of floods to higher temperature (Ivancic and Shaw, 2015; Wasko et al., 2019; Wasko and Nathan, 2019).

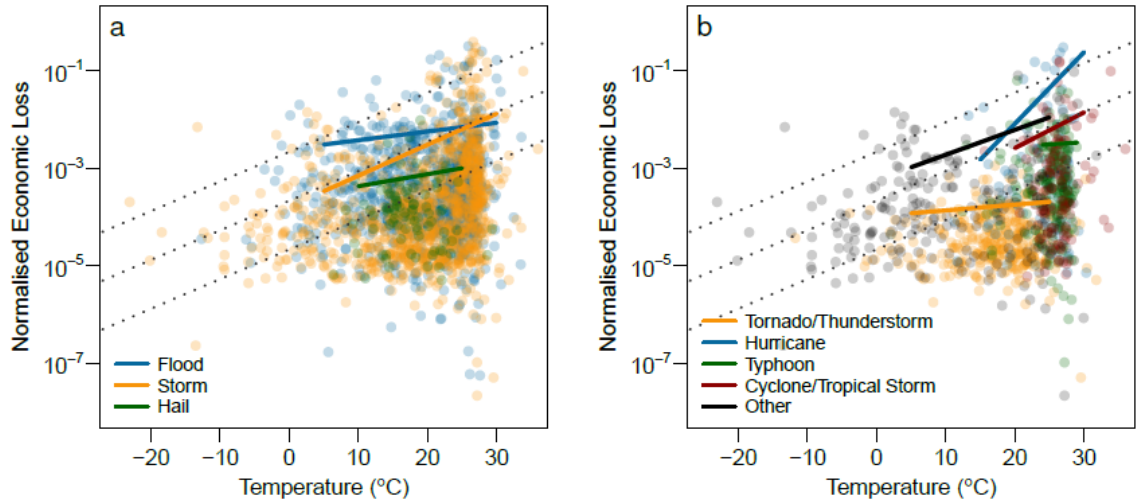


Figure 4. Dependence of economic loss sensitivity to temperature depending on peril type and storm mechanism. (a) Sensitivity of economic loss to temperature for peril classifications of flood, storm, and hail. (b) Sensitivity of economic loss to temperature for storm catastrophes classified as a tornado, hurricane, typhoon, cyclone and unclassified (other). All fitted lines are for the 90th percentile quantile regression. Guidelines show sensitivity of 15% per °C. Table 1 presents sensitivities and p-values for each regression.

The storm data is subdivided further by storm mechanism (Figure 4b). Although hurricanes, typhoons, and cyclones are a result of similar weather phenomena, as they originate in different climatic regions they are classified separately to remove artefacts of spatial pooling. Indeed catastrophes such as hurricanes, typhoons, and cyclones are associated with higher temperatures (sit towards the right of the figure), possibly due to originating in the tropics where temperatures are warmer. Additionally, the economic loss for these catastrophes is much greater than those classified as thunderstorms. Hence, a mixing of storm mechanisms may have introduced an artefact in the pooled analysis of storms, with the positive association in temperature due to sampling different storm types originating from different locations. For each of the individual storm classifications a positive association between economic loss and temperature is still observed suggesting greater storm severity and economic loss with higher temperatures regardless of storm mechanism

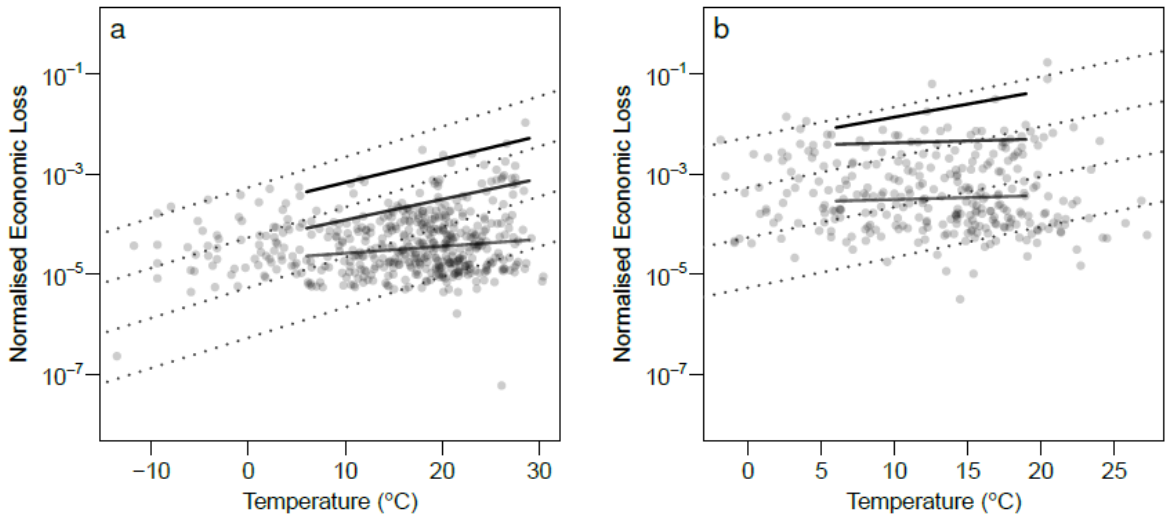
(and location). However, the statistical significance of these associations is less due to the smaller sample sizes (Table 1).

Table 1. Summary of economic loss-temperature sensitivities presented in Figure 4 and their statistical significance.

Classification Class	Classification	Sensitivity (% per °C)	p-value
Peril	Flood	4.2	0.07
	Storm	15.8	0.00
	Hail	5.8	0.68
Storm type	Tornado/Thunderstorm	2.7	0.31
	Hurricane	40.2	0.05
	Typhoon	2.3	0.90
	Cyclone/Tropical Storm	18.3	0.38
	Other	12.5	0.04

4.4 Validity of spatial pooling

It is prudent to address the validity of normalisation by conducting an analysis without pooling across the global scale. A sensitivity test using only data for the U.S. is presented in Figure 5a. The results are consistent with global trends (Figure 3) suggesting the global pooling results in a homogenous economic loss data set. When the results at a continental scale, for example Europe, are investigated, the sensitivities are subdued (Figure 5b). The 99th percentile continues to display a sensitivity of approximately 15%/°C consistent with global results (Figure 3a), but the median displays a sensitivity of 2%/°C. This is not surprising given the mixed signal in flooding throughout Europe and small data size (Blöschl et al., 2017; Hall et al., 2014). In context with the results presenting sensitivity to storm mechanism (Figure 4), this suggests that local and regional climatic conditions (Pielke and Landsea, 1999; Welker and Faust, 2013) need to be considered, as trends in extreme events can be mixed (Mallakpour and Villarini, 2015; Wasko, 2021) and also affected by the uncertainty in extreme value analysis (Hall et al., 2014). However, repeating the results classifying on storm mechanism just for the U.S., our largest economically homogenous sample, also showed positive associations with temperature for storms identified as tornado/thunderstorm or hurricane (not shown).



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378 *Figure 5. Sensitivity of economic loss to temperature (a) United States (b) Europe. The solid lines are*
379 *quantile regressions for the 50th, 90th and 99th percentiles in increasing opacity. Guidelines show a*
380 *sensitivity of 15% per ºC. Trends presented for Europe are not significantly different from zero. Trends*
381 *presented for the Unites States are significantly different from zero. Significance was tested at the*
382 *95% level.*

383 **4.5 Confounding due to unequal sampling**

384 Increased temperatures in recent years may correlate with recent catastrophes which are
385 sampled with greater frequency (Figure 1c) inducing a positive sensitivity, though this is
386 unlikely as previous studies have not found a trend with temperature anomalies at the
387 global scale (Miller et al., 2008). Figure 6 presents the results shown in Figure 3b with data
388 resampled to ensure that the number of catastrophes per year is a constant 20 events per
389 year. This removes possible bias associated with the number of events being skewed to
390 more recent, warmer, years. The results of resampling are consistent with the positive
391 sensitivity of economic losses with temperature for extreme percentiles presented earlier
392 (Figure 3) meaning the results presented here are not an artefact of sampling more recent
393 (warmer) events.

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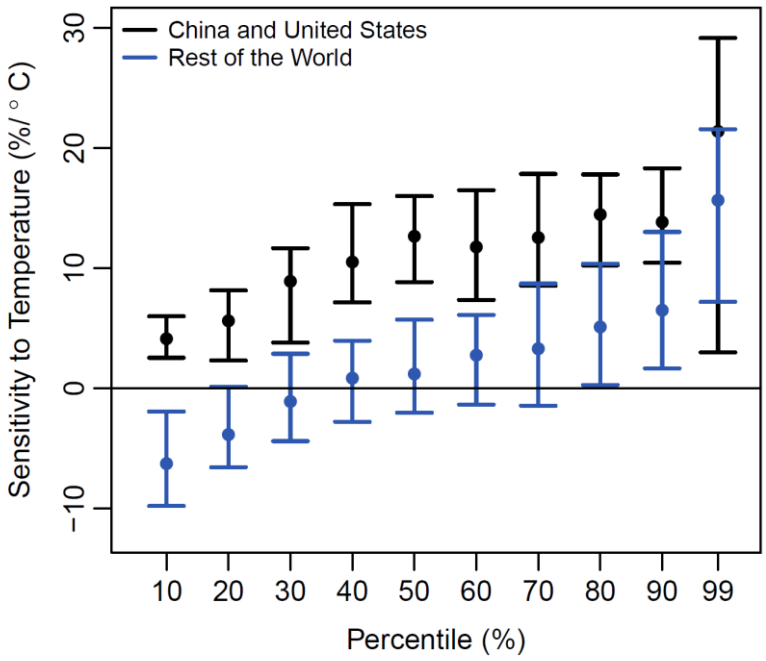

Figure 6. Resampled sensitivity of economic loss to temperature with percentile. Resampling is performed on data post 1990, sampling an equal 20 events for each year. Whiskers are 95% confidence intervals estimated from a bootstrap of 1000 replicates.

5. Discussion

Historical trends in economic loss are often investigated, and an identification of such a trend attributed to climatic change due to the historically increasing greenhouse gasses increasing temperatures and changing atmospheric circulations. It is hence common practice, and entirely valid, to substitute historical global temperature anomalies for the temporal trend as both are strongly correlated. But this practice is not necessarily informative of changes to damage due to changed storm intensity, as storm intensity is correlated to the absolute temperature and not anomalies as per Equation 3. For this reason, we associated local temperature with the economic cost of a catastrophic event. Despite changes in local temperature having better predictive ability of extreme rainfalls than temporal trends (Agilan and Umamahesh, 2015, 2017; Mondal and Mujumdar, 2015), and historical trends in extreme rainfall severity showing a strong similarity to historical temperature increases (Sun et al., 2021; Wasko and Nathan, 2019; Zhang et al., 2019) there is significant discussion in the literature on whether day-to-day variability is representative of a meaningful (temporal) physical relationship (Wasko, 2021; Zhang et al., 2017).

For example, there is no guarantee that a global temperature anomaly is experienced universally with global warming. Global warming differs by season and latitude, with the largest warming in winter and in high-latitudes (e.g., the coldest climates). Hence, it may be that the local temperature associations presented here are coupled with this trend, though stratifying on region continued to show consistent positive associations with temperature, suggesting this is not the case. There is also the issue of mixing 'weather' types (Haerter and Berg, 2009; Magan et al., 2020; Molnar et al., 2015; Wasko et al., 2015) where different weather events originate in different regions and at different temperatures (Section 4.3) which can alias to induce a positive signal between storm intensity and temperature. Separating out the mixing of events, such as hurricanes which originate in warmer areas, positive associations with temperature for each individual weather type were still found (Figure 4b), with the results consistent with modelled intensification of hurricane Harvey (van Oldenborgh et al., 2017). Catastrophes that were not been attributed to a storm mechanism (labelled 'other') were presented in black (Figure 4b). It is not known whether these storms have simply not been classified and hence may be a mix of the existing classifications or are a mix of storms of varying sizes with a similar storm mechanism. However, the economic loss associated with these storms does exhibit a sensitivity with temperature at a rate of approximately 12.5%/°C consistent with greater storm severity at higher temperatures.

The originating season of weather event has also been suggested as a confounding factor with temperature associations suggested to be a function of seasonality (Zhang et al., 2017). The data presented in Figure 3a was also stratified on season and showed consistent positive sensitivities. Despite our best efforts to remove any artefacts, there remains a possibility that due to pooling across space, positive associations of temperature and economic loss are due to economic loss event mechanisms generally originating from climates with higher temperatures. However, even if this was to be true, a shift to the more intense storm mechanisms associated with higher temperatures is not inconsistent with climate change (Berg et al., 2013). For example, the poleward shifts of the tropics is likely to bring with it changing weather types (Grise et al., 2018; Seidel et al., 2008; Staten et al., 2018) and increased tropical cyclone activity (Daloz and Camargo, 2018).

Finally, it needs to be noted that linearity was assumed between the logarithm of standardised economic loss and temperature. This was verified by plotting the empirical percentiles (Figure 2) but there is no guarantee that this linearity will exist beyond the temperature ranges presented here, or in the future, if the changes in weather patterns are outside those that can be captured by assuming linearity. In the absence of better evidence we continued with the assumption of linearity in this manuscript but note flood damage functions can take many function forms (Li et al., 2016).

6. Conclusions

Previous studies that have attempted to link economic loss with temperature anomalies at a global scale did not find a historical trend in economic loss. Here, we investigated the sensitivity (association) of catastrophe loss with local temperature on a per catastrophe basis. Consistent with existing literature, we found little evidence for increased economic loss in time due to storms increasing in severity. However, we did find higher local temperatures are associated with greater economic loss. The positive association is commensurate with the intensity of the event, that is, the more extreme the catastrophe, the more positive the association. This is consistent with the physical reasoning of greater storm intensity and severity at higher temperatures, and historical trends of increased severity of precipitation and flood extremes with climate change.

The focus here was on catastrophe severity and not the frequency of catastrophes. If catastrophe frequency was to increase (Mallakpour and Villarini, 2015; Molnar et al., 2015) then economic losses as an aggregation could be expected to increase also (Held et al., 2013; Mills et al., 2002). It is likely that both greater storm intensities at higher temperatures, and, an increased sampling of more catastrophic storm types such as hurricanes (originating at higher temperatures), result in the positive association of economic losses and local temperatures observed here. Although our analysis cannot be directly linked to rising global temperatures as a result of climate change the results suggest any possible future shift in storm type with higher temperatures, coupled with increasing storm severity, may further exacerbate economic losses from natural catastrophes.

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