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John McAneney\textsuperscript{a,b}, Benjamin Sandercock\textsuperscript{a,c}, Ryan Crompton\textsuperscript{a,b}, Thomas Mortlock\textsuperscript{a,b}, Rade Musulin\textsuperscript{a,d}, Roger Pielke Jr\textsuperscript{a,e} and Andrew Gissing\textsuperscript{a,b}

\textsuperscript{a}Risk Frontiers, St Leonards, Australia; \textsuperscript{b}Department of Environmental Sciences, Macquarie University, Sydney, Australia; \textsuperscript{c}Department of Applied Finance & Actuarial Studies, Macquarie University, Sydney, Australia; \textsuperscript{d}FBAlliance Insurance, Schaumburg, IL, USA; \textsuperscript{e}Sport Governance Centre, University of Colorado, Boulder, CO, USA

ABSTRACT
The paper updates normalisation of the Insurance Council of Australia’s Disaster List in the light of debate about the contribution of global warming to the rising cost of natural disasters. Normalisation estimates losses from historical events in a common year, here ‘season’ 2017 defined as the 12-month period from 1 July 2017. The number and nominal cost of new residential dwellings are key normalising factors and post-1974 improvements in construction standards in tropical cyclone-prone parts of the country are explicitly allowed for. 94% of the normalised losses arise from weather-related perils – bushfires, tropical cyclones, floods and severe storms – with the 1999 Sydney hailstorm the most costly single event (AUD5.6 billion). When aggregated by season, there is no trend in normalised losses from weather-related perils; in other words, after we normalise for changes we know to have taken place, no residual signal remains to be explained by changes in the occurrence of extreme weather events, regardless of cause. In sum, the rising cost of natural disasters is being driven by where and how we chose to live and with more people living in vulnerable locations with more to lose, natural disasters remain an important problem irrespective of a warming climate.

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Australia; Climate Change; Insurance; Natural disaster costs; Loss normalisation

Introduction
Despite broad agreement in the scientific literature and assessments by the Intergovernmental Panel on Climate Change (IPCC) that there is little evidence that insurance or economic losses arising from natural disasters are becoming more costly because of anthropogenic climate change (IPCC, 2012; 2014), the topic remains highly politicised (Pielke, 2018). Many commentators assume a direct causal relationship between disaster losses and rising global air temperatures (e.g. http://www.insurancebusinessmag.com/
Regardless of the degree to which various types of extreme weather events may or may not be changing, climate change resulting from the emission of greenhouse gases is an issue that can no longer be avoided by Boards of Directors of financial service providers. Encouraged by signals arising from the 2015 World Climate Change Conference in Paris, the Australian Prudential Regulatory Authority (APRA) is now seeking more systematic monitoring and disclosure … of climate change risks from its regulated entities, which include insurers and reinsurance companies. APRA considers it's unsafe … to ignore risks just because there is uncertainty, or even controversy and expects climate change risks to be explicitly considered and managed as appropriate (G. Summerhayes, 17 February 2017: http://www.apra.gov.au/Speeches/Pages/Australias-new-horizon.aspx).

In its statement, APRA draws a distinction between physical and transitional risks where:

1. physical risks stem from the direct impact of climate change on our physical environment – through, for example, resource availability, supply chain disruptions or damage to assets from severe weather, [and]
2. transition risks stem from the much wider set of changes in policy, law, markets, technology and prices that are part of the now agreed transition to a low-carbon economy.

With this public policy context in mind, this paper examines one component of physical risks using a time series of Australian insurance sector losses. While this loss metric ignores damage arising from non-insured threats such as heatwaves (Coates, Haynes, O’Brien, McAneney, & Dimer de Oliveira, 2014), changing rainfall patterns and drought, and rising sea levels (IPCC, 2014), insurance losses possess the important attribute of being explicitly measured rather than modelled, or just guessed, as is often the case for estimates of economic losses. Our study updates previous loss normalisation studies (Crompton & McAneney, 2008; Crompton, 2011) of the Insurance Council of Australia’s (ICA) Natural Disaster Event List (hereafter ‘Disaster List’). Normalised losses are estimates of the cost if historic events were to impact current societal and demographic conditions (Bouwer, 2019) and loss normalisation is a necessary step before attempting to draw conclusions about trends in the costs of natural disasters and/or climate change attribution (Pielke, 2018).

The ICA Disaster List now extends back to January 1966. The database is national in terms of geography and multi-peril in line with most homeowner and contents insurance policies in this country (McAneney, McAneney, Musulin, Walker, & Crompton, 2016). Perils responsible for loss entries include bushfires (wildfires), earthquakes, floods, severe storms including hailstorms and tropical cyclones (TC). Earlier Australian normalisation studies (Crompton & McAneney, 2008; Crompton, 2011) enjoy wide currency amongst insurers and reinsurers engaged in the Australian market and provided a framework for the 2014 Productivity Commission enquiry into natural disaster funding in this country (Productivity Commission, 2015).

In what follows, event losses in the ICA Disaster List are normalised to season 2017, defined as the 12-month period beginning 1 July 2017. Since the Crompton (2011) study, two additional national Censi of Population and Housing have been conducted, one in 2011 and a second in 2016, and, by virtue of these data improvements as well as
cross-referencing Disaster List events with location data contained in Risk Frontiers’ proprietary database, PerilAUS, the granularity of the normalisation process is now much improved. After a discussion of the salient results, the study concludes with a brief discussion of policy implications.

**Loss normalisation methodology**

Our methodology follows that of Crompton (2011) whereby an insured loss in season $i$ ($L_i$) in the dollars of the day is converted to a season 2017 normalised loss ($L_{2017}$) according to:

$$L_{2017} = L_i \times N_{ij} \times D_{ik} \times Z_i \times B_{ia}$$

(1)

where,

- $i$ is the 12-month ‘season’ extending from 1 July year $i$ to 30 June year $i + 1$ during which the loss event occurred. Employing seasons (Australian financial years) in this way rather than calendar years serves to separate successive austral summers when most but not all severe events occur.
- $j$ is the set of Urban Centres/Localities (UCLs) impacted by the event. The UCL structure is one of seven interrelated structures of the Australian Standard Geographical Classification grouping of Census Collection Districts that together form geographical areas defined by population size (Australian Bureau of Statistics (ABS) – [www.abs.gov.au](http://www.abs.gov.au)). For more detail on UCLs, the reader is referred to Appendix 1.
- $k$ is the set of States and Territories containing impacted UCLs. Where these were not recorded in the Disaster List, these were identified by cross-referencing entries with those in PerilAUS.
- $a$ is the Wind Region defined by the Building Code of Australia and containing impacted UCLs. These comprise four regions with different Ultimate Design windspeeds (3-s sustained open terrain gust speeds at 10 m height) according to Australian New Zealand Standard AS/NZ1170:2:2002: Region A – Normal (41 ms$^{-1}$); Region B – Intermediate (51.9 ms$^{-1}$); Region C – Tropical cyclones (64.5 ms$^{-1}$); and Region D – Severe tropical cyclones (88 ms$^{-1}$).
- $N_{ij}$ is the dwelling number adjustment factor defined as the ratio of the total number of residential dwellings in UCL $j$ in season 2017 to the total number in season $i$. By way of example, Tropical Cyclone Winifred (1985) impacted UCLs Innisfail and Babinda in Queensland and the event dwelling number adjustment factor is calculated as the sum of all dwellings in both Innisfail and Babinda in season 2017, divided by the sum of all dwellings in season 1985.
- $D_{ik}$ is the dwelling value adjustment factor, defined by the ratio of the nominal value of new dwellings in State/Territory $k$ in season 2017 to the nominal value of new dwellings in State/Territory $k$ in season $i$. In keeping with the Australian Bureau of Statistics’ (ABS) own approach, this study employed a Henderson Moving Average Filter with a term of five (two seasons either side of the target season) to smooth dwelling values from 1966 to 2017 ([www.abs.gov.au](http://www.abs.gov.au)). At the endpoints, asymmetric weightings were applied to maximise the amount of data that could be used. Changes in $D_{ik}$ are due to three main factors: inflation, improvements in the quality of housing stock and changes in the average size of dwellings. These factors all contribute to the cost of...
re-building after a disaster event. In keeping with the fact that damage to the land is not covered by insurance, dwelling values exclude the price of land.

- $Z_i = S_i,_{\text{total}}/S_i,_{\text{new}}$ adjusts for the changing size of new dwellings vis-à-vis the total building stock after accounting for demolitions (Crompton, 2011). (Insurance policies generally require re-building to be undertaken to the same size as the original home, so we account for this.) $S_i,_{\text{total}}$ is the ratio of the average size of all existing dwellings in season 2017 to the average size of all dwellings in season $i$, and $S_i,_{\text{new}}$ is the ratio of the average size of new dwellings in season 2017 to the average size of new dwellings in season $i$. Dwelling size data is available on a national level and has been drawn from Building Activity Reports (ABS – www.abs.gov.au).

- $B_{i,a}$ is the building code adjustment factor, which defaults to unity for all natural peril events other than TC. For any particular TC, $B_{i,a}$ is calculated by first considering the proportion of the total damage caused by wind or wind-induced rainfall ingress vis-à-vis cyclone-induced flooding and then applying damage functions to the former to estimate the percentage damage to dwellings built before and after new construction regulations. Depending on location, these regulations were introduced in 1974, 1975 or 1980, after TC Tracy destroyed Darwin in Christmas 1974 (Walker, 1975). The approach adopted here is identical to that described in Crompton and McAneney (2008) and employs damage functions first published by Walker (1995) and reproduced in Crompton and McAneney (2008).

Results

Changes to the Disaster List: Crompton (2011) normalised 195 Disaster List events, 178 of which had normalised losses of more than AUD 10 million, whereas our current study considered 297 events, 245 of which had normalised losses in excess of the same threshold. A substantial number of the additional event losses are from older events that have been recovered from archival document searches by ICA staff (K. Sullivan, ICA, pers. com.); in total, we have normalised 102 new events, 73 of which occurred since 2011. Most significant of the changes to the Disaster List since our previous studies include entries for TCs Elsie, Dinah, Barbara and Elaine, all of which occurred during the 1966 season.

Normalised losses: Table 1 ranks the top 10 most costly loss events normalised to 2017 values with the 1999 Sydney hailstorm the most expensive at AUD 5.6 billion. Six different perils contribute to these top 10 losses: hailstorm, tropical cyclone, bushfires, floods, one earthquake and an East Coast Low storm (extra-tropical cyclone).

The aggregated ‘seasonal’ raw losses in dollars of the day and the normalised losses are given in Figure 1(A,B), respectively. The key result is that our normalisation methodology is successful in explaining the increase in nominal losses as evidenced by the absence of any significant trend in the normalised losses. The regression in Figure 1(B) explains less than 1% of the variance about the trend line and its slope is slightly negative because the largest seasonal loss (1966) is also the first of the time series. (McAneney, van den Honert, and Yeo (2017) demonstrate the dependence of regression statistics on the choice of start and finish dates and the bias that this can introduce in attribution studies.) If the time series is begun in 1967 (data not shown) the slope of the trendline becomes marginally positive but the trend is still not statistically significantly different
from zero \((p = .67)\). That conclusion is also unchanged if only weather-related perils are considered (Figure 2), whereupon the \(p\)-value reduces to .46.

The average annual loss for the Disaster List is AUD 1.8 billion across its 52-year period. Since the Disaster List accounts for about 90% of the industry claims experience – not all insurers are members of the ICA – the annual average insured cost of natural disasters is ∼AUD 2 billion with an standard error of the same magnitude.

Table 2 shows the breakdown of normalised losses by State and Territory. Since 1966 events in Queensland, closely followed by New South Wales, have been most costly. Together these two states account for 70% of the national normalised losses.

Table 3 shows the breakdown of the accumulated normalised losses by peril category. TC and hail have been the most costly and responsible for 29% and 27% of the aggregated normalised losses respectively. The remainder of the losses are roughly equally spread between floods, bushfires and storms, and then earthquakes, which account for 5% of the total normalised losses. As discussed below, we believe storm losses to have been underestimated.

**Coherence of normalised losses with underlying peril activity:** Appendix 2 shows time series of the normalised insured losses broken down by peril and aggregated by seasons and in Appendix 3 we explore changes in the activity of the underlying peril, in other words, changing numbers of severe hailstorms, for example, as opposed to changes in the losses caused by hail. For losses due to severe storms, flooding and hail (Figures A1, A2, and A5), no statistically significant trends emerge. In the case of flooding losses (Figure A2) the result is curious given that insurers have not consistently covered riverine flood damage and *a priori* we might have expected to find an increase in losses over time, especially in recent years. Nonetheless, the result is consistent with the lack of trends in modelled flood discharges going back to 1900 (Figure A6).

For damage from severe storms (Figure A1) no events are listed prior to the mid-1970s. We believe this to be a feature of the under-reporting of smaller event losses in the early administration of the Disaster List and also the use of a fixed event threshold for inclusion in the Disaster List of AUD 10 million (formerly AUD 5 million). It should be noted that an event loss of AUD 5 million in 1966 could translate to a normalised loss today up to AUD 500 million depending upon where it took place. It is also possible that some storm losses

### Table 1. Top 10 most expensive normalised losses.

<table>
<thead>
<tr>
<th>Rank</th>
<th>Season</th>
<th>Event</th>
<th>Location</th>
<th>State/Territory</th>
<th>Nominal loss (Millions of AUD)</th>
<th>Normalised loss (Millions of AUD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1998</td>
<td>Sydney Hailstorm</td>
<td>Sydney</td>
<td>NSW</td>
<td>1700</td>
<td>5574</td>
</tr>
<tr>
<td>2</td>
<td>1974</td>
<td>Cyclone Tracy</td>
<td>Darwin</td>
<td>NT</td>
<td>200</td>
<td>5042</td>
</tr>
<tr>
<td>3</td>
<td>1966</td>
<td>Cyclone Dinah</td>
<td>Multiple</td>
<td>QLD/NSW</td>
<td>34</td>
<td>4685</td>
</tr>
<tr>
<td>4</td>
<td>1989</td>
<td>Newcastle Earthquake</td>
<td>Newcastle</td>
<td>NSW</td>
<td>862</td>
<td>4244</td>
</tr>
<tr>
<td>5</td>
<td>1973</td>
<td>Flooding Ex-Cyclone Wanda</td>
<td>Brisbane</td>
<td>QLD/NSW</td>
<td>68</td>
<td>3160</td>
</tr>
<tr>
<td>6</td>
<td>1982</td>
<td>Ash Wednesday Bushfires</td>
<td>Multiple</td>
<td>VIC/SA</td>
<td>176</td>
<td>2344</td>
</tr>
<tr>
<td>7</td>
<td>1984</td>
<td>Brisbane Hail Storm</td>
<td>Brisbane</td>
<td>QLD</td>
<td>180</td>
<td>2274</td>
</tr>
<tr>
<td>8</td>
<td>2010</td>
<td>Brisbane &amp; Lockyer Valley Flooding</td>
<td>SE Queensland</td>
<td>QLD</td>
<td>2022</td>
<td>2260</td>
</tr>
<tr>
<td>9</td>
<td>2006</td>
<td>ECL Severe Storm</td>
<td>Multiple</td>
<td>NSW</td>
<td>1480</td>
<td>2197</td>
</tr>
<tr>
<td>10</td>
<td>1966</td>
<td>Black Tuesday Bushfires</td>
<td>Hobart &amp; SE Tasmania</td>
<td>TAS</td>
<td>40</td>
<td>2157</td>
</tr>
</tbody>
</table>

*These events, which comprise two or more entries in the Disaster List, have been combined into a single event loss. 
*ECL is an East Coast Low, a severe storm impacting the eastern seaboard.
have been catalogued under hailstorms but deconstructing this history, even if this were possible, lies beyond the scope of this study. If our supposition of underreporting in the early part of the loss history is correct, then it means that our estimate of the average annual normalised loss should more appropriately be considered a lower bound and strengthens the conclusion that insured losses are not increasing in a normalised sense.

In terms of severe storm activity, only rainfall (Figure A7) shows any significant trend and this is negative ($p < 5\%$) but the main feature of this figure is the elevated incidence of hail and heavy rain in seasons 2009–2011. By inspection it looks as if the incidence of hail and heavy rain is mean-reverting but the short time series rules out more definitive analyses. Severe windspeeds show no trend over time ($p = .49$).
In the case of tropical cyclone losses (Figure A3), the regression trend is significant ($p = .04$) and this is almost true of bushfire losses Figure A4 ($p = .05$) but both regression lines have negative slopes and do not support expectations for an increase in normalised losses. For bushfire this is consistent both with previous studies (McAneney, Chen, &

Table 3. Breakdown of normalised losses by peril category. Percentages have been rounded up to single digit values.

<table>
<thead>
<tr>
<th>Peril</th>
<th>Nominal loss (millions of AUD)</th>
<th>Normalised loss (millions of AUD)</th>
<th>Proportion of normalised losses (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cyclone</td>
<td>5384</td>
<td>26,132</td>
<td>29</td>
</tr>
<tr>
<td>Hail</td>
<td>9672</td>
<td>25,060</td>
<td>27</td>
</tr>
<tr>
<td>Flooding</td>
<td>5276</td>
<td>13,658</td>
<td>15</td>
</tr>
<tr>
<td>Bushfire</td>
<td>3067</td>
<td>11,184</td>
<td>12</td>
</tr>
<tr>
<td>Storm</td>
<td>5089</td>
<td>9475</td>
<td>10</td>
</tr>
<tr>
<td>Earthquake</td>
<td>941</td>
<td>4652</td>
<td>5</td>
</tr>
<tr>
<td>Tornado</td>
<td>263</td>
<td>357</td>
<td>0</td>
</tr>
<tr>
<td>Other</td>
<td>505</td>
<td>645</td>
<td>1</td>
</tr>
</tbody>
</table>
Pitman, 2009; Crompton, McAneney, Chen, Pielke, & Haynes, 2010; Crompton, McAneney, et al., 2011) and with the absence of trends in the numbers of bushfire ignitions and burnt areas observed since 2001 (Appendix 3). No national databases of bushfire frequency or of areas burnt exist prior to this year.

For tropical cyclone, the clear reduction in losses observed over time (Figure A3) is consistent with declining numbers of landfalling cyclones observed since the late 1800s on the eastern seaboard south of Cairns (Callaghan & Power, 2011). Other evidence points to a longer-term decline in tropical cyclone activity in this area, beginning in the late 1700s/early 1800s (Haig, Nott, & Reichart, 2014). Whether human-caused climate change is contributing towards this decline is unknown to this point, but given the level of interannual, decadal and interdecadal variability, Callaghan and Power (2011) suggest it imprudent to assume that this decline in landfalling TC numbers will continue based on simple extrapolation of past trends.

Discussion

Methodological: Loss normalisation attempts to give a present-day perspective of historical events. It requires credible adjustment factors to translate historical losses to current societal conditions and having coherent data for these factors over the entire loss history. Following on from Crompton and McAneney (2008) and Crompton (2011), but in marked contrast with other normalisation studies, our approach deals explicitly with improved construction standards of newer homes in TC-prone areas. McAneney et al. (2007) suggest that these improvements have reduced insurance losses by some 67%. It could be argued that similar adjustments might be necessary for riverine flood and bushfire losses if risk-informed insurance premiums were to encourage more prudent land use planning, but there is no evidence that this is happening yet, and just how this might play out in the future is unknown. We’ll come back to this issue in later discussion.

Limitations to our methodology were discussed in detail in Crompton and McAneney (2008). Chief amongst these is our acceptance of the veracity of the Disaster List entries. Beyond cross-referencing with contemporaneous entries in PerilAUS, which revealed no anomalies amongst major events, and some research into the cost of individual key events such as Cyclone Tracy (Mason & Haynes, 2010), there is little alternative but to do so. As noted by Crompton and McAneney (2008), there has been a trend towards an increasing number of smaller events being included in the Disaster List and it might be timely that the ICA reconsiders its threshold cost for inclusion.

A second feature of our methodology is our use of normalisation factors developed for residential properties to normalise damage to all insured assets, including commercial and industrial buildings, motor vehicles, etc. In the absence of specific data on the breakdown of losses by a line of business and the availability of alternative normalisation factors, this shortcoming is unavoidable. Nonetheless for those events where we do have this detail, damage to residential homes contributes a significant component – roughly one half on average – of the total insured event loss and a lot more in particular cases (Roche, McAneney, Chen, & Crompton, 2013).

Some might argue that improving emergency management practices and resources, in the case of bushfire for example, might mean the lack of trend in the normalised losses
points to improving resilience and simply adjusting for increasing numbers and values of property disguises the true extent of a purportedly worsening climate (Nicholls, 2011). This view misses the key observation that most property losses take place under a few days of so-called ‘catastrophic’ conditions when fire behaviour is well beyond the control of firefighting agencies (Crompton, McAneney, et al., 2010; Crompton, McAneney, et al. 2011). This is being increasingly recognised since the 2009 Black Saturday fires in Victoria as the early evacuation of at-risk populations and saving of lives takes precedence over property protection, with the Wye River (2015) and the Sir Ivan (2017) fires two recent examples.

Similar arguments can be made in respect of the role of improved weather forecasts where there is no evidence that these have resulted in reduced property losses in severe bushfires, although they have undoubtedly saved lives (Crompton, McAneney, et al., 2011). The 2009 Black Saturday fires is a case in point of a bushfire disaster with large losses despite near perfect weather forecasts.

Adjusting for the Consumer Price Index (CPI) (https://tradingeconomics.com/australia/inflation-cpi) has been an oft-used normalisation methodology but one that performs poorly in our case. Figure 3 shows how employing CPI results in an apparent increasing trend in the adjusted losses post-2000. This increase is not matched by any comparable trends in peril incidence and intensity (Appendices 2 and 3). We believe this to be an artefact of CPI failing to correctly capture the full extent of changes in relevant societal and demographic factors. In contrast, our chosen normalisation process is successful in explaining the totality of the changes in demographics and wealth that have taken place and which have collectively contributed to the increase in the nominal losses over time (cf. Figure 1(A,B)). In particular, once we have normalised weather-related losses for changes that we know to have taken place (Figure 2), no residual signal remains to be explained by changes in the occurrence of extreme weather events, regardless of cause. And while more complicated adjustment models could be envisaged, they

![Figure 3. Historical event losses adjusted by Consumer Price Index (CPI). The increasing trend is not consistent with the underlying peril data (see text).](image-url)
are not justified given the performance of our adopted approach. The coherence of the normalised losses with the underlying peril data adds further confidence in the fidelity of our chosen methodology.

**Normalised losses:** The key result emerging from our study is that normalised losses aggregated by either season (or calendar year [data not shown]) exhibit no statistically significant trend over time. This outcome should come as no surprise given identical conclusions drawn from many other similar studies across different perils and jurisdictions (e.g. Pielke and Landsea, 1998; Pielke et al., 2008; Crompton and McAneny, 2008; Barredo, 2009, 2010; Di Baldassarre et al., 2010; Crompton et al., 2010; Crompton, McAneny, et al., 2011 and others reviewed by Bouwer, 2011; Barredo, Saurí, and Llasat, 2012; Barthel and Neumayer, 2012; Visser, Petersen, and Ligtvoet, 2014; Pielke, 2018; Mechler and Bouwer, 2015; Chen et al., 2018; Ye and Fang, 2018; Weinkle et al., 2018; Bouwer, 2019). We conclude that the principal driver of the rising cost of natural disasters continues to be societal factors such as where and how we choose to live.

With normalised losses approaching AUD 10 billion, 1966 emerges as the most costly of all seasons (Table 4). Perils in that season include two tropical cyclones, a bushfire and a flood; normalisation factors for these events are driven by the large increase in dwelling numbers and dwelling values. TCs Dinah and Elaine caused significant destruction with the former costing AUD 5.1 billion in normalised losses and inflicting the third largest insured loss of all events in the Disaster List (Table 1). Elaine exacted a normalised cost of AUD 2.3 billion and ranks at number 11. TC Dinah has a dwelling number adjustment factor of 8.3 reflecting large population growth in South East Queensland since 1966 and a dwelling value factor of 39.2. Dwelling value factors are very large for all seasons prior to 1970, after which house values increased dramatically during a period of high inflation that peaked at 17.5% in 1976 (https://tradingeconomics.com/australia/inflation-cpi).

Again in respect to the aggregated losses, only four seasons since 2000 rank in the top 10 (Table 4) with 2010 coming in at fifth, a reminder that recent years have not been especially anomalous. The ranking of normalised losses is slightly different when these are aggregated by calendar year with 1967 the most costly at AUD 11.3 billion; this view is relevant for insurers whose reinsurance policies are aligned by calendar year.

**Implications for policy**

The question – is climate change, human-caused or other, responsible for some quantifiable part of the increasing cost of weather-related natural disasters? – is often incorrectly

<table>
<thead>
<tr>
<th>Rank</th>
<th>Season</th>
<th>Nominal loss (millions of AUD)</th>
<th>Normalised loss (millions of AUD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1966</td>
<td>90</td>
<td>9681</td>
</tr>
<tr>
<td>2</td>
<td>1989</td>
<td>1293</td>
<td>6552</td>
</tr>
<tr>
<td>3</td>
<td>1998</td>
<td>1892</td>
<td>6285</td>
</tr>
<tr>
<td>4</td>
<td>1974</td>
<td>215</td>
<td>5449</td>
</tr>
<tr>
<td>5</td>
<td>2010</td>
<td>4151</td>
<td>4742</td>
</tr>
<tr>
<td>6</td>
<td>1973</td>
<td>114</td>
<td>4630</td>
</tr>
<tr>
<td>7</td>
<td>2014</td>
<td>3844</td>
<td>4229</td>
</tr>
<tr>
<td>8</td>
<td>1984</td>
<td>390</td>
<td>4097</td>
</tr>
<tr>
<td>9</td>
<td>2009</td>
<td>2190</td>
<td>3075</td>
</tr>
<tr>
<td>10</td>
<td>2016</td>
<td>2942</td>
<td>2993</td>
</tr>
</tbody>
</table>
conflated with a larger question as to whether or not anthropogenic climate change is real (Pielke, 2018). The lack of positive trends in normalised event loss histories of insurance (or economic losses), as observed here (Figure 2) is sometimes exploited by partisan actors to argue that climate change is unimportant. Conversely, others attribute the rise in the nominal value of weather-related event losses directly to climate change and then cite these as proof positive that action in this space is urgent. Both interpretations are misleading.

Rather, the results that emerge in this study and others like it simply reflect the fact that a climate change signal in insured losses, if present, is expected to be small to this juncture, and its detection in datasets characterised by large year-to-year and longer-term volatility is fraught (IPCC, 2014; Bender et al., 2010; Crompton, Pielke, & McAneney, 2011). Even if we just focus on the peril itself, attribution remains challenging: McAneney et al. (2017), for example, were unable to detect changes in either the frequency of floods or their peak heights in a high-quality, 122-year data set from the Ba River catchment of Fiji. The importance of that study is that it deals with flooding in a region where low lying Pacific Islands are seen as being particularly vulnerable to sea-level rise and which has seen contemporaneous increases in air temperature (Kumar, Stephens, & Weir, 2014). With less self-consistent datasets, such as the North Atlantic hurricane record (HURDAT2 database), which is unavoidably compromised by changes in observation platforms (Landsea, Harper, Hourau, & Knaff, 2006; Chen, McAneney, & Cheung, 2009; Landsea & Franklin, 2013), and, even within the satellite era, by improvements in coverage, resolution and signal processing (Landsea et al., 2006; Klotzbach, 2006), the task is much harder (Klotzbach, Bowen, Pielke Jr, & Bell, 2018). Logic suggests that any relationship between increasing mean global air temperatures and extreme weather will be complex, and both peril and location-dependent.

Normalisation provides insight into how past events might look today; it does not forecast the future and it would be incorrect to draw a conclusion from our work that changes in the frequency or intensity of extreme events will have no impact on future losses or that investment in proactive adaptation measures is unnecessary. At a minimum, a changing climate introduces additional uncertainty into forecasts of the future, and since uncertainty generally comes with an economic cost, proactive actions may make economic sense even in the absence of increasing normalised disaster losses. Further, the relatively slow turnover in housing stock combined with Australia’s skewed spatial distribution of the population (Chen & McAneney, 2006) creates the possibility of a disaster ‘mitigation gap’ developing if future climate change effects materialise faster than building codes can be enacted and housing stock fortified.

Lastly, insurance premiums are sometimes advocated as a driver of risk-reducing behaviours through the economic signals they send to property owners about exposure to risk (Kunreuther, 1978, 1996, 2006; McAneney et al., 2016). This outcome, however, is not axiomatic: rising insurance premiums in flood-prone areas, for example, may lead homeowners not to insure against this peril. On the other hand, naïve confidence in the management of upstream dams (e.g. van den Honert & McAneney, 2011) or in structural mitigation works like levees might perversely encourage councils to allow more building in areas prone to larger but less frequent floods (Burby, 2006; Gissing, van Leeuwen, Tofa, & Haynes, 2018). Either way, the upshot is that future insured losses from floods may become less correlated with the economic costs arising from this peril. A similar argument can be made in respect of bushfire (wildfire) losses. As loss data does not reflect climate change and as insurers
usually issue short duration policies on physical assets, we posit that it’s unlikely that the insurance system will drive needed adaptation measures.

It needs to be recognised that tackling climate change and reducing the cost of natural disasters are both important issues but addressing these will require different policy actions and societal responses. Moreover, large natural peril event losses will remain a problem independent of the degree to which they might be influenced by changes in the climate.

**Note**

1. PerilAUS contains information on natural peril events that have caused either loss of life or material damage to property and is considered complete since 1900 (e.g. Coates et al. (2014); Crompton et al. (2010) and Haynes et al. (2010)).

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**References**


### Appendices

**Appendix 1. Dwelling value factors and urban centres/localities**

Dwelling value factors ($D_{iik}$) were calculated using State/Territory data containing the impacted UCLs. In cases where multiple States or Territories contain impacted UCLs, an arithmetic average of the dwelling value factors for each State/Territory was used. The average nominal value of a new dwelling is calculated by dividing the value of residential building work completed within a season by the number of residential dwellings completed within the same time frame. Data for the value of residential building work completed within a season and the number of residential dwellings completed are available on a quarterly basis (Australian Bureau of Statistics (ABS) – [http://www.abs.gov.au](http://www.abs.gov.au)).

Broadly, an Urban Centre is defined as a cluster of contiguous Statistical Area 1’s (SA1s) that are ‘of urban character’ with ‘an aggregate population exceeding 1000 persons contained within’ (ABS – [http://www.abs.gov.au](http://www.abs.gov.au)). A Locality is defined as a cluster of contiguous Statistical Area 1s (that do not necessarily have to be ‘of urban character’) containing between 200 and 999 persons. The number of dwellings in each UCL has been reported in all census years since 1966 in the Censi of Population and Housing (ABS – [http://www.abs.gov.au](http://www.abs.gov.au)). All data points collected from censuses are attached to the date of the census night. Dwelling numbers were linearly interpolated between successive census years.

It is common for new UCLs to be created and existing UCLs to merge into other, larger UCLs. For example, many older Western Sydney and Blue Mountains UCLs have been aggregated into Sydney and Blue Mountains over time, as those urban areas have expanded and subsumed smaller towns. Occasionally events in the Disaster List took place in UCLs that no longer exist today, or conversely, occurred in places where there are now UCLs that did not exist in season $i$. Each of these situations was examined on a case-by-case basis. In some instances where an UCL only appears once in either 2017 or season $i$, data is ignored and the factor determined from the remaining UCLs. Other cases requiring special attention include the 1968 Blue Mountains bushfires that impacted what is now the Blue Mountains UCL. In 1968 this UCL did not exist; in fact, there were few UCLs covering that area, none of which exist today. By way of a solution, the Blackheath UCL was used as an approximation for the purposes of calculating the normalising factors in the nearby impacted area. This approach must be done with care, as even geographically close towns can have quite different growth rates. In this particular case, the growth rate of the Blue Mountains roughly matches that of Blackheath (which itself is in the Blue Mountains), and as such is the best option given the available data.
Appendix 2. Times series of losses by weather-related perils

Figure A1. Normalised insurance losses caused by severe storms by financial year: 1966–2017. The absence of losses prior to 1976 is discussed in the text but is believed to be due to underreporting.

Figure A2. As for Figure A1 but for flooding losses.
Figure A3. As for Figure A1 but for tropical cyclone losses.

Figure A4. As for Figure A1 but for bushfire losses.
Appendix 3. Time trends in the underlying climate-related perils

Confidence in the fidelity of the normalisation process is enhanced if the normalised loss history is consistent with patterns of behaviour of the underlying perils. In what follows we examine the latter for time periods when the data is considered complete.

**Bushfires:** There exists no consistent database detailing historical bushfire severity and frequency over the time period of interest: 1966–2017. This being the case, we have created one using the latest version of MODIS Burned Area product (Version 6) (NASA LP DAAC, 2018) to determine the frequency of ignitions and the area burnt since 2001. No data exists prior to 2001. The MODIS mapping algorithm detects the approximate date of burning on a per-pixel basis at 500 m resolution. Burnt areas and a number of ignitions were aggregated for each season (1 July to 30 June) both on a national basis and also for latitudes less than −26 degrees. The latter categorisation was chosen to correlate more closely with the spatial distribution of damaging events in Risk Frontiers’ PerilAUS database and, in particular, to eliminate fires in the Northern Territory where the fire is used as a land management tool and, while large areas are burnt each year, little property damage occurs.

No significant linear relationship was found between areas burnt or numbers of ignitions and time – all p values are greater than .05 (data not shown). This is unsurprising given the short 17-year database.

**Flooding:** In respect of riverine flooding we use the daily gridded rainfall data from the Australian Water Availability Project (AWAP) (Jones et al., 2009) in conjunction with a semi-distributed rainfall-runoff model to derive a 117-year storm discharge history (1900–2017) for Australian river catchments. These catchments are those that feature in the National Flood Information Database (Leigh et al., 2010; McAneney et al., 2016). Catchments are aggregated by Australian Climate Zone classifications (see below).

AWAP provides daily (24-h, from 9 am AEST the day before to 9 am the current day) rainfall maps across Australia on a 0.05° grid (~5 km²) from 1900 to present (Jones et al., 2009). AWAP is derived only from observations; it does not use a climate model. It uses all available rain station data across the country held in the Australian Data Archive for Meteorology. Data quality at any location is dependent on the density of observations.

Australian Climate Zones are distinguished by differences in rainfall totals and seasonal patterns (Bureau of Meteorology [BOM], 2018). The median annual rainfall (based on the 100-year period from
1900 to 1999) and seasonal incidence (the ratio of the median rainfall over the period November to April to the period May to October) are employed to identify six zones: Summer dominant; Summer; Uniform; Winter; Winter dominant and Arid. These six classification groups identify the season of the highest rainfall in each area.

Figure A6. Number of proxy flood events register per climate zone per year: 1900–2107.

Figure A7. Number of severe storm events per ‘season’ in Capital Urban Centre Localities (Appendix 1).
The rainfall-runoff model used a curve-number-based approach (Soil Conservation Service, 2002), and incorporates simple physical catchment properties such as shape, hydraulic length, slope, land use and hydrologic soil type, to model river discharge response.

Heavy precipitation days (>10 mm/24 h, as per the World Meteorological Organization’s definition) were identified in the record and the peak discharge response retained. Catchments were grouped according to Australian Climate Classification zones and the annual frequencies of storm discharge events per climate zone calculated. We refer to riverine storm discharge during heavy precipitation events as ‘proxy flood’ events; over the long-term, the two phenomena are closely correlated.

Figure A6 shows the annual frequency of proxy flood events per climate zone over the period 1900–2017. As can be seen, there are no significant (to 95% confidence interval) linear trends for any of the six climate zones, although the time series exhibit pronounced interannual to multidecadal fluctuations. While not examined in any detail here, this volatility is likely the result of regional climate forcing such as El Niño Southern Oscillation (ENSO), and the Interdecadal Pacific Oscillation (IPO), both of which are known to be significant drivers of rainfall variability in Australia (Verdon et al., 2004).

Tropical cyclones: Callaghan and Power (2011) document a declining number of landfalling cyclones since the late 1800s (and perhaps from the late 1700s (Haig et al. 2014)) on the eastern seaboard south of Cairns. Landfall numbers are in part modulated by decadal variability in El Niño-Southern Oscillation and show a considerable variation on a multi-decadal timescale. This observed decline is consistent with the direction of the projections of Knutson et al. (2015) under global warming, but Callaghan and Power (2011) warn that to this juncture the role of global climate change in this observed decline is unknown.

Severe storms: Severe storm data were sourced from the BOM Severe Storms Archive (www.bom.gov.au/australia/stormarchive/about.shtml). For our purposes and in keeping with the Bureau’s definitions, severe weather is defined as an event that has wind gusts in excess of 90 km/h or hail in excess of 2 cm diameter or heavy rainfall likely to cause flash flooding. Thresholds for heavy rainfall vary geographically but are often in excess of 50 mm/30 min. Windspeed is measured at 10 m height. Storm events encompassing all three attributes are possible but for our purposes the perils were examined independently.

These data were combined with Geographical Information Data from the 2016 census across Australia between 1 January 1990 and 31 December 2017, with 1990 chosen as a start date to encompass improvements in data recording that took place during the 1980s. To account for localised reporting bias (more frequent reporting in areas with denser population), only events within Capital City Urban Centre Localities (populations > 50,000) were analysed. ‘Seasons’ again begin 1 July and end 30 June to incorporate southern hemisphere seasonality.

Figure A7 shows numbers of hail events, rain, and severe winds for Capital City UCLs. No significant linear trends are observed although the period 2009 to 2011 stands out as particularly stormy at least in terms of hail and heavy rain events.