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Quantifying catastrophic and climate impacted hazards based on local expert opinions

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Abstract

The analysis of catastrophic and climate impacted hazards is a challenging but important exercise, as the occurrence of such events is usually associated with high damage and uncertainty. Often, at the local level, there is a lack of information on rare extreme events, such that available data is not sufficient to fit a distribution and derive parameter values for the frequency and severity distributions. This paper discusses local assessments of extreme events and examines the potential of using expert opinions in order to obtain values for the distribution parameters. In particular, we illustrate a simple approach, where a local expert is required to only specify two percentiles of the loss distribution in order to provide an estimate for the severity distribution of climate impacted hazards. In our approach, we focus on so-called heavy-tailed distributions for the severity, such as the Lognormal, Weibull and Burr XII distribution. These distributions are widely used to fit data from catastrophic events and can also represent extreme losses or the so-called tail of the distribution. An illustration of the method is provided utilising an example that quantifies the risk of bushfires in a local area in Northern Sydney.

Keywords: Catastrophic Risks, Climate Impacted Hazards, Expert Opinions, Local Level Decision Making, Loss Distribution Approach

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1) Introduction

Extreme events, such as flooding, storms, droughts and bushfires are already part of the natural cycle of weather patterns in Australia and contribute to around $1 billion of insured losses annually (Compton and McAneney, 2008). The most recent IPCC AR5 WG2 report states with high confidence that "existing environmental stresses will interact with, and in many cases be exacerbated by, shifts in mean climatic conditions and associated change in the frequency or intensity of extreme events, especially fire, drought and floods." (IPCC, 2014: 16). This indicates that climate change is likely to affect the occurrences of extreme events and their associated damage. Preparatory measures in the form of mitigation and adaptation are required to alleviate the risks at all levels of government. The particular challenge of climate change adaptation and the need to build community resilience to natural disasters for Australia has also been pointed out by, e.g., Newton (2009), Roiko et al (2012), Ross and Carter (2011).

Irrespective of the level of mitigation policy, the long life time of Greenhouse Gases means that mitigation efforts will take a long time to have an impact and that it is necessary to plan for adaptation to damages arising from climatic change. The effects of climate change on extreme events vary across locations, signifying the role of local government decision-making. At present, local government decision makers' are in a state of inertia due to the complexity and range of uncertainties surrounding extreme event analysis and adaptation decision-making, see, e.g., Mathew et al (2012). The precautionary principle encourages early action to protect the environment when there is potential for serious or irreversible damage (UN, 1992). This rationalises the implementation of preparatory measures against extreme events (Stern, 2006) placing decision makers liable to make appropriate decisions for the welfare of their community. It is also possible that, in the future, government officials will become legally bound to make wise adaptive measures.

The main issue decision makers' face is the absence of proper guidance to understand the effects of various uncertain parameters in analysing extreme events and assessing their damage. In general, extreme event analysis is challenging because of data scarcity and the unknown effects of climate change on the frequency and severity of the events. Another analysis challenge is caused by the absence of long records of observations where statistical trends can be drawn. Even if historical observations are present, they may or may not represent future occurrences of extreme events as the effects of climate change can alter the frequency and severity of the events. Further to this, assessing the quantitative damage due to extreme events over a period of time introduces other parameters of uncertainty including the discount rate and growth rate, see, e.g., Trück et al (2010), Mathew et al (2012). With a focus on the local level, this paper discusses cases where the available data is insufficient to fit a distribution or derive parameter values of distributions for modelling extreme event severity or frequency.

In the absence of local observations, one way to estimate parameter values of distributions is to engage local experts to solicit their opinions (Schröter et al, 2005; Næss et al, 2006). While most people have an intuitive understanding of the mean of a probability distribution, without additional statistical training it is much more difficult to understand or specify the variance of a probability distribution. This problem becomes even more pronounced in the context of asymmetric or heavy-tailed distributions that are usually required for modelling catastrophic or climate-impacted hazards. Given the difficulty an expert in the field may have in appropriately specifying the variance or scale parameter of a distribution, we believe that such prior beliefs about the severity distribution of events may be more accurately captured by asking experts for quantile values rather than values for means and variances of a distribution.

This paper will explain in detail how parameters of a probability distribution can be determined so that the estimated distribution is consistent with two quantile values that have been specified by an expert. We will present algorithms and closed-form solutions for the computation of the parameters. In particular, we will illustrate the approach using asymmetric and heavy-tailed distributions such as the Lognormal, Weibull and Burr XII distribution. All or some of these distributions have been utilised in studies focused on extreme events and have been applied to hurricanes (Levi and Partrat, 1991; Braun, 2011), earthquakes (Braun, 2011), extreme rainfall (Esteves, 2013; Papalexiou et al., 2013), floods (Mathew et al., 2012), climate sensitivity (Pycroft et al., 2011) and sea-level rise (Pycroft et al. 2014). Using the so-called loss distribution approach (LDA) that has gained popularity in the financial sector for modelling insurance claims or losses arising from operational and credit risks within the banking industry (Klugman, *et al.,* 1998; Bank for International Settlements, 2001) we will then illustrate how the derived distributions can be used to quantify existing catastrophic and climate impacted hazards also over a longer time horizon.

The remainder of the article is set up as follows. Section 2 outlines the framework of estimating potential risks from catastrophic and climate impacted events. The section also illustrates the derivation of parameter values for the severity distributions of catastrophic events based on expert estimates. Section 3 provides a case study for the analysis of risks from bushfires for the Northern Sydney Ku-ring-gai area. Section 4 discusses the use of these estimates for quantifying losses from climate impacted events over a longer time horizon, while Section 5 concludes the paper and provides directions for future research.

2) Modelling Catastrophic Events

In the following, we illustrate how to determine the aggregate loss distribution for extreme climate impacted hazards using the so-called loss distribution approach (LDA). We further show how to calculate measures for the risk from catastrophic events, for example the expected loss or higher quantiles of the aggregate loss distribution from climate impacted events over a longer time horizon. Such measures are of particular interest to local decision makers when investments into climate change adaptation projects are being considered.

The LDA is a statistical approach for generating an aggregate loss distribution using an appropriate distribution for the frequency and severity of an event type. The approach is particularly popular in the finance and insurance industry, see, for example, Klugman et al (1998), Bank of International Settlement (2001). One of the most frequently used specifications of this approach is to apply a Poisson distribution for the frequency and a Lognormal distribution for the severity of a particular hazard (Klugman et al., 1998)

To compute the probability distribution of the aggregate loss over a one year time horizon, we need to estimate the probability distribution function of a single event loss and its frequency for one year. For example, if we are interested in the risk from bushfires for a local region, under the LDA we need to estimate the probability distribution functions of residential property loss from bushfires and the bushfire frequency over a one year horizon. Under optimal circumstances, the estimation procedure should utilise internal and external data as well as expert judgements, see, e.g., Shevchenko and Wüthrich (2006). Unfortunately, at the local level there is often hardly any historical data available on losses from extreme climatic events. Under such circumstances it is then not possible to fit a distribution to historical data from observed events. Also, climatic change or characteristics of the region such as additional dwellings and infrastructure investments may have changed the expected occurrence and impact of catastrophic events. Therefore, we suggest using expert estimates on the frequency and severity of climate impacted hazards to create a model that can appropriately describe the risk. Having established probability distribution functions for the occurrence and magnitude of catastrophic events, it will then be possible to compute the cumulative loss distribution for a particular year, but also over a longer period of time.

In the LDA, the frequency distribution and severity distribution are assumed to be independent and can then be modelled separately. In this section we will outline how expert estimates can be used to determine a probability distribution for the frequency of and severity of catastrophic or climate impacted events. We will also illustrate a procedure that can be used to derive a distribution for aggregate losses for a single year or over a longer time horizon, what is of particular interest for investments into climate change adaptation.

2.1 The loss distribution approach (LDA)

The LDA (Klugman et al., 1998, Bank of International Settlement, 2001) is used in this paper to generate an aggregate loss distribution. We define the cumulative loss G over a time horizon as

$$G = \sum_{i=1}^{N} X_i \qquad (1)$$

where N is the number of events over a considered time period (usually one year), modelled as a random variable from a discrete distribution. The $X_i, i = 1, ..., N$ denote severities of the events modelled as independent random variables from a continuous distribution.

The LDA, allows for the computation of the expected loss, i.e. the average outcome, but also for the computation of the loss at a given confidence level α. As mentioned above, the distribution for the number of events can be defined over any time horizon, for example, one month, 6 months, one year, 5 years, etc. However, for rare events like catastrophic losses or operational risks in the banking sector, the distribution is usually estimated for a one year time horizon. We decided to follow this approach and specify the distribution for the frequency also for a time horizon of one year. However, by considering several subsequent years in the simulation analysis, we are also able to derive outcomes for losses arising from extreme climate events over a longer time horizon. The methodology to adapt the approach for multiple years is explained in Section 4.1.

With a focus on one year, the expected loss, *EL*, and the loss at a given confidence level α, $L(\alpha)$, are then defined by

$$EL = \int_0^\infty x dG(x) \qquad (2)$$

and

$$L(\alpha) = \inf\{x \mid G(x) \geq \alpha\} \qquad (3)$$

The expected loss is the expected value of the aggregate loss distribution function *G*, whereas the loss at a confidence level α is simply the α-percentile of the aggregate loss distribution. Using Monte Carlo simulation allows us to generate the aggregate loss distribution of the event and obtain percentile estimates, such as the 90% and 99% quantile for the aggregate losses. The accuracy of the estimation depends on the adequacy of the parameter estimates but also on the number of simulations in the Monte Carlo approach; refer to Fishman (1996) for an explanation. As a result, it is usually recommended to run a high number of simulations.

2.2 Estimating the frequency distribution

The frequency of events is usually modelled using a discrete probability distribution such as, e.g., the Bernoulli, Binomial, Poisson or Geometric distribution. Discrete distributions apply to a random variable whose set of possible values is finite or countable. Hence the frequency of an event, as a countable discrete random variable, can be modelled by a discrete distribution.

In this paper, we assume that the annual frequency of a catastrophic event N can be modelled using a Poisson distribution with parameter λ. The probability mass function of the Poisson distribution is given by

$$P(N = k) = \frac{\lambda^k}{k!} e^{-\lambda}, \qquad (4)$$

where k denotes the number of events and λ is the sole parameter of the Poisson distribution.

For the Poisson distribution, the expected number of events per year is

$$E[N] = \lambda. \qquad (5)$$

Figure 1 provides a plot of the probability mass function (PMF) of the Poisson distributions with values for $\lambda=0.5$ and $\lambda=5$. For $\lambda=0.5$, corresponding to an average of 0.5 events per year, one can see that the distribution is skewed to the right. The highest probability is allocated to zero events, $P(N=0)=0.6065$, while the probability for one event is approximately 30%. Therefore, less than 10% of the probability mass are allocated to observing two events or more for $\lambda=0.5$. For $\lambda=5$, corresponding to an average number of 5 events per year, the distribution is more symmetric and the highest probabilities are assigned to observing four or five events with $P(N=4)=P(N=5)=0.1755$. There is a probability of observing three events or less of $P(N\leq3)=0.2650$ and a probability of observing more than five events of $P(N\geq6)=0.3840$.

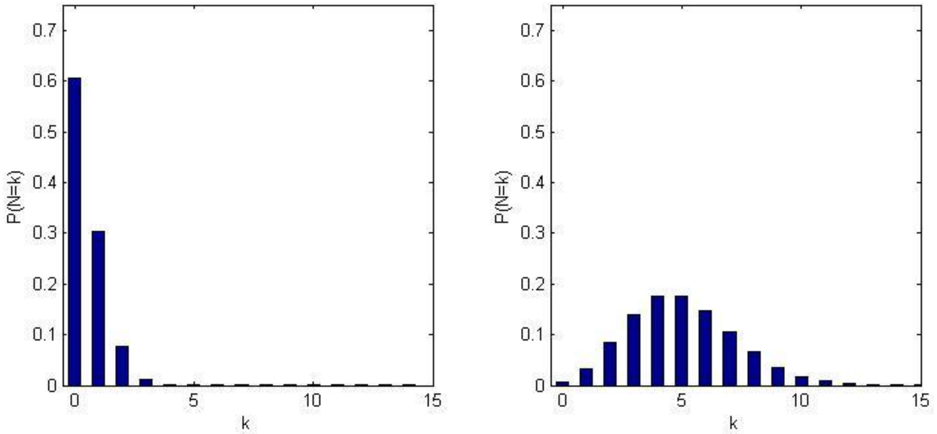

Figure 1: Probability mass function (PMF) for a Poisson distribution with $\lambda=0.5$ (left panel) and $\lambda=0.5$ (right panel).

For our empirical analysis, with a focus on expert elicitation, we assume that an expert will be able to give an estimate for the expected number of events.[2]

2.3 Estimating severity using quantiles

Extreme events are rare and accordingly it can be difficult to obtain sufficient historical data to fit a distribution. However, as decision makers are faced with the possibility of extreme losses, calculating a distribution that estimates the probability of future events is important. The approach we present involves the elicitation of an expert estimate for the value of two quantiles for the severity of the losses and then using these estimates to calculate the parameters of the probability distribution.
Thus, our approach only requires an expert to specify provide two different quantiles or percentiles for the severity of losses, i.e. $P(X < x_1) = p_1$ and $P(X < x_2) = p_2$ in order to derive the parameters of the severity distribution. Such a specification is usually much easier than providing actual parameters for a distribution, since the approach does not require the expert to understand the impact of the location, scale or shape parameters on the shape of a heavy-tailed distribution or potential losses.

[2] For applications of combining expert estimates with the empirically observed frequency of events using Bayesian analysis, see for example, Shevchenko and Wüthrich (2006), Mathew et al (2011) or Mathew et al (2012).

In our empirical application, we will use the median of the distribution, i.e. p_1=0.5, and a more extreme outcome for the distribution, the 95th percentile p_2=0.95, however, the approach can be applied as long as the expert provides estimates for any two arbitrary quantiles of the distribution. Further, it is important to keep in mind that the applied Lognormal, Weibull and Burr Type XII distributions are highly skewed to the right and may exhibit heavy tails. Due to the skewed shape of the distribution, the mean is typically influenced by extreme values of the distribution and significantly greater than the median. Therefore, it will typically be easier for an expert to specify the median as a more robust statistic of the distribution, separating the higher half of the potential losses from the lower half.

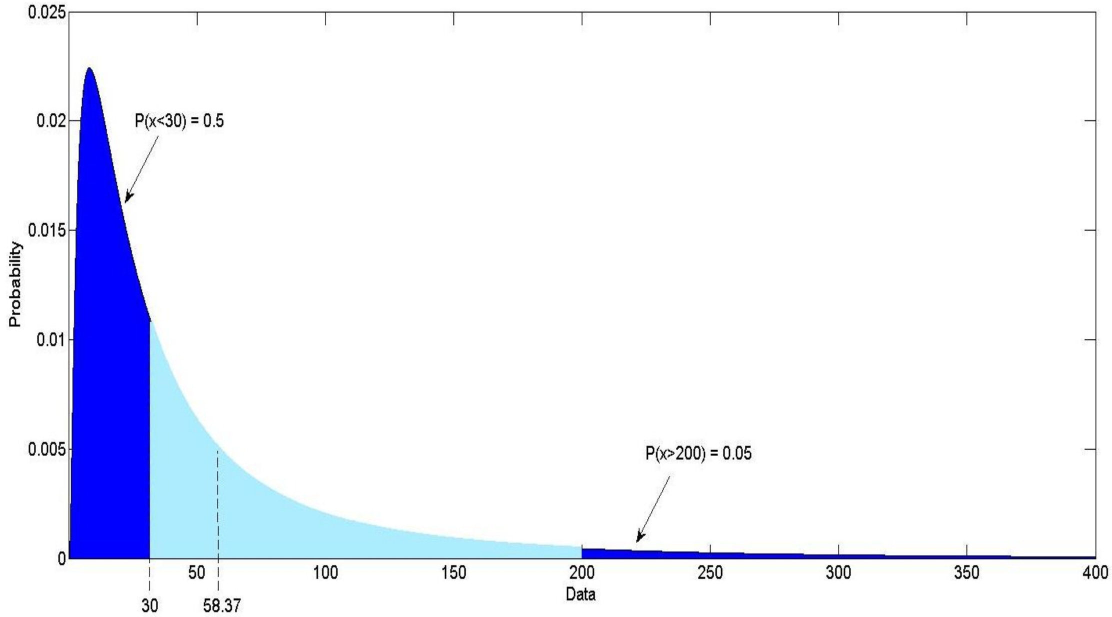

Figure 2: Probability density function (PDF) for a Lognormal distribution, with parameters $\mu = 3.40$ and $\sigma = 1.15$. The distribution exactly matches the conditions (i) P(X < 30) = 0.5, and, (ii) P(X < 200) = 0.95. The plot also illustrates that the mean of the specified distribution, E(X)=58.37, is significantly greater than the median $q_{0.5}$*=30 of the distribution.*

Figure 2 presents an exemplary probability density function (PDF) for the Lognormal distribution, where the parameters $\mu = 3.40$ and $\sigma = 1.15$ were calculated based on an expert specifying (i) the median to be equal to 30, i.e. P(X < 30) = 0.5, and, (ii) the 95th percentile of the distribution to be equal to 200, i.e. P(X < 200) = 0.95. The dark blue area between 0 and 30 to the left of the specified median illustrates that there is 50% chance for the loss to be less or equal than 30. On the other hand, the dark blue area to the right of 200, the specified 95th percentile, is equal to 0.05, indicating that there is only a 5% chance of observing losses that are greater than 200. Thus, the specified distribution with $\mu = 3.40$ and $\sigma = 1.15$ perfectly matches the conditions specified by the expert. The figure also illustrates that the mean of the distribution, *E(X)=58.37,* is clearly greater than the median which is indicative of the heavy-tailedness of the Lognormal distribution. This is a property of fat tailed distributions that is in contrast to the Gaussian normal distributions where the mean and median coincide. As mentioned in the previous paragraph and also based on previous experience with expert quantile estimations, we believe that it will be easier for a local expert to provide information on the median of the distribution than on the mean.

The following sub-sections will illustrate how to compute parameter values for a Lognormal, a Weibull and a Burr XII distribution. As noted in the introduction, these distributions have been applied to the analysis of extreme events, such as hurricanes (Levi and Partrat, 1991; Braun, 2011), earthquakes (Braun, 2011), extreme rainfall (Esteves, 2013; Papalexiou et al, 2013), floods (Mathew et al, 2012), climate sensitivity (Pycroft et al, 2011) and sea-level rise (Pycroft et al, 2014).

2.3.1 The Lognormal Distribution

The Lognormal distribution with parameters μ and σ can be stated in terms of the normal distribution. If the severity X follows a Lognormal distribution, i.e. $X \sim \text{Lognormal}(\mu, \sigma)$, log(X) is normally distributed with parameters μ and σ, i.e. log(X) ~ N(μ, σ). The Lognormal distribution has been widely used for the analysis of extreme risk in the finance industry and the Bank for International Settlements identifies the Lognormal distribution as the default option for modelling the severity of losses from operational risks (BIS, 2010). Amongst many other applications, the distribution has been applied to indices for property losses resulting from catastrophic events in the US (Burnecki et al., 2000) and climate sensitivity (Calel et al, 2013).

Now, let's assume that an expert is able to provide two different quantiles for the severity of losses, i.e. $P(X < x_1) = p_1$ and $P(X < x_2) = p_2$. Then the parameters of the Lognormal distribution can be estimated using this information only. In our empirical application, we will use the median of the distribution (p_1=0.5) and the 95th percentile (p_2=0.95), however, the approach is applicable to any two quantiles of the distribution.

The inverse cumulative distribution function (CDF) of the normal distribution is

$$F^{-1}(p; \mu, \sigma) = \Phi^{-1}(p)\sigma + \mu, \qquad (6)$$

where Φ^{-1} denotes the CDF of the standard normal distribution. From equation (6), we can derive equations for the parameters of the Lognormal distribution in terms of the probabilities p_1 and p_2 and the corresponding percentile values x_1 and x_2. We get the following closed-form expressions for μ and σ, see, e.g., Cook (2010).

$$\mu = \frac{x_1\Phi^{-1}(p_2) - x_2\Phi^{-1}(p_1)}{\Phi^{-1}(p_2) - \Phi^{-1}(p_1)} \qquad (7)$$

and

$$\sigma = \frac{x_2 - x_1}{\Phi^{-1}(p_2) - \Phi^{-1}(p_1)}\,. \qquad (8)$$

Therefore, it is straightforward to obtain the parameter estimates for the Lognormal distribution. As mentioned above with $X \sim \text{Lognormal}(\mu, \sigma)$ we get log(X) ~ N(μ, σ), such that μ and σ can be derived using the following expressions:

$$\mu = \frac{\log(x_1)\Phi^{-1}(p_2) - \log(x_2)\Phi^{-1}(p_1)}{\Phi^{-1}(p_2) - \Phi^{-1}(p_1)} \qquad (9)$$

and

$$\sigma = \frac{\log(x_2) - \log(x_1)}{\Phi^{-1}(p_2) - \Phi^{-1}(p_1)}\,. \qquad (10)$$

The derived parameters of equation (9) and (10) will then satisfy the conditions $P(X < x_1) = p_1$ and $P(X < x_2) = p_2$ specified by the expert.

2.3.2 The Weibull Distribution

The Weibull distribution was originally formulated to test the tensile strength of brittle materials[3] (Weibull, 1951) and has been applied to a wide range of uses. This includes, for example, the modelling of insurance claims resulting from natural catastrophe events in the US (Chernobai et al., 2006), losses from operational risks in the banking industry (Chernobai et al., 2010), reinsurance premiums based on fire loss data (Cummins et al., 1990), the modelling of extreme returns from investments (Goncu et al., 2012) and wind speed frequency distributions for use in the analysis of wind energy potentials (Justus et al., 1976; Stevens and Smulders, 1979; Seguro and Lambert, 2000). The Weibull distribution is defined by a shape parameter k, and a scale parameter λ, and is denoted by the following CDF:

$$F(x;\lambda,k) = 1 - \exp\left(-\left(\frac{x}{\lambda}\right)^k\right) \qquad (11)$$

The inverse CDF of the Weibull distribution can then be expressed as

$$F^{-1}(p;\lambda,k) = \lambda(-\log(1-p))^{1/k}. \qquad (12)$$

Again, we assume that an expert is able to provide two different quantiles for the severity of losses, i.e. $P(X < x_1) = p_1$ and $P(X < x_2) = p_2$. Using equation (12), we can then solve for the shape parameter k and scale parameter λ

$$k = \frac{\log(-\log(1-p_2)) - \log(-\log(1-p_1))}{\log(x_2) - \log(x_1)} \qquad (13)$$

$$\lambda = \frac{x_1}{(-\log(1-p_1))^{1/k}} \qquad (14)$$

to obtain a Weibull distribution satisfying the conditions specified by the expert.

2.3.3 The Burr XII Distribution

The Burr XII distribution is a continuous probability distribution for non-negative random variables. If has three parameters, a scale parameter α, and two shape

[3] Weibull's 1951 paper was titled 'A statistical distribution function of wide applicability'.

parameters c and k. Due to its three parameters, the Burr XII distribution can capture a wide range of values for skewness and kurtosis. Like the Lognormal distribution, it belongs to the class of heavy-tailed distributions what makes it very suitable for modelling extreme or catastrophic losses. It also has become widely utilised for modelling the distribution of household income[4] and has been applied to modelling insurance claims and losses from operational risks, see e.g. Chernobai et al. (2006), Cummins et al. (1990), Embrechts and Schmidli (1994), just to name a few. It has also been applied to the analysis of the duration of volcanic eruptions (Gunn et al., 2013) and the modelling of irregularities in tree diameter (Tsogt and Lin, 2012). The Burr Type XII distribution also includes other distributions as special cases, for example the Lognormal, Gamma or Pareto Type II distribution and has the Weibull distribution as a limiting case (Rodriguez, 1977). So it is clearly the most flexible out of the three distributions considered in this study.

The Burr Type XII distribution is a three-parameter family of distributions with CDF

$$F(x; \alpha, c, k) = 1 - \left(1 + \left(\frac{x}{\alpha}\right)^{c}\right)^{-k}, \tag{15}$$

where c and k are shape parameters and α is a scale parameter. Given the specification of two different quantiles for the severity of losses, $P(X < x_1) = p_1$ and $P(X < x_2) = p_2$ by an expert, we are also able to estimate a Burr distribution that can match these quantiles. Note that due to the fact that the Burr Type XII distribution has three parameters and only two conditions need to be matched, there is not a unique solution for the parameter values. We therefore decided to set the scale parameter α equal to the median specified by the expert, i.e. we set $\alpha = x_1$ with $P(X < x_1) = 0.5$. This procedure also significantly facilitates the estimation of the remaining two parameters. Unfortunately, there is no closed-form solution as for the Lognormal and Weibull distribution. Instead an optimisation algorithm is used to solve for estimates of the two shape parameters c and k that match the conditions.[5]

2.4 Simulation of Aggregate Losses

Having defined the specification of the frequency and severity distributions, this section outlines how we combine these functions into estimates for the aggregate losses. Combining the frequency and severity of the losses is a well-known actuarial technique (Klugman et al, 1998). Usually, Monte Carlo simulation is used to compound the severity and frequency distribution and calculate the aggregate losses for an event type, see, e.g., Fishman (1996).

With the utilisation of Monte Carlo simulation we generate an annual loss distribution using a simple simulation algorithm that follows the following steps:

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[4] Note that the Burr XII distribution is also known as the Singh and Maddala distribution within discussions of household income distributions – refer to Singh and Maddala (1976) and Jäntti and Jenkins (2010) for further details.

[5] Tools for performing this optimisation are available, for example, in R or Matlab, but the estimation can also be conducted with Microsoft Excel using the Solver Analysis Tool. The optimisation will need to solve for the two shape parameters c and k that yield $(F(x_1) - p_1)^2 + (F(x_2) - p_2)^2 = 0$.

1. Take a random draw from the frequency distribution: suppose this simulates N events per year.
2. Take N random draws from the severity distribution: denote these simulated losses by $L_1, L_2, \ldots, L_N$.
3. Sum the N simulated losses to obtain the simulated annual loss $G = L_1+L_2+\ldots+L_N$.
4. Return to Step 1, and repeat k times. Then we will obtain $G_1, G_2, \ldots, G_k$ annual losses, where k is a large number that enables us to derive a distribution for the aggregate losses.

Note that the number of simulation runs should be chosen to be at an appropriately high level, k=10000, for example, or even higher given that the simulation is intended to be conducted for extreme events that are severe but rare. In our empirical study we have decided to use 100,000 simulation runs.[6]

As mentioned above, this section defines the LDA for a simulation approach focused on a one period example. However, if the intended analysis involves the comparison of different adaptation strategies over a longer period of time, it will be necessary to simulate not just for one year but over a longer period of time. The described algorithm can be easily adjusted for this purpose and the simulated losses for each year t=1,2, …, T can be discounted using a specified discount rate *d*. It might also be necessary to adjust the model parameters of the frequency and severity distribution through time. An example is the case where an increase in the frequency and/or severity of the catastrophic event is assumed to occur over time, what may be a possible scenario for climate impacted hazards. Assuming that the effects on the parameters of the frequency and/or severity distribution through time can be quantified correctly, it is then possible to produce figures for the costs or benefits of different adaptation strategies. The case study for bushfire risk in Ku-ring-gai in section 3.2 presents an application of the procedure for conducting an assessment of the frequency and/or severity of an extreme event over a long time horizon (i.e. 40 years) and produces cost estimates for property loss.

3) Empirical Results

3.1 Case Study - Bushfires in the Ku-ring-gai area

In this section we apply the developed framework to a case study of bushfires in the Ku-ring-gai local government area in Northern Sydney, Australia. Bushfires have been chosen as an example, as there is a growing literature that suggests an increase in the number of days with weather conducive for bushfire occurrences, which also means that the extended fire seasons may reduce the number of days suitable for controlled burning which is an important adaptation measure currently practised in Australia (Lucas et al, 2007). Also the IPCC 2014 reports state that “there is high confidence that increased incidence of fires in southern Australia will increase risk to people, property and infrastructure” (IPCC, 2014: 25). Many Australian local governments have been recognising that worst case bushfire damages can be more frequent. For instant, the Final Report of the 2009 Victorian Bushfires Royal

[6] Note that for catastrophic or climate impacted hazards, the frequency parameter λ is typically rather small with $\lambda \ll 1$. Therefore, in many of the simulation runs, we will get zero events even when a longer time horizon of, e.g., 40 years is being considered.

Commission noted that it would be a mistake to treat the Black Saturday bushfire event that claimed hundreds of lives and destroyed thousands of homes as a 'one-off' event and that "with populations at the rural–urban interface growing and the impact of climate change, the risks associated with bushfire are likely to increase" (VBRC, 2010). Amongst other considerations, the Ku-ring-gai area has been chosen as the basis for the analysis as it has a high risk of bushfire due to the prevalence of 18,000 hectares of bushland and 89 kilometres of urban/bushland interface (Taplin et al, 2010). In addition, the area has 13,000 homes (equivalent to 36% of the total) with a high risk rating for property damage (Chen, 2005). Thus the bushland and houses at the bushland interface place the Ku-ring-gai local government area highly vulnerable to bushfire damage.

We compute parameter values for a Lognormal, Weibull and Burr Type XII distribution, using information we have elicited from a local government's bushfire expert for the Ku-ring-gai area. The expert specified the following information about frequency and severity of bushfires at the local level:

(i) Under current conditions, a severe bushfire is expected to happen approximately once every ten years (λ=0.1), while only one in five of these fires would damage houses.

(ii) For severity, the expert provided information on the 50th percentile of the distribution, i.e. the median, and a 95th percentile estimate of the severity distribution, i.e. a worst-case scenario. The estimates provided by the expert for these quantiles are $q_{0.5}$=30 and $q_{0.95}$=200 houses damaged, respectively.[7]

3.2 Estimating the Severity using Expert Opinions

As reviewed in Section 2.3, property loss distributions have been built using an expert estimate that the median number of houses damaged in a bushfire would be 30 and the worst case (95th percentile) of the losses would be 200 houses, i.e. $P(X < 30) = 0.5$, and $P(X < 200) = 0.95$. Utilising the estimates provided by the expert and the framework described in Section 2, we estimate the parameters for the Lognormal, Weibull and Burr XII distributions. These parameter estimates are provided in Table 1 and are classified into whether they are a location, scale of shape parameter.

With these parameter estimates specified, we can now review the resulting estimates of the number of houses damaged for a wider range of percentiles. The PDFs for the number of houses damaged based on the derived Lognormal, Weibull und Burr XII distribution are shown in Figure 3. As we are focusing on extreme events the probability of losses are low, but the importance of this exercise is that a wider range of probabilities have been quantified and can be applied using the LDA. Figure 3 also illustrates that the functional form of the distributions results in notably different

[7] As mentioned in Section 2.3, it was usually easier for an expert to specify the median as a more robust statistic of the distribution. The median could easily be illustrated as the value, separating the higher half of the potential losses from a bushfire from the lower half. Also, calculations to derive distributional parameters based on a specified mean would have required a higher computational effort. Note that uncertainty associated with the quantile estimates could also be accounted for with the use of Bayesian inference and multiple expert estimates, see, for example, Mathew et al (2012), Trück et al (2010).

PDFs using the same expert estimates. We have plotted the PDFs across three different axis specifications to highlight the differences in the tails of the distributions. The distributions lead to different estimates for the overall number of houses damaged in a bushfire. Irrespective of the differences in terms of the number of houses damaged, the percentile estimates for the 50th and 90th percentiles match those the expert has given us – refer to Table 2 for confirmation of these estimates. Table 2 also reinforces the observation there there are notable differences in the 25th and 99.5th percentile estimates. The estimates for the Burr XII and Lognormal distributions contain the largest tails with 99.5th percentile estimates exceeding those of the Weibull distribution by a factor of 2.18 and 1.40, respectively. This is not a surprising result, as these two distributions are more heavy-tailed than the Weibull distribution. In particular, the Burr distribution provides a significantly higher probability for extreme losses than the Weibull but also than the Lognormal distribution.

Table 1: Estimated parameters for the derived Lognormal, Weibull and Burr XII severity distributions for the number of destroyed houses in a bushfires in the Ku-ring-gai area.

	Location parameter	Scale parameter	Shape parameter	
Lognormal	3.40 (μ)	1.15 (σ)		
Weibull		48.24 (λ)	0.77 (k)	
Burr XII		30.00 (α)	1.55 (k)	1.00 (c)

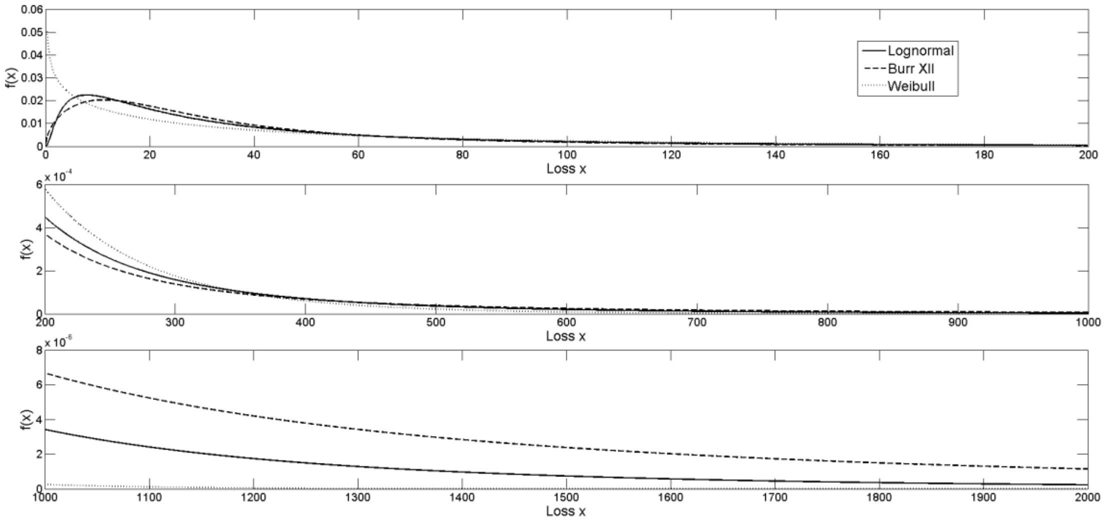

Figure 3: Probability density functions (PDF) for losses from a bushfire based on the provided information by the local bushfire expert for Ku-ring-gai P(X < 30) = 0.5, and P(X < 200) = 0.95. The figure provides a plot of the derived Lognormal (bold), Weibull (dotted) and Burr XII (dashed) distribution for 0<X≤200 (upper panel), 200≤X≤1000 (middle panel) and 1000≤X≤2000 (lower panel).

Table 2: Descriptive statistics for the number of destroyed houses based on the derived Lognormal, Weibull and Burr XII distributions for the severity of a bushfire.

		Percentiles					Mean
		25	50	95	99	99.5	
No. Houses Damaged	Lognormal	13.80	30.00	200.00	439.38	587.01	58.37
	Weibull	9.55	30.00	200.00	349.94	418.79	56.14
	Burr XII	14.76	30.00	200.00	579.43	911.16	68.72

3.3 Considering long time horizons - discounting and the impact of climate change

In Section 2 we illustrated how the annual aggregate loss L for a given year can be calculated. If the total loss over a number of years needs to be calculated, discounting will be necessary to convert the future monetary units into present monetary amounts so that a valid comparison can be made with all of the costs defined in present monetary terms.

Based on the methodology discussed in the paper, the discounted present value of the cumulative loss (*DPVL)* over the considered time horizon T can then be calculated using the simulated annual aggregate loss L_t as well as an applied growth rate g, and discount rate d, using the following formula:

$$DPVL = \sum_{t=0}^{T} \frac{L_t (1+g)^t}{(1+d)^t} \qquad (16)$$

The growth rate g represents economic growth and can be thought of as capturing the rising costs for the replacement of property and/or infrastructure. It may also represent an increased exposure to risk or an increase in economic damage over the time horizon considered. For instance, suppose an expert estimates a damage of 100 houses today in a bushfire risk zone which is likely to increase to 110 houses ten years later due to additional dwellings in the bushfire risk zone. Under such circumstances a growth rate of approximately 1% may be used to represent this increase in exposure to risk in the conducted analysis. In contrast, L_t should reflect forecasts of the change in frequency and severity of the natural hazard and may therefore also capture changes due to climatic change.

Within the climate change literature there has been a great deal of debate in the climate change literature regarding the ‘correct value’ of the discount rate (Nordhaus, 2008; Quiggin, 2008; Tol and Yohe, 2009; IPCC, 2007; Garnaut, 2008). One reason for the discount rate controversy is that the value of a discount rate can be derived either in a financial sense, where the discount rate reflects the cost of capital or the cost of acquiring funds, see, e.g., Nordhaus (2008), or in an economic sense, where the discount rate considers the importance of present consumption against future consumption (Stern, 2006).

While Government commissioned reports by Stern (2006) and Garnaut (2008) recommend the use of low social discount rates, their arguments have been criticised by various authors (Dasgupta, 2007; Weitzman, 2007; Nordhaus, 2008). Irrespective of this discussion, the time scale being used in the analysis will be an important consideration. The latest IPCC AR5 WGIII report notes that an issue with using a simple arbitrage argument for setting the discount rate to the interest rate (i.e. the cost of capital or the cost of acquiring funds) is that "we do not observe safe assets with maturities similar to those of climate impacts" (IPCC, 2014a: 31). So when the analysis is focused on a time scale where intergenerational welfare is irrelevant, such as, e.g., adaptation measures against losses that are likely to occur over the next five to ten years, the discount rate should be chosen based on the (risk-free) market interest rate. As noted in the latest IPCC AR5 WGIII report, "when projects are financed by a reallocation of capital rather than an increase in aggregate saving (reducing consumption), the discount rate should be equal to the shadow cost of capital" (IPCC, 2014a: 31).

Discounting is important for analysing options that are expected to be long-term investments (Hepburn, 2007). Ng (2011) explains this importance using a simple example: the NPV (Net Present Value) of a Million US dollars 200 years from now discounted at 1.4% (used by Stern) has a PV (Present Value) of US$59,618, but has a PV of only US$35 if discounted at 5% (market rate) i.e. a difference of a factor of 1,700 between the two calculations. The choice of an appropriate discount rate is important as the results of economic analysis may be sensitive to the value chosen. While the economic vs. financial discount rate debate (or in other words, the normative vs. positive approach) remains beyond the likely local government focus on climate adaptation, an extended time dimension does imply that the sensitivity of different discount rates needs to be understood. The discount rate is an important factor and when there is not a clear agreement on the choice of the discount rate in the analysis, sensitivity tests that include the variation of the discount rate will assist in the understanding of its effect on the final result and decision.

As we have prescribed the use of discount rates and highlighted the importance of different discount rate formulations based on the timescale being reviewed, Table 3 lists some example discount rates that can be utilised by local decision makers within Australia for different timescales (i.e. 5 years, 10 years and beyond). Discount rates consistent with the normative and positive approach are provided. Accordingly, the next section performs a sensitivity test of the base scenario with a discount rate of 4% with the review of a scenario that employs a lower discount rate (1.35%) consistent with the normative approach.

3.4 Estimates of total losses for Ku-ring-gai

With estimates for the severity of bush fire events established in Section 3.2, this section produces estimates of the total losses from bushfires based on the derived probability distributions for the number of severe bushfires that are associated with property losses. We then modify our assumptions to review additional scenarios based on a normative approach to setting discount rates and changes in the damages due to climate change impacts.

To calculate the total losses the following data has been used. The mean cost of reconstruction per house is $422,000. The current risk prone property value is approximated by the property construction cost, which is obtained by subtracting the average land value per property from the average property sale price. The regional land value is estimated by the NSW Valuer General (DOL 2009) and the regional average property sales price is obtained from Hatzvi and Otto (2008).

Table 3 – Examples of discount rates for use within Australia and different time horizons.

Garnaut (2008) – Normative approach	Interest Rate		Ramsey Rule ($\delta+\eta g$)
	5 year	10 year	
1.35 and 2.65	2.90	3.33	3.93

Note: the interest rates listed are the bond yields for August 29, 2014. The calculation of the discount rate based on the Ramsey Rule utilises an average growth rate of 1.965 for the period between 1961 and 2013. η is set to 2 and δ to 0 based on IPCC (2014a): 34.

Recall that the frequency of bushfires for the Ku-ring-gai area was specified by an expert to be λ=0.1. Further, due to the efforts of fire brigades and other existing resources, the expert has specified that the number of severe bushfires that would actually lead to property damage would be 1 out of 5 events, i.e. only 20% of the bushfires. The expert also specified that total losses would not exceed 1000 properties. This means that we have needed to modify the process prescribed in Section 2 such that the frequency of events (Poisson distribution) interacts with a binomial function that accounts for the actual occurrence of lost houses per event. In addition, we have imposed a restriction so that the upper bound of losses is equal to 1000 properties.

Table 4 contains the estimates for the NPV of total losses from property damage that result from the adjusted LDA over a time horizon of 40 years. The total losses have been computed using three sets of assumptions related to equation (16). The base scenario utilises a discount rate of 4%, approximately in line with the rate computed using the Ramsey Rule that is shown in Table 3. Two additional scenarios have been applied to review the sensitivity of the values chosen in the base scenario. The lower discount rate scenario decreases the discount rate to 1.35% to be in line with that used by Garnaut (2008), which was set based on a normative approach to discounting.

We also examine two different scenarios including impacts of climate change: in the first one we assume that there will be a doubling in the frequency of bushfires over the 40 year time horizon while the severity of the bushfires is not affected.[8] In the second climate change scenario, we assume the same increase in frequency, but also assume that the severity of the fires is increased and houses are damaged by 33% of the bushfires instead of 20% as initially specified by the expert.

Note that the 25th percentile estimate for the NPV of property damage in Millions of Australian Dollars ($M) is zero across all but one of the scenarios due to the low frequency of severe bushfire events (λ=0.1) with only one out of five of these events generating a loss in houses. Given these specifications, we would expect to observe a severe bushfire in the Ku-ring-gai area on average approximately every ten years,

[8] Note that we assume a linear increase in the frequency such that after 20 years the frequency parameter has increases from λ=0.1 in year 0, to λ=0.1025 in year 1, λ=0.105 in year 2, λ=0.1075 in year 3, … , λ=0.15 in year 20, … , λ=0.2 in year 40.

while 80% of these events would not damage any houses. Therefore, considering a 40 year time horizon, for a relatively high percentage of the simulation runs, there will be no losses during these 40 years, what explains the 25th percentile of the cumulative loss distribution to be equal to zero.

Table 4 – Simulated discounted present values (NPV) of the cumulative losses from bushfires for the Ku-ring-gai area for a 40 year time horizon in Millions of Australian Dollars ($M). The base case assumes a discount rate of 4% and zero change in climate impact. The lower discount rate scenario decreases the discount rate to 1.35% (as used in Garnaut, 2011). The climate change impact scenarios assume a linear increase in the frequency of bushfires from λ=0.1 in year 0, to λ=0.1025 in year 1,…., λ=0.2 in year 40. The second climate change scenario assumes that on top of an increase in the frequency, bushfires become more severe such that houses are damaged by 33% of the bushfires instead of 20% as specified in the base case.

Losses in $M		Percentiles					Mean
		25	**50**	**75**	**95**	**99**	
Base case scenario (4% discount rate, 1% growth rate)							
NPV (Total Losses)	LN	0.00	1.43	9.42	38.83	87.42	8.60
	W	0.00	0.68	9.78	39.46	75.69	8.25
	B	0.00	1.52	9.13	37.21	102.18	8.76
Lower discount rate (1.35% discount rate, 1% growth rate)							
NPV (Total Losses)	LN	0.00	2.54	15.88	61.79	136.62	13.77
	W	0.00	1.13	16.38	63.02	115.17	13.26
	B	0.00	2.67	15.05	60.10	163.43	14.17
Climate change impact with adaptation (4% discount rate, 1% growth rate, frequency to double over 40 year horizon)							
NPV (Total Losses)	LN	0.00	4.46	14.67	48.12	99.37	11.89
	W	0.00	3.96	15.56	48.29	86.07	11.58
	B	0.00	4.40	13.85	47.53	121.69	12.16
Climate change impact without adaptation (4% discount rate, 1% growth rate, frequency to double over 40 year horizon, damages occur in 33% of severe bushfires)							
NPV (Total Losses)	LN	3.07	10.91	25.78	69.75	130.97	19.78
	W	2.28	11.03	27.13	66.26	108.43	19.12
	B	3.12	10.44	23.99	71.29	159.47	19.93

In the base case scenario, the median estimate for total losses ranges from $0.68M and $1.52M depending on the distribution used. The mean estimates for the loss are $8.60M for the Lognormal case, $8.25M for the Weibull, and $8.76M for the Burr Type XII distribution. Note that these numbers show less variation across distributions than for the estimated severity distributions in Table 2. The differences across the distributions that were seen in the estimates of the severity of the bushfire (i.e. number of houses damaged) have been quelled when the calculation of total losses has been performed. This is due to the relatively low expected frequency of bushfires (λ=0.1), the occurrence of actual damage to houses per event (one in five bushfires) and the imposition of an upper limit of 1000 properties being lost in the most extreme case. However, for the 99th percentile of the simulated NPV, we still observe a significantly higher value for the Burr XII ($102.18M) than for the Lognormal ($87.42M) and the Weibull distribution ($75.69M). These numbers can be interpreted as suggesting that there is a 1% chance that the NPV of losses over the 40 year time horizon will exceed even $87.42M (in the Lognormal case). This number is approximately 10 times higher than the expected NPV of losses $8.60M and is a result of the skewness and the heavy tails of the Lognormal distribution. We also find that the average damage is clearly less sensitive to the type of fat tailed distribution used, however, other percentiles, in particular the 99th percentile, vary considerably. While local government stakeholders may often prefer to base their decisions on mean values, accounting for estimates of worst case scenarios should also be part of the decision process

Let us now consider the alternative scenarios, starting with the lower discount rate. A lower discount rate of 1.35%, instead of 4% in the base scenario, corresponds to placing greater weight also on later time periods and increases the simulated NPV of damage to houses from bushfires in the Ku-ring-gai area by approximately 60%. For example, for the Lognormal distribution, the NPV of the expected losses over the considered 40 year time period increases from $8.60M to $13.77M. These results emphasize the significant effect of the chosen discount rate, since all other parameters in the simulation exercise were exactly the same for both scenarios.

The introduction of increased climate change impacts with adaptation inflates the estimates due to a doubling in the frequency of bushfires. This leads to higher estimates for total losses by approximately 40%. The expected NPV of losses over the 40 year time horizon is now between $11.58M (Weibull) and $12.16M for the Burr XII distribution. The second climate change scenario reviews the case where also the severity is assumed to increase, such that damages occur for 33% of severe bushfires. This results in an increase in losses by approximately 65% in comparison to the first climate change scenario and by approximately 130% in comparison to the base case scenario. The expected NPV of losses over the 40 year time horizon ranges from $19.12M (Weibull) to $19.93M for the Burr XII distribution.

Overall, as expected the NPV estimates are sensitive to a lower discount rate and an increase in the frequency of bushfires. The most substantial effect is observed when both frequency and severity of bushfires is assumed to increase. Note that the exercise at hand is the estimation of losses for an extreme event and not the conduction of a cost benefit analysis; hence the differences between the scenarios should only be interpreted as being indicative of the impact of the different assumptions applied.

4) Conclusion

At the local level, there is often a lack of information on low frequency high severity events and the available data is often insufficient for the quantification of distributions of the frequency and severity of such events. With a focus upon local assessments of extreme events, this paper provides an example of eliciting expert estimates to develop a range of scenarios that are focused on the cumulative losses from bushfires in the Ku-ring-gai local government area, located within Sydney, Australia. The region is prone to bushfires and has provided a useful foundation for a focus on localised risk from catastrophic events and the potential impact of climate change.

We show how to estimate parameters for severity distributions in a straightforward and simple manner. In the case of this paper, this is when an expert provides conditions for two percentiles of the distribution, namely the median and an estimate for a higher percentile of the distribution. We illustrate the suggested approach for the Lognormal, Weibull and Burr XII distributions; three of the most common probability distributions for modelling catastrophic events. We also show how the elicitation of an expert estimate can be utilised within the loss distribution approach (LDA) to calculate aggregate losses for a single year or a longer time horizon. Our approach also allows for the calculation of high quantiles of the loss distribution. We find that the average damage is less sensitive to the type of fat tailed distribution used, however, higher percentiles, particularly the worst case damage (99^{th} percentile), vary considerably. Local government stakeholders may often prefer to base their decisions on mean values, however accounting for estimates of the worst case damage should be part of the decision process. In our study, we have relied on point estimates from one expert for simplicity, but we acknowledge that local experts are likely to give estimates in the form of ranges or may be uncertain about their estimates. Uncertainty associated with the quantile estimates can also be accounted for with the use of Bayesian inference and multiple expert estimates, see, for example Mathew et al (2012), Trück et al (2010). However, the analysis of these issues is beyond the focus of this paper.

We have illustrated the method, using a case study where we quantify the risk of bushfires for a local area in Northern Sydney. In doing so, we have adapted the LDA for a longer time period of time to highlight changes that occur across the estimates due to discounting and potential impacts of climatic change. Our results illustrate the significant effect of the chosen discount rate for the net present value of the simulated losses. For example, changing the discount rate from 4% (set based on the positive approach to discounting using the Ramsey Rule) to 1.35% (in line with the normative approach and one of the discount rates used in Garnaut (2008)) increases the mean NPV of losses from bushfires by approximately 60%. Our analysis also finds that climate change may have strong impacts on the simulated losses, in particular when both the frequency and severity of bushfires will increase over the considered time horizon.

Overall, we provide a framework for quantifying losses from extreme events and climate impacted hazards that can be based on local knowledge provided by an expert and does not require large amounts of historical data on catastrophic events. The implementation of the approach is straightforward and local governments should be able to perform a similar analysis so as to quantify risks and perform sensitivity testing. In addition to prescribing that a range of scenarios be used when discussing risk, we would also like to highlight the importance of engaging local experts and stakeholders when assessing the appropriate climate adaptation decisions based on the risk assessment. Such local consultation occurred when the Ku-ring-gai local government devised a ‘Climate Change Adaptation Strategy’; refer to Ku-ring-gai Council (2010) for further details. This is an important point as the exercise at hand was the estimation of losses for an extreme event and not the conduction of a cost benefit analysis. The assessment of the benefits of different adaptation measures has been left for future research and will also depend upon localised factors, such as existing infrastructure and the nature of the extreme event/s.

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