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Risk and Economic Analysis of Residential Housing Climate Adaptation Strategies for Wind Hazards in South-East Australia

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Executive summary

Decisions related to climate change and adaptation rely on information, data and modelling of climate projections, probabilistic hazard models, vulnerability and loss models, and risk reduction and cost of adaptation measures. Not surprisingly, these data and models are subject to significant uncertainty due to imprecise physical understanding of present and future climates, modelling errors associated with engineering and stochastic models of infrastructure performance, and other aleatory and epistemic uncertainties. For this reason, precise estimates of risks, costs and benefits of climate adaptation measures are not possible.

An alternate approach is a 'break-even' economic assessment. In this case, the conditions under which a climate adaptation strategy is cost-effective can be assessed, and decision or policy-makers can decide if such minimum conditions can be met in practice. The break-even approach is widely used in areas of modelling and parameter uncertainty, such as homeland security applications, and is well suited to climate change and adaptation policy decisions where uncertainties dominate hazard, vulnerability and consequence predictions.

A changing climate and higher wind speeds means that residential construction is likely to receive more damage in the future if design standards are maintained at the current level. The vulnerability of residential construction may be reduced by an adaptation strategy that increases design wind speeds specified by Australian Standards AS4055-2012 and AS1170.2-2011.

The report applied break-even analysis to compare the risks, costs and benefits of climate adaptation strategies for new housing in the Australian cities of Brisbane, Sydney and Melbourne. These cities are located in South-Eastern Australia and wind hazard is dominated by synoptic winds (thunderstorms and east-coast lows). Cyclonic winds were thus not considered. The 'benefit' of an adaptation measure is the reduction in damages associated with the adaptation strategy, and the 'cost' is the cost of the adaptation strategy. The measure for cost-effectiveness is Net Present Value (NPV) or net benefit equal to benefit minus the cost. Break-even estimates of risk reduction and adaptation cost for designing new housing to enhanced standards were calculated for three synoptic wind pattern scenarios to 2070: (i) no change, and (ii) B1 and (iii) A1FI emission scenarios. If the actual cost of adaptation exceeds the predicted break-even value, then adaptation is not cost-effective. Stochastic methods are used to predict levels of existing risk (economic loss). The effect of changes to the probabilistic model of existing wind hazards and changes to discount rate were also investigated.

Key findings are:

1. Increasing the design wind classifications in the Australian Standard "Wind Loads for Houses" AS4055-2012 for all new housing in South-Eastern Australia can lead to risk reductions of 50-80%, at a cost of no more than 1-2% of house replacement value. This means that new construction and alterations would be designed to resist at least 50% higher wind pressures, resulting in increased strength of building structural components and connections that will lead to significantly reduced wind vulnerability. Time of adaptation was taken as five years from 2013 giving earliest time of adaptation of 2018.
2. Wind damage losses for 'business as usual' (no adaptation measures) are significantly higher for Sydney than Brisbane and Melbourne. Mean damage risks for the B1 emissions scenario at 2070 can increase damage risks at 2070 for Brisbane by up to 40% when compared to the no change scenario. For Sydney and Melbourne the damage risks at 2070 are very similar to no change losses. Damage risks for Brisbane increase by up to 120% for the A1FI emission scenario, and mean losses for Sydney and Melbourne are 20% higher than the no change scenario. However, if current wind classifications are increased by one level then damage risks reduce by 50-80%.

3. Existing risk is highest for Sydney, so the benefits of adaptation will also be highest for Sydney.

    - In this case, if risk reduction is over 50%, discount rate is 4%, and there is no change of climate, the break-even analysis shows that adaptation is cost-effective if the adaptation cost is less than 9.3% and 5.5% of house replacement cost for foreshore and non-foreshore locations, respectively. The effect of a changing climate will increase the break-even adaptation cost to 9.7% and 5.7% of house replacement cost for foreshore and non-foreshore locations, for the A1FI emission scenario. For the medium (B1) emission scenario, minimum (break-even) risk reduction must exceed 6% and 9% for foreshore and non-foreshore locations, respectively. Given that risk reductions of 50-65% can be achieved for Sydney based on the vulnerability models described herein, and cost of adaptation is likely to be well less than 2%, then it is likely that designing new housing to enhance wind classifications is a cost-effective adaptation strategy for Sydney.

    - Assuming house replacement cost of $270,00 in 2012 dollars, the NPV of the adaptation strategy per house in Sydney in a non-foreshore location is approximately $12,000 to 2070 for no climate change. This increases to a NPV of nearly $13,000 for the A1FI emission scenario. Residential dwelling in Sydney are expected to increase by 46% from 2006 to 2036, or approximately 25,000 new houses per year. Based on these projections, the NPV for new houses built in 2018 alone would be at least $300 million, and this NPV would rapidly accumulate year by year as additional new houses are built. The net benefit of the adaptation strategy in Sydney is clearly significant even when applying cost and risk estimates that generally bias the case in favour of finding adaptation measures not to be cost-effective.

    - Even if there is no climate change the adaptation strategy in Sydney is still cost-effective. Hence, even if climate projections are wrong, adaptation measures satisfies a ‘no regrets’ or win-win policy.

4. Break-even adaptation costs for Brisbane are considerably lower than for Sydney. If risk reduction is a modest 50%, discount rate is 4% ,and worst (A1FI) emission scenario, the break-even analysis shows that adaptation is cost-effective only if the adaptation cost is less than 1.0% and 1.3% of house replacement cost for foreshore and non-foreshore locations, respectively. However, it is possible that actual adaptation costs can be this low, particularly since the AGO (2007) estimate adaptation costs to be 1.1-1.4% for Brisbane. However, given that risk reductions of 75-80% can be achieved for Brisbane based on the vulnerability models described herein, it is likely that designing new housing to enhance wind classifications is a cost-effective adaptation strategy for Brisbane for non-foreshore locations irrespective of climate scenario. The NPV is up to $2,000 per new house for 75% reduction in risk for non-foreshore locations and A1FI emission scenario. However, adaptation is not likely to be cost-effective for foreshore locations unless the A1FI emission scenario is expected.

    Even if there is no climate change the adaptation strategy in Brisbane is still cost-effective for non-foreshore locations in Brisbane.

5. Results and trends for Melbourne are not too dissimilar as those for Sydney; namely, adaptation is cost-effective for foreshore and non-foreshore locations, and all climate scenarios. The break-even risk reduction needs to exceed 14-23% to be cost-effective. This would seem to be relatively easy to achieve in practice as modelling in this report suggests risks reductions of 50-70% are achievable.

6. The economic assessment is highly sensitive to probabilistic wind field model. For example, an increase of wind gust speeds of +10% can nearly double damage risks. To a lesser extent, results are also sensitive to the wind vulnerability of housing, particularly lower regions of the vulnerability curves.

7. Discount rates lower than 4%, such as those used in the 2008 Garnaut Review (1.35%, 2.65%), result in higher break-even values which increases the likelihood of adaptation being cost-effective.

8. Deferring adaptation to 2025 reduces NPV by 25%. Net present value is maximised if wind speeds increase over time (A1FI emission scenario); however, NPV decreases with deferral of adaptation for all discount rates and climate scenarios. Earlier implementation of adaptation is preferred.
9. The above results are scenario-based by assuming that the probability of each climate scenario is 100%. The effect of likelihood of each climate scenario on NPV is assessed, for example, 50% likelihood of B1 and 50% likelihood of A1FI climate scenarios. The maximum adaptation cost to ensure 90% certainty that NPV>0 is sensitive to the probability of occurrence of each climate scenario. Incorporating degree of belief of climate scenarios is an important variable in decision-making.

1 Introduction

A changing climate may result in more intense and/or frequent tropical cyclones and storms, more intense rain events and flooding, sea level rise, and other climate-related hazards. The effect on infrastructure, particularly housing, will be significant if the frequency and/or intensity of these natural hazards increase. Changes to design and construction standards and retrofitting can reduce the vulnerability of new and existing infrastructure - but these can be very costly and disruptive to asset owners. Hence, there is a need to quantify the costs and benefits of adaptation strategies (retrofitting, strengthening, enhanced designs) and assess at what point in time climate adaptation becomes economically viable. There is increasing research that takes into account the changing climate risk in engineering to reduce the vulnerability of infrastructure - we define this as 'climate adaptation engineering'.

The terms 'risk' and 'risk management' appear in the titles and text of many climate impact and adaptation studies (e.g. VG 2007, ATSE 2008, EEA 2012). However, these reports dwell on lists of vulnerabilities and consequences, and on qualitative measures such as risk ranking. There is seldom mention of probabilities, or quantitative measures of the likelihood or extent of losses. While useful for initial risk screening, intuitive and judgement-based risk assessments are of limited utility to complex decision-making since there are often a number of climate scenarios, adaptation options, limited funds and doubts about the cost-effectiveness of adaptation options. In this case, the decision-maker may still be uncertain about the best course of action. This led the Australian Academy of Technological Sciences and Engineering (ATSE) in 2008 to conclude that there "is a need to assess the impact of climate change on Australia's physical infrastructure on a regional basis by using risk assessment methods to provide overviews of the likelihood, consequence, risk and adaptation capacity of Australia's physical infrastructure" and that "information in the form of probability distributions is required for the capacity of infrastructure components after adaptation." For this reason, there is a need for sound system and probabilistic modelling that integrates the engineering performance of infrastructure with the latest developments in stochastic modelling, structural reliability, and decision theory.

The impact of climate change is discussed, with emphasis on increases in economic (loss) risks expected for new housing subject to climate-induced changes in wind field. The risks are temporal and spatially dependent. Severe storms cause annual insured losses (1967-2005) of $46.7 million, $217.1 million, and $23.8 million in the Australian states of Queensland, New South Wales and Victoria, respectively (BITRE 2008 - note: 2005 Australian dollars). These losses account for nearly 25% of all losses from natural disasters in Australia. Severe thunderstorms are most common in New South Wales and Queensland, and East Coast Lows also form along the coasts of South Queensland to Tasmania causing extreme rainfall and wind events (Verdon-Kidd et al. 2010, King et al. 2012).

To reduce housing damage in the future one option may be to strengthen or retrofit existing construction. However, Stewart and Wang (2011) found such strategies often failed to be cost-effective, and if cost efficient, then only marginally so. Moreover, the existing regulatory framework in Australia constrains retrofitting existing buildings due to varying local and state government regulations, and industry would prefer to rely on changes to deemed-to-comply provisions for new construction because such provisions provide a higher level of certainty (Maddocks 2011). Other adaptation strategies may restrict construction of new housing in vulnerable (exposed) locations. A more feasible adaptation strategy may be one that increases design wind loads for new houses leading to long-term reduction of vulnerability (and damages) of houses (Stewart et al. 2012, 2013).

A cost-benefit analysis for strengthening a residence to withstand cyclones has been used to weigh different retrofit options on hazard mitigation (Li and Ellingwood 2009). Stewart et al. (2003) and Stewart (2003) developed a cost-benefit analysis decision-making framework to assess the economic viability of strengthened construction and other damage mitigation strategies for United States and Australian wind hazards. This work assumed a stationary climate, but some recent work has looked at climate change (e.g. Nishijima et al. 2012). Recent work by Stewart and Li (2010), Li and Stewart (2011) and Bjarnadottir et al. (2011a,b) have assessed the cost-effectiveness of retrofitting old construction or reducing the vulnerability of new construction for houses in North Queensland and Florida subject to tropical cyclones or hurricanes for climate scenarios where cyclonic wind speed can change from -5% to +25% by 2050. Specifically, Bjarnadottir et al. (2011a) found a net benefit ranging from $500 million to nearly $2 billion if all new housing in Miami-Dade County, Florida is strengthened if hurricane wind speeds increase by 5% over the next 50 years and the cost of strengthening is less than 5% of house replacement value. A particularly apt finding is that even if there is no change in wind field over the next 50 years in Florida, the net benefit can still reach $1.5 billion if all new housing in Miami-Dade County, Florida is strengthened (Bjarnadottir et al. 2011a). This implies that this adaptation strategy could result in a ''win–win'' situation for society even if current climate predictions over-estimate the severity of wind events in the future.

The Australian Standard for wind loads (AS 1170.2 2011) is the reference standard for design of all structures, including housing. The Australian Standard "Wind Loads for Houses" AS4055-2012 is based on AS1170.2-2011 and is used to determine the appropriate wind classification for design of residential (domestic) housing. In this case, residential housing is designed to resist ultimate limit state wind speeds with annual probability of exceedance of 1 in 500. The standard AS4055-2012 classifies design loads on houses into categories N1-N6 and C1-C4 for non-cyclonic and cyclonic regions, respectively. Each increase in wind classification (e.g. N1 to N2) raises the design wind speed that is equivalent to at least a 50% increase in design wind pressure, and internal pressure coefficients will increase for cyclonic regions. These wind classifications are then used in AS1684-2010 "Residential Timber-Framed Construction" and other standards called up by the Building Code of Australia to determine appropriate deemed-to-comply sizing and detailing requirements for residential construction. However, the wind classifications specified in AS4055-2012 may be inadequate if wind speeds increase due to a changing climate. Hence, an appropriate adaptation strategy may be one that increase wind classifications for new houses leading to reduced vulnerability of new construction.

Stewart et al. (2012, 2013) have assessed the damage risks, adaptation costs and cost-effectiveness of this adaptation strategy for residential construction in the Queensland cities of Cairns, Townsville, Rockhampton and Brisbane assuming time-dependent changes in frequency and intensity of cyclonic and non-cyclonic winds to 2100. Advanced spatial and temporal stochastic simulation methods were used to include uncertainty and variability of climate and building vulnerability on damage risks. Costs of adaptation, timing of adaptation, discount rates, future growth in new housing, and time-dependent increase in wind speeds with time were also included in the analysis - for exposures up to 2100. Note that this was work was based on an earlier version of the Australian Standard "Wind Loads for Houses" (AS4055-2006). The criteria for cost-effectiveness were:

(i) Net Present Value NPV (or net benefit equal to benefits minus the cost). If the NPV is positive, the proposal improves efficiency. If the NPV is negative, the proposal is inefficient (OBPR 2010).
(ii) Probability that NPV>0 since the analysis considers probabilistic characterisation of wind field and building vulnerability then the outcome NPV is also a stochastic variable.
(iii) Benefit-to-cost ratio (BCR).

The analysis considered direct losses (structural damage and contents losses) and indirect losses (business interruption, clean-up, loss during reconstruction, extra demands on social services, and changes to demand and supply of intermediate consumption goods). Four climate change scenarios were considered including no change, and 10% and 20% increases in wind speeds by 2100. It was found that, assuming 'business as usual' (no adaptation measures), a changing climate can increase mean wind damage losses for Cairns, Townsville, Rockhampton and South East Queensland by up to $20.0 billion by 2100 assuming a 4% discount rate.

There is considerable uncertainty associated with stochastic modelling of the existing wind field (no climate change), projections of changes to wind field due to a changing climate, wind vulnerability models for housing, and risk reduction and cost of adaptation. This necessarily makes any absolute predictions of NPV of climate adaptation somewhat speculative (e.g. Stewart et al. 2012, 2013). An alternate approach is a 'break-even' economic assessment. In this case, the conditions under which a climate adaptation strategy is cost-effective (NPV>0) can be assessed, and decision or policy-makers can decide if such minimum conditions can be met in practice. For example, consider a simple case where a break-even analysis may show that an adaptation measures is cost-effective if it reduces risk by at least 25% and at cost not exceeding $5,000. While precise predictions of risk reduction and adaptation cost may not be available, or only known approximately, if there is consensus that a higher risk reduction is easily achievable for an adaptation cost of $2,000-4,000 then the adaptation measure is clearly cost-effective. On the other hand, if there is general agreement that a 25% risk reduction is not possible even for an adaptation cost of $10,000 - then the adaptation measure is not cost-efficient as the cost exceeds the break-even value. In this case, if the actual cost of adaptation exceeds the predicted break-even value, then adaptation is not cost-effective. The break-even approach is widely used in areas of parameter uncertainty, such as homeland security applications (e.g. Mueller and Stewart 2011, Stewart and Mueller 2011, 2013), and is well suited to climate change and adaptation policy decisions where uncertainties dominate hazard, vulnerability and consequence predictions.

The report applies break-even analysis to compare the risks, costs and benefits of climate adaptation strategies for new housing in the Australian cities of Brisbane, Sydney and Melbourne. These cities are located in South-Eastern Australia and wind hazard is dominated by synoptic winds (thunderstorms and east-coast lows. Break-even estimates of risk reduction and adaptation costs for designing new housing to enhanced standards are calculated for three wind pattern scenarios to 2070: (i) no change, and (ii) B1 and (iii) A1FI emission scenarios. Stochastic methods are used to predict levels of existing risk (economic loss). The effect of changes to the probabilistic model of existing wind hazards and changes to discount rate are also investigated. Finally, the effect of relative likelihood of each climate scenario on NPV is assessed as incorporating degree of belief of climate scenarios is an important variable in decision-making.

2 Risk-Based Decision Analysis

2.1 Definition of Risk

The standard definition of risk is:

$$(\text{Risk}) = (\text{Hazard}) \times (\text{Vulnerability}) \times (\text{Consequences}) \tag{1}$$

where

- Hazard - probability there will be a climate hazard.
- Vulnerability - probability of damage or loss (that wind will damage a roof of a house) given the hazard.
- Consequences - loss or consequence (economic costs, number of people harmed) if the hazard is successful in causing damage.

Equation (1) can be re-expressed as:

$$E(L) = \sum \underbrace{\Pr(C)\Pr(H|C)}_{\text{HAZARD}} \underbrace{\Pr(D|H)}_{\text{VULNERABILITY}} \underbrace{\Pr(L|D)L}_{\text{CONSEQUENCES}} \tag{2}$$

where Pr(C) is the annual probability that a specific climate scenario will occur, Pr(H|C) is the annual probability of a climate hazard (wind, heat, etc.) conditional on the climate, Pr(D|H) is the probability of infrastructure damage or other undesired effect conditional on the hazard (also known as vulnerability or fragility) for the baseline case of no extra protection (i.e. 'business as usual'), Pr(L|D) is the conditional probability of a loss (economic loss, loss of life, etc.) given occurrence of the damage, and L is the loss or consequence if full damage occurs. In some cases, 'damage' may equate to 'loss' and so a vulnerability function may be expressed as Pr(L|H) which is equal to the product Pr(D|H)Pr(L|D). The summation sign in Eqn. (2) refer to the number of possible climate scenarios, hazards, damage levels and losses. If the loss refers to a monetary loss, then E(L) represents an economic risk.

2.2 Cost-Benefit Assessment

Two criteria may be used to assess the cost-effectiveness of adaptation strategies:

1. Net Present Value (NPV).
2. Probability of cost-effectiveness or Pr(NPV>0).

The 'benefit' of an adaptation measure is the reduction in damages associated with the adaptation strategy, and the 'cost' is the cost of the adaptation strategy. The net benefit or net present value (NPV) is equal to benefit minus the cost which is also equivalent to the present value or life-cycle cost of an adaptation strategy (sum of damage and adaptation costs) minus the 'business as usual' or 'do nothing' present value. The decision problem is to maximise the net present value

$$\text{NPV} = \sum E(L)\Delta R + \Delta B - C_{adapt} \tag{3}$$

where ΔR is the reduction in risk caused by climate adaptation measures, C_{adapt} is the cost of adaptation measures including opportunity costs that reduces risk by ΔR, ΔB is the expected co-benefit of adaptation such as reduced losses to other hazards, increased energy efficiency of new materials, etc., and E(L) is the 'business as usual' risk given by Eqn. (1). Climate adaptation measures should result in risk reduction (ΔR) that may arise from a combination of reduced likelihood of hazard, damage states, safety hazards and/or people exposed to the hazard. For any climate adaptation measure the risk reduction ΔR can vary from 0% to 100% (or even a negative number for an ill-suited adaptation measure).

Figure 1 shows a schematic of time-dependent increase in reduced damages and adaptation costs if an adaptation strategy is implemented in 2015. In this case we assume that the adaptation cost is constant with time and so is a one-off expense. The benefits increase with time due to reduced vulnerability, so the NPV accrues over time.

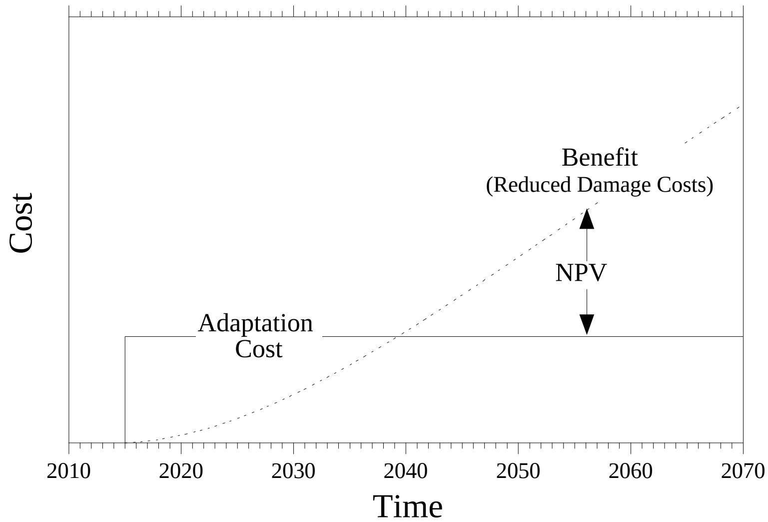


Figure 1 Schematic of Net Present Value (NPV), and Adaptation and Reduced Damage Costs

If parameters Pr(C), Pr(H|C), Pr(D|H), Pr(L|D) L, ΔR, ΔB and/or C_{adapt} are random variables then the output of the analysis (NPV) is also variable. This allows confidence bounds of NPV to be calculated, as well as the probability that an adaptation measure is cost-effective denoted herein as Pr(NPV>0). If NPV>0 then there is a net benefit and so the adaptation measure is cost-effective. Other notations and formulae can be used to provide optimal adaptation (e.g. Hall et al. 2012), but ultimately these also mostly rely on maximising NPV.

If the probability that a specific climate scenario will occur Pr(C) is too unreliable, then a decision analysis based on scenario analysis where climate scenario probability is decoupled from Eqn. (2) provides an alternative decision-making criteria. The above equations can be generalised for any time period, discounting of future costs and more detailed time-dependent cost and damage consequences. If the loss refers to the fatality of an individual, then E(L) represents an individual annual fatality risk which can be compared with appropriate societal risk acceptance criteria (Stewart and Melchers 1997).

2.3 Risk-Based Decision-Support Framework

The decision-support framework is based on Eqns. (1-3). Figure 2 summarises the major steps in developing risk-based decision support for assessing the risks, costs and benefits of climate adaptation measures. These are summarised as:

- Climate Hazard Modelling: Pr(H|C) - stochastic models of likelihood and extent of hazard. The probability that a specific climate scenario will occur Pr(C) represents a degree of belief for each climate scenario. This may be obtained from climate change literature or expert opinion.
- Engineering models: deterministic engineering and systems modelling of resistance of materials and structural systems to climate hazards.

❂ Vulnerability modelling: Pr(D|H) - stochastic and reliability modelling to predict the likelihood of damage conditional on hazard occurrence derived from engineering models (Strand ❁), model error (accuracy) of engineering models, and parameter uncertainty.

❃ Loss and Exposure: Pr(L|D) - likelihood of direct and indirect loss or consequence for specific levels of infrastructure vulnerability. Loss L is direct and indirect loss or consequence due to location and extent of infrastructure damage, for existing exposure and projections to 2100. National databases such as the National Exposure Information System (NEXIS), can provide exposure data of sufficient fidelity to determine the spatial characteristics and location of infrastructure (and people).

❄ Impact Risks (no climate adaptation): stochastic methods to assess damage and loss risks by integrating Strands ❀-❃. Results will identify which infrastructure (materials, designs, components) and hazards are 'risk-critical' to climate change.

❆ Climate adaptation measures: innovative use of materials and new engineering designs to develop performance models for climate adaptation measures. Emphasis placed on reducing the vulnerability of 'risk-critical' materials, designs, components, and connections.

❅ Costs of adaptation, and co-benefits (ΔB): direct and indirect costs of adaptation, as well as benefits such as embodied energy and enhanced thermal efficiency leading to reduced operating energy.

❇ Risk reduction (ΔR) of climate adaptation measures: stochastic and reliability modelling to develop vulnerability models for climate adaptation measures. Risk reduction inferred from reduction in vulnerability when compared to existing or 'business as usual' (no climate adaptation) vulnerability.

❉ Risk-based decision analysis: integration of Strands ❀-❇ in life-cycle cost and benefit analysis to assess if adaptation measures are efficient, in terms of monetary units or other (energy) criteria. Effect of timing and/or deferral of adaptation decisions assessed.

The challenging aspect of risk-based decision theory is predicting values of Pr(C), Pr(H|C), Pr(D|H), Pr(L|D) and ΔR. This information may be inferred from expert opinions, scenario analysis, and statistical analysis of prior performance data, as well as system and reliability modelling. Since there is uncertainty associated with such predictions, the use of probability distributions to describe mean, variance and distribution type is recommended.

There are significant challenges in characterising (in probabilistic terms) climate impact and adaptation in time and space. Quite rightly, there has been substantial research on climate variability as this will be the driver to climate impact. Future climate is projected by defining carbon emission scenarios in relation to changes in population, economy, technology, energy, land use and agriculture - a total of four scenario families, i.e., A1, A2, B1 and B2 are defined (IPCC 2000) and used in the IPCC's Third and Fourth Assessment Reports in 2001 and 2007, respectively. The A1 scenarios indicate very rapid economic growth, a global population that peaks in mid-century and declines thereafter, and the rapid introduction of new and more efficient technologies, as well as substantial reduction in regional differences in per capita income. Sub-categories of A1 scenario include A1FI and A1B, which represent the energy in terms of fossil intensive and a balance across all sources, respectively. The IPCC Fifth Assessment Report (AR5) to be released in 2014 will use Representative Concentration Pathways (RCPs) where RCP8.5, RCP6.0 and RCP4.5 are roughly equivalent to A1FI, A1B, and A1B to B1 CO_2 emissions, respectively.

To project spatially dependent future climates under different emission scenarios, various climate models have been developed. The IPCC suggests that it is necessary to use multiple Atmosphere-Ocean General Circulation Models (AOGCMs) to take into account the uncertainties of models in any impact assessment. The estimation of Pr(C) may be based on expert opinion about the likelihood of each emission scenario, and multiple AOGCMs may be used to infer the probabilistic characterisation of Pr(H|C) for future climate projections including wind, heat, rainfall, temperature and relative humidity.

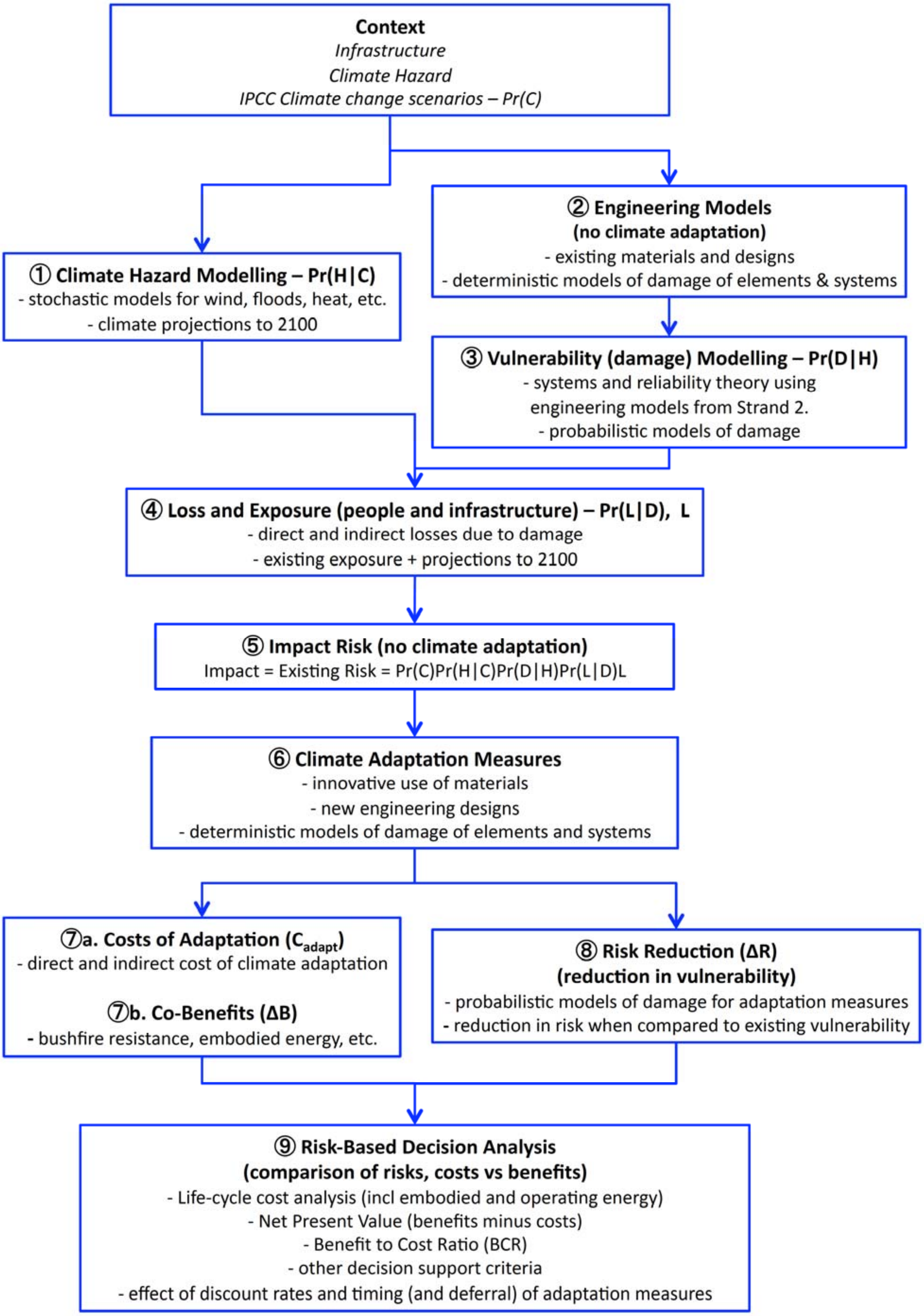


Figure 2 Flowchart of Decision-Support Framework for Assessing Cost-Effectiveness of Adaptation Measures

The stochastic modelling of infrastructure vulnerability (or fragility) is Pr(D|H) and is the probability of damage conditional on the occurrence of a specific hazard:

$$\Pr(D|H) = \Pr(R(\mathbf{X}) - H < 0) \tag{4}$$

where R(**X**) is the function for resistance or capacity, **X** is the vector of all relevant variables that affect resistance, and H is the known hazard level. The performance functions can be expressed in terms of structural damage or other losses, and are derived from engineering models. As a structure ages the effect of deterioration and other time-dependent processes may lead to higher values of Pr(D|H).

Vulnerability modelling will require probabilistic information on materials, dimensions, model errors, deterioration and other input variables (**X**) into engineering models which define the resistance function R(**X**) - these variables vary in time and space. The reliability analysis of components is relatively straightforward, however, a more demanding challenge is reliability modelling of structural systems in time and space. This will require advanced simulation modelling to accurately track component and member performance and failure, load sharing, failure of other components/members due to load redistribution, and progression of structural failure leading to economic and other losses. The outcome is an estimate of the probability of damage conditional on a specific wind speed, flood level, temperature, or other hazard. Another challenge is that infrastructure, particularly houses, are very complex systems comprising of hundreds to thousands of components and members of differing materials. Poor detailing and workmanship issues contribute to most damage - so the engineering and stochastic models need to consider these variables - such as screw fasteners being spaced too far apart, or some not connected to purlins and battens, etc. These are more challenging to model stochastically than more conventional 'engineered' constructions such as bridges, towers, etc. where materials are more uniform, and workmanship subject to more quality control measures.

The relationship between damage and loss often depends on the hazard and item of infrastructure being considered. For example, insurance or building performance data may be used to derive vulnerability models which are often expressed in terms of Pr(L|H). An examples of a vulnerability model for Australian houses subject to floods is shown in Figure 3 where the hazard H is the water depth above the floor.

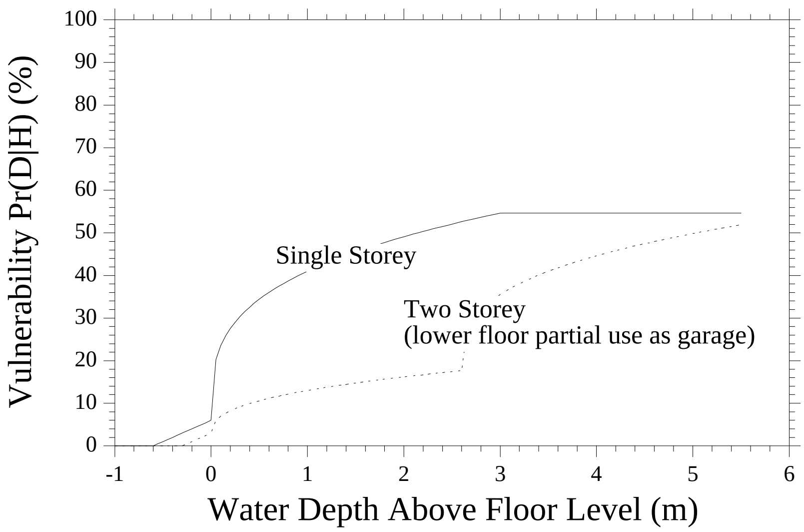


Figure 3 Flood Vulnerability Curves for Residential Construction in Brisbane (Adapted from Mason et al. 2012)

Exposure and loss data relates to direct and indirect loss or consequence due to location and extent of infrastructure damage, for existing exposure and future projections. Most existing studies consider direct losses related to building damage and contents losses. While these direct costs can be substantial, indirect losses caused by business interruption, clean-up, loss during reconstruction, extra demands on social services, and changes to demand and supply of intermediate consumption goods, etc. can also be significant. Moreover, post-disaster inflation can be very high following a major natural disaster.

Input-output (I-O) models are used to predict how a disaster (shock) on one or more sectors (e.g. construction, retail trade, utilities, manufacturing, professional and business service, educational services, health care, and government services) affect the demand and supply of intermediate consumption goods that cause a reduction in economic production (e.g. Greenberg et al. 2007, Hallegatte 2008). In other words, damage to capital stock will lower growth in the short-run by reducing productivity and sector outputs. The I-O model is the most widely used tool for regional economic impact analysis, and its use for natural hazard loss estimations dates from the 1970s (Rose 2004). While the I-O model is not without its difficulties, it can provide a useful starting point for assessing indirect losses due to extreme natural events.

Risk reduction (ΔR) may result from reduced vulnerability $Pr(D|H)$, $Pr(L|D)$ or exposure (L). For instance, changes to planning may reduce the number of new properties built in a flood plain which will reduce L, or more stringent design codes may reduce the vulnerability of new infrastructure. Systems and reliability modelling are essential tools to quantify the level of risk reduction, and the extent of risk reduction due to adaptation measures will depend on the hazard, location, and timing of adaptation.

The co-benefits of adaptation (ΔB) may include reduced embodied energy and reduced carbon footprint over the life cycle of the facility. This might consider the initial embodied energy associated with the dwelling including footings, structure and fit-out together with the recurrent embodied energy associated with refurbishment over the life cycle and the operational energy needed to operate a building.

Costs of adaptation, timing of adaptation, discount rates, future growth in infrastructure and spatial and time-dependent increase in climate hazards need to be included in any risk analysis. Of particular interest is uncertainty about the level of discount rates. Infrastructure projects are often assessed with discount rates of 4-10%. However, lower discount rates may be appropriate when considering intergenerational effects often associated with climate change policy decisions.

The Australian Office of Best Practice Regulation, U.S. Office of Management and Budget, and other regulatory agencies strongly recommend risk-neutral attitudes in their decision-making (e.g. OBPR 2010, OMB 1992, Faber and Stewart 2003, Sunstein 2002, Ellingwood 2006). This entails using mean or average estimates for risk and cost-benefit calculations, and not worst-case or pessimistic estimates. Paté-Cornell (2002) elaborates on this point by stating "if risk ranking is recognized as a practical necessity and if resource limitations are acknowledged, the maximum overall safety is obtained by ranking the risks using the means of the risk results (i.e., expected value of losses)."

This type of "rational" approach to risky decision making is challenging to governments and their agencies which might have other priorities and political concerns. Hardaker et al. (2009) note that "policy-making is a risky business", and that "Regardless of the varied desires and political pressures, we believe that it is the responsibility of analysts to forcefully advocate rational decision methods in public policy-making, especially for those with high risk. We believe that more systematic analysis of risky policy decisions is obviously desirable." If rational approaches to public policy making are not utilised, then politically driven processes "may lead to raising unnecessary fears, wasting scarce resources, or ignoring important problems." (Paté-Cornell 2002). Probability neglect is a form of risk aversion as decision-makers are clearly averse to events of large magnitude irrespective of the probability of it actually occurring. There is also cost neglect since much of the literature dwells on vulnerabilities and recommends adaptation measures with little attention paid to how much such adaptation measures will actually cost.

It is important to note that the issue of risk aversion is not a new one, but has been well researched and documented for politically sensitive and controversial decisions associated with nuclear power safety, aviation safety, pharmaceutical benefits scheme, environmental pollution, etc. In these cases, risk acceptance criteria has been developed based on annual fatality risks and net benefit analysis using expected (mean) values. In principle, decisions related to climate adaptation measures should be made with similar risk-based methodologies.

3 Wind Hazard Modelling

3.1 Probabilistic Model of Wind Hazard

Wind gust data has been recorded in Australia since 1939; hence the longest historical record is only around 70 years. Statistical and probabilistic approaches still suffers from sampling errors, and possibly some human and instrumental errors in data collection. Meanwhile, one advantage of using this approach for wind hazard modelling is that the observed data at the fixed locations of meteorological stations reasonably represent the characteristics of wind actions that buildings and infrastructure are exposed to; i.e. the recorded data at a site represent directly the time series of near-surface (typically at 10 m height) wind loads on a structure were it built at the site. Therefore, this approach offers fairly realistic wind load modelling and estimation in the context of structural design and vulnerability assessment.

Non-cyclonic gust speeds (winds not associated with tropical cyclones) dominate in South-East Queensland, and further south in Sydney and Melbourne. In other words, wind fields for Brisbane, Sydney and Melbourne are insensitive to cyclonic winds for all return periods. Hence, probabilistic models are thus developed only for non-cyclonic gust speeds in Brisbane, Sydney and Melbourne. For more details see Wang et al. (2013).

Non-cyclonic gust speed is modelled as a generalised extreme-value distribution. The cumulative distribution function for annual maximum non-cyclonic peak gust speed is (Wang et al. 2013):

$$F(V) = e^{-\left[1-k_g\left(\frac{v-v_g}{\sigma_g}\right)\right]^{1/k_g}} \quad (5)$$

where v_g, σ_g and k_g are the location, scale and shape parameters, respectively (see Table 1). If k_g=0 then Eqn. (5) becomes a Gumbel distribution:

$$F(V) = e^{-e^{-\left(\frac{v-v_g}{\sigma_g}\right)}} \quad (6)$$

Table 1 Non-Cyclonic Gust Speed Parameter Values (Wang et al. 2013)

LOCATION	v_g	σ_g	k_g
Brisbane	24.2760	3.2081	0
Sydney	29.2886	2.5717	0
Melbourne	25.8036	1.8252	0

Climate projections suggest that, for non-cyclonic winds, the mean wind speed (averaged over 10 minutes) may increase by up to 20% by 2070 along the east coast of Australia (CSIRO 2007). If the relationship between mean wind speed (averaged over 10 minutes) and peak gust wind speed is constant (i.e. gust factor is constant - Holmes 2001), then proportional increases in gust wind and mean wind speeds are identical. Equation (6) is thus modified to

$$F(V) = e^{-e^{-\left(\frac{\frac{v}{1+\frac{\gamma_{mean}(t)}{100}}-v_g}{\sigma_g}\right)}} \quad (7)$$

where the factor $\gamma_{mean}(t)$ represents the time-dependent percentage change in gust wind speed. Figure 4 shows the relationship between gust wind speed and return period calculated from Eqn. (7). The Coefficient of Variation (COV) of peak wind loads is up to 50%.

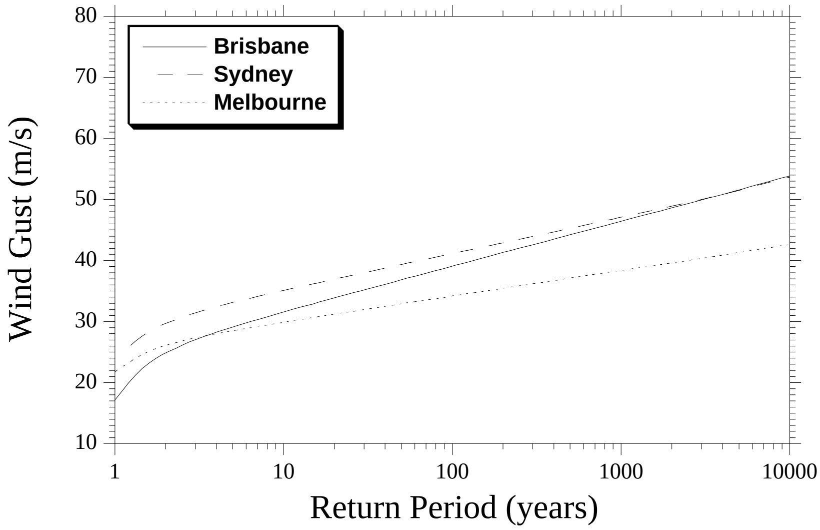


Figure 4 Influence of Return Period on Gust Wind Speed

Since Eqn. (7) was derived from a dataset from the past 60-80 years, projections beyond return periods of approximately 100-250 years are uncertain. Nonetheless, these projections form the basis of engineering design codes where design loads are based on return periods of up to 2,000 years (AS/NZS1170.2 2011). We also recognise that the uncertainty of wind field was not considered in the study, and projections are sensitive to probabilistic model selection (Wang et al. 2013). An example of this is changes in wind field predictions from Wang and Wang (2009) and Wang et al. (2013) using similar datasets. Wang and Wang (2009) used the shifted exponential distribution to predict non-cyclonic winds, whereas Wang et al. (2013) revised the 2009 study and recommended the generalised extreme-value distribution for non-cyclonic winds. Figure 5 shows the significant differences between the two prediction models for Brisbane. The latter model results in 16% lower predictions for a 10 year return period, and 37% lower predictions for a 10,000 year return period. The sensitivity of wind field to probabilistic model selection is dramatic.

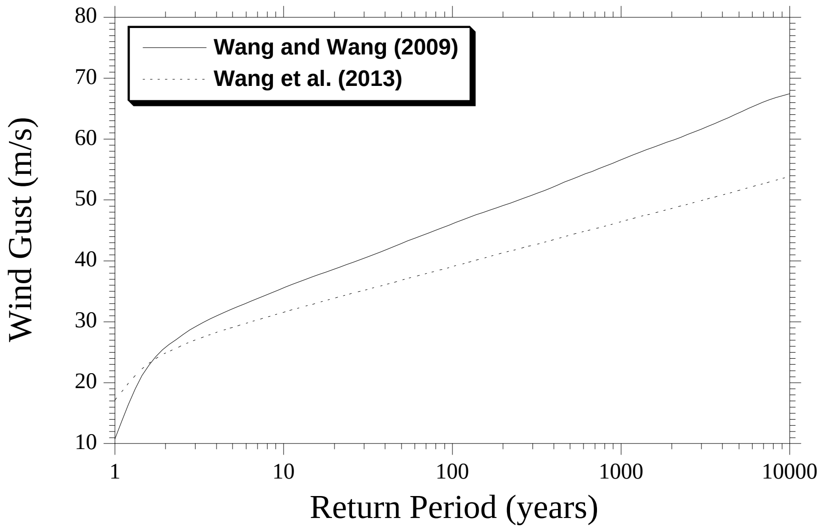


Figure 5 Effect of Probabilistic Model Selection Gust Wind Hazard

3.2 Wind Hazards for Australian Housing

The Australian Standard "Wind Loads for Houses" AS4055-2012 assesses design wind speeds for housing and so is used herein to determine terrain and shielding effects for houses in an urban environment for the following two exposure categories:

- foreshore (500 m from coast)
- non-foreshore (more than 500 m from coast)

The terrain category for the two exposure categories are obtained from AS4055-2012 and are shown in Table 2. The terrain multipliers specified in AS4055-2012 are influenced by region, terrain category and roof height and are equal to K_t=1.0 and K_t=0.83 for foreshore and non-foreshore locations, respectively (AS4055-2012). Average roof height is taken as 6.5 m since AS4055-2012 states that this height covers the majority of housing.

Since houses in the studied cities are in urban environments then AS4055-2012 assumes full shielding with K_s=0.85. Full shielding is defined to occur where at least two rows of houses surround the house being considered - this is appropriate for assessing wind events on large numbers of houses (AS4055-2012). Note that Nadimpalli et al. (2007) report that there is a "known conservatism of the wind standard methodology", and the Australian Wind Loading Standard AS1170.2-Supp 1 (2002) notes that K_s values between 0.8 and 0.9 are appropriate for suburban housing. When determining the wind classification for housing, AS4055-2012 adopts a correction factor of 0.95 for wind speed to "account for the variation of orientation of houses within suburbs and groups of suburbs". Since the shielding factor K_s directly affects wind speed, wind speeds can be reduced by 5% by applying this correction factor to K_s resulting in K_s=0.95×0.85≈0.80.

Since the risk assessment is to be conducted on a regional scale, local topographic features were not considered. The probabilistic wind field model described herein is relatively simple but it will allow the relative changes in damage risks due to temporal changes in wind hazard and building vulnerability to be estimated.

Table 2 Terrain Category and Wind Classification (AS4055-2012)

LOCATION	TERRAIN CATEGORY	WIND CLASSIFICATION	DESIGN GUST WIND SPEED
Brisbane			
Foreshore	TC1.5	N3	50 m/s
Non-Foreshore	TC3.0	N2	40 m/s
Sydney			
Foreshore	TC1.5	N2	40 m/s
Non-Foreshore	TC3.0	N1	34 m/s
Melbourne			
Foreshore	TC1.5	N2	40 m/s
Non-Foreshore	TC3.0	N1	34 m/s

3.3 Climate Projections for Wind Hazard

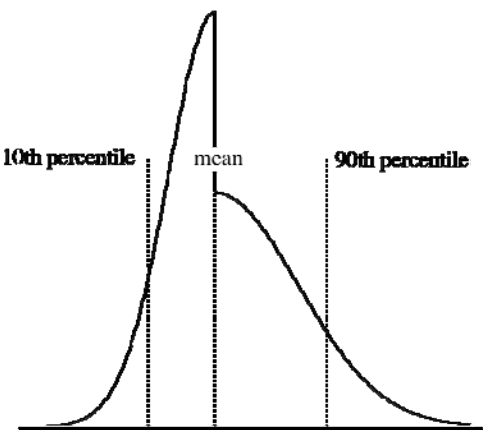
CSIRO (2007) suggest the average annual change in mean wind speed is projected to increase by 6% in Brisbane by 2070, with 10th and 90th percentiles of -2% and +19%, respectively, for the A1FI (high) emission scenario, and 10th and 90th percentiles of -1% to +10% for the B1 (medium) emission scenario. Projected changes in wind speeds for Sydney and Melbourne are lower than for Brisbane. The average annual change in mean wind speed for Sydney and Melbourne is projected to reduce by 0-1% by 2070, with 10th and 90th percentiles of -9% to -18% and +6% to +12%, respectively, for the A1FI and B1 emission scenarios. Note that climate projects are relative to 1990 levels.

Another consequence of enhanced greenhouse conditions is a 2 to 5 degrees poleward shift of tropical cyclones by 2100 (CSIRO 2007, Bengtsson et al. 2006, Leslie et al. 2007). A southern shift of 2 to 5 degrees of latitude is approximately 200 to 500 km, so regions historically less subject to cyclones (e.g. Brisbane and other areas in South East Queensland) may in the future be more vulnerable to more damaging wind speeds. However, Abbs (2012) predicts a poleward shift of only 100 km. A poleward (southern) shift of tropical cyclones of 1 to 3 degrees of latitude (100 - 300 km) will not affect cyclonic wind parameters for South East Queensland (Stewart and Wang 2011). However, a poleward shift of 5 degrees by 2100 dramatically increases cyclonic winds for South East Queensland.

Although there are still many uncertainties to accurately define the future trend of severe wind in Australia, considering recent findings for Australia, three wind pattern scenarios are considered based on CSIRO (2007) wind speed projections to 2070 for B1 and A1FI emission scenarios. Truncated normal distributions are used to represent uncertainty of changes in wind speeds at 2070 (γ_{mean}) where 10th and 90th percentiles provided by CSIRO (2007) allow the standard deviation of the two truncated normal distributions each with cumulative probabilities of 50% to be calculated, see Table 3 (σ_L is standard deviation of lower half of the distribution, and σ_U is standard deviation of upper half of the distribution). The 'no change' scenario consists of σ_L=σ_U=0%. A poleward shift of cyclones to South East Queensland is another possibility, though unlikely, wind pattern scenario, and is beyond the scope of the present study.

Table 3 Wind Pattern Scenarios for γ_{mean}(2070), and Corresponding Standard Deviations for Lower and Upper Halves of Truncated Normal Distribution (σ_L, σ_U)

	B1 EMISSION SCENARIO			A1FI EMISSION SCENARIO		
Location	10th	Mean	90th	10th	Mean	90th
Brisbane	-1%	+3%	+10%	-2%	+6%	+19%
	σ_L=3.1%, σ_U=5.5%			*σ_L=6.2%, σ_U=10.1%*		
Sydney	-8%	0%	+6%	-15%	-1%	+12%
	σ_L=6.2%, σ_U=4.7%			*σ_L=10.9%, σ_U=10.1%*		
Melbourne	-9%	-1%	+6%	-18%	-1%	+12%
	σ_L=6.2%, σ_U=5.5%			*σ_L=13.3%, σ_U=10.1%*		



The economic assessment of adaptation measures will be dependent on time-dependent changes in wind field parameters. This path dependency can be modelled as linear or non-linear changes with time. There is little information about how wind speeds will vary with time as most climate projections provide climate change results for the end of a time period (such as 2050) and do not provide intermediate predictions. However, it is clear that the rate of climate impact is expected to increase with time for high emission scenarios, but will reduce with time for low emission scenarios (for more details see Stewart and Wang 2011). Nonetheless, a time-dependent linear change of climate impact (in this case, wind speed) seems appropriate to 2070. Hence, the analyses to follow will assume a time-dependent linear change in wind speed for all emission scenarios. The effect of a non-linear time-dependent change in wind speed has a minor influence on damage risks (e.g. Stewart and Wang 2011).

4 Wind Vulnerability

A wind vulnerability function expresses building damage or loss as a function of wind speed. Several vulnerability models for wind hazard have been developed (Unanwa et al. 2000, Khanduri and Morrow 2003, Pinelli et al. 2004, Jain et al. 2005, Nishijima et al. 2012, Walker 2011a). In Australia, a widely used wind vulnerability model for North Queensland is that proposed by Walker (1994) based on insurance loss data and expert judgment. Considered to be the best available model at the time, the wind vulnerability model has been used by Harper (1999), Stewart (2003), Stewart and Li (2010), Waters et al. (2010), and others.

Henderson and Ginger (2007) developed a probabilistic model of component and connection strengths for high-set houses typically built in the 1960s and 1970s in Townsville, Darwin and other locations in Northern Australia. Their building vulnerability model for this type of pre-1980 construction is in good agreement with Walker's pre-1980 construction wind vulnerability model (Stewart and Li 2010). The Henderson and Ginger (2007) building vulnerability model also compared very well with damage data from Cyclones Althea and Tracy.

More recently, a suite of vulnerability curves are being developed by Geoscience Australia and James Cook University (Wehner et al. 2010). A suite of vulnerability curves representative of typical Australian building types were developed from a workshop attended by members of the Australian wind engineering community. Other experts were then asked to refine these curves for 203 housing types considering a wide variety of housing types, construction and age. Many of these curves are proprietary, however, some details are described by Wehner et al. (2010) and Ginger et al. (2010).

The vulnerability function for damage to residential construction is summarised as (Wehner et al. 2010):

$$\Pr(D|H) = 100\left\{1 - \exp\left[-\left(\frac{v}{e^{\beta}}\right)^{\frac{1}{\alpha}}\right]\right\} \qquad \Pr(D|H) \le 100\% \tag{8}$$

where v is the peak gust wind speed at a 10 m height, and α and β are parameters that describe the shape and position of the curve. These parameters are described in Table 4, for post-1996 (new) brick veneer residential housing with tiled roof. This comprises the majority of new housing. Note that Pr(D|H) is expressed as expected (mean) damage (insured value). Figure 6 shows percentage damage for the wind vulnerability curves described by Eqn. (8) and Table 4. Vulnerabilities for brick veneer housing with sheet metal roofing are very similar to those shown in Figure 6.

If Eqn. (8) is modified to include terrain and shielding multipliers, then:

$$\Pr(D|H) = 100\left\{1 - \exp\left[-\left(\frac{K_t K_s v}{e^{\beta}}\right)^{\frac{1}{\alpha}}\right]\right\} \qquad \Pr(D|H) \le 100\% \tag{9}$$

where the terrain multiplier (K_t) is given in Section 3.2, and shielding multiplier (K_s) is 0.80 (full shielding - see Section 3.2). Note that the vulnerability models ignore debris impact, and assumes no degradation of material or connection capacities.

Table 4 Parameters for Wind Vulnerability Model, for New Brick Veneer Residential Housing with Tile Roof

WIND CLASSIFICATION	α	β
Brisbane (Region B, AS1170.2-2011)		
N2	0.1481	4.0126
N3	0.1296	4.1245
N4	0.1233	4.2253
N5	0.1075	4.3654
Sydney, Melbourne (Region A, AS1170.2-2011)		
N1	0.1585	3.8909
N2	0.1530	3.9700
N3	0.1411	4.0682
N4	0.1267	4.2154

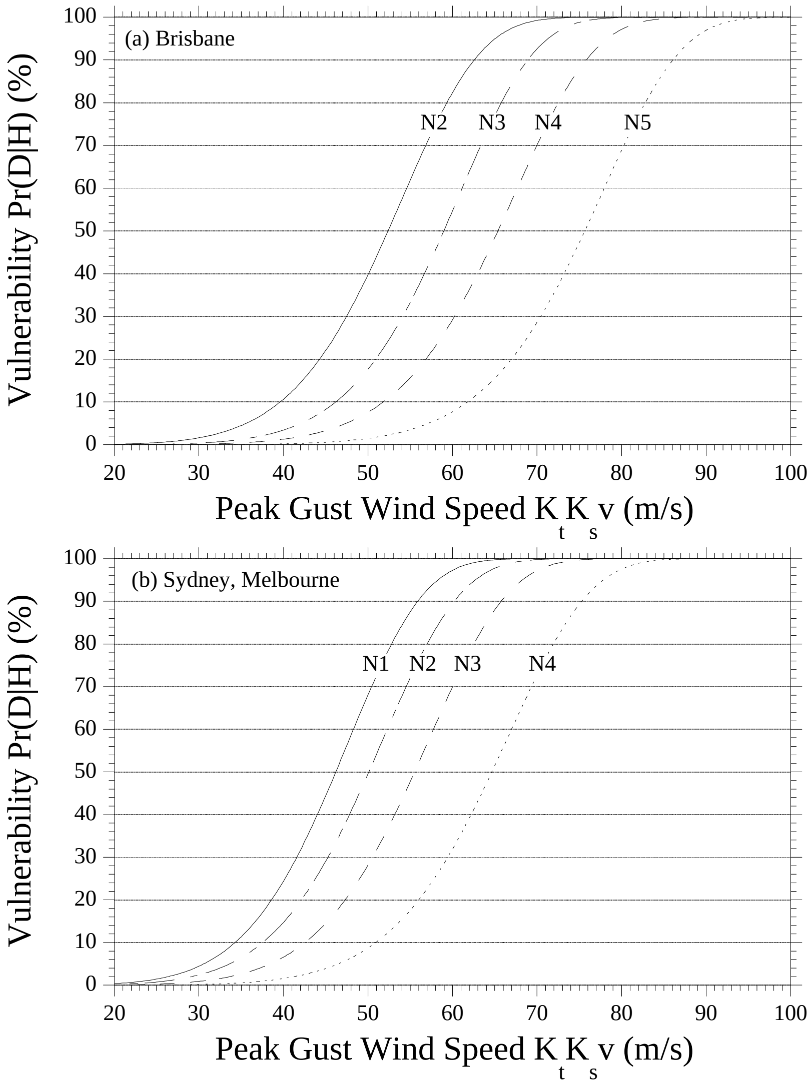


Figure 6 Wind Vulnerability Curves for (a) Brisbane and (b) Sydney and Melbourne, for New Brick Veneer Residential Housing with Tile Roof

It is clearly acknowledged by Ginger et al. (2010) that since the wind vulnerability curves were obtained from expert opinion they need to be validated with reliability data. Ginger et al. (2010) also note that “the insurance industry has commented that the present ranking over-predicts wind vulnerability as they understand it”. Hence, this wind vulnerability model is subject to considerable uncertainty - but it is the best one that is publicly available. Stochastic and structural reliability techniques are needed to accurately track component and member performance and failure, load sharing, failure of other components/members due to load redistribution, and progression of structural failure leading to economic and other losses (e.g. Henderson and Ginger 2007). However, it is a very useful starting point for quantifying the effectiveness of strengthened building standards (or enforcement). The general belief, from experimental testing, damage surveys and anecdotal evidence, is that many strengthening procedures, if properly designed and installed, will significantly reduce vulnerability. The wind vulnerabilities shown in Figure 6 clearly supports this belief.

The developers of the vulnerability curves proposed by Geoscience Australia and James Cook University (Figure 6) recognise that there is uncertainty and variability of wind vulnerability and suggest the use of 5^{th} and 95^{th} percent confidence intervals (Schofield et al. 2010). However, no data or methodology is provided to estimate these confidence intervals. Stewart et al. (2012, 2013) found that damage risks are not sensitive to moderate uncertainty of vulnerability curves, particularly since variability of wind speed is so high with COV exceeding 50%. Moreover, while the variability of performance of individual houses may be very high, the variability of the average performance across a region or city will be significantly less. Hence, uncertainty and variability of vulnerability curves are ignored in the present study.

5 Loss Function

Most existing studies consider direct losses related to structural damage and contents losses. Indirect losses caused by business interruption, clean-up, loss during reconstruction, extra demands on social services, and changes to demand and supply of intermediate consumption goods, etc. can also be significant (e.g. NAS 1999, Lindell and Prater 2003, Hallegatte 2008, Cavallo and Noy 2010). Moreover, post-disaster inflation can be up to 100% following a major natural disaster (e.g. Walker 2011b).

5.1 Direct and Indirect Losses

Direct costs are the immediate consequences of the disaster - generally those associated with structural damage and contents losses at the present price level (Hallegatte 2008). Most, if not all, direct loss models show damage and contents loss as a direct proportion (linear) of wind vulnerability.

House replacement value is clearly variable and depends on the location, type, size, age and condition of the house. The Australian Bureau of Statistics reported that the average cost per new house in Queensland, New South Wales and Victoria was $245,000 in 2007-08 (ABS 2008). When adjusted for inflation this is equivalent to approximately $270,000 in 2012 dollars. This cost represents the actual completion value of the residence based on the market or contract costs of jobs including site preparation, but excluding the value of the land and landscaping. No allowance is made for increases in floor area. The insured value of the house is higher than the replacement value due to many homeowners also holding contents insurance. The Australian Bureau of Statistics reports that the mean value of contents of a dwelling is approximately $70,000 in 2012 dollars (ABS 2006). It follows that the average insured value of a house is approximately 25% higher than house replacement value. The loss L is equal to insured value of the house, normalised to L=1.25 of house replacement value.

Indirect costs "include all losses that are not provoked by the disaster itself, but by its consequences" (Hallegatte and Przyluski 2010). Indirect losses arising from damage to housing might include (BTE 2001):

- residential clean-up
- household alternative accommodation
- disaster response and relief
- injuries and fatalities
- damage to social environment, cultural heritage and other intangible costs
- business and economic disruption

Fortunately, there are few deaths or serious injuries from housing damage during most cyclones or storms (BTE 2001). This is due to reduced vulnerability of housing following Cyclone Tracy, and improved forecasting of cyclones and storms. For this reason, the costs of fatalities and injuries arising from damage to housing is relatively minor compared to other direct and indirect costs, and so is not considered herein as a separate indirect cost.

Major causes of indirect losses to housing are the decrease in housing services (value attributed to lost housing services during period of reconstruction) and demand-surge or post-disaster inflation (Hallegatte 2008, Walker 2011b.) The data is very limited to accurately quantify how indirect losses increase with vulnerability. However, if we take indirect loss data from Hurricane Katrina (Hallegate 2008), Hurricane Rita (Pan 2011) and Cyclone Tracy (BTE 2001), then the Indirect Cost Ratio (ICR) defined as ratio of indirect-to-direct cost is (Stewart et al. 2012):

$$\mathrm{ICR} = 0.0058\left(\frac{206\,\Pr(D|H)}{100}\right) - 0.20 \qquad \mathrm{ICR} \geq 0 \qquad (10)$$

This model is shown in Figure 7, as are observed data based on Hurricane Katrina, Hurricane Rita and Cyclone

Tracy. These studies observed that indirect loss is zero if Pr(D|H)<15-20%. This is convenient because the transition between minor and major damage occurs at a damage loss of around 20% (e.g. Leicester et al. 1979). The ICR Model seems to under-predict indirect losses for cyclone Tracy and Hurricane Rita. However, there is some uncertainty about vulnerabilities for these events. Stewart et al. (2012, 2013) have shown that the use of alternate indirect loss models increases total damage risks by no more than 1-2%.

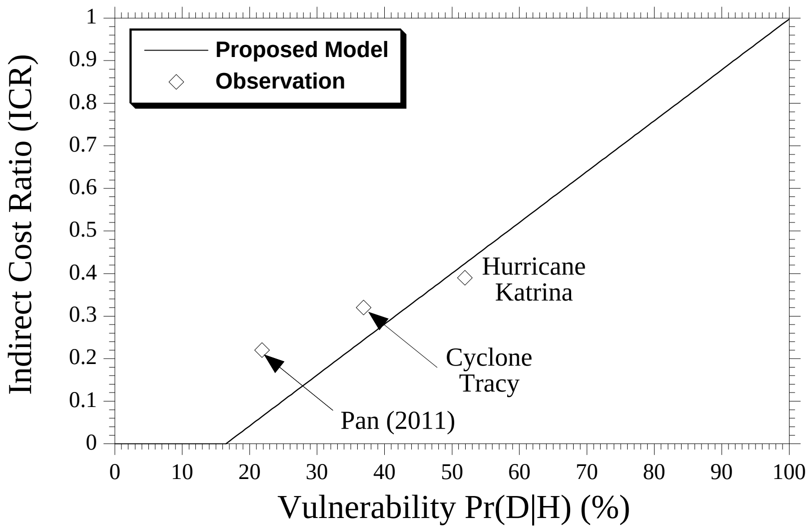


Figure 7 Indirect Cost Ratio (ICR) Model

5.2 Loss Function

The loss function for direct and indirect losses Pr(L|D) is

$$\Pr(L|D) = [1 + ICR] \tag{11}$$

where ICR is the indirect-to-direct cost ratio (see Section 5.1). Figure 8 shows the loss function where, total loss only begins to depart dramatically from direct costs when Pr(D|H)>20%.

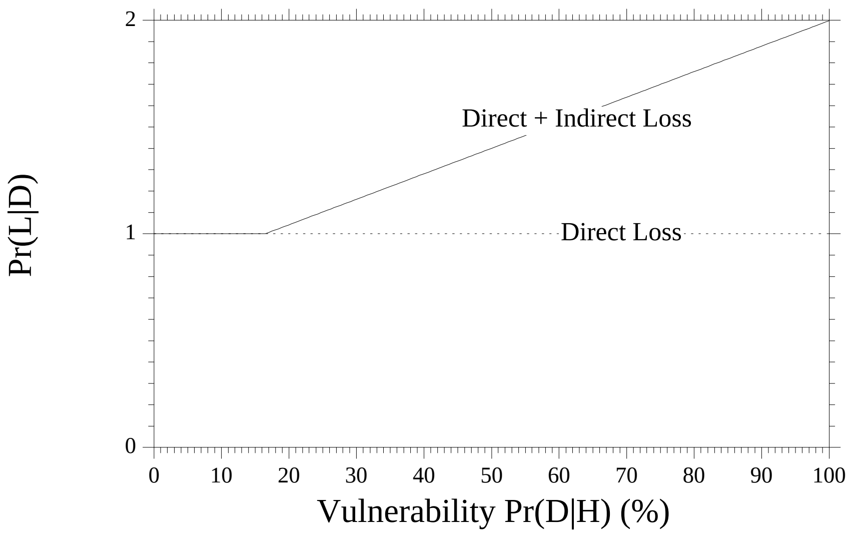


Figure 8 Direct and Indirect Costs as Function of Vulnerability

6 Existing or 'Business as Usual' Damage Risks

If we modify Eqn. (2) then the annual damage risk per house for a climate change scenario at time t is

$$E_{WC}(t) = \int_0^{\infty} \Pr(H = v|C)\Pr(D|H)\Pr(L|D)L\,dv = \int_0^{\infty} \left[\frac{dF_v(v,t)}{dv}\right]\Pr(D|H)\Pr(L|D)L\,dv \qquad (12)$$

where Pr(H=v|C) is the time-dependent probability density function for annual maximum wind speed, Pr(D|H) is wind vulnerability given by Eqn. (9), Pr(L|D) is loss function given by Eqn. (11), L is loss, $F_v(v,t)$ is the time-dependent cumulative function for annual maximum wind speed given by Eqn. (7), and WC is wind classification. Equation (12) assumes that damage is caused by the largest wind event in any calendar year, which will slightly underestimate damage risks in the event of a (very unlikely) lesser damaging event occurring in the same season. A time-dependent change of wind speeds will change annual maximum wind speeds which in turn affects the damage risks given by Eqn. (12). Note that in this scenario-based approach Pr(C)=100%. Also note that wind vulnerability asymptotes to close to zero as wind speed decreases (but never reaches zero even for wind speeds less than 20 m/s), so vulnerability is taken as zero if wind speed falls below a return period of 2 years.

Table 5 shows the annual damage risk $E_{WC}(t)$ per house as percentage of house replacement value for houses designed to wind classifications N1 to N5, for no change in climate, and direct and indirect costs. In other words, this reflects the existing level of annual risk. For houses designed to current wind classifications the inclusion of indirect costs increases direct damage risks by less than 2-6%. This is to be expected, as the most frequent level of damage to houses is less than 20%, while the ratio of indirect-to-direct costs can be quite high for large losses, the average increase is much less. It is also observed from Table 5 that houses built to current standards have annual damage risks of up to 0.8%, and damage risks are highest for Sydney due to higher vulnerability and gust hazard when compared to Brisbane and Melbourne.

Table 5 Annual Damage Risks (percentage of replacement value), for No Climate Change. Note: Boxed Values Represent Current Wind Classificaton for Each Location

	WIND CLASSIFICATION (AS4055-2012)				
LOCATION	N1	N2	N3	N4	N5
Brisbane					
Foreshore	-	0.27	0.06	0.02	0.00
Non-Foreshore	-	0.08	0.01	0.00	0.00
Sydney					
Foreshore	1.55	0.82	0.29	0.05	-
Non-Foreshore	0.48	0.24	0.08	0.01	-
Melbourne					
Foreshore	0.62	0.31	0.10	0.02	-
Non-Foreshore	0.19	0.09	0.03	0.00	-

Note that BITRE (2008) report that the average cost of severe storms is highest in NSW by a considerable margin. The damage risks in Table 5 show that the damage risks in NSW (Sydney) are significantly higher than in Queensland (Brisbane) and Victoria (Melbourne). This provides some supporting evidence that damage risks are considerably higher for Sydney.

Table 6 shows that mean damage risks for the B1 emissions scenario at 2070 can increase damage risks at 2070 for Brisbane by up to 40% when compared to the no change scenario (Table 5). For other cities the damage risks at 2070 are similar to no change losses. Damage risks for Brisbane increase by up to 120% for the A1FI emission scenario (Table 7), and mean losses in Sydney and Melbourne are 20% higher than the no change scenario. However, if current wind classifications are increased by one level (such as N2 to N3) then damage risks reduce by over 50%.

Table 6 Annual Damage Risks (percentage of replacement value), for B1 Emission Scenario at 2070. Note: Boxed Values Represent Current Wind Classificaton for Each Location

	WIND CLASSIFICATION (AS4055-2012)				
LOCATION	N1	N2	N3	N4	N5
Brisbane					
Foreshore	-	0.38	$\boxed{0.08}$	0.03	0.00
Non-Foreshore	-	$\boxed{0.11}$	0.02	0.00	0.00
Sydney					
Foreshore	1.58	$\boxed{0.84}$	0.30	0.05	-
Non-Foreshore	$\boxed{0.50}$	0.25	0.08	0.01	-
Melbourne					
Foreshore	0.60	$\boxed{0.30}$	0.10	0.01	-
Non-Foreshore	$\boxed{0.19}$	0.09	0.03	0.00	-

Table 7 Annual Damage Risks (percentage of replacement value), for A1FI Emission Scenario at 2070. Note: Boxed Values Represent Current Wind Classificaton for Each Location

	WIND CLASSIFICATION (AS4055-2012)				
LOCATION	N1	N2	N3	N4	N5
Brisbane					
Foreshore	-	0.54	$\boxed{0.13}$	0.04	0.00
Non-Foreshore	-	$\boxed{0.16}$	0.03	0.01	0.00
Sydney					
Foreshore	1.80	$\boxed{0.96}$	0.35	0.06	-
Non-Foreshore	$\boxed{0.56}$	0.29	0.09	0.01	-
Melbourne					
Foreshore	0.71	$\boxed{0.36}$	0.12	0.02	-
Non-Foreshore	$\boxed{0.22}$	0.11	0.03	0.00	-

7 Adaptation Strategy: Strengthen New Housing

The adaptation strategy involves the design of new housing to enhanced design codes; in this case, increasing the current wind classification by one category, see Table 8. For example, for Sydney this means that new construction would be designed for wind classification N3 rather than the current requirement of N2 for foreshore locations. This means that new construction and alterations would be designed to resist at least 50% higher wind pressures, resulting in increased strengths of structural components and their connections, leading to significantly reduced wind vulnerability of houses. The adoption of such an adaptation strategy would require amendments to the Building Code of Australia and AS4055 - and Maddocks (2011) suggests that industry would prefer to rely on changes to deemed-to-comply provisions because such provisions provide a higher level of certainty, and this is particularly so for residential construction.

Table 8 Adaptation Measure: Proposed Increase in Wind Classification (AS4055-2012)

		EXISTING SPECIFICATIONS		PROPOSED INCREASE IN WIND CLASSIFICATIONS	
LOCATION	TERRAIN CATEGORY	WIND CLASSIFICATION	DESIGN GUST WIND SPEED	WIND CLASSIFICATION	DESIGN GUST WIND SPEED
Brisbane					
Foreshore	TC1.5	N3	50 m/s	N4	61 m/s
Non-Foreshore	TC3	N2	40 m/s	N3	50 m/s
Sydney					
Foreshore	TC1.5	N2	40 m/s	N3	50 m/s
Non-Foreshore	TC3	N1	34 m/s	N2	40 m/s
Melbourne					
Foreshore	TC1.5	N2	40 m/s	N3	50 m/s
Non-Foreshore	TC3	N1	34 m/s	N2	40 m/s

Time of adaptation is an important variable. It seems reasonable that any proposal to change design standards and building regulation within the Building Code of Australia would take several years, and then more time before builders change their design of houses - we assume this process will take five years. Hence, we assume that a proposal to adopt the adaptation strategy proposed herein would result in a feasible time of adaptation of five years from 2013, hence t_{adapt}=2018. Sensitivity analyses will be conducted to assess the sensitivity of results to changes in these parameter values.

The analysis assumes that the cost of adaptation will be an additional cost, borne by the residential home owner, government or other agency. Either way, these are pro-active measures that, for appropriate climate adaptation programs, will benefit home owners, insurers, society (less social disruption) and government.

If we modify Eqn. (3) for this decision problem then the NPV for a single house built to enhanced standards at time t_{adapt} for a climate change scenario C_s (no change, A1, A1FI) is

$$NPV(T|C_s) = \sum_{t=t_{adapt}}^{T} \frac{\Delta R \times E_{WC}(t)}{(1+r)^{t-2018}} - \frac{C_{adapt}}{(1+r)^{t_{adapt}-2018}} \qquad (13)$$

where NPV is expressed as percentage of replacement value of the house, C_{adapt} is the cost of the adaptation strategy expressed as percentage of house replacement value, t_{adapt} is time of implementing the adaptation strategy, $E_{WC}(t)$ is the damage risk per house associated with current wind classification calculated from Eqn. (12), ΔR is the reduction in risk associated with increasing the current wind classification by one category (e.g. from N2 to N3), and r is the discount rate. Co-Benefits are assumed as ΔB=0.

Note that costs and benefits are normalised in terms of house replacement value at time of adaptation in 2018 where L=1.25 to include value of contents. Discounting applies for costs and benefits from 2019 onwards.

7.1 Risk Reduction (ΔR)

Figure 9 shows percentage reduction in vulnerability as a function of wind speed, as well as the range of wind speeds for foreshore and non-foreshore locations (i.e., lower value is non-foreshore 10 year return period, upper value is foreshore 1,000 year return period). Clearly, reduction of vulnerability due to adaptation measures depends on wind field characteristics and location. It is evident that designing new houses to enhanced wind classification will reduce vulnerability often by more than 70% for Brisbane, and more than 50% for Sydney and Melbourne. The reduction in vulnerability reduces only for very high wind speeds where damages asymptote to 100% resulting in reduced relative reductions in vulnerability. Vulnerability reduction is higher for non-foreshore locations due to lower wind speeds than foreshore locations. Similarly, vulnerability reduction will decrease as climate change becomes more severe and wind speeds increase.

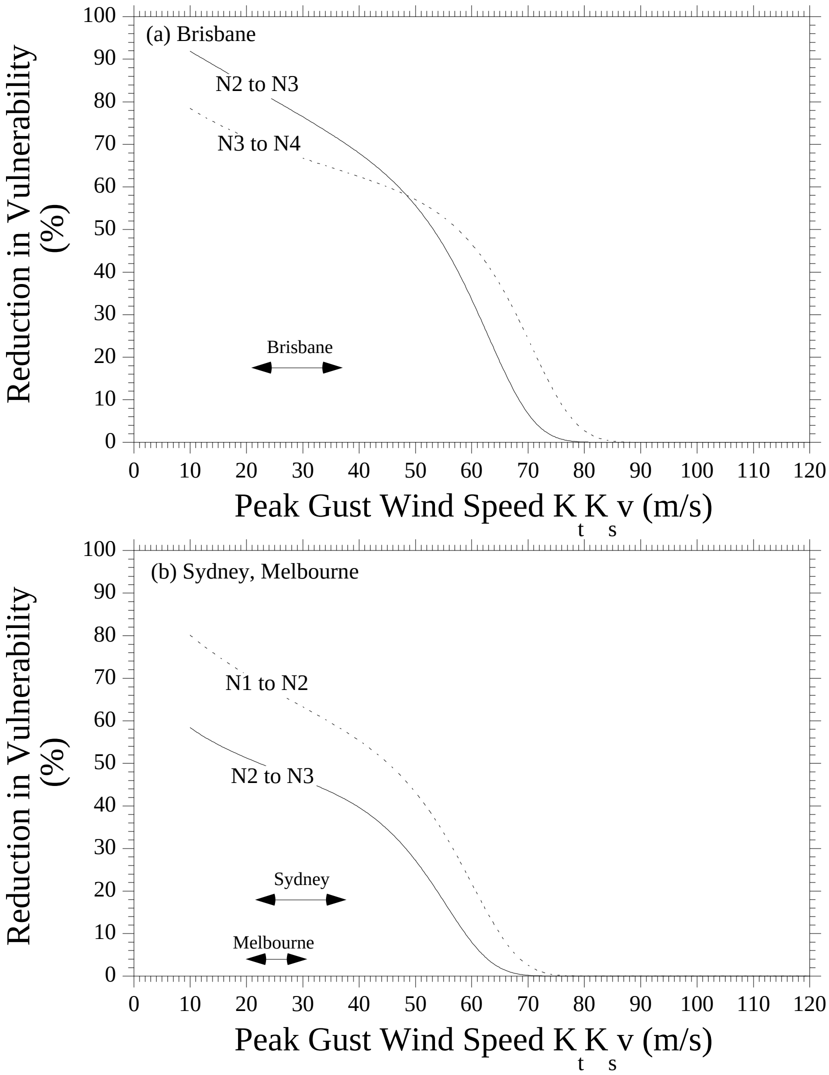


Figure 9 Reduction in Vulnerability for New Housing with Increase of Wind Classification

The overall reduction in risk calculated as percentage change in risk E_{wc} given by Eqn. (12) caused by the adaptation strategy is ΔR=75-80% for Brisbane, ΔR=50-65% for Sydney, and ΔR=50-70% for Melbourne. The risk reduction is relatively high because change in existing risks are based on integrating vulnerabilities across all winds speeds, and lower wind speeds have higher reductions in vulnerability. Clearly, the reduction in existing vulnerability is considerable for the scenarios considered for this adaptation strategy.

Applying structural adaptations for pre-1980 housing in Queensland also shows that reductions in vulnerability can be considerable. For example, screwed roof cladding and roof and batten upgrades can reduce vulnerability by 50-70% for wind speeds less than 50 m/s, and higher reductions in vulnerability are possible for other strengthening measures (King et al. 2012). Moreover, King et al. (2012) also note that "reducing the possibility of creating a dominant opening on the windward walls/windows also provides a significant improvement in resilience for housing located in non-cyclonic regions of Australia."

An overall risk reduction of ΔR=50-80% seems possible assuming the vulnerability models shown in Figure 6 are accurate. While there is uncertainty with the vulnerability models, there is clear acknowledgement from King et al. (2012) that structural adaptation can provide 'significant' improvements in vulnerability. Hence, a lower bound on risk reduction may be conservatively taken as ΔR=50%.

7.2 Cost of Adaptation (C_{adapt})

If residential construction is subjected to a change of wind classification due to increases in design wind forces, then AGO (2007) estimated the associated increase in cost of a new timber and concrete floor houses. Slab-on-ground construction is far more common for new houses, with approximately 80% of new houses being built with a concrete slab floor (CCAA 2003, 2007). The weighted average cost increase based on 80% concrete floors, and 20% timber floors is also shown in Table 9. If the average replacement value of a house is $270,000 then these increases gives C_{adapt} of 1-1.5% of the value of the house. These costs arise from larger structural members for the roof frame, wall frame, wall bracing, and foundations, as well as stronger fixings. The adaptation costs from AGO (2007) are from one source only, so there is uncertainty that these costs are realistic. However, it appears that adaptation costs for new construction will be modest.

Table 9 Adaptation Costs of New Housing with Increase of Wind Classification

CURRENT WIND CLASSIFICATION	PROPOSED INCREASE IN WIND CLASSIFICATION	AVERAGE COST OF ADAPTATION	
		2012 DOLLARS	% OF HOUSE VALUE
N1	N2	-	1.0%[1]
N2	N3	$2,800	1.1%
N3	N4	$3,800	1.4%

Note: [1] Assumed value

8 Results: Scenario-Based Analysis

The vulnerability, loss and adaptation costs are subject to considerable uncertainty due to lack of available data and models. The models described herein are the best available models, but as described previously, have their limitations and uncertainties. For this reason, calculations of risks, costs and benefits will be imprecise - although they will be useful in illustrating the comparative costs and benefits of adaptation. Hence, a 'break-even' analysis is conducted herein where minimum risk reduction or maximum cost of adaptation necessary for adaptation to be cost-effective is selected such that there is 50% probability that benefits equal cost - i.e. mean(NPV)>0. Decision-makers can then judge whether an adaptation strategy meets these break-even values. However, a risk averse decision-maker may wish the likelihood of cost-effectiveness to be higher before investing billions of dollars in an adaptation measure - to say 90% so there is more certainty about a net benefit and small likelihood of a net loss. Hence, adaptation measures are assessed for two metrics of cost-effectiveness:

1. Mean of NPV equals to zero - i.e., Pr(NPV>0)=50%.
2. Pr(NPV>0)=90%.

Results are calculated using Monte-Carlo event-based simulation methods. Unless notified otherwise the following parameters are used:

- date of implementing adaptation strategies is 2018 (t_{adapt}=2018)
- discount rate is r=4%
- discounting applies for costs and benefits from 2019 onwards
- indirect costs based on Eqn. (11)

Costs and benefits are calculated for the 52 year period 2018 to 2070 as 2070 is the limit of projections of wind hazard provided by CSIRO (2007). The stochastic variability of wind speed means that NPV is variable. The distribution of NPV is highly non-Gaussian which suggests that Monte-Carlo methods are well suited to this type of analysis. Note that in this scenario-based approach Pr(C)=100%.

8.1 Existing Stochastic Wind Field Model and a Changing Climate

Figures 10 to 15 show the maximum adaptation cost C_{adapt} for the adaptation measure (per new house) to be cost-effective for risk reductions of 10-100% for foreshore and non-foreshore locations in Brisbane, Sydney and Melbourne. These figures show:

1. the break-even cost of adaptation (i.e. maximum cost for mean(NPV)=0), and
2. the maximum cost of adaptation to ensure that there is 90% surety that benefits exceed the cost.

8.1.1 BRISBANE

Figure 10 shows that benefits of risk reduction are relatively low for Brisbane, due to the low level of existing risk as shown in Table 5 based on the latest stochastic wind field model (Wang et al 2013). However, if risk reduction is a modest 50% and worst (A1FI) emission scenario, the break-even analysis shows that adaptation is cost-effective only if the adaptation cost is less than 1.0% and 1.3% of house replacement cost for foreshore and non-foreshore locations, respectively. The break-even adaptation cost reduces by 0.2-0.5% for no change and B1 emission scenario. However, it is possible that actual adaptation costs can be this low, particularly since the AGO (2007) estimate adaptation costs to be 1.1-1.4% for Brisbane. The maximum cost of adaptation to ensure that there is 90% surety that benefits exceed the cost is 0.4-0.6% for all emission scenarios and locations (see Figure 11).

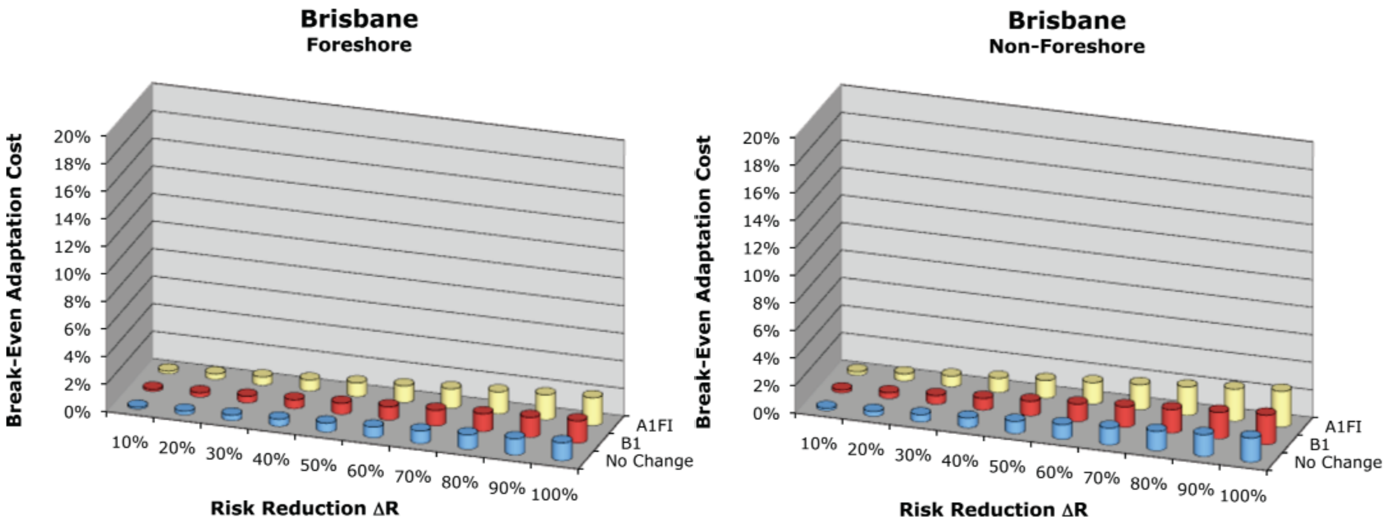


Figure 10 Break-Even Adaptation Costs for Foreshore and Non-Foreshore Locations in Brisbane

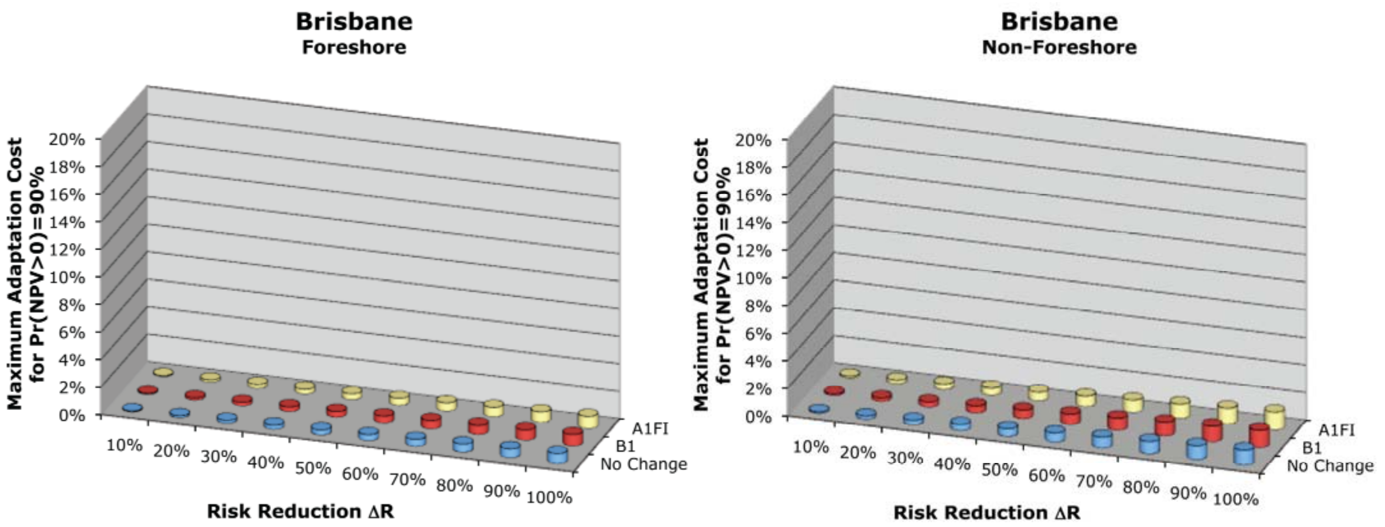


Figure 11 Maximum Adaptation Costs to Ensure Pr(NPV>0)=90% for Foreshore and Non-Foreshore Locations in Brisbane

Table 9 shows that the cost of adaptation for Brisbane is likely to be 1.4% for foreshore locations (N3 to N4), and 1.1% for non-foreshore locations (N2 to N3). If we adopt a cost of adaptation of 1.4% and 1.1% for these locations, and no change of climate then Table 10 show that the break-even risk reduction must exceed 100% (not possible) and 62% for foreshore and non-foreshore locations, respectively, to be 50% certain that NPV>0 for all climate projections. A changing climate (A1FI) reduces these break-even risk reductions to 70% and 42%, for foreshore and non-foreshore locations, respectively. The minimum risk reductions increase to ensure 90% certainty that NPV>0. Given that Section 7.1 shows that risk reductions of 75-80% can be achieved for Brisbane based on the vulnerability models described herein, then it is likely that designing new housing to enhance wind classifications is a cost-effective adaptation strategy for Brisbane for non-foreshore locations irrespective of climate scenario. However, adaptation is not likely to be cost-effective for foreshore locations unless the A1FI emission scenario is expected.

Table 10 Minimum Risk Reduction to Ensure (i) Mean(NPV)>0 (Break-Even Analysis), and (ii) Pr(NPV>0)=90%

LOCATION	ADAPTATION COST PER NEW HOUSE	MINIMUM RISK REDUCTION FOR MEAN(NPV)>0			MINIMUM RISK REDUCTION FOR PR(NPV>0)=90%		
		NO CHANGE	B1	A1FI	NO CHANGE	B1	A1FI
Brisbane							
Foreshore	1.4%	>100%	92%	70%	>100%	>100%	>100%
Non-Foreshore	1.1%	62%	52%	42%	100%	88%	87%
Sydney							
Foreshore	1.1%	6%	6%	6%	8%	11%	17%
Non-Foreshore	1.0%	9%	9%	9%	12%	17%	27%
Melbourne							
Foreshore	1.1%	15%	16%	14%	20%	32%	67%
Non-Foreshore	1.0%	23%	24%	23%	30%	47%	100%

Note: a risk reduction of >100% means that adaptation is not preferred.

We can look at this another way of course. The NPV per house is 0.2% for a non-foreshore location in Brisbane assuming a high (A1FI) emission scenario, modest risk reduction of 50% and cost of adaptation of 1.1%. Assuming house replacement cost of $270,000 in 2012 dollars, the NPV per house is approximately $500 to 2070. Section 7.1 found that risk reduction is 75-80% for Brisbane. If risk reduction is taken as 75%, NPV per house increases to 0.8% or $2,000 for the A1FI emission scenario.

Even if there is no climate change the adaptation strategy is still cost-effective for non-foreshore locations in Brisbane. The NPV is 0.2% for a risk reduction of 75% - or $500 per new house. Hence, even if climate projections are wrong, adaptation measures satisfies a ‘no regrets’ or win-win policy (Susskind 2010).

These results are different from Stewart and Wang (2011) and Stewart et al. (2012, 2013) which found that the mean NPV to 2100 per new house in Brisbane can reach up to $8,900 (3.4%) and $3,100 (1.2%) for foreshore and non-foreshore locations, respectively. This is due to the fact that the earlier work used a more conservative stochastic wind hazard model taken from Wang and Wang (2009), where Figure 5 shows the large difference between this model, and the new stochastic model developed by Wang et al. (2013). The vulnerability model has also changed, wind classification for foreshore locations increased from N2 to N3 in the latest version of AS4055 (2012), and policy period shortened to 2070. The large difference between wind model selection may mean that existing risks estimated in this study may under-estimate actual damage risks. If existing risks are increased by 100% (either due to increased wind hazard and/or higher vulnerability), then the break-even adaptation costs double to 2.0% and 2.6% of house replacement cost for A1FI emission scenario, 50% risk reduction, and foreshore and non-foreshore locations, respectively. These break-even adaptation costs are significantly higher than the AGO (2007) estimates of 1.1-1.4%, and so would be cost-effective. Clearly, results are sensitive to stochastic wind hazard and wind vulnerability modelling which in turn will affect existing risks.

8.1.2 SYDNEY

Table 5 shows that existing risk is highest for Sydney, so the benefits of risk reduction will also be highest for Sydney as shown in Figures 12 and 13. In this case, if risk reduction is over 50% and there is no change of climate, the break-even analysis shows that adaptation is cost-effective if the adaptation cost is less than 9.3% and 5.5% of house replacement cost for foreshore and non-foreshore locations, respectively. The effect of a changing climate on break-even adaptation costs is negligible, as this will increase the break-even adaptation cost to 9.7% and 5.7% for foreshore and non-foreshore locations, for the A1FI emission scenario. On the other hand, the maximum cost of adaptation to ensure that there is 90% surety that benefits exceed the cost will be less than the break-even costs. In this case, the adaptation is preferable if the risk reduction exceeds 50% and the adaptation cost is less than 6.8% and 4.0% of house replacement cost for foreshore and non-foreshore locations, respectively, and assuming no change in climate. As there is significant uncertainty associated with wind hazard projections for B1 and A1FI emission scenarios, the variability of NPV is higher for these scenarios. Hence, the maximum cost of adaptation to ensure that there is 90% surety that benefits exceed the cost will be up to 3% lower than for no climate change. This suggests that even a risk averse decision-maker would adopt the adaptation measure since the anticipated cost of adaptation is very low (less than 1.1%, see Table 9) and risk reduction exceeds 50%.

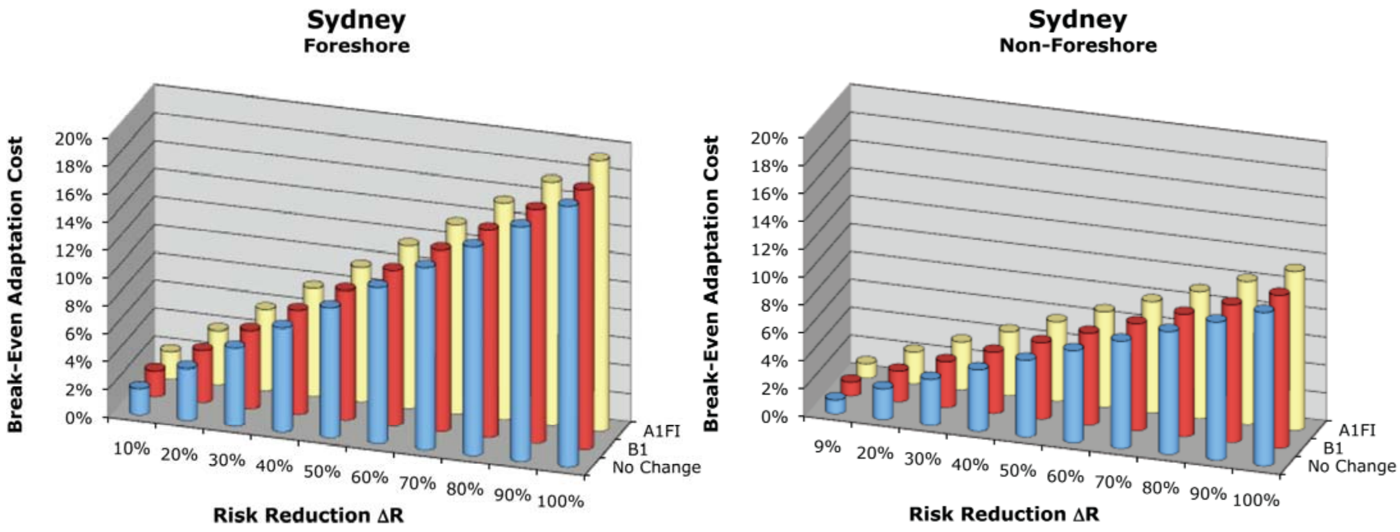


Figure 12 Break-Even Adaptation Costs for Foreshore and Non-Foreshore Locations in Sydney

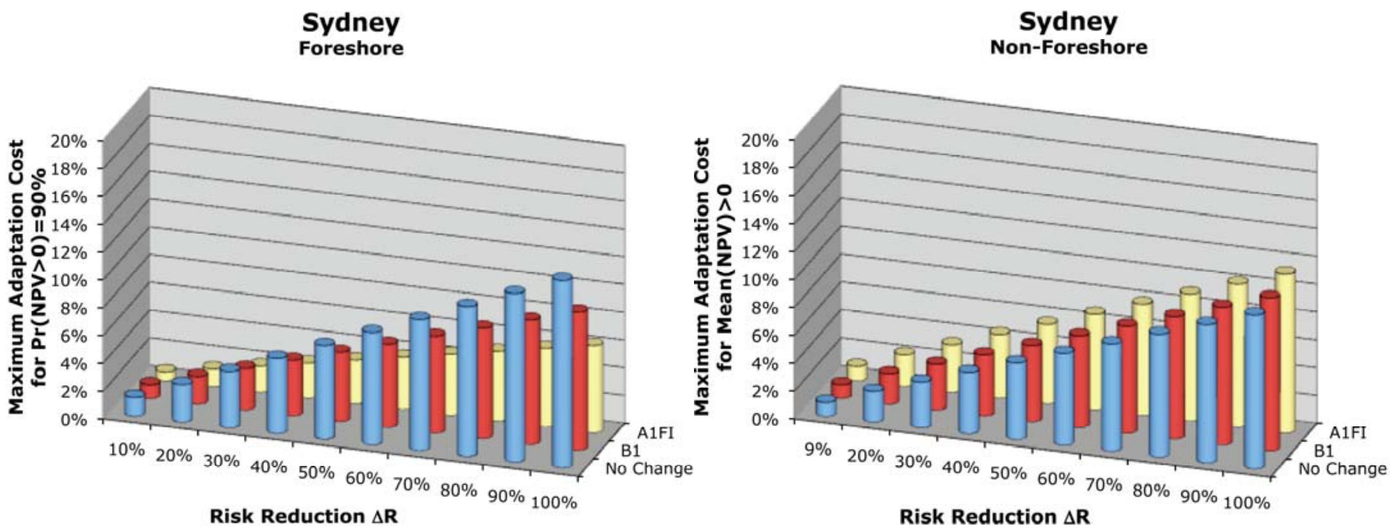


Figure 13 Maximum Adaptation Costs to Ensure Pr(NPV>0)=90% for Foreshore and Non-Foreshore Locations in Sydney

Table 9 shows that the cost of adaptation for Sydney is likely to be 1.1% for foreshore locations (N2 to N3), and less for non-foreshore locations (N1 to N2). If we adopt a cost of adaptation of 1.1% and 1.0% for these locations, and no change of climate then Table 10 show that the break-even risk reduction must exceed 6% and 9% for foreshore and non-foreshore locations, respectively, to be 50% certain that NPV>0 for all climate projections. The minimum risk reductions increase to ensure 90% certainty that NPV>0. For example, for the medium (B1) emission scenario, minimum risk reduction must exceed 11% and 17% for foreshore and non-foreshore locations, respectively. Given that Section 7.1 shows that risk reductions of 50-65% can be achieved for Sydney based on the vulnerability models described herein, then it is likely that designing new housing to enhance wind classifications is a cost-effective adaptation strategy for Sydney.

Stochastic modelling of wind field and vulnerability are uncertain. Hence, if existing risks are reduced by 50%, the break-even analysis shows that adaptation is cost-effective if the adaptation cost is halved to 4.6% and 2.6% of house replacement cost for foreshore and non-foreshore locations, respectively, assuming that risk reduction exceeds 50% and there is no change of climate. A changing climate will increase these break-even adaptation costs. These minimum costs still exceed AGO (2007) adaptation costs shown in Table 9, so the adaptation would still be cost-effective under these conditions. Or to look at this another way, a 50% reduction in existing risk will increase the break-even risk reductions shown in Table 10 by 100%.

The NPV of adaptation per house is 4.5% for a non-foreshore location in Sydney assuming a medium (B1) emission scenario, modest risk reduction of 50% and cost of adaptation of 1.0%. Assuming house replacement cost of $270,000 in 2012 dollars, the NPV per house is approximately $12,100 to 2070. This increases to a NPV of 4.7% or $12,700 for the A1FI emission scenario. Residential dwelling in Sydney are expected to increase by 46% or 768,900 houses from 2006 to 2036, or approximately 25,000 new houses per year (DOP 2008). Based on these projections, the NPV for new houses built in 2018 alone would be at least $300 million, and this NPV would rapidly accumulate year by year as additional new houses are built. The net benefit of the adaptation strategy is clearly significant even when applying cost and risk estimates that generally bias the case in favour of finding adaptation measures not to be cost-effective.

8.1.3 MELBOURNE

Results and trends for Melbourne are not too dissimilar to those for Sydney; namely, adaptation is cost-effective even for foreshore and non-foreshore locations, and all climate scenarios (see Figures 14 and 15, and Table 10). For example, break-even analysis shows that adaptation is cost-effective if the adaptation cost is less than 3.6% and 2.2% of house replacement cost for foreshore and non-foreshore locations, respectively, and 50% risk reduction. These break-even adaptation costs are significantly higher than the AGO (2007) estimates and so would be cost-effective under these conditions. Table 10 shows that break-even risk reduction needs to exceed 14-23% to be cost-effective. This would seem to be relatively easy to achieve in practice.

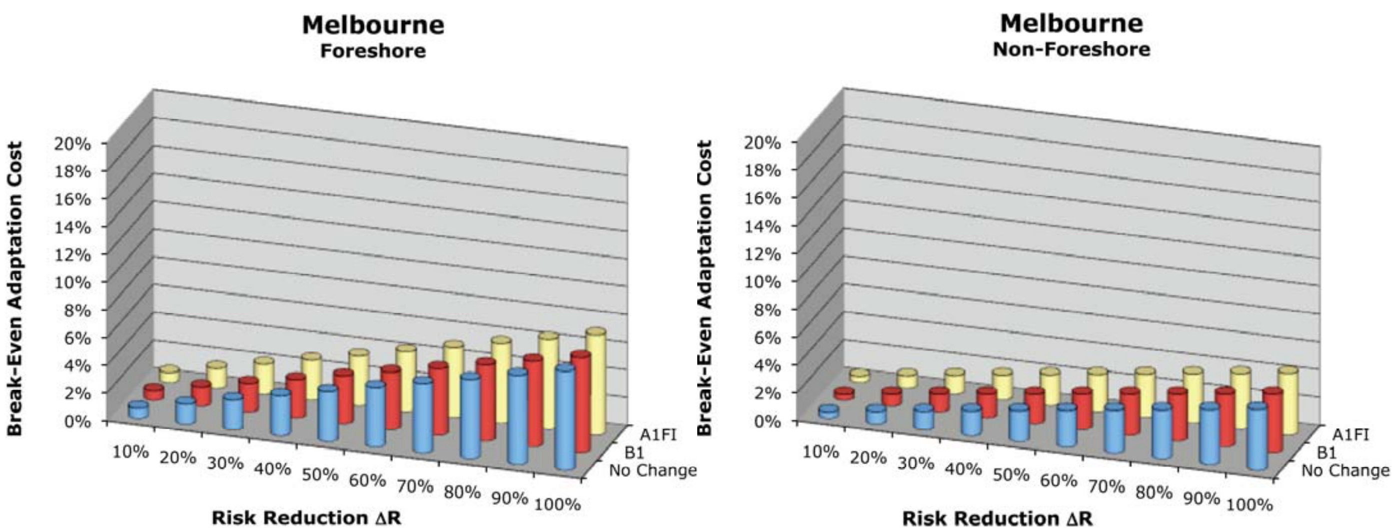


Figure 14 Break-Even Adaptation Costs for Foreshore and Non-Foreshore Locations in Melbourne

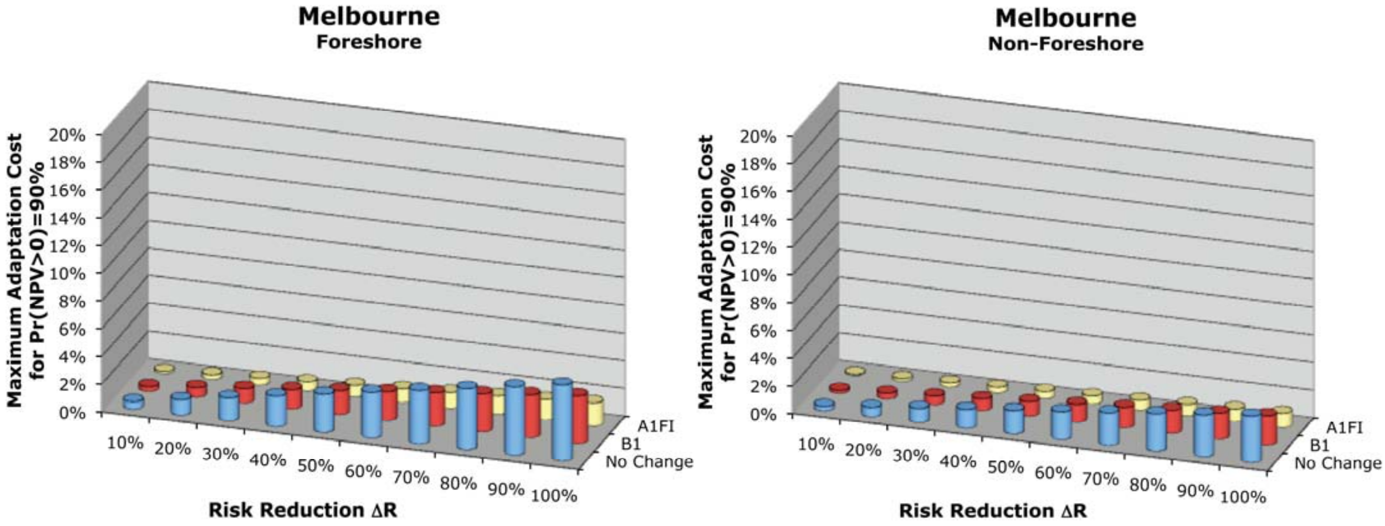


Figure 15 Maximum Adaptation Costs to Ensure Pr(NPV>0)=90% for Foreshore and Non-Foreshore Locations in Melbourne

8.2 Discount Rates

There is some uncertainty about the level of discount rate, particularly for climate change economic assessments (e.g. Dasgupta 2008). Infrastructure Australia recommends discount rates of 4%, 7% and 10% for infrastructure projects (IA 2008). The Australian Government Office of Best Practice Regulation (OBPR) recommends that the discount rate for regulatory interventions is 7%, and that sensitivity analyses consider discount rates of 3% and 10% (OBPR 2010). However, Maddocks (2011) in a report to the Australian Department of Climate Change and Energy Efficiency concludes that “Given the long life of infrastructure and the potential impact of climate change on future generations, a significantly lower discount rate (than 7%) may be appropriate.” Discount rates are generally assumed constant with time. However, this may not be appropriate when considering intergenerational effects often associated with climate change policy decisions (e.g. Boardman et al. 2011). Projects with significant effects beyond 30-50 years are considered intergenerational, and so a time-declining discount rate may be appropriate. However, there is some controversy about time-declining discount rates (e.g. Viscusi 2007), and the Australian OBPR states that “there is no consensus about how to value impacts on future generations” and “Rather than use an arbitrarily lower discount rate, the OBPR suggests that the effects on future generations be considered explicitly” (OBPR 2010). Nonetheless, the 2006 U.K. Stern Review adopted a discount rate of 1.4% (Stern 2006), and the Australian Garnaut Review adopted discount rates of 1.35% and 2.65% (Garnaut 2008). These relatively low discount rates were selected so as to not underestimate climate impacts on future generations. However, others suggest higher discount rates when assessing economic impacts of climate change (e.g, Nordhaus 2007).

Table 11 shows the effect that these discount rates have on the break-even adaptation cost, for 50% risk reduction and B1 emission scenario. As expected, the discount rate has a significant effect on NPV and the break-even cost of adaptation to ensure that mean(NPV)>0. A high discount rate of 7% or 10% reduces the cost-effectiveness of adaptation strategies because the benefit of reduction in damages into the future is reduced thus reducing NPV and lowering the maximum adaptation costs. Nonetheless, a 7% or 10% discount rate will still produce break-even adaptation costs for Sydney and Melbourne of 1.0-4.4% which are likely to be higher than actual adaptation costs. Discount rates of 1.35% and 2.65% used by Garnaut (2008) result in higher break-even values which increases the likelihood of adaptation being cost-effective.

Table 11 Break-Even Cost of Adaptation, for 50% Risk Reduction and B1 Emission Scenario

LOCATION	DISCOUNT RATE				
	1.35%	2.65%	4%	7%	10%
Brisbane					
Foreshore	1.4%	1.0%	0.8%	0.5%	0.4%
Non-Foreshore	1.8%	1.4%	1.1%	0.7%	0.5%
Sydney					
Foreshore	15.7%	11.9%	9.3%	6.1%	4.4%
Non-Foreshore	9.3%	7.0%	5.5%	3.6%	2.6%
Melbourne					
Foreshore	5.8%	4.4%	3.4%	2.2%	1.7%
Non-Foreshore	3.5%	2.7%	2.1%	1.4%	1.0%

8.3 Change in Probabilistic Model of Existing Wind Hazard

Table 12 shows the cumulative damage risk to 2070 for changes in existing wind gust speeds from -20% to +20%. In this case, the wind gust given by Eqn. (7) is increased by -20%, -10%, -5%, +5%, +10% and +20% for all return periods. With reference to Table 12, a small reduction in wind gusts of only 5% can nearly halve the existing risk (0% change in wind hazard). Conversely, an increase of wind gusts of +10% can nearly double damage risks. Estimates of risk are clearly sensitive to small changes in wind hazard.

Table 12 Cumulative Damage Risk (percentage of replacement value) to 2070 for B1 Emission Scenario

LOCATION	CHANGE IN EXISTING WIND HAZARD						
	-20%	-10%	-5%	0%	+5%	+10%	+20%
Brisbane							
Foreshore	0.29%	0.72%	1.09%	1.61%	2.35%	3.36%	6.56%
Non-Foreshore	0.47%	1.05%	1.51%	2.13%	2.96%	4.05%	7.28%
Sydney							
Foreshore	4.37%	9.40%	13.34%	18.61%	25.55%	34.44%	60.18%
Non-Foreshore	2.70%	5.66%	7.95%	10.97%	14.92%	19.92%	34.24%
Melbourne							
Foreshore	1.60%	3.45%	4.90%	6.84%	9.40%	12.72%	22.39%
Non-Foreshore	1.03%	2.16%	3.03%	4.18%	5.69%	7.62%	13.18%

The effect of change of wind hazard on the maximum cost of adaptation to ensure Mean(NPV)>0 and Pr(NPV>0)=90% is shown in Table 13, for modest 50% risk reduction and B1 emission scenario. Not surprisingly, the beak-even costs of adaptation are sensitive to wind hazard. For example, if wind gusts increase by 10% in Brisbane then maximum costs of adaptation increase to 1.7-2.0% for adaptation to be cost-effective, and actual costs are likely to be lower then these break-even values.

Table 13 Effect of Change in Wind Hazard on Maximum Cost of Adaptation to Ensure Mean(NPV)>0 and Pr(NPV>0)=90%, for 50% Risk Reduction and B1 Emission Scenario

LOCATION	BREAK-EVEN ADAPTATION COST MEAN(NPV)>0					MAXIMUM ADAPTATION COST TO ENSURE PR(NPV>0)=90%				
	-20%	-10%	0%	+10%	+20%	-20%	-10%	0%	+10%	+20%
Brisbane										
Foreshore	0.2%	0.4%	0.8%	1.7%	3.3%	0.1%	0.2%	0.4%	0.9%	2.0%
Non-Foreshore	0.2%	0.5%	1.1%	2.0%	3.6%	0.1%	0.3%	0.6%	1.2%	2.1%
Sydney										
Foreshore	2.2%	4.7%	9.3%	17.2%	30.1%	1.2%	2.5%	5.0%	9.2%	16.2%
Non-Foreshore	1.4%	2.8%	5.5%	10.0%	17.1%	0.7%	1.3%	3.0%	5.4%	9.3%
Melbourne										
Foreshore	0.8%	1.7%	3.4%	6.4%	11.2%	0.4%	0.9%	1.7%	3.2%	5.6%
Non-Foreshore	0.5%	1.1%	2.1%	3.8%	6.6%	0.3%	0.6%	1.1%	1.9%	3.3%

8.4 Time of Adaptation

Deferring time of adaptation for 5-10 years is generally a feasible option since reduction of vulnerability for any time period is a worthwhile endeavour, effects of a changing climate tend to worsen into the future so benefits of adaptation in the next decade or so are lower compared to those later in the century. There is also the benefit of reduced present (discounted) value of adaptation cost if this cost is deferred. Stewart et al. (2012, 2013) have shown that while adaptation that is implemented as early as possible has the highest NPV, deferred adaptation of 5-20 years also yields a high NPV and high likelihood that adaptation is cost-effective.

If time of adaptation is deferred to seven years to 2025, damage risks for any risk reduction to 2070 decrease by 25-27% (for any emission scenario) due to reduced policy horizon of 45 years (2025-2070). However, the present value (in 2018 dollars) of adaptation reduces by 24% as the cost is deferred by 7 years at a 4% discount rate. The NPV will thus decrease by approximately 25% and so adaptation less likely to be cost-effective. If adaptation is deferred 12 years to 2030, damage risks to 2070 decrease by 40-45% (for any climate scenario) due to reduced policy horizon of 40 years (2030-2070). However, the present value (in 2018 dollars) of adaptation reduces by only 37% at a 4% discount rate. The NPV will thus decrease further. Figure 16 shows the effect of time of adaptation and discount rate on mean NPV, for non-foreshore locations in Sydney, for no change and A1FI emission scenario and 50% risk reduction. Net present value is maximised if wind speeds increase over time (A1FI emission scenario); however, NPV decreases with deferral of adaptation for all discount rates and climate scenarios. Clearly, earlier implementation of adaptation is preferred.

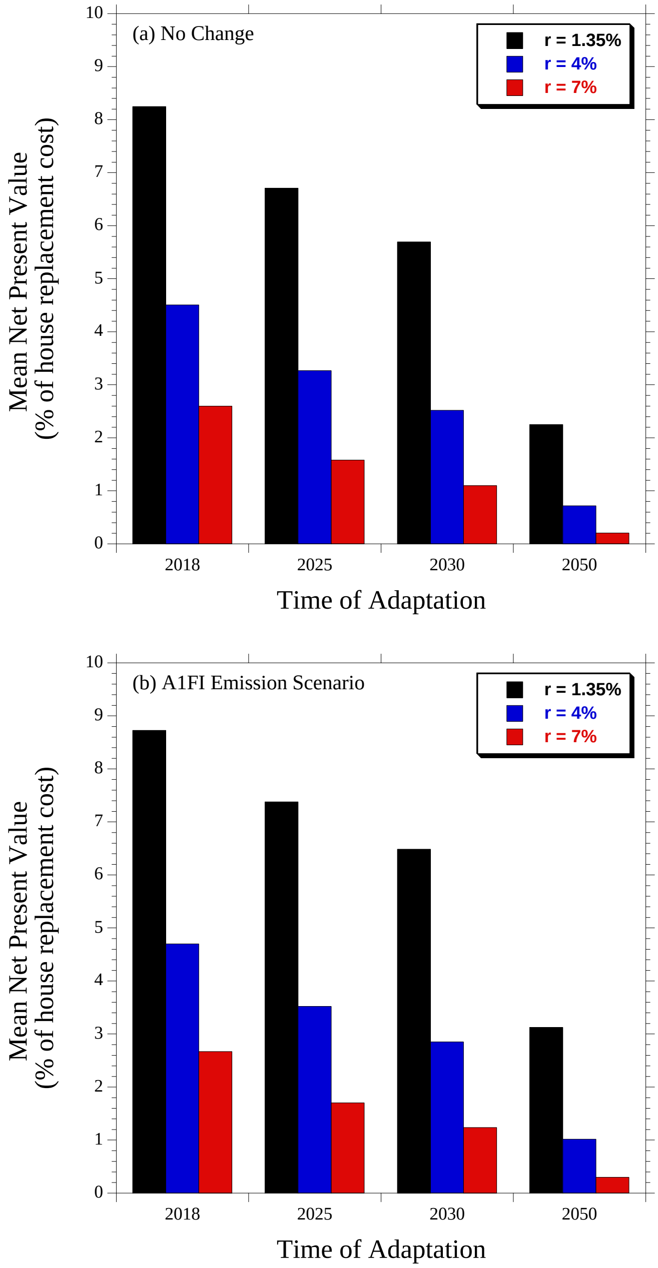


Figure 16 Net Present Values by 2070 for Non-Foreshore Locations in Sydney, for Various Times of Adaptation, and Risk Reduction of 50% and Adaptation Cost of 1%, for (a) No Change and (b) A1FI Emission Scenario

9 Results: Likelihood of Climate Scenarios

The previous section described results for a scenario-based analysis by assuming that the probability of climate scenario Pr(C) is 100%. However, there is unlikely to be such certainty about any climate scenario, in this case, ones based on CO_2 emission scenarios. One approach is to estimate the relative likelihood of the occurrence of each climate scenario, such as by expert opinion, Bayesian probability updating when new data/models are available, etc. In our case there are three climate scenarios, so $\Sigma Pr(C)=100\%$.

It is observed from Figures 10, 12 and 14 that the break-even adaptation cost is quite insensitive to the climate scenario, so break-even adaptation cost will not be significantly affected by climate scenario likelihood. On the other hand, Figures 11, 13 and 15 do show that maximum adaptation cost to be 90% sure that adaptation is cost-effective is sensitive to the climate scenario, and hence, to climate scenario likelihood. The probability of each climate scenario (or degree of belief) is somewhat subjective, and dependent on the knowledge, experience, and biases of the decision-maker. The overall NPV at time T is calculated as

$$\mathrm{NPV}(\mathrm{T}) = \sum_{s=1}^{S} \Pr(\mathrm{C}_s)\mathrm{NPV}(\mathrm{T}|\mathrm{C}_s) \qquad (14)$$

where S is the total number of climate scenarios considered (S=3), C_s is the s^{th} climate scenario, and $NPV(T|C_s)$ is given by Eqn. (13).

For sake of illustration, the effect of climate scenario likelihood is assessed for non-foreshore locations in Sydney and 50% risk reduction, see Table 14. As expected, climate scenario likelihood has little effect on the break-even adaptation cost as this metric is less sensitive to climate scenario. However, the maximum adaptation cost to be 90% sure that adaptation is cost-effective is sensitive to the climate scenario. In this case, a weighted average of NPV given by Eqn. (14) reduces variability of NPV, resulting in a higher 10^{th} percentiles of NPV and so higher maximum adaptation costs. For example, if there is 100% certainty of no change the maximum adaptation cost is 4.0% for adaptation to be preferred, however, this increases to 4.2% if there is higher likelihood of no change (80%) and low 10% likelihoods for B1 and A1FI scenarios.

Equation (14) and Table 14 is clearly a simplification of what is a challenging issue of degree of belief in climate scenarios and how it might influence the cost-effectiveness of adaptation policy options. Nonetheless, it illustrates how this may affect uncertainty and variability of NPV, and its effect on decision-making.

Table 14 Effect of Climate Scenario Likelihood on Maximum Cost of Adaptation to Ensure Mean(NPV)>0 and Pr(NPV>0)=90%, for 50% Risk Reduction and Non-Foreshore Exposure in Sydney

PROBABILITY OF CLIMATE SCENARIO			MAXIMUM ADAPTATION COST FOR ADAPTATION TO BE PREFERED OPTION	
PR(NO CHANGE)	PR(B1)	PR(A1FI)	MEAN(NPV)>0	PR(NPV>0)=90%
100%	0%	0%	5.5%	4.0%
0%	100%	0%	5.5%	3.0%
0%	0%	100%	5.7%	1.9%
33.3%	33.3%	33.3%	5.6%	3.5%
80%	10%	10%	5.5%	4.2%
50%	50%	0%	5.5%	4.0%
50%	25%	25%	5.6%	3.8%
20%	40%	40%	5.6%	3.2%
0%	50%	50%	5.6%	2.6%

10 Further Work

This report highlights that a risk-based approach to optimising adaptation requires the following information:

1. Effect of climate scenarios on frequency and intensity of hazards
2. Vulnerability of infrastructure to hazards
3. Loss functions
4. Risk reduction for adaptation measures
5. Cost of adaptation measures

The break-even approach to economic assessment of the costs and benefits of adaptation is used due to considerable modelling and parameter uncertainty of the above variables.

More accurate predictions of hazard, vulnerability, risk reduction and economic assessment are challenging. A key aim of the CSIRO Climate Adaptation Flagship Cluster ‘Climate Adaptation Engineering for Extreme Events’ is to develop improved modelling of heat, wind and flood hazards, vulnerabilities, risk reductions and decision-support for housing, commercial and industrial buildings, bridges and culverts, electrical distribution systems and railway infrastructure. Led by the University of Newcastle, the cluster brings together researchers from across Australia with a wide range of expertise. Research partners are:

- University of Newcastle
- James Cook University
- University of New South Wales
- Swinburne University of Technology
- University of Western Australia
- CSIRO Climate Adaptation Flagship

Key aims of the research are to:

- Develop new design criteria and innovative use of materials that will reduce vulnerability of new infrastructure to existing and future climate scenarios.
- Ensure any new developments reduce climate risk and energy use but also maximise durability and sustainability over the life-cycle of the infrastructure.
- Develop economic models of damage and other losses, and decision-making criteria that consider the challenges of climate adaptation in terms of costs and benefits.
- Ensure economic models consider a broad suite of factors such as interests of stakeholders, time-preferences of stakeholders, and how investment decisions in climate adaptation may affect other areas of the economy.

This will support more efficient and resilient infrastructure to help 'future proof' new and existing infrastructure to a changing climate.

11 Conclusions

A ‘break-even’ economic assessment is developed to assess the conditions under which a climate adaptation strategy is cost-effective. For instance, if the actual cost of adaptation exceeds the predicted break-even value, then adaptation is not cost-effective. Decision or policy-makers can then decide if such minimum conditions can be met in practice. Residential construction is vulnerable to wind hazards, and a changing climate and higher wind speeds means that residential constructions are likely to receive more damage in the future if its design standard is maintained at the current level. The vulnerability of residential construction may be reduced by an adaptation strategy that increases design wind speeds specified by Australian Standards AS4055-2012 and AS1170.2-2011. The measure for cost-effectiveness is Net Present Value (NPV) or net benefit equal to benefit minus the cost.

Increasing the design wind classifications in the Australian Standard “Wind Loads for Houses” AS4055-2012 for all new housing can lead to risk reductions of 50-80%, at a cost of no more than 1-2% of house replacement value. A break-even analysis is conducted for new housing in the Australian cities of Brisbane, Sydney and Melbourne. If risk reduction is over 50%, discount rate is 4%, and there is no change of climate, the break-even analysis shows that adaptation is cost-effective for Sydney if the adaptation cost is less than 9.3% and 5.5% of house replacement cost for foreshore and non-foreshore locations, respectively. The NPV for new houses built in 2018 in Sydney alone would be at least $300 million, and this NPV would rapidly accumulate year by year as additional new houses are built. The net benefit of the adaptation strategy in Sydney is clearly significant even when applying cost and risk estimates that generally bias the case in favour of finding adaptation measures not to be cost-effective.

Break-even adaptation costs for Brisbane and Melbourne are considerably lower than for Sydney. However, it is likely that designing new housing to enhance wind classifications is a cost-effective adaptation strategy for Brisbane for non-foreshore locations irrespective of climate scenario. The break-even risk reduction needs to exceed 14-23% for adaption to be cost-effective in Melbourne for foreshore and non-foreshore locations. This would seem to be relatively easy to achieve in practice as modelling in this report suggests risks reductions of 50-70% are achievable for Melbourne.

Discount rates lower than 4%, such as those used in the 2008 Garnaut Review (1.35%, 2.65%), result in higher break-even values which increases the likelihood of adaptation being cost-effective. The economic assessment is very sensitive to probabilistic wind field model. For example, an increase of wind gust speeds of +10% can double damage risks. To a lesser extent, results are also sensitive to the wind vulnerability of housing, particularly lower regions of the vulnerability curves. Deferring adaptation to 2025 reduces NPV by 25%. Earlier implementation of adaptation is preferred.

The break-even adaptation cost and maximum adaptation cost to ensure 90% certainty that NPV>0 may be sensitive to the probability of occurrence of each climate scenario. Incorporating degree of belief of climate scenarios is an important variable in decision-making.

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