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School of Civil, Environmental and Mining Engineering

FINAL REPORT

AN IMPROVED APPROACH TO UNDERSTANDING THE DRIVERS OF NATURAL HAZARD RISK, BY CONSIDERING SOCIAL VULNERABILITY AND HAZARD LIKELIHOOD

By

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Statement of Authorship

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ABSTRACT

A natural hazard becomes a natural disaster when individuals, communities and infrastructure are impacted (Smith, Martin & Cockings 2016). The economic and social repercussions of natural disasters create a need for improved approaches to reduce natural hazard risk. To enable this, a better understanding of what influences hazard risk, and how these drivers can be affected, is required. The conceptual framework proposed in this report presents a method to breakdown and understand natural hazard risk, for a non-specific hazard in a non-specific location. The framework incorporates hazard, exposure, vulnerability to evaluate current risk, and uses an exploratory scenario approach to evaluate future risk. This understanding enables decision makers to form long term plans to reduce natural hazard risk. A sensitivity analysis of the drivers of hazard risk has been included in the framework alongside mitigation to inform effective and targeted mitigation strategies.

The conceptual framework was applied to a case study to understand the influence of Social Vulnerability on Hazard Risk by considering a bushfire hazard in Greater Adelaide. The case study application demonstrates how the framework can be used to make decisions in real world contexts and assesses the impact of mitigation on reducing hazard risk. The conceptual framework successfully identified the areas in Greater Adelaide with the highest Social Vulnerability and Bushfire Hazard Likelihood and assessed how these will change in the future. The implementation of certain mitigation and co-benefit policies positively impacted the Social Vulnerability and Hazard Risk in Greater Adelaide. Having demonstrated its utility, it is recommended that the conceptual framework be applied to other natural hazards, to better understand the influence of Social Vulnerability on Natural Hazard Risk.

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1 INTRODUCTION

A natural disaster results when individuals, communities and infrastructure are impacted by a natural hazard (Smith, Martin & Cockings 2016). The economic and social repercussions of natural disasters create a need for improved approaches to natural disaster risk reduction. In 2015, natural disasters caused in excess of US$70 billion damage globally (Guha-Sapir & Below 2009). The total number of people affected by these disasters was 103,037,856, which is better represented as approximately 4 times Australia's population (Guha-Sapir & Below 2009). To reduce the time and cost of recovery, mitigation strategies can be employed (He & Zhuang 2016; Islam & Lim 2015; King 2005; McAllister 2016; Truong & Trück 2016). Allocation of funds to mitigation strategies is difficult to achieve for two main reasons: the benefits of mitigation measures are often long term, and the perception of risk is often inaccurate due to the infrequency of natural hazards (Van Delden et al. 2015).

Natural hazard risk has been widely recognised as a coupled human and natural system (Arneth, Brown & Rounsevell 2014; Cutter & Finch 2008; Monticino et al. 2007; O'Connell & O'Donnell 2014; Pooyandeh & Marceau 2013; Spies et al. 2014; Walsh & McGinnis 2008). These complex coupled systems can greatly, and unintentionally, be affected by policies and choices made by decision makers (Spies et al. 2014). Furthermore, it is accepted that the future state of the world is highly uncertain, so the influence of policies and choices on risk in the future is largely unknown. This uncertainty of the future is termed 'deep uncertainty', which describes the presence of multiple plausible futures, each with an unknown probability of occurrence and their own associated uncertainties (Buurman & Babovic 2016; Maier et al. 2016). Decision making using intuition and experience, therefore, is inefficient for these systems – especially for mitigation strategies which aim to reduce risk in the future. This motivates the need for a decision support system to analyse the efficacy of mitigation strategies under deep uncertainty, to enable a systematic and transparent decision-making process. To achieve this, it is necessary to understand what comprises natural hazard risk and how this risk is affected (Klonner et al. 2016).

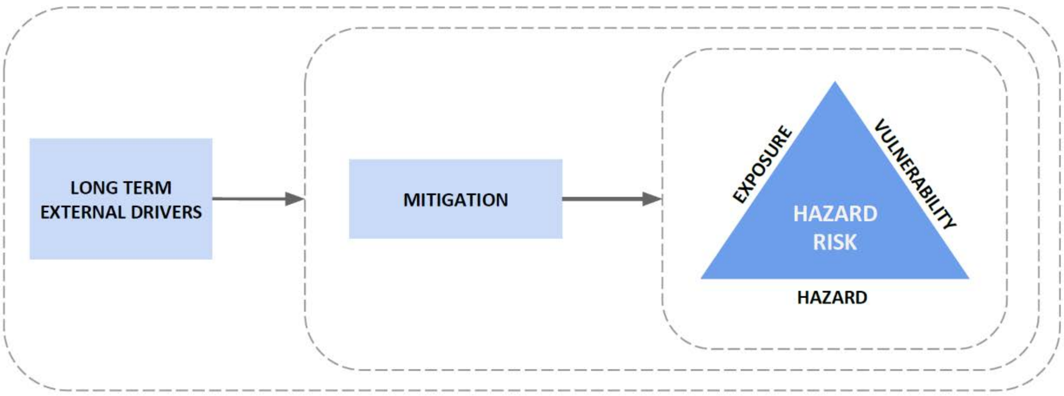


Figure 1-1 Visual representation of the links between risk, mitigation and long term external drivers

Hazard risk is shaped by three main components; hazard, exposure and vulnerability – termed the "risk triangle", as shown in Figure 1-1. Exposure and vulnerability incorporate the people and infrastructure that are exposed to the hazard, and their vulnerability, respectively. Focussing the measure of risk on social vulnerability emphasises how an individual or community's ability to respond to, or recover after, a hazard event affects the impact of a natural hazard.

Mitigation strategies may be used to target the components of hazard risk. The effectiveness of mitigation depends on its effect on hazard, exposure or vulnerability. However these are also impacted by external drivers, which are factors that affect risk but cannot be influenced through policy and decision making (Van Delden et al. 2015). Examples of external drivers that influence natural hazard risk include climate, population, demographic, and economics (Van Delden et al. 2015). These long term external drivers are spatially explicit and temporally dynamic. Thus, natural hazard risk is assessed spatially and temporally, and should consider the impact of deep uncertainty. A method for dealing with deep uncertainty in the future is to use exploratory scenarios, which describe plausible future states of the hazard risk system due to changes in the external drivers. Therefore, to understand the dynamic nature of hazard risk and to develop long term planning approaches that consider deep uncertainty, exploratory scenarios should be used. However, limited research has considered the effect of exploratory scenarios on all three components of hazard risk: vulnerability, exposure, and hazard.

To understand how mitigation affects risk under deep uncertainty, the interaction between mitigation and the components of the risk triangle is important. The idea of risk mitigation is thoroughly considered in the literature; however, these assessments have used their own definition of risk, and have not explicitly considered exposure and vulnerability in their assessment of hazard risk. To understand how natural hazards affect community resilience and recovery, it is important to consider the impact of social vulnerability on hazard risk. Analysing social vulnerability spatially and temporally allows risk reduction techniques to be targeted to the most vulnerable people.

The aim of the research is to produce a conceptual framework for an integrated hazard modelling platform that can be used to understand the influence of social vulnerability on hazard risk in a spatial and temporal dimension. The conceptual framework is for a non-specific hazard in a non-specific location; it outlines an approach for understanding the long-term drivers of hazard risk to inform planning of mitigation strategies to reduce social vulnerability and natural hazard risk. The framework is applied to a case study assessing the social vulnerability and hazard risk in Greater Adelaide using a bushfire hazard. The case study demonstrates how the conceptual framework can be applied to answer real world questions.

2 LITERATURE REVIEW

2.1 Relationship between Risk, External Drivers and Mitigation

Natural hazard risk is defined by many elements. Figure 2-1 represents the factors affecting risk, including vulnerability, exposure, hazard, mitigation and external drivers. It shows how the areas of interest in this literature review are interconnected. It is important to understand this relationship to appreciate why these elements need to be coupled.

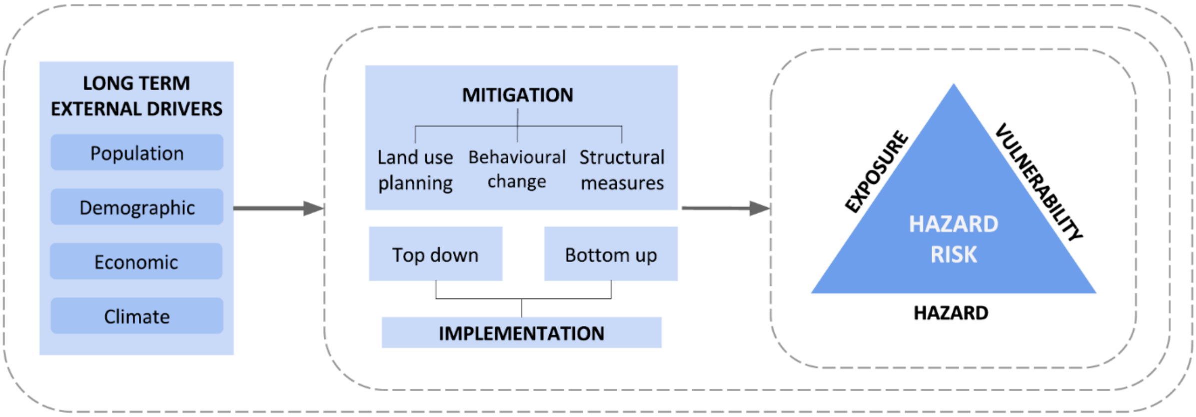


Figure 2-1 Diagram of the relationships between hazard risk, mitigation and external drivers

2.1.1 Components of risk

Within the risk triangle, hazard, exposure and vulnerability are the three components that shape risk (Dwyer et al. 2004). These elements are important to consider in order to quantify and understand how risk changes, and thus how it can be minimised. In the context of natural hazard risk management, hazard is the specific natural event that has an associated magnitude and likelihood (Dwyer et al. 2004). Severity of these hazards can be impacted by factors such as geographical location and climate, however there is uncertainty in the event's occurrence, magnitude and spatial extent (Dwyer et al. 2004). Exposure is the people, communities, resources, assets and infrastructure that are affected by the hazard (IPCC 2012). For example, a hazard that occurs in a densely-populated city such as New York City will have a much greater scope to affect people, communities, infrastructure, and political and economic institutions, relative to a hazard in the middle of the Sahara Desert. Finally, vulnerability is the characteristics and circumstances of an individual or community that have the propensity to magnify the disaster; age, gender, socio-economic status, or any combination of these, are likely to affect the consequences of the hazard (Cutter, Boruff & Shirley 2003; Dwyer et al. 2004; Frigerio & De Amicis 2016). Factors that affect vulnerability can have an impact on the sensitivity to risk (e.g. age, health), but also someone's response capacity (e.g. socio-economic status, community relationships) (Moser 2010). Hazard, exposure and vulnerability are dynamic (IPCC 2012), hence consideration of these elements changing with space and time is important.

Much research has been undertaken into defining vulnerability. De Groeve, Poljansek and Vernaccini (2015) and Wu, Yarnal and Fisher (2002) recognised that physical vulnerability can be accounted for in the exposure element of risk, whereas vulnerability can define social, economic and political vulnerability, as well as the coping ability of the community. In relation to natural hazards in the literature, vulnerability is usually referred to as social vulnerability but incorporates many diverse influencing factors (Cutter, Boruff & Shirley 2003; Cutter & Finch 2008; Frigerio & De Amicis 2016). McKenzie and Canterford (2016) identified thirteen social vulnerability characteristics that help assess vulnerability specific to bushfire hazard, including youth, old age, single parent families, volunteers, and income, among other factors. While these factors could be used to assess vulnerability to multiple hazards, they are specifically targeted to bushfire risk. The demographic characteristics chosen in the definition of vulnerability change the purpose and usefulness of the vulnerability assessment.

2.1.2 External drivers

External drivers affect the different elements of risk, however it can be challenging to influence these through policy and decision making (Van Delden et al. 2015). Four examples of external drivers that influence natural hazard risk are climate, population, economics, and demographics (Van Delden et al. 2015). Changes in climate and climate patterns influence the occurrence and size of natural hazard events (Bambara et al. 2015), for example, increased rainfall will increase the risk of flood occurrence. Population increases are predicted to increase exposure to natural hazards (GFDRR 2016) and the potential disaster losses will also be increased by population growth (Chang, S et al. 2012). As global population continues to increase, more and more people will be living in more hazardous areas, such as flood plains, bushfire zones, and coastal areas (Chang, S et al. 2012). The movement of people into hazardous areas will increase risk through increasing exposure. Economic conditions will directly affect asset value and hence the costs associated with individual natural hazard events (Chang, S et al. 2012). Finally, demographics of a region will also affect an individual's vulnerability to a natural hazard event (Chang, W-Y et al. 2012). For example, an elderly person may have more difficulty evacuating promptly in a bushfire event as they may have mobility issues or not be able to drive. Demographics will also impact the sense of community, and individual attitude to hazards, which in turn will define the challenges to mitigation and resilience.

2.1.3 Mitigation strategies

A mitigation option is a measure put in place to reduce the risk posed by a hazard. Mitigation options can be targeted to reduce one or more of hazard, exposure or vulnerability. Mitigation options can take the form of direct policy measures, for example implementing planned burns to reduce bushfire risk or through the co-benefit of social policies and community resilience, for example increasing school funding could increase community education levels and reduce social vulnerability . Mitigation options are categorised by both their type and their implementation method. A mitigation strategy is a set of mitigation options.

2.1.3.1 Types of mitigation options

The literature categorises mitigation options based on their development and how they intend to mitigate risk. Mitigation options have been categorised into land use planning, human behavioural change, and structural measures (Asgary & Halim 2011; Dawson et al. 2011; Dickinson et al. 2015; Wouter Botzen & Van Den Bergh 2012). These categories each have different effects on the hazard, exposure and vulnerability elements of risk (Islam & Lim 2015).

Land use planning mitigation options are categorised as those which identify and alter land use in areas at risk to natural disasters (Dawson et al. 2011). Human behavioural change mitigation options are those developed on the basis of understanding the behaviour of humans in a natural disaster event, and the factors that influence human behaviour and social interactions (Dickinson et al. 2015). Mitigation options categorised as structural measures include the physical construction of infrastructure to mitigate, or changing building codes (Botzen, Aerts & van den Bergh 2009; Dawson et al. 2011; McAllister 2016).

These categories define very different mitigation options which affect the exposure and vulnerability of risk differently and to different degrees (Asgary & Halim 2011). Hence, the different categories of mitigation options have varied degrees of effectiveness (Ghanbarpour, Saravi & Salimi 2014). The effectiveness of the mitigation option may also vary depending on the hazard. For example, Ghanbarpour, Saravi and Salimi (2014) found that structural measures were more practical for reducing flood risk than behavioural change and land use planning.

2.1.3.2 Implementation of mitigation options

Literature identifies that mitigation options can be implemented through alternate methods, which include top-down or bottom-up implementation (Azim & Islam 2016; Dawson et al. 2011). Implementation through top-down policy may be on a government or industry level. Implementation through bottom-up may include raising public awareness, training or education (Dawson et al. 2011). The way in which a mitigation option is implemented can influence its effectiveness (Asgary & Halim 2011). The effectiveness of bottom-up methods depends on the attitudes of individuals and how they perceive the hazard risk (Ancog, Florece & Nicopior 2016; Dickinson et al. 2015; Gan, Jarrett & Gaither 2015). For example, educational programs may advise individuals to evacuate their property in the event of a natural disaster, however, whether this is done or not is the decision of the homeowner (Dickinson et al. 2015). Hence, to ensure human response methods are most effective, how and why individuals respond to a hazard risk must be understood when developing the mitigation option (Gan, Jarrett & Gaither 2015).

Government policy can be an effective and powerful tool to mitigate natural hazard risk (Handmer, Loh & Choong 2007). Governments generally have the resources and authority to take action for implementing mitigation options (Alesch, Arendt & Petak 2012). The effectiveness of government policy also relies on the reception of individuals to the policy. As shown by Ghanbarpour, Saravi and Salimi (2014), an insight into individual willingness to accommodate natural hazard mitigation can be used as a planning tool in risk management. People who live in areas vulnerable to natural hazards may be doing so due to lack of knowledge or understanding of their exposure, and in these cases top-down approaches may be less effective than community based initiatives (Azim & Islam 2016). Community involvement in the natural hazard planning processes can enable decision makers to better facilitate sustainable natural hazard management schemes (Ghanbarpour, Saravi & Salimi 2014). In communities where mistrust of government initiatives and policies is common, implementation of solely top-down approaches may be ineffective (Handmer, Loh & Choong 2007). According to Azim and Islam (2016), people will only adapt or change living patterns to reduce their natural hazard vulnerability if it doesn't increase their vulnerability to other issues, such as employability and health.

To ensure effectiveness of mitigation, the most appropriate mitigation type and implementation method should be considered. The relationship between this mitigation option and vulnerability and exposure should also be understood, and used to determine the most effective mitigation option.

2.2 Dynamic Hazard Modelling

To model changing hazard risk in time and space, the dynamic components of hazard risk must be modelled first. Spatial and temporal changes in vulnerability, exposure, and hazard have all been modelled individually or as a combination of two or more of these.

2.2.1 Spatial dimension

Modelling the spatially explicit nature of exposure and vulnerability has been undertaken extensively in the literature, using indicators to quantify vulnerability and exposure and then mapping these indicators over a geographical space.

A number of indicators have been proposed in the literature for quantifying vulnerability. Examples of common indicators used to quantify social vulnerability in the literature are age, education, income, family/household structure, morbidity, employment and potential for loss of employment, ethnicity and local language skills, and gender (Cutter, Boruff & Shirley 2003; Dwyer et al. 2004; Frigerio & De

Amicis 2016; Phung et al. 2016). Dwyer et al. (2004) proposed a method for combining these common indicators to yield a single measure of vulnerability based on consultation with experts about the perceived risk caused by these indicators. Cutter, Boruff and Shirley (2003) also quantified the impact of social vulnerability to natural hazards with a social vulnerability index (SoVI). The need for a SoVI to tailor the measure of vulnerability to a cultural context was highlighted by Chen et al. (2013). The literature contains a large amount of research into vulnerability indices for different regions, including America (Cutter et al. 2008; Cutter, Boruff & Shirley 2003; Wu, Yarnal & Fisher 2002), Europe (Frigerio & De Amicis 2016), Australia (Dwyer et al. 2004), and Asia (Chen et al. 2013; Chow, Chuang & Gober 2012). Furthermore, indices specific to certain natural hazard events have been developed. Examples of this have been seen for heatwave by Zhu et al. (2014) and Chow, Chuang and Gober (2012), and for flooding by Phung et al. (2016). Spatial mapping of vulnerability indices has been thoroughly undertaken in the literature.

A number of indicators have also been proposed to quantify exposure in the literature, primarily based on property exposure and occupancy rates (Wadey, Nicholls & Hutton 2012). Exposure to hazards has been found to vary spatially on multiple scales, from constant exposure when a hazard prone area is inhabited, to diurnal variation in exposure due to changes in population density throughout the day as a result of people commuting between work and home (Schmitt 1956; Smith, Martin & Cockings 2016).

The need to model vulnerability and exposure spatially to properly assess natural hazard risk has been highlighted in the literature, and as such spatial mapping of coupled vulnerability and exposure indices has been widely undertaken. Frigerio, I et al. (2016) developed an exposure map which used a risk matrix to spatially combine the social vulnerability index with seismic hazard zones. Emrich and Cutter (2011) also constructed similar maps for the Southern United States that used a risk matrix to depict place vulnerability. Chow, Chuang and Gober (2012), however, spatially mapped a combined vulnerability and exposure index for extreme heat based on data from 1990 and 2000. The importance of including vulnerability alongside exposure in planning practices has also been recognised (Lee 2014).

2.2.2 Temporal dimension

> *"Tomorrow's risk is being built today. We must therefore move away from risk assessments that show risk at a single point in the present and move instead towards risk assessments that can guide decision makers towards a resilient future."*
>
> Global Facility for Disaster Reduction and Recovery, GFDRR (2016)

It is accepted that the future state of the world is largely unknown. Decision makers are faced with the growing problem of developing appropriate solutions to problems we might not even know exist. Most mitigation strategies are static and focus only on current natural hazard risk (GFDRR 2016). The uncertainty of the future is termed 'deep uncertainty' and is linked to the dynamic external drivers such as climate change, population growth, new technologies, economic developments and societal perspectives and preferences (Chang, W-Y et al. 2012; Haasnoot et al. 2013). Deep uncertainty describes the presence of multiple plausible futures, each with an unknown probability of occurrence – global uncertainty – which each have their own associated uncertainties – local uncertainty (Buurman & Babovic 2016; Maier et al. 2016). A visual representation of deep uncertainty is shown in Figure 2-2. Global uncertainty is represented by the three branches, and local uncertainty represented by the shading around each. Buurman and Babovic (2016) recognised the contribution of "unknown unknowns", which are events we cannot foresee or which are completely unexpected. Hence, it is important to consider how the application of mitigation strategies for natural hazards will affect natural hazard risk under deep uncertainty.

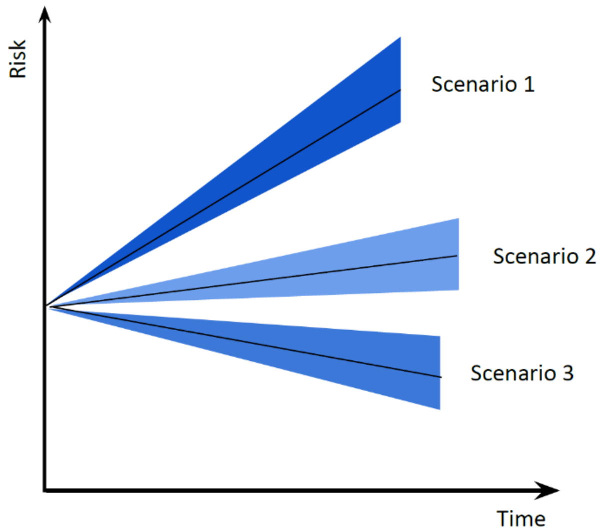


Figure 2-2 Visualisation of deep uncertainty, adapted from Maier et al. (2016)

One method for consideration of natural hazard risk into the future would be to extrapolate the current exposure and vulnerability data into a future period to develop mitigation strategies. Another method is to use a range of plausible future scenarios to assess future risk from various mitigation options, which incorporates the presence of deep uncertainty. A review of the literature has shown that both extrapolation and scenario methods have been extensively used to model natural hazards in the temporal dimension. The impact of mitigation on natural hazards using scenario methods has also been considered in the literature. Dawson et al. (2011) used future scenarios to analyse the net present risk to flood damage in 2020 and 2050 with and without mitigation measures. Botzen, Aerts and van den Bergh (2009) also looked at the willingness of homeowners to adopt structural mitigation measures into the future under three climate scenarios: present temperature conditions; present temperature conditions + 1^{o}C; and present temperature conditions + 2^{o}C. Both these cases, however, used their own definition of risk, and did not include an analysis of vulnerability and exposure in their investigation.

The consideration of mitigation options in the future and their influence on future natural hazard risk should incorporate a temporal variation of exposure and vulnerability. Both exposure and vulnerability are dynamic due to the influence of dynamic external drivers and hence will change throughout the future (IPCC 2012). Thus, to assess the appropriateness of a mitigation strategy, the interaction between the mitigation strategy and the future exposure and vulnerability is an important consideration. Temporal variation in exposure has received some attention in the literature, however, quantifying temporal variation in social vulnerability using scenarios has not been considered in the hazard space. Furthermore, assessments of temporal variation in exposure applied constant social vulnerability in their assessments of hazard risk.

Forzieri et al. (2016) investigated changes in multi-hazard exposure in Europe under different climate scenarios, however, this assessment did not consider social vulnerability in its definition of risk, and a rigorous analysis of changes in population and infrastructure were also not included in the exposure assessment. Similarly, the investigations by Wu, Yarnal and Fisher (2002) used coupled climate and population growth scenarios to analyse changes in exposure and flood hazard. Their assessment of risk considered spatially mapped social vulnerability, however, it was assumed that social vulnerability remained constant in each location under each scenario.

The consideration of temporal changes in social vulnerability has mostly been retrospective. Cutter and Finch (2008) retrospectively investigated changing social vulnerability within the United States for discrete intervals of 10 years, dating back to 1960. Cutter and Finch (2008) went on to use crude linear extrapolation of past trends to consider vulnerability for no more than 2 years into the future (Cutter & Finch 2008). Although linear extrapolation forward one time step allowed prediction to 2010, this prediction was not validated as it was later found that the required variables from the 2010 Census data was no longer comparable (Emrich & Cutter 2011).

Hall, Sayers and Dawson (2005), however, used climate and socio-economic scenarios to test long term changes in hazard, exposure and vulnerability. Four climate and four-socio economic scenarios were used to approximate potential future projections of flood risk. This included applying the socio-economic scenarios to the Social Flooding Vulnerability Indices to obtain a quantified assessment on the effect of each scenario on relevant variables. However, they did not present a methodology for this process, and they acknowledged that the presented quantified analysis could have produced other equally plausible future vulnerability representations for the scenarios. Their assessment of vulnerability focused on policy analysis rather than an understanding of the vulnerability of communities in relation to their sensitivity to risk and their response capacity.

2.3 Critical Review and Research Gaps

The work undertaken in literature to assess the impact of mitigation on natural hazard risk, quantified using vulnerability and exposure, is highlighted in Table 2-1.

There has been extensive research undertaken on mapping risk as a function of hazard, exposure and vulnerability. Most of this research has considered the spatial element of risk, however there has been little investigation into temporal changes of risk which considers all three aspects of the risk triangle: hazard, exposure and vulnerability.

There has also been extensive research on mitigation options, where different hazards and respective implementations have been considered. The missing link between mitigation and risk in research to date is shown in Table 2-1. Despite acknowledging that the “risk that actually prevails in the future will be further modified by [hazard] management activity” (Hall, Sayers & Dawson 2005) there has been little research that has coupled mitigation with all three elements of the risk triangle.

Ancog, Florece and Nicopior (2016) assessed the impact of mitigation on forest fires using surveys of local farmers to investigate what mitigation strategies they implemented. The data was then analysed along-side recorded fire locations to assess the correlation between mitigation options and fire risk. The results also considered the social vulnerability of the survey participants to assess the relationship between different socio-economic groups and their willingness to adopt different mitigation strategies. However, this assessment considered only an empirical retrospective link between mitigation and hazard, risk and exposure, and the links were considered separately rather than coupled to inform mitigation impact on an overall risk.

Similarly, Dickinson et al. (2015) considered the interaction between different social types and mitigation behaviours, and reviewed the results of empirical wildfire literature to generate hypotheses about the relationship between social vulnerability and wildfire risk. Dickinson et al. (2015) developed a conceptual framework for this relationship, however, the framework did not extend to include the relationship between mitigation and hazard and exposure. Frigerio and De Amicis (2016) and Zhu et al. (2014), however, developed conceptual frameworks for assessing hazard risk which considered vulnerability, exposure and hazard. However, these conceptual frameworks did not extend to include the assessment of how mitigation options may impact these elements of hazard risk.

The benefit of exploring the interaction between mitigation and the components of the risk triangle is to ensure the most appropriate mitigation type and implementation methods are considered. Additionally, through the incorporation of vulnerability, there is potential to assess how risk reduction could be targeted to areas of more vulnerable populations.

Table 2-1 Identification of knowledge gaps in the impact of mitigation on natural hazard risk

	Conceptual Framework	Hazard Considered	Risk Dimension						Mitigation		
			Spatial dimension:			Temporal dimension[1]:					
			Hazard	Exposure	Social Vulnerability	Hazard	Exposure	Social Vulnerability	Land Use	Structural	Behavioural
Cutter, Boruff and Shirley (2003)					X						
Cutter and Finch (2008)					X						
Bennett, Kadfak and Dearden (2016)					X						
Smith, Martin and Cockings (2016)		Flood	X	X							
Kershaw and Millward (2012)		H/wave	X	X							
Lee (2014)		Flooding	X	X	X						
Emrich and Cutter (2011)		Multiple	X	X	X						
Tate and Cutter (2010)		Multiple	X	X	X						
Chow, Chuang and Gober (2012)		H/wave	X	X	X						
Phung et al. (2016)		Flood	X	X	X						
Zhu et al. (2014)	X	Seismic	X	X	X						
Frigerio and De Amicis (2016)	X	Seismic	X	X	X						
Forzieri et al. (2016)		Multiple	X	X		X	X				
Wu, Yarnal and Fisher (2002)		Storms	X	X	X	X	X				
Hall, Sayers and Dawson (2005)		Flood	X	X	X	X	X				
Albano et al. (2016)		Storm	X						X		X
Butry et al. (2010)		Fire	X	X						X	X
Ancog, Florece and Nicopior (2016)		Fire	X	X					X	X	X
Wadey, Nicholls and Hutton (2012)		Flood	X	X		X				X	
Botzen, Aerts and van den Bergh (2009)		Flood	X	X		X					X
Dawson et al. (2011)		Flood	X	X		X	X		X	X	X
Ghanbarpour, Saravi and Salimi (2014)		Flood	X	X		X	X		X	X	X
Egbelakin et al. (2013)		Seismic								X	
Gan, Jarrett and Gaither (2015)		Fire							X		X
Kanowski, Whelan and Ellis (2005)		Fire							X	X	X
Dickinson et al. (2015)	X	Fire							X	X	X

Exploratory scenarios allow the performance of different mitigation options to be tested under alternate plausible futures. Application of exploratory scenarios to the hazard and exposure elements of risk has been undertaken extensively in the literature, including by Forzieri et al. (2016), Ghanbarpour, Saravi and Salimi (2014) and Hall, Sayers and Dawson (2005), and a clear methodology has been demonstrated for this process.

Qualitative changes in social vulnerability under different scenarios were also considered by Bennett, Kadfak and Dearden (2016), although their assessment was not extended to quantify changes in social vulnerability for use in a risk assessment. Hall, Sayers and Dawson (2005) briefly mentioned quantifying changes in social vulnerability by applying socio-economic scenarios to Social Flooding Vulnerability Indices, however, they did not present a methodology for this process, and acknowledged that other projected results may be equally plausible.

Outside hazard literature, van Delden et al. (2005) presents a methodology for quantifying narrative storylines for scenarios, however, this methodology has not been applied to social vulnerability in the hazard space. Furthermore, application of this methodology to social vulnerability has not been paired with scenario analyses of exposure and hazard.

2.3.1 Research gap 1

The literature has thoroughly considered risk mitigation; however, these assessments have not explicitly considered vulnerability in their definition of hazard risk. Thus, an understanding of the drivers of the vulnerability elements of natural hazard risk is a gap in the research. Furthermore, understanding the interaction between mitigation and the elements of risk is important in the identification of mitigation options that can be used to target specific aspects of vulnerability. Thus, using the drivers of vulnerability, exposure and hazard to inform mitigation strategies is a gap in the research.

2.3.2 Research gap 2

The literature has established the merit of using exploratory scenarios to develop a long-term planning approach to hazard mitigation. However, limited research has considered the effect of exploratory scenarios on all three components of hazard risk: vulnerability, exposure, and hazard. In particular, there is a gap in quantifying projections in social vulnerability indices using exploratory scenarios.

3 OBJECTIVES

To address the identified research gaps, the research objectives have been identified below.

Objective 1 To develop a conceptual framework for an integrated hazard risk modelling platform that can be used to assess the impact of Hazard Risk, considering Social Vulnerability. Hazard Risk will be assessed in a spatial and temporal dimension over a period that considers long term planning (approximately 50 years into the future). Its function is to support decision makers in understanding the drivers of Hazard Risk, and inform long term planning. The integrated approach:

a) Details a method for understanding the drivers of Hazard Risk;
b) Incorporates exploratory scenarios that affect vulnerability and exposure to evaluate how they change over the planning horizon;
c) Uses the drivers of risk to inform mitigation options for long term planning;
d) Links the effects of mitigation to risk.

Objective 2 To apply the conceptual framework to a case study to understand the influence of Social Vulnerability on Hazard Risk by considering a bushfire hazard in Greater Adelaide with the aim of developing an understanding of the drivers of Hazard Risk.

The case study for Greater Adelaide will be used to:

a) Develop an understanding of current Hazard Risk;
b) Develop an understanding of the dynamic nature of Hazard Risk;
c) Assess future Hazard Risk;
d) Assess the impact of mitigation options that target Social Vulnerability and Hazard Likelihood.

4 PROPOSED FRAMEWORK FOR AN INTEGRATED HAZARD RISK MODELLING PLATFORM

The methodology is presented in multiple parts; these parts explain the processes used to achieve the Research Objectives proposed in Section 3. This section discusses the theory behind the conceptual framework, and its novelty in addressing the shortcomings of conceptual frameworks existing in literature.

The schematic diagram presented in Figure 4-1 shows the elements of the proposed conceptual framework. The conceptual framework has been developed to facilitate long term planning of mitigation strategies to reduce natural hazard risk in areas with high social vulnerability.

The Hazard Risk Model – indicated by the green envelope of the conceptual framework schematic presented in Figure 4-1 – assesses risk spatially and temporally. The model couples hazard, exposure and vulnerability into a measure of Hazard Likelihood and Social Vulnerability, which is then used to quantify a single measure of Hazard Risk using a risk assessment. The model considers all three components of Hazard Risk to form a single measure of risk. This enables an understanding of the drivers of hazard, exposure and vulnerability, and their influence on the overall risk, which was identified as a gap in the existing literature in Section 2.

The conceptual framework also proposes a methodology for using exploratory scenarios to develop a long-term planning approach for Hazard Risk mitigation. The framework proposes a methodology for quantifying projections in Social Vulnerability indices using exploratory scenarios, which is a shortcoming of existing long-term Hazard Risk assessments, as identified in Section 2. The orange envelope in Figure 4-1 captures how the external drivers shape the exploratory scenarios, which in turn impact the inputs to the Hazard Risk Model. The methodology for quantifying projections in Social Vulnerability using exploratory scenarios, detailed in Section 4.1.1.2, captures the impact of the external drivers and exploratory scenarios on the dynamic Social Vulnerability inputs.

Having coupled hazard, exposure, and vulnerability into a single measure of risk, and projected their respective long-term changes using exploratory scenarios, the conceptual framework also includes a proposed methodology for understanding the interaction between mitigation strategies and these risk components, which was identified as a gap in the research in Section 2.3.

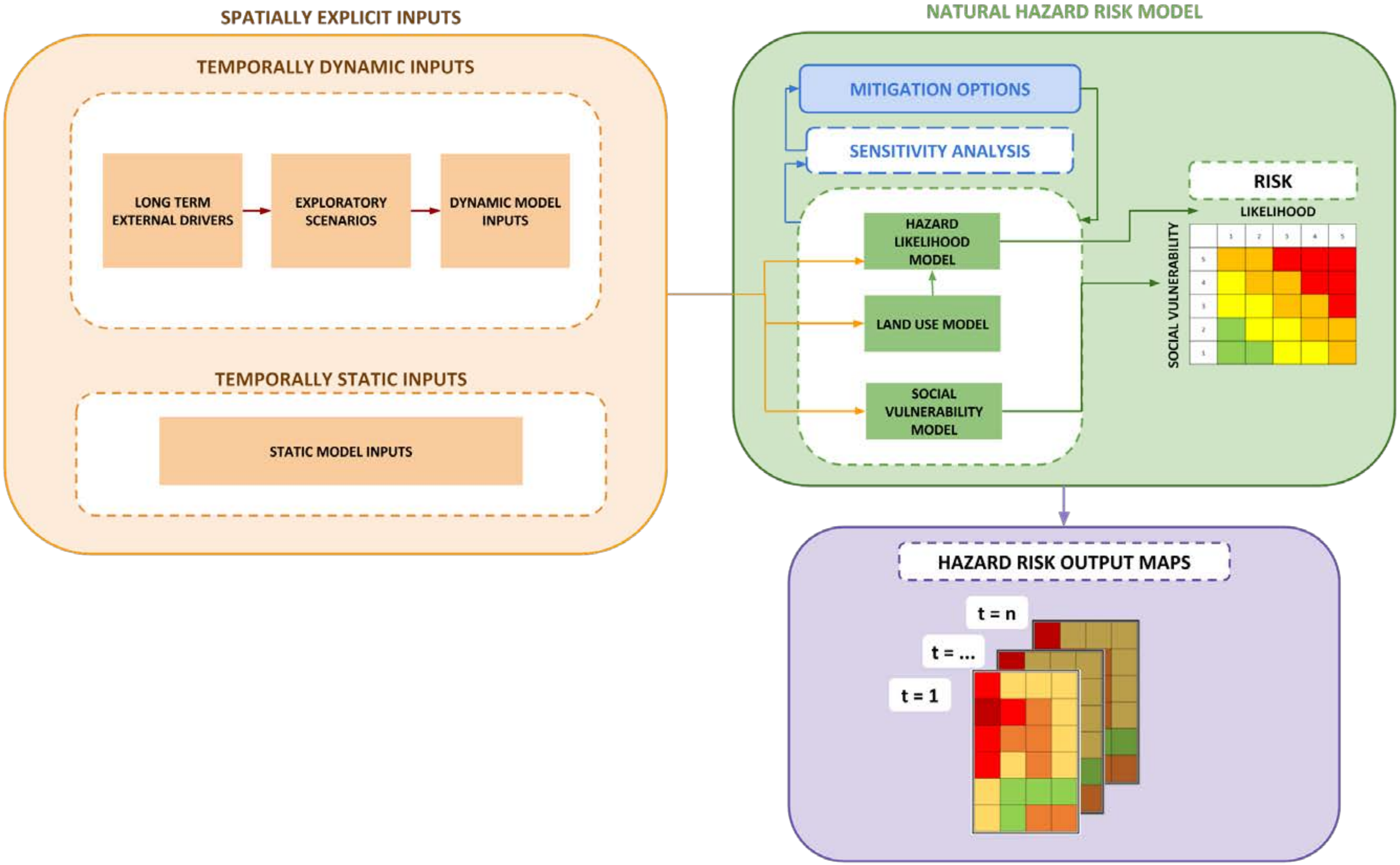


Figure 4-1 Schematic diagram of the proposed conceptual framework for understanding the drivers of natural Hazard Risk, by considering Social Vulnerability and Hazard Likelihood. Hazard Risk is assessed spatially and uses exploratory scenarios to assess temporally dynamic risk under future uncertainty.

This methodology focuses on using an understanding of the drivers of risk to inform plausible mitigation strategies which will be targeted to different aspects of risk. For example, in the case study presented in Section 5, there is a focus on reducing risk to the most socially vulnerable areas. The blue Mitigation envelope is included inside the Natural Hazard Risk Model, to include feedback loops to the Hazard Likelihood and Social Vulnerability model envelopes. These feedback loops enable the impact of the changing drivers and Hazard Risk to be seen in the assessment of how effective a mitigation strategy may be.

To identify drivers which are dominant controls of the system, and thus effectively reduce risk by targeting mitigation to these drivers, a sensitivity analysis is included within the Natural Hazard Risk Model in the conceptual framework. The dynamic Hazard Likelihood and Social Vulnerability models are fed into the sensitivity analysis to ensure drivers which create the highest response in Hazard Risk over the entire long-term planning time frame are identified. The results of the sensitivity analysis are then fed into the mitigation envelope, to help identify plausible mitigation strategies. Literature has already highlighted the importance of model sensitivity analyses to support the calibration and verification stages of model development (Shin et al. 2013), and has recommended the use of sensitivity analysis to support model-based decision-making (Pianosi & Wagener 2015). However, the novelty of the conceptual framework is that it links the sensitivity analysis to the drivers of the Hazard Risk Model, and enables the sensitivity of all the drivers to the overall risk and its components to be identified.

The proposed framework outputs the results of the Natural Hazard Risk Model as spatially explicit Hazard Risk maps for each of the discrete time intervals considered, as shown in the purple results envelope in Figure 4-1. By testing different scenarios and mitigation options, spatially explicit Hazard Risk maps for different mitigation strategies can also be developed and compared to inform long term planning.

4.1.1 Natural hazard risk

Within the Natural Hazard Risk Model in Figure 4-1, Hazard Risk is quantified using a risk assessment matrix from the National Emergency Risk Assessment Guidelines (NERAG) (AGAGD 2015), shown in Figure 4-2. This matrix assessment of risk evaluates risk priority (1 to 5 in increasing priority) based on the likelihood of the risk (Extremely Rare to Almost Certain) and the consequence of the risk (Insignificant to Catastrophic). The risk assessment matrix in Figure 4-2 follows the same methodology as AIDR (2015), however, the consequence of the Hazard Risk is measured by the Social Vulnerability of the location, as Hazard Risk to socially vulnerable areas is the focus of the conceptual framework.

SOCIAL VULNERABILITY

HAZARD LIKELIHOOD	1	2	3	4	5
5	M	H	H	VH	VH
4	M	M	H	H	VH
3	L	M	M	H	H
2	L	L	M	M	H
1	VL	L	L	M	M

RISK LEVEL	
VH	Very High
H	High
M	Medium
L	Low
VL	Very Low

Figure 4-2 Risk assessment matrix used to combine the influence of Social Vulnerability and Hazard Likelihood – which encapsulate the hazard, likelihood and exposure elements of the risk triangle – to quantify a single measure of risk, adapted from AGAGD (2015). The risk matrix is applied to each location at each time interval to develop spatially and temporally dynamic maps of Hazard Risk.

Hazard Likelihood is calculated as a function of the hazard and exposure elements of risk; Social Vulnerability represents the vulnerability element of risk. This assessment of Likelihood and Social Vulnerability is conducted spatially, which allows Hazard Risk to be determined spatially. Subsequently, the Hazard Risk assessment is applied to each location for each time period, such that the framework is able to assess spatially distributed risk over time.

Hazard Likelihood and Social Vulnerability are quantified based on five discrete intervals, as shown in Figure 4-2, before being combined to assess risk in five discrete intervals from Very Low to Very High. The five risk levels allow even low Likelihood events to have a high risk if the Social Vulnerability of the event is very high. For example, if an area had Hazard Likelihood of 2 and a Social Vulnerability of 5 this will have a Hazard Risk value of High.

Depending on the spatial resolution of the data and the scale of the area being assessed, the use of 5 discrete intervals to measure Hazard Likelihood and Social Vulnerability, may result in some resolution of the data being lost. Creating a larger number of discrete intervals will allow for more defined ranking of the Hazard Risk for each area.

4.1.1.1 External drivers

External drivers to the Hazard Risk system include population, demographics, economics and climate. The conceptual framework considers the impact of these drivers on the elements of Hazard Risk and the resultant measures of Hazard Likelihood and Social Vulnerability. Plausible changes in Hazard Likelihood, Social Vulnerability and Hazard Risk in the future as a result of these external drivers are tested using exploratory scenarios in the conceptual framework. The application of exploratory scenarios to all elements of the risk triangle, particularly changes in Social Vulnerability, addresses a gap in existing literature. As highlighted in Figure 4-1, the external drivers shape the exploratory scenarios, which impact the model inputs. Thus, for the Hazard Risk system, climate and socio-economic scenarios are developed to explore changes in the climate, population, demographic and economic external drivers.

Climate is an external driver that impacts natural hazard occurrence, and may be explored using climate scenarios. Climate changes affect factors like temperature, rainfall, and humidity, among others. The Representative Concentration Pathways (RCPs) developed by the IPCC for the fifth Assessment Report (AR5) model four independent pathways for future atmospheric greenhouse gas concentrations (Moss et al. 2008). The use of RCPs to project climate data into the future is a well-recognised and established method. The RCPs were developed by experts in the Integrated Assessment and Climate Modelling community, and serve as inputs to climate model simulations to develop climate scenarios (Moss et al. 2008). The RCPs considered only radiative forcing literature in their development, and do not consider the influence of any climate policy action. Thus, as they are not policy prescriptive, they may be applied to develop climate scenarios for testing mitigation of climate and socio-economic drivers (Moss et al. 2008). Therefore, the conceptual framework applies the RCPs to develop climate scenarios for modelling the dynamic climate drivers.

Socio-economic drivers, such as population, demographics and economics, may also be explored with multiple plausible future scenarios. Socio-economic scenarios are developed by first identifying stakeholders, issues, and the drivers of change. Using stakeholder engagement, axes which differentiate the scenarios are then selected, and narratives are developed for the scenarios. An example of axes that could be applied in developing socio-economic scenarios are Challenges to Mitigation versus Challenges to Resilience, as applied by Riddell et al. (2015). In this case, the ideal scenario occurs when Challenges to Mitigation and Challenges to Resilience are both low, and the most challenging scenario occurs when both are high (Riddell et al. 2015). Alternatively, Hall, Sayers and Dawson (2005) applied axes of Governance (Autonomy-Independence) and Values (Community-Consumerism) when developing scenarios to investigate economic futures of England. When developing the socio-economic scenarios, changes in the dynamic population, economic and demographic drivers should be highlighted as key characteristics of the scenario narratives. Detail is needed in the scenario narratives to allow the qualitative information to be turned into quantitative data or changes. This facilitates more comprehensive modelling of the future using scenarios.

4.1.1.2 Social Vulnerability

The conceptual framework in Figure 4-1 uses sixteen indicators that cover a range of social vulnerability aspects to quantify Social Vulnerability now and in the future using socio-economic scenarios. The methodology for applying the socio-economic scenarios to the Social Vulnerability indicators, and combining the indicators to measure Social Vulnerability for each scenario, is presented in Figure 4-3. The steps highlighted in blue in Figure 4-3 detail the methodology for quantifying projections in social vulnerability indices using scenarios, which addresses a gap in existing literature.

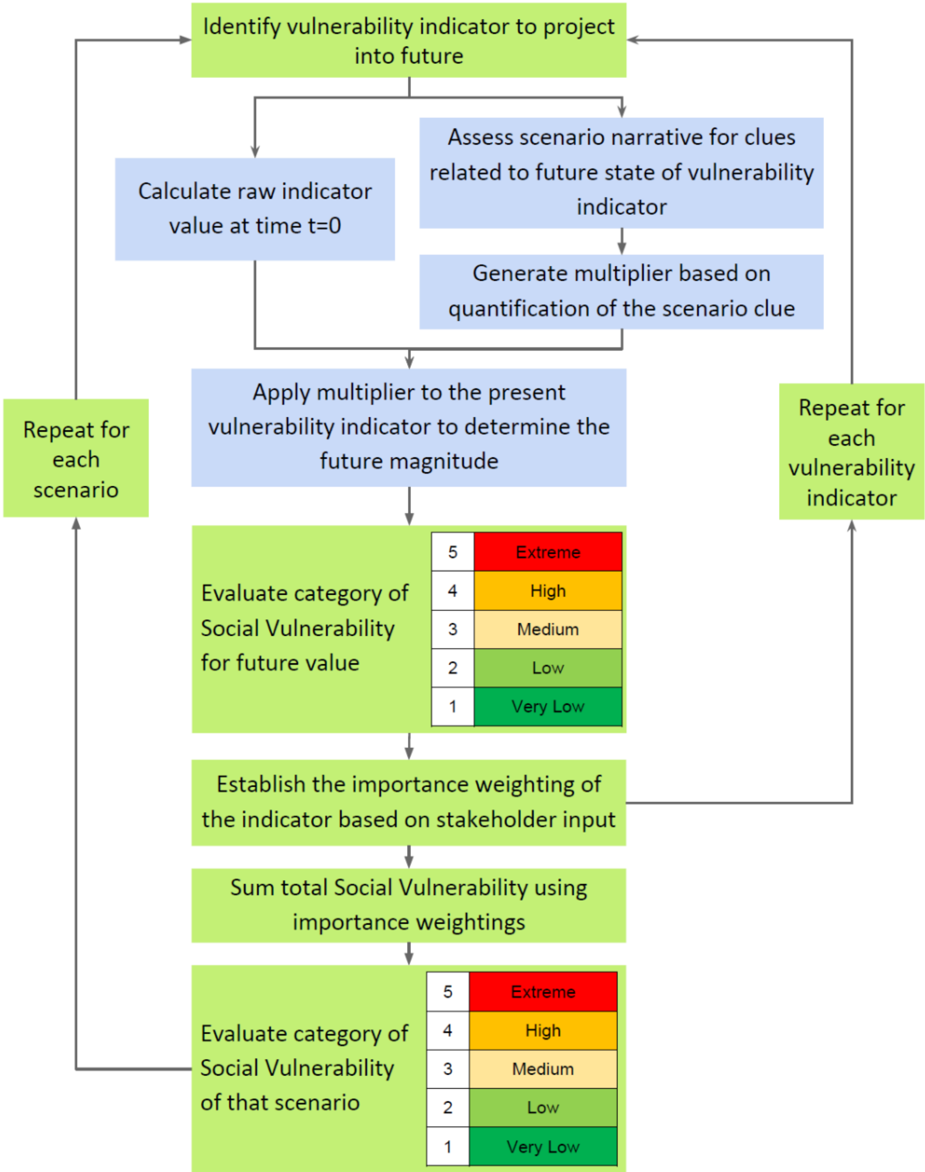


Figure 4-3 Proposed methodology for combining social vulnerability indicators to quantify a single measure of Social Vulnerability using exploratory scenarios. The steps highlighted in blue show the proposed methodology to projecting social vulnerability indicators in line with future socio-economic scenarios, which is a gap in the existing literature

The methodology for aligning the vulnerability multipliers, presented in Figure 4-3, requires quantification of the narrative storyline for each scenario, whereby the changes in the model inputs that are qualitatively explained in the scenario storylines are assigned a future quantitative value. This methodology follows the procedure presented in van Delden et al. (2005), but with the focus on quantifying storylines to multipliers for vulnerability indicators.

As presented in Figure 4-3, the first step in the storyline quantification process is to identify storyline clues about the vulnerability indicator being projected. Clues are meaningful statements in the text that contain relevant information about a state, change in state, a quality, a trend, or an interaction relevant to the indicator (van Delden et al. 2005). Thus, the projections rely on description of the changes undergone by each Social Vulnerability indicator in the scenario storyline, and so, the level of detail contained in the scenarios is integral to the meaningfulness of the projections. This idea ties into the development process for the socio-economic scenarios, as detailed in Section 4.1.1.1. The clues should ideally have spatial and temporal specification, and difficulties in scenario quantification arise when insufficient detail is presented in the storyline (van Delden et al. 2005). From these clues, a multiplier is developed to represent the numerical change in the indicator as described by the clue. This multiplier is then applied to the raw indicator value at the present time, to model the value of the indicator in the future under that scenario. The Social Vulnerability based on the projected indicator value is then evaluated on a scale of 1 to 5 (very low Social Vulnerability to very high Social Vulnerability).

The process is repeated for each social vulnerability indicator. A single measure of Social Vulnerability is then calculated from a summation of the Social Vulnerability due to each indicator, considering the importance weighting of each indicator. From the literature, the importance and relevance of different vulnerability indices depends on the differing objectives and goals of different parties. Thus, the priorities of stakeholders can be incorporated using importance weightings. In the absence of stakeholder and expert input, equal weightings should be applied for each of the vulnerability indices, to avoid assumptions of relative importance. The total Social Vulnerability is then evaluated on a scale of 1 to 5, in the same manner as the individual indicators. This process is repeated for each scenario, such that Social Vulnerability is quantified for each scenario, to be applied to the risk assessment matrix, as detailed in Section 4.1.1.

The indicators used in the assessment of Social Vulnerability are displayed in Table 4-1, and are widely recognised in the literature as being key characteristics of social vulnerability in the event of a hazard. Table 4-1 explains in detail the relevance of each of the indicators to how people may respond to or recover from a hazard. As discussed in Section 2, however, there is a need for vulnerability indicators to be tailored to a cultural context. Thus, the relevance of all sixteen indicators to Social Vulnerability in a specific region may need to be assessed during the application of the framework.

Table 4-1 Social Vulnerability indicators used in the conceptual framework to quantify a single measure of vulnerability. The indicators are recognised by literature as being key characteristics affecting hazard response and recovery.

Indicators	**Relevance**	**References**
Personal wealth	Low income communities have fewer individual and community resources available for recovery. Low income households may also be underinsured or uninsured.	Cutter, Boruff and Shirley (2003), McKenzie and Canterford (2016)
Age	Young children and elderly people are considered to be the most vulnerable age groups in society as they depend on others for care. Elderly are also often more frail and prone to health issues.	Chen et al. (2013), Cutter, Boruff and Shirley (2003), Frigerio and De Amicis (2016), McKenzie and Canterford (2016)
Employment	An elevated unemployment rate in an area can result in a slower recovery. In the event of a disaster, certain industries may be unable to operate, increasing unemployment further.	Chen et al. (2013), Cutter, Boruff and Shirley (2003), Frigerio and De Amicis (2016)
Housing stock and tenancy	This indicator considers the type of dwelling, the ownership and the location, which all indicate the socio-economic situation of a family or individual.	Chen et al. (2013), Cutter, Boruff and Shirley (2003) McKenzie and Canterford (2016)
Proficiency in local language	People who are not proficient in the local language may struggle to access or understand various emergency messages or information.	Cutter, Boruff and Shirley (2003), Frigerio and De Amicis (2016), McKenzie and Canterford (2016)
Race and Ethnicity	Individuals of diverse backgrounds may experience language and cultural barriers. This impacts their ability to respond to or prepare for emergencies.	Chen et al. (2013), Cutter, Boruff and Shirley (2003), Frigerio and De Amicis (2016)
Indigenous	Indigenous people are more likely to experience socio-economic disadvantages in relation to health, education and employment.	McKenzie and Canterford (2016), Cutter, Boruff and Shirley (2003)
Infrastructure dependence	Regions with a high dependence on employment in public utilities and other government led infrastructure may experience greater vulnerability due to the amplified effect of economic changes.	Cutter, Boruff and Shirley (2003)
Family structure	This will consider different factors affecting families. In larger families, there may be less finances available to care for dependents. Single parents may have dependent children but they do not have additional support.	Chen et al. (2013), Cutter, Boruff and Shirley (2003), Frigerio and De Amicis (2016) McKenzie and Canterford (2016)
Volunteering	People who volunteer within their community commonly have social networks that can support them in times of need.	McKenzie and Canterford (2016)
New to region	Individuals or families new to an area may not be familiar with the local area and unware of procedures for preparing for, or responding to, an emergency.	McKenzie and Canterford (2016)
Education	People with lower levels of education may be less capable of understanding information related to risks. Level of education also relates to socio-economic status.	Chen et al. (2013), Cutter, Boruff and Shirley (2003), McKenzie and Canterford (2016), Frigerio and De Amicis (2016)
Needs assistance	Those who require assistance with self-care are heavily reliant on others and more vulnerable as a result.	McKenzie and Canterford (2016)
Car ownership	Access to a car may be necessary to evacuate in an emergency.	McKenzie and Canterford (2016)
Unoccupied dwellings	Absentee owners may be less prepared in the event of a hazard as they may not attend local community meetings or prepare their property for the event of a hazard.	McKenzie and Canterford (2016)
Population Growth	This indicates the degree of urbanisation. Increased population growth may cause unbalance between population and resources.	Chen et al. (2013), Cutter, Boruff and Shirley (2003), Frigerio and De Amicis (2016)

The social vulnerability indicators cover different socio-economic characteristics which may affect someone's ability to respond to a hazard. For example, age captures the difficulties that young and elderly people would have evacuating by themselves in the event of a hazard, and their dependence on other people to evacuate. Education, however, captures the ability of people with lower levels of education to understand information related to risk, and their possible reluctance to evacuate or undertake mitigation measures as a result of misunderstanding the severity of the risk. The social vulnerability indicators also consider socio-economic characteristics which affect the ability of someone to recover after a hazard event. For example, personal wealth captures how low-income communities have low individual and community financial resources to recover, as well as how low-income households are also more likely to be un- or under-insured. Regions with large population growth may also result in an imbalance between population and resources. The range of Social Vulnerability indicators helps to model the complex interaction of socio-economic scenarios and their influence on the highly dynamic socio-economic characteristics of Social Vulnerability.

4.1.1.3 Hazard Likelihood

Hazard Likelihood is a function of the hazard itself, and its likelihood of occurrence, which encapsulate the hazard and exposure elements of risk. Thus, the Hazard Likelihood Model needs to incorporate all the climate and socio-economic drivers which affect how likely a hazard is to occur at a particular location.

Climate drivers should be incorporated into the measure of Likelihood, as different climates facilitate the occurrence of different natural hazards. For example, tropical climates are more likely to facilitate cyclones, while arid climates are more likely to result in drought. The climate drivers are temporally dynamic, and so changes in Hazard Likelihood as a result of these climate drivers should be modelled using climate scenarios (Reguero et al. 2015; Whitman, Sherren & Rapaport 2015). Natural land characteristics, including factors such as topography, soil type and native vegetation, also influence the likelihood of a hazard occurring (Esser et al. 2004; Fontaine et al. 2012; Keefer et al. 1987). For example, bushfire relies on vegetation to ignite and spread, so the type of vegetation influences the likelihood of a bushfire occurring (Esser et al. 2004). Topographic factors, such as slope, are also drivers for some natural hazards such as bushfire, landslide and flooding. While land characteristics such as slope are dynamic, they can take thousands of years to change. Hence, over the conceptual framework timeframe, the expected change is negligible and therefore, the land characteristics are considered as static over the temporal scale. The land characteristics are spatially explicit and should be incorporated into the model to show how Hazard Likelihood varies spatially.

Land use also influences the likelihood of a hazard occurring (Glavovic, Saunders & Becker 2010; Schilling et al. 2014). For example, residential areas with large amounts of concrete can increase the likelihood of a flood occurring due to high runoff. However, an equivalent amount of water in a vacant forest would be less likely to result in a flood, as the soil would need to become fully saturated before runoff occurs. Alternatively, a bushfire would not be likely to occur in a residential area due to a lack of vegetation, however, it may have a high likelihood of occurring in a vacant forest. Changes in land use are a result of changing socio-economic drivers and policy implementation, such as urban sprawl due to population growth (Riddell et al. 2015). Socio-economic scenarios should be applied to model how changes in land use change the likelihood of a hazard occurring.

Many Hazard Likelihood models that encapsulate hazard and exposure have been published in literature, and thus, it may be appropriate to couple the Social Vulnerability model with an existing Hazard Likelihood model for the region being considered.

4.1.2 Mitigation options

The conceptual framework facilitates developing an understanding of the drivers of Hazard Risk to socially vulnerable areas. From this understanding, drivers which are highly influential in the level of Hazard Risk may be identified, and mitigation options may be developed to target these drivers.

A sensitivity analysis can be used to identify which drivers have a large influence on the dynamics of the Hazard Risk. From the results of the sensitivity analysis, plausible mitigation options which may be used to target these highly influential drivers can then be identified. The sensitivity of the Hazard Likelihood and Social Vulnerability to the drivers may be assessed separately, as the appropriateness of a sensitivity analysis method depends on the nature of the model. The Social Vulnerability model considers a weighted sum of the Social Vulnerability indicators which are based on recorded statistics. Due to the nature of the model, a traditional sensitivity analysis may not be appropriate, particularly if the Social Vulnerability indicators are equally weighted. In this case, the Social Vulnerability due to each indicator may need to be individually assessed to identify mitigation options.

The Hazard Likelihood model describes a complex human and natural system; the influence of the climate and socio-economic drivers on the overall Hazard Likelihood is much more complex. This means that highly influential drivers may not be easily identified by analysing individual driver maps. In this case, therefore, a global sensitivity analysis (GSA) is appropriate for testing the sensitivity of the Hazard Likelihood output to the dynamic drivers. Complex systems are often characterised by non-uniform and non-normal distributions, and thus, it is recommended that a density based method be used to assess the sensitivity of the Hazard Likelihood model. Density based methods are more appropriate for analysing the sensitivity of complex systems (Pianosi & Wagener 2015). An example of a density based sensitivity analysis method is the PAWN method, developed by Pianosi and Wagener (2015). The results of the GSA highlight the climate and socio-economic drivers that Hazard Likelihood is most sensitive to. For each highly influential driver, the possibility of mitigating for that driver can be assessed.

The feasibility and impact of mitigation options depend on the type of hazard, as noted in Section 2.1.3, and the way mitigation methods are implemented also has an impact on their efficacy. The best mitigation options are those that affect influential inputs, and are feasible in terms of cost and implementation. For example, building flood levies which are robust to withstand any flood may also be infeasible for the financial capacity of the region being considered. Thus, consultation with experts should be used to identify mitigation options. The other issue raised here is that whilst a mitigation option could be effective in targeting one hazard, it may be detrimental to another. For example, while clearing vegetation can remove the risk of bushfire, it could increase the risk of flooding. This motivates the need to include consideration of multiple hazards.

The socio-economic characteristics of the region may also influence the most appropriate method of mitigation. For communities with a large distrust or low support for the government, top-down mitigation strategies may be ineffective. As discussed in Section 2.1.3, in small towns with greater community connectedness, bottom-up, community based initiatives, may be more effective. Hence, the method of implementation should be considered when assessing the feasibility of a mitigation option.

The influence of the plausible mitigation options may be assessed by incorporating their effect on the inputs into the Social Vulnerability and Hazard Likelihood models and analysing the resultant changes. For example, if increasing local government funding to volunteering organisations to increase rates of volunteering is identified as a plausible mitigation option, then the effect that may be achieved by implementing this mitigation option may be tested by changing the volunteering rates in the model. From this analysis, recommendations may be made about mitigation strategies that could be used to effectively target risk of certain areas to particular hazards.

5 GREATER ADELAIDE CASE STUDY

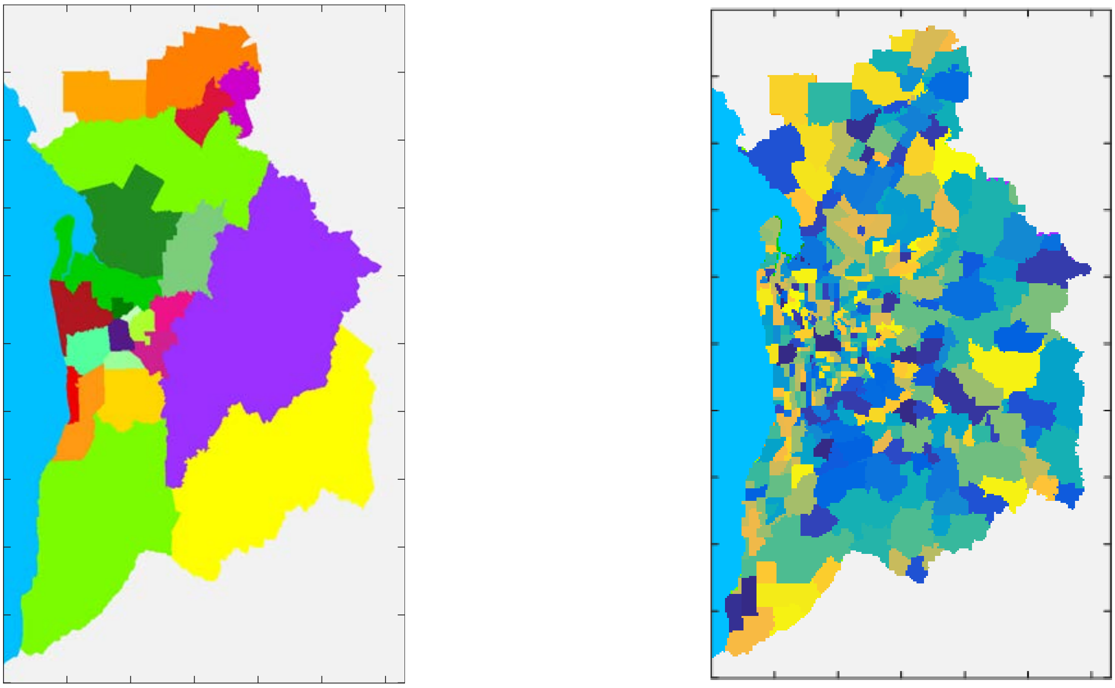
Section 5 applies the conceptual framework to a case study of Social Vulnerability and its effect on Hazard Risk in Greater Adelaide using a bushfire hazard. The application to the case study demonstrates the process of applying the conceptual framework in order to quantify Social Vulnerability, Hazard Likelihood and Hazard Risk and develop an understanding of the important drivers of risk to inform plausible mitigation strategies.

5.1 Background

Australia has a history of bushfires that have caused major damage to infrastructure and communities. To illustrate the value of the contribution this framework can make, the case study of bushfire hazard in Greater Adelaide is considered, however other hazards and locales could equally be used.

Adelaide is the capital city of South Australia, shown in Figure 5-1. With a population of approximately 1.3 million, it is the fifth most populous city in Australia. Adelaide is situated between the Gulf St Vincent to its West, and the Mount Lofty Ranges to its East. This has caused Adelaide to grow elongated, stretching approximately 100km from North to South, as illustrated in Figure 5-1. Within Greater Adelaide, there are 27 Local Government Areas (LGAs) and 511 State Suburb Codes (SSC), which are shown in Figure 5-2. Adelaide's climate is highly variable and Mediterranean.

Figure 5-1 Map showing the location of the case study (Google Maps 2017), and a satellite image of Greater Adelaide, illustrating the sprawl of urban area between the coast and Mt Lofty Ranges (Google Maps 2017)



(a) (b)

Figure 5-2 (a) Local Government Areas (LGAs) in the Greater Adelaide region, and (b) State Suburb Codes (SSCs) in the Greater Adelaide region. For the SSC map, a legend is not provided, as there are 511 SSCs within Greater Adelaide. A list of these SSCs, however, is provided in Appendix D.

In recent years, Adelaide has experienced an ageing population, as well as instabilities in its economy due to a shift from manufacturing to more service based industries. The projected trends in these demographics has led Adelaide's future Social Vulnerability to be of interest to decision makers. Additionally, South Australia and Greater Adelaide have a long history of bushfires. Most recently, the 2015 Pinery Bushfire was a catastrophic bushfire which occurred primarily in the lower Mid North and West Barossa Valley regions, immediately North of Greater Adelaide and the township of Gawler. This fire burned from the 25th of November to 2nd December 2015, killing two people and burning 85,000 hectares of land, which included destroying 91 homes (McLoughlin 2015). Thus, using the conceptual framework to assess bushfire risk with a focus on Social Vulnerability in Greater Adelaide is particularly relevant given the current and projected future demographics and climate.

5.2 Framework Development

5.2.1 Overview

The general framework presented in Section 4 is adapted for the case study, and allows the sub-objectives outlined in Figure 5-13 to be achieved. This adapted framework is presented in Figure 5-3, and defines the inputs and modelling processes specific to the case study of Greater Adelaide.

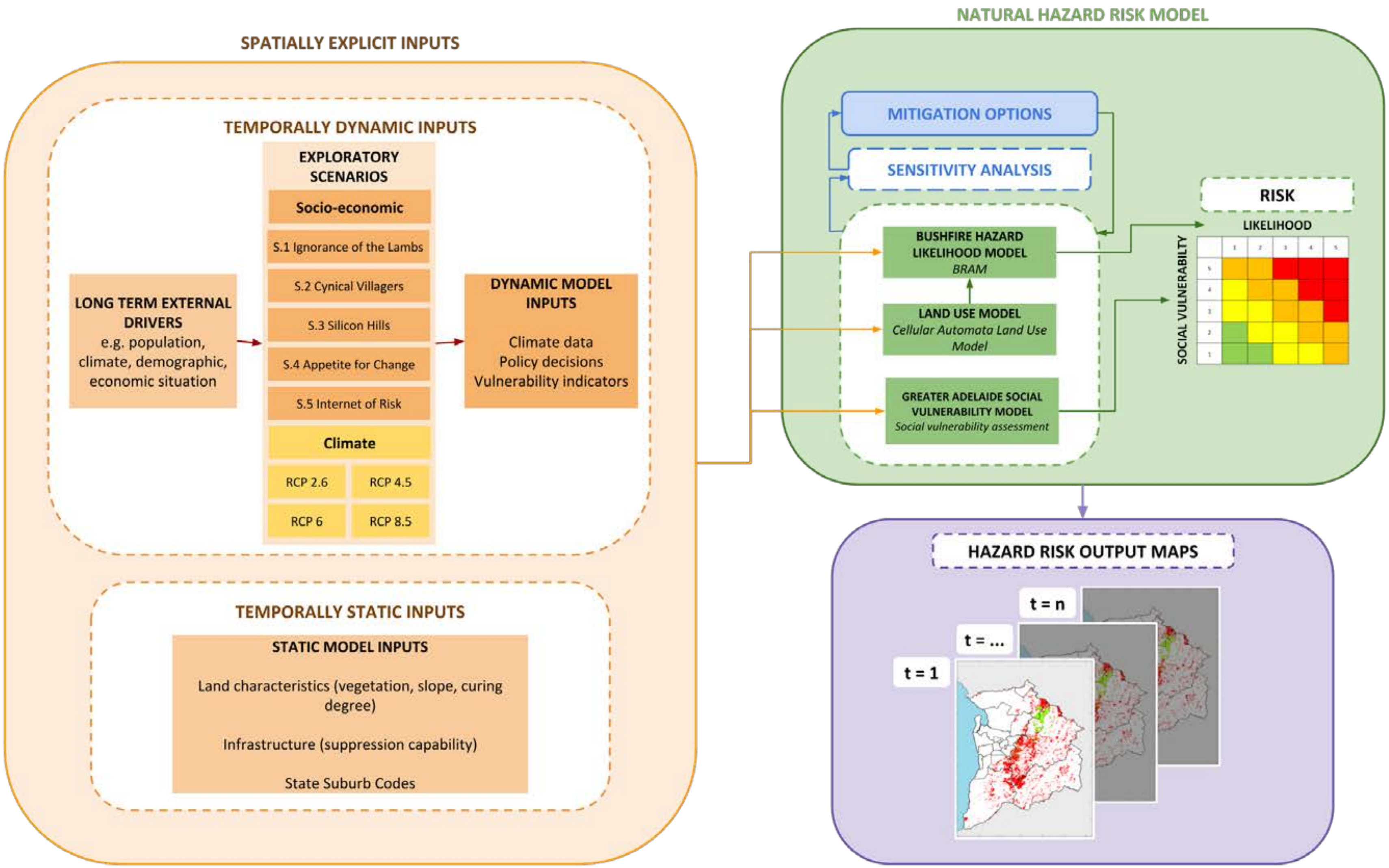


Figure 5-3 Schematic diagram for the case study application of the conceptual framework to bushfire in Greater Adelaide, adapted from the generic framework outlined in Section 4.1 to include the inputs and processes specific to the case study. Hazard Risk is assessed spatially and uses exploratory scenarios to assess temporally dynamic risk under future uncertainty.

The Hazard Risk Model, indicated in Figure 5-3 by the green envelope, assesses the spatial and temporal risk for Greater Adelaide. The model uses a measure of Hazard Likelihood calculated using a Bushfire Risk Assessment Model (BRAM) and the Social Vulnerability assessment for each State Suburb Code to quantify the Hazard Risk using the Risk Matrix.

The orange envelope in Figure 5-3 captures how the various spatially explicit inputs impact the Hazard Risk Model. The long term external drivers of population, economics, demographics and climate are influenced by the socio-economic and climate scenarios to form the dynamic model inputs for the Social Vulnerability and Hazard Likelihood Model. Several of the inputs are temporally static and therefore remain constant throughout the dynamic assessment of Hazard Risk.

The results from the Hazard Risk Model informs the areas in Greater Adelaide under the greatest hazard risk. Mitigation strategies are tested in the Hazard Risk Model to identify which strategies are most suitable to reduce Hazard Risk for the areas of greatest Social Vulnerability. As presented in Figure 5-3, sensitivity analyses are used to inform appropriate mitigation strategies. The sensitivity analysis identifies the dominant system inputs and allow for application of mitigation strategies that effectively reduce Hazard Risk. The feedback loops enable the impact of the changing external drivers and Hazard Risk to be understood in the assessment of the mitigation strategies.

The proposed case study framework outputs the results of the current and future Hazard Risk Model as spatially explicit Hazard Risk maps, as shown in the purple results envelope in Figure 5-3. By testing the different socio-economic and climate scenarios and mitigation options, spatially explicit Hazard Risk maps for different mitigation strategies can be developed and compared to inform long term planning. Table 5-1 outlines which components of the case study framework, presented in Figure 5-3, are adapted from other sources, and where further work has been contributed. A summary of the Hazard Risk Model inputs for the Greater Adelaide case study and the respective sources of these inputs is presented in Table 5-2.

Table 5-1 Break down of the modelling approaches for the case study conceptual framework into the sources of information and new contributions made

Component		Explanation and Source	Contribution made
Hazard Risk Model	Risk Matrix	Adopted from AGAGD (2015).	
Social Vulnerability Model	Social Vulnerability Indicators	The indicators are adopted from Chen et al. (2013), Cutter, Boruff and Shirley (2003), Frigerio and De Amicis (2016), McKenzie and Canterford (2016). Implemented as a model using Matlab.	
	2050 Social Vulnerability	Methodology adapted from (van Delden et al. 2005) and developed to be applied to defining social vulnerability multipliers. Implemented as a model using Matlab.	✓
Hazard Likelihood Model	Hazard Likelihood Model	Adopted from the bushfire risk assessment model (BRAM) developed by Van Delden et al. (2017). Conceptualisation for Greater Adelaide adopted from the Department of Environment, Water and Natural Resources (DEWNR) and implemented in Matlab.	✓
	Ignition Potential	Statistical Analysis methodology created and performed as part of this research for Greater Adelaide.	✓
Global Sensitivity Analysis	Hazard Likelihood Model	The case study applies the PAWN method using the Matlab toolbox, SAFE (Sensitivity Analysis for Everyone) (Pianosi, Sarrazin & Wagener 2015).	✓

Table 5-2 Break down of the Hazard Risk Model inputs for the case study conceptual framework into the sources of information and new contributions made.

Input	Source
Climate Data	Provided by DEWNR and projected in line with RCP scenarios.
Vegetation Data	Provided by DEWNR.
Suppression Capability	Provided by DEWNR.
Land Use	Provided by van Delden and Hurkens (2011) for the current assessment and adopted from Riddell et al. (2015) for the future assessment.
Social Vulnerability	Australian Bureau of Statistics 2011 Census.

5.2.2 Hazard Risk Model

As detailed in Section 4.1.1, the Hazard Risk Model centres around a risk assessment which quantifies Hazard Risk based on the Social Vulnerability and Hazard Likelihood. The spatially explicit nature of Hazard Risk is modelled by dividing the area into discrete cells, and then assessing Hazard Risk in each of these cells based on the external driver values at that location. Based on the land use data available for Greater Adelaide, the Hazard Risk Model divides the region into 100m x 100m cells, over an area of 63 km (East-West) and 100 km (North-South). This area is the region recognised as Greater Adelaide, shown and contextualised in Figure 5-4.

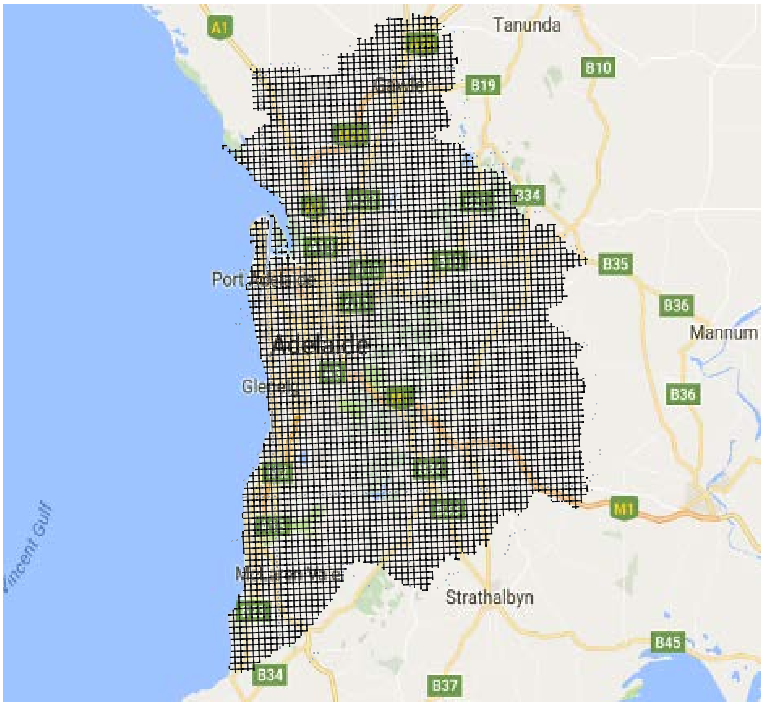


Figure 5-4 The Greater Adelaide region is divided into 100m x 100m cells for the case study so that the spatially explicit nature of the hazard risk may be shown by calculating hazard risk in each of these cells. This is a visual representation ONLY, and does not show all the cells in the 63km x 100km area. Figure from Google Maps (2017).

For each cell in Figure 5-4, the Social Vulnerability and Hazard Likelihood are calculated for that location, and the risk assessment is then applied. The result of the Hazard Risk Model is a map of the risk assessment results from each cell in Greater Adelaide. This idea is conceptualised in Figure 5-5.

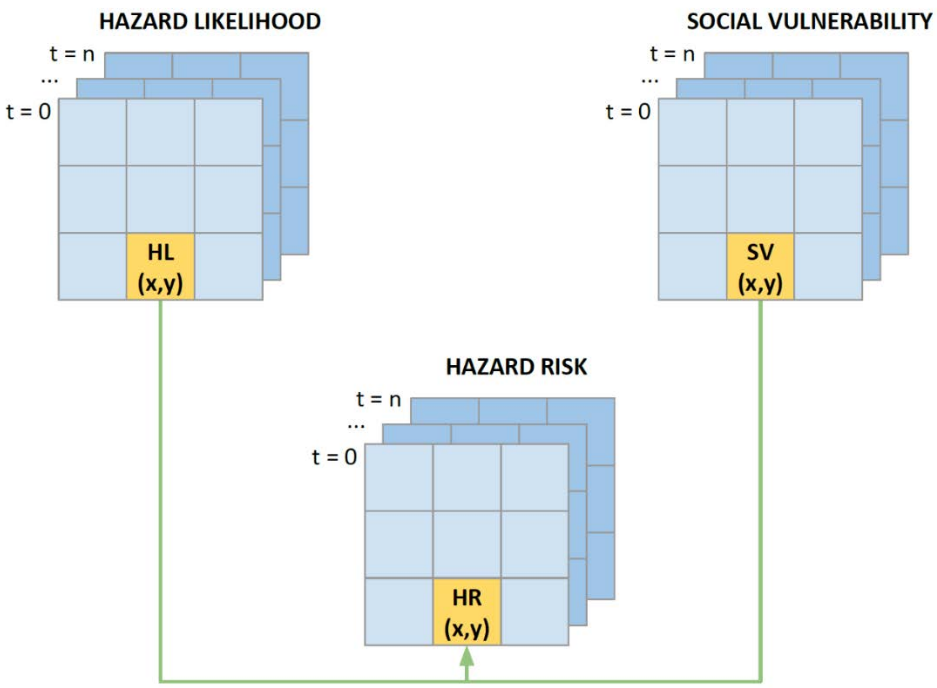


Figure 5-5 Conceptualisation of the computational Hazard Risk (HR) Model for bushfire. The model assesses the hazard risk in each location using a risk assessment. The risk assessment considers the hazard likelihood and social vulnerability at that location at that point in time. The risk assessment is applied to each location in the spatial domain to produce a spatial map of hazard risk for the point in time being assessed.

5.2.2.1 Social Vulnerability Model

The case study Social Vulnerability Model assesses the spatially explicit Social Vulnerability using fourteen social vulnerability indicators. The methodology for combining these indicators to quantify a single measure of Social Vulnerability is outline in Figure 5-6.

The indicators used in the Social Vulnerability Model in Figure 5-6 to assess social vulnerability for each cell in Greater Adelaide are shown in Table 5-3. These indicators are chosen based on the relevant indicators from the conceptual framework, outlined in Section 4.1.1.2. For each indicator, a variable – which is measured using Census data sourced from the Australian Bureau of Statistics (2017) – is selected to quantify the social vulnerability based on that indicator. The final selection of indicators used to assess Social Vulnerability was limited by variables included in the Census data.

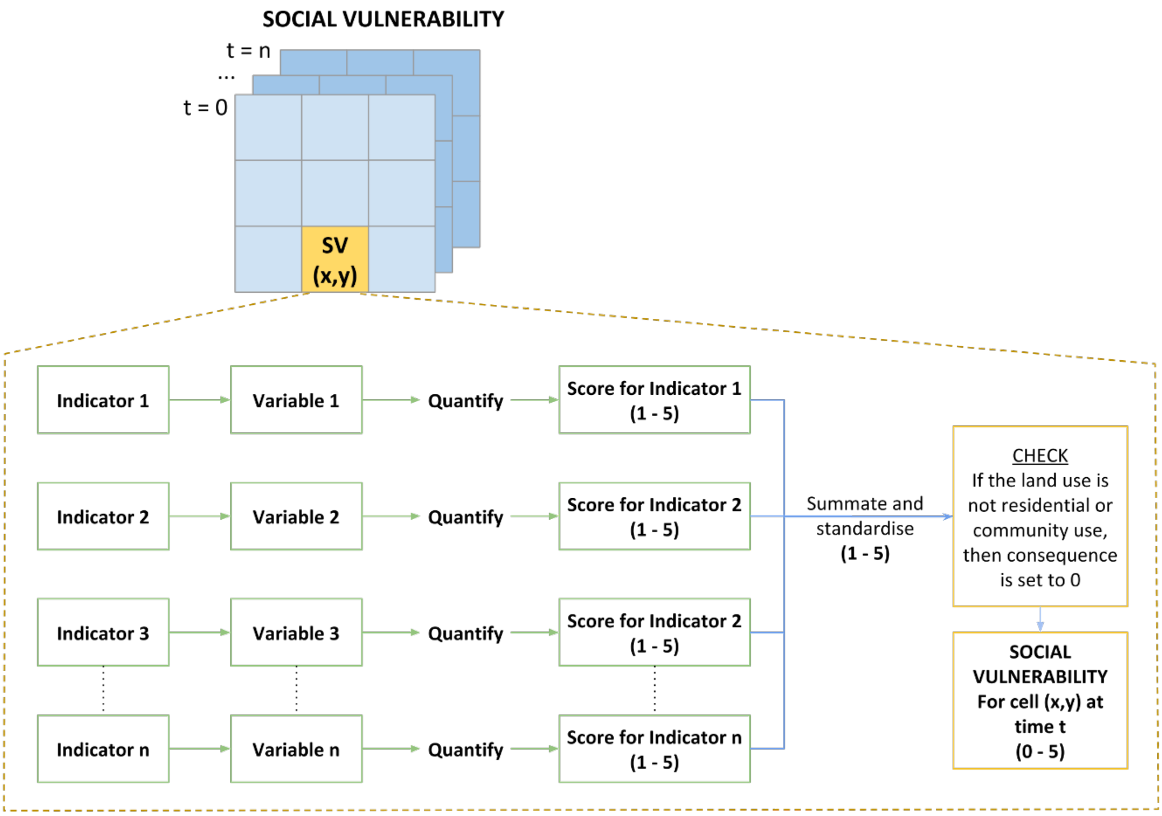


Figure 5-6 Overview of computational Social Vulnerability Model for bushfire for assessing spatially explicit Social Vulnerability.

2011 Census data are used for the variables outlined in Table 5-3 to measure the current Social Vulnerability in Greater Adelaide. 2011 Census data are the most recent Census data available for the variables. These data are available on a State Suburb Code (SSC) resolution. Thus, for each cell, the indicator variables are calculated based on the value of the indicator variables for the SSC that the cell lies in. The map of spatially explicit social vulnerability produced by the Social Vulnerability Model, therefore, has a SSC resolution.

Table 5-3 Vulnerability indicators and their quantifiable variables, sourced from ABS

Indicators	Variable	Units
Personal wealth	Estimates of Personal Income (weekly) - Median total income	$
Age	Estimated Resident Population - Persons - 0-14 years	%
	Estimated Resident Population - Persons - 65 years and over	%
Employment	Labour Force Statistics - Unemployment rate	%
Insufficient English	Proficiency in Spoken English - Not proficient in spoken English	%
Indigenous	Aboriginal and Torres Strait Islander - Proportion of population	%
Family structure	Family Structure - Count of dependent children per parent	Dependents per parent
Volunteering	Voluntary Work for an Organisation or Group	%
New to region	Address One Year Ago - Elsewhere in Australia or Overseas	%
Education	Highest Year of School Completed – Year 12 or equivalent	%
Need assistance	Need for Assistance to undertake Core Activities	%
Car ownership	Motor Vehicles – One or more motor vehicles per dwelling	%
Population Growth	Total Estimated Residential Population in 2011 – Total Estimated Residential Population in 2006	%
Public Housing	Number of Dwellings Rented from State Housing Authority	%

As outlined in Figure 5-6, the social vulnerability due to each indicator is evaluated on a scale of 1 to 5 (Very Low to Very High Social Vulnerability). Ideally, quantified bounds for the Social Vulnerability categories should be defined for each indicator variable through stakeholder input. For example, a stakeholder may define a 40% of the population being elderly as Very High Social Vulnerability, and so this quantified bound would be applied in the Social Vulnerability Model. In the absence of stakeholder input, however, the bounds used to define the Social Vulnerability categories are quantified from the percentile ranking of that cell's indicator value in relation to the other cells in the spatial domain. For some indicators, a higher value correlates to a higher vulnerability (e.g. unemployment levels), however for others, a high value correlates to a low vulnerability (e.g. median income). Thus, in the absence of stakeholder input for an indicator where a higher indicator value means higher Social Vulnerability, the 20th percentile corresponds to the upper bound for Very Low Social Vulnerability, and the 40th, 60th and 80th percentiles corresponds to the upper bounds for Low, Medium and High Social Vulnerability, respectively. Indicators above the 80th percentile are categorised as Very High Social Vulnerability. Table 5-4 summarises this definition of Social Vulnerability category bounds using percentiles.

Table 5-4 Process for quantifying the value of a vulnerability indicator to generate an indicator score

Percentile Range – depends on indicator type:		Level of vulnerability for the indicator	
High value indicates high vulnerability	**High value indicates low vulnerability**	**Qualitative**	**Quantitative**
0% – 20%	80% - 100%	Very low	1
20% - 40%	60% - 80%	Low	2
40% - 60 %	40% - 60 %	Medium	3
60% - 80%	20% - 40%	High	4
80% - 100%	0% – 20%	Very high	5

Social Vulnerability is also dependent on the land use type at each location. The Social Vulnerability Model assumes zero risk for bodies of water, vacant and forest areas, on the basis that Social Vulnerability does not apply where there are no people. Therefore, where the land use is residential and community land use types (e.g. residential, rural residential, commercial, and public institutions including education) the calculated Social Vulnerability is applied. For all other land uses, the Social Vulnerability is zero, as shown in the penultimate step in Figure 5-6.

5.2.2.2 Hazard Likelihood Model

The Hazard Likelihood Model, presented in Figure 5-7, calculates the likelihood of bushfire in each cell location in Greater Adelaide. The Hazard Likelihood Model is based on a bushfire risk assessment model (BRAM) developed by Van Delden et al. (2017) following work by Taylor and Wallace (2011) in conjunction with DEWNR Fire. The BRAM is currently used by the Tasmanian Fire Service to evaluate the likelihood of a bushfire occurring. The model couples the assessment of exposure and hazard in its evaluation of Hazard Likelihood. The Hazard Likelihood Model, detailed in Figure 5-7, considers Ignition Potential (IP), Suppression Capability (SC) and Fire Behaviour (FB) as the three components of Bushfire Likelihood. The Ignition Potential in Figure 5-7 considers the likelihood of a fire starting due to lightning or being man lit, using historical data to assess the potential of either occurrence. The Suppression Capability is related to how quickly a fire is detected and suppressed. The head fire intensity is used for the Fire Behaviour and is a function of climate data, rate of spread, vegetation, and slope. These factors are combined to produce a spatial assessment of the likelihood of a bushfire occurring. Where there is no vegetation, the Bushfire Likelihood is assumed to be zero.

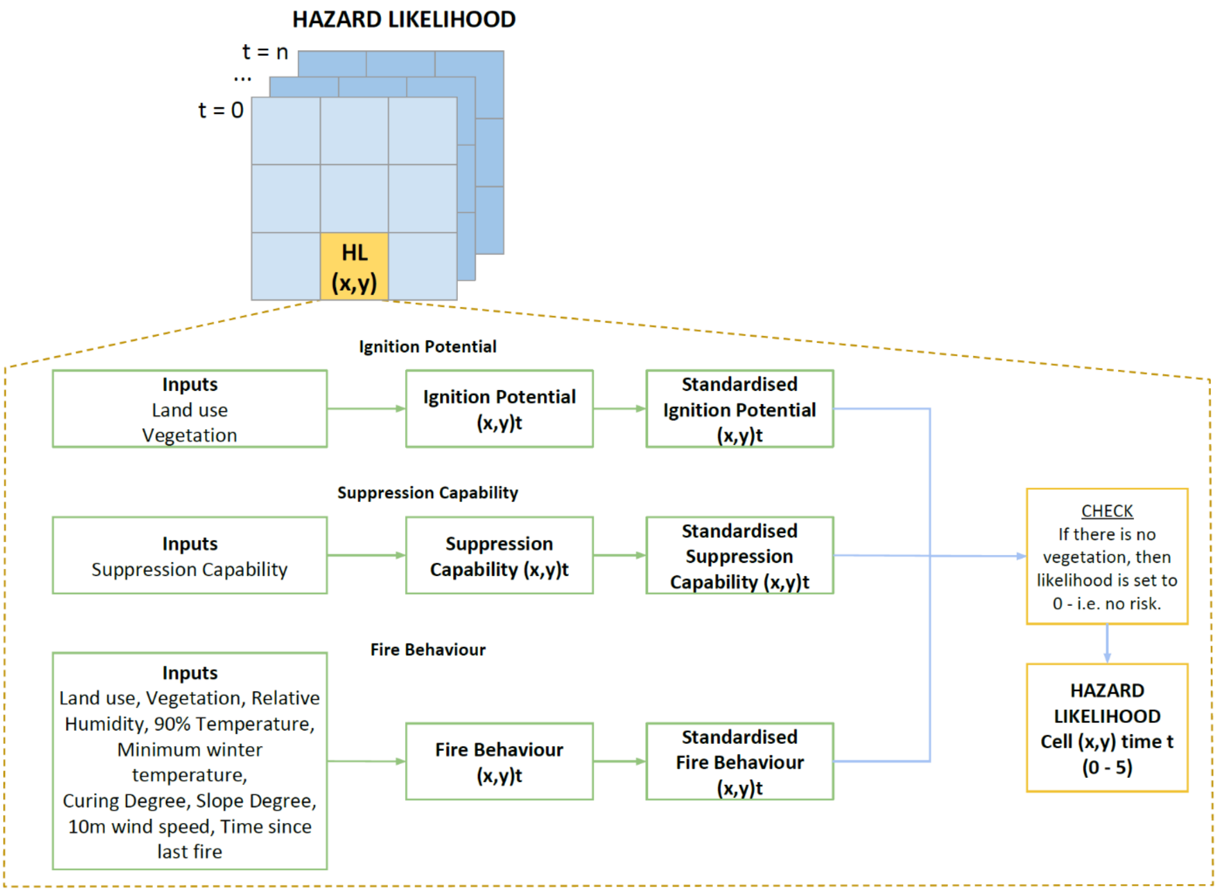


Figure 5-7 Overview of Bushfire Risk Assessment Model (BRAM) used to assess the spatially explicit bushfire Hazard Likelihood in Greater Adelaide

Ignition Potential

The Hazard Likelihood Model calculates the Ignition Potential for a given cell (IP_{xy}) based on a summation of the Ignition Potential (Eq. 1) due to land use ($IP_{LU,xy}$) and the Ignition Potential due to vegetation type ($IP_{V,xy}$). These parameters are quantified by converting land use and vegetation to an equivalent Ignition Potential (Eq. 2 and Eq. 3).

$$IP_{xy} = IP_{LU,x,y} + IP_{V,x,y} \quad \text{Eq. 1}$$

$$IP_{LU,xy} = f(LU) \quad \text{Eq. 2}$$

$$IP_{V,xy} = f(V) \quad \text{Eq. 3}$$

This conversion is developed from a statistical analysis of historic data for land use and vegetation at the points of ignition. For the case study, this statistical analysis is carried out on data provided by DEWNR from 2011-2016 in Greater Adelaide. In the data, there are 2045 samples. The analysis considers the average number of fires per year per unit area of each vegetation and land use type in Greater Adelaide as a measure of the propensity to ignite.

The results from the statistical analysis are used to inform the conversion of qualitative land use and vegetation types into quantitative measures of their Ignition Potential. Figure 5-8 and Figure 5-9 show the results for the average number of fires per year per unit area of each vegetation and land use type. As an example, shown in Eq. 4, to calculate the Ignition Potential for Vacant land, in 2011-2012 there were 23 fires on Vacant land in Greater Adelaide, and 8572ha of Vacant land:

$$IP_{Land\ Use:\,Vacant,11-12} = \frac{23}{8572} = 0.0027 \qquad \text{Eq. 4}$$

However in 2012-2013, there were 110 fires on Vacant land, and 8598ha of Vacant land, and the calculation would be as in Eq. 7:

$$IP_{Land\ Use:\,Vacant,12-13} = \frac{110}{8598} = 0.0128 \qquad \text{Eq. 5}$$

Continuing this for the years 2013-2014, 2014-2015, and 2015-2016, the number of fires per area of land use is calculated for each year; these are the blue bars shown in Figure 5-8. The mean of these values is taken, as calculated in Eq. 6, to determine the mean number of fires per year per area of land use or vegetation type. This value is used as the Ignition Potential conversion factor, and shown as a green bar on Figure 5-8.

$$IP_{Land\ Use:Vacant} = \frac{0.0027 + 0.0128 + 0.0058 + 0.0041 + 0.005}{5} = 0.0061 \qquad \text{Eq. 6}$$

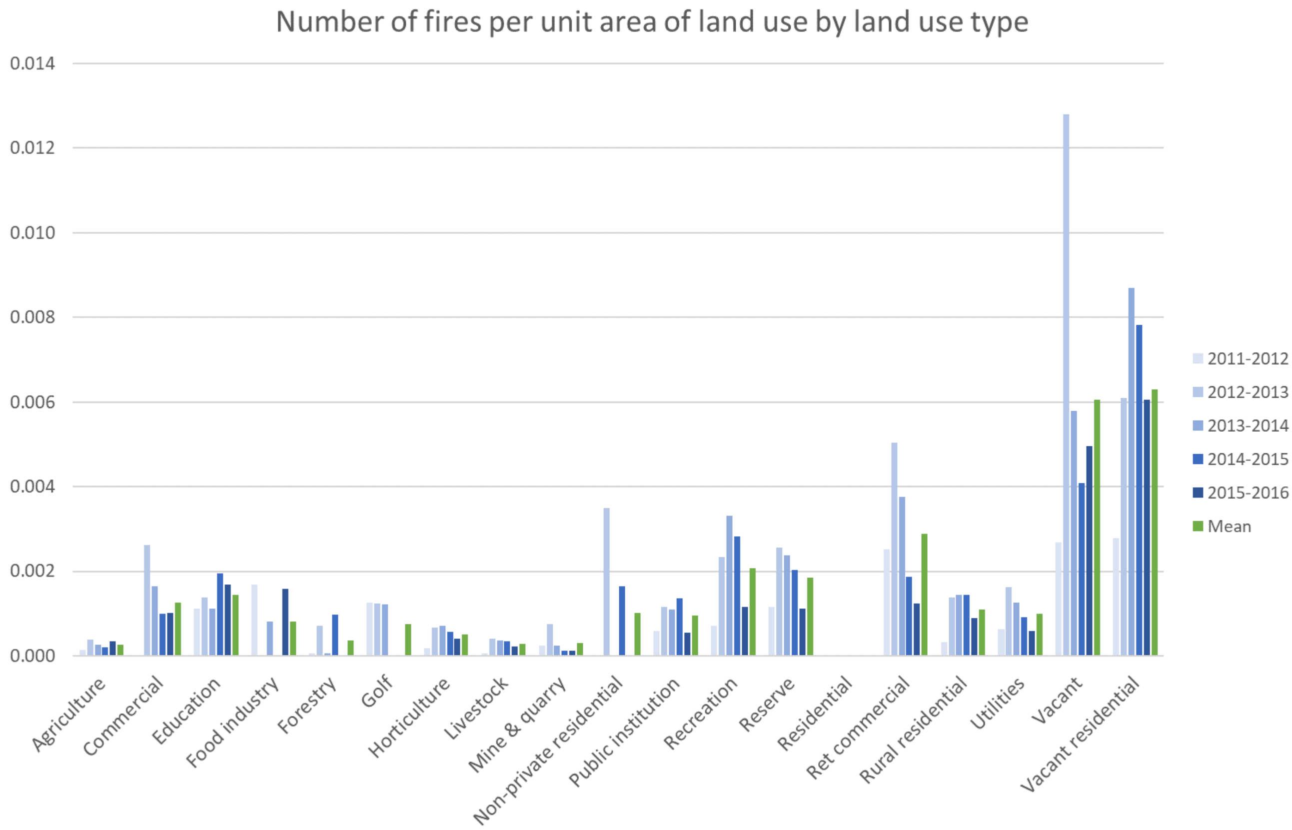


Figure 5-8 Graph of the ignitions per year per land use per area of land use used to determine the ignition potential for each land use type

From Figure 5-8, it is observed that while the highest number of fires per year per unit area of land use type occurred for Vacant land in 2012-2013, the mean highest number of fires per year per unit area was for Vacant Residential land use. As such, the Vacant Residential land use has the Ignition Potential. Vacant land use has the second highest Ignition Potential. Residential showed no recorded ignitions, and as such had an Ignition Potential of 0. Agriculture, Mines and Quarries, Forestry, Livestock and Horticulture all showed low average numbers of fires per year per unit area of land use.

The assessment for Ignition Potential of vegetation types used the same approach as land use, with the results shown in Figure 5-9. The Mallee woodlands have the highest mean number of fires per year per unit area of Eucalyptus woodland, however in 2012-2013, 2013-2014, and 2014-2015, there was only 1 fire in each year. It is because of the low amount of area that this has been described as highly prone to ignition. A similar trend is seen for Coastal Shrubland. Acacia Shrubland has no recorded fires for the 2011-2012 period, causing its Ignition Potential of 0. By contrast, Grasses have an average of 280 fires per year, but account for 380441ha of Greater Adelaide, which makes its Ignition Potential almost negligible.

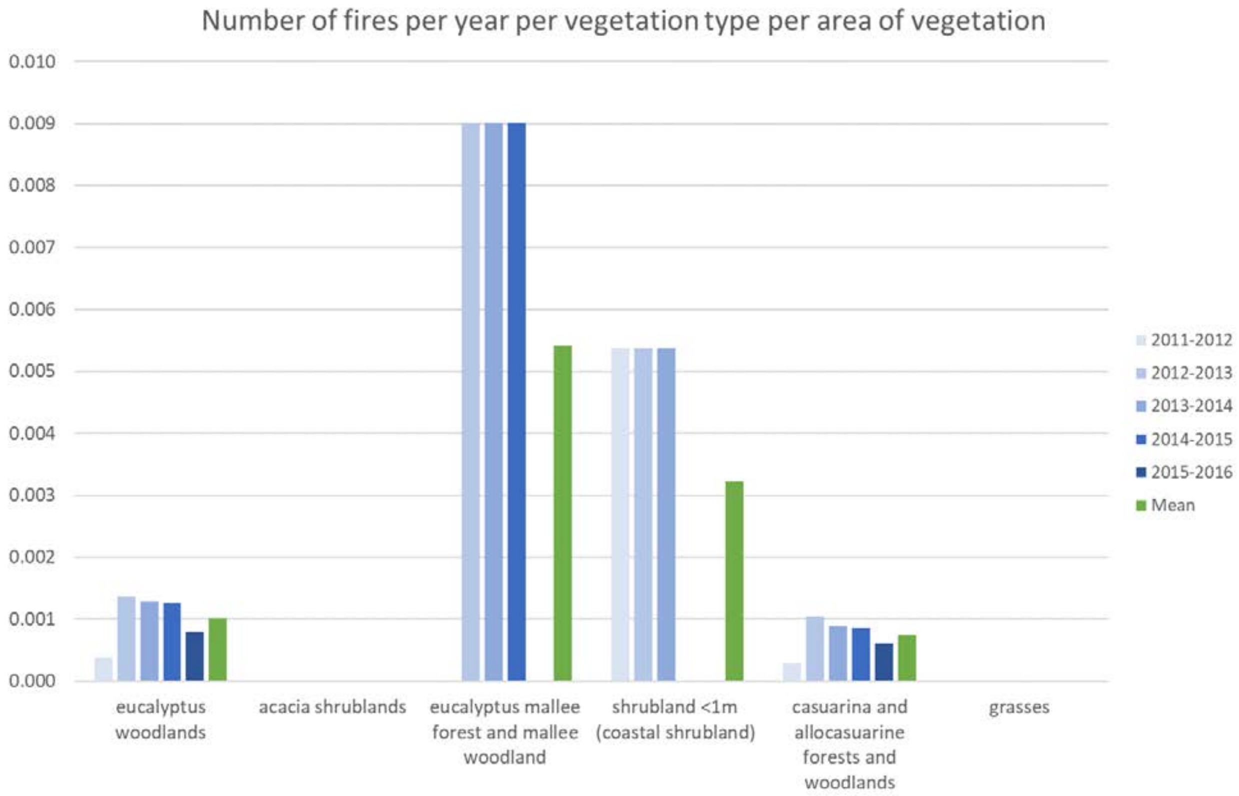


Figure 5-9 Graph of the ignitions per year by vegetation per area of vegetation type used to determine the ignition potential for each vegetation type

Where there is no vegetation, there is no Ignition Potential, therefore areas with no vegetation are given an overriding Ignition Potential of zero. Using the results of this statistical analysis, the Ignition Potential of the Greater Adelaide area is determined.

The resultant Ignition Potentials for each vegetation and land use type in Greater Adelaide using the statistical analysis are presented in Table 5-5 and Table 5-6.

Table 5-5 Ignition Potential (IgPot) for each land use type in Greater Adelaide determined using statistical analysis historical data provided by DEWNR.

Land use	Ignition Potential for land use (mean fires per ha per year)
Residential	0.000
Agriculture	0.036
Livestock	0.041
Mine and quarry	0.054
Forestry	0.076
Horticulture	0.071
Golf	0.135
Food industry	0.155
Public institution	0.128
Utilities industry	0.140

Land use	Ignition Potential for land use (mean fires per ha per year)
Non-private residential	0.241
Rural residential	0.153
Commercial	0.212
Education	0.178
Reserve	0.245
Recreation	0.306
Ret commercial	0.425
Vacant	0.958
Vacant residential	0.832

Table 5-6 Ignition Potential (IgPot) for each vegetation type in Greater Adelaide determined using statistical analysis historical data provided by DEWNR.

Vegetation code	Ignition Potential for vegetation (mean fires per ha per year)	Description
0	0.006	Mixed chenopod, samphire or forblands
1	0.677	Eucalyptus woodlands
2	0.000	Acacia shrublands
3	0.002	Eucalyptus mallee forest and mallee woodland
4	0.000	Shrubland, coastal shrubland
5	N/A	Casuarina and allocasuarine forests and woodlands
6	0.589	Grasses

Suppression Capability

The Suppression Capability indicates the probability of an initial response to bushfire being successful, and the bushfire having no significant consequence. Suppression Capability is determined by how quickly a fire may be detected and suppressed. For Greater Adelaide, the Suppression Capability is determined using data on the number of fire stations or towers, road access, and presence of air support for fire suppression. The Suppression Capability was supplied for each cell in Greater Adelaide by DEWNR. For each cell, the Suppression Capability is rated from a score of 1 to 5 based on factors which affect the aircraft response time, brigade response time, accessibility to the site and the fire detection. To calculate the aircraft response time, priority response times and airbase locations are assessed. The brigade locations and road network determine the brigade response time. To rate the accessibility level, the slope, rockiness and other access issues are assessed. Finally, the detection is based on population density, tower locations, land use and vegetation.

Fire Behaviour

Fire Behaviour is the energy intensity per cell (kW/m), and takes into consideration different Fire Behaviours for grassland $\left(FB_{G,xy}\right)$ and woodland $\left(FB_{W,xy}\right)$ (Eq. 7). The Bushfire Likelihood Model classifies a vegetation type as woodland or grassland. The Fire Behaviour for grassland and woodland areas are a function of the climate variables and spatial characteristics (Eq. 8 and Eq. 9).

$$FB_{xy} = FB_{G,xy} + FB_{W,xy} \qquad \text{Eq. 7}$$

$$FB_{G,xy} = f(U_{10}, T_{90}, RH, CuringD, LU) \qquad \text{Eq. 8}$$

$$FB_{W,xy} = f(SlopeD, TSLF, U_{10}, RH, T_{90}, T_{\min}) \qquad \text{Eq. 9}$$

The Bushfire Attack Levels (BAL) from Table 3.1 in AS3959-2009 are used to categorise the energy intensity to values from 1 to 5 (Very Low intensity to Very High intensity). The BAL levels are determined using Radiant Heat Flux. To convert the Fire Behaviour of each cell to Radiant Head Flux Eq. 7 is used. The BAL levels used to define the levels of Fire Behaviour are summarised in Table 5-7.

$$Radiant\ heat\ flux_{xy} = 60(1 - \mathrm{e}^{-\frac{FB_{xy}}{30000}}) \qquad \text{Eq. 10}$$

Table 5-7 BAL levels used as upper and lower bounds to define categories of Fire Behaviour (very low to very high Fire Behaviour) in the Hazard Likelihood Model

Fire Behaviour Category	Lower bound BAL level (kW/m^2)	Upper bound BAL level (kW/m^2)
Very High	40	∞
High	28	40
Medium	14	28
Low	7	14
Very Low	0	7

5.2.3 External drivers

For the case study framework, Hazard Risk is affected by four external drivers – population, climate, demographic and economic. These external drivers impact the model inputs for Social Vulnerability and Hazard Likelihood. From Figure 5-3, the inputs are spatially explicit and can be either temporally static or dynamic. In order to account for the temporally dynamic nature of the external drivers, exploratory scenarios are used.

5.2.3.1 Socio-economic external drivers

Exploratory scenarios are driven by external drivers and emulate multiple plausible futures. Five alternate futures scenarios exist for Greater Adelaide that consider the changes from 2013 to 2050, as developed by members of South Australia's State Mitigation Advisory Group (SMAG) (Riddell et al. 2015). The socio-economic scenarios allow for an understanding of how the external drivers of population, economic and demographic may change in the future. These scenarios focus on the future state of Greater Adelaide under different levels of challenges to mitigation and resilience (Riddell et al. 2015), as illustrated in Figure 5-10. The stakeholder engagement process determined that mitigation and resilience are considered as the main approaches to minimising natural disaster risk (Riddell et al. 2015). Mitigation is conceptualised as a top-down approach and resilience is conceptualised as a bottom-up approach. The SMAG participants determined that together this was an effective method to reduce disaster risk in Greater Adelaide (Riddell et al. 2015).

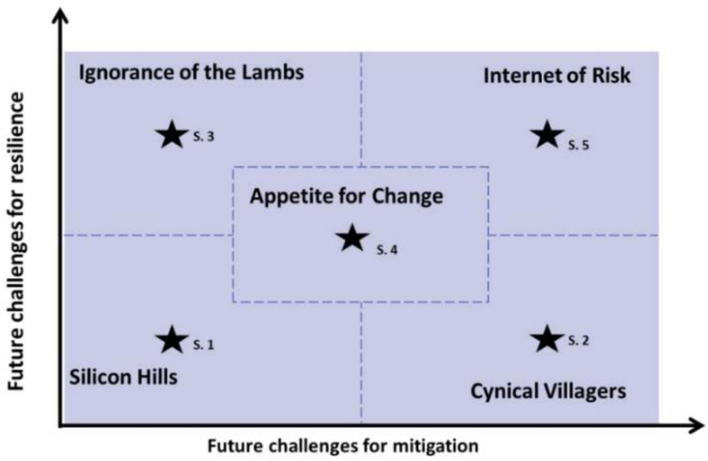


Figure 5-10 Exploratory scenarios S.1 – S.5 illustrated by their relative future challenges to mitigation and resilience

The purpose of the socio-economic scenarios for Greater Adelaide is to assist decision makers in strategically considering multiple plausible futures (Riddell et al. 2015). To elicit the scenarios, the process considered the critical elements in hazard risk reduction and how this will change in the future. The Greater Adelaide socio-economic scenarios focus on the challenges and the opportunities for Greater Adelaide as it manages Hazard Risk in the future (Riddell et al. 2015). These scenarios provide an understanding on how the dynamic external drivers may change, which will influence Hazard Risk and Social Vulnerability (Riddell et al. 2015).

Figure 5-11 presents an overview of the main scenario drivers and outcomes for the Greater Adelaide Socio Economic scenarios and demonstrates how and where each scenario differs from the others. It compares each of the five scenarios on key drivers for the future of Greater Adelaide in 2050 as determined by SMAG, including population, land use planning, economics and education and awareness. For most of the key scenario drivers the performance for Greater Adelaide is measured from weak to strong or low to high, as indicated by the legend in Figure 5-11.

	Silicon Hills	Cynical Villagers	Ignorance of the Lambs	Appetite for Change	Internet of Risk
Population in 2050	1.9 M	1.5 M	2.5 M	1.8 M	1.5 M
Economy					
Community resilience					
Building stock resilience					
Residential land use developments	*Gradual growth urban and rural areas*	*Large increase in rural residential, mixed with other land uses*	*Residential commuter communities in the hills*	*Infill, some sprawl on the fringe and rural residential development*	*Large increase in rural residential*
Land use planning					
Education & awareness					
Structural mitigation					

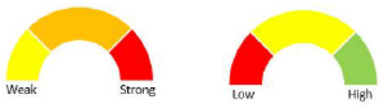


Figure 5-11 The main scenario drivers and outcomes for the 5 socio-economic exploratory scenarios for Greater Adelaide (Riddell et al. 2015).

The narrative storylines presented in Riddell et al. (2015) outline the differences and similarities between each socio-economic scenario and provdes an insight into how Greater Adelaide will look in 2050. Silicon Hills represents the best case, where future challenges to mitigation and resilience are both low. In this scenario, Greater Adelaide moves into a well-balanced economy with highly skilled immigrants and engaged locals (Riddell et al. 2015). Cynical Villagers represents a future with low challenges to resilience and high challenges to mitigation. In the Cynical Villagers scenario there is low population growth, with an aging population and the community is less connected and more vulnerable (Riddell et al. 2015). Ignorance of the Lambs represents the situation where there are low future challenges to mitigation but high future challenges to resilience, due to an increased commuter lifestyle and increased population growth (Riddell et al. 2015). The Appetite for Change scenario narrative details slow population growth and Greater Adelaide continuing on its current trajectory of mixed socio-economic status and an ageing population (Riddell et al. 2015). Appetite for Change represents a future with moderate challenges to resilience and mitigation. The Internet of Risk represents the worst case of high challenges to resilience and mitigation. This scenario sees a future where Greater Adelaide experiences a loss of connectedness, low population growth and high inequality (Riddell et al. 2015). The results in this study are presented for three scenarios: Ignorance of the Lambs, Silicon Hills, and Cynical Villagers. These scenarios represent the best-case scenario

(Silicon Hills), worst-case scenario for challenges to mitigation (Cynical Villagers), and worst-case scenario for challenges for resilience (Ignorance of the Lambs).

The socio-economic scenarios for Greater Adelaide also cause changes in the land use spatially and over time. Land use is influenced by external drivers and affects Social Vulnerability, as areas which are not a residential or urban land use type (e.g. vacant forests) do not contain people, and so are not considered socially vulnerable. Similarly, the land use type will affect the Hazard Likelihood, as land uses which do not have vegetation (e.g. industry) will not be able to burn and so are considered to have no hazard likelihood. To understand how the socio-economic scenarios influence the land use in Greater Adelaide, a land use model is applied.

A previously developed land use model for Greater Adelaide (van Delden & Hurkens 2011) enables the assessment of land use changes over time under different plausible future scenarios to develop the Greater Adelaide land use model. The Greater Adelaide Land Use Model is a cellular automata model, which is common in hazard modelling as they represent geographic space in grid form. The cells of the grid may transition between land use states due to decisions related directly to changes in the neighbourhood environment caused by external drivers to the system (Clarke 2014; Hosseinali, Alesheikh & Nourian 2014). Thus, the dynamic nature of the system as a result of changing external drivers may be modelled.

The plausible future land use scenarios are defined by changes in external drivers, policy, and infrastructure decisions, among other possible inputs. Land use changes are driven by an area's attractiveness to people and business. The attractiveness is dependent on several factors, including existing activity in neighbouring cells, and local characteristics, like accessibility. Land use changes are also determined by socio-economic factors, biophysical factors, and policy options.

The land use model for Greater Adelaide was calibrated using historic land changes. The outputs have a spatial resolution of 100mx100m, and a temporal resolution of 1 year. The land use changes for Greater Adelaide are simulated from 2013 to 2050, for each socio-economic scenario considered.

5.2.3.2 Climate external drivers

The external driver of climate influences the likelihood of a bushfire hazard occurring. This external driver is dynamic, and highly uncertain into the future. Representative Concentration Pathways (RCP), which provide several possible greenhouse gas concentration trajectories resulting from different anthropogenic futures, give 4 different possible scenarios for the global climate in the future. Using RCP projections is a well-recognised and established method to understand how the climate may alter in the future. Figure 5-12 presents the expected CO_2 concentrations for the next 100 years for each of the four scenarios. RCP 4.5 and RCP 8.5 are used to determine the climate data for the case study of Greater Adelaide. These two RCP scenarios are used as they represent a worst-case scenario (RCP 8.5) and a moderate case (RCP 4.5).

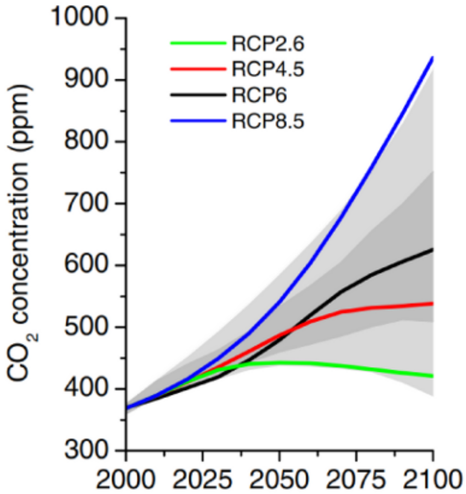


Figure 5-12 Representative Concentration Pathways for climate change (IPCC 2017)

5.3 Framework application

5.3.1 Overview

The case study framework presented in Section 5.2 can be used to assist real world decision making about natural Hazard Risk and mitigation. The flowchart in Figure 5-13 outlines the sub-objectives of the case study framework (shaded blue) and the results of each of these sub-objectives (shaded green).

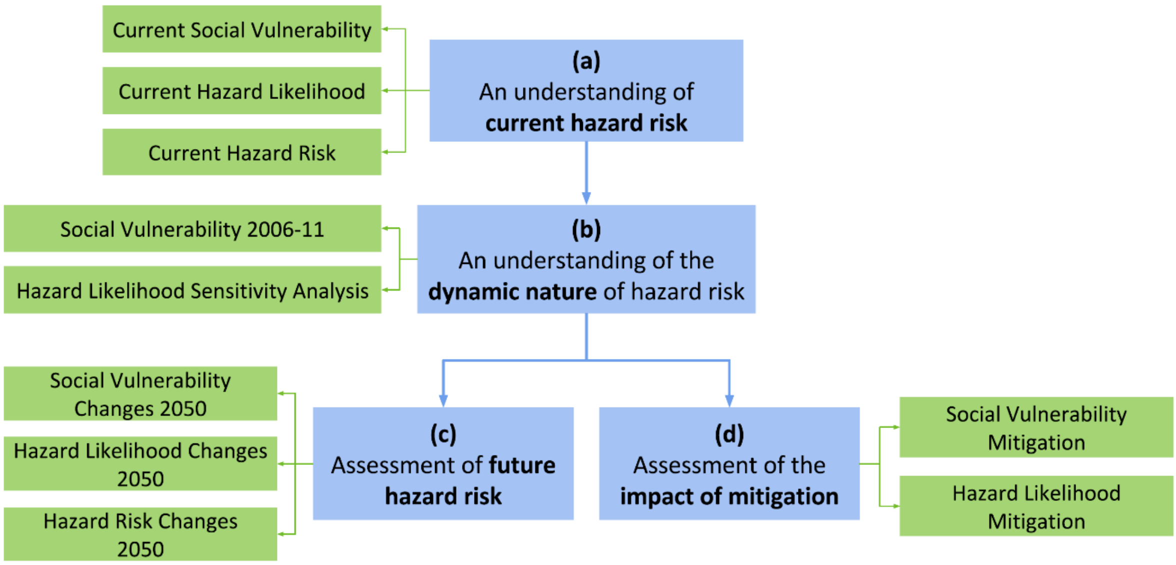


Figure 5-13 Flowchart of the knowledge tree that is built to gain a thorough understanding of the system of hazard risk. Blue bubbles show the sub-objectives of the case study, and the green bubbles show the results that will be presented to demonstrate this understanding.

To achieve the first sub-objective of developing an understanding of the current Hazard Risk, the current Social Vulnerability and Hazard Likelihood in Greater Adelaide are assessed by applying the Social Vulnerability and Hazard Likelihood models under current conditions, as outlined in Section 5.3.2.1 for Social Vulnerability and Section 5.3.2.2 for Hazard Likelihood. How these components influence the current Hazard Risk in Greater Adelaide is also assessed using the Hazard Risk Model under current conditions, as described in Section 5.3.2.3.

The second sub-objective of developing an understanding of the dynamic nature of Hazard Risk looks at the temporal variability of the Hazard Risk components. The dynamic nature of Social Vulnerability is assessed by comparing the Social Vulnerability indicators for each State Suburb Code (SSC) in 2006 and 2011 using Census data sourced from the Australian Bureau of Statistics (2017), as outlined in Section 5.3.3.1. The dynamic nature of Hazard Likelihood is assessed using a sensitivity analysis on the Hazard Likelihood Model, as outlined in Section 5.3.3.2.

To achieve the third sub-objective of assessing future Hazard Risk, changes in Social Vulnerability, Hazard Likelihood and Hazard Risk between now and 2050 are examined using exploratory scenarios. The application of socio-economic scenarios to assess possible changes in Social Vulnerability is outlined in Section 5.3.4.1. The application of climate and socio-economic scenarios to assess possible changes in Hazard Likelihood is outlined in Section 5.3.4.2.

The final sub-objective of assessing the impact of mitigation on Hazard Risk is achieved by modelling the influence of mitigation strategies which target Social Vulnerability and Hazard Likelihood, and comparing the results of the risk assessment with and without mitigation. The methodology for achieving this sub-objective is detailed in Section 5.3.5.

5.3.2 Understanding of current Hazard Risk

5.3.2.1 Social Vulnerability

To assess the Social Vulnerability under current conditions, the framework developed for the case study application is used, as outlined in Section 5.2.2.1. The result of this is a spatially explicit map of Social Vulnerability, and 14 spatially explicit maps of Social Vulnerability due to the 14 selected indicators that were discussed in Section 5.2.2.1. Through assessing and comparing these component indicators, trends, areas of concern, and any indicators of influence can be found.

5.3.2.2 Hazard Likelihood

To understand Hazard Likelihood for the current time, the framework developed for the case study is applied, as described in Section 5.2.2.2. The result is a spatially explicit map of Hazard Likelihood, and maps generated in the process of producing this for: Fire Behaviour, Ignition Potential, and

Suppression Capability. These maps are able to be analysed, alongside the maps of the inputs of Vegetation, Land Use, and Slope Degree. By comparing these maps, a better understanding may be formed about the influencing factors and trends seen in the results.

5.3.2.3 Hazard Risk

Section 0 outlines how Social Vulnerability and Hazard Likelihood are brought together in the case study to assess Hazard Risk. The result of this will be a spatially explicit map of Hazard Risk, which can be assessed in conjunction with the maps of Social Vulnerability, Hazard Likelihood, and their components. By building on the comparisons made from the results of current Social Vulnerability and Hazard Likelihood, the result of Hazard Risk ties together all the inputs, adding another layer of observations. These observations ultimately build our understanding of current Hazard Risk.

5.3.3 Understanding of dynamic nature of Hazard Risk

5.3.3.1 Social Vulnerability

To understand the temporal dynamics of Social Vulnerability, historic Census data are used to assess the variability of each Social Vulnerability indicator. The difference between the 2006 and 2011 Census data for each indicator is calculated for each LGA within Greater Adelaide. An LGA resolution is considered to assess the indicator dynamics as it allows a more valuable visual representation of these dynamics.

The dynamic assessment of Social Vulnerability is used to identify indicators which have the potential to vary greatly in the future, and thus should be projected using the socio-economic scenarios. For example, indicators which show high variability between 2006 and 2011 across the majority of the SSCs are assumed to also be highly dynamic in the future. Therefore, analysing historic indicators separately can assist in developing an understanding of the spatial variance of Social Vulnerability in the future. The assessment identifies which indicators are of particular interest in the future projection in line with socio-economic scenarios. Conversely, it is assumed that the indicators which are not highly variable from 2006 to 2011 across the suburbs will vary less into the future and thus will not cause significant changes in the Social Vulnerability in 2050. For this reason, they are of less interest.

Ideally a GSA is used to understand the dominant controls of the system to better inform mitigation options. However, a GSA is not worthwhile for the Social Vulnerability Model as the assessment of Social Vulnerability for the case study of bushfire in Greater Adelaide considers an equal weighting of vulnerability indicators.

The result of this analysis are graphs showing a comparison of the indicator in 2006 and 2011. The proportions used to calculate each indicator are compared for positive or negative changes between

2006 and 2011, except for population growth, family structure and personal wealth indicators. Family structure and population growth are excluded as there are no relevant data available for 2006. Personal wealth is ignored due to the influence of inflation on median incomes over time. By comparing the fluctuations observed for each indicator, a better understanding of the indicators that are likely to change into the future can be achieved.

5.3.3.2 Hazard Likelihood

To understand the drivers of Hazard Likelihood, a GSA of the Hazard Likelihood Model is used to assess which model inputs are most influential in promoting changes to the output Hazard Likelihood.

The case study uses the density based PAWN method to undertake a GSA on the Hazard Likelihood Model component of the conceptual framework. From the GSA, an understanding of the dominant controls of the Hazard Likelihood system is developed. The PAWN method can be implemented using the Matlab toolbox, SAFE (Sensitivity Analysis for Everyone) (Pianosi, Sarrazin & Wagener 2015). Table 5-8 details the various sub-components of Hazard Likelihood, and identifies where sensitivity analyses are appropriate or not appropriate.

Table 5-8 Reason for the inclusion or exclusion of sensitivity analyses for model components of the Hazard Likelihood Model

Component	Sub-Component	Sensitivity analysis	Reasoning
Hazard Likelihood	Fire Behaviour (FB)	✓	It is worthwhile to undertake a sensitivity analysis to determine the most sensitive Fire Behaviour inputs. This will inform the development of mitigation strategies to be targeted to the most sensitive inputs.
	Suppression Capability (SC)	✕	A sensitivity analysis would not be valuable on this sub-component of the model; it only has one input, which is constant through time.
	Ignition Potential (IP)	✓	Performing a sensitivity analysis on Ignition Potential is beneficial to determine the most sensitive inputs.
	Hazard Likelihood (total)	✓	A sensitivity analysis on Hazard Likelihood is worthwhile to understand which components (FB, SC, IP) are more sensitive.

The PAWN method requires a range to be specified for each model parameter. The sensitivity of a model output to uncertainty in the model parameters can be strongly influenced by the ranges used (Shin et al. 2013; Wang et al. 2013). Thus, it is important that these parameter sets contain values which are plausible (Shin et al. 2013). The model parameter ranges used in the sensitivity analysis are based on the minimum and maximum values of the 2015 climate and spatial data, as shown in Table

5-9. For the Land Use and Vegetation variables, the bounds of 0 to 16 and 0 to 7, respectively, refer to discrete Land Use or Vegetation types, which are defined as an input to the model.

Table 5-9 Variables changed for the sensitivity analyses, and the ranges of values used, for each of the sensitivity analyses conducted

Component to be analysed	Variables	Variable upper bound	Variable lower bound
Fire Behaviour	Ambient air temperature (T90) (°C)	28	33
	Relative humidity (%)	35.607	39.877
	10m wind speed (m/s)	21	50
	Minimum wind temperature (°C)	5	9
	Vegetation type	0	7
	Land use	0	16
	Slope degree (%)	0	36.542
	Time Since Last Fire (years)	0	65
Ignition Potential	Land Use	0	16
	Vegetation	0	6
Hazard Likelihood	Ambient air temperature (T90) (°C)	28	33
	Relative humidity (%)	35.607	39.877
	10m wind speed (m/s)	21	50
	Minimum wind temperature (°C)	5	9
	Vegetation type	0	7
	Land use	0	16
	Slope degree (%)	0	36.542
	Time Since Last Fire (years)	0	65
	Suppression Capability	0	5

5.3.4 Assessment of future Hazard Risk

5.3.4.1 Social Vulnerability

The Social Vulnerability model considers changes in the future by quantifying projections in Social Vulnerability indices for each of the five socio-economic scenarios considered for Greater Adelaide. The methodology for quantifying Social Vulnerability projections for the case study is summarised in Figure 5-14. This methodology is adapted from the blue-highlighted steps in the conceptual framework methodology for Social Vulnerability detailed in Figure 4-3.

In the methodology outlined in Figure 5-14, the indicator values for each scenario are projected to 2050, using multipliers applied to the 2011 Social Vulnerability data. The multipliers are aligned with each of the five socio-economic scenarios for each Social Vulnerability indicator. The socio-economic scenario narrative storylines, however, describe changes to general regions of Greater Adelaide, and do not provide detailed analysis for each state suburb area. Hence, the dynamic assessment of vulnerability for the case study uses multipliers applied to five areas for Greater Adelaide – East, West, North, South and Hills, as illustrated in Figure 5-15.

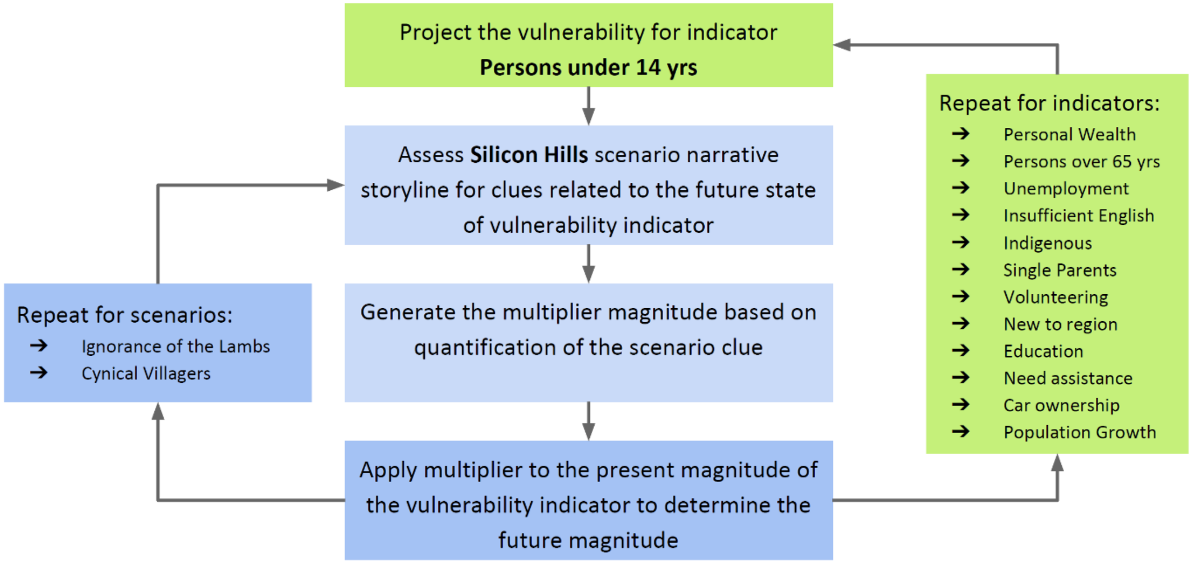


Figure 5-14 Overview of quantification procedures for determination of future vulnerability indicator multipliers for the case study

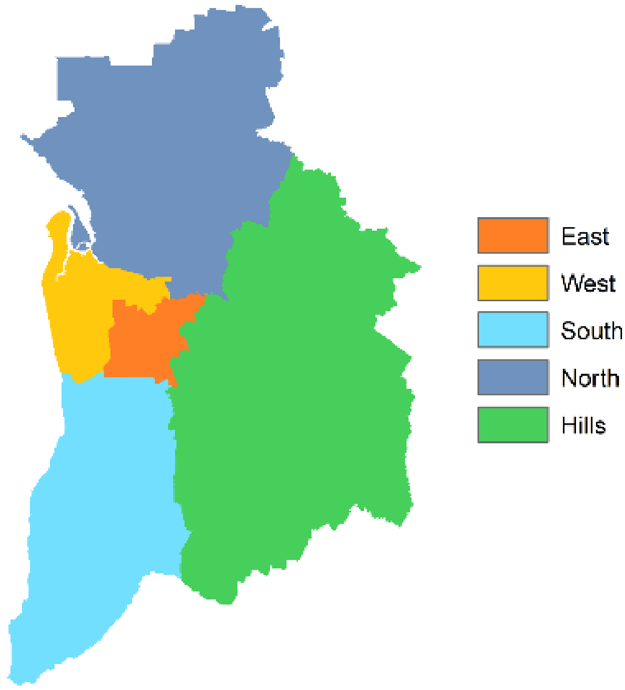


Figure 5-15 Delineation of Greater Adelaide into the five areas used to project Social Vulnerability

The multipliers that are used for Social Vulnerability indicators in the case study are presented here for the indicators of interest. The remaining multipliers are presented for each socio-economic scenario in Appendix D.

Figure 5-16 shows the multipliers that are applied to the indicator of Unemployment for 2050, representing factor increases (red) or decreases (green) in the proportion of unemployed people.

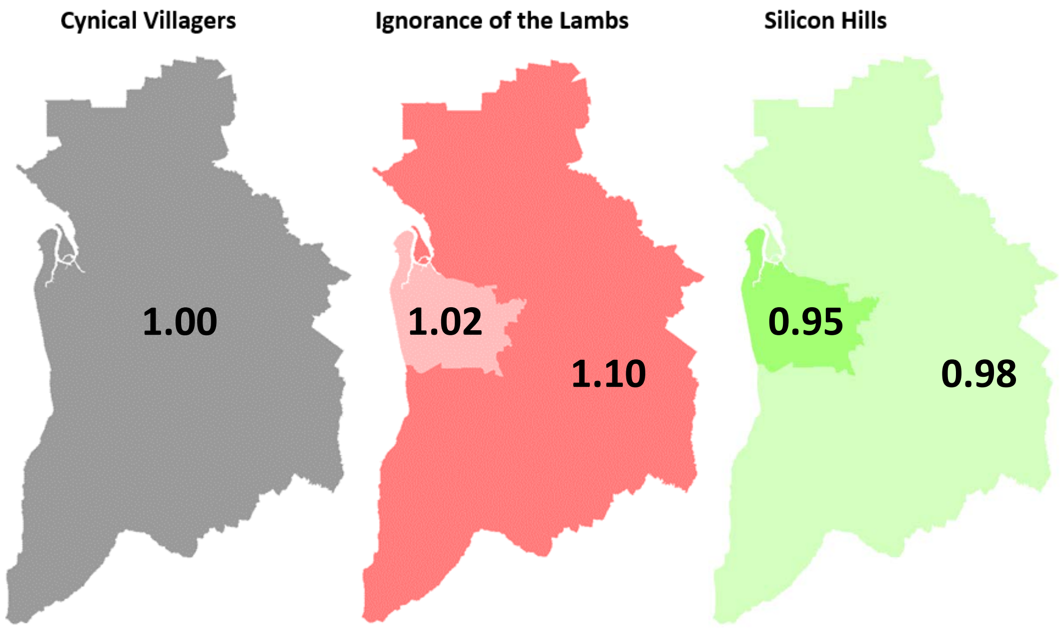


Figure 5-16 Multipliers applied to project changes in the proportion of people who are unemployed for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

Figure 5-17 shows the multipliers that are applied to the indicator of English Proficiency for 2050, representing factor increases (red) or decreases (green) in the proportion of people with very low English proficiency.

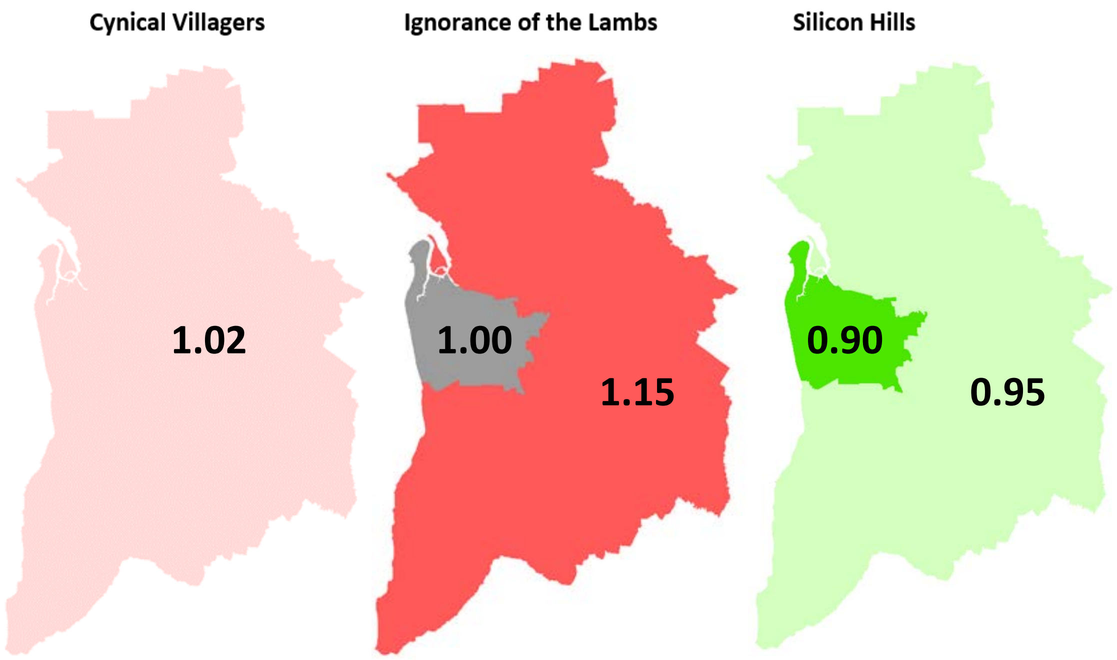


Figure 5-17 Multipliers applied to project changes in the proportion of people with very low English proficiency for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

Figure 5-18 shows the multipliers that are applied to the indicator of Education for 2050, representing factor increases (green) or decreases (red) in the proportion of people finishing year 12.

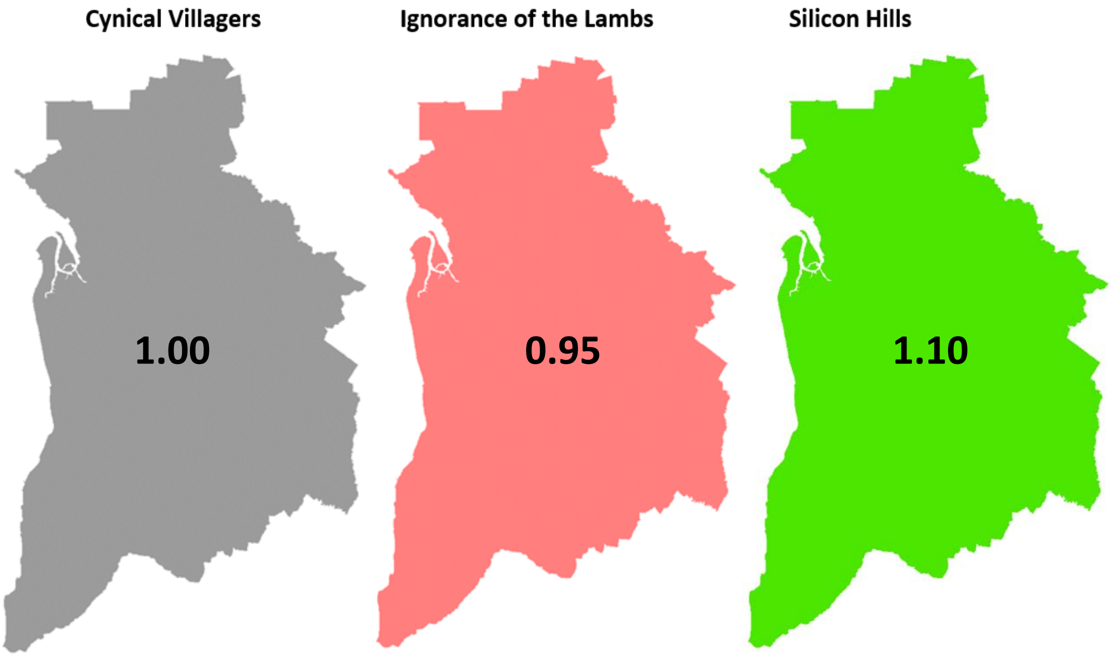


Figure 5-18 Multipliers applied to project changes in the proportion of people who have completed year 12 for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

Figure 5-19 shows the multipliers that are applied to the indicator of Proportion of Elderly People for 2050, representing factor increases (red) or decreases (green) in the proportion of elderly people people who are new to the area.

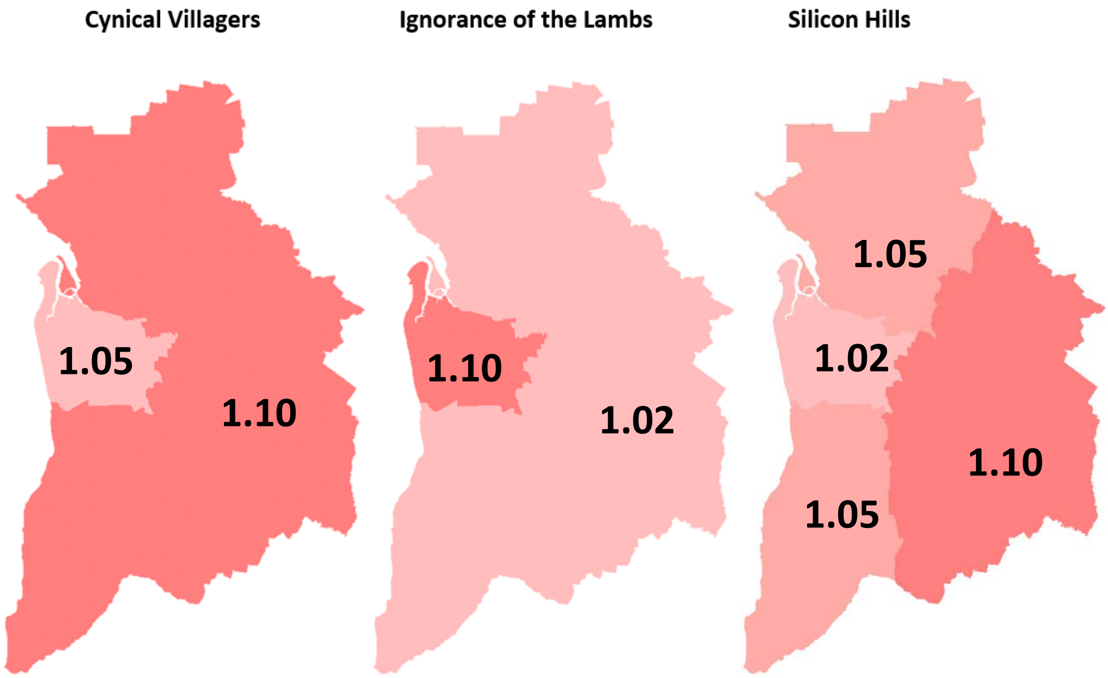


Figure 5-19 Multipliers applied to project changes in the proportion of elderly people for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

Figure 5-20 shows the multipliers that are applied to the indicator of Recently Moved to the Area for 2050, representing factor percentage increases (red) or decreases (green) in the proportion of people who are new to the area.

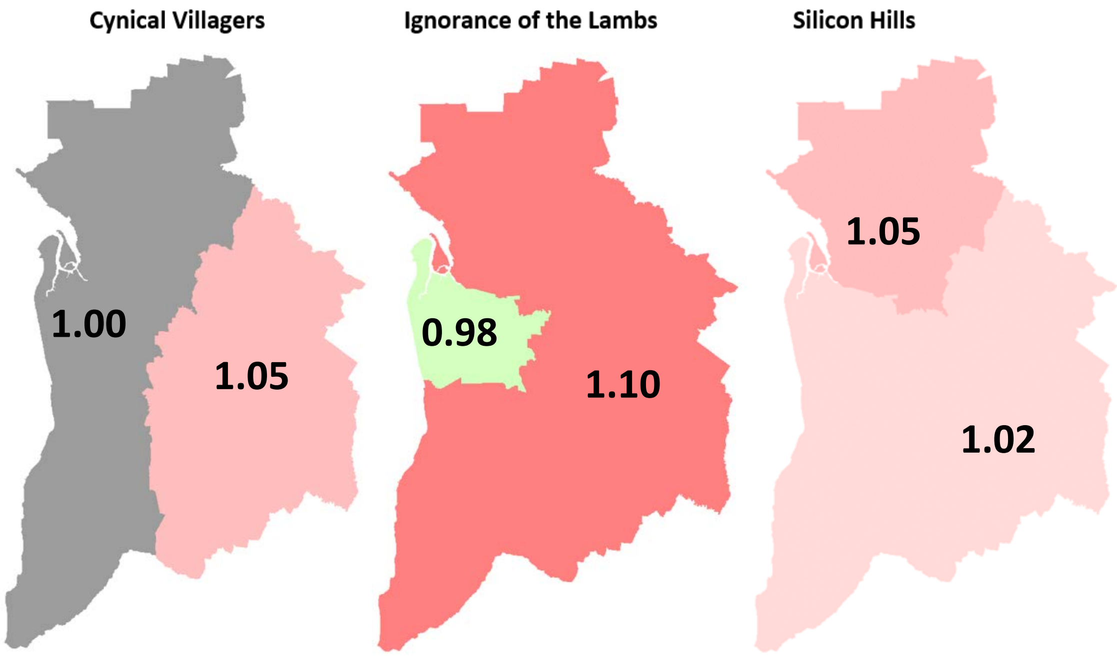


Figure 5-20 Multipliers applied to project changes in the proportion of people who have recently moved to the area for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

Following quantification of projected Social Vulnerability indices, a spatial assessment using the methodology in Figure 5-6 is undertaken for each socio-economic scenario. In the absence of stakeholder input, the bounds defining the categories of Social Vulnerability (Very Low to Very High Social Vulnerability) are quantified from the percentile ranking of that cell's indicator value in relation to the other cells in both the spatial and temporal domains, as detailed in Section 5.2.2.1. The effect of changes in land use under the socio-economic scenarios on Social Vulnerability in the future are also considered in the penultimate step of Figure 5-6.

The dynamic assessment of Social Vulnerability produces maps of Social Vulnerability in Greater Adelaide in 2050 for each socio-economic scenario. The changes between the current Social Vulnerability and the 2050 Social Vulnerability are presented as change maps, showing increases or decreases in 2050 relative to the current Social Vulnerability. Like in Section 5.3.2.1, where an understanding of current Social Vulnerability is built, these changes can be broken down into the component indicators, to assess how the overall Social Vulnerability is affected, and observe any trends.

5.3.4.2 Hazard Likelihood

The Hazard Likelihood Model considers changes in Hazard Likelihood in the future by applying the climate and socio-economic scenarios for Greater Adelaide to the temporally dynamic Hazard Likelihood inputs.

The temporally dynamic drivers for Hazard Likelihood are the climate variables (U_{10}, T_{90}, RH and T_{min}), time since last fire (TSLF), and land use. The climate variables and TSLF are inputs to Fire Behaviour only, while land use is an input to Fire Behaviour and Ignition Potential – thus, both these measures of Hazard Likelihood are temporally dynamic. The changes in land use are informed by the five socio-economic scenarios for Greater Adelaide, while the changes in the climate variables are informed by the RCP climate scenarios. In the base case without mitigation, TSLF is assumed to increase by one year each year, i.e. it is assumed that no fires occur between now and 2050.

Some inputs to the Hazard Likelihood Model, however, remain temporally static, such as the slope. This is a spatially explicit variable, and only one input map of the slope on a 100mx100m resolution is used. Suppression Capability is also static, as it is dependent on accessibility and the ability to notice and supress a fire. This limits the assessment of Hazard Likelihood into the future as it is likely that changing the land use and the effects of urban sprawl and infill will affect Suppression Capability.

The Hazard Likelihood Model in Figure 5-7 is applied using the variables for each combination of climate and socio-economic scenarios. Thus, the results of the dynamic assessment of Hazard Likelihood are hazard likelihood maps for Greater Adelaide in 2050 under each of the climate and socio-economic scenarios.

5.3.5 Assessment of impact of mitigation options

Mitigation and risk reduction strategies which target Social Vulnerability and Hazard Likelihood in Greater Adelaide are identified using the process outlined in Figure 5-21, and discussed in Section 5.3.5.1 and Section 5.3.5.2, respectively.

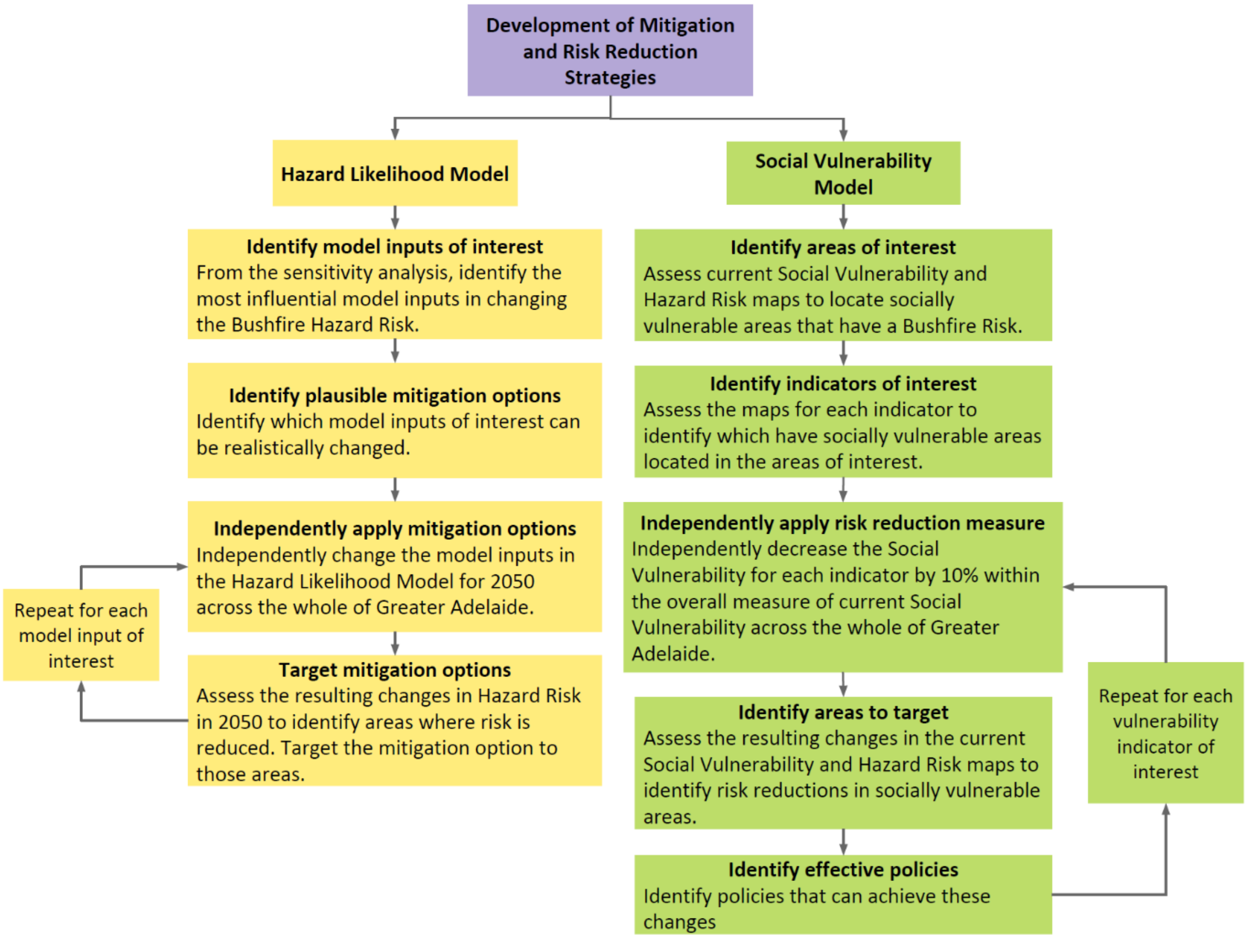


Figure 5-21 Outline of the process used to identify mitigation/risk reduction strategies which target Hazard Likelihood and Social Vulnerability to reduce Hazard Risk

5.3.5.1 *Social Vulnerability*

It is not realistic to implement mitigation options that directly change Social Vulnerability to hazards, such as decreasing unemployment in an area. Social Vulnerability, however, can be reduced as a co-benefit of social policies. For example, to increase the proportion of people who complete year 12 (Education indicator) in socially vulnerable areas, more funding can be allocated to schools within these areas to improve education programs that encourage students to stay at school. An additional co-benefit of increasing the level of education could be a decrease in unemployment and an increase in personal wealth. Therefore, mitigation strategies targeting Social Vulnerability take the form of indirect policies.

There is a circular relationship between social policies, and the narrative storylines of the socio-economic scenarios. Thus, the possible influence of social policies on Social Vulnerability in the future may not be modelled using the socio-economic scenarios for Greater Adelaide. Instead, they are assessed under current Social Vulnerability conditions for Greater Adelaide, as described in Figure 5-21. The current spatial map of Social Vulnerability is used to identify areas of high Social

Vulnerability, and the spatial maps of each individual indicator are analysed to identify which indicators contribute to these areas of high total Social Vulnerability. From these influential indicators, those which may be changed by indirect policies are identified. Changes in these indicators from indirect policies are modelled by reducing the Social Vulnerability of these indicator values by a plausible amount, in consultation with experts and stakeholders. These results are coupled with current Hazard Likelihood to assess the potential changes that may be achieved in Hazard Risk under current conditions due to the influence of indirect policies on Social Vulnerability. The mitigation tests implemented to assess the potential influence of indirect policies on Social Vulnerability are shown in Table 5-10.

Table 5-10 Mitigation tests implemented to assess the potential influence of indirect policies on Social Vulnerability and Hazard Risk

Target Indicator	Aim	Strategy
Education	Increase levels of education	Increase the education indicator (proportion of people who have completed year 12) by 10% in all areas
Volunteering	Increase levels of volunteering	Increase the volunteering indicator (proportion of people who volunteer) by 10% in all areas
Personal Wealth	Increase personal wealth	Increase the personal wealth indicator (median income) by 10% in all areas
Young People	Decrease proportion of young people	Decrease the young people indicator (proportion of young people) by 10% in all areas

5.3.5.2 Hazard Likelihood

The influence of mitigation on Hazard Likelihood is assessed in 2050 under each of the climate and socio-economic scenarios. As described in Figure 5-21, the results from the GSA of the Hazard Likelihood Model are used to identify the drivers which are most influential in promoting changes in Hazard Likelihood. From these high influence drivers, feasible mitigation options are identified through consultation with experts. For the case study, consultation with Mike Wouters, a Senior Fire Ecologist from DEWNR, is undertaken to develop feasible mitigation strategies and implementation locations for bushfire in Greater Adelaide. Potential changes to Hazard Likelihood because of these mitigation strategies are assessed by changing the model inputs to reflect the mitigation strategy. These changes are analysed in the results of the Hazard Likelihood Model for 2050 under the climate and socio-economic scenarios in comparison to the results without mitigation. The influence of these mitigation strategies on Hazard Risk in 2050 is assessed by combining the results of Hazard Likelihood under mitigation, with the Social Vulnerability in 2050 under each scenario without mitigation. The influence of planned burning as a mitigation strategy to reduce the influential Time Since Last Fire driver is assessed by implementing a planned burn in 2049 to all eucalyptus woodland areas.

6 RESULTS AND DISCUSSION

6.1 Current Risk

The results for the case study are presented for the current case, and broken down into the components of Hazard Risk, in order to analyse the impacts of different factors.

6.1.1 Current Social Vulnerability

The current Social Vulnerability map for Greater Adelaide is shown in Figure 6-1. The Social Vulnerability across Greater Adelaide is highly variable. Social Vulnerability does not apply where there are no people and these areas are scattered over Greater Adelaide. Figure 6-1 illustrates that the Eastern region and the Hills have the lowest overall Social Vulnerability. The Western regions have the greatest density of areas with High or Very High Social Vulnerability. In the Northern region of Greater Adelaide, Social Vulnerability is greatly varied, ranging from Very Low to Very High Social Vulnerability.

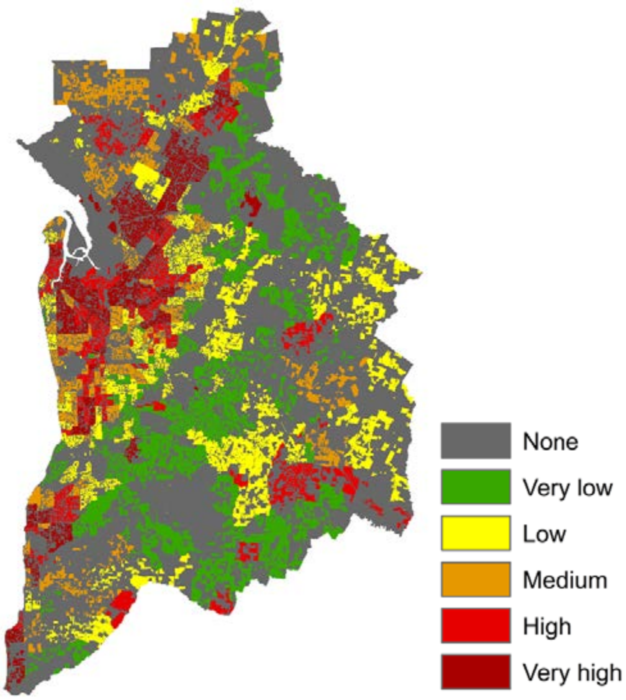


Figure 6-1 Current Social Vulnerability for Greater Adelaide using an SSC resolution and based on equal weighting of the vulnerability indicators.

Social Vulnerability for the Greater Adelaide case study is comprised of 14 indicators. Figure 6-2 and Figure 6-3 illustrate the variable impact of the different indicators on the overall Social Vulnerability.

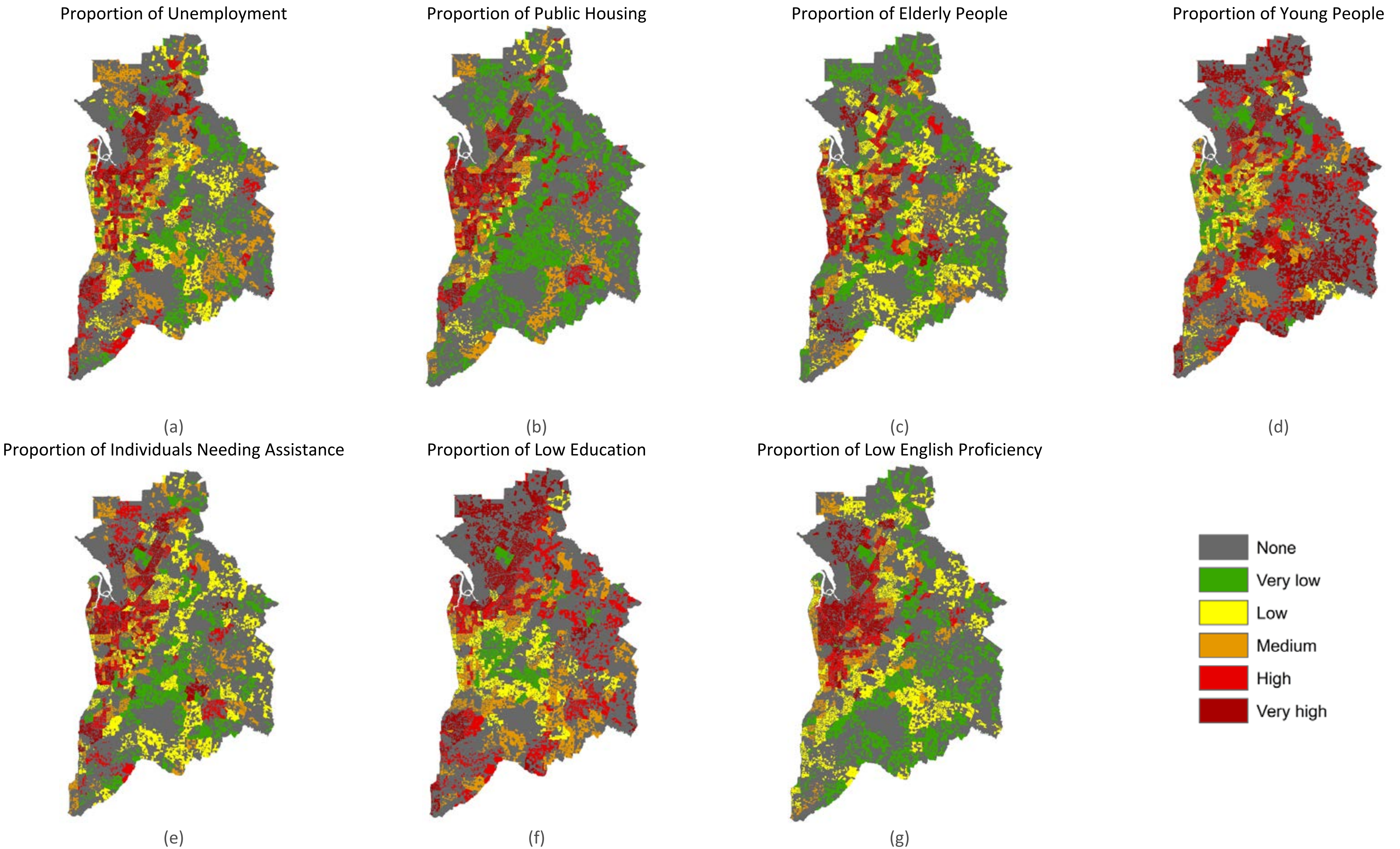


Figure 6-2 Spatially distributed social vulnerability for Greater Adelaide under current socio-economic conditions due to individual social vulnerability indicators, where red indicates very high social vulnerability and green indicates very low social vulnerability.

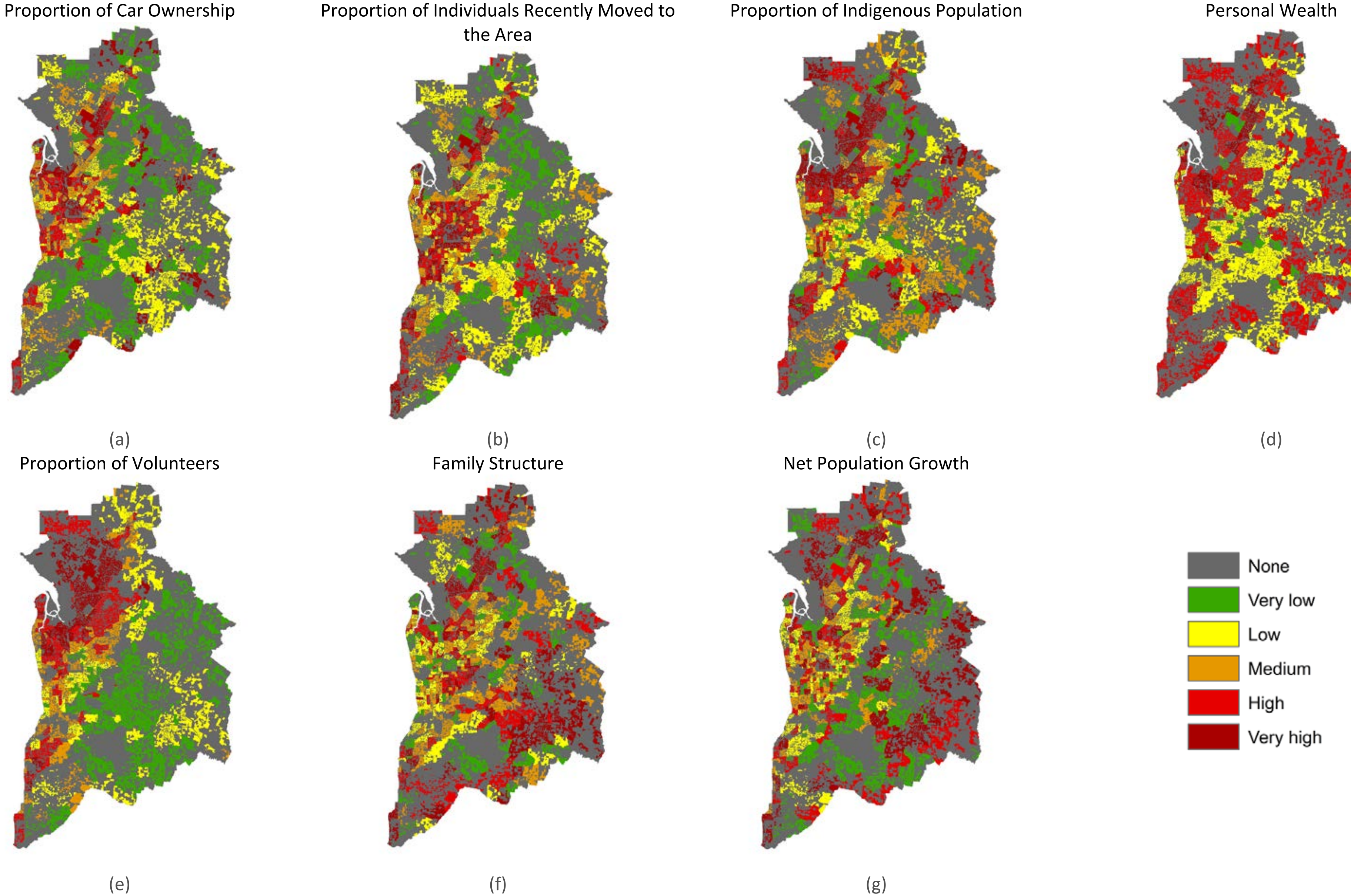


Figure 6-3 Spatially distributed social vulnerability for Greater Adelaide under current socio-economic conditions due to individual social vulnerability indicators, where red indicates very high social vulnerability and green indicates very low social vulnerability.

The 14 indicators presented in Figure 6-2 and Figure 6-3 illustrate that Social Vulnerability is highly spatially variable in Greater Adelaide. Several of the regions of Greater Adelaide experience a High Social Vulnerability due to multiple indicators. For example, High Social Vulnerability in the Western region occurs in several indicators, including Proportion of Elderly, Proportion of Individuals Needing Assistance, Proportion of low English Proficiency and Proportion of Public Housing. The low overall Social Vulnerability experienced in the Eastern region is due to Low Vulnerability from Car Ownership, Volunteering, Indigenous, Personal Wealth, Education and Young People indicators. The Volunteering, Car Ownership, English Proficiency, Needs Assistance, Elderly People, Public Housing and Unemployment indicators all present Low Vulnerability in the Hills and hence, cause an overall Low Social Vulnerability. The large variance in overall Social Vulnerability in the North and South of Greater Adelaide is due to the large differences in the Vulnerability levels between suburbs for most of the Social Vulnerability indicators.

Several of the Social Vulnerability maps indicate relationships between two or more indicators. The Proportion of Unemployment, presented in Figure 6-2(a), shows High and Very High Vulnerability areas align with the High and Very High regions for Proportion of Public Housing (Figure 6-3(b)). For both indicators, there is High Vulnerability in the Western, Northern, CBD and coastal Southern regions of Greater Adelaide. For Unemployment, the Adelaide Hills show varying Social Vulnerability ranging from Very Low to Medium, with few areas indicating High Vulnerability. For Public Housing, the Hills, outer Northern and outer Southern regions show mostly Very Low Social Vulnerability.

The Proportion of Elderly people has an inverse relationship to the Proportion of Young People, presented in Figure 6-2(c) and Figure 6-3(d), respectively. For the Proportion of Elderly People, the Western, CBD, Eastern and inner Northern regions show High Vulnerability. However, for the Proportion of Young People, the Northern, Hills and Southern regions have the highest Vulnerability.

The Proportion of Individuals Needing Assistance in Figure 6-2(e) shows that the Western, Northern, inner Southern and Mount Barker regions of Greater Adelaide have High to Very High Vulnerability. The Hills region has a mostly Low Vulnerability for people needing assistance.

The inner Greater Adelaide region presented low Social Vulnerability for Education, while the outer regions, North, South and Hills, had High to Very High Social Vulnerability, as shown in Figure 6-2(f). The areas experiencing the highest vulnerability due to low education were the Northern and Southern regions. The CBD and Eastern suburbs have Very Low Social Vulnerability for Education.

The Proportion of Low English Proficiency, presented in Figure 6-2(g), causes High Vulnerability concentrated in the inner Northern and Western regions and the vulnerability progressively lowers as the distance to the CBD increases. The Vulnerability due to English Proficiency varies from Very Low to Low for the Southern, outer Northern and Hills regions of Greater Adelaide. The regions of Greater Adelaide have little variance in their Social Vulnerability due to low English Proficiency.

The Proportion of Car Ownership in Greater Adelaide causes high spatial variance of Social Vulnerability, illustrated in Figure 6-3(a). The Western suburbs and CBD have High Vulnerability due to lower proportions of Car Ownership. There are also small areas in the Southern, Northern, Eastern and Hills regions that experience a High Vulnerability, however these areas mostly have Very Low and Low Vulnerabilities.

The Proportion of Individuals who have Recently Moved to the Area, in Figure 6-3(b), causes High and Very High Social Vulnerability to be experienced in the Western suburbs, CBD and in the Mount Barker area of the Adelaide Hills. A small number of suburbs in the Southern and Northern regions also experience High Social Vulnerability. The remaining regions of Greater Adelaide have a varied Social Vulnerability, from Very Low to Medium.

The Proportion of Indigenous Peoples has a variable impact on Social Vulnerability, shown in Figure 6-3(c). In all regions of Greater Adelaide there are areas with High and Very High Vulnerability, and areas in near proximity with Very Low and Low Vulnerability. The regions with the highest vulnerability due to the indigenous population are the inner Northern and Western suburbs.

The Social Vulnerability due to Personal Wealth for Greater Adelaide in Figure 6-3(d), shows that most areas experience either a High or a Low Vulnerability. The Northern, Western and Southern regions have mostly High or Very High Vulnerability, whilst the CBD and Eastern regions show Low Vulnerability. The Adelaide Hills have patches of Low Vulnerability and patches of High Vulnerability.

The Social Vulnerability caused by the Proportion of Volunteers is low in the CBD, Eastern and Hills regions of Greater Adelaide as presented in Figure 6-3(e). The Northern suburbs appear most vulnerable due to this indicator. The Western and Southern regions experience greater spatial variance in Social Vulnerability, with these areas varying from low to high vulnerability.

High variance in Social Vulnerability is experienced for the Family Structure and Net Population Growth indicators, shown in Figure 6-3(f) and Figure 6-3(g), respectively. All regions of Greater Adelaide have a mixture of very low, low, medium and high vulnerability. For both indicators, the Hills region, followed by the Northern suburbs has the greatest density of very high and high social vulnerability. The Western regions experience mostly a medium or high Social Vulnerability for the Net Population Growth.

6.1.2 Current Hazard Likelihood

To understand the current spatial distribution of Hazard Likelihood for Greater Adelaide, it is analysed in conjunction with its components, Fire Behaviour, Ignition Potential and Suppression Capability.

6.1.2.1 Hazard Likelihood

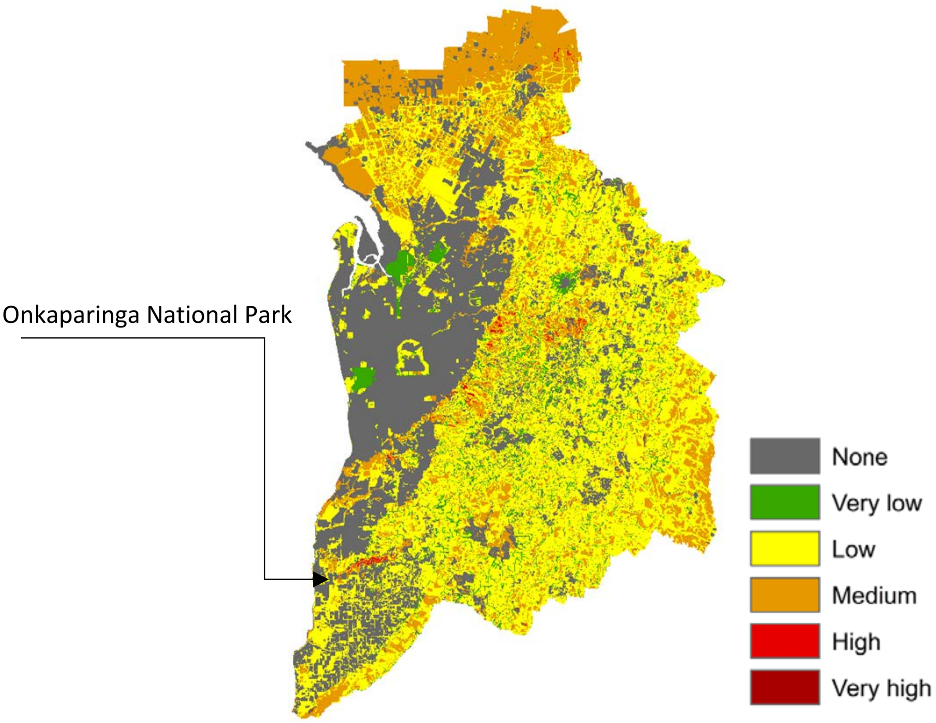


Figure 6-4 Current Hazard Likelihood for Greater Adelaide.

Hazard Likelihood is the summation of Fire Behaviour, Ignition Potential and Suppression Capability, as shown in Figure 6-4. The Bushfire Hazard Likelihood Model uses a higher weighting on Fire Behaviour (0.5) than Ignition Potential (0.25) and Suppression Capability (0.25).

From Figure 6-4, very few areas seem to have a high Hazard Likelihood, however, these high Likelihood areas appear to be where the component parts are all high. For example, Onkaparinga National Park and the Eucalyptus Woodlands in the Adelaide Hills. These areas have fuel, and have low accessibility, which influence Ignition Potential and Fire Behaviour, and Suppression Capability, respectively.

The Northern regions have a medium Hazard Likelihood, and appears to be the regions with the highest density of medium Likelihood in Greater Adelaide. These areas correspond to medium Fire Behaviour and Suppression Capability, and low to very low Ignition Potential.

6.1.2.2 Fire behaviour

Figure 6-5 presents the spatial distribution of Fire Behaviour for Greater Adelaide. The use of Bushfire Attack Level scales the bushfire intensity from Very Low to Very High for each cell.

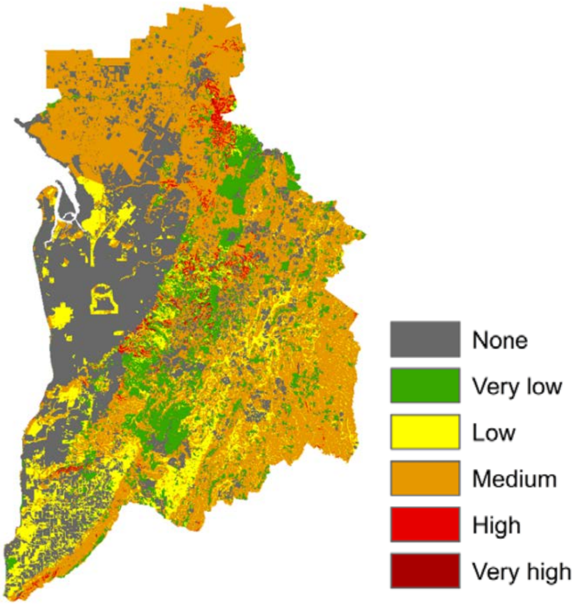


Figure 6-5 Current Fire Behaviour for Greater Adelaide

Fire Behaviour considers different energy intensities for grassland and woodland vegetation types. Areas without vegetation are assumed to have zero Fire Behaviour.

The Vegetation map in Figure 6-6 shows the spatial distribution of vegetation types. It shows that inner Greater Adelaide contains mostly no vegetation.

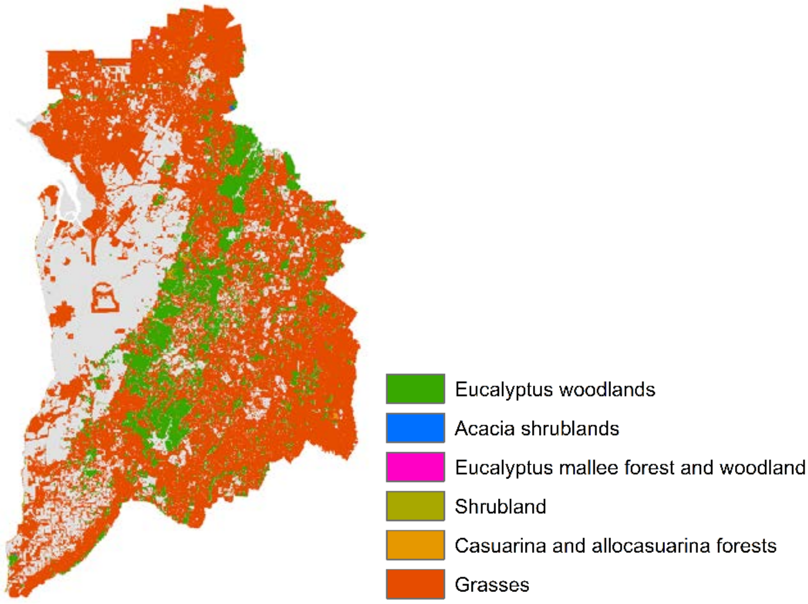


Figure 6-6 Current Vegetation map of Greater Adelaide

Comparing Figure 6-5 and Figure 6-6, the spatial correlation between Eucalyptus Woodlands with Very Low Fire Behaviour and Grasses with Medium Fire Behaviour can be seen. Figure 6-6 also shows a large amount of grass and eucalyptus woodland in the Hills, Northern and Southern regions of Greater Adelaide.

The areas of Eucalyptus Woodlands correspond mostly to areas with Very Low values of Fire Behaviour in Figure 6-5, however there seem to be more areas with High or Very High intensity in the Eucalyptus woodlands regions compared to Grassland. However, the reason for this could be due to another input in the Fire Behaviour Model.

Figure 6-7 shows the spatial variance of slope in Greater Adelaide. Steep slopes are seen in the Adelaide Hills and Mount Barker regions corresponding to areas of woodland and grassland, which are two vegetation types where fires can occur. The areas of steep slopes have a greater variance in Fire Behaviour values, from very low to very high. Low sloped areas generally appear to have a more consistent Fire Behaviour rating.

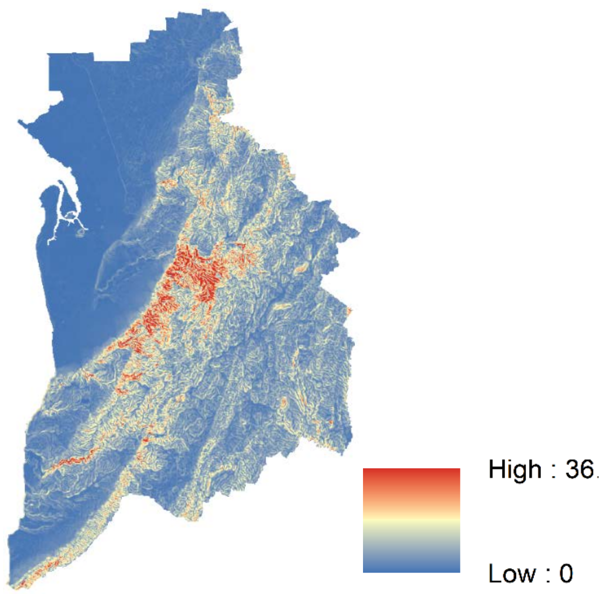


Figure 6-7 Spatial variance of slope in Greater Adelaide, measured in degrees

The spatial variance of Time Since Last Fire for Greater Adelaide is presented in Figure 6-7. The areas of high Time Since Last Fire do not correspond to a High Fire behaviour, from Figure 6-5, but instead produce a range of Fire Behaviour levels. The areas with low Time Since Last Fire appear to produce more spatially consistent Fire Behaviour levels.

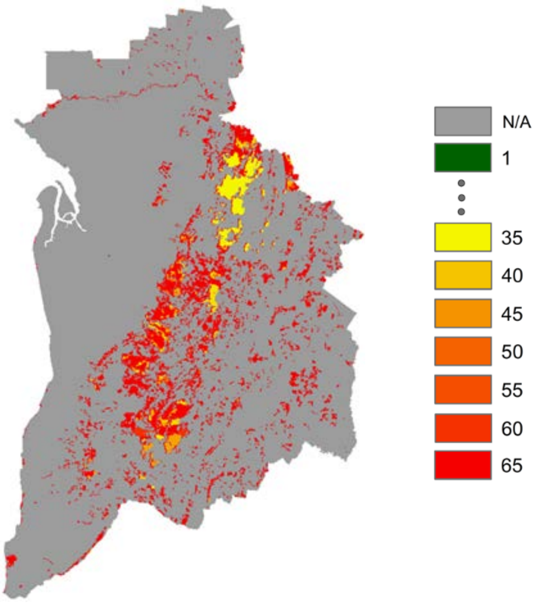


Figure 6-8 Current Spatial variance of Time Since Last Fire for Greater Adelaide, measured in years

6.1.2.3 Ignition potential

As detailed in Section 5.2.2.2, Ignition Potential, shown in Figure 6-9, was developed using the results of the statistical analysis of historical ignitions' land use and vegetation characteristics.

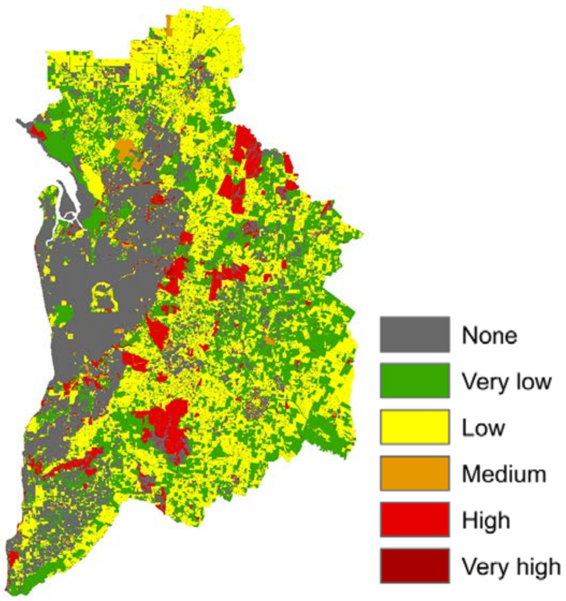


Figure 6-9 Current Ignition Potential for Greater Adelaide

The Ignition Potential map in Figure 6-9 shows that much of Greater Adelaide has Low or Very Low Ignition Potential areas, however there are pockets of High Ignition Potential among these areas. When compared to the map of vegetation introduced in Figure 6-6, it can be seen that many areas of High Ignition Potential risk coincide with eucalyptus woodlands. These High Ignition Potential pockets correspond to areas with a Forest land use, as seen in Figure 6-10.

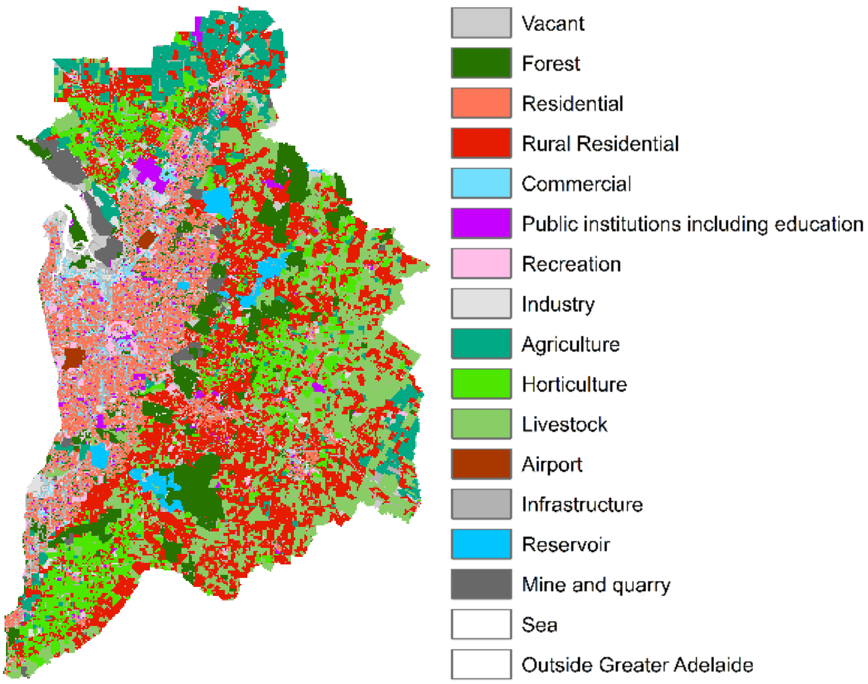


Figure 6-10 Current Land use map of Greater Adelaide

6.1.2.4 Suppression capability

The third component of the Hazard Likelihood, as introduced in Section 5.2.2.2, is Suppression Capability, shown in Figure 6-11.

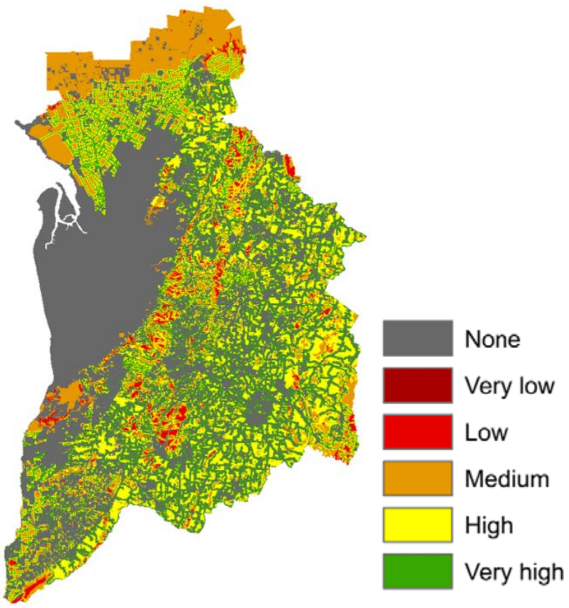


Figure 6-11 Current Suppression Capability for Greater Adelaide

The metropolitan area has High Suppression Capability, due to the ease of access by road and ability to detect and report fires. Outside of the Greater Adelaide metropolitan area, there are lower

Suppression Capabilities due to increased vegetation, more difficulty of access, and lower density of fire stations.

Assessing the Suppression Capability alongside the vegetation map in Figure 6-6, the Eucalyptus Woodlands areas are in similar areas to the Very Low suppression, which is a function of the poor access and detection in a woodland.

6.1.3 Current Hazard Risk

Current Bushfire Hazard Risk is shown in Figure 6-12. This risk is comprised of the Social Vulnerability and Hazard Likelihood.

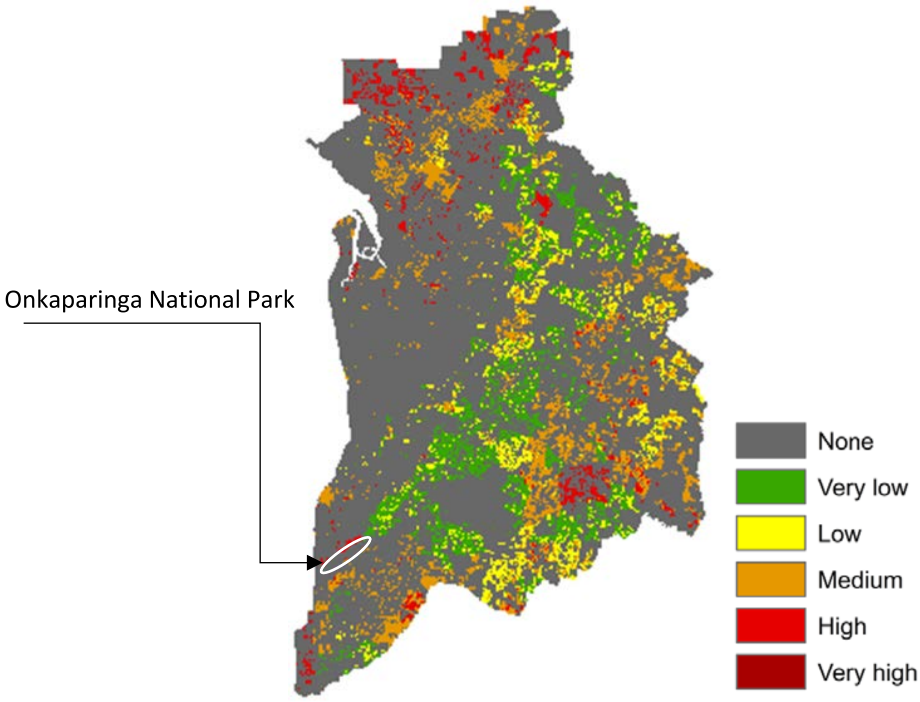


Figure 6-12 Current Bushfire Hazard Risk for Greater Adelaide taken from the summation of the Social Vulnerability and Hazard Likelihood.

The Bushfire Hazard Risk is spatially varied, ranging from Very Low to Very High. In this case study, the areas of no risk correspond to where there is no Hazard Likelihood or no Social Vulnerability. For example, Onkaparinga National Park is a High Likelihood area, but as there are no people in this area, Social Vulnerability is zero, and as such, the area has been accorded a zero hazard risk. Areas of High Hazard Risk are seen in the North, South and Hills of Greater Adelaide. Most of the Hills region experiences a Very Low to Medium Hazard Risk, however there are several spots with a High Hazard Risk. In the North and South of Greater Adelaide, the Hazard Risk is mostly Medium or High. The inner metropolitan region of Greater Adelaide mostly experiences no Bushfire Hazard Risk due to negligible Hazard Likelihood.

6.2 Understanding the Dynamics of Hazard Risk

To understand the dynamic nature of the Hazard Risk, the temporal variability of the Hazard Risk components are assessed and presented for Social Vulnerability in Section 6.2.1 and Hazard Likelihood in Section 6.2.2.

6.2.1 Understanding the Dynamics of Social Vulnerability

To understand the dynamics of Social Vulnerability the 2006 and 2011 ABS census data for the vulnerability indicators for each LGA in Greater Adelaide are compared, as discussed in Section 5.3.3.1.

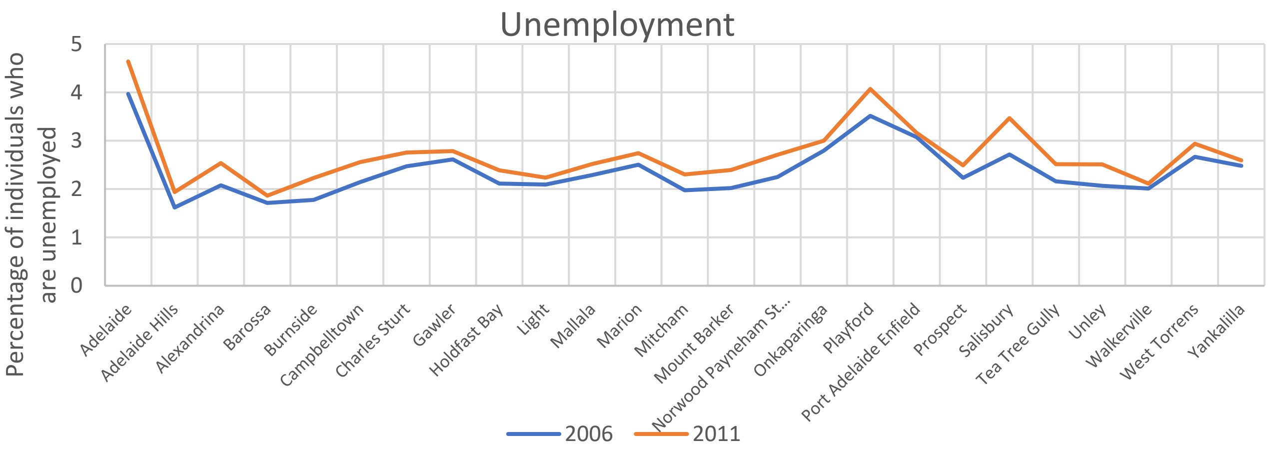


Figure 6-13 Difference in proportion of people unemployed between 2011 and 2006 for each Local Government Area in Greater Adelaide.

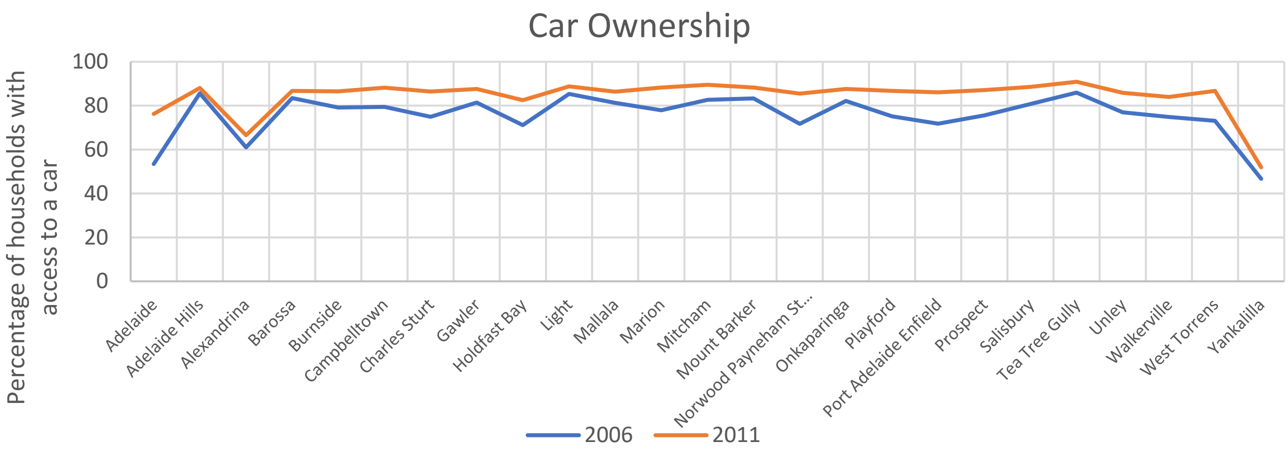


Figure 6-14 Difference in the proportion of households with access to at least one car in 2011 and 2006 for each Local Government Area in Greater Adelaide.

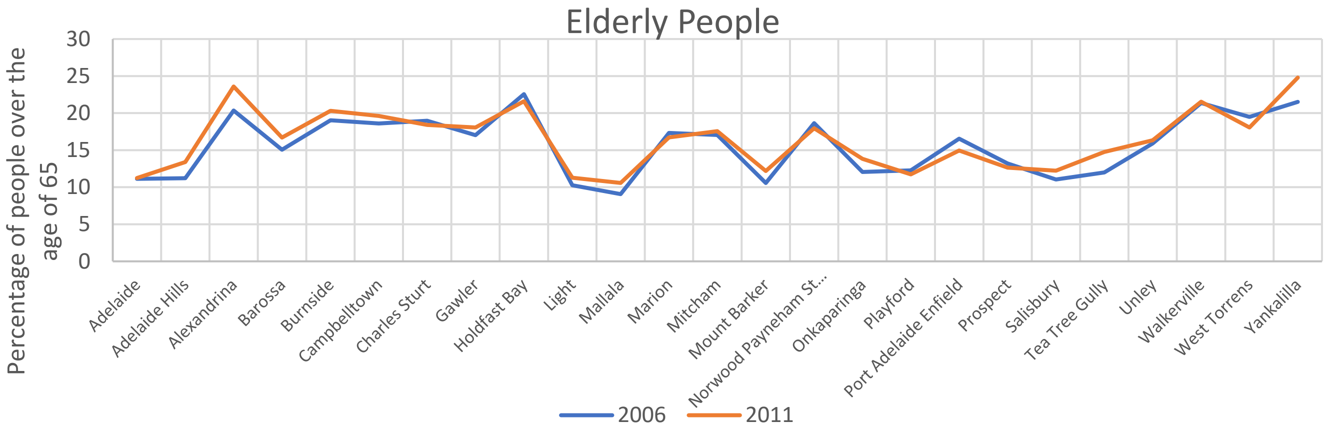


Figure 6-15 Difference between the proportions of elderly people (aged > 65) in 2011 and 2006 for each Local Government Area in Greater Adelaide.

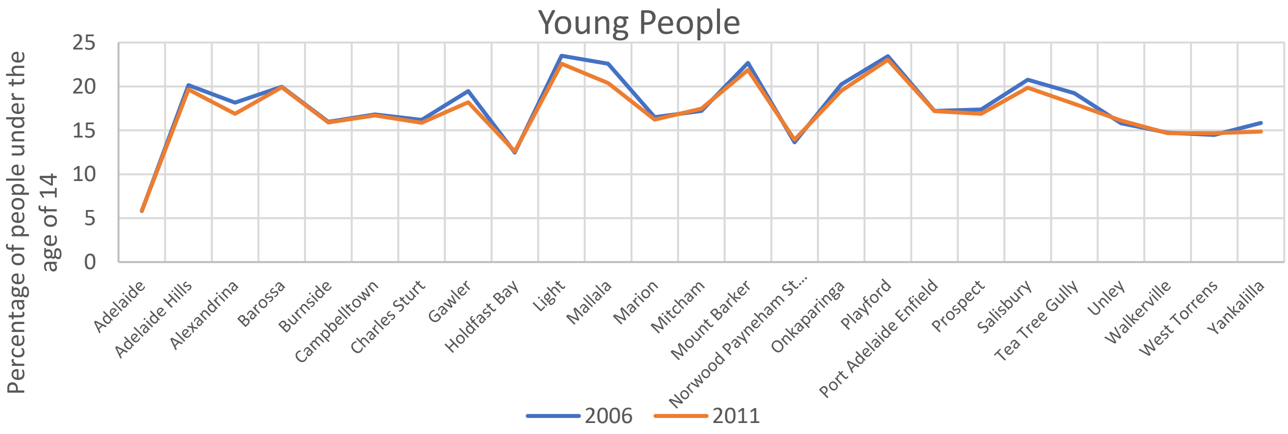


Figure 6-16 Difference between the proportions of young people (aged < 15) in 2011 and 2006 for each Local Government Area in Greater Adelaide.

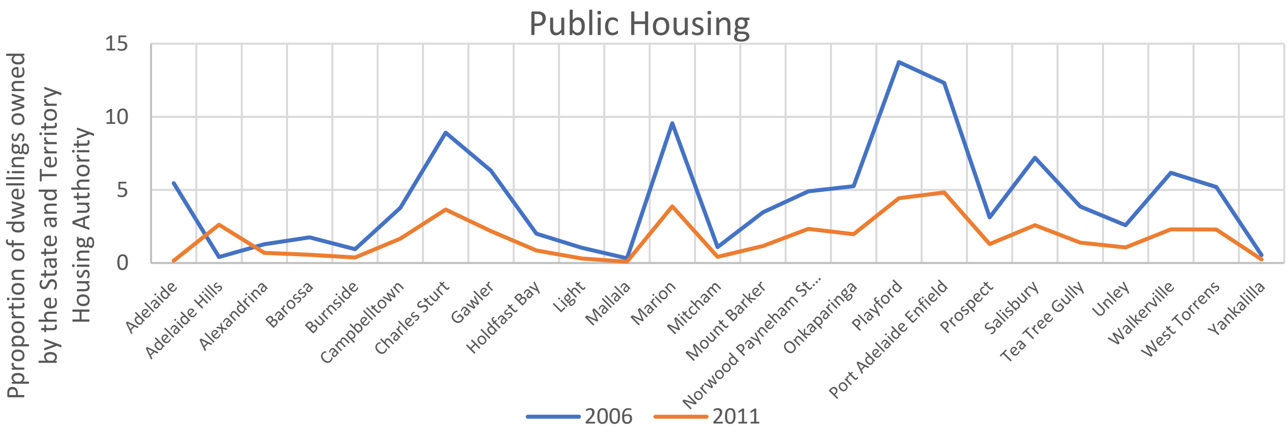


Figure 6-17 Difference between the proportions of dwellings that are owned by the State of Territory Housing Authority in 2011 and 2006 for each Local Government Area in Greater Adelaide.

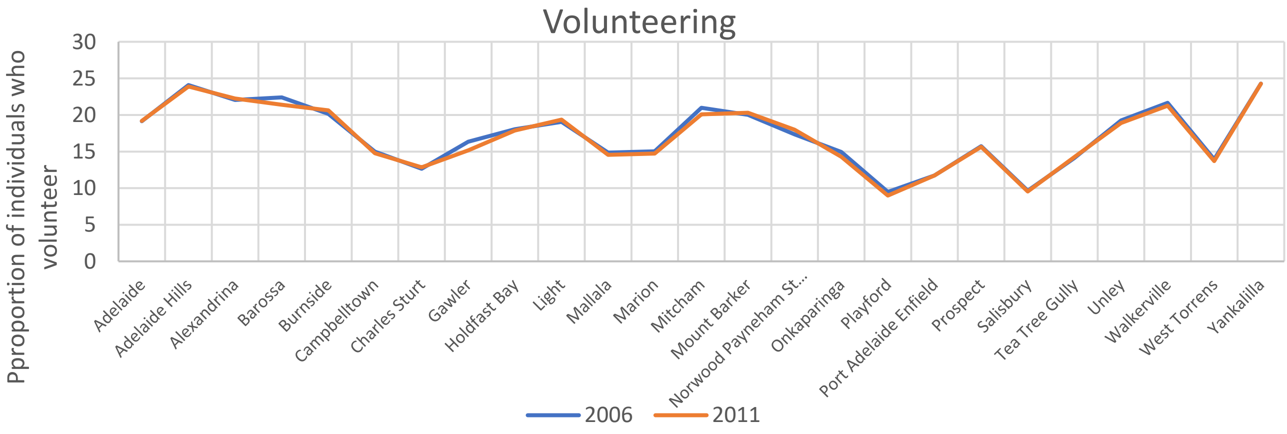


Figure 6-18 Difference between proportions of people who volunteer in 2011 and 2006 for each Local Government Area in Greater Adelaide.

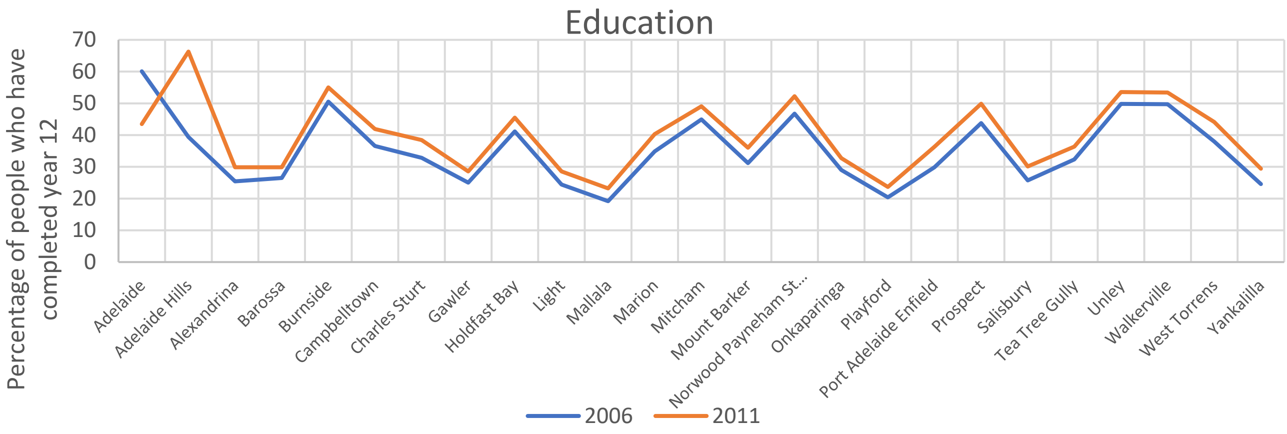


Figure 6-19 Difference between the proportions of people who have completed year 12 in 2011 and 2006 for each Local Government Area in Greater Adelaide.

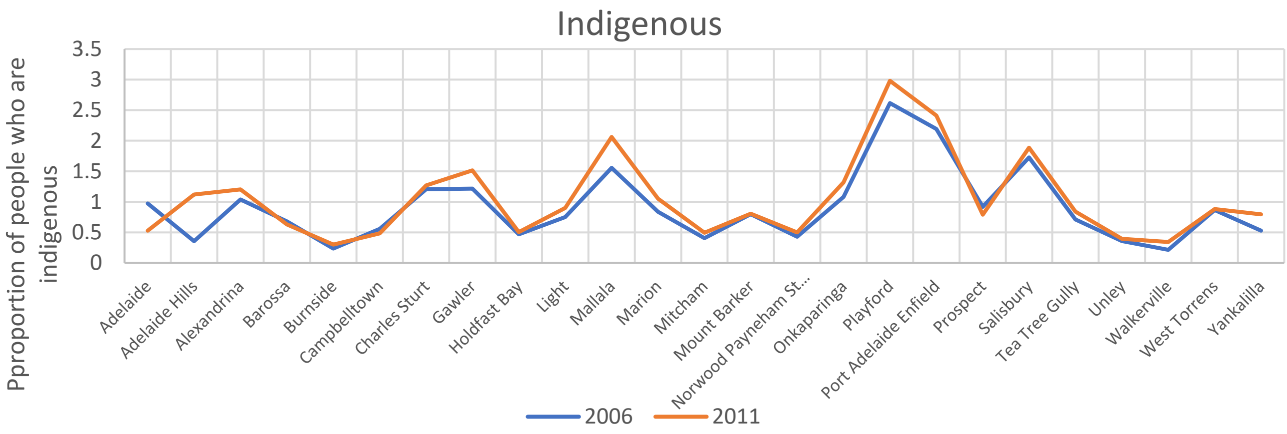


Figure 6-20 Difference between proportions of people who are Indigenous in 2011 and 2006 for each Local Government Area in Greater Adelaide.

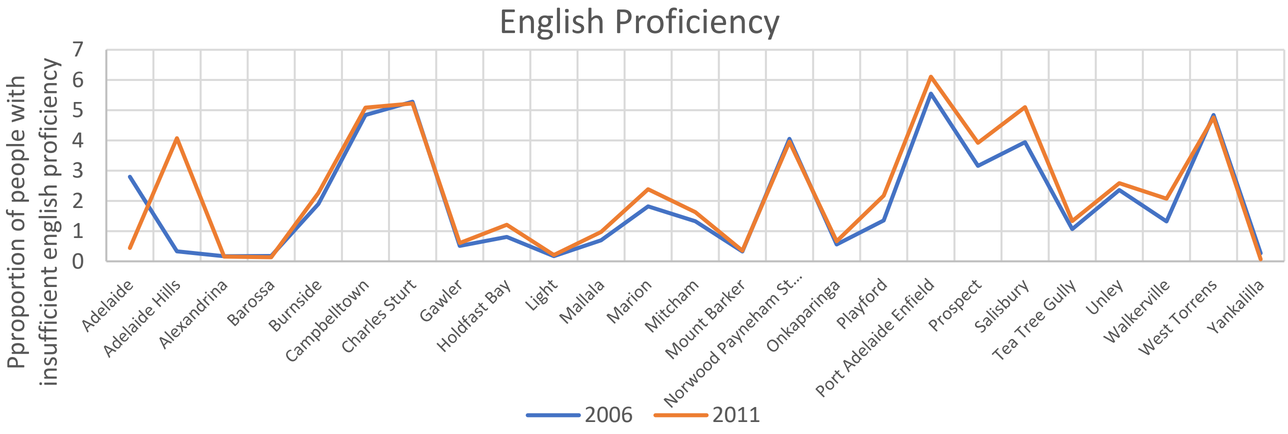


Figure 6-21 Difference between proportions of people who have insufficient English proficiency in 2011 and 2006 for each Local Government Area in Greater Adelaide.

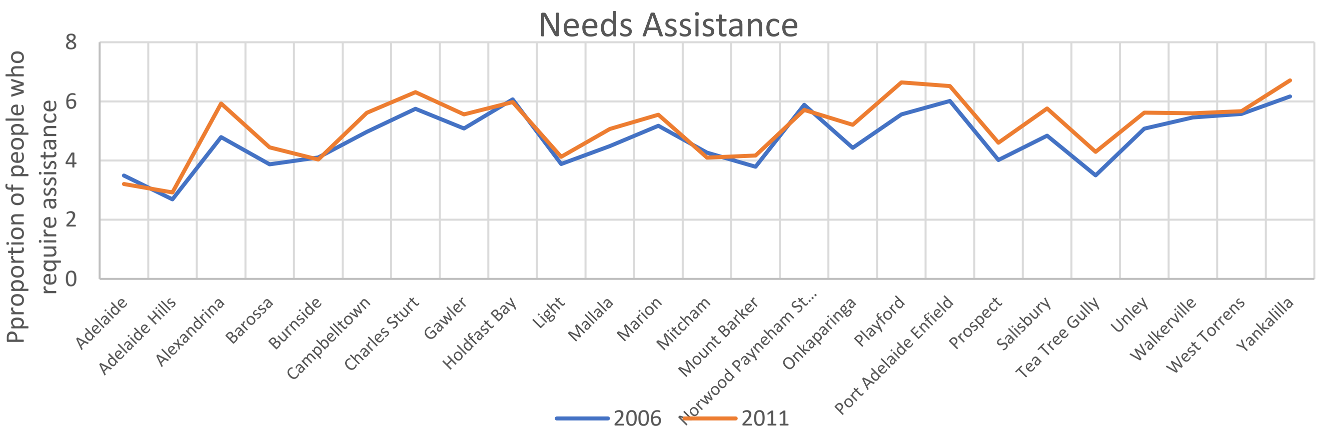


Figure 6-22 Difference between proportions of people who need assistance in 2011 and 2006 for each Local Government Area in Greater Adelaide.

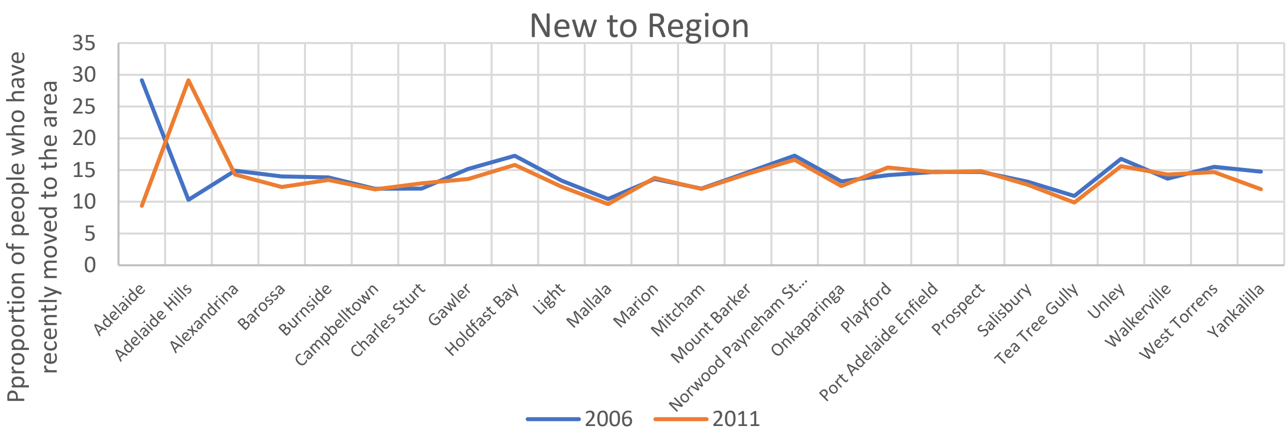


Figure 6-23 Difference between proportions of people who are new to the region in 2011 and 2006 for each Local Government Area in Greater Adelaide.

From Figure 6-13 to Figure 6-23, the Unemployment, Car Ownership, Education, Needs Assistance, Public Housing, English Proficiency and Indigenous Vulnerability Indicators all show the greatest change from 2006 to 2011. As the case study considers an equal weighting of all 14 indicators to evaluate Social Vulnerability, the future Social Vulnerability of Greater Adelaide is likely to be highly dynamic due to the variable nature of the vulnerability inputs. Most indicators showed a negative increase between 2006 and 2011, except for the Young People (Figure 6-16), Public Housing (Figure 6-17) and Education (Figure 6-19) indicators which showed a decreased Social Vulnerability.

From Figure 6-13, the Unemployment indicator showed a significant increase between 2006 and 2011. Therefore, it is an indicator of interest and should be further investigated for how it may influence future changes in Social Vulnerability. For each Local Government Area in Greater Adelaide, there was an increase in unemployment between 2006 and 2011 and hence, an increase in Social Vulnerability. The LGAs of Adelaide, Alexandrina, Mount Barker, Playford, Salisbury and Unley showed the greatest historic increase in the proportion of unemployed people.

The difference in proportion of households with access to a car from 2006 and 2011, shown in Figure 6-14, showed significant increase for all LGAs historically. The increase occurs for all LGAs, except the changes range from approximately 5% to 25%. Hence, this is an indicator of interest for understanding the future changes in Social Vulnerability. The LGAs of Adelaide, Campbelltown, Charles Sturt, Holdfast Bay, Norwood Payneham and St Peters, Port Adelaide Enfield and West Torrens showed the greatest historic increase in the Car Ownership indicator.

Figure 6-17 shows the difference between the proportions of public housing dwellings between 2006 and 2011. There is high variability between 2006 and 2011 for this indicator and hence, it is an indicator of interest for the dynamic assessment of Social Vulnerability. Most LGAs showed a significant decrease in the proportion of dwellings that are owned by the State and Territory Housing Authority, except for Adelaide Hills, Mallala and Yankalilla, all which are rural regions of Greater Adelaide.

For the Education Vulnerability Indicator, all LGAs, except Adelaide, showed a significant increase in the proportion of people who completed year 12 from 2006 and 2011, as shown in Figure 6-19. The increase in Education levels was mostly consistent between the LGAs, with most LGAs showing approximately a 5% increase. However, the Adelaide Hills showed a much greater increase of 25% between 2006 and 2011. The historic changes in the proportion of individuals who have completed year 12 indicate that the Education indicator is one of interest and its influence of Social Vulnerability in 2050 should be assessed.

From Figure 6-20, the Indigenous indicator showed significant variability between 2006 and 2011. Therefore, to understand the future state of Social Vulnerability, the impact of the proportion of indigenous people should be analysed in the future. Adelaide Hills, Alexandrina, Burnside, Gawler, Light, Mallala, Marion, Mitcham, Onkaparinga, Playford, Port Adelaide Enfield, Salisbury, Tea Tree Gully, Walkerville and Yankalilla all showed varying increases in the proportion of Indigenous people. There was a decrease from 2006 to 2011 experienced in Adelaide, Barossa, Campbelltown and Prospect.

The English Proficiency Indicator showed high variability between 2006 and 2011, shown in Figure 6-21 and hence, it is an indicator of interest for the future assessment of Social Vulnerability. Most areas showed an increase in Social Vulnerability due to insufficient English from 2006 and 2011. However, there was a minimal decrease experienced in Adelaide, Barossa, Charles Sturt, Mount Barker, Norwood Payneham and St Peters and Yankalilla.

Figure 6-22 presents the difference between the proportion of people who need assistance from 2006 and 2011. This indicator experiences high variability historically, hence an assessment on the impact of the proportion of people who need assistance on future Social Vulnerability is worthwhile. Most LGAs show an increase in the Needs Assistance Indicator between 2006 and 2011. However, a decrease is experienced in Adelaide, Burnside, Holdfast Bay and Mitcham.

The Vulnerability indicators for Elderly People, Young People, Volunteering and New to Region showed little variability between 2006 and 2011, as presented in Figure 6-15, Figure 6-16, Figure 6-18 and Figure 6-23, respectively. Therefore, they are not indicators of interest as they do not present significant historical changes. Hence, an investigation into changes that may occur to these indicators into the future and their influence on future Social Vulnerability is not worthwhile.

6.2.2 Understanding the Drivers of Bushfire Likelihood

As discussed in Section 5.3.3.2, sensitivity analyses are required to determine the most sensitive model inputs and create a better understanding of the system's behaviour. The results of the sensitivity analysis undertaken for Fire Behaviour, shown in Figure 6-24, indicate that Fire Behaviour is most sensitive to Vegetation (V), Slope Degree (SlopeD) and Time Since Last Fire (TSLF).

The high sensitivity of Fire Behaviour to Vegetation is reasonable, as areas without Vegetation have zero fire risk. Additionally, the type of vegetation also dictates the behaviour of the fire. These results also show that Fire Behaviour is least sensitive to the climate dependent variables. To separate out the climate variables, the sensitivity analysis shown in Figure 6-25 considers the sensitivity of Fire Behaviour only to the climate variables.

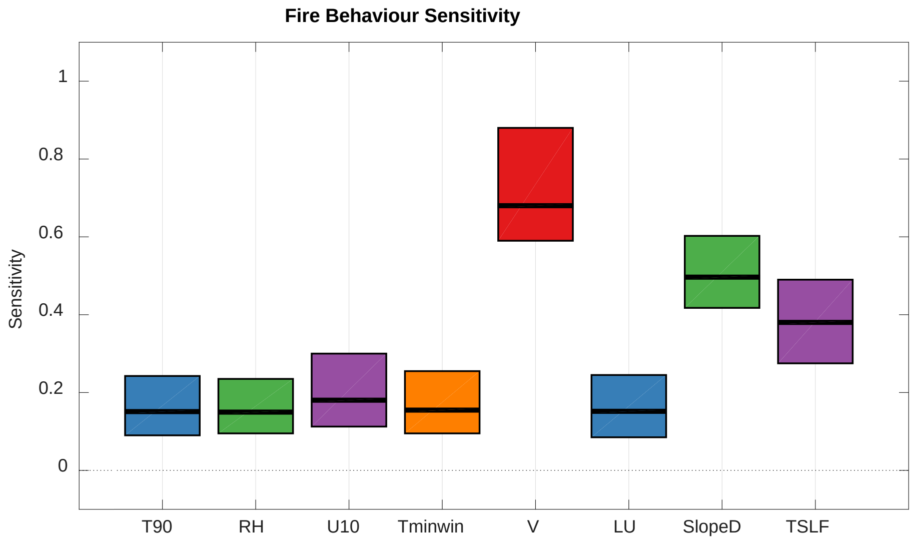


Figure 6-24 Sensitivity analysis of Fire Behaviour

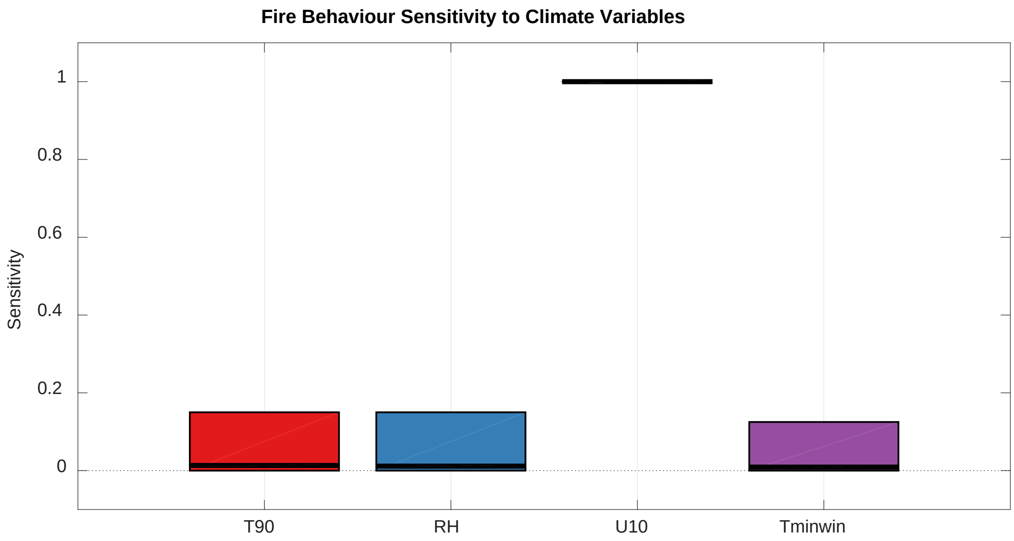


Figure 6-25 Sensitivity analysis of Fire Behaviour to climate variables

Considering only changes in the climate variables, the sensitivity analysis shows that Fire Behaviour is sensitive to the wind speed at 10m, however, it is not largely sensitive to other climate variables. Thus, future climate scenarios have little impact on changes in Fire Behaviour. As Fire Behaviour is the only component of Hazard Likelihood containing climate dependent variables, the future climate scenarios will have little influence on Hazard Likelihood in 2050.

The results of the sensitivity analysis undertaken for Ignition Potential, shown in Figure 6-26, indicate that Ignition Potential is highly sensitive to vegetation type, and has low sensitivity to Land Use. The high sensitivity of Vegetation compared to Land Use is likely due to Ignition Potential being 0 where there is no Vegetation.

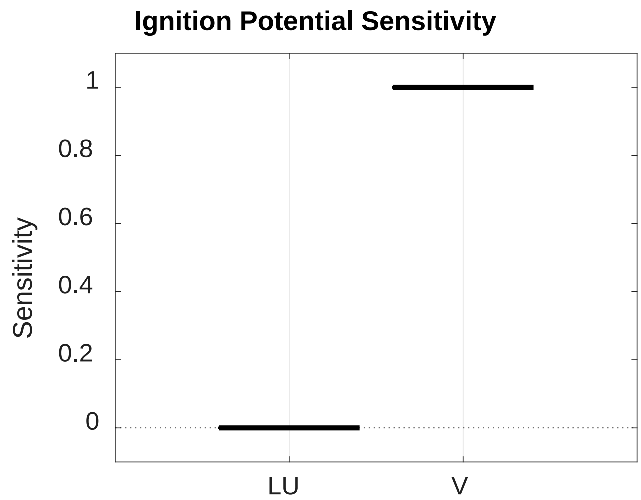


Figure 6-26 Sensitivity analysis of the ignition potential model

Figure 6-27 shows the results of a sensitivity analysis conducted on Hazard Likelihood. The high sensitivity of Vegetation (V) is partially attributable to its dual influences on Fire Behaviour and Ignition Potential. Other highly sensitive inputs are Suppression Capability (SC), Slope Degree (SD) and the Time Since Last Fire (TSLF).

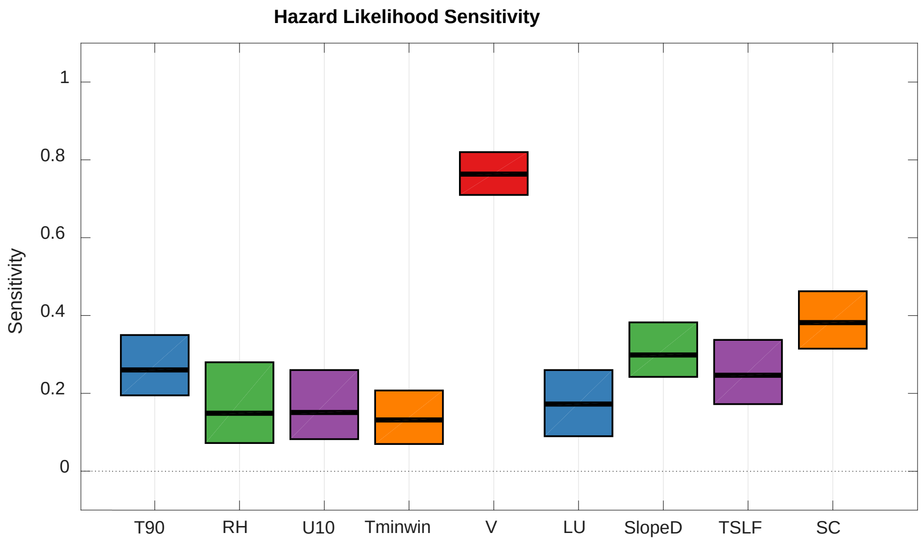


Figure 6-27 Sensitivity Analysis of Hazard Likelihood

Mitigation options which target these sensitive variables may be more influential in reducing Bushfire Likelihood in Greater Adelaide, and thus Bushfire Hazard Risk in Greater Adelaide.

6.3 Future Hazard Risk

The results of future Social Vulnerability, Hazard Likelihood and Hazard Risk in 2050 under the Ignorance of the Lambs, Silicon Hills and Cynical Villagers socio-economic scenarios and the RCP 8.5 climate scenario are shown in Section 6.3.1, Section 6.3.2 and Section 6.3.3, respectively. The results of future Hazard Likelihood and Hazard Risk under RCP 4.5 are not shown, as they showed negligible difference to the results for RCP 8.5. This is due to the very low sensitivity of the Hazard Likelihood Model to the temporally dynamic climate variables, as discussed in the results in Section 6.2.2.

6.3.1 Social Vulnerability in 2050

The changes in the total measure of Social Vulnerability between now and 2050 under the Ignorance of the Lambs, Silicon Hills and Cynical Villagers scenarios are shown in Figure 6-28.

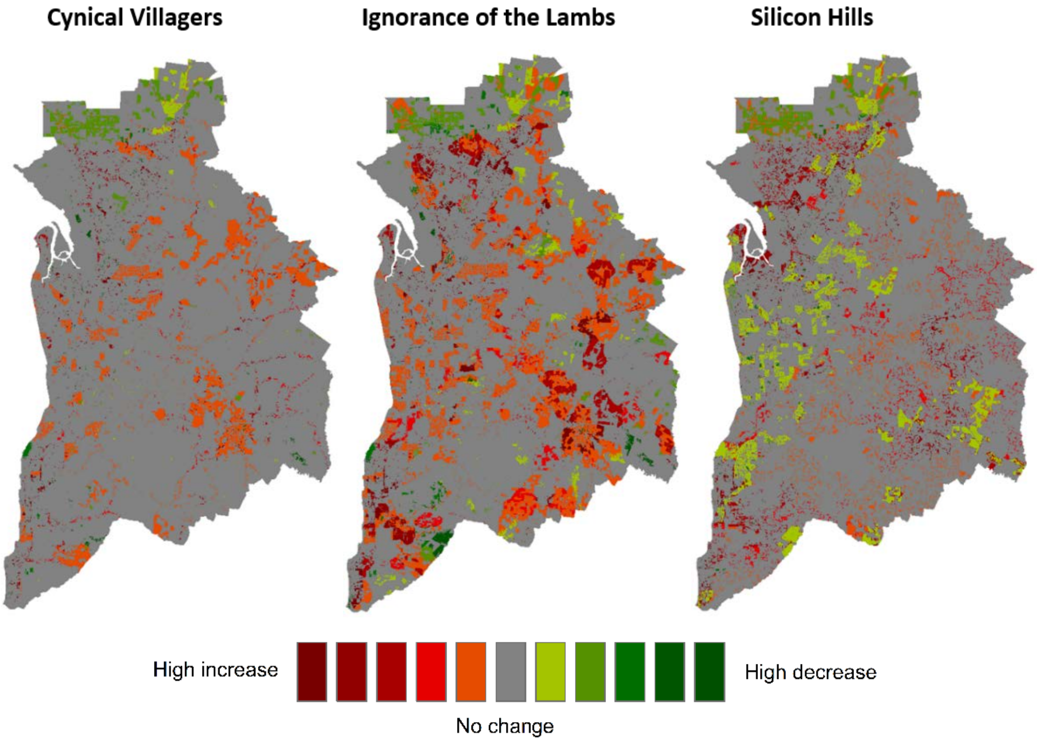


Figure 6-28 Change in Social Vulnerability between now and 2050 under the (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

The Cynical Villagers and Ignorance of the Lambs scenarios predominantly show an increase in Social Vulnerability, while the Silicon Hills scenario shows a larger number of areas where Social Vulnerability decreases. This is to be expected for Silicon Hills, as it is the best-case scenario, however, changes in the indicators under this scenario still cause increases in Social Vulnerability in some locations. In general, this is due to changes in land use where a location is changed to having a community based land use in 2050. For example, under current conditions a location does not have a Social Vulnerability associated with it, however, due to changes in the land use type, in 2050 there is a Social Vulnerability assigned to the location. The Ignorance of the Lambs scenario shows the largest magnitude of change and the largest number of locations where there is an increase in Social Vulnerability in 2050.

There are no distinct areas that show an increase in Social Vulnerability across all three scenarios. If this were so, it would give cause to investigate what might be a problem area. The Ignorance of the Lambs scenario shows areas of high increase in Social Vulnerability for pockets in the North, Hills and

South areas, due to the increase in rural residential land and urban sprawl. These are areas that could be new problem areas.

The indicators which had the highest observed variability in 2006-2011 were unemployment levels, level of English proficiency, proportion of people living in public housing, proportion of indigenous people, level of education, proportion of dwellings with access to a car, proportion of people who have completed year 12 and proportion of people needing assistance. Due to this variability, the changes in these indicators are important to consider in the future. However, the scenario driven approach relied on adequate information to determine the future changes in these indicators.

Of these higher variability indicators, only unemployment levels, level of education, and level of English proficiency were adequately described in the scenarios, and the results are presented below. Also shown are the results for the indicators of proportion of elderly people, and proportion of recently moved to the area, as these are both integral to the different scenario story lines. These indicators are also important in the context of Greater Adelaide, which has an ageing population, and is seeing a loss of certain industries and businesses.

6.3.1.1 Unemployment

Figure 6-29 shows the changes in Social Vulnerablity due to Unemployment in 2050 as an increase or decrease relative to their current levels.

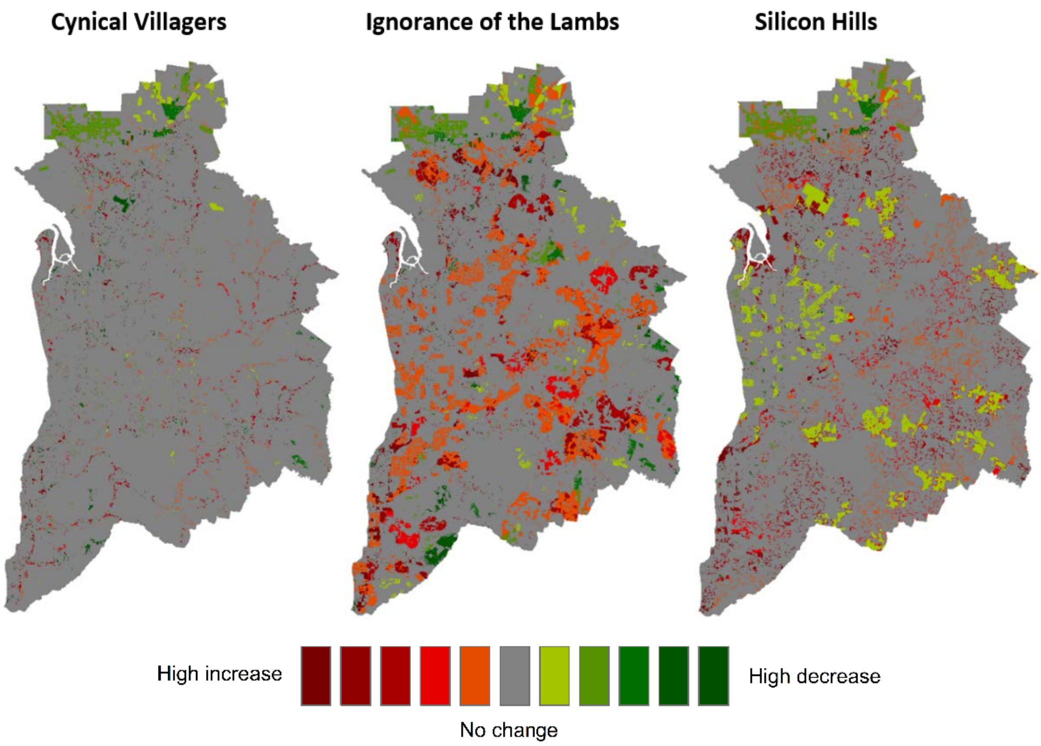


Figure 6-29 Changes in Social Vulnerability due to the proportion of people who are unemployed for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

For the proportion of unemployment, decreases in Social Vulnerability due to this indicator are observed for the Silicon Hills scenario, more prominently in the East, West, and Hills regions. The green pockets in the Hills region are where the indicator decreases from “Medium” to “Low” vulnerability.

In the Cynical Villagers scenario, the scattered changes in Social Vulnerability due to unemployment that can be seen are due to changes in land use for the scenario. In contrast, the Ignorance of the Lambs scenario, which poses high future challenges for resilience, has increases in the proportion of unemployed people, and hence Figure 6-29(b) shows whole suburbs that have an increase in Social Vulnerability due to changes in unemployment.

6.3.1.2 English Proficiency

Figure 6-30 shows the changes in Social Vulnerablity due to English Proficiency in 2050 as an increase or decrease relative to their current levels.

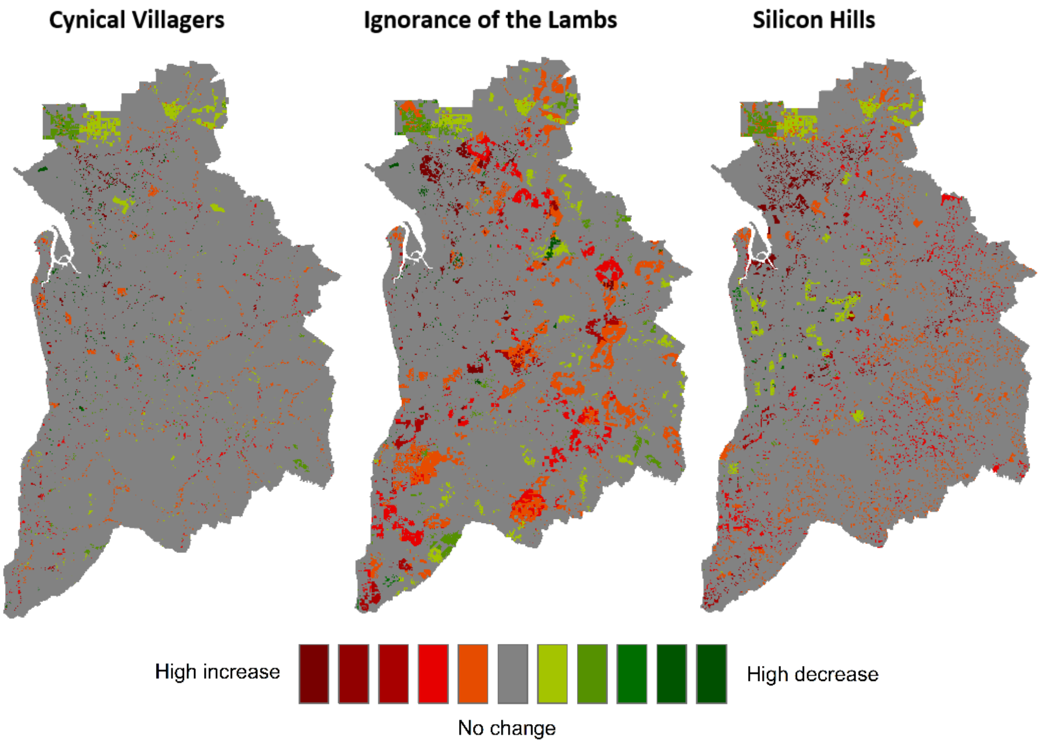


Figure 6-30 Changes in Social Vulnerability due to the proportion of people with very low English proficiency for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

The proportion of people with insufficient English increases by a small amount for all regions in the Cynical Villagers scenario, which causes the small increases in Social Vulnerability due to lack of English Proficiency in all areas. In general, the scattered changes seen in Figure 6-30(a) are due to the changing land uses rather than an impact on the magnitude of vulnerability. In the Ignorance of the Lambs scenario the percentage increase in the indicator is higher for the North, South and Hills regions. This creates changes in the Social Vulnerability due to insufficient English of whole suburbs, as seen from the clumped changes in Figure 6-30(b). Finally, the Silicon Hills scenario shows mixed changes in Social Vulnerability due to this indicator. The more positive percentage indicator change in the East and West regions affects positive changes in these regions, shown in Figure 6-30(c). The smaller change in the North, South and Hills regions does not influence change in the Social Vulnerability of suburbs; the increases in Social Vulnerability in these regions can be explained by the changes in land use from a non-vulnerable to a vulnerable land use (i.e. from vacant to residential).

6.3.1.3 Education

Figure 6-31 shows the changes in Social Vulnerablity due to Education in 2050 as an increase or decrease relative to their current levels.

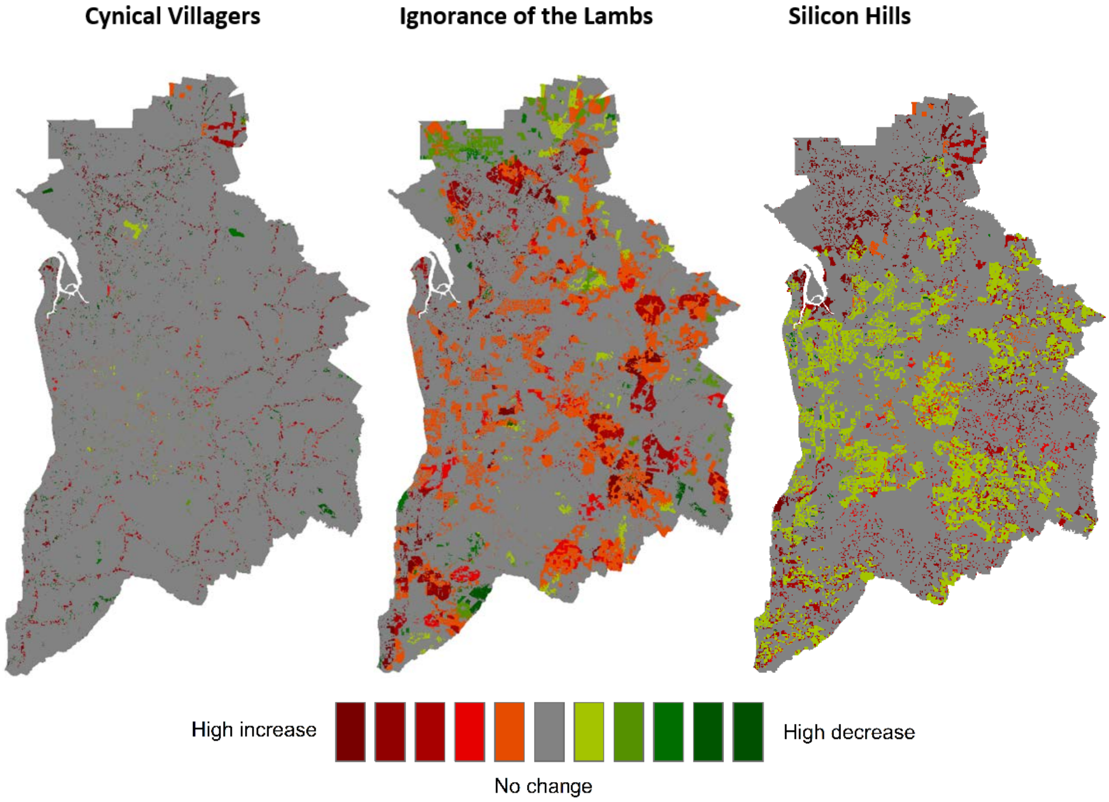


Figure 6-31 Change in Social Vulnerability due to the proportion of people who have completed year 12 for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

The proportion of education, measured by the completion of year 12, is distinctly different across the different socio-economic scenarios. In the Cynical Villagers scenario, the proportion of people who have completed year 12 remains constant. The scattered changes seen in the Cynical Villagers scenario reflect land use changes within the scenario. Vulnerability due to education in the Ignorance of the Lambs scenario had the highest density increase of Social Vulnerability due to education, with the highest increases notably in the Hills region as a large portion of migrants and refuges moves towards these low-cost development areas. The decreases in education are enough to affect change in Vulnerability of many suburbs. The Silicon Hills scenario explores a situation where enrolments and investment in public schools are increased, causing an increase in education. In the Silicon Hills scenario, this translates to a relatively dense decrease in vulnerability due to education throughout the GA region, except for the upper North area – which shows a sparse high increase in vulnerability. The middle-band of the Hills also shows sparse high increases in vulnerability.

6.3.1.4 Proportion of Elderly People

Figure 6-32 shows the changes in social vulnerablity due to Elderly People in 2050 as an increase or decrease relative to their current levels.

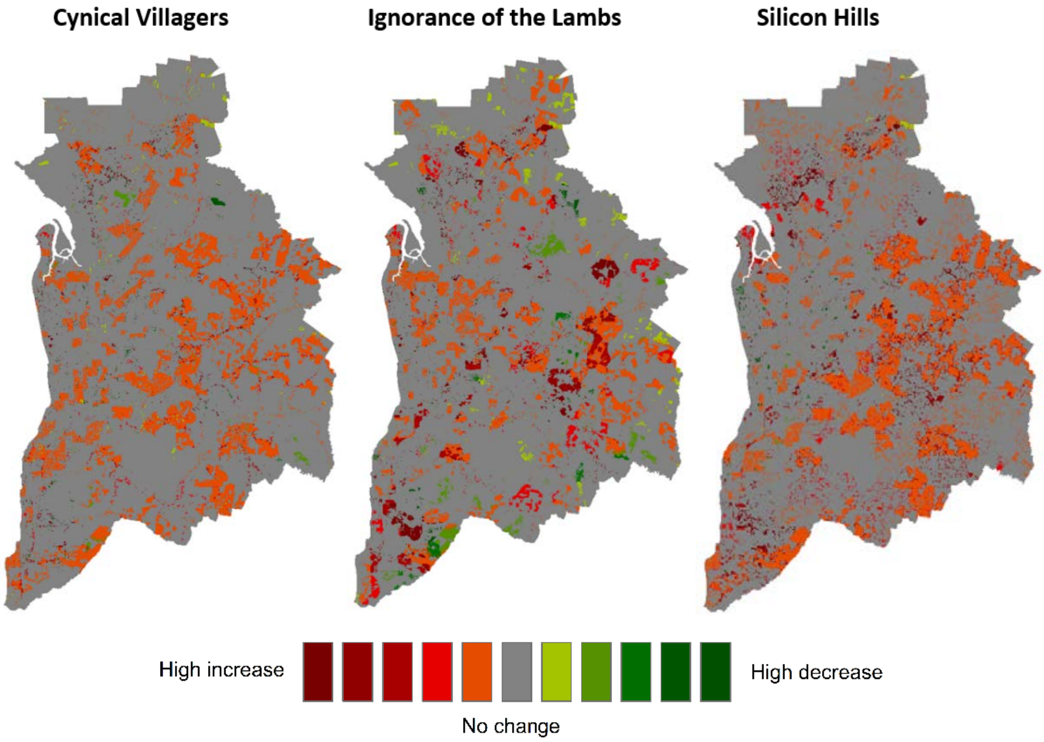


Figure 6-32 Changes in Social Vulnerability due to the proportion of elderly people for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

Greater Adelaide has an ageing population, which is captured by the growing proportion of elderly people in all areas under each scenario. All three scenarios experience relatively dense increases in Social Vulnerability due to the increasing proportion of elderly people, however depending on the lifestyle choices of the scenarios, the spatial distribution of this was different. The Ignorance of the Lambs scenario shows some small pockets in the Hills and South regions of high increases in Social Vulnerability due to this indicator, which is due to the changing land use and commuter villages.

6.3.1.5 Recently Moved to the Area

Figure 6-33 shows the changes in social vulnerablity due to Recently Moved to the Area in 2050 as an increase or decrease relative to their current levels.

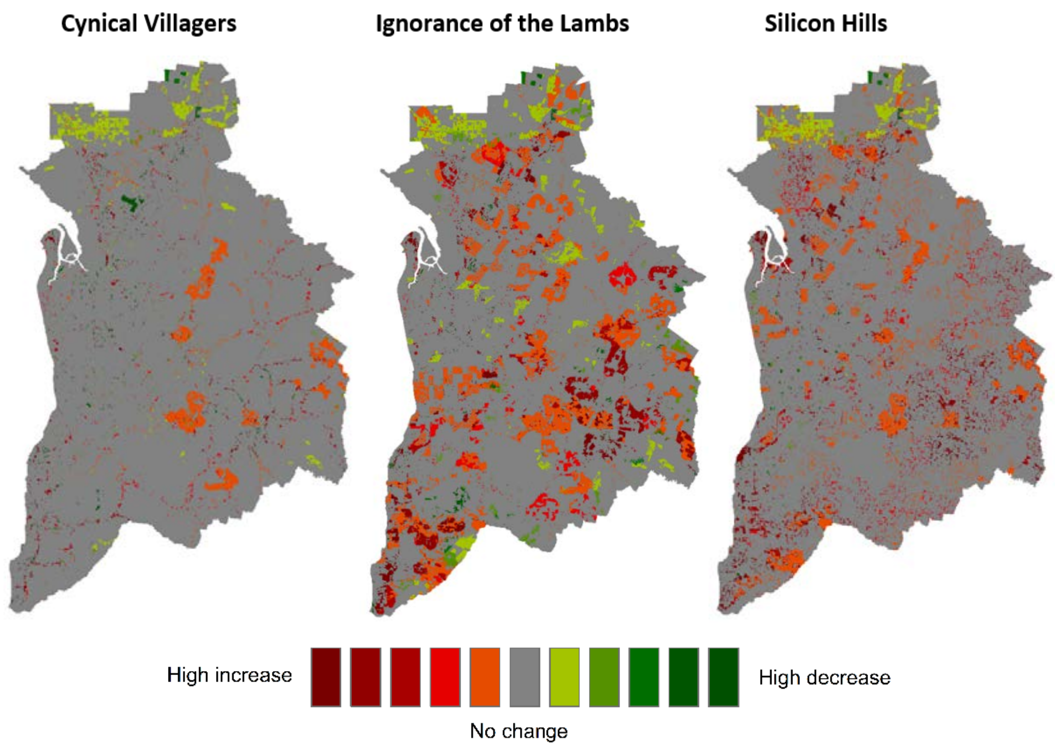


Figure 6-33 Change in Social Vulnerability due to the proportion of people who have recently moved to the area for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

For the Cynical Villagers scenario, there are dense areas of increased Social Vulnerability due to high proportions of new arrivals in the Hills region, as the ageing population move to the Hills to retire. The Ignorance of the Lambs scenario shows a high density of changes in Social Vulnerability due to new arrivals in the area throughout the North, South and Hills regions. This is due to the expansion of residential land use and increasing commuter lifestyle, which attests to the pockets of increased new arrivals to the area. By contrast, there are relatively low density increases in vulnerability in Silicon Hills scenario throughout Greater Adelaide as a large portion of new residents migrate from overseas.

6.3.2 Hazard Likelihood in 2050

Future Hazard Likelihood is dependent on changes in the dynamic variables of Fire Behaviour and Ignition Potential. Change maps are used to show how Hazard Likelihood and its components change in 2050 under the different scenarios compared to the current situation.

Figure 6-34 highlights the changes in the Fire Behaviour between now and 2050 under Cynical Villagers, Ignorance of the Lambs and Silicon Hills scenarios.

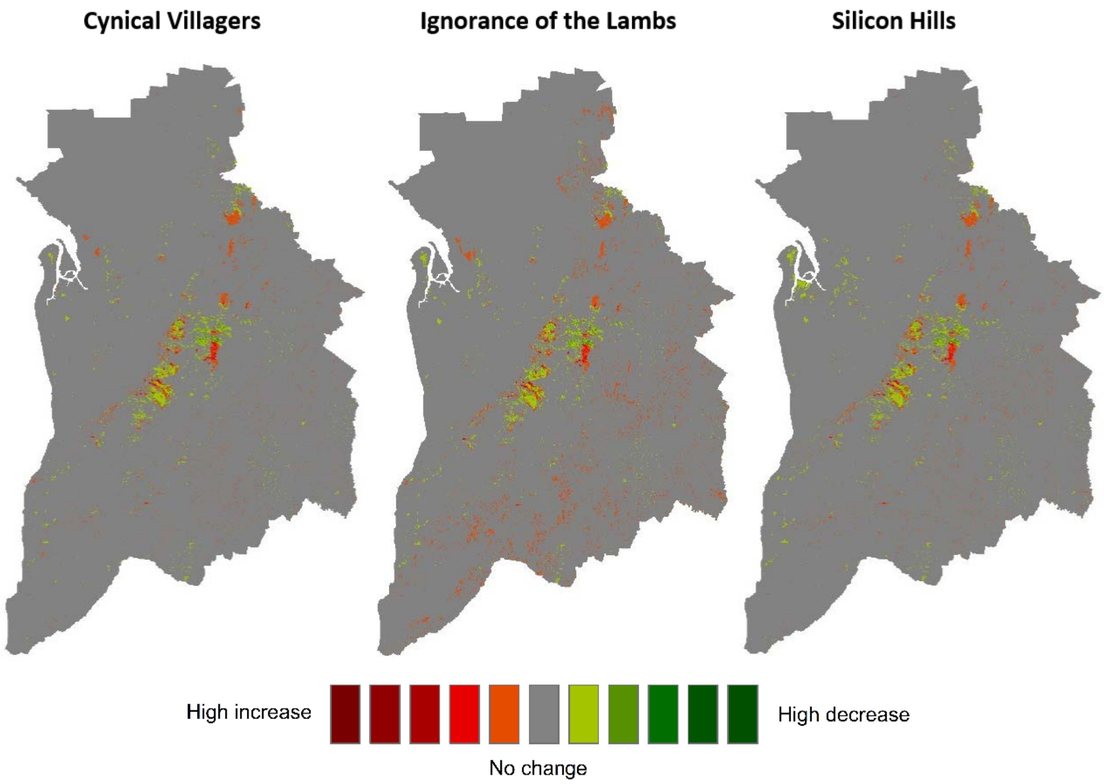


Figure 6-34 Changes in Fire Behaviour between now and 2050 under the (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

From the sensitivity analysis, it was observed that Fire Behaviour is not highly sensitive to climate variables, therefore only the socio-economic scenario results are shown. Vegetation and Slope Degree are constant, and as these are two sensitive inputs to Fire Behaviour, the little change in Fire Behaviour across the scenarios could be attributed to this. Land Use and Time Since Last Fire are the only variables changing for each scenario, which is why there are only small areas of change. The increase in Time Since Last Fire, however, is constant across all three scenarios, while the changes in Land Use are different for each scenario – and thus Land Use is attributed to the difference in Fire Behaviour between the scenarios. For example, in (b) Ignorance of the Lambs, there is a rise in commuter suburbs, which explains the scattered increase in Fire Behaviour in the Mount Barker and Adelaide Hills regions relative to scenarios (a) and (c).

Changes in the 2050 Ignition Potential from the current Ignition Potential under Cynical Villagers, Ignorance of the Lambs and Silicon Hills scenarios are illustrated in Figure 6-35. Ignition Potential is a function of vegetation and land use type. However, Vegetation is considered constant, so changes in Ignition Potential are only due to changes in Land Use. As was similarly seen in Fire Behaviour, Ignorance of the Lambs considers commuter suburbs and urban sprawl into the Hills, North and South, so results in the greatest increase in rural residential land use. Thus, this scenario produced the highest increase in Ignition Potential.

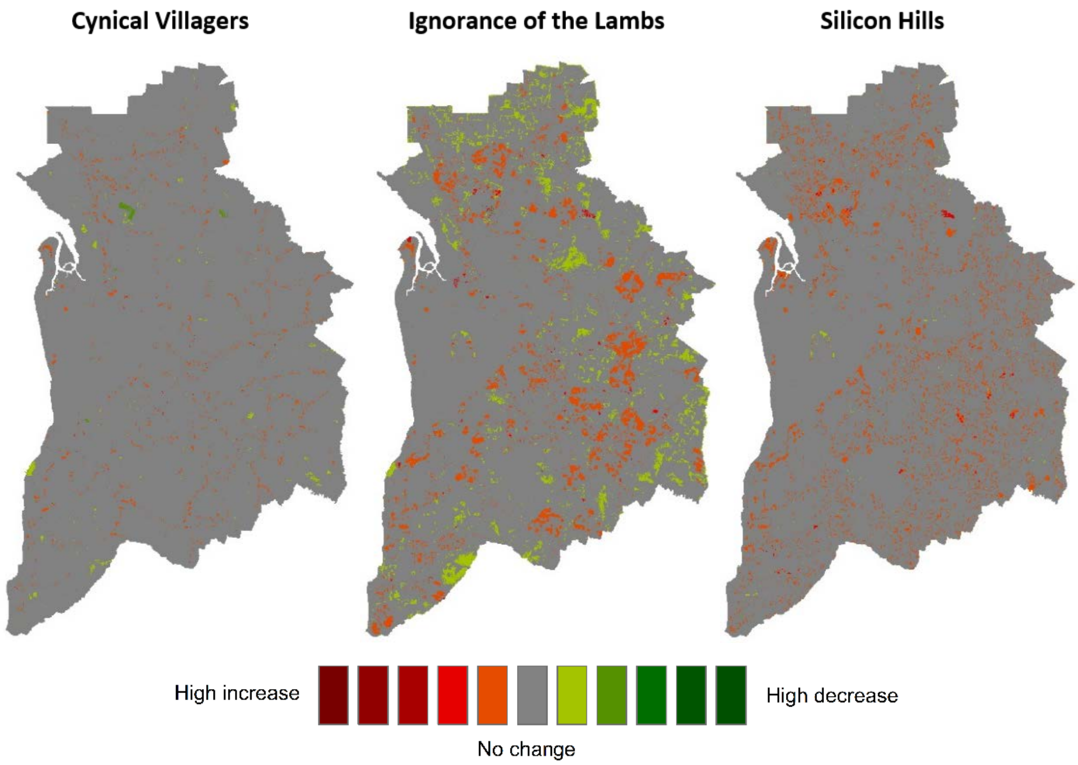


Figure 6-35 Changes in Ignition Potential between now and 2050 for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

Changes in 2050 Hazard Likelihood from the current Hazard Likelihood for the three scenarios are illustrated in Figure 6-36.

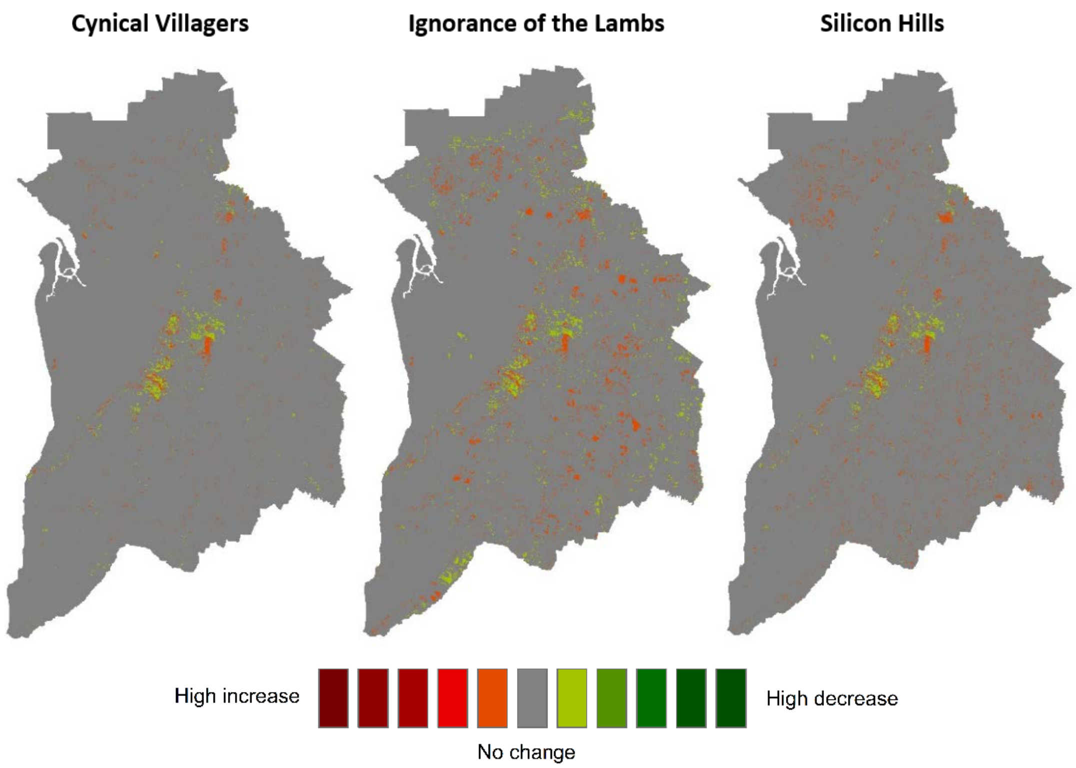


Figure 6-36 Change in Hazard Likelihood between now and 2050 for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

For all three scenarios, similar changes in Hazard Likelihood for the eastern suburbs of Greater Adelaide and along the north-western border of the Adelaide Hills are observed. The Hazard Likelihood decreases within the Eastern areas, but increases along the North-Western border of the Adelaide Hills, similar to the changes in Fire Behaviour, depicted in Figure 6-34. This is due to changes in Land Use and their influence on Ignition Potential and Fire Behaviour. Ignorance of the Lambs shows the largest number of areas with increases in Hazard Likelihood within the Hills, North and South. This can be attributed to the urban sprawl within these areas.

6.3.3 Hazard Risk in 2050

The Hazard Risk for the three exploratory scenarios is shown in Figure 6-37.

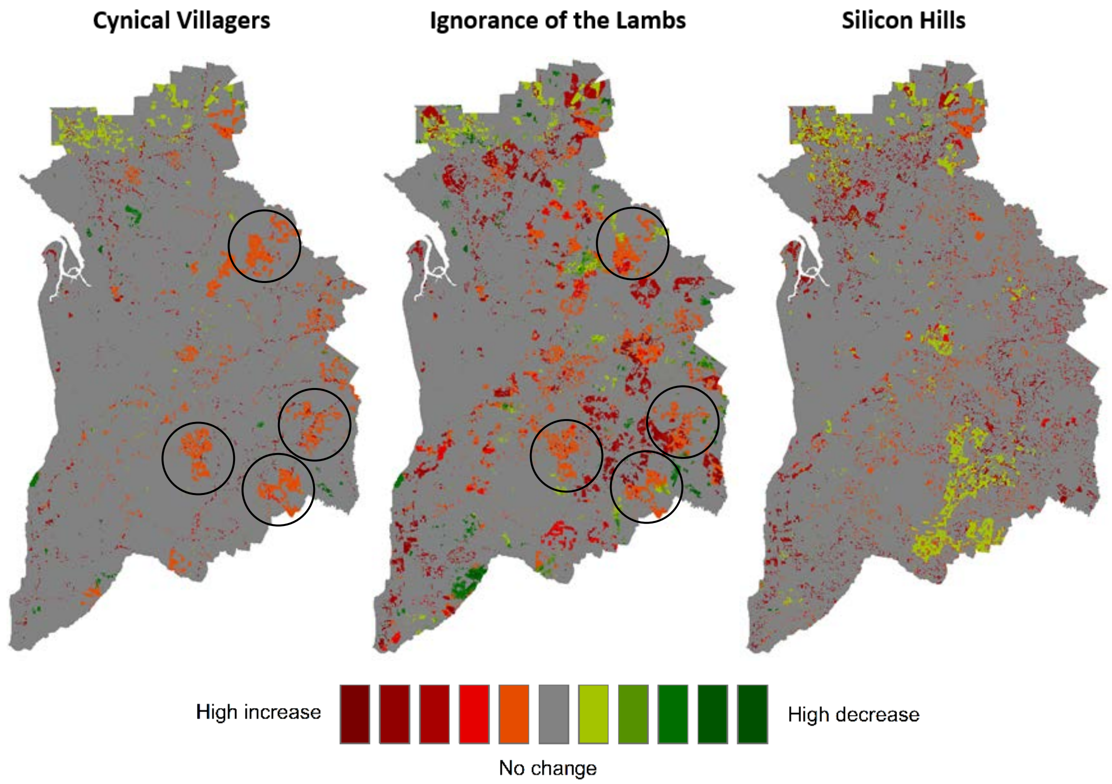


Figure 6-37 Change maps for Hazard Risk for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

The Cynical Villagers socio-economic scenario shows the least change in Hazard Risk for 2050. As Cynical Villagers is the high community resilience scenario, the lowest impact on Social Vulnerability would be expected. The scenario details low population growth and increased urban sprawl. The increased urban sprawl is shown through the increased Hazard Risk in the Hills region. Ignorance of the Lambs has the greatest change in hazard risk, with this change being mostly negative. As the scenario is the low community resilience scenario, a large shift in Social Vulnerability would be expected. Ignorance of the Lambs centres around high population growth and a shift towards increasingly commuter lifestyle.

This increased population growth and decline in rural living will mean that more people are living in areas that were previously rural, hence increasing the total area in Greater Adelaide susceptible to hazards. Hazard risk is seen in the Hills, South and North for present and 2050, due to the lack of vegetation in the inner regions of Greater Adelaide.

Hazard Likelihood shows minimal differences between the three scenarios, as shown in Figure 6-51. This suggests that the changes in Social Vulnerability, shown in Figure 6-28, drives these differences between the scenarios. The comparison of changes in Social Vulnerability between present and 2050, Figure 6-28, and changes in Hazard risk between present and 2050, Figure 6-37, have correlation between the areas of reduced risk and areas of increased risk.

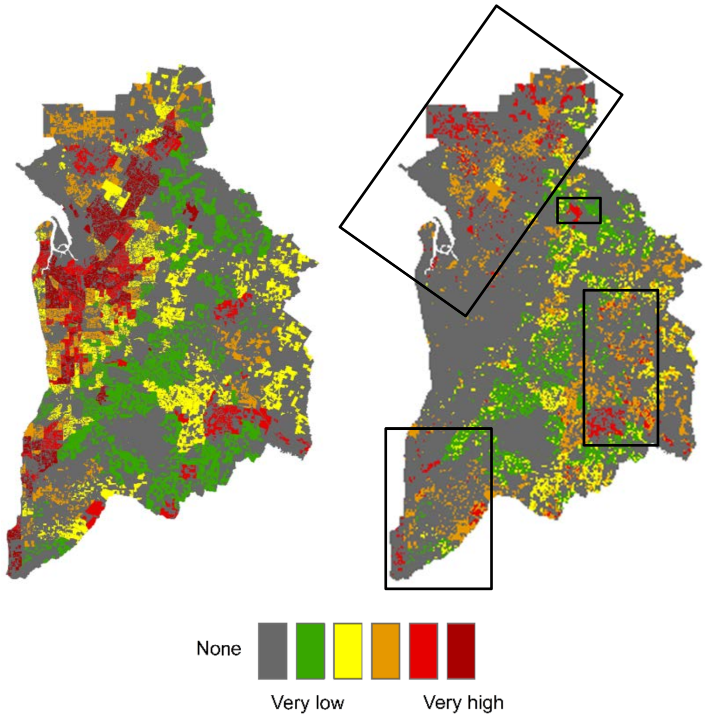
The Ignorance of the Lambs scenario shows areas of high increase in Hazard Risk for pockets in the North, Hills and South areas, due to the increase in rural residential land and urban sprawl. These are areas that could be new problem areas. The pockets of low increase in Hazard Risk seen in the Cynical Villagers scenario also indicate potential problem areas. These are originally low and very low risk areas, shown in Figure 6-12, which only increase by one level, so their severity is not as great as the problem areas in the Ignorance of the Lambs scenario. There areas are marked on Figure 6-37 that show correlating increases in Hazard Risk across the Cynical Villagers and Ignorance of the Lambs scenarios, which suggests another set of potential problem areas.

6.4 Mitigation

As detailed in Section 5.3.5, the deeper understanding of the system of natural hazard risk obtained from these results can be used to develop mitigation options.

6.4.1 Mitigation options targeting Social Vulnerability

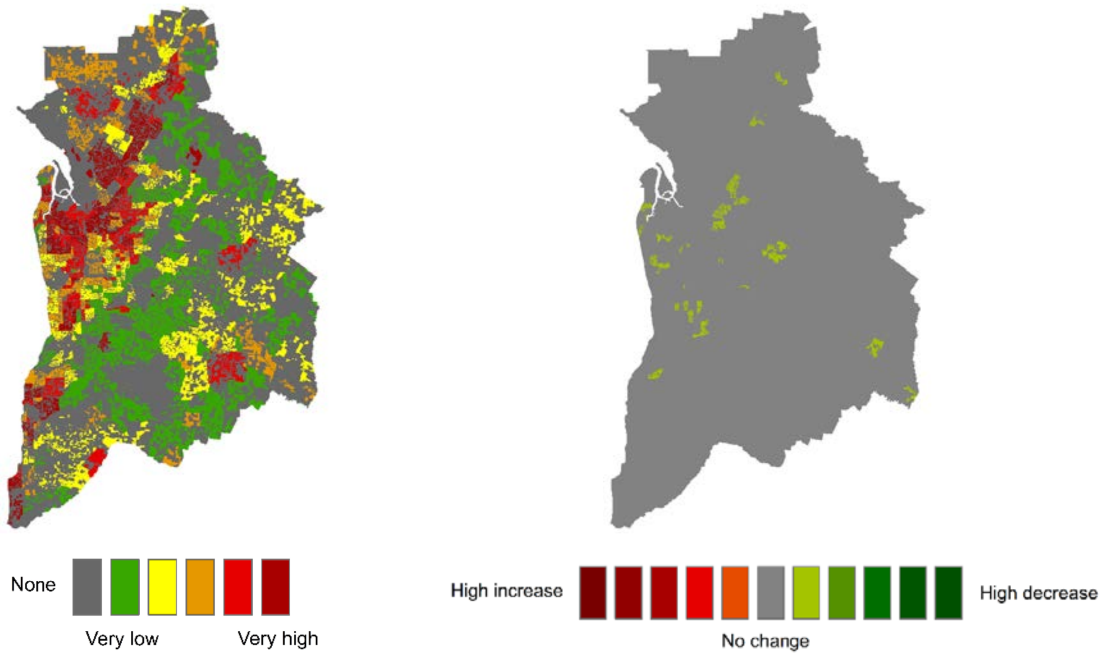
The process outlined in Figure 5-21, was used to identify effective risk reduction measures targeting Social Vulnerability for the case study. From the current Social Vulnerability map and the current Bushfire Hazard Risk map, the areas of interest (socially vulnerable areas with an associated risk) were identified predominantly in the North, lower South and the Hills, as shown in Figure 6-38.



(a)¶ (b)

Figure 6-38 Areas of interest, hence socially vulnerable areas with an associated risk (a) current Social Vulnerability, (b) current Bushfire Hazard Risk

The current Social Vulnerability and the change in current Social Vulnerability as a result of a 10% increase in the Level of Education is shown in Figure 6-39 (a) and Figure 6-39 (b) respectively. Figure 6-40 (a) and Figure 6-40 (b) show the subsequent current Hazard Risk and change in current Hazard Risk compared to the no mitigation case, respectively.



(a) (b)

Figure 6-39 Social Vulnerability due to Level of Education with mitigation causing a 10% increase in Education, shown as (a) the Vulnerability with mitigation, (b) the change in Vulnerability compared to the no mitigation case

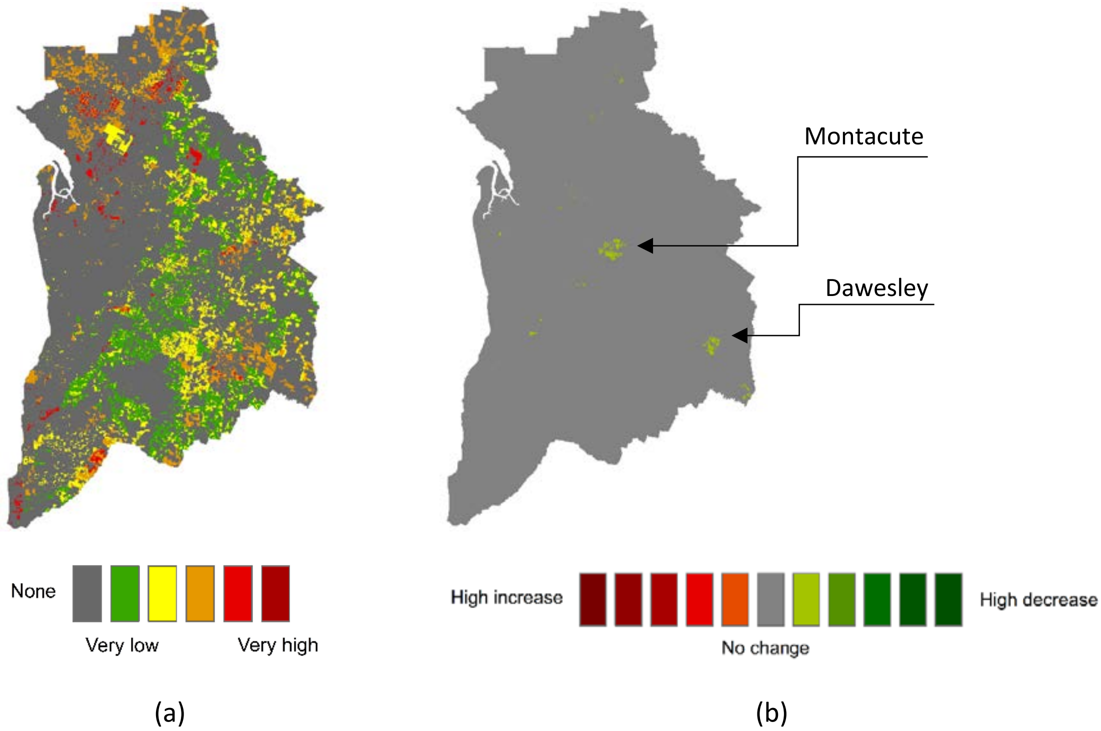
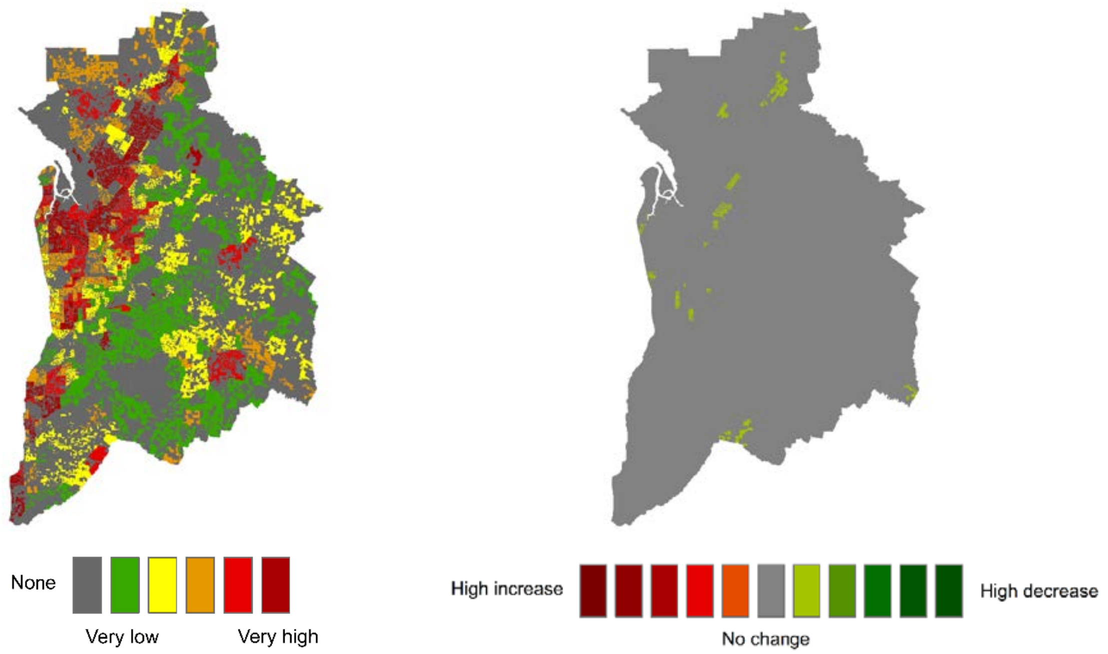


Figure 6-40 Hazard risk due to Level of Education with mitigation causing a 10% increase in Education, shown as (a) the risk with mitigation, (b) the change in risk compared to the no mitigation case

Increasing the Level of Education by 10% across the whole of Greater Adelaide decreases the Social Vulnerability of several suburbs, as seen in Figure 6-39 (b). However, the very low decrease indicates a change by one increment only. From Figure 6-39 (a) the suburbs in the Hills region decreased from Low to Very Low Social Vulnerability. However, in the South, West and North regions, many of the one increment decreases are from high to medium or very high to high.

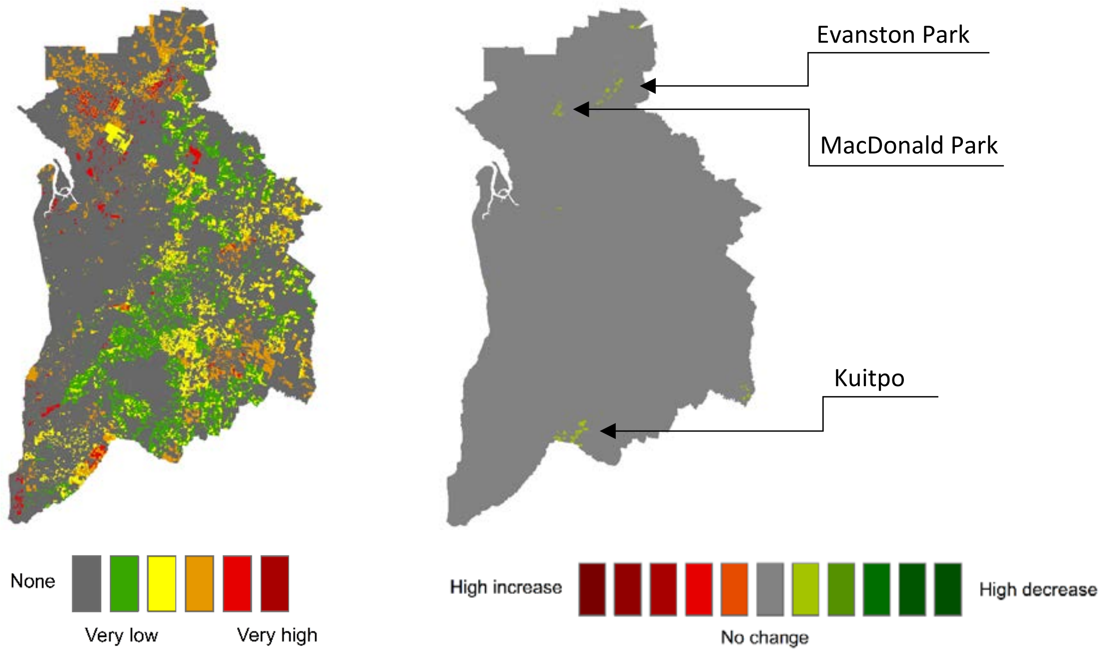
From Figure 6-40 (b), the change in Hazard Risk following an increase in Education is small. This is because the majority of suburbs which experienced a reduction in Social Vulnerability due to a 10% increase in Education are located in areas with no vegetation or high suppression capability, and thus have no risk to bushfire. However, the suburbs that did experience a change in Hazard Risk, particularly the country towns of Montacute and Dawesley, reduced from low to very low Hazard Risk, as seen from Figure 6-40 (a) and Figure 6-40 (b), respectively. Therefore, in the context of the case study, implementing a policy that would increase the proportion of people completing year 12 by 10% is not particularly effective in reducing the Hazard Risk to socially vulnerable populations.

The current Social Vulnerability and the change in current Social Vulnerability as a result of a 10% increase in the proportion of people volunteering is shown in Figure 6-41 (a) and Figure 6-41 (b) respectively. The subsequent current Hazard Risk and change in current Hazard Risk compared to the no mitigation case are shown in Figure 6-42 (a) and Figure 6-42 (b), respectively.



(a) (b)

Figure 6-41 Social Vulnerability due to Level of Volunteering with mitigation causing a 10% increase in Volunteering, shown as (a) the Vulnerability with mitigation, (b) the change in Vulnerability compared to the no mitigation case

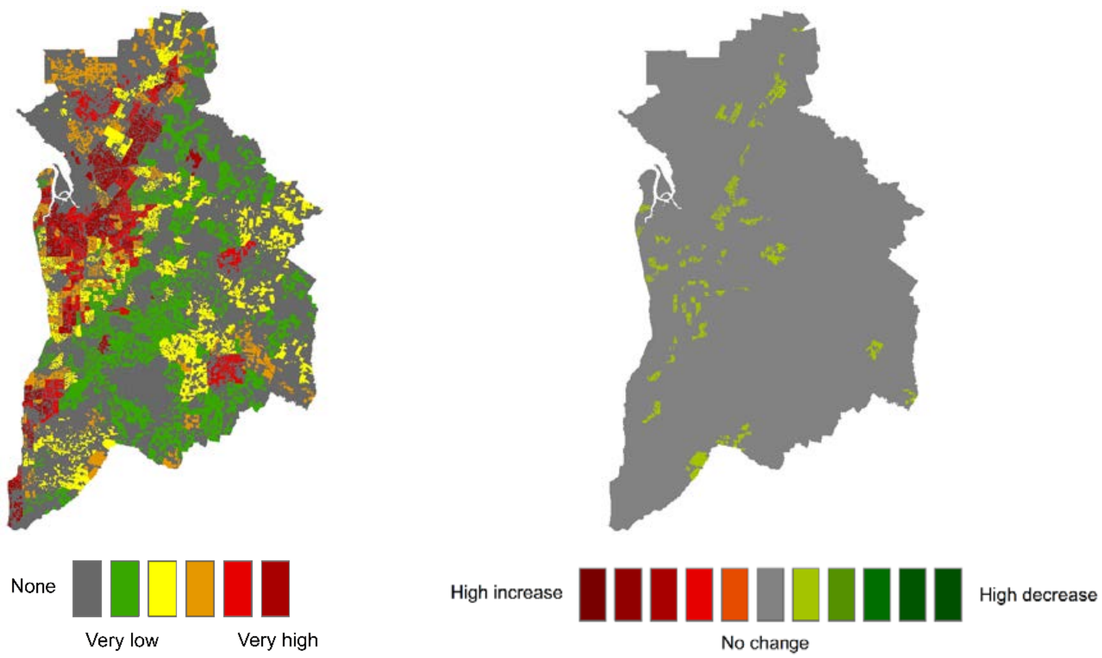


(a) (b)

Figure 6-42 Hazard risk due to Level of Volunteering with mitigation causing a 10% increase in Volunteering, shown as (a) the risk with mitigation, (b) the change in risk compared to the no mitigation case

From Figure 6-41 (b), a one level reduction in Social Vulnerability due to a 10% increase in the proportion of people volunteering is experienced by several suburbs, particularly in the North and West regions. The Social Vulnerability of the majority of these suburbs was reduced to medium or high levels as seen from Figure 6-41 (a). Similar to increasing the Level of Education, most of the suburbs affected by this risk reduction measure are located in areas with no vegetation or high suppression capability, and thus have a zero Hazard Risk, which is seen in Figure 6-42 (b). However, both the Social Vulnerability and the Bushfire Hazard Risk is reduced in Kuitpo, a suburb in the South, from low to very low. The Social Vulnerability and subsequently the Hazard Risk was reduced from medium to low in MacDonald Park, and from High to Medium in Evanston Park, both of which are suburbs in the North. Therefore, to reduce the risk of Bushfire Hazard to the most vulnerable populations through increasing the proportion of people volunteering, the relevant policy would need to be targeted in the areas of MacDonald Park and Evanston Park.

The Social Vulnerability due to a 10% increase in Personal Wealth and the change in vulnerability compared with the no mitigation case is shown in Figure 6-43 (a) and Figure 6-43 (b), respectively. The subsequent Hazard Risk and the change in Hazard Risk compared to the no mitigation case is shown in Figure 6-44 (a) and Figure 6-44 (b).



(a) (b)

Figure 6-43 Social Vulnerability due to Level of Wealth with mitigation causing a 10% increase in Wealth, shown as (a) the Vulnerability with mitigation, (b) the change in Vulnerability compared to the no mitigation case

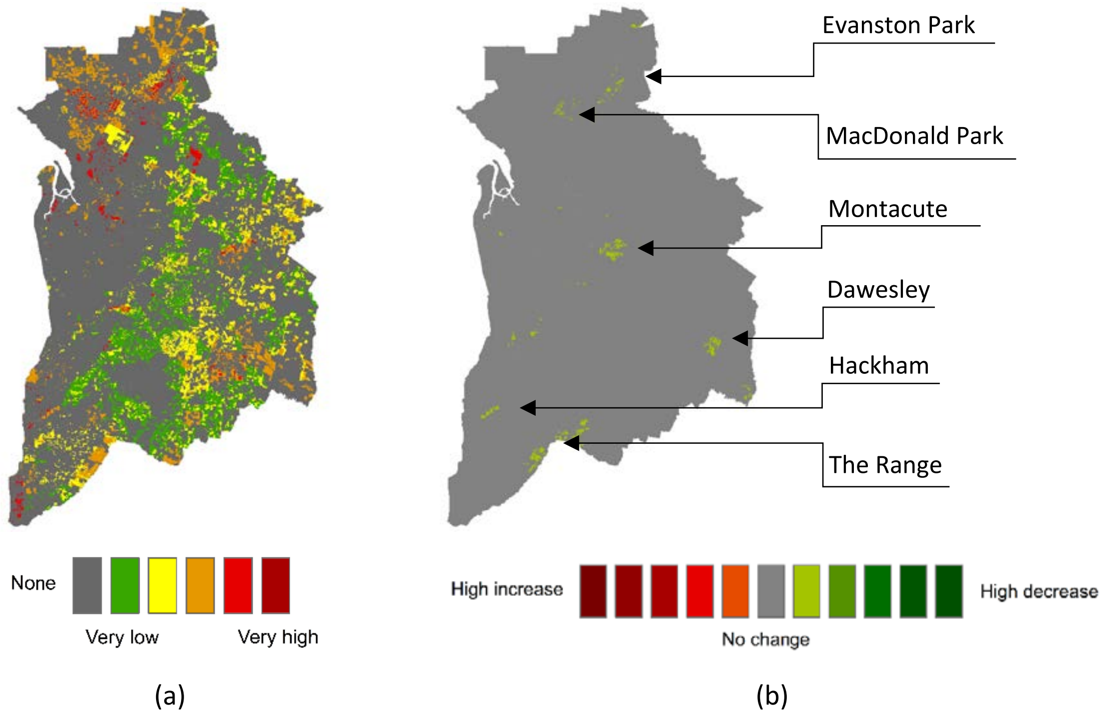


Figure 6-44 Hazard risk due to Level of Wealth with mitigation causing a 10% increase in Wealth, shown as (a) the risk with mitigation, (b) the change in risk compared to the no mitigation case

From Figure 6-43 (b), increasing the Personal Wealth by 10% across Greater Adelaide results in a decrease in Social vulnerability by one increment within a number of suburbs, mainly in the West, East and North – with a small number in the Hills and South. The Social Vulnerability for most of the affected suburbs in the West was reduced from High to Medium or from Very High to High. However, due to the high suppression capability and little to no vegetation in the Western suburbs, the Bushfire Hazard Risk in these suburbs is zero regardless, as seen in Figure 6-44 (b). Therefore, increasing Personal Wealth in these suburbs would not impact the level of Bushfire Hazard Risk.

Similar to a 10% increase in the Level of Education, a 10% increase in Personal Wealth reduced the Social Vulnerability of Montacute and Dawesley from Low to Very Low, and subsequently reduced their Hazard Risk by one increment, from Low to Very Low. A 10% increase in Personal Wealth did reduce the Bushfire Hazard Risk in these areas, however, they are not considered socially vulnerable suburbs. Thus it would not be worthwhile implementing a policy to increase Personal Wealth in these areas, in terms of hazard risk reduction.

A 10% increase in Personal Wealth reduced the Bushfire Hazard Risk in a small number of suburbs. The Social Vulnerability and Bushfire Hazard Risk was reduced by one increment, from High to Medium in Evanston Park, and Medium to low in MacDonald Park. In Hackham and The Range, the Social Vulnerability was reduced from Very High to High and High to Medium, respectively. The subsequent Hazard Risk in both suburbs was reduced from High to Medium. A policy that increases Personal Wealth by 10% in these areas would reduce the risk to Bushfire Hazards to vulnerable populations.

The Social Vulnerability due to a 10% decrease in the proportion of Young People and subsequent change in Social Vulnerability compared with the no mitigation case are show in Figure 6-45 (a) and Figure 6-45 (b), respectively. The resulting Hazard Risk and change in Hazard Risk compared with the no mitigation case are show in Figure 6-46 (a) and Figure 6-46 (b), respectively

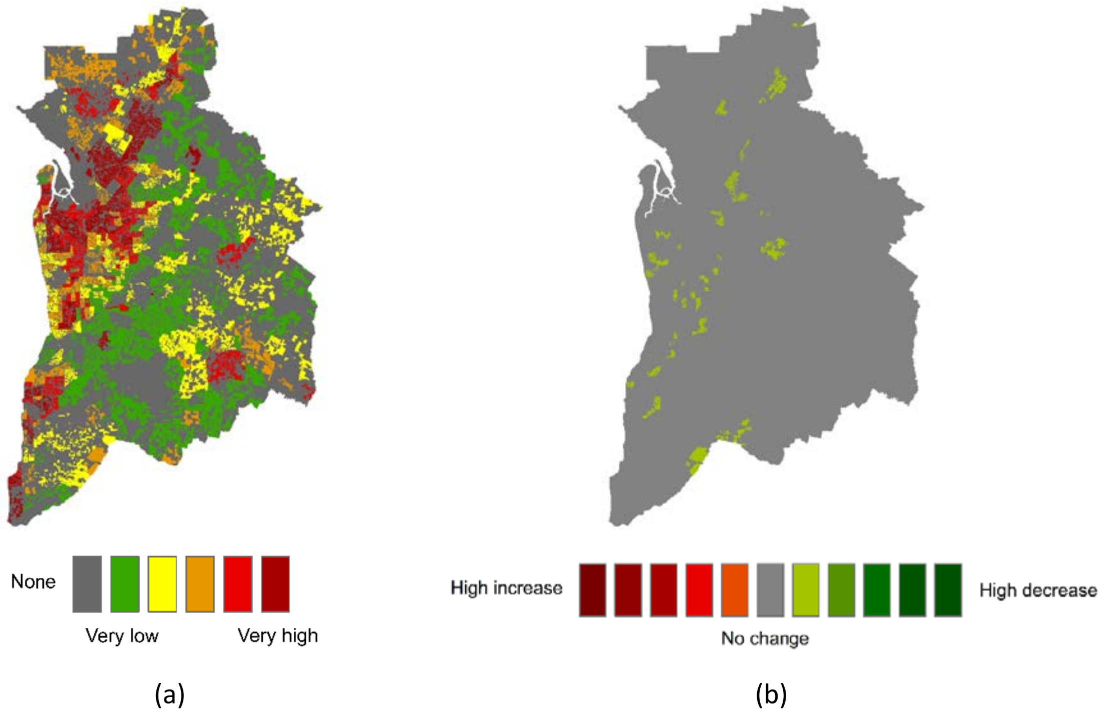


Figure 6-45 Social Vulnerability due to Level of Young People with mitigation causing a 10% decrease in Young People, shown as (a) the Vulnerability with mitigation, (b) the change in Vulnerability compared to the no mitigation case

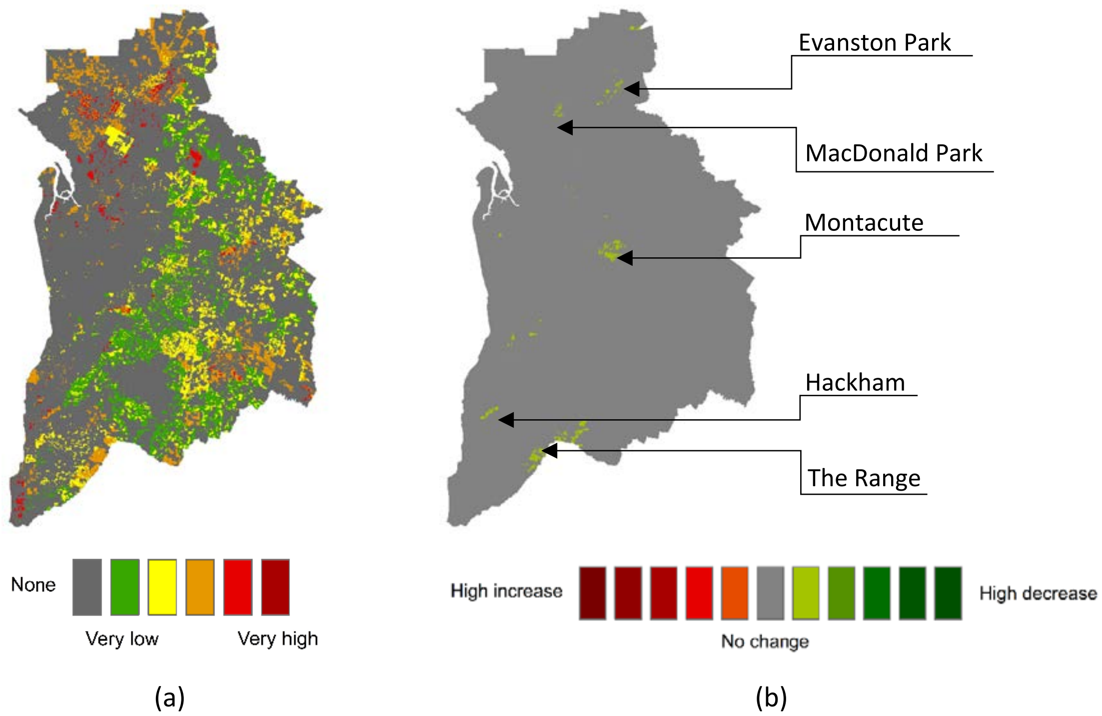
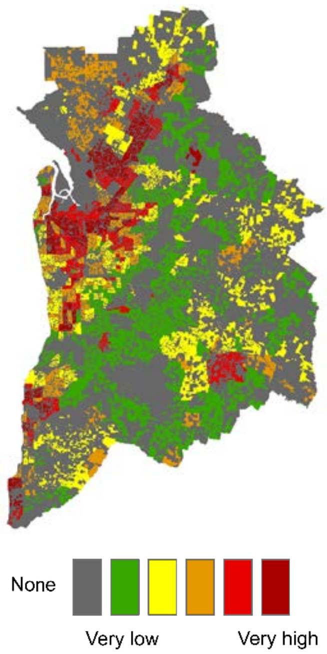


Figure 6-46 Hazard risk due to Level of Young People with mitigation causing a 10% decrease in Young People, shown as (a) the risk with mitigation, (b) the change in risk compared to the no mitigation case

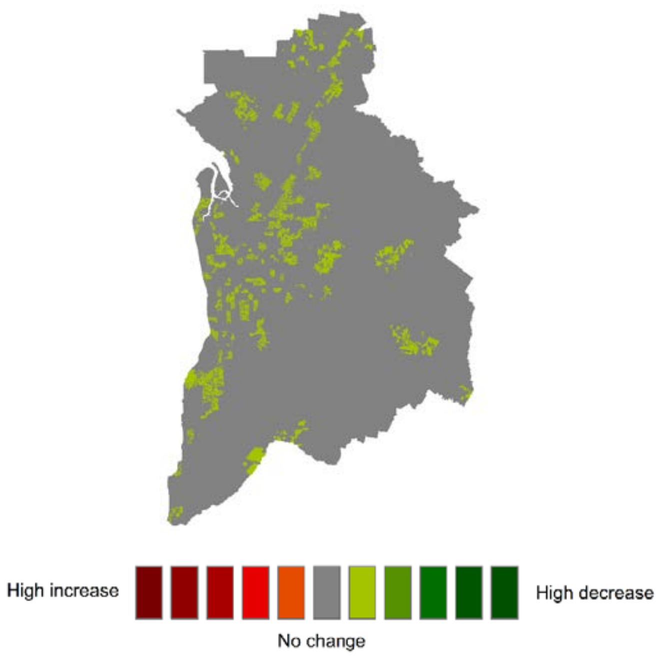
Reducing the proportion of young people (0-14 years) by 10% has a similar effect to increasing Personal Wealth by 10%. Social Vulnerability is mainly decreased in the Western and Eastern suburbs with fewer decreased in the South, North and Hills as seen in Figure 6-45 (b). However, the reduction in Social Vulnerability in the Western suburbs is not translated through to the Hazard Risk map shown in, Figure 6-46. This is due to the high suppression capability and little to no vegetation in those areas.

The Social Vulnerability and Hazard Risk in Montacute, an Adelaide Hills suburb, decreased from low to very low. It is not an area with a vulnerable population and thus decreasing the proportion of young people in this suburb would not be worthwhile. Both the Social Vulnerability and Bushfire Hazard Risk was reduced from High to Medium in Evanston Park and from Medium to Low in MacDonald Park, two Northern suburbs. The Social Vulnerability in Hackham and The Range, two Southern suburbs, was reduced from Very High to High and High to Medium, respectively, and the Hazard Risk in both suburbs were reduced from High to Medium. Therefore, it would be worthwhile implementing a policy to reduce the proportion of young people. An example of such a policy would be one that encourages young families in these areas to move to areas that have a zero Hazard Risk, i.e. the Western suburbs.

Figure 6-47 and Figure 6-48 shows the effect of increasing Level of Education, Volunteering and Personal Wealth by 10%, and decreasing Young People by 10%. The Social Vulnerability and change in Social Vulnerability compared with the no mitigation case are show in Figure 6-47 (a) and Figure 6-47 (b), respectively. The Hazard Risk and change in Hazard Risk compared with the no mitigation case are show in Figure 6-48 (a) and Figure 6-48 (b), respectively.

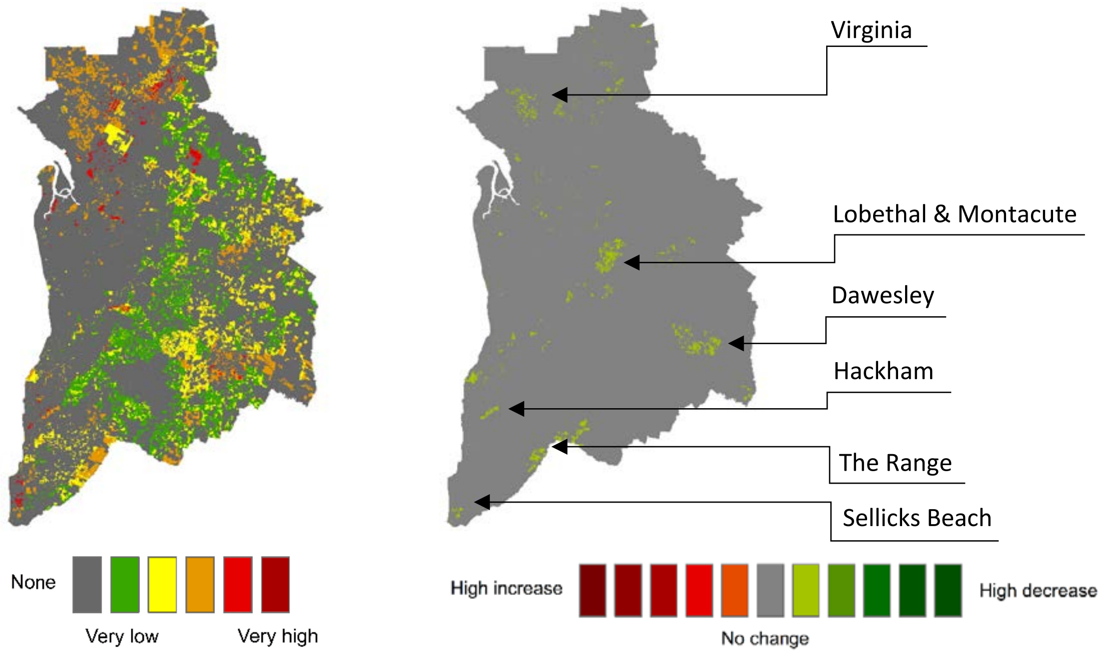


(a)



(b)

Figure 6-47 Social Vulnerability with mitigation for the 4 indicators, shown as (a) the Vulnerability with mitigation, (b) the change in Social Vulnerability compared to the no mitigation case



(a) (b)

Figure 6-48 Hazard risk with mitigation for the 4 indicators, shown as (a) the risk with mitigation, (b) the change in risk compared to the no mitigation case

When changing all four Indicators simultaneously, the Social Vulnerability and Hazard Risk are still only reduced by one risk level as seen in Figure 6-47 (b) and Figure 6-48 (b), respectively. Therefore, for the suburbs where the Hazard Risk can be reduced using a single indicator, the additional benefit of affecting change for other indicators would have to be considered, as minimal additional risk reduction is achieved. Other factors, such as cost, time, resources, and co-benefits, would play into this decision.

However, changing all four indicators has reduced the Social Vulnerability and Hazard Risk in a number or areas that were not previously effected when the indicators were changed independently. For example, the Social Vulnerability and Hazard Risk in Virginia, a Northern suburb, and Lobethal, a suburb in the Adelaide Hills, were reduced by one risk level from high to medium when all four Social Vulnerability indicators were changed. The Social Vulnerability of Sellicks Beach, a suburb in the South, was also reduced by one increment from very high to high and the Hazard Risk was reduced from high to medium, when changing all four indictors. Several other suburbs where effected when changing all four indictors, however, they were areas of low vulnerability and low risk and thus were not of significance.

Therefore, implementing polices to increase Education, Personal Wealth and the Proportion of People Volunteering and decrease the Proportion of Young People in Virginia, Lobethal, and Sellicks Beach, the Hazard Risk of vulnerable populations will decrease.

The socially vulnerable suburbs effected by the risk reduction measures imposed, as identified above, are summarised in Table 6-1. This summary table aids decision makers in identify what indicators of interest can be altered to reduce the risk in targeted areas. The areas of low Social Vulnerability and Hazard Risk which resulted in risk reductions are not included in Table 6-1, as these areas are not considered areas of interest. Table 6-1 also identifies the approximate population of the effected suburbs, which provides an approximation of the potential number of people that a risk reduction measure can influence.

Table 6-1 Summary of the socially vulnerable suburbs effected by the risk reduction measures imposed

Suburb (areas to target)	Indicator	Level of Social Vulnerability		Level of Hazard Risk		Approximate number of people effected
		No risk reduction measure	With risk reduction measure	No risk reduction measure	With risk reduction measure	
MacDonald Park	Proportion of People Volunteering	Medium	Low	Medium	Low	456
	Personal Wealth	Medium	Low	Medium	Low	
	Proportion of Young people	Medium	Low	Medium	Low	
	All four indicators	Medium	Low	Medium	Low	
Evanston Park	Proportion of people Volunteering	High	Medium	High	Medium	4003
	Personal Wealth	High	Medium	High	Medium	
	Proportion of Young people	High	Medium	High	Medium	
	All four indicators	High	Medium	High	Medium	
Hackham	Personal Wealth	Very high	High	High	Medium	4103
	Proportion of Young people	Very high	High	High	Medium	
	All four indicators	Very high	High	High	Medium	
The Range	Personal Wealth	High	Medium	High	Medium	217
	Proportion of Young people	High	Medium	High	Medium	
	All four indicators	High	Medium	High	Medium	
Virginia	All four indicators	High	Medium	High	Medium	1747
Lobethal	All four indicators	High	Medium	High	Medium	2343
Sellicks Beach	All four indicators	Very high	High	High	Medium	2337

From Table 6-1, it is clear that the Hazard Risk within MacDonald Park, Evanston Park, Hackham and The Range can be reduced by changing multiple vulnerability indicator by 10%, however, for each indictor the Social Vulnerability and Hazard Risk in each of the suburbs is reduced by the same amount. Therefore, only one indicator needs to be targeted in these suburbs to reduce their Bushfire Hazard Risk. However, Virginia, Lobethal and Sellicks Beach, require all four indicators to be changed to cause a risk reduction. Furthermore, Evanston Park and Hackham have the largest populations, and only require one indictor to be changed to cause a reduction in risk, therefore, targeting these two suburbs can potentially reduce the risk of bushfire to a large number of people using fewer resources. Compared to Virginia, Lobethal and Sellicks Beach which have fewer residents and require all four indictors of interest to be changed to yield a reduction in risk. MacDonald Park only has approximately, 456 residents and has the lowest risk compared to the other suburbs, therefore is less of a priority.

6.4.2 Mitigation options targeting Bushfire Likelihood

As previously discussed, the sensitivity analyses undertaken on Bushfire Likelihood and its components indicate that Bushfire Likelihood is most sensitive to Vegetation, Slope Degree, and Time Since Last Fire.

Vegetation type and Slope Degree are spatially explicit, but are constant over the temporal scale considered. In terms of mitigation strategies, vegetation type at a particular location may not be changed, i.e. it is infeasible to change an area with Eucalyptus Woodland vegetation to coastal vegetation. While clearing vegetation would reduce the Bushfire Likelihood to zero, this mitigation option is unreasonable for the spatial scales considered in the case study, and would be opposed by communities for environmental, aesthetic and tourism reasons. Reducing the Slope Degree in Greater Adelaide by cut and fill methods is an unreasonable mitigation option for the spatial scale. These parameters strongly influence the spatial distribution of Bushfire Likelihood, but may not be reasonably changed.

The Time Since Last Fire, however, is spatially explicit and temporally dynamic. Hence, the results of the sensitivity analysis indicate that mitigation options which directly influence the Time Since Last Fire, such as planned burning, may be beneficial in reducing Bushfire Hazard Risk in the future. The impacts of planned burning to woodland areas in 2049 are shown in Figure 6-50 to Figure 6-52. Time Since Last Fire affects the Fire Behaviour of woodland vegetation. Figure 6-49 (a) shows the time since last fire for all woodland areas in Greater Adelaide in 2050 without mitigation, while Figure 6-49 (b) shows the Time Since Last Fire for all woodland areas in Greater Adelaide with the mitigation option of a single planned burn to all woodland areas in 2049. Although this is an unrealistic strategy, it is used here to obtain an upper bound estimate of what could be achieved with prescribed burning.

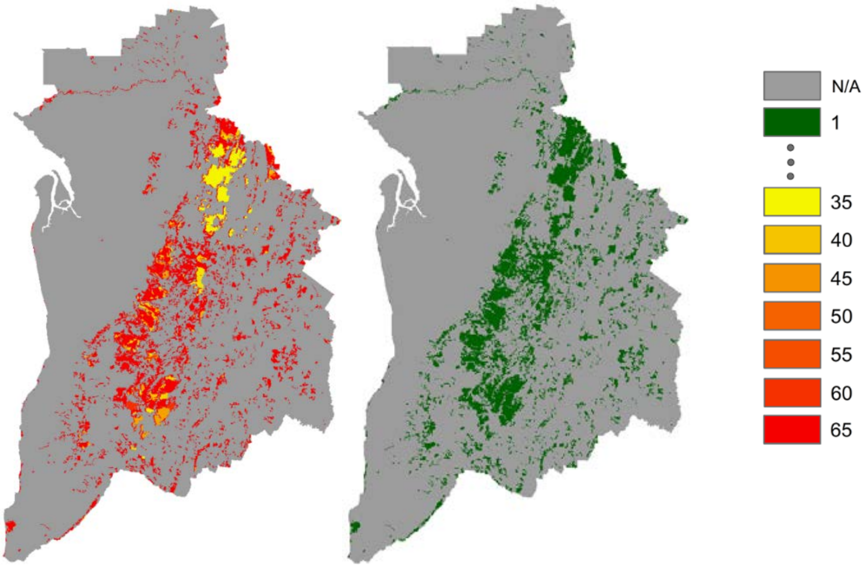


Figure 6-49 Time Since Last Fire in 2050 for all areas with woodland vegetation in Greater Adelaide in (a) without planned burning mitigation, (b) considering the mitigation option of planned burning all woodland areas in 2049.

Change maps for the three scenarios, comparing the Fire Behaviour, Hazard Likelihood, and Hazard Risk in 2050 with mitigation to the case with no mitigation in 2050, are shown in Figure 6-50, Figure 6-51, Figure 6-52, respectively.

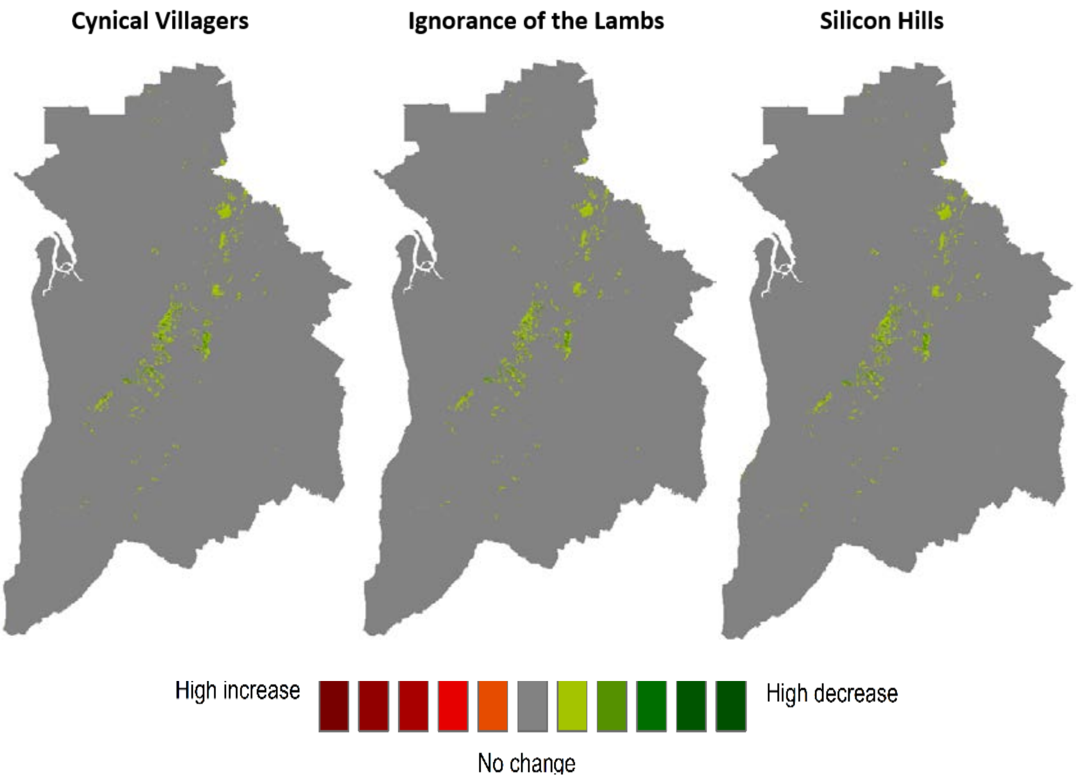


Figure 6-50 Changes in Fire Behaviour in 2050 for the (a) Cynical Villagers, (b) Ignorance of the Lambs, (c) Silicon Hills scenarios with a planned burn in 2049 where green shows a decrease, and red shows an increase, relative to the case without mitigation

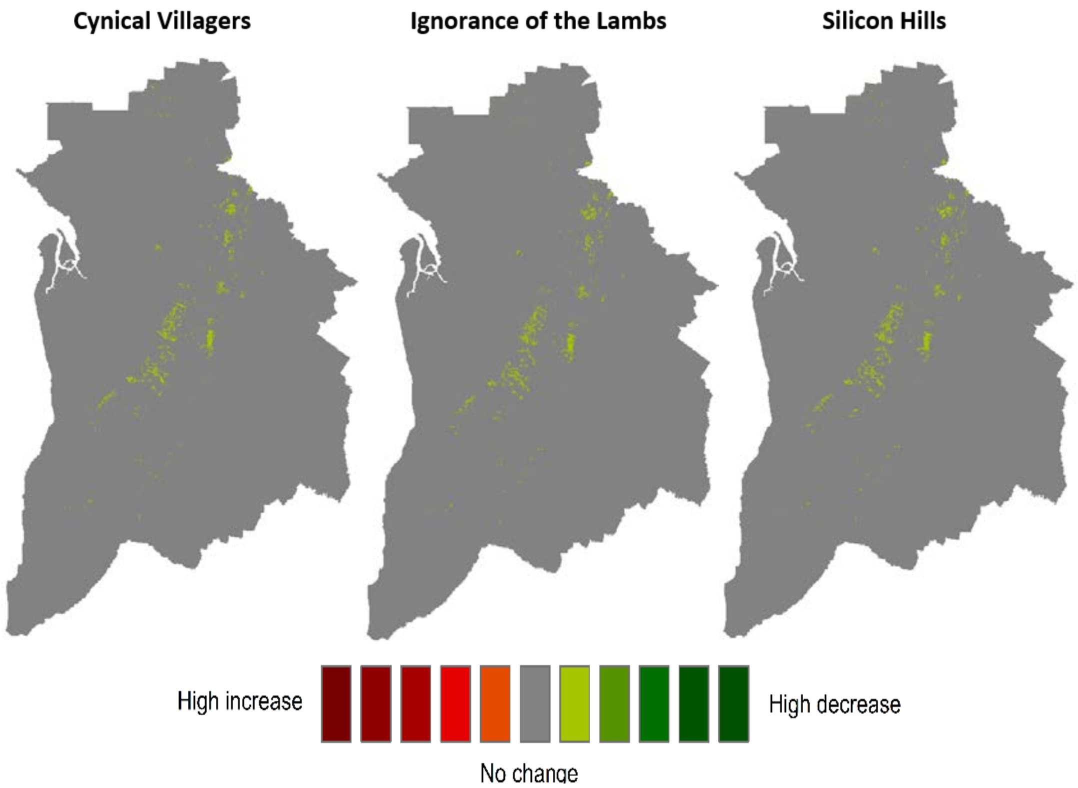


Figure 6-51 Changes in Hazard Likelihood in 2050 for the (a) Cynical Villagers, (b) Ignorance of the Lambs, (c) Silicon Hills scenarios with a planned burn in 2049 where green shows a decrease, and red shows an increase, relative to the case without mitigation

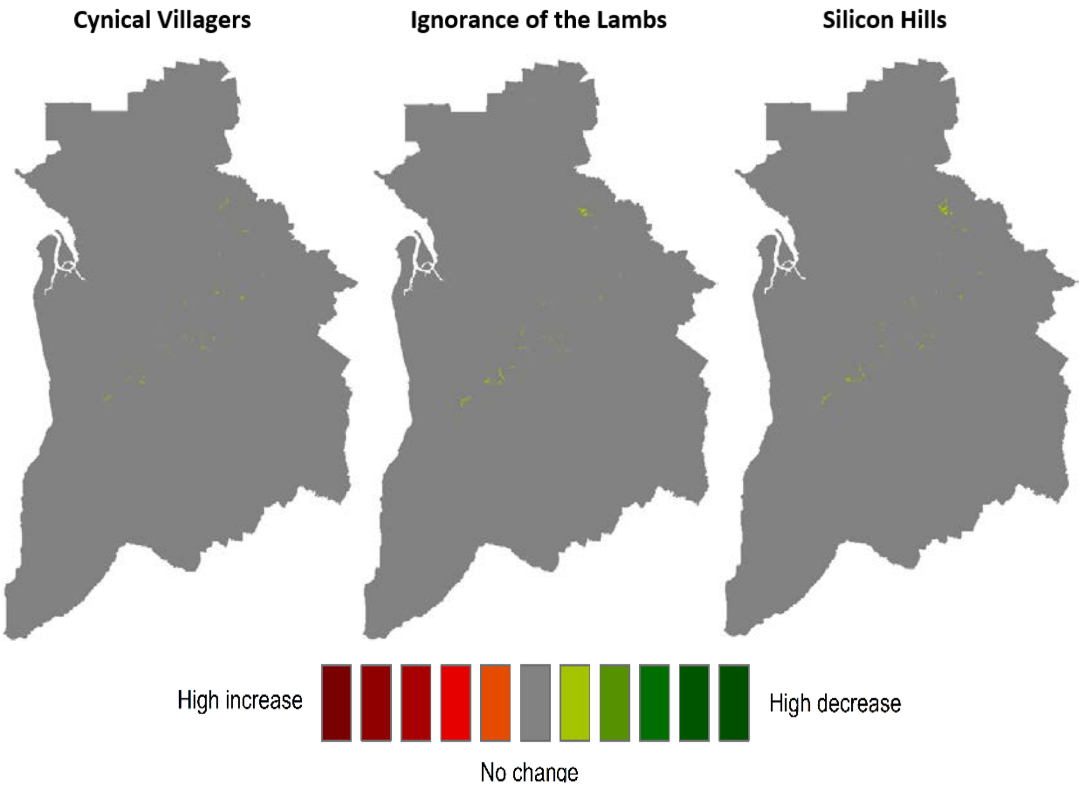


Figure 6-52 Changes in Hazard Risk in 2050 for the (a) Cynical Villagers, (b) Ignorance of the Lambs, (c) Silicon Hills scenarios with a planned burn in 2049 where green shows a decrease, and red shows an increase, relative to the case without mitigation

From Figure 6-50, this mitigation option is successful in decreasing the Fire Behaviour in a number of locations along the Mount Lofty Range by one “standardised level” for all three scenarios. Figure 6-51 shows that this reduction in Fire Behaviour results in a decrease in the Hazard Likelihood at most of the same locations by one risk level, for example from low to very low. However, the density of change is less than that for Fire Behaviour due to the influence of Ignition Potential and Suppression Capability at these locations.

Figure 6-52, however, shows that the mitigation option of planned burning all woodland areas in 2049 has little effect on Hazard Risk. This is because the majority of the woodland areas affected by the planned burning are not areas with “community” land use, and thus these locations do not have a social vulnerability associated with them. Hence, when Hazard Likelihood is combined with Social Vulnerability at these locations, the risk is considered to be zero.

This is an intuitive result, as it is not reasonable to plan burn residential properties, and thus, this result highlights the importance of selecting mitigation options which influences Hazard Likelihood in a manner that is applicable to “community” land use areas.

7 LIMITATIONS

The limitations of the framework primarily arise during its application to the case study. The following sections outline the limitations associated with components of the framework when applied to the case study.

7.1 Social Vulnerability

The Social Vulnerability Model calculates the vulnerability for Greater Adelaide. This application uses vulnerability indicators that are more applicable to Western countries. This is acceptable for the case study as it demonstrates how the framework can be tailored to different locations. Equal weightings are applied to each vulnerability indicator in calculating Social Vulnerability, however stakeholder input might suggest that some indicators of vulnerability are more influential than others. This would imply that the weightings should not be equal, thus limiting the current assessment of Social Vulnerability. Furthermore, the Social Vulnerability Model uses percentiles to assess relative Social Vulnerability rather than absolute Social Vulnerability. The absolute and relative risks have different applications and meaning to a decision maker; in some cases, the relatively higher vulnerability areas may be of more interest than only areas that meet a certain threshold of vulnerability. It is unknown how sensitive the results are to these assumptions, which constitutes a limitation of the results.

7.2 Hazard Likelihood

The Hazard Likelihood Model does not account for the rate of spread of a bushfire between cells. The rate of spread is calculated, but the direction and flow is not considered for a greater distance than 100m. The literature, however, highlights the importance of considering the rate of spread as a component of understanding bushfire behaviour and resultant risk (Beer 1991; Cruz et al. 2015). The Hazard Likelihood Model, therefore, is limited in its assessment of bushfire risk as it considers the likelihood of a fire occurring in each cell in isolation and does not distinguish between whether a fire originated or spread to that area.

Additionally, a sensitivity analysis to assess the influence of how uncertainty in the Hazard Likelihood Model input data effects the results, of has not been undertaken. Environmental data is subject to natural variability and the data may be influenced by biased measurements or imprecision, which creates uncertainty in the inputs. The effect of these data on the model outputs should be investigated. Furthermore, projections of this data in line with RCP trends is also subject to local uncertainty.

7.3 Hazard Risk

Objective 2, to apply the framework to a case study of Bushfire Hazard Risk in Greater Adelaide, is limited by the ability of the model to adequately reflect reality. The Hazard Likelihood and Social Vulnerability Models are idealised models used to describe complex natural processes and anthropogenic characteristics.

Throughout the framework, in the assessing of the components of Hazard Risk, 5 intervals have been used to scale components from Very Low to Very High. By increasing the number of intervals used, better resolution could be achieved to identify the most at risk areas.

Expert knowledge and judgement inform many aspects of the case study. In addition to the previously discussed weighting of indicators in the Social Vulnerability assessment, other decisions can reflect the decision makers' or experts' opinions. Examples of these decisions include: the customisation of the Hazard Risk Matrix in Figure 4-2; the weighting of Ignition Potential, Suppression Capability and Fire Behaviour; the Ignition Potential conversion tables; the choice of bounds that are absolute rather than relative for Social Vulnerability indicators and other standardising tables. The conceptual framework facilitates these decisions to be made, and allows for customisation of the framework to suit the decision maker.

Furthermore, the case study has only considered a single hazard in the assessment of Hazard Risk. To develop more informed planning and mitigation strategies that reduce the risk of socially vulnerable populations to natural hazards, multiple hazards should be considered.

7.4 Mitigation Strategies

The assessment of the impact of mitigation strategies targeted to Social Vulnerability is limited. Mitigation strategies appropriate for Social Vulnerability take the form of policies and community resilience. Whilst the nature of exploratory scenarios is not policy driven, there are inevitably situations which could only be achieved through policy decisions. For example, a future in which there are zero carbon emissions will rely on policy incentives to achieve this, hence only policy which is in line with this agenda can make sense when combined with the scenario. This creates a circular relationship between social mitigation strategy implementation and the future projections. To avoid this, the mitigation strategies related to Social Vulnerability were tested independently from the socio-economic projections. Hence, the influence of mitigation targeted to Social Vulnerability was not assessed for the Hazard Risk in 2050. When applying the generic framework, this interaction of policy and scenarios must be considered.

8 POTENTIAL FOR FUTURE RESEARCH

Due to the nature of the conceptual framework, there are several opportunities for refinement and for widening the application domain. Several components of the framework are in a developing stage, and would benefit from additional research to refine the methodology and explore new areas of innovation.

8.1 Social Vulnerability

The implementation of the Social Vulnerability would benefit from input by experts to identify the importance and relevance of each indicator. Furthermore, a sensitivity analysis can be undertaken to assess the influence of assigning weights to each indicator on the overall Social Vulnerability.

8.2 Hazard Likelihood

To account for the rate of spread in the Hazard Likelihood Model, the Hazard Likelihood Model can be coupled with a more detailed Fire Behaviour Model which considers the rate of spread. Furthermore, a sensitivity analysis can be used to understand the effect of the uncertainty in the Hazard Likelihood Model input data on the results.

8.3 Hazard Risk

To achieve a better resolution of Hazard Risk across Greater Adelaide, or any region under analysis, the risk matrix within the framework can be defined with more than 5 discrete intervals to measure Hazard Likelihood and Social Vulnerability.

8.4 Multi-Hazard Conceptual Framework

The literature review also revealed that few multi-hazard assessments have been carried out. An extension of the framework could include incorporating multiple hazards, and assessing if and how cost saving measures can be made through mitigation. A key interest in this area would be looking at Social Vulnerability and how vulnerable areas that are susceptible to multiple hazards can be put at lower risk.

8.5 Mitigation Strategies

This research demonstrated how mitigation can be informed by the sensitivity analyses and implemented into the Hazard Risk Model. Changes in the Hazard Risk due to mitigation have been discussed, however a development of the methodology could be made to rank and compare mitigation strategies. This would require creating a method to quantify the total benefit of a mitigation strategy.

Also, further consultation is required to assess the plausibility of mitigation strategies, especially in relation to policies that can affect social vulnerability.

The literature review also uncovered that little work had been done to implement and assess adaptive mitigation strategies. The creation of a methodology to assess adaptive mitigation strategies would increase the usefulness of the framework as a decision making tool. This would require being able to rank strategies, determine turning points at which strategies need to be changed, and allowing for feedback to the model that would be used to decide between changing or continuing a mitigation strategy. The exploratory scenario approach, which is already incorporated in the framework, will assist in the integration of adaptive mitigation.

9 CONCLUSION AND RECOMMENDATIONS

To assist in improving decisions regarding mitigation for natural hazards, tools to inform and evaluate these decisions are required. As set out to achieve in Objective 1, the conceptual framework presents a method to breakdown and understand natural hazard risk. The framework incorporates hazard, exposure, and vulnerability to evaluate current risk, and employs an exploratory scenario approach to evaluate future risk. The conceptual framework details a methodology for understanding the drivers of Hazard Risk using sensitivity analyses, and uses the identified drivers to inform targeted and practical mitigation options for long term planning. The incorporation of mitigation feedback loops into the Hazard Risk Models enables the impact of applying mitigation options on reducing Hazard Risk to be observed.

The second objective demonstrated how the conceptual framework could be tailored to a specific hazard and location through the case study application to Greater Adelaide. The case study was used to develop an understanding of the influence of Social Vulnerability on Hazard Risk by considering a bushfire hazard, with the aim of developing an understanding of the drivers of Hazard Risk. The case study results showed an understanding of the current and dynamic nature of Hazard Risk. Investigating the dynamic nature of the components informed an understanding of how to approach evaluating the future risk for 2050. The future risk was explored using three socio-economic scenarios for Greater Adelaide, all which indicated that the Hazard Risk is altered for Greater Adelaide in 2050.

A trial of planned burning mitigation showed that little impact was imparted on the Hazard Risk. This was due to the almost mutual exclusivity of eucalyptus woodland areas and community land use types. Although there was an improvement in Hazard Likelihood due to the strategy, it did not impact any areas with Social Vulnerability, therefore the mitigation option did not significantly reduce Hazard Risk. By contrast, co-benefit social policies that positively impacted Social Vulnerability indicators had a positive effect in reducing Hazard Risk. The mitigation and co-benefit strategies need refining, and consultation with industry would allow for more targeted approaches. However, these trials have demonstrated how mitigation options can be assessed using the conceptual framework.

In future applications, closer consultation with industry, experts, and decision makers will enable a more comprehensive implementation of the Hazard Risk Model. Given its ability to be tailored to a particular geographical location, hazard, and decision maker’s priorities, each application of the framework will yield different results. At the centre of each application, however, will be a deepened and more fluent understanding of the drivers of natural hazard risk, and how these can be harnessed to improve the approach to natural hazard risk reduction.

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APPENDIX A – BUSHFIRE MODEL CODE

Bushfire Hazard Risk Model Main Code

```
clear all       % clears variables
clc             % clears command window
clf             % clears figure
```

F17W37 HONOURS 2017 BUSHFIRE HAZARD RISK MODEL

This program will determine risk to natural disasters varying in both spatial and temporal dimensions

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Constant Maps Input

```
ExploratoryScenarios % Calculates and imports data about Exploratory Scenarios that does not
need re-calculation in each loop
% INPUT STATIC MAP AND CLIMATE DATA
InputConstantMaps
% figure
% imagesc(AdelInOut)
```

Bushfire Model Loops for each cell at time t

```
for YearNum = [2015 2050]% 2020 250] % 2020 2050];  % This will need to be changed after more
input files are created
    YearNum;
    for rcp = [45]
        rcp;
        % INPUT DYNAMIC MAP AND CLIMATE DATA
        [RH,T90,Tminwin,TSLF]=InputMaps(YearNum,rcp,nrow,ncol,TSLF_0);
    if YearNum == 2015
        for ScenNum = [1 2 4]
            % Annual Time Loop to update LU map and climate inputs
            Scenario_name= Scenario(ScenNum);

            % Create "field" name to save structured matrices
            if YearNum == 2015
                field = 'GA2015';
            elseif YearNum == 2050
                if ScenNum == 1
                    field = 'CynicalVillagers';
                elseif ScenNum == 2
                    field = 'IgnorangeoftheLambs';
                elseif ScenNum == 3
                    field = 'InternetofRisk';
                elseif ScenNum == 4
                    field = 'SiliconHills';
                elseif ScenNum == 5
```

```
                field = 'AppetiteforChange';
            end
        end

        % INPUTS
        % Input LU map for current scenario and current year
        % inputs: Scenario, ScenNum, YearNum, LUtype, nLUtype
        % outputs; LU
         LU = InputLUMaps(Scenario,ScenNum,YearNum,nLUtype,LUTypeLabels,LUtype);

        % IGNITION POTENTIAL
        % inputs: LU, V
        % outputs are: IP (standardised)
        IgPotStd = IgnitionPotential(LU,V,nrow,ncol,AdelInOut);
        for r = 1:1000
            for c = 1:630
                if AdelInOut(r,c) == 0
                    IgPotStd(r,c) = -1;
                end
            end
        end
        IgPotStd_struct.(field).(strcat('rcp',num2str(rcp))) = IgPotStd; % used as input
to MCK
        filename = strcat('Ignition Potential',{' '},num2str(YearNum),'.asc');
        fid = fopen(char(filename),'wt');
        fprintf(fid,'%s','ncols');
        fprintf(fid,'  %s\n','630');
        fprintf(fid,'%s','nrows');
        fprintf(fid,' %s\n','1000');
        fprintf(fid,'%s','xllcorner');
        fprintf(fid,' %s\n','1310000');
        fprintf(fid,'%s','yllcorner');
        fprintf(fid,' %s\n','1620000');
        fprintf(fid,'%s','cellsize');
        fprintf(fid,' %s\n','100');
        fprintf(fid,'%s','NODATA_value');
        fprintf(fid,' %s\n','-1');
        fclose(fid);
        dlmwrite(char(filename),IgPotStd,'delimiter',' ','newline','pc','-append');


        % SUPPRESSION CAPABILITY
        % inputs: SC
        % outputs: SC (standardised)
        SCStd= SuppressionCapability(SC,nrow,ncol,AdelInOut,V);
        filename = strcat('Suppresion Capability',{' '},num2str(YearNum),'.asc');
        fid = fopen(char(filename),'wt');
        fprintf(fid,'%s','ncols');
        fprintf(fid,'  %s\n','630');
        fprintf(fid,'%s','nrows');
        fprintf(fid,' %s\n','1000');
        fprintf(fid,'%s','xllcorner');
        fprintf(fid,' %s\n','1310000');
        fprintf(fid,'%s','yllcorner');
        fprintf(fid,' %s\n','1620000');
        fprintf(fid,'%s','cellsize');
        fprintf(fid,' %s\n','100');
        fprintf(fid,'%s','NODATA_value');
```

```
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),SCStd,'delimiter',' ','newline','pc','-append');

            % FIRE BEHAVIOUR
            %inputs: LU, V, RH, U10, Tminwin, CureDeg, SlopeDeg, T90, TSLF
            % outputs: FBehav (standardised)
            FBehavStd =
Firebehaviour(CuringD,T90,RH,U10,Tminwin,V,LU,SlopeD,TSLF,nrow,ncol,AdelInOut);
            for r = 1:1000
                for c = 1:630
                    if AdelInOut(r,c) == 0
                        FBehavStd(r,c) = -1;
                    end
                end
            end
            FBehavStd_struct.(field).(strcat('rcp',num2str(rcp))) = FBehavStd; %used as input
to MCK
            filename = strcat('Fire Behaviour',{' '},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),FBehavStd,'delimiter',' ','newline','pc','-append');

            % HAZARD LIKELIHOOD
            % inputs: standardised IP, SC, FBehav
            % outputs: standardised Hazard Likelihood
            HazLikeStd = HazardLikelihood(IgPotStd,SCStd,FBehavStd,LU,nrow,ncol);
            for r = 1:1000
                for c = 1:630
                    if AdelInOut(r,c) == 0
                        HazLikeStd(r,c) = -1;
                    end
                end
            end
            HazLikeStd_struct.(field).(strcat('rcp',num2str(rcp))) = HazLikeStd; %used as
input to MCK
            filename = strcat('Hazard Likelihood',{' '},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
```

```
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),HazLikeStd,'delimiter',' ','newline','pc','-append');

            % Hazard Consequence
            HazConsStd = Vulnerability(LU,nrow,ncol,YearNum,ScenNum);

            for r = 1:1000
                for c = 1:630
                    if AdelInOut(r,c) == 1
                        if LU(r,c) == 2 || LU(r,c) == 3 || LU(r,c) == 4 || LU(r,c) == 5 ||
LU(r,c) == 7  % only areas where people are present are vulnerable
                            HazConsStd(r,c) = HazConsStd(r,c);
                        else
                            HazConsStd(r,c) = 0;
                        end
                    elseif AdelInOut(r,c) == 0 % out of Greater Adelaide
                        HazConsStd(r,c) = -1;
                    else
                        HazConsStd(r,c) = 0;
                    end
                end
            end
            HazConsStd_struct.(field) = HazConsStd;
            filename = strcat('Hazard Consequence',{' '},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),HazConsStd,'delimiter',' ','newline','pc','-append');

            % HAZARD RISK

            HazRiskMatrix = HazardRisk(AdelInOut,LU,HazLikeStd,YearNum,nrow,ncol,HazConsStd);

            HazRisk_struct.(field).(strcat('rcp',num2str(rcp))) = HazRiskMatrix;

            filename = strcat('Hazard Risk',{' '},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
```

```
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),HazRiskMatrix,'delimiter',' ','newline','pc','-append');

        end
    elseif YearNum == 2050
        for ScenNum = 1:5
            % Annual Time Loop to update LU map and climate inputs
            Scenario_name= Scenario(ScenNum);

            % Create "field" name to save structured matrices
            if YearNum == 2015
                field = 'GA2015';
            elseif YearNum == 2050
                if ScenNum == 1
                    field = 'CynicalVillagers';
                elseif ScenNum == 2
                    field = 'IgnorangeoftheLambs';
                elseif ScenNum == 3
                    field = 'InternetofRisk';
                elseif ScenNum == 4
                    field = 'SiliconHills';
                elseif ScenNum == 5
                    field = 'AppetiteforChange';
                end
            end

            % INPUTS
            % Input LU map for current scenario and current year
            % inputs: Scenario, ScenNum, YearNum, LUtype, nLUtype
            % outputs; LU
             LU = InputLUMaps(Scenario,ScenNum,YearNum,nLUtype,LUTypeLabels,LUtype);

            % IGNITION POTENTIAL
            % inputs: LU, V
            % outputs are: IP (standardised)
            IgPotStd = IgnitionPotential(LU,V,nrow,ncol,AdelInOut);
            for r = 1:1000
                for c = 1:630
                    if AdelInOut(r,c) == 0
                        IgPotStd(r,c) = -1;
                    end
                end
            end
            IgPotStd_struct.(field).(strcat('rcp',num2str(rcp))) = IgPotStd; % used as input
to MCK
            filename = strcat('Ignition Potential',{' '},char(Scenario_name),{'
'},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
```

```
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),IgPotStd,'delimiter',' ','newline','pc','-append');


            % SUPPRESSION CAPABILITY
            % inputs: SC
            % outputs: SC (standardised)
            SCStd= SuppressionCapability(SC,nrow,ncol,AdelInOut,V);

            % FIRE BEHAVIOUR
            %inputs: LU, V, RH, U10, Tminwin, CureDeg, SlopeDeg, T90, TSLF
            % outputs: FBehav (standardised)
            FBehavStd =
Firebehaviour(CuringD,T90,RH,U10,Tminwin,V,LU,SlopeD,TSLF,nrow,ncol,AdelInOut);
            for r = 1:1000
                for c = 1:630
                    if AdelInOut(r,c) == 0
                        FBehavStd(r,c) = -1;
                    end
                end
            end
            FBehavStd_struct.(field).(strcat('rcp',num2str(rcp))) = FBehavStd; %used as input
to MCK
            filename = strcat('Fire Behaviour',{' '},char(Scenario_name),{'
'},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),FBehavStd,'delimiter',' ','newline','pc','-append');

            % HAZARD LIKELIHOOD
            % inputs: standardised IP, SC, FBehav
            % outputs: standardised Hazard Likelihood
            HazLikeStd = HazardLikelihood(IgPotStd,SCStd,FBehavStd,LU,nrow,ncol);
            for r = 1:1000
                for c = 1:630
                    if AdelInOut(r,c) == 0
                        HazLikeStd(r,c) = -1;
                    end
```

```
                end
            end
            HazLikeStd_struct.(field).(strcat('rcp',num2str(rcp))) = HazLikeStd; %used as
input to MCK
            filename = strcat('Hazard Likelihood',{' '},char(Scenario_name),{'
'},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),HazLikeStd,'delimiter',' ','newline','pc','-append');

            % Hazard Consequence
            HazConsStd = Vulnerability(LU,nrow,ncol,YearNum,ScenNum);

            for r = 1:1000
                for c = 1:630
                    if AdelInOut(r,c) == 1
                        if LU(r,c) == 2 || LU(r,c) == 3 || LU(r,c) == 4 || LU(r,c) == 5 ||
LU(r,c) == 7  % only areas where people are present are vulnerable
                            HazConsStd(r,c) = HazConsStd(r,c);
                        else
                            HazConsStd(r,c) = 0;
                        end
                    elseif AdelInOut(r,c) == 0 % out of Greater Adelaide
                        HazConsStd(r,c) = -1;
                    else
                        HazConsStd(r,c) = 0;
                    end
                end
            end
            HazConsStd_struct.(field) = HazConsStd;
            filename = strcat('Hazard Consequence',{' '},char(Scenario_name),{'
'},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
```

```
            dlmwrite(char(filename),HazConsStd,'delimiter',' ','newline','pc','-append');

            % HAZARD RISK

            HazRiskMatrix = HazardRisk(AdelInOut,LU,HazLikeStd,YearNum,nrow,ncol,HazConsStd);

            HazRisk_struct.(field).(strcat('rcp',num2str(rcp))) = HazRiskMatrix;

            filename = strcat('Hazard Risk',{' '},char(Scenario_name),{'
'},num2str(YearNum),'.asc');
            fid = fopen(char(filename),'wt');
            fprintf(fid,'%s','ncols');
            fprintf(fid,'  %s\n','630');
            fprintf(fid,'%s','nrows');
            fprintf(fid,' %s\n','1000');
            fprintf(fid,'%s','xllcorner');
            fprintf(fid,' %s\n','1310000');
            fprintf(fid,'%s','yllcorner');
            fprintf(fid,' %s\n','1620000');
            fprintf(fid,'%s','cellsize');
            fprintf(fid,' %s\n','100');
            fprintf(fid,'%s','NODATA_value');
            fprintf(fid,' %s\n','-1');
            fclose(fid);
            dlmwrite(char(filename),HazRiskMatrix,'delimiter',' ','newline','pc','-append');
        end
    end

    end
end
```

Map Comparison

save map comparisons for each variable, and for each socio-economic and climate scenario

```
for ScenNum = [1 2 4]
    for rcp = [45]
        if ScenNum == 1
            field = 'CynicalVillagers';
            f2 = 'Cynical Villagers';
        elseif ScenNum == 2
            field = 'IgnorangeoftheLambs';
            f2 = 'Ignorance of the Lambs';
        elseif ScenNum == 3
            field = 'InternetofRisk';
            f2 = 'Internet of Risk';
        elseif ScenNum == 4
            field = 'SiliconHills';
            f2 = 'Silicon Hills';
        elseif ScenNum == 5
            field = 'AppetiteforChange';
            f2 = 'Appetite for Change';
        end

        % Hazard Risk
```

```
        f1 = 'Hazard Risk';

MapComparison(f1,HazRisk_struct.(field).(strcat('rcp',num2str(rcp))),f2,HazRisk_struct.GA2015
.(strcat('rcp',num2str(rcp))),AdelInOut);
        % Hazard Likelihood
        f1 = 'Hazard Likelihood';

MapComparison(f1,HazLikeStd_struct.(field).(strcat('rcp',num2str(rcp))),f2,HazLikeStd_struct.
GA2015.(strcat('rcp',num2str(rcp))),AdelInOut);
        % Hazard Consequence
        f1 = 'Hazard Consequence';
        MapComparison(f1,HazConsStd_struct.(field),f2,HazConsStd_struct.GA2015,AdelInOut);
        % Ignition Potential
        f1 = 'Ignition Potential';

MapComparison(f1,IgPotStd_struct.(field).(strcat('rcp',num2str(rcp))),f2,IgPotStd_struct.GA20
15.(strcat('rcp',num2str(rcp))),AdelInOut);
        % Fire Behaviour
        f1 = 'Fire Behaviour';

MapComparison(f1,FBehavStd_struct.(field).(strcat('rcp',num2str(rcp))),f2,FBehavStd_struct.GA
2015.(strcat('rcp',num2str(rcp))),AdelInOut);

    end
end
```

Ignition Potential Function

calculates the ignition potential based on the land use and vegetation %

```
function [IgPotStd] = IgnitionPotential(LU,V,nrow,ncol,AdelInOut)
```

Convert land use map to ignition potential due to land use using a conversion table (hardcoded)

```
LUtoIPconv = [1 0.006296; 2 0.001849; 3 0.001026; 4 0.001100; 5 0.002885; 6 0.001450; 7
0.002073; 8 0.001007; 9 0.000265; 10 0.000511; 11 0.000281; 12 0; 13 0; 14 0; 15 0.000304; 16
0; 17 0];

for k=1:ncol %loop along columns of LU matrix
    for j=1:nrow %loop along rows of LU matrix
        for i=1:17 % loop along rows on conversion matrix to perform "lookup function"
            if AdelInOut(j,k) == 0
                IP_LU(j,k) = 0;
            elseif V(j,k) == 0 || V(j,k) == 255
                IP_LU(j,k) = 0;
            elseif LU(j,k) == LUtoIPconv(i,1)
                IP_LU(j,k) = LUtoIPconv(i,2);%new ignition potential due to land use matrix
created
            end
        end
    end
end
% figure
% colormap(hot(30))
% imagesc(IP_LU)
```

Convert vegetation map to ignition potential due to vegetation using a conversion table (hardcoded)

```
VtoIPconv = [0 0; 1 0.001; 2 0; 3 0.0054; 4 0.0032; 5 0.0054; 6 0.0007; 255 0];

for k=1:ncol %loop along columns of LU matrix
    for j=1:nrow %loop along rows of LU matrix
        for i=1:8 % loop along rows on conversion matrix to perform "lookup function"
            if AdelInOut(j,k) == 0
                IP_V(j,k) = 0;
            elseif V(j,k) == 0 || V(j,k) == 255
                IP_V(j,k) = 0;
            elseif V(j,k) == VtoIPconv(i,1)
                IP_V(j,k) = VtoIPconv(i,2);% new ignition potential due to vegetation matrix
created
            end
        end
    end
end
% figure
```

```
% colormap(hot(30))
% imagesc(IP_V)
```

Calculate total ignition potential (IP) due to land use ignition potential (IP_LU) and vegetation ignition potential (IP_V)

```
IP = 1000 * (IP_LU + IP_V);
% figure
% colormap(hot(30))
% imagesc(IP)
```

Standardise total ignition potential using conversion table for total ignition potential

```
StdIPconv = [-1000 0 0; 0.0001 1.5 1; 1.5 3.5 2; 3.5 5.5 3; 5.5 8 4; 8 12 5];
% standardising matrix is currently hardcoded in^^^
for k=1:ncol %loop along columns of LU matrix
    for j=1:nrow %loop along rows of LU matrix
        for i=1:6 % loop along rows on conversion matrix to perform "lookup function"
            if (IP(j,k) >= StdIPconv(i,1))&&(IP(j,k) <= StdIPconv(i,2))
                IgPotStd(j,k) = StdIPconv(i,3);% Calculate standardised total ignition
potential
            end
        end
    end
end
% figure
% colormap(hot(30))
% imagesc(IgPotStd)
```

Fire Behaviour Function

calculates the fire behaviour

```
function [FBehavStd] =
Firebehaviour(CuringD,T90,RH,U10,Tminwin,V,LU,SlopeD,TSLF,nrow,ncol,AdelInOut)
```

Grass

GRASS 1. Curing Coefficient [when CuringD = 100%, CureCoeff = 1]

```
for k=1:ncol % loop along columns of CuringD matrix
    for j=1:nrow % loop along rows of CuringD matrix
        CureCoeff(j,k)=(1.036/(1+103.99*exp(-0.0996*(CuringD(j,k)-20)))); % calculating the
curing coefficient
    end
end

%  GRASS 2. Dead Fuel Moisture Content of grassland at t=0 [f(T90,RH)]
```

```
for k=1:ncol % loop along columns of T90 matrix and RH matrix
    for j=1:nrow % loop along rows of T90 matrix and RH matrix
        DFMCgrass(j,k) = 9.58 - 0.205*T90(j,k) + 0.138*RH(j,k);
    end
end

%  GRASS 3. Fuel Moisture Coefficient [FMC = dep on DFMC and U10, using if statement]
for k=1:ncol % loop along columns of DFMCg matrix and U10 matrix
    for j=1:nrow % loop along rows of DFMCg matrix and U10 matrix
        if (DFMCgrass(j,k)>=12) && (U10(j,k)<10)        % if DFMCg >= 12% and U10 < 10km/h
            FMC(j,k)=0.684-0.0342*DFMCgrass(j,k);
        elseif (DFMCgrass(j,k)>=12) && (U10(j,k)>=10)  % if DFMCg >= 12% and U10 >= 10km/h
            FMC(j,k)=0.547-0.0228*DFMCgrass(j,k);
        else                                        % if DFMCg < 12%
            FMC(j,k)=exp(-0.108*(9.58 - 0.205*T90(j,k) + 0.138*RH(j,k)));
        end
    end
end

%  GRASS 4. check if cell grazed or ungrazed
%convert Landuse to grass type conversion table below
LUtoGTconv = [0 1; 1 1; 2 2; 3 2; 4 2; 5 2; 6 2; 7 2; 8 2; 9 2; 10 2; 11 2; 12 2; 13 2; 14 2;
15 1; 16 1]; % checking if LU type is grazed or ungrazed
            % 1 => ungrazed
            % 2 => grazed

for k=1:ncol % loop along columns of LU matrix
    for j=1:nrow % loop along rows of LU matrix
         if(V(j,k)==6)    %First check Vegetation layer to identify which cells are grassland
             for i=1:16 % loop along rows of conversion matrix to perform 'lookup function'
                if(LU(j,k)== LUtoGTconv(i,1)) %Then check the grassland cells in the LU model
to identify if it is grazed(2) or ungrazed(1)
                    GT(j,k)= LUtoGTconv(i,2); % check whether cell is grazed or ungrazed
based on LU type
                end
             end
         else
             GT(j,k) = 0;
         end
    end
end

% GRASS 5. Rate of Spread
for k=1:ncol % loop along cloumns of U10 matrix
    for j=1:nrow % loop along rows of U10 matrix
       %---ROS for ungrazed grassland---%
       if(GT(j,k)==1) && (U10(j,k)<5)
           ROSgrass(j,k)=(0.054+0.269*U10(j,k))*FMC(j,k)*CureCoeff(j,k);
       elseif(GT(j,k)==1) && (U10(j,k)>=5)
           ROSgrass(j,k)=(1.4+0.838*(U10(j,k)-5)^0.844)*FMC(j,k)*CureCoeff(j,k);
       %---ROS for grazed grassland---%
       elseif(GT(j,k)==2) && (U10(j,k)<5)
           ROSgrass(j,k)=(0.054+0.209*U10(j,k))*FMC(j,k)*CureCoeff(j,k);
       elseif(GT(j,k)==2) && (U10(j,k)>=5)
           ROSgrass(j,k)=(1.1+0.715*(U10(j,k)-5)^0.844)*FMC(j,k)*CureCoeff(j,k);
       else
           ROSgrass(j,k)=0;
       end
```

```
    end
end

% GRASS 6. Rate of Spread for the grassland adapted for the slope of the location
for k=1:ncol % loop along cloumns of U10 matrix
    for j=1:nrow % loop along rows of U10 matrix
        ROSDeg(j,k)=ROSgrass(j,k)*exp(0.069*SlopeD(j,k));
    end
end

% GRASS 7. Grassland Fire Behaviour
for k=1:ncol % loop along cloumns of LU matrix
    for j=1:nrow % loop along rows of LU matrix
        FBehavgrass(j,k)=1550*ROSDeg(j,k);
    end
end
```

Woodland

```
for k=1:ncol % loop along columns of T90 matrix and RH matrix
    for j=1:nrow % loop along rows of T90 matrix and RH matrix
% WOOD 1. Dead Fuel Moisture Content of Woodland [f(RH,T90)]
        DFMCwood(j,k)=5.658+0.04651*RH(j,k)+((0.0003151*RH(j,k)^3)/T90(j,k))-
0.184*T90(j,k)^0.77;

% WOOD 2. Forest Fire Danger Index for Woodland [FFDI=(DFMCwood, U10)] -
% with drought factor assumed 10
        FFDI(j,k)=337.8*DFMCwood(j,k)^(-2.1)*exp(0.0234*U10(j,k));

% WOOD 3. Wood Fuel Load
% The fuel load (t/ha) for eucalyptus woodland
%inputs to FuelEW
    % A =(TSLF-30)>= 0
        if ((TSLF(j,k)-30)>= 0)
           A(j,k)= TSLF(j,k)-30;
        else
           A(j,k)=0;
        end
    %B = (TSLF-31)>=0
        if ((TSLF(j,k)-31)>= 0)
           B(j,k)= TSLF(j,k)-31;
        else
           B(j,k)=0;
        end
    %C = (Tminwin-6.44014)>=0
        if ((Tminwin(j,k)-6.44014)>= 0)
           C(j,k)= Tminwin(j,k)-6.44014;
        else
           C(j,k)=0;
        end
    %D = (31-TSLF)>=0
        if((31-TSLF(j,k))>=0)
           D(j,k)=31-TSLF(j,k);
        else
           D(j,k)=0;
        end
```

```
    %E = (Tminwin-4.81713)>=0
        if ((Tminwin(j,k)-4.81713)>= 0)
           E(j,k)= Tminwin(j,k)-4.81713;
        else
           E(j,k)=0;
        end
    % Where FuelEW = 7.3566465+6.7698529*A-7.0113239*B+3.7082631*C-0.0888925*D*E

    % Wood Fuel Load Calculation
    if(TSLF(j,k)==0);
       Fuel(j,k)=0;
    elseif (V(j,k)==1);             % The fuel load (t/ha) for eucalyptus woodland
       Fuel(j,k)=7.3566465+6.7698529*A(j,k)-7.0113239*B(j,k)+3.7082631*C(j,k)-
0.0888925*D(j,k)*E(j,k);
    elseif(V(j,k)==2 || V(j,k)==3 || V(j,k)==4 || V(j,k)==5); % The fuel load (t/ha) for
woodland
       Fuel(j,k)=2.192*log(TSLF(j,k))+3.6;
    else
       Fuel(j,k)=0;
    end

% WOOD 4. Rate of Spread
            ROSwood(j,k) = 0.0012*FFDI(j,k)*Fuel(j,k);

% WOOD 5. Rate of Spread for the woodland adapted for the slope of the location
            ROSwoodDeg(j,k)=ROSwood(j,k)*exp(0.069*SlopeD(j,k));

% WOOD 6. Woodland Fire Behaviour
            FBehavwood(j,k) = 516.7*Fuel(j,k)*ROSwoodDeg(j,k);
    end
end
```

Calculate Fire Behaviour for Grassland & Woodland

```
FBehav = FBehavgrass + FBehavwood;
% figure
% imagesc(FBehav)
% Standardise total fire behaviour using BAL

%Convert FBehav=Intensity into Radiant Heat Flux

FBehav=60*(1-exp(-FBehav/30000)); %Equation provided by Graeme


StdFBconv = [0 7 1; 7 14 2; 14 28 3; 28 40 4; 40 1000 5]; % Conversion matrix using BAL
Levels (12.5=1,19=2,29=3,40=4,FZ=5)
for k=1:ncol %loop along columns of LU matrix
    for j=1:nrow %loop along rows of LU matrix
        if AdelInOut(j,k) == 0
            FBehavStd(j,k) = 0; % outside Greater Adelaide so not considering
        elseif V(j,k) == 0 || V(j,k) == 255
            FBehavStd(j,k) = 0; % no vegetation so no fire
        else        % convert Fire Behaviour to a standard likelihood
            for i=1:5 % loop along rows on conversion matrix to perform "lookup function"
                if (FBehav(j,k) >= StdFBconv(i,1))&&(FBehav(j,k) <= StdFBconv(i,2))
                    FBehavStd(j,k) = StdFBconv(i,3); % Calculate standardised total fire
```

```
behaviour

                end
            end
        end
    end
end
```

Hazard Likelihood Standardise Function

calculates the hazard likelihood from the ignition potential, suppression capability and fire behaviour

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [HazLikeStd] = HazardLikelihood(IgPotStd,SCStd,FBehavStd,LU,nrow,ncol)

% Input the significance factors (these are used to imply whether the factors are included in
the analysis
%HARDCODED ATM WILL NEED TO CHANGE IN FUTURE

IgPotSig=1;    %0=not included, 1=included
SCSig=1;       %0=not included, 1=included
FBehavSig=1;   %0=not included, 1=included

% Input weighted averages for ignition potential,suppression capability and fire behaviour
influence of the likelihood
%HARDCODED ATM WILL NEED TO CHANGE IN FUTURE

IgPotWeight=0.25;
SCWeight=0.25;
FBehavWeight=0.5;

WeightCondn=IgPotWeight+SCWeight+FBehavWeight; %calculation of total weightings to check they
equal to 1

%if statement to tell user that Weight Condition has not been met
if (WeightCondn~=1);
    disp('ERROR!! The summation of the weightings for the ignition potential, suppression
capabilities and fire behaviour do not equal 1')
end

% Loop to calculate the Hazard Likelihood for each cell using the weightings and signifcance
factors for Ignition Potential, Suppression
% Capability and Fire Behaviour
for k=1:ncol %loop along columns of LU matrix
    for j=1:nrow %loop along rows of LU matrix

HazLike(j,k)=IgPotSig*IgPotWeight*IgPotStd(j,k)+SCWeight*SCSig*SCStd(j,k)+FBehavSig*FBehavWei
ght*FBehavStd(j,k); %calculation of Hazard Likelihood
    end
end
% figure
% imagesc(HazLike)
% title('HazLike')

%%%%%%%%%%%%%%%% Standardise hazard Likelihood %%%%%%%%%%%%%%%%
```

```
for k=1:ncol %loop along columns of HazLike Matrix
    for j=1:nrow %loop along rows of HazLike Matrix
        if (HazLike(j,k)>=0.5)&&(HazLike(j,k)<1.5);
            HazLikeStd(j,k)=1;
        elseif (HazLike(j,k)>=1.5)&&(HazLike(j,k)<2.5);
            HazLikeStd(j,k)=2;
        elseif (HazLike(j,k)>=2.5)&&(HazLike(j,k)<3.5);
            HazLikeStd(j,k)=3;
        elseif (HazLike(j,k)>=3.5)&&(HazLike(j,k)<4.5);
            HazLikeStd(j,k)=4;
        elseif (HazLike(j,k)>=4.5);
            HazLikeStd(j,k)=5;
        else
            HazLikeStd(j,k)=0;
        end
    end
end
% figure
% imagesc(HazLikeStd)
% title('HazLikeStd')

end
```

Social Vulnerability for each SSC Function

Read in vulnerability indicators for 2015 based on ABS 2011 census data Reads in vulnerability multipliers for 2050 that align with the 5 scenarios defined for Greater Adelaide Determine consequence (1 - 5) for each indicator Determine combined indicator consequence (1 - 5)

```
clc
clear
%clf
```

Define Council Areas

Used later to align suburbs in each council with scenario multipliers

```
LGA = dlmread('lga_100m.asc'); %read in council boundaries
LGA = LGA + 1; %add 1 to each council area (to make Adelaide 1)

% Make Ocean 28
for r = 1:1000
    for c = 1:630
        if LGA(r,c)==-9998
            LGA(r,c) = 28;
        end
    end
end

% Define Council plot labels
CouncilLabels = importdata('Councils.txt'); %import list of councils names
```

```
nLGA = size(CouncilLabels);
nLGA = nLGA(1); %add extra 'council area' to include ocean
for i = 1:(nLGA) %convert struc matrix to array of text strings
    LG(i) = CouncilLabels(i);
    LGA_number_code(i) = i; % to be used later in defining SSC_number_code
                            % will be used to code council number for each
                            % suburb
end

nLGA = nLGA + 1; %consider ocean as extra "council area"
LG(nLGA)={'Outside Greater Adelaide'}; %add extra text label for ocean
LGA_number_code(nLGA) = 28;

% Adelaide IN/OUT map
AdelInOut = textread('reg100m.asc','','headerlines',6);
% Assess nrows & ncols for use in loops
NRowCol = textread('reg100m.asc','%s');
ncol = str2num(NRowCol{2});
nrow = str2num(NRowCol{4});
NRowCol = [];
AdelInOut = AdelInOut(1:nrow,1:ncol);   % Removing excess rows/cols

for r = 1:1000
    for c = 1:630
        if AdelInOut(r,c) == 0
            LGA(r,c) = 28; % Outside Greater Adelaide
        end
    end
end

% % Plot council boundaries
% figure
% imagesc(LGA)
% title('LGAs of Greater Adelaide')
% colormap(colorcube(nLGA)); %define colour bar and corresponding text
% labels = LG;
% lcolorbar(labels);
```

Define State Suburb (SCC) Areas

```
SSC = imread('GA_SSC_2.tif'); %read in council boundaries
SSC = SSC + 1; %add 1 to each council area (to make Aberfoyl Park 1)

% Make Outside Greater Adelaide
for r = 1:1000
    for c = 1:630
        if AdelInOut(r,c) == 0
            SSC(r,c) = 512;
         elseif SSC(r,c) >= 1000
             SSC(r,c) = 512;
        end
    end
end

% Plot council boundaries from SSC to LGA conversion
% figure
```

```
% imagesc(SSC)
% title('SSCs of Greater Adelaide')

% Create matrix "SSC_data" to convert Suburb to LGA map
                         % col 1: SSC (suburb) names
                         % col 2: LGA of SSC (filled in later)
                         % col 3: # code for SSC
                         % col 4: # code for LGA (filled in later)
% Define Suburb (SSC) list
SSC_importlist = importdata('SSC.csv'); % read in list of SSC considered in GA
LGA_importlist = importdata('LGA.csv'); % read in list of LGAs corresponding to the list of
SSCs
for r = 1:size(SSC_importlist)
    SSC_names(r,1) = SSC_importlist(r); % input SSC name
    SSC_names(r,2) = LGA_importlist(r); % input LGA name
    SSC_number_code(r,1) = r; % tiff # for SSC
end

% Define number of SSCs
nSSC = size(SSC_importlist);
nSSC = nSSC(1); % 511 SSCs

% Read in code numbers for LGAs
for r = 1:nSSC
    for i = 1:nLGA
        if strcmp(SSC_names(r,2),LG(i))==1 % match LGA name in SSC list to LGA name in LG
list
            SSC_number_code(r,2)=LGA_number_code(i); % Assign the code # for that LGA
        end
    end
end

% Check SSC and LGA matching using a plot
LGA_from_SSC = zeros(1000,630);
for r = 1:1000
    for c = 1:630 % two outer loops -> loop through SSC map
        for i = 1:nSSC % loop through the list of SSCs
             if SSC(r,c) == SSC_number_code(i,1) % Identify SSC
                 LGA_from_SSC(r,c) = SSC_number_code(i,2);  % Plot LGA to new map
             end
        end
    end
end

for r = 1:1000
    for c = 1:630
        if AdelInOut(r,c) == 0
            LGA_from_SSC(r,c) = 28; % Outside Greater Adelaide
        elseif LGA_from_SSC(r,c) == 0
            LGA_from_SSC(r,c) = 20; % Assign Torrens Island LGA
        end
    end
end

% Plot council boundaries from SSC to LGA conversion
% figure
% imagesc(LGA_from_SSC)
% title('LGAs of Greater Adelaide (based on SSC)')
```

```
% colormap(colorcube(nLGA)); %define colour bar and corresponding text
% labels = LG;
% lcolorbar(labels);
```

Read in indicator conversions (North, South, East, West, Hills) for 2050 for each scenario

Indicators are (in order of rows): Median Income Proportion Young (0-14 years) (%) Proportion Elderly (65 and over) (%) Unemployment (%) Migrant English Proficiency (%) Indigenous population (%) Family Structure (%) Volunteer rates (%) Internal Migration/ Arrivals (%) Education (%) Disabilities (%) Car Ownership Net Population Growth (%) Public Housing (%)

```
% These indicator spreadsheets record conversion factors based on: NORTH, SOUTH, EAST, WEST,
HILLS
% NOTE: row -> indicator, column -> region (north, east etc.)

ic_internet_of_risk = (xlsread('indicator_conversions_Internet of Risk.csv'));
ic_appetite_for_change = (xlsread('indicator_conversions_Appetite for Change.csv'));
ic_cynical_villagers = (xlsread('indicator_conversions_Cynical Villagers.csv'));
ic_silicon_hills = (xlsread('indicator_conversions_Silicon Hills.csv'));
ic_ignorance_of_the_lambs = (xlsread('indicator_conversions_Ignorance of the Lambs.csv'));
```

Define multipliers based on councils

Convert indicator conversion tables from North/South/East/West/Hills to each council NOTE: Alexandrina, Barossa, Light, Mallala, Mid Murray, Murray Bridge and Yankalilla are not assigned indicator conversion factors as these councils are outside Greater Adelaide

```
    % EAST: Adelaide
          % Burnside
          % Campbeltown
          % Noorwood Paynem Saint Peters
          % Prospect
          % Unley
          % Walkerville
for i = [1 5 6 17 21 24 25] % assign EAST multipliers to these councils
    indicator_conversion_internet_of_risk_LGA(:,i) = ic_internet_of_risk(:,1);
    indicator_conversion_appetite_for_change_LGA(:,i) = ic_appetite_for_change(:,1);
    indicator_conversion_cynical_villagers_LGA(:,i) = ic_cynical_villagers(:,1);
    indicator_conversion_silicon_hills_LGA(:,i) = ic_silicon_hills(:,1);
    indicator_conversion_ignorance_of_the_lambs_LGA(:,i) = ic_ignorance_of_the_lambs(:,1);
end

    % WEST: Charles Sturt
          % Port Adelaide Enfield ( ASSUME port adelaide enfield in west rather than north)
          % West Torrens
for i = [ 7 20 26] % assign WEST multipliers to these councils
    indicator_conversion_internet_of_risk_LGA(:,i) = ic_internet_of_risk(:,2);
    indicator_conversion_appetite_for_change_LGA(:,i) = ic_appetite_for_change(:,2);
```

```
    indicator_conversion_cynical_villagers_LGA(:,i) = ic_cynical_villagers(:,2);
    indicator_conversion_silicon_hills_LGA(:,i) = ic_silicon_hills(:,2);
    indicator_conversion_ignorance_of_the_lambs_LGA(:,i) = ic_ignorance_of_the_lambs(:,2);
end

    % SOUTH: Holdfast Bay
          % Marion
          % Mitcham
          % Onkaparinga
for i = [9 12 14 18] % assign SOUTH multipliers to these councils
    indicator_conversion_internet_of_risk_LGA(:,i) = ic_internet_of_risk(:,3);
    indicator_conversion_appetite_for_change_LGA(:,i) = ic_appetite_for_change(:,3);
    indicator_conversion_cynical_villagers_LGA(:,i) = ic_cynical_villagers(:,3);
    indicator_conversion_silicon_hills_LGA(:,i) = ic_silicon_hills(:,3);
    indicator_conversion_ignorance_of_the_lambs_LGA(:,i) = ic_ignorance_of_the_lambs(:,3);
end

    % NORTH: Gawler
          % Playford
          % Salisbury
          % Tea Tree Gully
for i = [4 8 10 11 19 22 23] % assign NORTH multipliers to these councils
    indicator_conversion_internet_of_risk_LGA(:,i) = ic_internet_of_risk(:,4);
    indicator_conversion_appetite_for_change_LGA(:,i) = ic_appetite_for_change(:,4);
    indicator_conversion_cynical_villagers_LGA(:,i) = ic_cynical_villagers(:,4);
    indicator_conversion_silicon_hills_LGA(:,i) = ic_silicon_hills(:,4);
    indicator_conversion_ignorance_of_the_lambs_LGA(:,i) = ic_ignorance_of_the_lambs(:,4);
end

    % HILLS: Adelaide Hills
          % Mount Barker
for i = [2 15] % assign HILLS multipliers to these councils
    indicator_conversion_internet_of_risk_LGA(:,i) = ic_internet_of_risk(:,5);
    indicator_conversion_appetite_for_change_LGA(:,i) = ic_appetite_for_change(:,5);
    indicator_conversion_cynical_villagers_LGA(:,i) = ic_cynical_villagers(:,5);
    indicator_conversion_silicon_hills_LGA(:,i) = ic_silicon_hills(:,5);
    indicator_conversion_ignorance_of_the_lambs_LGA(:,i) = ic_ignorance_of_the_lambs(:,5);
end
```

Define multipliers based on SSCs

```
for i = 1:nSSC
    for j = 1:nLGA
        if SSC_number_code(i,2) == j
            indicator_conversion_internet_of_risk_SSC(:,i) =
indicator_conversion_internet_of_risk_LGA(:,j);
            indicator_conversion_appetite_for_change_SSC(:,i) =
indicator_conversion_appetite_for_change_LGA(:,j);
            indicator_conversion_cynical_villagers_SSC(:,i) =
indicator_conversion_cynical_villagers_LGA(:,j);
            indicator_conversion_silicon_hills_SSC(:,i) =
indicator_conversion_silicon_hills_LGA(:,j);
            indicator_conversion_ignorance_of_the_lambs_SSC(:,i) =
indicator_conversion_ignorance_of_the_lambs_LGA(:,j);
        end
```

```
    end
end
```

Read in indicators for each SSC

Indicators are (in order of rows in multiplier tables): Median Income Proportion Young (0-14 years) (%) Proportion Elderly (65 and over) (%) Unemployment (%) Migrant English Proficiency (%) Indigenous population (%) Family Structure (%) Volunteer rates (%) Internal Migration/ Arrivals (%) Education (%) Disabilities (%) Car Ownership Net Population Growth (%) Public Housing (%)

```
i1 = 'Median Income.csv';
i2 = 'Young population.csv';
i3 = 'Elderly Population.csv';
i4 = 'Unemployment.csv';
i5 = 'English Proficiency.csv';
i6 = 'Indigenous Population.csv';
i7 = 'Family Structure.csv';
i8 = 'Volunteering.csv';
i9 = 'New to region.csv';
i10 = 'Education.csv';
i11 = 'Need Assistance.csv';
i12 = 'Car Ownership.csv';
i13 = 'Population Growth.csv';
i14 = 'Public Housing.csv';

% If changing number of indicatorsL:
            % add in extra i(#)
            % change nIndicators
            % add in i(#) to loop for str

nIndicators = 14; % number of indicators

current_indicator = zeros(nIndicators,nSSC); % matrix of current indicator values
                                  % rows -> indicator
                                  % columns -> SSC number
j = 0;
for str = {i1, i2, i3, i4, i5, i6, i7, i8, i9, i10, i11, i12, i13, i14}
    j = j+1;
    indicator_i = xlsread(str{1}); % read in csv for current indicator
    for r = 1:size(indicator_i)
        current_indicator(j,r) = indicator_i(r); % convert into matrix structure for
current_indicator shown in pseudo code
    end
end
```

Calculate Future Indicator Values for each Scenario

future_indicator = current_indicator x indicator_conversion

```
future_indicator_internet_of_risk = zeros(nIndicators,nSSC); % predefine matrix sizes
future_indicator_appetite_for_change = zeros(nIndicators,nSSC);
```

```
future_indicator_cynical_villagers = zeros(nIndicators,nSSC);
future_indicator_silicon_hills = zeros(nIndicators,nSSC);
future_indicator_ignorance_of_the_lambs = zeros(nIndicators,nSSC);

for r = 1:nIndicators % future_indicator = current_indicator x indicator_conversion
    for c = 1:nSSC
        future_indicator_internet_of_risk(r,c) =
current_indicator(r,c)*indicator_conversion_internet_of_risk_SSC(r,c);
        future_indicator_appetite_for_change(r,c) =
current_indicator(r,c)*indicator_conversion_appetite_for_change_SSC(r,c);
        future_indicator_cynical_villagers(r,c) =
current_indicator(r,c)*indicator_conversion_cynical_villagers_SSC(r,c);
        future_indicator_silicon_hills(r,c) =
current_indicator(r,c)*indicator_conversion_silicon_hills_SSC(r,c);
        future_indicator_ignorance_of_the_lambs(r,c) =
current_indicator(r,c)*indicator_conversion_ignorance_of_the_lambs_SSC(r,c);
    end
end
```

Calculate Indicator Bounds (across now and all future scenarios)

```
% Concatenate all indicator values into one matrix (rows -> indicator,
% columns -> different councils under all scenarios)
all_indicator_values = [ current_indicator future_indicator_internet_of_risk
future_indicator_appetite_for_change future_indicator_cynical_villagers
future_indicator_silicon_hills future_indicator_ignorance_of_the_lambs];

% Determine [20% 40% 60% and 80%] quartile bounds
indicator_bounds = prctile(all_indicator_values,[20 40 60 80],2);
```

Determine standardised consequence for each indicator based on indicator bounds

```
for r = [ 2 3 4 5 6 7 9 11 13 14] % Higher indicator means bigger consequence
    for c = 1:nSSC
        % Standardise Current indicator
        if current_indicator(r,c) <= indicator_bounds(r,1)
            current_indicator(r,c) = 1;
        elseif current_indicator(r,c) <= indicator_bounds(r,2)
            current_indicator(r,c) = 2;
        elseif current_indicator(r,c) <= indicator_bounds(r,3)
            current_indicator(r,c) = 3;
        elseif current_indicator(r,c) <= indicator_bounds(r,4)
            current_indicator(r,c) = 4;
        else
            current_indicator(r,c) = 5;
        end

        % Standardise Internet of Risk Scenario Indicators
        if future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,1)
            future_indicator_internet_of_risk(r,c) = 1;
        elseif future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,2)
            future_indicator_internet_of_risk(r,c) = 2;
```

```
        elseif future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,3)
            future_indicator_internet_of_risk(r,c) = 3;
        elseif future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,4)
            future_indicator_internet_of_risk(r,c) = 4;
        else
            future_indicator_internet_of_risk(r,c) = 5;
        end

        % Standardise Appetite for Change Scenario Indicators
        if future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,1)
            future_indicator_appetite_for_change(r,c) = 1;
        elseif future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,2)
            future_indicator_appetite_for_change(r,c) = 2;
        elseif future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,3)
            future_indicator_appetite_for_change(r,c) = 3;
        elseif future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,4)
            future_indicator_appetite_for_change(r,c) = 4;
        else
            future_indicator_appetite_for_change(r,c) = 5;
        end

        % Standardise Cynical Villagers Scenario Indicators
        if future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,1)
            future_indicator_cynical_villagers(r,c) = 1;
        elseif future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,2)
            future_indicator_cynical_villagers(r,c) = 2;
        elseif future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,3)
            future_indicator_cynical_villagers(r,c) = 3;
        elseif future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,4)
            future_indicator_cynical_villagers(r,c) = 4;
        else
            future_indicator_cynical_villagers(r,c) = 5;
        end

        % Standardise Silicon Hills Scenario Indicators
        if future_indicator_silicon_hills(r,c) <= indicator_bounds(r,1)
            future_indicator_silicon_hills(r,c) = 1;
        elseif future_indicator_silicon_hills(r,c) <= indicator_bounds(r,2)
            future_indicator_silicon_hills(r,c) = 2;
        elseif future_indicator_silicon_hills(r,c) <= indicator_bounds(r,3)
            future_indicator_silicon_hills(r,c) = 3;
        elseif future_indicator_silicon_hills(r,c) <= indicator_bounds(r,4)
            future_indicator_silicon_hills(r,c) = 4;
        else
            future_indicator_silicon_hills(r,c) = 5;
        end

        % Standardise Ignorance of the Lambs Scenario Indicators
        if future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,1)
            future_indicator_ignorance_of_the_lambs(r,c) = 1;
        elseif future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,2)
            future_indicator_ignorance_of_the_lambs(r,c) = 2;
        elseif future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,3)
            future_indicator_ignorance_of_the_lambs(r,c) = 3;
        elseif future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,4)
            future_indicator_ignorance_of_the_lambs(r,c) = 4;
        else
            future_indicator_ignorance_of_the_lambs(r,c) = 5;
```

```
        end
    end
end

for r = [1 8 10 12] % Higher indicator means lower consequence, eg. median income
    for c = 1:nSSC
        % Standardise Current indicator
        if current_indicator(r,c) <= indicator_bounds(r,1)
            current_indicator(r,c) = 5;
        elseif current_indicator(r,c) <= indicator_bounds(r,2)
            current_indicator(r,c) = 4;
        elseif current_indicator(r,c) <= indicator_bounds(r,3)
            current_indicator(r,c) = 3;
        elseif current_indicator(r,c) <= indicator_bounds(r,4)
            current_indicator(r,c) = 2;
        else
            current_indicator(r,c) = 1;
        end

        % Standardise Internet of Risk Scenario Indicators
        if future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,1)
            future_indicator_internet_of_risk(r,c) = 5;
        elseif future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,2)
            future_indicator_internet_of_risk(r,c) = 4;
        elseif future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,3)
            future_indicator_internet_of_risk(r,c) = 3;
        elseif future_indicator_internet_of_risk(r,c) <= indicator_bounds(r,4)
            future_indicator_internet_of_risk(r,c) = 2;
        else
            future_indicator_internet_of_risk(r,c) = 1;
        end

        % Standardise Appetite for Change Scenario Indicators
        if future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,1)
            future_indicator_appetite_for_change(r,c) = 5;
        elseif future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,2)
            future_indicator_appetite_for_change(r,c) = 4;
        elseif future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,3)
            future_indicator_appetite_for_change(r,c) = 3;
        elseif future_indicator_appetite_for_change(r,c) <= indicator_bounds(r,4)
            future_indicator_appetite_for_change(r,c) = 2;
        else
            future_indicator_appetite_for_change(r,c) = 1;
        end

        % Standardise Cynical Villagers Scenario Indicators
        if future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,1)
            future_indicator_cynical_villagers(r,c) = 5;
        elseif future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,2)
            future_indicator_cynical_villagers(r,c) = 4;
        elseif future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,3)
            future_indicator_cynical_villagers(r,c) = 3;
        elseif future_indicator_cynical_villagers(r,c) <= indicator_bounds(r,4)
            future_indicator_cynical_villagers(r,c) = 2;
        else
            future_indicator_cynical_villagers(r,c) = 1;
        end
```

```
        % Standardise Silicon Hills Scenario Indicators
        if future_indicator_silicon_hills(r,c) <= indicator_bounds(r,1)
            future_indicator_silicon_hills(r,c) = 5;
        elseif future_indicator_silicon_hills(r,c) <= indicator_bounds(r,2)
            future_indicator_silicon_hills(r,c) = 4;
        elseif future_indicator_silicon_hills(r,c) <= indicator_bounds(r,3)
            future_indicator_silicon_hills(r,c) = 3;
        elseif future_indicator_silicon_hills(r,c) <= indicator_bounds(r,4)
            future_indicator_silicon_hills(r,c) = 2;
        else
            future_indicator_silicon_hills(r,c) = 1;
        end

        % Standardise Ignorance of the Lambs Scenario Indicators
        if future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,1)
            future_indicator_ignorance_of_the_lambs(r,c) = 5;
        elseif future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,2)
            future_indicator_ignorance_of_the_lambs(r,c) = 4;
        elseif future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,3)
            future_indicator_ignorance_of_the_lambs(r,c) = 3;
        elseif future_indicator_ignorance_of_the_lambs(r,c) <= indicator_bounds(r,4)
            future_indicator_ignorance_of_the_lambs(r,c) = 2;
        else
            future_indicator_ignorance_of_the_lambs(r,c) = 1;
        end
    end
end
```

Calculate overall consequence in each council for each scenario based on weightings

Weightings: Median Income = 1 Proportion Young (0-14 years) (%) = 1 Proportion Elderly (65 and over) (%) = 1 Unemployment (%) = 1 Migrant English Proficiency (%) = 1 Indigenous population (%) = 1 Single Parent Families (%) = 1 Volunteer rates (%) = 1 Internal Migration/ Arrivals (%) = 1 Education (%) = 1 Disabilities (%) = 1 Car Ownership = 1 Net Population Growth (%) = 1 Public Housing (%)

```
weight = ones(1,nIndicators); % weighting for each indicator

current_vuln = zeros(1,nSSC); % predefine matrix sizes
future_vuln_internet_of_risk = zeros(1,nSSC);
future_vuln_appetite_for_change = zeros(1,nSSC);
future_vuln_cynical_villagers = zeros(1,nSSC);
future_vuln_silicon_hills = zeros(1,nSSC);
future_vuln_ignorance_of_the_lambs = zeros(1,nSSC);

for c = 1:nSSC % cummulative addition of each indicator based on it's weighting
    for r = 1:nIndicators
        current_vuln(c) = current_indicator(r,c)*weight(r) + current_vuln(c); % add up
consequence based on each indicator
        future_vuln_internet_of_risk(c) = future_indicator_internet_of_risk(r,c)*weight(r) +
future_vuln_internet_of_risk(c);
        future_vuln_appetite_for_change(c) =
future_indicator_appetite_for_change(r,c)*weight(r) + future_vuln_appetite_for_change(c);
```

```
        future_vuln_cynical_villagers(c) = future_indicator_cynical_villagers(r,c)*weight(r)
+ future_vuln_cynical_villagers(c);
        future_vuln_silicon_hills(c) = future_indicator_silicon_hills(r,c)*weight(r) +
future_vuln_silicon_hills(c);
        future_vuln_ignorance_of_the_lambs(c) =
future_indicator_ignorance_of_the_lambs(r,c)*weight(r) +
future_vuln_ignorance_of_the_lambs(c);
    end
end

% concatenate future vulnerabilities into a single matrix
all_future_vuln = [current_vuln future_vuln_internet_of_risk future_vuln_appetite_for_change
future_vuln_cynical_villagers future_vuln_silicon_hills future_vuln_ignorance_of_the_lambs];
% Standardising to integers 1-5
standardisingvalues = prctile(all_future_vuln,[20 40 60 80],2); % values used to standardise
sum of vuln indicators

%for current_vuln
for c=1:nSSC
if current_vuln(c)<=standardisingvalues(1)
    current_vuln(c)=1;
    elseif current_vuln(c)<=standardisingvalues(2)
        current_vuln(c)=2;
    elseif current_vuln(c)<=standardisingvalues(3)
        current_vuln(c)=3;
    elseif current_vuln(c)<=standardisingvalues(4)
        current_vuln(c)=4;
    else
        current_vuln(c)=5;
end
end

%for future_vuln_internet_of_risk
for c=1:nSSC
if future_vuln_internet_of_risk(c)<=standardisingvalues(1)
        future_vuln_internet_of_risk(c)=1;
    elseif future_vuln_internet_of_risk(c)<=standardisingvalues(2)
        future_vuln_internet_of_risk(c)=2;
    elseif future_vuln_internet_of_risk(c)<=standardisingvalues(3)
        future_vuln_internet_of_risk(c)=3;
    elseif future_vuln_internet_of_risk(c)<=standardisingvalues(4)
        future_vuln_internet_of_risk(c)=4;
    else
        future_vuln_internet_of_risk(c)=5;
end
end

%for future_vuln_appetite_for_change
for c=1:nSSC
if future_vuln_appetite_for_change(c)<=standardisingvalues(1)
        future_vuln_appetite_for_change(c)=1;
    elseif future_vuln_appetite_for_change(c)<=standardisingvalues(2)
        future_vuln_appetite_for_change(c)=2;
    elseif future_vuln_appetite_for_change(c)<=standardisingvalues(3)
        future_vuln_appetite_for_change(c)=3;
    elseif future_vuln_appetite_for_change(c)<=standardisingvalues(4)
        future_vuln_appetite_for_change(c)=4;
    else
```

```
        future_vuln_appetite_for_change(c)=5;
end
end

%for future_vuln_cynical_villagers
for c=1:nSSC
if future_vuln_cynical_villagers(c)<=standardisingvalues(1)
        future_vuln_cynical_villagers(c)=1;
    elseif future_vuln_cynical_villagers(c)<=standardisingvalues(2)
        future_vuln_cynical_villagers(c)=2;
    elseif future_vuln_cynical_villagers(c)<=standardisingvalues(3)
        future_vuln_cynical_villagers(c)=3;
    elseif future_vuln_cynical_villagers(c)<=standardisingvalues(4)
        future_vuln_cynical_villagers(c)=4;
    else
        future_vuln_cynical_villagers(c)=5;
end
end

%for future_vuln_silicon_hills
for c=1:nSSC
if future_vuln_silicon_hills(c)<=standardisingvalues(1)
        future_vuln_silicon_hills(c)=1;
    elseif future_vuln_silicon_hills(c)<=standardisingvalues(2)
        future_vuln_silicon_hills(c)=2;
    elseif future_vuln_silicon_hills(c)<=standardisingvalues(3)
        future_vuln_silicon_hills(c)=3;
    elseif future_vuln_silicon_hills(c)<=standardisingvalues(4)
        future_vuln_silicon_hills(c)=4;
    else
        future_vuln_silicon_hills(c)=5;
end
end

%for future_vuln_ignorance_of_the_lambs
for c=1:nSSC
if future_vuln_ignorance_of_the_lambs(c)<=standardisingvalues(1)
        future_vuln_ignorance_of_the_lambs(c)=1;
    elseif future_vuln_ignorance_of_the_lambs(c)<=standardisingvalues(2)
        future_vuln_ignorance_of_the_lambs(c)=2;
    elseif future_vuln_ignorance_of_the_lambs(c)<=standardisingvalues(3)
        future_vuln_ignorance_of_the_lambs(c)=3;
    elseif future_vuln_ignorance_of_the_lambs(c)<=standardisingvalues(4)
        future_vuln_ignorance_of_the_lambs(c)=4;
    else
        future_vuln_ignorance_of_the_lambs(c)=5;
end
end
```

Output vulnerability matrices to .csv to be read into Vulnerability module in Bushfire Model main code

```
csvwrite('Hazard_Con_Current.csv',current_vuln);
csvwrite('Hazard_Con_Internet_of_risk.csv',future_vuln_internet_of_risk);
csvwrite('Hazard_Con_Appetite_for_Change.csv',future_vuln_appetite_for_change);
```

```
csvwrite('Hazard_Con_Cynical_Villagers.csv',future_vuln_cynical_villagers);
csvwrite('Hazard_Con_Silicon_Hills.csv',future_vuln_silicon_hills);
csvwrite('Hazard_Con_Ignorance_of_the_Lambs.csv',future_vuln_ignorance_of_the_lambs);
```

Plotting Modules

```
SaveIndicatorCSVs; % Save individual maps as .asc files
                   % Within this module is a MapComparison module that also
                   % saves comparison maps for each indicator as .asc files
```

Social Vulnerability Standardise Function

assign vulnerability (consequence) index to each cell based on what council the cell lies in

```
function [HazConsStd] = Vulnerability(LU,nrow,ncol,YearNum,ScenNum)


% Define Council Boundaries
LGA = dlmread('lga_100m.asc'); %read in council boundaries
LGA = LGA + 1; %add 1 to each council area (as Adelaide is coded as 0)

% Add council labels to coloured raster map
CouncilLabels = importdata('Councils.txt'); %import list of councils
nLGA = size(CouncilLabels);
nLGA = nLGA(1); %add extra 'council area' to include ocean
for i = 1:(nLGA) %convert struc matrix to array of text strings
    LG(i) = CouncilLabels(i);
end
% Make Ocean 28
for r = 1:1000
    for c = 1:630
        if LGA(r,c)==-9998
            LGA(r,c) = 28;
        end
    end
end
nLGA = nLGA; %consider ocean as extra "council area"
%LG(nLGA)={'Ocean'}; %add extra text label for ocean

% LGA legend
% figure
%  colormap(colorcube(nLGA)); %define colour bar and corresponding text
%  labels = LG;
%  lcolorbar(labels);
%  imagesc(LGA)


% read in raster map of LGA
for r = 1:1000 %change raster value for ocean to nLGA+1 to allow for colour map palette
    for c = 1:630
        if LGA(r,c)==-9998
            LGA(r,c)=nLGA+1;
        end
```

```
    end
end

% read in raster map of SSC
SSC = imread('GA_SSC_2.tif'); %read in SSC boundaries
SSC = SSC + 1; %add 1 to each council area (to make Aberfoyl Park 1)

% Adelaide IN/OUT map
AdelInOut = textread('reg100m.asc','','headerlines',6);
% Assess nrows & ncols for use in loops
NRowCol = textread('reg100m.asc','%s');
ncol = str2num(NRowCol{2});
nrow = str2num(NRowCol{4});
NRowCol = [];
AdelInOut = AdelInOut(1:nrow,1:ncol);   % Removing excess rows/cols

% Define number of SSCs
SSC_importlist = importdata('SSC.csv'); % read in list of SSC considered in GA
nSSC = size(SSC_importlist);
nSSC = nSSC(1); % 511 SSCs

% Make Outside Greater Adelaide
for r = 1:1000
    for c = 1:630
        if AdelInOut(r,c) == 0
            SSC(r,c) = 512;
         elseif SSC(r,c) >= 1000
             SSC(r,c) = 512;
        end
    end
end

%imagesc(LGA) %show map of council boundaries


% Read in Vulnerability indicator for each council
% vulnerability index of 1 to 5 already calculated for each council in HazardConsequence.m
if YearNum == 2015
    VulnIndex = csvread('Hazard_Con_Current.csv');
elseif YearNum == 2050
    if ScenNum == 1 %cynical villagers
        VulnIndex = csvread('Hazard_Con_Cynical_Villagers.csv');
    elseif ScenNum == 2 % ignorance of the lambs
        VulnIndex = csvread('Hazard_Con_Ignorance_of_the_Lambs.csv');
    elseif ScenNum == 3 % internet of risk
        VulnIndex = csvread('Hazard_Con_Internet_of_risk.csv');
    elseif ScenNum == 4 % silicon hills
        VulnIndex = csvread('Hazard_Con_Silicon_Hills.csv');
    elseif ScenNum == 5 % appetite for change
        VulnIndex = csvread('Hazard_Con_Appetite_for_Change.csv');
    end
end

 %VulnIndex = csvread('Hazard_Con_Council.csv'); % read in vulnerability indices


% Assign vulnerability to each council area
Vulnerability_Mat = zeros(1000,630);
```

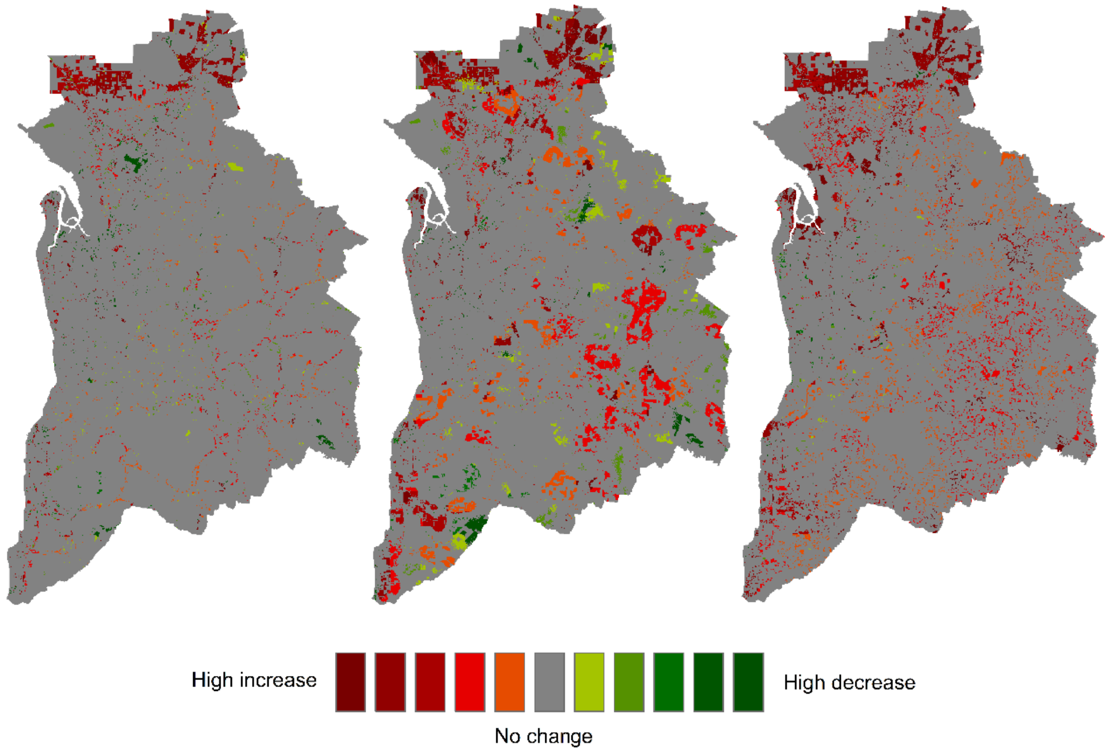
```
for r = 1:1000
    for c = 1:630
        if (LU(r,c)== 0||LU(r,c)==1||LU(r,c)==15||LU(r,c)==16) % if vacant, forest, sea or
outside GA, then vulnerability = 0
            Vulnerability_Mat(r,c) = 0;
        else % otherwise, calculate the vulnerability in that cell
            for i = 1:nSSC %don't need to consider ocean, as this vulnerability is just 0
                if SSC(r,c)== i
                    Vulnerability_Mat(r,c) = VulnIndex(i);
                end
            end
        end
    end
end


% Convert vulnerability (0-1) to standardised vulnerability (1-5)
HazConsStd = Vulnerability_Mat;


% %  figure
%  imagesc(Vulnerability_Mat);
%  HMLcolourscale = [176/255 226/255 1; 0 204/255 0; 128/255 255/255 0; 1 1 0; 239/255
175/255 27/255; 255/255 128/255 0; 1 0 0; 153/255 0 0];
%  colormap(HMLcolourscale);
%  colorbar;
```

Hazard Risk Standardise Function

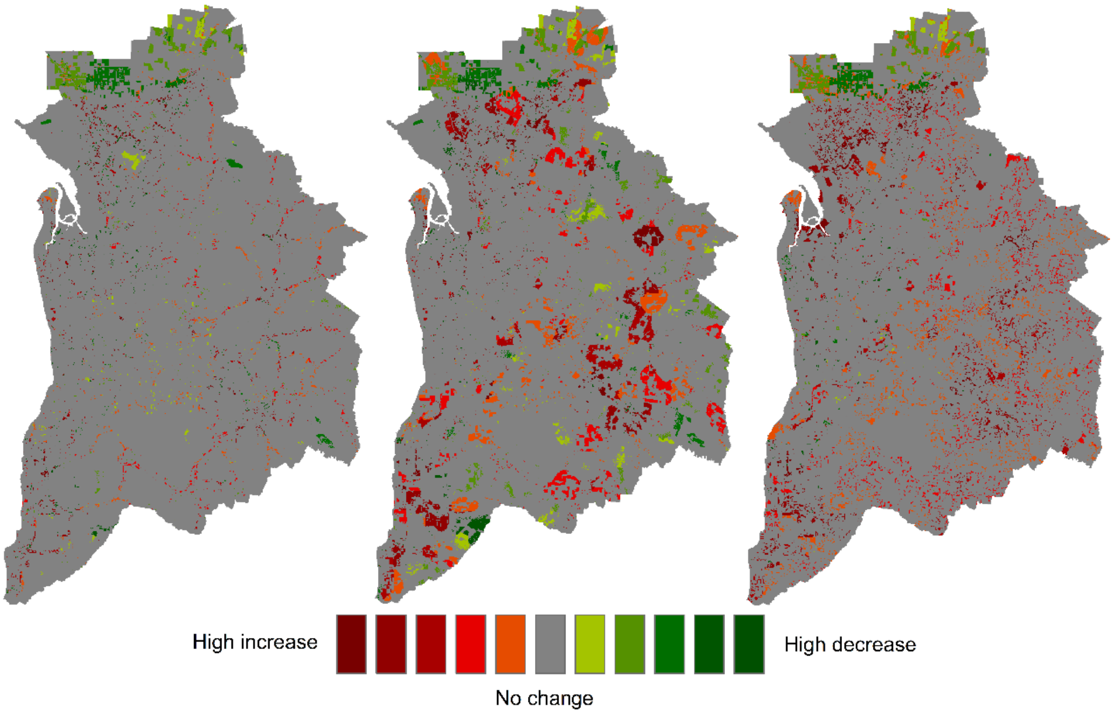
```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Hazard Risk - calculates the hazard risk from the hazard likelihood and social
vulnerability
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

function [HazRiskMatrix] = HazardRisk(AdelInOut,LU,HazLikeStd,YearNum,nrow,ncol,HazConsStd);

% Calculation of the Hazard Risk Matrix based on likelihood and consequence (Building Stock
Risk)

%The HazRiskMatrix is the matrix based on the consequence (Vulnerability) and likelihood of
%a bushfire occurring

%The HazRiskLevelMatrix follows this principle (1=Very Low, 2=Low 3=Medium, 4=High and
5=Extreme)

% Hazard Risk Level Matrix (will make CSV at some point!!!!!)
HazRiskLevelMatrix= [1 1 2 3 3; 1 2 3 3 4; 2 3 3 4 4; 3 3 4 4 5; 3 4 4 5 5];

% HAZARD RISK = f( Hazard Consequence, Hazard Likelihood)

for k=1:ncol %loop along columns of BSRisk and HazLike Matrix
    for j=1:nrow %loop along columns of BSRisk and HazLike Matrix
        if (AdelInOut(j,k) == 0); %if outside adelaide
            HazRiskMatrix(j,k) = -1;
        elseif (HazConsStd(j,k)==0); %if not vulnerable (i.e. forest)
            HazRiskMatrix(j,k) = 0;
```

```
        elseif HazLikeStd(j,k)==0;      % if Likelihood zero then no risk
            HazRiskMatrix(j,k)=0;
        else
            HazRiskMatrix(j,k)= HazRiskLevelMatrix((HazLikeStd(j,k)),(HazConsStd(j,k)));
%calculates the value of cell of the Hazard Matrix based on the Hazard Likelikehood and
Hazard Consequence in the Hazard Risk Matrix
        end
    end
end

end
```

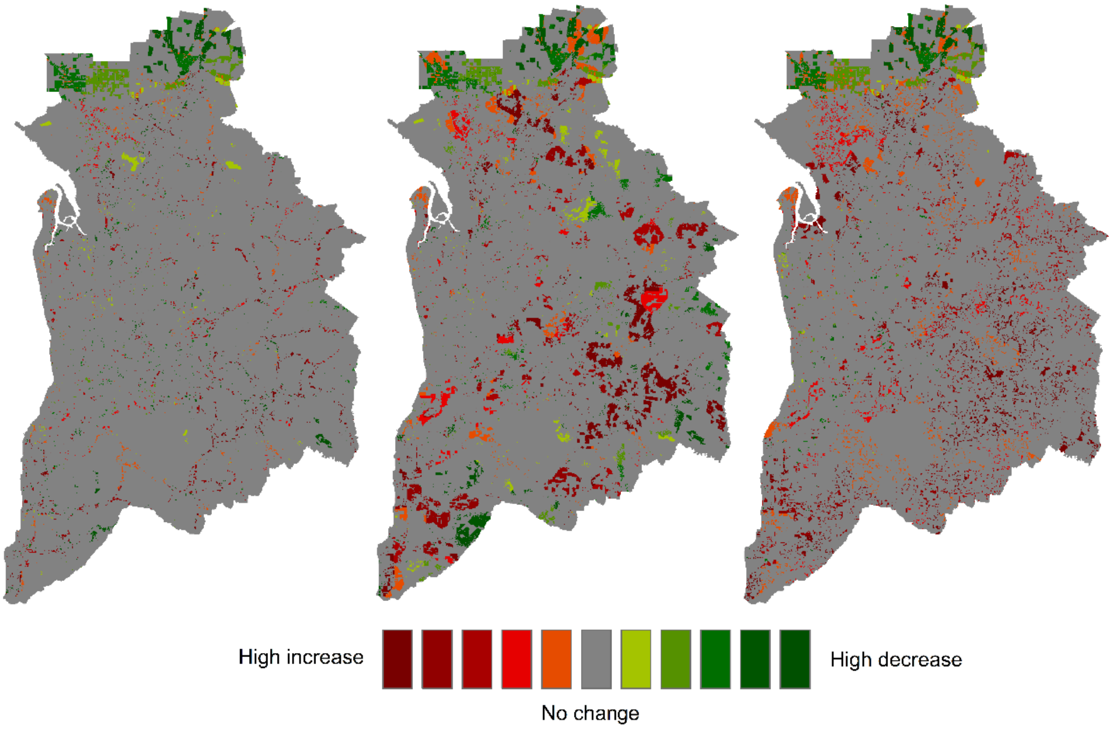
APPENDIX B – REMAINING INDICATORS OF SOCIAL VULNERABILITY



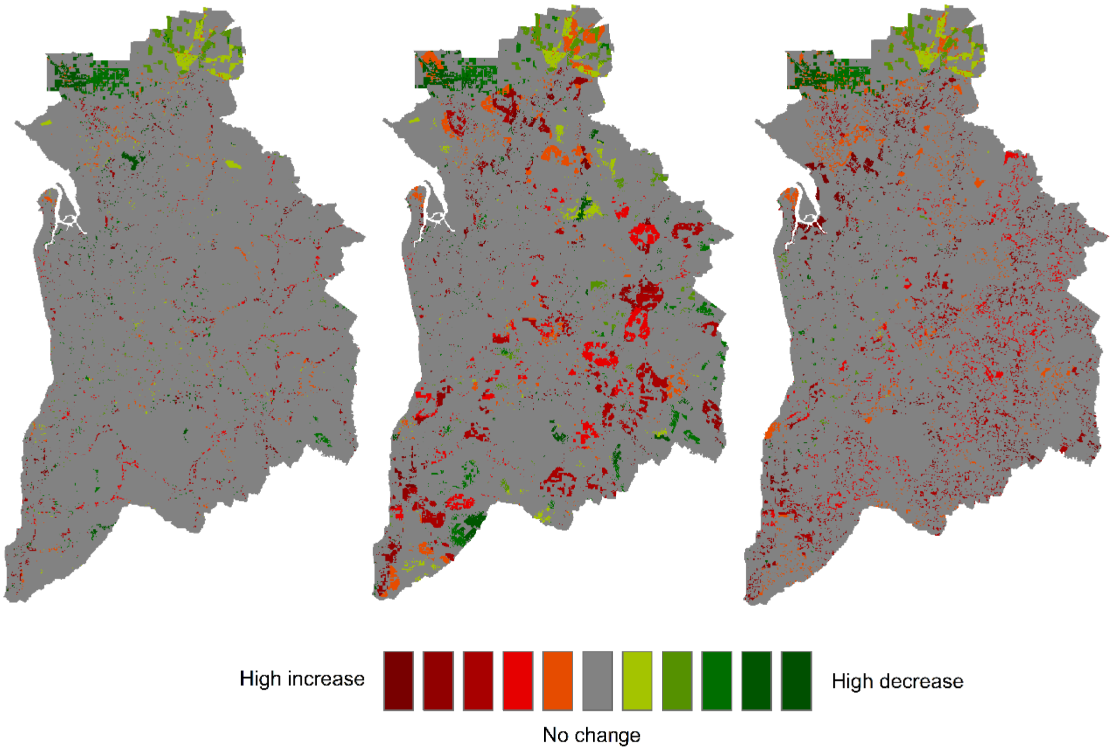
Changes in Social Vulnerability due to the proportion cars per person for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



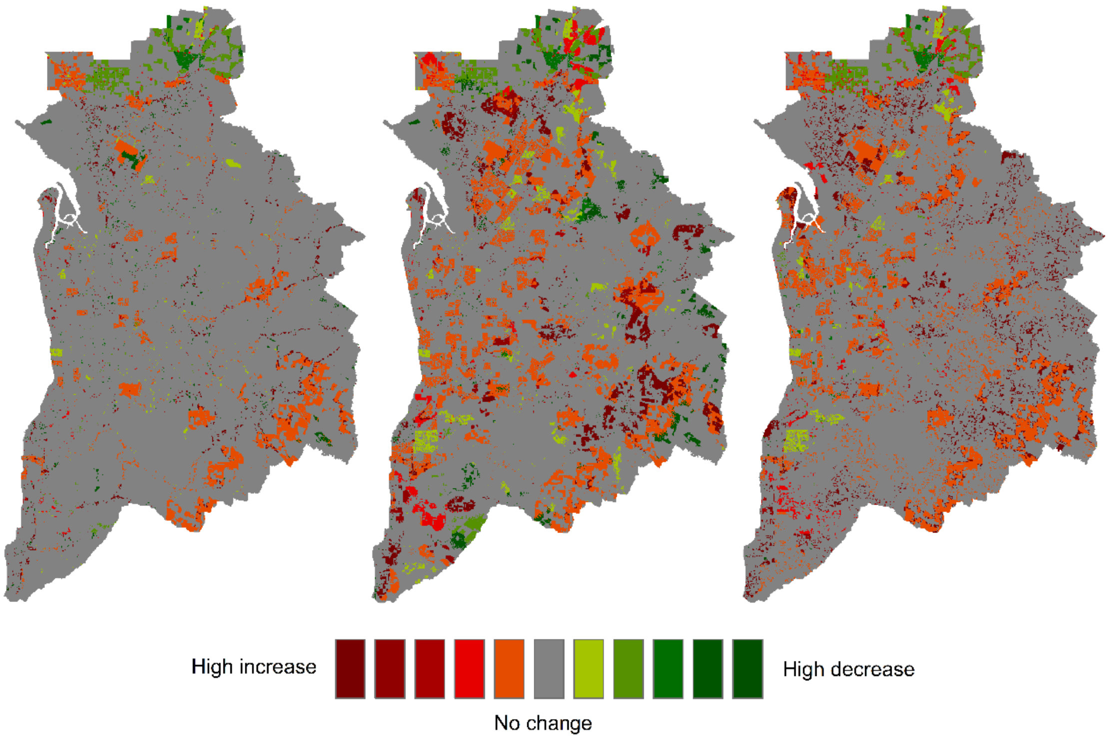
Changes in Social Vulnerability due to the proportion of population with disabilities for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



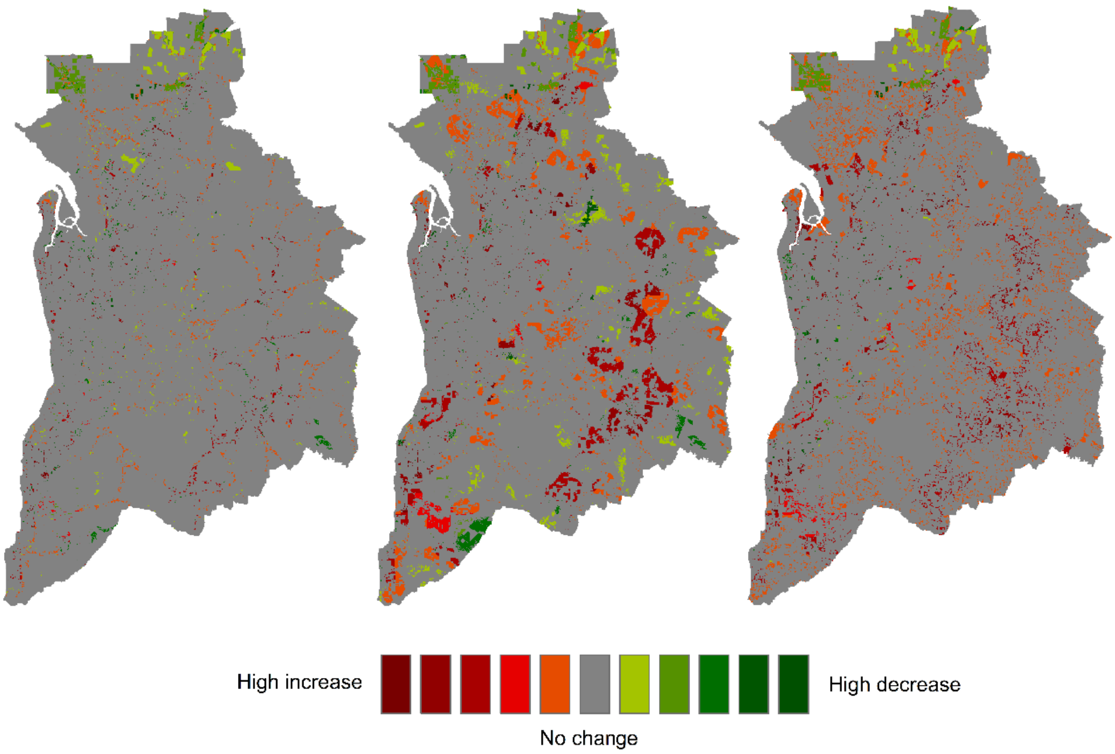
Changes in Social Vulnerability due to the family structure for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



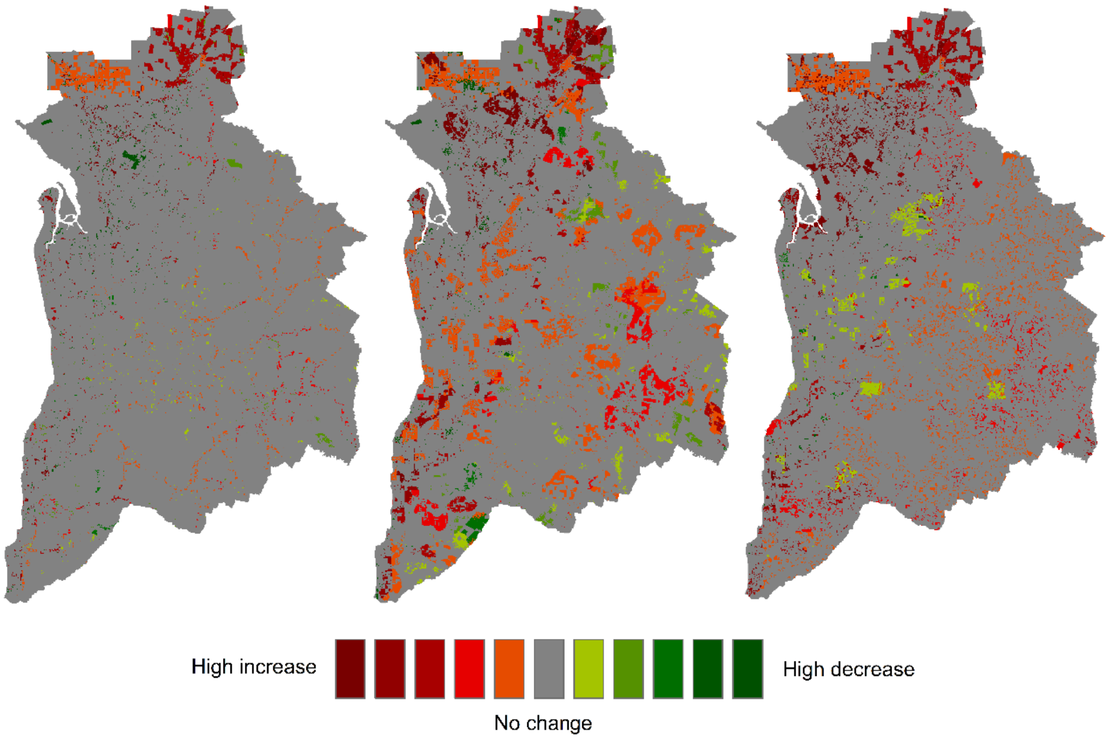
Changes in Social Vulnerability due to the proportion of the population who are indigenous for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



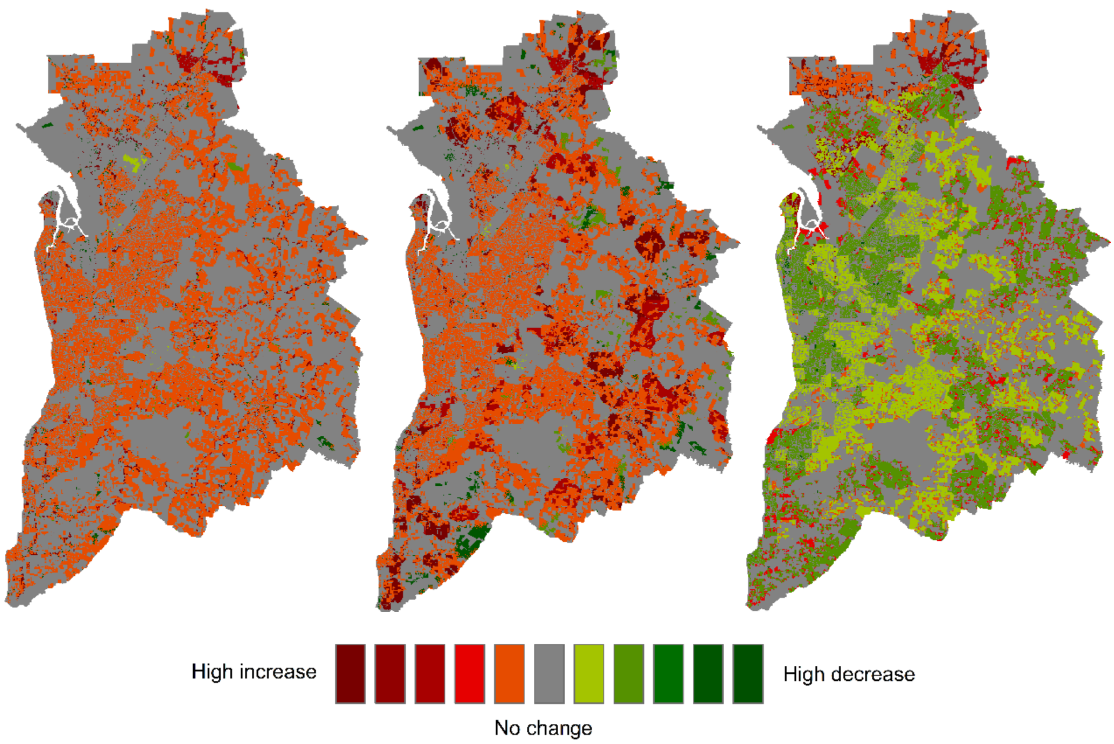
Changes in Social Vulnerability due to the net population growth for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



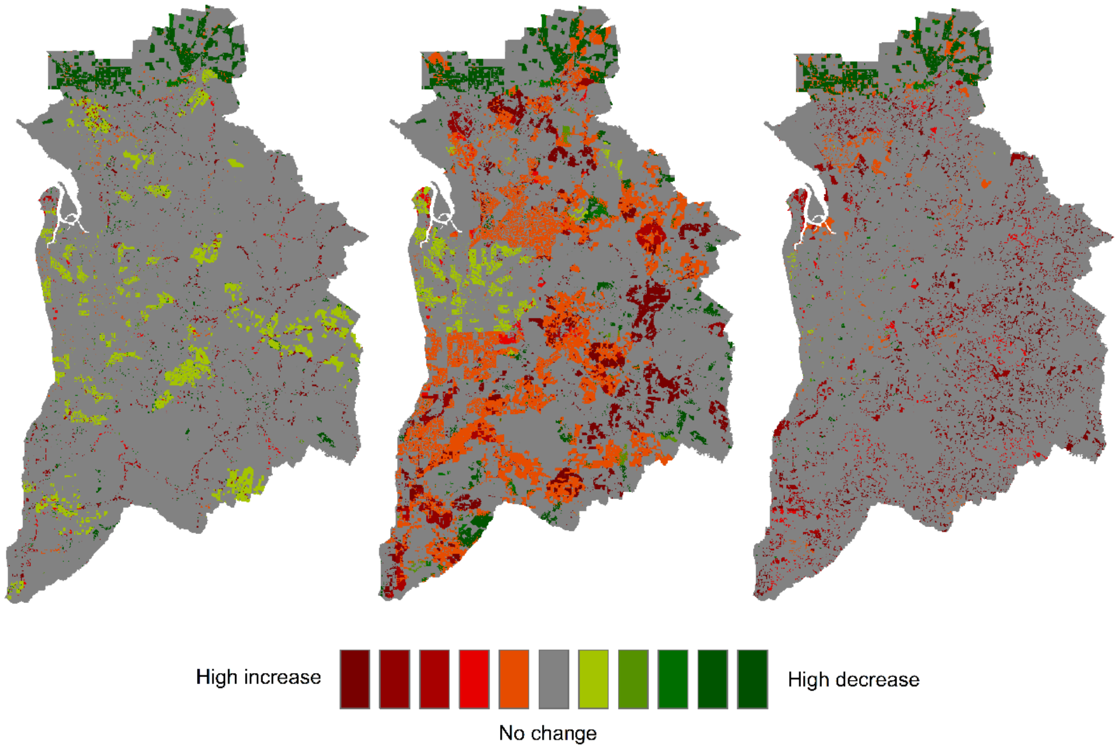
Changes in Social Vulnerability due to amount of public housing for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



Changes in Social Vulnerability due to the proportion of population that volunteers for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



Changes in Social Vulnerability due to the personal wealth of the population for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios



Changes in Social Vulnerability due to the proportion of young people (0-14years) in the population for (a) Cynical Villagers, (b) Ignorance of the Lambs, and (c) Silicon Hills scenarios

APPENDIX C – LIST OF STATE SUBURB CODES (SSCS) IN GREATER ADELAIDE

Table 0-1 List of SSCs and their corresponding LGAs in Greater Adelaide

SSC	LGA
Aberfoyle Park	Onkaparinga
Adelaide	Adelaide
Adelaide Airport	West Torrens
Albert Park	Charles Sturt
Alberton	Port Adelaide Enfield
Aldgate	Adelaide Hills
Aldinga	Onkaparinga
Aldinga Beach	Onkaparinga
Allenby Gardens	Charles Sturt
Andrews Farm	Playford
Angle Park	Port Adelaide Enfield
Angle Vale	Playford
Ascot Park	Marion
Ashford	West Torrens
Ashton	Adelaide Hills
Athelstone	Campbelltown
Athol Park	Charles Sturt
Auldana	Burnside
Balhannah	Adelaide Hills
Banksia Park	Tea Tree Gully
Barossa Goldfields	Barossa
Basket Range	Adelaide Hills
Beaumont	Burnside
Bedford Park	Mitcham
Belair	Mitcham
Bellevue Heights	Mitcham
Beulah Park	Burnside
Beverley	Charles Sturt
Bibaringa	Playford
Biggs Flat	Mount Barker
Birdwood	Adelaide Hills
Birkenhead	Port Adelaide Enfield
Black Forest	Unley
Blackwood	Mitcham
Blair Athol	Port Adelaide Enfield
Blakeview	Playford
Blakiston	Mount Barker
Blewitt Springs	Onkaparinga
Bolivar	Salisbury
Bowden	Charles Sturt
Bradbury	Adelaide Hills
Brahma Lodge	Salisbury
Bridgewater	Adelaide Hills
Brighton	Holdfast Bay
Broadview	Port Adelaide Enfield
Broadview	Charles Sturt
Brompton	West Torrens
Brooklyn Park	Mitcham
Brown Hill Creek	Mount Barker
Brukunga	Mount Barker
Buckland Park	Playford
Bugle Ranges	Mount Barker
Bull Creek	Mount Barker
Burnside	Burnside
Burton	Salisbury
Callington	Mount Barker
Camden Park	West Torrens
Campbelltown	Campbelltown
Carey Gully	Adelaide Hills
Castambul	Adelaide Hills
Cavan	Salisbury
Chain Of Ponds	Adelaide Hills
Chandlers Hill	Onkaparinga
Chapel Hill	Mount Barker
Charleston	Adelaide Hills
Cheltenham	Charles Sturt
Cherry Gardens	Onkaparinga
Cherryville	Adelaide Hills
Christie Downs	Onkaparinga
Christies Beach	Onkaparinga
Clapham	Mitcham
Clarence Gardens	Mitcham
Clarence Park	Unley
Clarendon	Onkaparinga
Clearview	Port Adelaide Enfield
Clovelly Park	Adelaide Hills
College Park	Marion
Collinswood	Prospect

Colonel Light Gardens	Prospect
Coromandel East	Mitcham
Coromandel Valley	Mitcham
Coromandel Valley	Onkaparinga
Cowandilla	Mitcham
Crafers	West Torrens
Crafers West	Adelaide Hills
Crafers West	Adelaide Hills
Craigburn Farm	Mitcham
Craigmore	Playford
Cromer	Adelaide Hills
Croydon	Charles Sturt
Croydon Park	Port Adelaide Enfield
Cudlee Creek	Adelaide Hills
Cumberland Park	Mitcham
Darlington	Onkaparinga
Davoren Park	Playford
Daw Park	Mitcham
Dawesley	Mount Barker
Dernancourt	Port Adelaide Enfield
Devon Park	Port Adelaide Enfield
Direk	Salisbury
Dorset Vale	Adelaide Hills
Dover Gardens	Marion
Dry Creek	Salisbury
Dudley Park	Port Adelaide Enfield
Dulwich	Burnside
Eastwood	Burnside
Echunga	Mount Barker
Eden Hills	Mitcham
Edinburgh	Salisbury
Edinburgh North	Playford
Edwardstown	Marion
Elizabeth	Playford
Elizabeth Downs	Playford
Elizabeth East	Playford
Elizabeth Grove	Playford
Elizabeth North	Playford
Elizabeth Park	Playford
Elizabeth South	Playford
Elizabeth Vale	Salisbury
Enfield	Port Adelaide Enfield
Erindale	Burnside
Ethelton	Port Adelaide Enfield

Evandale	Norwood Payneham St Peters
Evanston	Gawler
Evanston Gardens	Gawler
Evanston Park	Gawler
Evanston Park	Playford
Everard Park	Unley
Exeter	Port Adelaide Enfield
Fairview Park	Tea Tree Gully
Felixstow	Norwood Payneham St Peters
Ferryden Park	Port Adelaide Enfield
Findon	Charles Sturt
Firle	Norwood Payneham St Peters
Fitzroy	Prospect
Flagstaff Hill	Onkaparinga
Flaxley	Mount Barker
Flinders Park	Charles Sturt
Forest Range	Adelaide Hills
Forestville	Unley
Forreston	Adelaide Hills
Freeling	Light
Frewville	Burnside
Fulham	West Torrens
Fulham Gardens	Charles Sturt
Fullarton	Unley
Gawler	Gawler
Gawler Belt	Gawler
Gawler East	Gawler
Gawler River	Gawler
Gawler South	Gawler
Gawler West	Gawler
Gemmells	Mount Barker
Gepps Cross	Port Adelaide Enfield
Gilberton	Walkerville
Gilles Plains	Port Adelaide Enfield
Gillman	Port Adelaide Enfield
Glandore	West Torrens
Glanville	Port Adelaide Enfield
Glen Osmond	Burnside
Glenalta	Mitcham
Glenelg	Holdfast Bay
Glenelg East	Holdfast Bay
Glenelg North	Holdfast Bay

Glenelg South	Holdfast Bay
Glengowrie	Marion
Glenside	Burnside
Glenunga	Burnside
Globe Derby Park	Salisbury
Glynde	Norwood Payneham St Peters
Golden Grove	Tea Tree Gully
Goodwood	Unley
Gould Creek	Playford
Grange	Charles Sturt
Green Fields	Salisbury
Green Hills Range	Mount Barker
Greenacres	Port Adelaide Enfield
Greenhill	Adelaide Hills
Greenwith	Tea Tree Gully
Gulfview Heights	Tea Tree Gully
Gumeracha	Adelaide Hills
Hackham	Onkaparinga
Hackham West	Onkaparinga
Hackney	Norwood Payneham St Peters
Hahndorf	Mount Barker
Hallett Cove	Marion
Hampstead Gardens	Port Adelaide Enfield
Happy Valley	Onkaparinga
Harrogate	Mount Barker
Hawthorn	Mitcham
Hawthorndene	Mitcham
Hay Valley	Mount Barker
Hazelwood Park	Burnside
Heathfield	Adelaide Hills
Heathpool	Norwood Payneham St Peters
Hectorville	Campbelltown
Hendon	Charles Sturt
Henley Beach	Charles Sturt
Henley Beach South	Charles Sturt
Hewett	Light
Highbury	Tea Tree Gully
Highgate	Unley
Highland Valley	Mount Barker
Hillbank	Playford
Hillcrest	Port Adelaide Enfield
Hillier	Gawler

Hilton	West Torrens
Hindmarsh	Charles Sturt
Holden Hill	Port Adelaide Enfield
Hope Forest	Mount Barker
Hope Valley	Tea Tree Gully
Houghton	Adelaide Hills
Houghton	Adelaide Hills
Hove	Holdfast Bay
Humbug Scrub	Playford
Huntfield Heights	Onkaparinga
Hyde Park	Unley
Ingle Farm	Salisbury
Inglewood	Adelaide Hills
Ironbank	Adelaide Hills
Joslin	Norwood Payneham St Peters
Jupiter Creek	Mount Barker
Kalbeeba	Barossa
Kangarilla	Onkaparinga
Kangaroo Flat	Light
Kanmantoo	Mount Barker
Kensington	Norwood Payneham St Peters
Kensington Gardens	Burnside
Kensington Park	Burnside
Kent Town	Norwood Payneham St Peters
Kenton Valley	Adelaide Hills
Kersbrook	Adelaide Hills
Keswick	West Torrens
Keswick Terminal	West Torrens
Kidman Park	Charles Sturt
Kilburn	Port Adelaide Enfield
Kilkenny	Charles Sturt
Kings Park	Unley
Kingsford	Light
Kingston Park	Holdfast Bay
Kingswood	Mitcham
Klemzig	Port Adelaide Enfield
Korunye	Mallala
Kudla	Gawler
Kuitpo	Onkaparinga
Kurralta Park	West Torrens
Largs Bay	Port Adelaide Enfield
Largs North	Port Adelaide Enfield

Leabrook	Burnside
Leawood Gardens	Mitcham
Lenswood	Adelaide Hills
Lewiston	Mallala
Linden Park	Burnside
Littlehampton	Mount Barker
Lobethal	Adelaide Hills
Lockleys	West Torrens
Longwood	Adelaide Hills
Lonsdale	Onkaparinga
Lower Hermitage	Adelaide Hills
Lower Mitcham	Mitcham
Lynton	Mitcham
Macclesfield	Mount Barker
MacDonald Park	Playford
Magill	Campbelltown
Malvern	Unley
Manningham	Port Adelaide Enfield
Mansfield Park	Port Adelaide Enfield
Marble Hill	Adelaide Hills
Marden	Norwood Payneham St Peters
Marino	Marion
Marion	Marion
Marleston	West Torrens
Marryatville	Norwood Payneham St Peters
Maslin Beach	Onkaparinga
Mawson Lakes	Salisbury
Maylands	Norwood Payneham St Peters
McLaren Flat	Onkaparinga
McLaren Vale	Onkaparinga
Meadows	Mount Barker
Medindie	Walkerville
Medindie Gardens	Prospect
Melrose Park	Mitcham
Middle Beach	Mallala
Mile End	West Torrens
Mile End South	West Torrens
Millbrook	Adelaide Hills
Millswood	Unley
Mitcham	Mitcham
Mitchell Park	Marion
Moana	Onkaparinga

Modbury	Tea Tree Gully
Modbury Heights	Tea Tree Gully
Modbury North	Tea Tree Gully
Montacute	Adelaide Hills
Morphett Vale	Onkaparinga
Morphettville	Marion
Mount Barker	Mount Barker
Mount Barker Junction	Mount Barker
Mount Barker Springs	Mount Barker
Mount Barker Summit	Mount Barker
Mount Crawford	Adelaide Hills
Mount George	Adelaide Hills
Mount Osmond	Burnside
Mount Pleasant	Barossa
Mount Torrens	Adelaide Hills
Munno Para	Playford
Munno Para Downs	Playford
Munno Para West	Playford
Mylor	Adelaide Hills
Myrtle Bank	Unley
Nailsworth	Prospect
Nairne	Mount Barker
Netherby	Mitcham
Netley	West Torrens
New Port	Port Adelaide Enfield
Newton	Campbelltown
Noarlunga Centre	Onkaparinga
Noarlunga Downs	Onkaparinga
North Adelaide	Adelaide
North Brighton	Holdfast Bay
North Haven	Port Adelaide Enfield
North Plympton	West Torrens
Northfield	Port Adelaide Enfield
Northgate	Port Adelaide Enfield
Norton Summit	Adelaide Hills
Norwood	Norwood Payneham St Peters
Novar Gardens	West Torrens
O'Halloran Hill	Marion
O'Sullivan Beach	Onkaparinga
Oakbank	Adelaide Hills
Oakden	Port Adelaide Enfield

Oaklands Park	Marion
Old Noarlunga	Onkaparinga
Old Reynella	Onkaparinga
One Tree Hill	Playford
Onkaparinga Hills	Onkaparinga
Osborne	Port Adelaide Enfield
Ottoway	Port Adelaide Enfield
Outer Harbor	Port Adelaide Enfield
Ovingham	Charles Sturt
Paechtown	Mount Barker
Pages Flat	Onkaparinga
Panorama	Mitcham
Para Hills	Salisbury
Para Hills West	Salisbury
Para Vista	Salisbury
Paracombe	Adelaide Hills
Paradise	Campbelltown
Parafield	Salisbury
Parafield Gardens	Salisbury
Paralowie	Salisbury
Paris Creek	Mount Barker
Park Holme	Marion
Parkside	Unley
Pasadena	Mitcham
Payneham	Norwood Payneham St Peters
Payneham South	Norwood Payneham St Peters
Penfield	Playford
Penfield Gardens	Playford
Pennington	Charles Sturt
Peterhead	Port Adelaide Enfield
Petwood	Mount Barker
Piccadilly	Adelaide Hills
Plympton	West Torrens
Plympton Park	Marion
Pooraka	Salisbury
Port Adelaide	Port Adelaide Enfield
Port Gawler	Mallala
Port Noarlunga	Onkaparinga
Port Noarlunga South	Onkaparinga
Port Willunga	Onkaparinga
Prospect	Prospect
Prospect Hill	Mount Barker

Queenstown	Port Adelaide Enfield
Red Creek	Alexandrina
Redwood Park	Tea Tree Gully
Reeves Plains	Mallala
Regency Park	Port Adelaide Enfield
Reid	Gawler
Renown Park	Charles Sturt
Reynella	Onkaparinga
Reynella East	Onkaparinga
Richmond	West Torrens
Ridgehaven	Tea Tree Gully
Ridleyton	Charles Sturt
Rockleigh	Adelaide Hills
Rose Park	Burnside
Rosedale	Barossa
Rosewater	Port Adelaide Enfield
Roseworthy	Light
Rosslyn Park	Burnside
Rostrevor	Campbelltown
Royal Park	Charles Sturt
Royston Park	Norwood Payneham St Peters
Salisbury	Salisbury
Salisbury Downs	Salisbury
Salisbury East	Salisbury
Salisbury Heights	Salisbury
Salisbury North	Salisbury
Salisbury Park	Salisbury
Salisbury Plain	Salisbury
Salisbury South	Salisbury
Sampson Flat	Playford
Sandy Creek	Barossa
Scott Creek	Adelaide Hills
Seacliff	Holdfast Bay
Seacliff Park	Holdfast Bay
Seacombe Gardens	Marion
Seacombe Heights	Marion
Seaford	Onkaparinga
Seaford Heights	Onkaparinga
Seaford Meadows	Onkaparinga
Seaford Rise	Onkaparinga
Seaton	Charles Sturt
Seaview Downs	Marion
Sefton Park	Port Adelaide Enfield
Sellicks Beach	Onkaparinga

Sellicks Hill	Onkaparinga
Semaphore	Port Adelaide Enfield
Semaphore Park	Charles Sturt
Semaphore South	Port Adelaide Enfield
Shea-Oak Log	Mount Barker
Sheidow Park	Marion
Skye	Burnside
Smithfield	Playford
Smithfield Plains	Playford
Somerton Park	Holdfast Bay
South Brighton	Holdfast Bay
South Plympton	Marion
Springfield	Mitcham
St Agnes	Tea Tree Gully
St Clair	Charles Sturt
St Georges	Burnside
St Ives	Mount Barker
St Kilda	Salisbury
St Marys	Mitcham
St Morris	Norwood Payneham St Peters
St Peters	Norwood Payneham St Peters
Stepney	Norwood Payneham St Peters
Stirling	Adelaide Hills
Stonyfell	Burnside
Sturt	Marion
Summertown	Adelaide Hills
Surrey Downs	Tea Tree Gully
Taperoo	Port Adelaide Enfield
Tatachilla	Onkaparinga
Tea Tree Gully	Tea Tree Gully
Tennyson	Charles Sturt
Teringie	Adelaide Hills
The Range	Onkaparinga
Thebarton	West Torrens
Thorngate	Prospect
Toorak Gardens	Burnside
Torrens Park	Mitcham
Torrensville	West Torrens
Totness	Mount Barker
Tranmere	Campbelltown
Trinity Gardens	Norwood Payneham St Peters

Trott Park	Marion
Tusmore	Burnside
Two Wells	Mallala
Uleybury	Playford
Underdale	West Torrens
Unley	Unley
Unley Park	Unley
Upper Hermitage	Adelaide Hills
Upper Sturt	Adelaide Hills
Uraidla	Adelaide Hills
Urrbrae	Mitcham
Vale Park	Walkerville
Valley View	Tea Tree Gully
Verdun	Adelaide Hills
Virginia	Playford
Vista	Tea Tree Gully
Walkerville	Walkerville
Walkley Heights	Salisbury
Ward Belt	Light
Warradale	Marion
Wasleys	Light
Waterfall Gully	Burnside
Waterloo Corner	Salisbury
Wattle Park	Burnside
Wayville	Unley
Welland	Charles Sturt
West Beach	West Torrens
West Croydon	Charles Sturt
West Hindmarsh	Charles Sturt
West Lakes	Charles Sturt
West Lakes Shore	Charles Sturt
West Richmond	West Torrens
Westbourne Park	Mitcham
Whites Valley	Onkaparinga
Willaston	Gawler
Williamstown	Barossa
Willunga	Onkaparinga
Willunga South	Onkaparinga
Windsor Gardens	Port Adelaide Enfield
Wingfield	Port Adelaide Enfield
Wistow	Mount Barker
Woodcroft	Onkaparinga
Woodforde	Adelaide Hills
Woodside	Adelaide Hills

Woodville	Charles Sturt
Woodville Gardens	Port Adelaide Enfield
Woodville North	Charles Sturt
Woodville Park	Charles Sturt
Woodville South	Charles Sturt
Woodville West	Charles Sturt
Wynn Vale	Tea Tree Gully
Yatala Vale	Tea Tree Gully
Yattalunga	Playford

APPENDIX D – FUTURE VULNERABILITY INDICATOR MULTIPLIERS

Table 0-1 Social Vulnerability future multipliers for each indicator and the five Greater Adelaide regions for the Ignorance of the Lambs socio-economic scenario.

Indicator	Region				
	East	West	South	North	Hills
Proportion of Young People	0.95	0.95	1.1	1.1	1.1
Proportion of Old People	1.1	1.1	1.02	1.02	1.02
Education	0.95	0.95	0.95	0.95	0.95
Personal Wealth	0.8	0.8	0.8	0.8	0.8
Unemployment	1.05	1.05	1.1	1.1	1.1
Net population growth	1.3	1.3	2.1	2.1	2.7
Migrant English	1	1	1.15	1.15	1.15
Volunteers	0.95	0.95	0.95	0.95	0.95
Recently moved to area	0.98	0.98	1.1	1.1	1.1
Indigenous	1	1	1	1	1
Family Structure	1	1	1	1	1
Disabilities	1	1	1	1	1
Car Ownership	1	1	1	1	1

Table 0-2 Social Vulnerability future multipliers for each indicator and the five Greater Adelaide regions for the Cynical Villagers socio-economic scenario.

Indicator	Region				
	East	West	South	North	Hills
Proportion of Young People	0.98	0.98	0.98	0.98	0.98
Proportion of Old People	1.05	1.05	1.1	1.1	1.1
Education	1	1	1	1	1
Personal Wealth	0.8	0.8	0.8	0.8	0.8
Unemployment	1	1	1	1	1
Net population growth	1.1	1.1	1.15	1.15	1.25
Migrant English	1.02	1.02	1.02	1.02	1.02
Volunteers	1	1	1	1	1
Recently moved to area	1	1	1	1	1.05
Indigenous	1	1	1	1	1
Family Structure	1	1	1	1	1
Disabilities	1	1	1	1	1
Car Ownership	1	1	1	1	1

Table 0-3 Social Vulnerability future multipliers for each indicator and the five Greater Adelaide regions for the Silicon Hills socio-economic scenario.

Indicator	Region				
	East	West	South	North	Hills
Proportion of Young People	1	1	1	1	1
Proportion of Old People	1.02	1.02	1.05	1.05	1.1
Education	1.1	1.1	1.1	1.1	1.1
Personal Wealth	1.2	1.2	1.2	1.2	1.2
Unemployment	0.95	0.95	0.98	0.98	0.98
Net population growth	1.6	1.6	1.4	1.4	1.5
Migrant English	0.9	0.9	0.95	0.95	0.95
Volunteers	1.02	1.02	1.02	1.02	1.02
Recently moved to area	1.02	1.02	1.02	1.05	1.02
Indigenous	1	1	1	1	1
Family Structure	1	1	1	1	1
Disabilities	1	1	1	1	1
Car Ownership	1	1	1	1	1

APPENDIX E – CONTACT DETAILS

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