LOCAL URBAN COMMUNITIES AND EXTREME WEATHER EVENTS: MAPPING SOCIAL VULNERABILITY TO FLOOD\textsuperscript{1,2}

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ABSTRACT: Interest in the impacts of climate change and extreme weather events on regions throughout the world has taken on a new and more urgent focus in recent years. As attention has turned to understanding climate change adaptation, researches have begun considering the ways in which social vulnerability to climate related events can be understood and analysed so as to aid in policy development. This paper continues this growing research theme by developing a social vulnerability index for flood using the Gold Coast region as an example. Using data from a variety of sources the paper illustrates how when the social dimension of flood vulnerability is incorporated into an understanding of the physical threat of flood, a more meaningful focus on potential adaptation measures is attained.

1. INTRODUCTION

In the middle of the last century 30 percent of the globe’s approximately 2.5 billion people lived in cities. Now, a little more than 50 years later, half the world’s population live in urban settlements. Historically the concentration of population in the urban form has been to the greater social benefit: to defend together, to produce together and to exchange amongst each other. The consequences of global warming, however, are exacerbated by urban settlement. Large concentrations of people fixed in space are particularly vulnerable to the structural effects of global and regional climate change such as rising sea-levels.

\textsuperscript{1} This paper was presented at the 32nd ANZRSAI Conference held in Adelaide from 30\textsuperscript{th} Nov – 3\textsuperscript{rd} Dec 2008.

\textsuperscript{2} The research reported in this paper comes from a Department of Climate Change project titled ‘Climate change, Health impacts and Urban Adaptability: Case Study of the Gold Coast’. Funding support was provided by the Department of Climate Change, the Gold Coast City Council and the Queensland Department of Infrastructure and Planning. The authors would like to thank Professor Ben Tswgaf, Mr. Rick Evans, Ms. Katrin Lowe, Ms. Joanne Pascoe for assistance during this project.
dwindling water supply (for domestic, industrial and energy use) and the general loss of environmental elasticity and capacity. The structural effects of global warming are, however, not confined to a widely-defined geography of climate. They include, in addition, a temporal dimension. There is, in short, indicative and gathering evidence of climatic instability with a global rise in the frequency and intensity of extreme weather events such as floods, heat waves, cold snaps and cyclones (IPCC, 2007a&b; McMichael et al., 2003).

The impact of the increasing frequency and intensity of extreme weather events on an ever greater spatial concentration of population has in the last decades emerged as the most readily perceived manifestation of ‘climate change’. It is not surprising therefore that the economic and physical costs associated with extreme weather events have, in recent years, become an important part of the academic and policy literature (Mills 2005, Warren et al. 2006, Changnon 2004, Comfort 2006, Waugh 2006). In the US, for example, in the wake of hurricane Katrina a range of research has reported the economic and insurance implications of the disaster (Kunrether 2006, Daniels et al. 2006, Comfort et al. 2006, Baade et al. 2007) as well as the social and health impacts (Cutter et al. 2006, Coker et al. 2006).

Research into extreme weather events however is not confined to its consequences. A growing set research has attempted to understand and measure human vulnerability to these events (Alwang et al. 2001, Adger et al. 2004, Downing and Patwardhan 2004, Rygel et al. 2006, Clark et al. 1998). The definition of ‘vulnerability’, however, is not constant with researchers from different disciplines taking different meanings and concepts as their points of departure. Social scientists tend to conceive of vulnerability in terms of socio-economic and demographic factors that reflect the capacity of individuals and/or groups (i.e. the community) to cope with or adapt to the challenges of (climate induced) disruption. ‘Hard science’, in contrast, focuses more on the forecast of the physical geography of a particular climatic event (i.e. risk of flood) assuming, by default, the social geography to be constant (Adger et al. 2004). In building policy and programs to address issues associated with climate change events we need to address both the potential physical dimensions of impact and the varying vulnerability of individuals and groups to the event. That is there is a need for the development of a social geography of risk. The need for such a focus is echoed by Clark et al. (1998 62):

_The crux of vulnerability to global environmental change is as follows: people stand to experience impacts from hazards of global change in varying degrees that fall along a spectrum from positive to negative, based on their position in the social and physical worlds._

The focus on both the ‘social and physical worlds’ means being able to describe, analyse and map vulnerability across varying spatial scales (regions, cities, communities and neighbourhoods) taking into account the physical geography of the potential climate change event while also accounting for the social, economic and demographic characteristics of the communities or neighbourhoods at risk. Such analysis will generate a more comprehensive, socio-spatial understanding
of the risks of extreme weather events allowing for better adaptation preparation and damage limitation response (Rygel et al. 2006).

This paper contributes to the investigation of the social effects of climate change. It describes a method for developing an index of social vulnerability using the example of flood risk across residential communities of Gold Coast City, Australia. The paper continues below with a review of existing techniques for estimating socio-spatial vulnerability. It continues with the development and explication of an index of (social) vulnerability for flood in Gold Coast City, Australia. The paper concludes with consideration of possible refinements to the tool and discussion of its role in the development of adaptation responses to extreme weather events.

2. SOCIO-SPATIAL VULNERABILITY AND EXTREME CLIMATE CHANGE EVENTS

As an area of applied social science research the spatial mapping or social ecology of socio-economic disadvantage and/or vulnerability predates climate change concern. The development of indices and visualisation tools with which to describe patterns of vulnerability stretches back to at least Snow’s iconic 1854 study of cholera deaths in London. In the twentieth century, the work of the Chicago school (see Theodorson 1982 for an overview), post war social area analysis (see Timms 1970) and other work on ecological segregation (e.g. Duncan and Duncan 1955) developed the understanding of the city as social space. More recent work, deploying advances in spatial modelling powered by electronic computing, has continued urban socio-spatial analysis with investigations into the emerging forms of the ‘post-Fordist’ or contemporary city (Baum et al. 2006, Walks 2001, Taylor and Hoyler 2000).

Building on this tradition the analysis and visualisation of the social ecology of climate change risk takes as its starting point the inter-play between the physical geography of a given climate change event and the wider urban social structure. Such ‘hazards-of-place’ or ‘vulnerability of place’ analysis extends conventional socio-spatial investigation with the addition of a climate change dimension to the patterning of vulnerability in human settlement. Following Cutter et al. (2003) this approach sees place vulnerability as a combination of biophysical vulnerability and social vulnerability which, in turn, are a function of the interplay between the potential for a given hazard to occur and the socio-geographic weave of the fabric of place. The estimation of place vulnerability is, consequently, firmly tied to an adequate understanding of the existing patterns of community settlement and development. The consequences of this approach are summarised by Cannon (1994, 14-15):

*There are no really generalised opportunities and risks in nature, but instead there are sets of unequal access to opportunities and unequal exposures to risks which are a consequence of the socio-economic system...It is more important to discern how human systems themselves place people in relation to each other and to the environment than it is to interpret natural systems. (emphasis added).*

The dimensions of exposure included in the vulnerability relation, dependent
as they are on physical events or processes, are well conceptualised (See Clark 1998; Renn 1992). In general the geography of exposure is related to the physical characteristics of the location, offset against any mitigation programs. The result, clearly, is a variation across space in exposure and therefore risk. While comparatively easy to conceptualise, the estimate of the structure of exposure is, often, no simple matter. The topographical mapping of exposure has often generated considerable debate about assumptions necessary to project discrete data across dimensional space.

The socio-spatial dimension of climate change vulnerability, on the other hand, are less theoretically conceptualised as empirically accounted for by a range of indicators. Common indicators include: socio-economic status and poverty; health status and the presence of disabilities; age; household and family structure; racial background and ethnicity; and the social capital and social networks associated with adaptive capacity (Cutter et al. 2003, Tapsell et al. 2002, Morrow 1999, Rygel et al. 2006). A number of these potential variables and indicators are very familiar having, for more than 50 years, repeatedly proven their statistical power in urban social analysis. Perhaps unsurprisingly socio-economic status and poverty are more often than not key to understanding social vulnerability to extreme events (Clark et al. 1998). It is almost a truism that in a market society the access of an individual or household to social opportunity is impeded by a lack of income; or in mirror reflection income is positively correlated with the ability to benefit from wider life chances. Similarly, it may be readily conceived, with income being associated with latent resilience or the capacity to cope with adversity, low income households and individuals lack, at a statistical level, the capacity to provide for extreme events in an appropriate manner and the resources required to recover from even modest loss. Investigation of the aftermath of natural disasters supports the above hypotheses, showing households with lower incomes to suffer both higher mortality rates that the norm and greater housing loss (see Blaikie et al. 1994) while, after the event, having less access to transport and other essential support mechanisms (see Morrow 1999, 1997). Low income also limits the range of dwelling type available to an individual or family and the choice of residential community. As such the economics of low income and housing choice, expressed in lower standards of housing and greater locational exposure to the forces of nature (eg. living on a flood plain), also tend to increase vulnerability.

While income or its lack is readily seen as the key component associated with social vulnerability other factors are also important. At the individual level older people, with reduced physical capacity often manifest in a lack of mobility, are likely to be at elevated levels of vulnerability to the impacts of extreme weather events. Not only are elderly individuals at a disadvantage when rapid movement over unfamiliar terrain is required (e.g. to avoid flood water or fire), but their often frail state of physical wellbeing may manifest in increased isolation. Older people more likely to lock themselves in their homes because of security fears, with evidence suggesting that this fear of crime behaviour increases their social isolation prior to the event resulting in a lower likelihood they will receive assistance from their neighbours during the emergency (Naughton et al. 2002,
Fernandez et al. 2002). Similarly single parent households are more at risk not only because they are frequently low income households (Rygel et al. 2006), but also because of the difficulty in caring for and keeping track of dependent children (Clark et al. 1998). Significant health problems such as long term illness or disability have also been found to be associated with elevated risk in the event of extreme weather impact (Morrow 1999). The extent to which social vulnerability is associated with race or ethnicity is ambiguous. Thus, for example, there is no shortage of evidence that African-Americans were among the hardest hit during hurricane Katrina. However, in this not atypical context being African American was highly correlated with, almost a proxy for, lack of income. In other contexts there is some, albeit less stark evidence to suggest that social vulnerability might be higher for particular ethnic or racial groups as a direct result of poor language skills or differing cultural practices (Gladwin and Peacock 1997, Yelvington 1997) or due to discriminatory practices (Fothergill 1999, Clark et al. 1998, Peacock and Girard 1997).

The biggest human impact of a severe weather event is often the least dramatic. After the immediate dangers have abated impacted communities face the daunting task of restoring the built environment and the equilibrium of social life. Both are tedious projects extending long after the attention of wider society (and often the general public administration) has been diverted by other issues and priorities. In this context the capacity of people to deal with the systemic disruption of their lives, unrelenting economic anxiety and feelings of permanent loss are severely tested (Tapsell et al. 2002). The psychological distress of such situations can take a number of symptomatic forms – anxiety, depression and sleep disorder are the most common. By convention these various symptoms are grouped together as post traumatic stress disorder (PTSD). Research, especially in the US, has lent increasing credence to the notion of lasting stress in impacted communities. A longitudinal study of Dade County survivors of Hurricane Andrew (the 1992 forerunner of Hurricane Katrina) found between 20 to 30 percent of adults presented with PTSD symptoms at 6 months and 2 years after the event (Norris et al., 1999: 2). The research found PTSD levels did not decline in the 18 months between surveys and concluded “psychological problems may linger long after the initial danger has happened and passed – clearly past the crisis period when services abound” (Norris et al., 1999; 24).

Vulnerability to extreme weather events can, in sum, be thought of as an articulation of a physical geography of exposure and a social structure of risk mediated through a capacity to absorb and recover from event effects. An adequate modelling of such risk should therefore account for the non-random impacts of:

• the physical geography of the event;
• the social stratification of risk;
• the uneven distribution of individual life chances; and
• social interaction and organisation.

In a study of Gold Coast City, Australia we investigate the complexities of these requirements.
3. SOCIAL VULNERABILITY AND FLOOD: GOLD COAST, AUSTRALIA

Located on the south east Queensland coast between the state capital, Brisbane, to the north and the border of New South Wales to the south, Gold Coast city spans 1402 square kilometres and features a 70 kilometres ocean boundary (see Figure 1). Home to approximately 500,000 people, it is the nation’s 6th largest and fastest growing city. The greater urban area is drained by three major rivers: the Nerang River in the central Gold Coast, and the Coomera and the Logan rivers to the north. Most of the area adjacent to these rivers and much of the land between the coastal strip and the hinterland was once wetland. As part of the Gold Coast development, the wetlands and swamps have been drained creating a landscape of constructed waterways (over 260 km) and artificial islands many of which are covered in upmarket homes. The narrow sandbar between the waterways and the sea is a site of intense urban development containing, for example, the tallest residential structure in Australia (Q1 building). The concentration of development adjacent to the coast exposes residents to the significant storm surge danger.

In 1974 extreme weather, rough seas and 1250 mm of rain in two days combined to flood greater Gold Coast city. The level of the Nerang river more than doubled to a height of 9.5 meters. Over 2000 people were evacuated and the city’s infrastructure was severely damaged. Parts of the city were isolated, telephone services were disrupted and many exclusive canal developments were inundated. Subsequently many mitigation strategies for flood have been put in place. Nevertheless both the Gold Coast City Council and the Australian federal government recognise that the region remains particularly vulnerable to extreme weather events. Recent research has found the Gold Coast to have the greatest number of buildings at risk of a 100 year return flood in Australia (Abbs 2002). The at risk profile of the Gold Coast is, moreover, likely to be exacerbated by a combination of, all things being equal, continued rapid population growth and a growing proportion of social groups, especially the aged and income deficient service workers, particularly vulnerable to climate sourced stresses and hazards.

3.1 Building the social vulnerability index

The literature on climate change vulnerability indices recognises a wide range of potential measures and methods (see Adger et al. 2004). The approach we use in this paper was first used by Langlois and Kitchen (2001) to describe social deprivation for Montreal, Canada and subsequently used by Baum (2004, 2008) to analyse deprivation in Australian suburbs. The original index uses multivariate analysis to construct a dimensional measure of socio-economic deprivation and is readily transferable to an analysis of social vulnerability and extreme weather events.

Figure 1. Gold Coast City
The guiding premise behind the index developed by Langlois and Kitchen (2001) is that deprivation can be measured with reference to an overall indicator of deprivation (a necessary condition) combined with situations where deprivation is most thought to occur. Here we argue that social vulnerability in terms of flood depends on the geography of exposure (a necessary condition) plus the socio-spatial structure with relevance to social vulnerable groups and individuals. Schematically, Figure 2, shows possible combinations of factors associated with the various situations of flood vulnerability. Local flood exposure is considered to be a necessary condition for flood vulnerability. Once this condition is satisfied, the overlaps with the range of components that make up the broader socio-spatial structure define specific situations of flood vulnerability. The dual variation in exposure and the socio-spatial structure will be traced in the index defined by the intersection of the two dynamics.

The Griffith University Social Vulnerability Index for Flood (GUSVIF) is, in mathematical summary, constructed with reference to the following equation:

\[
GUSVIF_i = \frac{E_i \ast (1 + \sum \hat{S}_j)}{n}
\]

where \(E_i\) refers to the exposure for community \(i\); \(\hat{S}_j\) refer to social factor \(j\) for community \(i\); and \(n\) refers to the total number of components included in the index. The result is a simple weighted index that accounts for the social vulnerability/risk of flood across communities.

3.2 Exposure (flood risk)

The first component of the index (\(E_i\) in equation 1) is estimated using Gold Coast City Council flood data. Most notably among the methods reported in the literature to account for flood risk are indicative floodplain extents and floodplain maps (Tapsell et al. 2002, Clark et al. 1998) and the use of surge height models (Rygel et al. 2006). In this work we use the designated flood level for a 100 year flood event as our measure. The raw data, which includes a 2.3 metre storm surge assumption, was provided on a 5 by 5 metre grid. The data was aggregated and averaged over Census Collectors Districts (CCDs). The result was a potential water inundation level for each CCD. The variation in this level across census districts provided a robust indicator of the geography of physical exposure/risk.

3.3 Social vulnerability

This section focuses on developing the components of social vulnerability that are used in combination with the physical flood risk data to develop the overall index. Within the existing literature there has been a range of indicators developed to account for the potential social, economic, health and other vulnerabilities which are associated with flood. In building our individual components of social vulnerability we use Australian Bureau of Statistics 2006 Census data and the method of principal components analysis. To match the spatial scale of the exposure variable, census data was obtained for the 875
The individual variables used to build the components of social vulnerability are:

- MED_HH_INC: median household income (Australian dollars 2006);
- MED_IND_INC: median individual income (Australian dollars 2006);
- AGE65: % of residents in a CCD aged 65 years or above;
- ASSIST: % of residents in a CCD who require assistance with daily tasks;
- MED_AGE: median age;
- WIDOWED: % of residents in a CCD who are widowed;
- MLFP: Male labour force participation rate in the CCD;
- FLFP: Female labour force participation rate in the CCD;
- AV_HH_SIZE: Average Household Size in CCD;
- AV_P_BB: Average Number of people per bedroom in CCD;
- SEPERATE: % people separated or divorced in CCD;
- MARRIED: % people married in CCD;
- SING_PAR: % of single parent families;
- NO_CAR: % households with no cars;
- F_UNR: Female unemployment rate in CCD;
To capture ‘social vulnerability’ the 19 individual variables were included in a principal components analysis. The variables were entered into a correlation matrix and a Varimax orthogonal rotation with Kaiser normalisation was applied (Table 1). The criterion for the retention of a factor was an eigen value greater than one. Analysis isolated five factors or components accounting for 72% of the variance. The first factor is labelled AGED and reflects the presences of higher proportions of people aged over 65 years in the CCD. The variables contributing to this factor are % of residents in a CCD aged 65 years or above, median age, % of residents in a CCD who require assistance with daily tasks and % of residents in a CCD who are widowed. The second factor accounts for the potential presence of higher levels of social engagement and higher levels of social networks or social capital. We assume that people who are in the labour force will, other things being equal, have wider social contacts than those outside the labour force, and that the size of households is positively associated with wider social links and social capital. The variables comprising factor 2 are: Male labour force participation rate in the CCD, Female labour force participation rate in the CCD, Average Household Size in CCD and Average Number of people per bedroom in CCD. The third factor (not used in the final analysis) is the reverse of Factor 2 and was designed as a proxy for social isolation. The variables comprising this factor are: % people separated or divorced, % people married and % of single parent families. The fourth factor, the indispensable dimension of social analysis in a market society, is a representation of available money. It contains two variables; median household income and median individual income. The fifth and last factor takes account of race and ethnicity. It contains two variables: the % Persons born overseas who arrived in past five years in CCD and, the % of people with poor English skills in CCD. The reliability or stability of the 5 components were tested with an analysis of the inter-correlation between variables. The Cronbachs’ Alpha coefficients were: aged 0.83; engagement/support 0.64; social isolation/marital status 0.46; income 0.65; ethnicity 0.55. The coefficient for the third factor, representing social isolation, was unacceptably low. The factor was discarded. The other four dimensions were retained.

The next step in the development of the index was the estimate of a ‘score’ for each CCD representing the social structure. A ready scoring method is to multiply the standardised value of each variable by the factor loading derived from the principal components analysis, and to aggregate the results. An alternative approach, following the example of Western and Larnach (1998), would polarise variable values by assigning a value of 1 for those CCD variables with a score above the sample median and 0 for the rest (i.e. variable scores below the mean). Horn (1965) supports the polarisation method and finds it yields comparable results to other techniques. This work adopts the second option. Once the ‘polarised’ variables were produced factor scores, being for
each CCD component the number of variables with above median incidence, were estimated. In the case of the aged dimension of CCD 3160330, the application of the median test allocated 0 to the variable ‘median age’, requiring its discard. The following variables with incidence above the Gold Coast median were retained: % of residents aged 65 years or above, % of residents who are widowed, and % of residents in a CCD who require assistance with daily tasks. Each variable assumes a value of 1 and hence the aggregate score for the CCD 3160330 ‘aged’ factor is 3. The minimum score for any CCD factor would be 0, while the maximum score for a CCD would be equivalent to the total number of variables included in the factor.

**Table 1. Rotated Component Matrix Component**

<table>
<thead>
<tr>
<th>Component Description</th>
<th>Component 1</th>
<th>Component 2</th>
<th>Component 3</th>
<th>Component 4</th>
<th>Component 5</th>
</tr>
</thead>
<tbody>
<tr>
<td>% people aged 65+</td>
<td>.914</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Median age</td>
<td>.856</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% people widowed</td>
<td>.855</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% of people who require daily assistance</td>
<td>.695</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male labour force participation rate</td>
<td>.792</td>
<td>.746</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Household Size</td>
<td></td>
<td>.740</td>
<td>.701</td>
<td></td>
<td>.585</td>
</tr>
<tr>
<td>Female labour force participation rate</td>
<td></td>
<td></td>
<td>.701</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Average Number of people per bedroom</td>
<td></td>
<td></td>
<td></td>
<td>.854</td>
<td>.585</td>
</tr>
<tr>
<td>% people separated or divorced</td>
<td></td>
<td></td>
<td></td>
<td>.854</td>
<td>.585</td>
</tr>
<tr>
<td>% people married</td>
<td></td>
<td></td>
<td></td>
<td>-.644</td>
<td></td>
</tr>
<tr>
<td>% of single parent families</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.585</td>
</tr>
<tr>
<td>% households with no cars*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.585</td>
</tr>
<tr>
<td>Median individual income</td>
<td></td>
<td>.823</td>
<td></td>
<td>-.601</td>
<td></td>
</tr>
<tr>
<td>Median household income</td>
<td></td>
<td></td>
<td>.823</td>
<td>-.601</td>
<td>.585</td>
</tr>
<tr>
<td>Female unemployment rate*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.585</td>
</tr>
<tr>
<td>Male unemployment rate*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.585</td>
</tr>
<tr>
<td>% Persons born overseas who arrived in past five years</td>
<td></td>
<td></td>
<td></td>
<td>.755</td>
<td></td>
</tr>
<tr>
<td>% of people with poor English skills</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.687</td>
</tr>
<tr>
<td>population density*</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>.585</td>
</tr>
<tr>
<td>% variance explained (total 71.7)</td>
<td>30.4</td>
<td>16.1</td>
<td>10.3</td>
<td>9.1</td>
<td>5.8</td>
</tr>
</tbody>
</table>

**Notes:** * variables with loadings less than 0.5 are not included in the final component score.
As an additional step, each score was rescaled following the method outlined by Langlois and Kitchen (2001). The rescaling follows equation (2) below:

\[
\hat{S}_{ji} = \frac{(S_{ji} - \min_j)}{(\max_j - \min_j)}
\]

where \(0 \leq \hat{S}_{ji} \leq 1\); and \(S_{ji}\) is the factor score for locality \(i\) on principal component \(j\); \(\max_j\) and \(\min_j\) are the highest and lowest factor score on component \(j\). As the minimum for each factor score is zero and the maximum is equal to the number of components used in each score this reduces to calculating an unweighted average score \(j\) for each community \(i\).

4. MAPPING FLOOD VULNERABILITY

The application of the methodology described above results in an individual social vulnerability for flood score for each of the communities (CCDs) on the Gold Coast. The advantage of calculating such a score lies in the ability to visualise social risk via a series of maps and to compare the diverse social vulnerability scores with the risk implied by only using the bio-physical indicator of risk (i.e. flood risk).

Mapping only the physical geography of flood exposure reveals three locales of particular vulnerability (Figure 3). They are:

- Area A, located on the northern boundary the Gold Coast proximate to Beenleigh and adjacent the Logan and Albert rivers;
- Area B includes areas in and around Coomera and the lower Coomera river; and
- Area C, located in the central area of the Gold Coast downstream at the mouth of the Nerang river catchment.

The articulation of the flood exposure and social vulnerability in the GUSVIF refines the results of a purely physical analysis. The majority of communities across the Gold Coast have negligible or low levels of socio-physical vulnerability. GUSVIF scores range from 0 to 3.11 with a mean of 0.36 and a standard deviation of 0.53. Mapping GUSVIF shows communities close to the coast, adjacent to the existing waterways in central and northern parts of the Gold Coast to have the highest levels of vulnerability (Figure 4). These results broadly echo those of the unqualified flood risk analysis outlined in Figure 3. The inclusion of social vulnerability, however, allows for finer grained discrimination. Vulnerability in the central region of Gold Coast urban development around Broadbeach (area C of Figure 3) for example ranges from high to relatively low even though the physical risk of flood is similar.
Figure 3. Flood Risk, Gold Coast City Council
Figure 4. GUSVIF, Gold Coast City Council
The mosaic of analytical discrimination introduced by GUSVIF into the area is clearly shown in Figure 5. Areas ‘A’ and ‘B’ are polar opposites although they are both at high levels of flood risk. Area ‘A’ has one of the highest GUSVIF scores (1.96) reflecting both a high risk of flood and a socially vulnerable local community. In area B the high risk of flood is offset by a community social analysis suggests is well equipped to absorb and recover from flood impacts. The result is a low GUSVIF scores (0.52). Similar differences can be seen in Figures 6 and 7 which provides detail of the northern regions of the Gold Coast around Coomera (Figure 6) and adjacent to the City of Logan (Figure 7). Again, the coarse physical analysis of flood risk is transformed into a mosaic of difference reflecting variations in social structure and, thus, vulnerability to the same event.

Going beyond consideration of the particular example, the dimensionality provided by the inclusion of social vulnerability in the analysis may be more generally appreciated with a plot of the (physical) exposure variable against the broader social vulnerability index. This plot of the variation introduced into the measure of flood vulnerability by moving from a simple measure based on a physical event to a broader social indicator is shown in Figure 8. If the introduction of social vulnerability had been redundant the plot would approximate a uniform line. At low levels of flood risk this, unsurprisingly, is, virtually, the case. The conclusion to be drawn is that an elevated risk of physical flood is a necessary but not sufficient condition for social vulnerability. However, as the risk/height of physical flood increases so does the variation between GUSVIF scores. The immediate conclusion is, of course, that for a given level of flood risk vulnerability can vary considerably depending on social structure. For example, for a flood level of 2.2 metres, the GUSVIF varies from 0.560 to 2.224. In general, however, the variation of GUSVIF at elevated risk of flood suggests that once the necessary condition of flood has been met, the impact of flood is not a physical but a social phenomenon.

5. DISCUSSION

The Griffith University Social Vulnerability Index for Flood is a contribution to the study of the emerging consequences of extreme weather events and climate change. The development of the index was driven by the increasing research and policy interest in if not mitigating the effects of global warming then, at least, adapting to its impacts. For more than half the world’s population concentrated in urban settlements such research is particularly urgent. The index modified an existing methodology used to describe and visualise relative socio-economic deprivation across cities (Langlois and Kitchen 2001) to produce an indicator of social vulnerability to flood that takes account of both the physical geography of a climate change event (exposure) and a social geography of vulnerability.
Figure 5. Detailed GUSVIF for central Gold Coast (note hatching indicates communities with high exposure)
Figure 6. Detailed GUSVIF for Coomera, Gold Coast (note hatching indicates communities with high exposure)
Figure 7. Detailed GUSVIF for north Gold Coast (note hatching indicates communities with high exposure)
Our research has shown that vulnerability to an extreme weather event, such as flooding, is more than simple exposure to a force of nature articulated in the physical world. The combination of the bio-physical risk and the social and economic characteristics of communities illustrate the diversity of potential outcomes in the face on an extreme event. This articulation of vulnerability as a consequence of both bio-physical and social factors illustrates how individuals and communities stand to experience impacts from hazards of climate change in varying degrees. Vulnerability is not equal across all groups, but will fall along a spectrum from positive to negative based on the position of individuals and their communities in the physical and social worlds. By focusing attention on the uneven spatial impacts across communities, analysis as we have presented here draws attention away from general, often broad-brush adaptation approaches and allows a more targeted approach to be considered.

Social vulnerability maps of the type produced here, for example, can be used by planners to pin-point concentrations of high risk households and to design responses for their specific requirements (e.g., the needs of the immobile, social...
isolated, single person household are different to those of the impoverished family). The visual nature of the mapped index is a considerable quality. It allows the gist of the analysis to be appreciated if not at a glance then, at least, easily and rapidly. The tool and its pictorial representation has great potential in public educational initiatives and evacuation plans (Morrow 1999) and can be built into ‘what if scenario’ exercises used in planning workshops. Interactive on-line planning and policy development, to help in management of potential issues and to allow better coordination across agencies and non-government bodies, is another clear opportunity.

This paper presents an exploratory approach to measuring and visualising social vulnerability to climate change events. It goes almost without saying the work has its limitations. The indicators and proxies used to describe both exposure and social vulnerability were necessarily driven by the availability of data. Absent of this limitation, several improvements can be readily suggested. The measure of exposure, while used elsewhere, would be improved by some accounting for the potential of intervening factors such as current mitigation infrastructure. The conception of social structure was also dependent upon available data and as with all work of empirical nature the extent to which such data captures a particular social dimension is open to question. For instance, we have used labour force participation and household size as a proxy for social networks and social capital. Clearly this draws a bow of some dimension and a more robust indicator of social networks and social capital would be useful. Despite these issues the method outlined in this paper provides a starting point for a readily applied, robust assessment of socio-spatial vulnerability to extreme weather events. The approach could with little difficulty be applied to other extreme events, such as storm surge or heat waves. Research is currently underway to apply this approach to mapping urban vulnerability to extreme temperature and, while this paper has focused on a relatively small geographical area, there is no reason to suspect its application to wider regions would not be rewarding.
REFERENCES


