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ORIGINAL ARTICLE

Community resilience to crime: A study of the 2011 Brisbane flood

Rebecca Wickes[1] | **Renee Zahnow**[2] | **Jonathan Corcoran**[3] | **Anthony Kimpton**[3]

[1]School of Criminology and Criminal Justice, Griffith University, Brisbane, Australia

[2]School of Social Science, The University of Queensland, Brisbane, Australia

[3]School of Earth and Environmental Sciences, The University of Queensland, Brisbane, Australia

Correspondence
Rebecca Wickes, School of Criminology and Criminal Justice, Griffith University, 176 Messines Ridge Rd, Mount Gravatt QLD 4122, Australia.
Email: r.wickes@griffith.edu.au

Abstract

Understanding and enhancing community resilience is a global priority as societies encounter a rising number of extreme weather events. Given that these events are typically both sudden and unexpected, community resilience is typically examined after the disaster so there can be no before and after comparisons. As such, the extent to which existing community capacities buffer the effects of a traumatic event remains largely unexamined and untested in the literature. Drawing on a longitudinal study of 148 Brisbane suburbs, we examine the key community processes associated with community resilience to the crime before and after the 2011 Brisbane floods. We introduce a novel disaster severity index to simultaneously capture the direct and indirect impacts of the flood and embed this measure within our modeling framework. Results from the models provide important insights for predisaster preparedness and postdisaster rebuilding and recovery.

KEYWORDS

community, disaster, resilience, social capital

Highlights

- Neighborhood adaptive capacities were resistant to the flood.
- The bespoke flood severity index was strongly associated with lower levels of resilience to property crime postevent.
- Pre-event adaptive capacities did not lead to resilience to property crime postevent.

INTRODUCTION

Globally, the frequency and intensity of extreme weather events is increasing. Scholars predict this upward trajectory of event severity and regularity will continue in the coming decades, which will have significant social and economic impacts for individuals, communities, and nation-states (Intergovernmental Panel on Climate Change, 2021). In response to these concerns, governments at all levels are prioritizing community resilience through the development of policies and strategies to mitigate, respond to and recover from environmental disasters (Gemenne et al., 2020). Such initiatives often aim to build community resilience in the predisaster context to minimize disaster vulnerability and to prepare for effective, collective responses when disasters occur (Arbon, 2014; Cutter et al., 2010).

Community resilience can be conceptualized as the community's ability to respond to sudden or unplanned impacts and changes through adaptations that result in either neutral or positive outcomes (Adger et al., 2005; Forgette & Boening, 2009; Norris et al., 2008). Resilient communities are those which adapt to the postdisaster environment and demonstrate predisaster or improved levels of community functioning (Adger et al., 2005; Forgette & Boening, 2009; Norris et al., 2008). The extent to which community resilience is revealed following a disaster largely depends on the severity of the disaster and the characteristics of the local context in which a disaster occurs. Community resilience is, at least in part, a function of local strengths such as socioeconomic advantage (Browning et al., 2006). Community resilience will, therefore, vary across the disaster-affected area as the ability to absorb impacts and cope with an adverse event will differ according to the social-structural conditions of the local area.

The sociodemographic context of the community and the social processes that protect communities from a range of social problems in times of disaster quiescence are remarkably similar to those that enhance community resilience postdisaster. These include neighborhood advantage, lower concentrations of vulnerable groups, residential stability, the presence of social networks, and the ability of community residents to work together to solve local problems (Cutter et al., 2003, 2008; Sampson et al., 2002). Norris and et al.'s (2008) theoretical work on community resilience provides a detailed classification of these characteristics through four interconnected “adaptive capacities” that they argue are necessary for community resilience: (1) social capital; (2) economic resources; (3) communication and information; and (4) community competence. These adaptive capacities are assumed to be in place before the onset of a disaster but can evolve as communities respond to the disaster event.

While academic research has attempted to better understand community resilience and its antecedents in recent years, scholarship remains largely theoretical or conceptual in nature (Breton 2001; Manyena 2006; Matarrita-Cascante et al., 2017; Norris et al., 2008), or focused on the development and testing of community resilience indicators (Cutter et al., 2008; Magis 2010; Sherrieb et al., 2010). The few empirical studies that explore community resilience rely on case studies of particularly high-risk areas following a disaster (Imperiale & Vanclay, 2016; Langridge et al., 2006), or on places experiencing sustained crisis and change such as rural communities facing decline (Chenoweth & Stehlik, 2001). From this literature, a community's social capital, its ability to access necessary resources, the presence of leaders to mobilize residents and residents' collective action orientation are all deemed important. However, often in studies that seek to measure community resilience, the outcomes are indistinguishable from the indicators (see, e.g., Kimhi & Shamai, 2004). This problem is predominantly a function of the conceptual overlap of community resilience with other related yet distinct concepts like vulnerability, preparedness, and recovery. Few studies, therefore, robustly examine “how independently assessed community resources influence the post-disaster wellness of constituent populations” (Norris et al., 2008, p. 145). At the time of our review, only a handful of studies address community resilience in the pre- and postdisaster context (Hawdon & Ryan, 2012; Sweet 1998; Wickes et al., 2015, 2017; Zahnow et al., 2017).

We argue there is a pressing need for longitudinal assessments of community resilience to assist with the identification of predisaster community adaptive capacities that can predict postdisaster community functioning. Yet the sudden and unexpected nature of disasters makes it exceedingly difficult to gather data measuring the adaptive capacities of a given area before a catastrophic event occurs. In January 2011, the Australian city of Brisbane experienced an unprecedented flood event whereby over 15,000 homes were inundated with flood waters. The impacts of this extreme weather event also extended to the central business district, shopping centers and businesses, major arterial roads, riverside pedestrian facilities, distribution hubs, and many low-lying sporting and recreational amenities. Recovery efforts were initiated in the days and weeks following the flood. Once the clean-up commenced, tens of thousands of volunteers descended upon designated registration centers to participate in the clean-up (Rafter, 2013). Neighbors who had never spoken to one another worked together and shared resources, which many claimed was testament to the “resilience” and the “spirit” of the Brisbane community (George, 2013). It became apparent in the days and weeks following the flood that this resilient response was specific to particular communities. In other areas of Brisbane, residents were unable to access resources for recovery and communities faced protracted periods of dysfunction.

The aim of the current study is to examine the extent to which pre-disaster adaptive capacities (as conceptualized in Norris and et al.'s (2008) stress, resistance, and resilience model), and changes to these capacities postdisaster, impact community resilience to crime after the 2011 Brisbane flood. We draw on Waves 3 and 4 of the Australian Community Capacity Study (ACCS), which is a longitudinal study of communities in Australia. Given that Wave 3 was completed 1 month prior the January flood event while Wave 4 was conducted 15 months after the flood, these data provide a unique opportunity to examine predisaster adaptive capacities, how they may have changed as a consequence of the flood and how changes to (or stability of) these adaptive capacities to influence community resilience to crime in the postdisaster context. Using a bespoke flood severity index, we also assess the extent to which flood severity influences these relationships.

In this study, we use local property crime rates as a proxy to capture community resilience pre and post the flood. We contend that local crime rates are a valid indicator of how well community members can work together after a significant shock. As property crime is distinct from, but related to the adaptive capacities we employ in this study, we can conceptually and analytically separate the adaptive capacity indicators from an outcome that independently assesses how well a community is functioning postdisaster.

LITERATURE REVIEW

Defining community resilience

Community resilience definitions vary widely and can include both individual and community-level responses to disasters or significant change. A core tenet across all definitions of community resilience is that a resilient community is one that can effectively respond to and recover from disasters such as floods, fires, hurricanes, or terrorist attacks. Communities with greater resilience respond and adapt better to changing conditions and can maintain positive (or neutral) trajectories following change, relative to communities with lower resilience (Eshel et al., 2015). Norris and colleagues (2008, p. 130) suggest that community resilience is best understood as "a process linking a set of adaptive capacities to a positive trajectory of function and adaptation after a disturbance." This definition emphasizes the conditions, resources, and mechanisms that allow a community to absorb impacts and cope with an event. It also provides for re-organization, change, and adaptation that can occur post the event and considers the relationships between the adaptive capacities that influence resilience across the social system in which a community is located.

Most of the empirical community resilience research focuses on the availability of "capitals" (e.g., social, economic, and cultural capitals; Hawkins & Maurer, 2010; Pfefferbaum et al., 2017) and resources (e.g., natural, built, human, social, and financial; Magis, 2010; Pais & Elliot, 2008). Regardless of which concept is chosen, disaster scholarship is largely concerned with the benefits stockpiled by individuals and communities through membership to a given social network (see Aldrich, 2019; Breton, 2001; Kimhi & Shamai, 2004; Magis, 2010). Studies of community resilience illustrate the relevance of these dimensions, yet they do not sufficiently capture the temporality of community resilience and the dynamic nature of a community's adaptive capacities.

In this paper, we extend the current empirical literature by employing the stress, resistance, and resilience model developed by Norris et al. (2008) as our research framework. Three aspects of this model distinguish it from other theoretical perspectives of community resilience and justify its use herewith. First, it incorporates temporality by contrasting pre- and postevent functioning. Community functioning predisaster is an important determinant of community resilience, yet this is largely absent from empirical research (Adger et al., 2005; Marshall et al., 2007; Norris et al., 2008). Second, the model conceptualizes the stressor (i.e., a flood event in our study) in terms of its severity and duration. The stress experienced after a disaster may be short-lived for some events, but not for others (e.g., the aftermath of the 9-11 terrorist attack) and this is likely to impact community resilience. A final nuance of the model is its focus on the adaptive capacities that may lead to more resilient outcomes for communities. We summarize these adaptive capacities below.

Adaptive capacities

Community resilience involves translating predisaster resources into intended postdisaster outcomes. Norris and her colleagues (2008) identify a set of "adaptive capacities" that are measurable and independent indicators of social, physical, and human resources available in the predisaster phase that can contribute to postdisaster community functioning. These adaptive capacities are networked and dynamic, representing community characteristics developed predisaster that are "robust, redundant, or rapidly accessible and thus able to offset a new stressor, danger, or surprise" (Norris et al., 2008, p. 136). The model centralizes four adaptive capacities: economic resources; social capital; information and communication; and community competence, which they argue should be central in community resilience research.

Social science research has long recognized the centrality of economic resources and social capital for community functioning. Access to economic resources, at the community and individual level, consistently predicts greater community resilience but exists alongside other adaptive capacities that influence community resilience (Aldrich, 2012; Cutter et al., 2003, 2010; Norris et al., 2008, 2010). The positive effects of social capital and community competence for collective outcomes have also been considered extensively in neighborhood effects' research. While the two terms are often used interchangeably, we use *social capital* in this paper to represent local networks and the shared social norms arising from these networks (Putnam, 2000). We apply the term *community competence* to represent how these networks and social norms translate into community action that benefits the community (Sampson et al., 1997). This process is often termed collective efficacy in the literature and it is clearly articulated in Browning et al.'s (2006, p. 662) research on heat-related mortalities where they argue that disaster outcomes are a function of the "socially produced conditions of vulnerability" that exist in particular neighborhoods. Research demonstrates the relative stability of social processes such as social norms and collective efficacy over time (Zahnow et al., 2021) and even during periods of considerable stress (Wickes et al., 2017). Yet, the extent to which communities' predisaster social capacities (i.e., social capital, community competence) are associated with postevent community functioning after controlling for the severity of disaster remains unclear.

In this paper, we use Norris and et al.'s (2008) model of stress resistance and resilience as a framework to examine the extent to which the Brisbane flood event (1) altered communities' adaptive capacities (pre- to postflood); (2) the extent to which pre-event adaptive capacities and/or changes in adaptive capacities were associated with changes in property crime pre- to postdisaster; and (3) the moderating influence of flood severity (as represented in Figure 1). Community resilience, as we have argued earlier in this paper is a difficult concept to measure. Defined as an adaptation to a given event, community resilience must be assessed independently from indicators of adaptive capacities (Norris et al., 2008). Norris et al. (2008) propose that community resilience can be evidenced through a community's wellness after a disaster event. In the current study, we use the neighborhood property crime

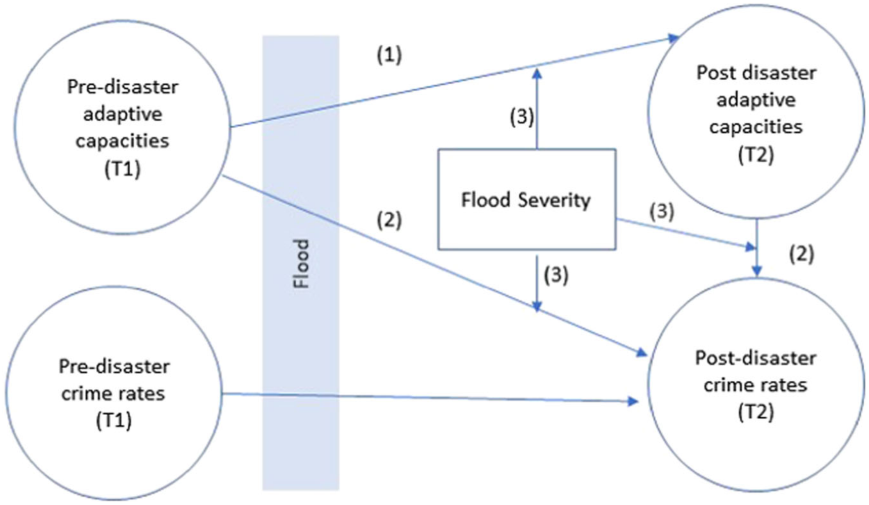

FIGURE 1 Adaptive capacities, flood severity, and postdisaster property crime. [Color figure can be viewed at wileyonlinelibrary.com]

rate as an indicator of community wellness.[1] Drawing on community resilience scholarship, we argue that *decreases* in a community's adaptive capacity after the flood event will be associated with *increases* in property crime postdisaster. As Frailing and Harper (2020) demonstrate, property crimes are "predatory acts of theft that have little to do with surviving a disaster" and thus increases in property crime are a useful indicator of community dysfunction postdisaster.[2] Conversely, we contend that *increases* in a community's adaptive capacity will lead to *decreases* in property crime. We also suggest that flood severity might influence changes in a community's adaptive capacities, which in turn will impact changes in property crime. As demonstrated in Norris and et al.'s (2008) original model, event severity is associated with the depletion or destruction of the capacities needed for resilience after a disaster. Flood severity might also directly impact changes in postdisaster property crime rates. We develop a novel disaster severity index of a flood event comprising information on the proportion of households unable to escape their neighborhood due to road and major thoroughfare flooding during the flood event; the proportion of households unable to access a shopping center or supermarket during the flood event; and the economic impact of the flood event by dividing all neighborhood property damage by all neighborhood property value. Thus, we are longitudinally assessing the moderating influence of flood severity changes to a community's adaptive capacities and their subsequent influence on community resilience for the first time.

DATA AND METHODS

We integrate data from four sources: the ACCS' social survey; Queensland Police Service's (QPS) incident data; Queensland Reconstruction Authority's (QRA) property data; and the Australian Bureau of Statistics' (ABS, 2012) Census of Population and Housing.[3]

The ACCS' social survey is a longitudinal panel study of Australian communities in two major cities: Brisbane and Melbourne. The study seeks to better understand social processes associated with the spatial and temporal distribution of crime and disorder across urban communities. Here we employ data from Waves 3 and 4 of the ACCS. We focus on the Brisbane sample to examine community resilience in the wake of the Brisbane flood event in January 2011. Wave 3 of the ACCS was conducted between August and December 2010 thus immediately before this flood event, and providing a predisaster baseline measures of adaptive capacities across 148 Brisbane neighborhoods. Forty-three of the sampled neighborhoods were flooded. The fourth wave of the ACCS was conducted approximately 15 months after the flood in the same 148 neighborhoods. The Brisbane ACCS Waves 3 and 4 samples comprise a random selection of 4403 and 4132 participants, respectively. The Wave 3 sample includes 2248 longitudinal participants and an additional top-up sample of 2155. The Wave 4 sample comprises 2473 longitudinal participants (those who participated in Waves 1, 2, and 3) and an additional top-up sample of 1659.[4] The consent and completion rates for the ACCS were 68.52% at Wave 3 and 46.27% at Wave 4. This rate is equal to the number of interviews completed proportional to the number of in-scope contacts. The in-scope survey

[1] We note that our measure of community resilience (property crime rates) is one of several possible measures of "community wellness," however, due to data limitations at the time of the flood, it is the only reliable data source we could procure for the purposes of this study.

[2] Moreover, property crime is the most reliably reported crime and is less likely to fluctuate as a consequence of police-led initiatives pre or post a disaster property crime time also tends to increase after disasters in some contexts (see Frailing & Harper (2020) for a full discussion of the relationship between disasters and property crime). For these reasons, we argue property crime is a reliable measure of community functioning that can be examined independently from the adaptive capacities in Norris and et al.'s (2008) stress, resistance, and resilience model.

[3] At the time, the data were collected, the ACCS team did not receive express permission to make the data publicly available. The *Privacy Act 1988 (Cth)* in Australia prohibits us from making any data available that has not been expressly approved for use by the participants. Data can be made available for replication purposes.

[4] An independent samples *t*-test ($t = 0.0237$, $df = 146$ ns) showed the attrition rate was not statistically different in the flooded or nonflooded suburbs in the Wave 4 sample.

population included all people aged 18 years or over who were usually resident in private dwellings with landline telephones[5] in the 148 selected neighborhoods. The average survey length was 24 minutes.

We also use the QRA's property data to compute our disaster severity index, the incident data from the QPS' crime incident data to capture annual property crime, and the ABS' 2006 and 2011 census data to capture community composition. Measures employed from each of these data are described in turn below. Summary statistics for all variables are presented in Table 1.

Variable information

Dependent variable

Our dependent variable is derived from QPS incident data and is the average annual rate of predisaster and postdisaster property crime per 100,000 residents thus for 2009/2010 and 2011/2012, respectively. Property crime includes unlawful entry, theft, stealing, arson, handling stolen goods, property damage, and unlawful use of a motor vehicle. We focus specifically on property crime for the reasons specified earlier and given that such crime events are typically anchored at spatial locations. Incident rates were converted to logarithms to reduce right skew.

Independent variables

This study examines the association between predisaster adaptive capacities purported to be important for community resilience and changes in property crime pre- and postdisaster. Drawing on Norris and et al.'s (2008) model of community resilience, we explore the influence of four adaptive capacities (i.e., social capital; community competence; economic resources; and information and communication) on changes in property crime pre- to postdisaster. Our proxy measures of each adaptive capacity are described in detail below.

We adopt a latent variable approach to compute our indicators of social capital and information and communication, given that factor analysis is a well-established technique in the social sciences. Latent variables typically provide a better approximation of the true scores of theoretical constructs than raw indicators by minimizing the measurement error associated with a single indicator (Mellgren et al., 2010). Please see Table 2 for the goodness of fit information on these latent variables.

[5]In Australia, 90% of the population was covered by landline phones in 2008, and in 2011 (representing Wave 4 of the ACCS) the number of mobile phone-only users was estimated to still be just 19% (Australian Communications and Media Authority, 2012). By comparison, in the United States, there were over 45% mobile-only users in 2014 (Blumberg & Luke, 2015).

Social capital

We measure social capital using 10 items from the ACCS survey with four drawn from the intergenerational closure scale, a further three from the frequency of neighboring scale, and the remaining three as individual items for measuring community relationships. The measure employed in the analyses comprises a neighborhood-level latent factor score computed using confirmatory factor analysis (CFA) in MPlus (version 7). This model had a χ^2 value that was statistically significant and met the criteria indicating good fit to the data (see Table 2). The factor loadings for all indicators of the latent variable were positive and statistically significant.

Information and communication

We include two indicators of neighborhood information and communication both drawn from the ACCS survey. The first measures residents' willingness to cooperate with the police and their perceptions of local government (for a full list of items see Appendix A). Responses to the scale items were aggregated to the neighborhood level. The neighborhood-level factor score was again computed using CFA in MPlus. This model of information and communication had a χ^2 value that was statistically significant but met the criteria for good fit to the data (see Table 2). The factor loadings for all indicators of the latent variable were positive and statistically significant. The estimated factor scores were employed in the analyses. The second indicator of information and communication was the suburb mean number of services residents reported to exist in their local community.

Economic resources

To capture economic resources, we include a factor score computed from three items drawn from ABS census data (factor loadings are in parenthesis): median household income (0.788); the proportion of persons who completed university education (0.964); and occupational diversity (0.913). The factor has an eigenvalue of 2.38. We calculated a Blau index of occupational diversity drawing on the eight major occupational categories reported by the ABS. The Blau index is defined as:

$$1 - \Sigma p_i^2, \tag{1}$$

where p is the proportion of neighborhood members in a given occupational category and i is the number of different occupational categories (Blau, 1977). This index captures the probability that randomly selected individuals will belong to distinct occupational categories thus a score of 0 indicates a homogenous group where everyone belongs to the same occupational category, and a 1 indicates a heterogeneous group where everyone belongs to a distinct occupational category.

Community competence

We measured the proportion of residents who recognize and act to resolve community problems as an indicator of community competence. This variable was derived from seven items in the ACCS that asked respondents to report

TABLE 1 Summary statistics and *t*-test results ($N = 148$).

Variables	Predisaster Mean	SD	Min.	Max.	Postdisaster Mean	SD	Min.	Max.	*t*
Property crime (log)	9.069	0.821	6.465	11.479	9.316	0.779	7.466	11.488	−2.643**
Ethnic diversity	0.257	0.148	0.038	0.784	0.281	0.166	0.063	0.715	−6.025***
Residential mobility	42.320	8.972	23.455	79.320	38.202	10.303	14.860	74.087	6.448***
Proportion of households renting	23.014	12.563	1.754	51.137	26.498	13.618	2.362	57.429	−8.113***
Proportion of residents aged 65+ years	9.584	4.855	2.478	26.361	10.945	4.700	2.555	29.005	−7.027***
Population density	8.988	8.294	0.080	33.811	10.180	1.941	0.100	34.754	−7.423***
Social capital	6.76e-06	0.197	−0.411	0.511	0.00001	0.220	−0.470	0.688	−0.0007
Economic resources	0.054	1.020	−1.796	2.598	0.041	1.012	−1.370	2.706	0.4847
Information and communication	−6.76e-06	0.077	−0.268	0.146	−6.76e-06	0.025	−0.077	0.062	−0.0001
Community services	4.80e-18	0.215	−0.658	0.463	6.76e-06	0.0002	−0.007	0.004	−0.0004
Community competence	0.129	0.191	0	1.196	0.397	0.579	0	4.598	−5.356***

Abbreviation: SD, standard deviation.
*$p < 0.05$.
**$p < 0.01$.
***$p < 0.001$.

TABLE 2 Fit indices for factor models

Measure	χ^2	*df*	CFI	TLI	RMSEA	SRMR Within	SRMR Between	AIC
Wave 3								
Social capital	480.704*	64	0.971	0.960	0.038	0.027	0.047	113302.619
Information and communication	84.399*	25	0.993	0.988	0.023	0.014	0.078	59237.247
Wave 4								
Social capital	504.716*	64	0.965	0.951	0.041	0.031	0.056	105321.027
Information and communication	101.015*	25	0.991	0.985	0.027	0.012	0.139	54903.384

Abbreviations: AIC, akaike information criterion; CFI, comparative fit index; df, degrees of freedom; RMSEA, root-mean-square error of approximation; SRMR, standardized square root mean residual; TLI, tucker Lewis index; χ^2, χ^2 goodness of fit statistic.
*χ^2 are statistically significant ($p < .001$).

the extent to which several community problems were an issue in their neighborhood with response options,0 (*No problem*), 1 (*Somewhat of a problem*) and 2 (*Big problem*). If the respondent indicated either some problem or a big problem they were asked if they did something to resolve the issue in the last 12 months (0 = *no*; 1 = *yes*). To compute our measure of community competence, we calculated the proportion of residents who recognized and responded to at least one community problem in the last 12 months (see Appendix A for a list of all survey items used in these analyses).

Flood impact severity

The severity of a disaster has a significant impact on postdisaster recovery and resilience. Two separate flood impact indicators are employed at different stages of the modeling process. In Models 1, 2, and 3, we employed a dichotomous variable to indicate whether or not a neighborhood was flooded. Neighborhoods that experienced flooding on streets, residential or commercial blocks, or government-owned land were assigned a 1 while all nonflooded neighborhoods were assigned in a 0. We also construct our disaster severity index from existing administrative data sources to embed both direct and indirect effects. Through embedding both, we moved beyond the many existing indices that capture: the community's vulnerability to an event (e.g., Cutter et al., 2003; Hubbard et al., 2014); the risk or likelihood that such an event will occur (e.g., Fedeski & Gwilliam 2007; Merz et al., 2011); and the direct impacts while disregarding the indirect impacts such as network disruptions (e.g., Blong 2003; Camarasa Belmonte et al., 2011). Through spatial intersection of the three formerly disparate datasets, the disaster severity index comprises three key measures: proportion of households unable to *escape* their neighborhood due to flooding on roads or major thoroughfares; the proportion of households unable to *access* a shopping center or supermarket due to flooding; and *economic impact* as all neighborhood property damage divided by all neighborhood property value. This factor was reliable ($\alpha = .798$) and has a potential range of 0–1 (see Appendix B for computation of the disaster severity index). All nonflooded neighborhoods were assigned a 0 and flooded neighborhood values ranged from 0.0004 to 0.624 on the index.

Control variables

We include a range of variables derived from the Australian Bureau of Statistics census data to control for neighborhood structural characteristics known to be associated with community resilience (Wickes et al., 2015, 2017; Zahnow et at., 2017). Using census data, we created the following variables at the neighborhood level: residential mobility (the percentage households renting and the percentage households at a different address five years prior); ethnic diversity (Blau index to capture language diversity for each neighborhood); age composition (percentage persons aged 65 years or above), and neighborhood population density.

Spatial lag variables

To minimize potential bias from spatial autocorrelation we also include the spatial lag (using rook contiguity) of preflood property crime and flood impact.

Analytic strategy

We adopt a hybrid fixed-effects analytic approach (obtained in a random-effects model) to examine the influence of preflood neighborhood characteristics and changes in characteristics on changes in property crime pre- to postflood. A hybrid fixed effects model is used to isolate the effects of predictor variables on property crime between neighborhoods and within neighborhoods over time. This is the most appropriate model because we are interested in examining the influence of both neighborhood change over time and neighborhood variation in neighborhood characteristics on community resilience.[6] The model was fit by the maximum likelihood method and all analyses were conducted in STATA 13.0. Collinearity diagnostics were computed and the mean VIF was 2.44.

RESULTS

To examine the utility of computing fixed effects models, we commenced our analyses with a set of statistical tests checking for significant differences between each of the independent and control variables pre- and postdisaster. The *t*-test results are presented with summary statistics (see Table 1). They revealed that both flooded and nonflooded neighborhoods experienced changes pre- to postflood that required investigation.[7] Independent samples *t*-tests revealed statistically significant differences between the flooded and nonflooded neighborhoods as they relate to pre- to postdisaster means and changes in the variables of interest (full results are available upon request). The mean scores for neighborhood social capital (predisaster mean = −0.031; postdisaster mean = 0.173; $t = -2.771$, $p < .01$) and economic resources (predisaster mean = 0.363; postdisaster mean = 0.511; $t = -2.728$, $p < .01$) were significantly higher postdisaster in flooded neighborhoods. In nonflooded neighborhoods the mean score for social capital was not significantly different from predisaster levels and economic resources were lower postdisaster (predisaster mean = −0.088; postdisaster mean = −0.176; $t = -2.960$, $p < .01$). Mean scores for ethnic diversity, the proportion of households renting and population density were significantly higher postdisaster in both flooded and non-flooded neighborhoods. Significant changes pre- to postdisaster in mean scores for residential mobility and proportion of residents aged 65 years and over were evident only in nonflooded neighborhoods. Residential mobility (predisaster mean = 42.976; postdisaster mean = 37.480; $t = 8.093$, $p < .001$) was significantly lower postdisaster while proportion of residents aged 65 years or over (predisaster mean = 9.131; postdisaster mean = 11.051; $t = -8.919$, $p < .001$) was higher postdisaster in nonflooded neighborhoods.

Our substantive analyses proceed in four stages. Model 1 examines the association between being flooded and changes in property crime pre- to postdisaster controlling for the spatial spillover effects of crime and flooding.[8] Model 2 includes structural variables and in model 3 we add our measures of neighborhood adaptive capacities purported to influence community resilience. Model 4 includes interaction terms to examine the influence of flood severity on adaptive capacities and

[6] When using panel data one can use a random or fixed effects estimator. The fixed effects estimator is based on the time series component of the data while random effects estimation uses both the cross-section and time-series components of the data (Andresen, 2012). Our research question is most fully addressed by the hybrid model (see Philips & Greenberg, 2008).

[7] *t*-tests examining between-group differences preflood revealed significant differences in the sociodemographic characteristics of flooded ($n = 46$) compared to nonflooded ($n = 100$) neighborhoods. This was expected given that the groups were not randomly allocated, rather social structural forces influence where individuals reside and, therefore, the extent to which neighborhoods vulnerable to flooding tend to be characterized by particular sociodemographic characteristics. As we are interested here in modeling *changes* in neighborhoods this is not problematic and the hybrid fixed effects modeling approach controls for nonchanging contextual differences between neighborhoods.

[8] Note this is the equivalent of fixed-effects models as it contains only "between" level variables.

TABLE 3 Adaptive capacities, flood severity, and property crime.

	Model 1	Model 2	Model 3	Model 4
Between neighborhood effects				
Flooded	0.155	0.144	0.110	0.017
	(0.287)	(0.507)	(0.467)	(0.465)
Ethnic diversity		1.378**	0.467	0.549
		(0.450)	(0.475)	(0.472)
Residential mobility		0.322***	0.181*	0.188*
		(0.080)	(0.076)	(0.076)
Population density		−0.0002	0.014	0.014
		(0.008)	(0.009)	(0.008)
% 65+ years		0.037**	0.012	0.010
		(0.011)	(0.012)	(0.012)
Social capital			−0.844*	−0.807
			(0.424)	(0.421)
Information and communication			−0.978	−1.302
			(1.294)	(1.293)
Economic resources			−0.269***	−0.269***
			(0.074)	(0.073)
Community competence			0.257	0.252
			(0.174)	(0.172)
Community services			−0.033	−0.018
			(0.082)	(0.081)
Spatial lag crime	0.00002***	6.40e-06	1.77e-06	1.75e-06
	(3.87e-06)	(4.45e-06)	(4.16e-06)	(4.12e-06)
Spatial lag flooded	−1.112	−0.125	0.258	0.136
	(0.331)	(0.295)	(0.278)	(0.283)
Within neighborhood effects				
Flooded		0.030	0.004	0.004
		(0.051)	(0.053)	(0.053)
Ethnic diversity		1.045	0.904	0.904
		(0.538)	(0.542)	(0.541)
Residential mobility		0.002	−0.002	−0.002
		(0.058)	(0.058)	(0.058)
Population density		0.024	0.024	0.024
		(0.013)	(0.013)	(0.013)
%65+ years		0.059***	0.045**	0.045**
		(0.011)	(0.013)	(0.013)
Social capital			−0.095	−0.095
			(0.259)	(0.259)
Information and communication			0.426	0.426
			(0.373)	(0.373)

	Model 1	Model 2	Model 3	Model 4
Economic resources			−0.019	−0.019
			(0.087)	(0.086)
Community competence			0.134*	0.134*
			(0.055)	(0.055)
Community services			−0.100	−0.100
			(0.059)	(0.059)
Flooded × disaster severity index				1.061*
				(0.526)
Constant	8.820***	8.835***	8.735***	8.687***
	(0.094)	(0.167)	(0.308)	(0.306)
R^2 overall	0.169	0.372	0.502	0.516
R^2 within	.	0.293	0.349	0.349
R^2 between	0.179	0.376	0.511	0.525

Note: Two hundred ninety-two observations from 146 areas. Standard errors in parentheses.
*$p < .05$.
**$p < .01$.
***$p < .001$.

property crime in flooded neighborhoods. The results are reported in Table 3 and are discussed in detail below.

In Model 1, there was no evidence that being flooded was associated with changes in property crime pre- to postdisaster. There was evidence of spatial associations for property crime demonstrated by the spatially lagged variable ($\beta = .00002$, $p < .001$). In Model 2, we included neighborhood structural variables that may be important for predicting community resilience. We partitioned the variance associated with each of these measures into the within and between effects by taking the grand mean across both time points (between effect) and the difference from the grand mean pre- and postdisaster (within effects). Looking first at the pooled effects, the results revealed that on average over time there was a positive and significant association over time between neighborhood ethnic diversity ($\beta = 1.378$, $p < .01$), residential mobility ($\beta = .322$, $p < .001$), percentage residents aged 65 years and over ($\beta = .037$, $p < .01$), and increases in property crime. Within the neighborhood increases in the percentage of residents aged 65 years and over ($\beta = .059$, $p < .001$) over time were also associated with increases in property crime pre- to postdisaster.

Models 3 and 4 include measures of neighborhood adaptive capacities. In Model 3, we examine the effect of neighborhood adaptive capacities on pre- to postdisaster changes in property crime while controlling for structural characteristics. Model 4 builds on the previous analysis with the inclusion of an interaction term that examines neighborhoods that were flooded and whether the severity of flood impact was associated with (a) decreases in adaptive capacities and (b) increases in property crime. The results of Model 3 indicate a significant protective effect of neighborhood social capital and economic resources against increases in property crime pre- to postdisaster. Neighborhoods with lower levels of social capital ($\beta = -.0844$, $p < .05$) and lower levels of economic resources ($\beta = -.269$, $p < .001$) experience greater increases in property crime pre- to postdisaster. Neighborhoods with higher levels of residential mobility also experienced greater increases in property crime ($\beta = .181$, $p < .05$). Pre- to postdisaster, within the neighborhood increases of the percentage residents aged 65 years or over ($\beta = .045$, $p < .001$) were associated with greater increases in property crime. Pre- to postdisaster increases in community competence were also associated with increases in property crime ($\beta = .135$, $p < .05$). While at first this association seems counterintuitive, it makes sense that as the number of problems in the neighborhood increases, the potential for recognizing and responding to such problems also increases (see Hipp & Wickes, 2018). In Model 4 we examined whether the severity of flood impact was associated with pre- to postdisaster changes in property crime in flooded neighborhoods. There was no evidence flood severity moderated the association between any of the adaptive capacities and property crime and the inclusion of the interaction effects did not improve model fit statistics. Therefore, we do not present the model results in this manuscript. The results of the models are available from the authors on request. Yet within flooded neighborhoods, the severity of flood impact was positively associated with changes in property crime pre- to postdisaster ($\beta = 1.061$, $p < .05$). This finding demonstrates that those neighborhoods that experienced more severe flooding displayed lower levels of resilience. All other estimates were unchanged.

DISCUSSION AND CONCLUSION

The aim of this study was to examine the extent to which pre-existing adaptive capacities of urban neighborhoods were associated with levels of property crime after a major disaster event. Our novel approach allowed us to apply the stress, resistance, and resilience model developed by Norris and colleagues (2008). We also employed novel survey data coupled with census data, crime incident data, and a bespoke flood severity index to measure pre- and post-disaster adaptive capacities and their connection to changes in property crime before and after the flood. Our results revealed three key findings. Our first finding revealed the significant impact of flood severity on levels of property crime, even after controlling for the adaptive capacities that in theory should support communities in times of crisis. Previous studies of the Brisbane flood relied predominantly on proxy measures of flood severity by merely reporting whether or not an area experienced flooding using a binary measure to denote the presence of absence of flood impact (Wickes et al., 2015; Zahnow et al., 2017). Yet, as we demonstrate herewith, the effects of the flood were widespread and not all communities were impacted to the same degree. By capturing direct and indirect effects of the flood—including the proportion of households that were unable to escape their neighborhood, residents' access to a shopping center or supermarket within their neighborhood as well as the average property value multiplied by the number of damaged properties—we provide a more comprehensive assessment of flood severity and its impact on crime.

Cutter and Derakhshan (2020, p. 25) contend that "community capital appears to be an ascribed characteristic of community that is not easily changed." This aligns with our results which revealed that neighborhood adaptive capacities were resistant to the flood. We found that social capital remained remarkably stable following the flood. Moreover, social capital and community competence increased within flooded communities. While some studies suggest that disasters can erode social ties and this in turn inhibits community resilience postdisaster (Erikson 1976; Frankenberg et al., 2012), there was no evidence of this in our study. As found in other studies (Kamel & Loukaitou-Sideris, 2004), the Brisbane flood event renewed communities and increased participation. We argue that the flood provided a critical test of community strength through requiring communities of people to collaborate in removing debris and cleaning away the mud. Yet, our third finding indicates that the pre-event adaptive capacities did not lead to resilience to crime in the postevent context. Neither social capital nor information and communication adaptive capacities protected against increases in crime over time. In contrast to what we predicted, increases in community competence led to *increases* in property crime. The latter result seems counterintuitive at first glance; however, we argue that this may indeed provide support for the stress, resistance, and resilience model. Prior research that has found increases in property crime postdisaster assume this is likely due to a breakdown of community norms and networks (Frailing & Harper, 2007, 2020; Quarantelli, 2007). Yet, we note that these studies did not have data to assess predisaster levels of adaptive capacities and thus could not assess if this was the case. In our study, increases in property crime may reflect improvements in community competence, which we operationalized as informal social control and the enhanced willingness to report problems to local authorities. In many neighborhoods, the flood event would have provided the first real opportunity for local residents to witness their community coming together to respond to a threat. Witnessing this cooperation may have reaffirmed their belief that others in their local area could work together and support each other when faced with a significant challenge. Further, police were the first responders to the disaster and worked closely with residents in the immediate aftermath of the event, likely strengthening police-citizen relations. We argue that witnessing collective support from fellow residents and from police would have a positive impact on residents' willingness to report problems to local police when they arose.

It is possible that the null findings between adaptive capacities and levels of property crime are in part a function of the measure we used in our analyses. Although our variables were aligned with the stress, resistance, and resilience model, we were reliant on crime data as a proxy for population wellness. Unfortunately, reliable community-level mental health data for all of the Brisbane ACCS neighborhoods were not available for use. Norris and colleagues (2008, p. 133) define population wellness as "high and non-disparate levels of mental and behavioral health, role functioning, and quality of life in constituent populations." Crime is an indicator of both how well a community is functioning and the quality of life in the community. A vast literature reveals that crime clusters in communities where other problems also cluster such as substance abuse (Stockdale et al., 2007) and mental health issues (Kim, 2008; Truong & Ma, 2006). However, it is possible that different measures of community wellness may be differentially linked with the adaptive capacities examined herewith. While unable to test this directly from available data, we do hope future research will shed further light on those measures of population wellness that may serve as stronger indicators of community resilience than what we have employed. Additionally, data limitations may explain the relative stability in adaptive capacities within flooded communities. Our measure of economic resources was constructed using census data that is collected every five years. Though the 2011 census occurred six months following the Brisbane flood event, a shorter period (e.g., immediately before the event and then six months after the event) would reveal changes that are more directly attributable to the flood. Unfortunately, such data was unavailable for all communities in the ACCS sample and thus we are reliant on a more distal period in our analyses herewith.

The results of the study provide critical insights into community resilience, particularly around resilience to crime after a disaster event, and indicate that the community-level processes that enhance resilience are relatively stable to exogenous shocks. Yet, the neighborhood adaptive capacities identified in the stress, resistance, and resilience model did not fully explain resilience 16 months after the event. This may have been because Brisbane neighborhoods were resistant to the flood. Norris et al. (2008, p. 132) propose that the ideal outcome after disaster is one of resistance, whereby "resources have effectively blocked the stressor and accordingly, there is virtually no dysfunction, no matter how temporary." This appears to be the case for the Brisbane flood event. Ecological crises—particularly fire, floods, and droughts—are regular occurrences in Australia. Such exposure to ecological crises may bring about resistance to these events. Effective strategies at local, state, and national levels to mitigate the harms associated with crises that occur relatively frequently no doubt support local efforts to recover quickly. Walters (2015) argues that recovery in Brisbane was more to do with strong institutions and low levels of inequality than the presence of strong local communities. Walters further questions the utility of community resilience as a useful concept for understanding disaster response and recovery, instead suggesting that local community may be more important in "rural or coastal settlements" with "relatively small and often well-integrated institutional and social environments" (Walters, 2015, p. 51). The findings of this study lend some support to these claims.

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AUTHOR BIOGRAPHIES

Rebecca Wickes is a Professor in the School of Social Sciences at Monash University in Melbourne, Australia. Her research focuses on demographic changes in urban communities and their influence on community regulation, crime, and disorder. She has published substantive work in journals such as *Criminology, Journal of Quantitative Criminology, Journal of Research in Crime and Delinquency, Social Science Research, Urban Studies, American Journal of Community Psychology, the Journal of Urban Affairs,* among others. She is the lead investigator of the Australian Community Capacity Study, a multisite, longitudinal study of place.

Dr Renee Zahnow is a Senior Lecturer in Criminology in the School of Social Science at the University of Queensland. Her research focuses on place-based patterns of crime and victimization; she is particularly interested in understanding the link between the regularities of daily human mobility, social and behavioral norms, and the propensity for crime and deviance. She has published in various journals, including *Criminology*, *Urban Studies*, *Journal of Environmental Psychology*, *Annals of the American*

Association of Geographers, *Environment and Behavior*, and *Crime and Delinquency*.

Jonathan Corcoran is a Professor in the School of Earth and Environmental Sciences and Director of the Queensland Centre for Population Research at the University of Queensland. Jonathan joined the university in 2005 following previous appointments at the University of Glamorgan and the UK National Mapping Agency, Ordnance Survey. Jonathan's research interests lie in the application of quantitative geographical methods for urban modeling in addition to the use of geo-analytical, geovisualisation, and prediction techniques. His work has been published in journals such as *Journal of Urban Affairs, Applied Geography, Applied GIS,* and *Journal of Research in Crime and Delinquency.*

Anthony Kimpton is a Postdoctoral Research Fellow at the University of Queensland with research interests including urban mobility; land use; social sustainability; social equity; environmental crime; place; spatial models; urban analytics; data science; and data visualization. His research publications can be located across: Applied Geography; Applied Spatial Analysis and Policy; Environment and Planning A; Environment and Planning B; Journal of Research in Crime and Delinquency; Urban Policy and Research; Land Use Policy; and Progress in Planning, and aims to support evidence-based policy to ensure smart and equitable cities where communities are socially sustainable, inclusive, and thrive.

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APPENDIX A: ITEMS FOR ADAPTIVE CAPACITIES

Community competence

Please tell me how much of a concern the following problems are in your community (no problem; somewhat of a problem; a big problem)

Drugs; public drinking; people loitering or hanging out; people being attached or harassed because of their skin color, ethnic origin or religion

Vandalism and graffiti; traffic problems like speeding or hooning; young people getting into trouble

Social capital

Intergenerational closure (strongly agree; agree; neither agree or disagree; disagree; strongly disagree)	**Frequency of neighboring** (often; sometimes; rarely; never):	**Community relationships:**
Adults in this community know who the local children are; there are adults in this community that children can look up to; parents in this community generally know each other; you can count on adults in this community to watch out that children are safe and do not get into trouble	How often do you and people in your community: do favors for each other; visit in each other's homes or on the street; ask each other advice about personal things such as child rearing or job openings	Apart from the people that you live with, how many relatives and friends live in your community; would you say that you know: none of the people in the community; a few of them; many of them; most of the people in your community; How many times have you had contact with a neighbor in the previous week?

Information and communication

Cooperation with police: If the situation arose how likely would you be to do the following (very likely, likely, neither likely or unlikely, unlikely or very unlikely):	**Perceptions of local government**(strongly agree; agree; neither agree or disagree; disagree; strongly disagree):	**Knowledge of community services** Please indicate if the following programs or services exist in your community (yes/no):
Call the police; help police find someone suspected of committing a crime by providing them with information; report dangerous or suspicious activities; willingly assist police	My local councilor is concerned about problems that affect my community; my local MP cares about my community; I have confidence in my local government	Community newsletter or bulletin; Crime prevention program; Neighborhood watch; religious organizations; ethnic or nationality clubs; business or civic groups

Economic resources

Median household income; occupation diversity (Blau); percentage of residents completed posthigh school education

APPENDIX B: COMPUTING THE DISASTER SEVERITY INDEX

To estimate direct flood damage alongside capturing indirect flood impact, six formerly disparate datasets were employed. (1) The Queensland Reconstruction Authority's (QRA) flood damage valuations provide repeated valuations of direct flood damage to properties. (2) The Queensland Department of Natural Resources and Mines' (DNRM) Digital Cadastral DataBase (DCDB) provides property boundaries. (3) The Australian Business Research's Queensland Valuations and Sales (QVAS) dataset provides the property type and value. (4) The Australian Bureau of Statistics provide the spatial boundaries of the Brisbane Statistical Division and the State Suburbs. (5) MapInfo Street Pro provides road networks. (6) The DNRM also provides the maximal extent of the flood, which was derived from remotely sensed imagery. These spatial data were spatial merged using ArcGIS and the following steps were as follows. The DCDB land parcel polygons and QRA flood damage valuation points were spatially merged to provide an ordinal scale of property damage (i.e. "no damage," "minor," "moderate," "severe," and "total"). Blong's (2003) study features comparative ordinal scale of property damage and is the basis of the damage multiplier employed within our disaster severity index. While our data has five values and Blong's central damage value (CDV) scale has six values, we were able to determine correspondences by examining the qualitative data contained within the data (Table 1). The field-merged QVAS dataset provided the type and the pre- and postdisaster values of the land parcels. These land parcels and accompanying damage multipliers and valuations were spatially merged and aggregated to the Australian Bureau of Statistics' (ABS) state suburb boundaries to represent communities. Note that "0" was imputed as the damage multiplier for all undamaged land parcels.

The network analysis of residents unable to escape their neighborhood or access a supermarket during the disaster also required multiple steps. First, the DNMR's maximal extent of the flood was used to reverse-clip the MapInfo Street Pro road network. Second, the ArcGIS network analysis tool was used to determine which residential land parcels (determined by QVAS land use) could still access another suburb or supermarket (also determined by QVAS land use) during the height of the flood. Last, these counts were aggregated to the neighborhood to determine the proportion of households unable to escape their neighborhood or access supermarkets during the maximal extent the flood.

The final calculations of the disaster severity index are as follows. Relative Replacement Ratio (RRR) was assigned to land use types based upon Blong's fixed Replacement Ratio (Table 2). RRR was used rather than a fixed Replacement Ratio since Blong's figures reflected property replacement in Sydney during 2003, and since we are principally interested in the variability in severity rather than absolute values. Following, RRR is multiplied by CDV to calculate Damage Cost (DC). Last, all DC, property valuations, suburb escapes, and supermarket accesses were aggregated to the neighborhood and converted to proportions to arrive at three indicators of flood impact severity: 1) the neighborhood proportion unable to escape the neighborhood during the flood; 2) the neighborhood proportion unable to access supermarkets during the flood; and 3) the economic impact to property valuations during the flood.

TABLE 1 Conversion from QRA damage valuations to Blong's (2003) CDV.

Blong's calculated central damage values (p. 12)			Damage valuations	Recode
CDV	Damage label	Qualitative descriptor	Damage label	Imputed multiplier
0	-	-	"No damage"	0
0.02	"Light"	Under floor level	-	0.02
0.1	"Moderate"	Water above floor	"Minor"	0.1
0.4	"Heavy"	-	"Moderate"	0.4
0.75	"Severe"	Partial collapse, or >1 m inundation	"Severe"	0.75
1	"Collapse"	Demolished, or off foundations	"Total"	1

Abbreviations: CDV, central damage value; QRA, Queensland Reconstruction Authority.

TABLE 2 Calculating the relative replacement ratio from land use code and median valuations.

luc1	lud1	Valuation (median)	RR (valuation [n]/ valuation [2])
0	NONE	0	0.000
1	VACANT URBAN LAND	152500	0.616
2	SINGLE UNIT DWELLING	247500	1.000
3	MULTI UNIT DWELLING (FLATS)	395000	1.596
4	VACANT - LARGE HOUSESITE	105000	0.424
5	DWELLING - LARGE HOUSESITE	152500	0.616
6	OUTBUILDINGS	100000	0.404
7	GUEST HOUSE/PRIVATE HOTEL	660000	2.667
8	BUILDING UNITS (PRIMARY USE ONLY)	1300000	5.253
9	GROUP TITLE (PRIMARY USE ONLY)	2700000	10.909
10	COMBINED MULTI DWELLING & SHOPS	392500	1.586
…	…	…	…
99	COMMUNITY PROTECTION CENTRE	160000	0.646