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Climate change and natural disasters: Government mitigation activities and public property demand response

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ABSTRACT

The level of public response to extreme catastrophes is considerably greater than concern over climate change. This research compares the public's responses to extreme disasters and climate change when governments intervene to mitigate long-term climate change impacts. To do so we examine the property market behaviour in response to beach erosion and cyclone damage in Queensland, Australia. The results show that the impact on the property market of the public's response to the negative impact of cyclones is more marked than its response to the negative impact of beach erosion. The relative non-responsiveness to beach erosion can be seen as a product of both local government intervention strategies and the recreational and aesthetic attractions of beaches. This study, therefore, provides useful insights for the development of sustainable coastal development strategies.

1. Introduction

As a consequence of changing climate, the frequency of natural hazards such as floods, bushfires and intense tropical cyclones has been increasing. While climate change is a phenomenon which is evolving gradually over the long term, extreme natural disaster events are already present. Hence, the adaptation and mitigation of these events are already well recognised (IPCC, 2014). While many governments are seeking remedies, public concern is also becoming a force in the development of adaptation and mitigation measures. Over the past several decades the literature in various disciplines (see, Ford et al., 2011) has provided insights into how the public's short-term behavioural and investment decisions change such as evidenced in farming practices (e.g. Niles et al., 2015; Wheeler et al., 2013). Nevertheless, there is a lack of research addressing climate change and natural hazard effects on the public's long-term investment decisions, particularly where governments have attempted to mitigate their adverse impacts. In this study, we aim at bridging the gaps in the literature by comparing public's long-term investment decision making invoked by climate change and extreme disasters as it relates to property market behaviour.

While climate change in terms of rising greenhouse gas (GHG) emissions is a steadily increasing phenomenon, the frequency of natural hazards attributed to changing climate has also been increasingly globally (Energy and Climate Intelligence Unit, 2017; van Aalts, 2006) and is negatively influencing the value of natural capital and the capacity for sustainable development (Rajapaksa et al., 2017a; Managi and Guan, 2017). The reduction of GHG emissions has been identified as the key remedy by governments and agreement has been reached by them on policies to affect these reductions (Intergovernmental Panel on Climate Change (IPCC, 2014). Indeed, most governments already have implemented mitigation and adaptation policies (Ford et al., 2011). However, public responses to climate change are less clear cut (e.g., Ray et al., 2017) and in general minimal in their effect. However, the experiencing of the increased frequency of climatic hazards (often aggravated by climate change) is shown to heighten the public's climate change risk perceptions and increase their propensity to embrace adaptation measures (Islam et al., 2016; Capstic et al., 2015). Where the public's response has been significant, they have moved away from

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vulnerable areas where property market values would be affected. For example, after the Tohoku earthquake, despite the action taken by the Japanese government to reduce the impact of radiation, residents are still avoiding certain areas (Munro and Managi, 2017).

A reduction in the value of properties damaged by disasters is now a common phenomenon (see Ortega and Taṣpınar, 2018; Rajapaksa et al., 2017b). Therefore, disaster-prone areas often request policy action (Rey-Valette et al., 2018). In this paper, our research focus is specifically on beach erosion and cyclones in Australia. Approximately 85% of the Australian population resides along its coast. The unfavourable impacts of climate change contain several serious implications for the government and councils because the coastlines play a major role in Australia's economy, environment and the life style (Department of Climate Change and Energy Efficiency, 2010). In particular, given the detrimental effects of beach erosion and cyclones on Australia's coastlines, it has been hypothesised that these impacts would negatively affect the values of Australia's coastal residential properties.

We use case studies of coastal properties in Queensland, Australia to test this hypothesis relating to: (1) beach erosion and (2) a cyclone. Beach erosion is a gradual process whereas a cyclone is a temporally rapid phenomenon. Employing the hedonic property pricing (HP) valuation method, this research quantifies the impacts of beach erosion and cyclones on coastal property values. More specifically, spatial HP valuation analysis is used. Our results show that extreme weather events such as cyclones negatively impact the public's property purchasing decisions, however beach erosion does not necessarily discount property values. We suggest that the local government's beach erosion mitigation interventions may crowd out the public's negative perceptions.

The rest of the paper is organized as follows. Section 2 discusses literature related to climate change, natural hazards and government intervention with a special focus on beach erosion and cyclones. The spatial hedonic model and methodology is discussed in section 3. The results of the empirical analysis are then provided followed by discussion and conclusions.

2. Climate change, natural hazards and government intervention

Climate change has many impacts – including the increase of sea levels and associated increases in beach erosion (Zhang et al., 2004). In addition, it may aggravate extreme weather events such as storms and floods. Based on the International Geographical Union's Commission on coastal environment, erosion has become prevalent on sandy beaches that make up approximately one-fifth of the world's coastline (Bird, 1987). The Commission has noted that the causes are both, natural and directly or indirectly related to human activities.

In the next few decades, land-based activities along coastlines need to be adapted to the impacts of climate induced beach erosion to reduce the continuing impacts on the coastal environment (El-Nahry and Doluschitz, 2010). Policymakers therefore need to consider the cost of the impacts of beach erosion on coastal settlements when implementing coastal management strategies (Rehdanz, 2006a,b).

The nexus of coastal (dis)amenities and the coastal property market is based on numerous international studies using the HP valuation method. Most have customarily used beach width as a key proxy for beach quality. The main justification is that beach width provides a combination of storm protection and recreational benefits for coastal property owners (Landry and Hindsley, 2011). A study conducted by Gopalakrishnan et al. (2011) revealed that beach width positively affects coastal property values. The study indicates that the long-term net value of coastal residential property can fall by as much as 52% when the beach erosion rate triples. A similar study conducted in South Carolina investigating the effects of beach width on coastal property markets found that for a 10% increase in beach width, the corresponding coastal property value increases by 2.6% (Anning et al., 2009). Similarly, they found that the effect diminishes when the distance to beach increases. This is because coastal residents still prefer to live within proximity to the beach as long as the beach quality is at a satisfactory level (Halkos and Matsiori, 2018). From an Australian perspective, a study carried out by Anning et al. (2009) revealed a strong preference for proximity to the ocean in Sydney's coastal regions.

Due to the increase in the rate of recurrence and intensity of tropical storms, there has been widespread destruction of coastal properties by strong winds and inundation that come together with tropical storms. The consequent negative effect on coastal property values from tropical storms and floods has serious implications for policymakers when designing coastal management strategies. Floods, the most common of natural disasters, have had particularly severe effects. Between 1985 and 2009, floods represented 40% of all natural disasters globally and accounted for 13% of deaths and 53% of the number of people affected by all natural disasters (Atreya et al., 2013). Several studies have documented the reduction of residential property values in a flood zone (Samarasinghe and Sharp (2010); Bin and Landry, 2013; Rajapaksa et al., 2016, 2017b). Bin et al. (2008) examined the effect of flood hazards on the coastal housing market of Carteret County, North Carolina. The results suggested that location within a floodplain lowers the average property value by 7.3%. In an Australian study, Rajapaksa et al. (2016) show an identifiable property value discount in flood risk areas. However, despite the flood risk, residents were found to be generally willing to stay near water bodies. Other studies indicate residents' heterogeneity of behaviour for environmental amenities as well as disamenities. Du and Huang (2018) show that the amenity values of open spaces are heterogeneous while another study shows that residents discount flood risks differently [see, Rajapaksa et al., 2017c].

In response to climate change and frequent disasters, Australia's current adaption and mitigation policies relating to beach erosion include coastal protection works such as breakwaters, groynes and seawalls (Short, 2009). Although such measures have proven useful to a certain extent, they 'harden' the coast and affect natural systems related to beach erosion and formation (Short, 2009). As a consequence, these defences can further exacerbate erosion. An example is that seawalls can deflect and concentrate wave induced erosion. Equally, groynes prevent movement of sediments thereby leading to further erosion down a coastline (Short, 2009). In Australia, a number of policies have already been adopted which include ongoing research exploring options to minimise the impacts of severe weather events using observation of past events and their effects, testing of new building practices and better prediction of future climate and severe weather patterns (CSIRO, 2013). These initiatives are designed to prepare businesses and coastal communities to become more resilient to the impacts from severe weather events in the future.

3. Empirical analysis

3.1. Study area

In Australia where approximately 50% of its coast is composed of sand and mud, there is extreme susceptibility to shoreline erosion (Short, 2009). Although beach erosion in most of the coastline is a natural process with usually minimal or no impact on human settlement and coastal infrastructure, there are a few significant localities such as Australia's major cities in which the dynamic nature of shorelines has become a major and expensive problem. This is related to human interference and/or encroachment on shorelines (Short, 2009). For example, research indicates that some of the beaches in the Sunshine Coast's coastal suburbs, which are the main areas of study of this research are at risk of being decimated in less than a hundred years' time if no action is taken by the local government (Holznagel, 2008). In particular, places such as Mooloolaba and Alexandra Headland (two of the seven chosen study areas in this study) are listed as areas which are likely be destroyed by beach erosion in less than a hundred years' time.

While projections of tropical cyclones in the Australian region are uncertain, the available studies suggest that there may be an increase in the proportion of tropical cyclones in categories 3–5 in Australia (Department of Climate Change and Energy Efficient, 2009; Department of Environment, 2013). By 2030, projections show that there may be a 60% increase in severe storm intensity and a 140% increase by 2070 (Department of Environment, 2013). Such an increase would pose major risks to coastal cities and communities whose planning guidelines and building codes do not take into consideration the risk of severe cyclones (Department of Climate Change and Energy Efficient, 2009).

Cyclone Yasi, which hit Queensland in the first week of February 2011, was one of the most powerful cyclones ever to have affected Queensland (Bureau of Meteorology, 2011; CSIRO, 2013). The hardest hit coastal communities included Tully, Mission Beach, Innisfail and Cardwell, all of which were selected as study sites for this paper. Cyclone Yasi left 150,000 homes without power and the estimated damage cost was reported to be around AUD3 billion (Colgan et al., 2011). Apart from damaging several coastal suburbs in Northern Queensland, other economic effects of Cyclone Yasi included a 14.5% and 16% increase in fruit and vegetable prices respectively in the March quarter 2011 (ABS, 2011). Given the extent of damage caused by this and other cyclones, the Sunshine Coast has been identified as one of the world's climate change 'hotspots' (Department of Environment, 2013).

3.2. Data collection and variables

For this study we collected a total of 1413 property transaction records. For the first case study - which estimates the impacts of beach erosion on the Sunshine Coast's coastal property values - a final dataset was collected consisting of 913 individual real estate sales transactions representing houses sold between January 2006 and December 2012. Three suburbs namely Buddina (320 observations), Alexandra Headland (204 observations) and Mooloolaba (389 observations) were chosen for this analysis given these suburbs were officially declared as erosion prone by the Sunshine Coast Council on January 2012. The study areas for the storm surge analysis were selected based on cyclone reports published online by the Australian Bureau of Meteorology, which identified the suburbs that had been damaged the most by Cyclone Yasi. These study areas include Tully, Innisfail, Mission Beach and Cardwell. All residential properties selected from these four towns in Northern Queensland had been badly damaged by Cyclone Yasi in 2011. For this analysis, a total of 500 real estate sales transactions from 2003 to 2012 were included.

In this study we hypothesised that property values are discounted due to extreme weather events and beach erosion. Hence we included distance to beach (*LogBeach*), distance to water bodies (*LogWaterBody*) and a dummy variable for cyclone (*ExtremeWeatherEvent*) with other control variables. After an extensive literature review (see, for review, Sirmans et al., 2005), selected structural variable characteristics were included – specifically, number of bedrooms (*Bedroom*), number of bathrooms (*Bathroom*), number of garage (*Garage*) and land size (*LogLandSize*). All four were expected to have a positive influence on residential sales prices. In this study, the neighbourhood explanatory variables were represented by the road distance in metres to the nearest school (*LogSchool*) and the road distance in metres to the nearest shopping mall (*LogShoppingMall*). Lastly, weekly median household income (*LogRealMedian*) was also included as a neighbourhood explanatory variable in this study to capture the demographic and socioeconomic aspects of each individual suburb.

The most important environmental characteristics in this research was the impact of beach erosion on the Sunshine Coast's coastal property values. Therefore, in order to estimate its impact on residential property values, the direct distance in metres to a beach (*LogBeach*) was included. Another environmental explanatory variable included in this study was the road distance in metres to the nearest park (*LogPark*). Proximity to parks or open spaces have been shown to have a positive influence on residential property values because of its recreational and leisure values [Poudyal et al., 2009b].

Next, the direct distance in metres to the nearest water body (*LogWaterBody*) was included as an environmental explanatory variable. Based on the literature it was hypothesised that living close to a water body increases residential property values (Rajapaksa et al., 2016). A dummy variable (*ExtremeWeatherEvent*) was added to capture the effects of extreme weather events - such the 2010–2011 Queensland floods, as well as the 2011 kin. tides event - on Sunshine Coast's residential property values. This variable provides a means of accounting for the before-and-after[1] effects of extreme weather events that could potentially have an impact on Sunshine Coast's residential property values ('1' if property was sold after the extreme weather event and '0' otherwise).

In order to estimate the impacts of cyclones on Tully, Innisfail, Mission Beach and Cardwell's residential property values, a dummy variable *Cyclone* was included as an environmental explanatory variable in the estimation to capture the before-and-after effects of Cyclone Yasi. *Cyclone* is a dummy variable that takes the value of 1 if the residential property in Tully, Innisfail, Mission Beach or Cardwell was sold after 2011 (Cyclone Yasi incident) and takes the value of 0 otherwise. Apart from the explanatory variables, nine year dummy variables were also created for this analysis and which are used to account for the volatility in terms of the housing market and which may influence property values (see, Athukorala et al., 2016). For instance, D2004 takes the value of 1 if the residential property was sold in 2004 and takes the value of 0 otherwise (Table 1).

3.3. Methodology

The extensive utilisation of the HP valuation method in measuring and quantifying the impacts of environmental externalities on residential property values is testament to its reliability as an evaluating tool for estimating the implicit marginal contribution of environmental externalities. HP analysis allows consistent estimation of the marginal contribution of each individual housing characteristics (Malpezzi, 2002; Baranzini et al., 2008; Lewis et al., 2008) as well as environmental amenities (see, Mei et al., 2017; Poudyal et al., 2009a) and disamenities (see, Rajapaksa et al., 2016; Bin and Landry, 2013). In its simplest algebraic form, the HP valuation method is basically a functional relationship between the price 'P_i' of a heterogeneous good '' and its quality characteristics which are represented by a vector 'x_i' as;

$$P_i = f(x_i; \beta) + u_i$$

In the context of this research, the heterogeneous good '" is defined as the coastal residential property with a price of 'P_i', and the vector 'x_i' consists of the residential property's structural, neighbourhood and environmental characteristics. 'β' signifies a vector of coefficients that reflect the influence of the different characteristics while the error term 'u_i'is generally assumed to be identically and independently distributed. In relation to this study, the estimated marginal effects of the specific variable can be used to evaluate the benefits or losses arising from the marginal changes in the supply of environmental goods (Tyrvainen and Miettinen (2000)). These implicit prices provide valuable information about residents' willingness to pay for an environmental externality. The general functional form can be estimated using an OLS estimator as follows.

$$lnp = \alpha + \sum \beta_i x_i + \varepsilon$$

where, x_i is a vector of explanatory variables (structural, neighbourhood and socio-economic variables), β_i - vector of coefficients - describe the implicit prices of the corresponding explanatory variables and ε is a

[1] For example, Athukorala et al. (2016) used a similar approach to capture the impact of bushfire on property value in North Queensland suburbs.

Table 1
Variable description.

Variables	Description	Expected sign
Bedroom	Number of bedrooms	+
Bathroom	Number of bathrooms	+
Garage	Number of garages	+
LogLandSize	Log size of the land (square metres)	+
LogBeach	Log direct distance to sea (metres)	+
D400	Dummy; 1 if property is located within 400 metres from beach and 0 otherwise	–
LogWaterBody	Log direct distance to nearest water body (metres)	–
LogSchool	Log road distance to nearest school (metres)	+/-
LogPark	Log road distance to nearest park (metres)	–
LogShoppingMall	Log road distance to nearest shopping mall (metres)	+/-
LogRealMedian	Log weekly median family income ($AUD)	+
ExtremeWeatherEvent	Dummy; 1 if property was sold after extreme weather events such as the 2010-2011 Queensland floods / 2011 Brisbane king tides and 0 otherwise	–
Cyclone	Dummy; 1 if property was sold after 2011 (after Cyclone Yasi) and 0 otherwise	–
D2004	Dummy; 1 if residential property was sold in 2004 and 0 otherwise	+/-
D2005	Dummy; 1 if residential property was sold in 2005 and 0 otherwise	+/-
D2006	Dummy; 1 if residential property was sold in 2006 and 0 otherwise	+/-
D2007	Dummy; 1 if residential property was sold in 2007 and 0 otherwise	+/-
D2008	Dummy; 1 if residential property was sold in 2008 and 0 otherwise	+/-
D2009	Dummy; 1 if residential property was sold in 2009 and 0 otherwise	+/-
D2010	Dummy; 1 if residential property was sold in 2010 and 0 otherwise	+/-
D2011	Dummy; 1 if residential property was sold in 2011 and 0 otherwise	+/-
D2012	Dummy; 1 if residential property was sold in 2012 and 0 otherwise	+/-

normally distributed random error term. Our interest variables – beach erosion and cyclones can also be included as explanatory variables to estimate the impact of such events on property prices.

The influence of spatial variables on observations in HP valuation models is a major econometric issue where estimation is involved. The value of a given property also affects the value of neighbourhood properties. Disregarding this spatial dependence effect may cause the OLS estimation for ‘β’ coefficients to be biased and inconsistent. That is, the assumption of an independently and identically distributed error term in the OLS estimation can be violated owing to the spatial effects present in the HP valuation models (Anselin, 2013). Testing for the presence of spatial variability of residential properties in HP valuation models can be carried out through spatial econometric techniques. Generally, the spatial lag model or the spatial error model are used based on *Moran's I* statistics. First, an OLS model is estimated and then tested for spatial autocorrelation using *Moran's I* test as;

$$\boldsymbol{Moran's\ I} = \frac{\boldsymbol{n}}{\sum_i \sum_j \boldsymbol{w_{ij}}} \frac{\sum_i \sum_j \boldsymbol{w_{ij}}(\boldsymbol{x_i} - \bar{\boldsymbol{x}})(\boldsymbol{x_j} - \bar{\boldsymbol{x}})}{\sum_j (\boldsymbol{x_i} - \bar{\boldsymbol{x}})^2}$$

where, x is the mean of the x and w_{ij} is the elements of weight matrix. The spatial weight matrix indicates whether property ‘*i*’ and ‘*j*’ are close. It is ‘$n \times n$’ matrix, where ‘*n*’ is the number of observations. The *Moran's I* statistics range from -1 (extreme negative spatial dependence) to +1 (extreme positive spatial dependence). The distance is inversely proportional to the weight assuming that beyond distance ‘D’ there is no spatial effect.

$$w_{ij} = \begin{cases} {}^{1}\!/_{d_{ij}}\ if\ d_{ij} \le D \\ 0\ otherwise \end{cases}$$

where, d_{ij} is the distance between ‘*i*’ and ‘*j*’ and ‘*D*’ is the band of spatial dependence. The distance can be estimated using ‘x’ and ‘y’ coordinates.

Generally, two types of spatial models – spatial lag model and spatial error model - are estimated in the literature. The spatial lag model can be expressed as;

$$\boldsymbol{p} = \boldsymbol{\rho W p} + \boldsymbol{\alpha} + \sum \boldsymbol{\beta_i x_i} + \boldsymbol{\varepsilon}$$

where, ‘ρ’ is the spatial autocorrelation parameter and ‘*Wp*’ is the spatial lagged dependent variable. In this model the error term is assumed to be independent and identically distributed and the spatial impact is incorporated as a lagged dependent variable (Anselin, 2013).

In the spatial error model it is assumed that the spatial effect is correlated with the error term. The spatial error model can be expressed as;

$$\boldsymbol{p} = \boldsymbol{\alpha} + \sum \boldsymbol{\beta_i x_i} + \boldsymbol{u}$$

$$\boldsymbol{u} = \boldsymbol{\lambda W u} + \boldsymbol{\varepsilon}$$

where, ‘λ’ is the coefficient of the spatially correlated error and ‘*Wu*’ the spatially lagged error term.

4. Results

The empirical analysis of this study is based on two case studies: the impact of beach erosion and cyclones on the property market.

4.1. Impact of beach erosion

The mean sale price of the selected sample which is used to gauge the effects of beach erosion, is AUD 706,283 (SD = 412,457). The average number bedrooms, 3.6, varies from 1 to 7. All houses have at least one bathroom and a garage. The land size varies from 110 m^2 to 1574 m^2. The closest house to a beach is 2.2 m and the furthest in the sample was 1770 m from the beach (see, Table 2).

We estimated two models to capture the effect of beach erosion on the property market. In the first model the log value of distance to the beach (*LogBeach*) is the most interesting variable whereas in the second model we introduced another dummy variable (*D400*), to capture the impact of a property being within 400 m of a beach. The estimated models are statistically significant and show relatively higher explanatory power (Adj R-sq = 0.60). Following OLS estimation, the models were tested for spatial autocorrelation. The Lagrangian Multiplier (LM) statistics indicated the presence of a spatial lag effect[2]. The spatial lag models were then estimated using maximum likelihood (ML). The ML results are presented in the same table for comparison purposes (Table 3). The results are comparable, but the coefficients estimated through ML are preferred since the estimation was corrected for spatial lag effect.

Most of the explanatory variables across all eight SLE models were

[2] The robust LM lag statistics show the need to correct for spatial lag effect (see, Table 3).

Table 2
Descriptive statistics of the selected sample for beach erosion analysis.

Variable	Mean	Std. dev.	Minimum	Maximum
Sale price	706283	412,457	80000	3900000
Bedroom	3.65	0.837	1	7
Bathroom	2	0.769	1	6
Garage	1.91	0.766	1	6
LandSize	646.29	131.17	110	1574
Beach	723	383	2.20	1770
D400	0.240	0.46	0	1
WaterBody	312.86	278.37	1	1150
School	1373	622.9	35	2800
Park	2021	1394	31	5900
ShoppingMall	2887.62	1441.77	350	5700
Median	1096	169.89	635	1426
ExtremeWeatherEvent	0.287	0.453	0	1
Buddina	0.349	0.477	0	1
AlexandraHeadland	0.223	0.417	0	1
Mooloolaba	0.427	0.495	0	1

Table 3
Impact of beach erosion.

Variable	Model 1		Model 2	
	OLS	ML	OLS	ML
Bedroom	0.045***	0.0478***	0.0451***	0.0477***
	(0.0144)	(0.0132)	(0.0144)	(0.0132)
Bathroom	0.133***	0.112***	0.133***	0.113***
	(0.0172)	(0.0159)	(0.0172)	(0.0159)
Garage	0.0375***	0.0421***	0.0375***	0.0424***
	(0.0136)	(0.0126)	(0.0136)	(0.0126)
LogLandSize	0.546***	0.415***	0.546***	0.415***
	(0.0558)	(0.0559)	(0.0558)	(0.0558)
LogBeach	−0.253***	−0.235***	−0.253***	−0.222***
	(0.0234)	(0.0273)	(0.0307)	(0.0334)
D400	–	–	−0.000835	0.0291
			(0.0372)	(0.0431)
LogWaterBody	−0.164***	−0.175***	−0.164***	−0.175***
	(0.00986)	(0.0132)	(0.00988)	(0.0132)
LogSchool	0.0112	0.0241	0.0113	0.0251
	(0.0206)	(0.0292)	(0.0207)	(0.0294)
LogPark	0.117***	0.0945***	0.117***	0.0932***
	(0.0189)	(0.0285)	(0.0190)	(0.0286)
LogShoppingMall	0.0955***	0.148***	0.0955***	0.149***
	(0.0359)	(0.0551)	(0.0361)	(0.0553)
LogRealMedian	0.266***	0.120	0.266***	0.121
	(0.0670)	(0.0910)	(0.0671)	(0.0913)
Buddina	−0.18**	−0.163**	−0.18***	−0.163**
	(0.0428)	(0.0681)	(0.0428)	(0.0683)
Mooloolaba	−0.287***	−0.313***	−0.287***	−0.312***
	(0.0402)	(0.0565)	(0.0403)	(0.0567)
ExtremeWeatherEvent	−0.256***	−0.244***	−0.256***	−0.245***
	(0.0212)	(0.0196)	(0.0213)	(0.0197)
Constant	8.82***	10.2***	8.82***	10.1***
	(0.561)	(0.749)	(0.591)	(0.765)
rho	–	0.511***	–	0.513***
		(0.0504)		(0.0505)
Adj R-Squared	0.605	–	0.605	–
Robust LM Error	1.18			
Robust LM Lag	53.4***			
N	913	913	913	913

Note: *, ** and *** denote variables of 10%, 5% and 1% levels of significance, respectively. The standard error value for each variable is found in parentheses.

statistically significant at the 1% level. In terms of the structural explanatory variables, all *Bedroom, Bathroom, Garage* and *LogLandSize* had the correct expected sign. For instance, an additional bedroom increases property value by 5%. The land size is shown to exert a higher impact on residential property value.

The primary hypothesis is that residential property prices increase as the direct distance to a beach increases. This is because when residential properties are located further away from erosion prone beaches, the risks of erosion hazards are reduced and hence, residential property values are likely to increase. Although statistically significant at the 1% level, the coefficient sign of *LogBeach* showed a negative relationship between residential property prices and the direct distance to beach, conflicting with the hypothesis of this study. For instance, for every one-unit increase in direct distance to the beach, residential property values decrease by 0.23%. The results also imply that the property value increases when it is close to a water body. Thus, where there is good beach quality, resident's desire living closer to it in spite of the climate change induced beach erosion. It can be assumed that an important reason is that recreational and aesthetic advantages in living close to beaches far outweigh the threat of beach erosion. Other than beach, some properties are located close to inland water bodies (i.e. rivers, lakes) which exert amenity values for property owners. We included the distance to water bodies as a control variable (*LogWaterBody*). The statistically significant results of variable *LogWaterBody* also imply that people are particularly willing to live close to water bodies. These results are in line with previous research: Rajapaksa et al. (2016) show that people are willing to live close to a river in spite of flood risk. Globally, Kummu et al. (2011) show the majority of people prefer to live close to water bodies and that such a habitat preference is most prominent in Australia.

It is important to note in the context of this study that selected suburbs were declared as erosion prone by the Sunshine Coast Council only in 2012 (Department of Environment and Heritage Protection, 2013). Moreover, there was a lag in this announcement taking full effect and in reaching out to all residents living in those three suburbs. The most probable reason then for the negative relationship between *LogBeach* and residential sales prices in the three suburbs under study was that residents were well-aware of the mitigation policy that had already been implemented by the Sunshine Coast Council. The Council is already monitoring about ten locations in the Sunshine Coast and is also spending approximately AUD2.4 million to pump 125,000 cubic metres of sand onto the beach between Alexandra Headland and Maroochydore in an effort to mitigate beach erosion in that area (Sunshine Coast Daily, 2013b). The council activities, therefore can be seen as adding stability to the property market. The results are comparable to previous research. The development of infrastructure facilities and other amenities reduce the negative impacts of climate change on property markets (Rajapaksa et al., 2016). However, contradictorily, Munro and Managi (2017) found that active decontamination action by the Japanese government is not good enough to move people back to affected areas by the nuclear accident.

The properties in beach erosion prone areas are also affected by extreme weather events and hence we included a control variable to capture such events. The coefficient sign for *ExtremeWeatherEvent* is, however, negative and significant as hypothesised. This demonstrates the fact that residential properties that were sold after extreme weather events such as the 2010–2011 Queensland floods and the 2011 kin. tides had a lower value than residential properties that were sold before these extreme weather events. Several studies on the impacts of flood hazards on residential property prices have shown similar results (Rajapaksa et al., 2016; Bin and Landry, 2013). The variable D400 does not show a significant impact.

4.2. Impact of cyclones

Of the 500 transactions selected to analyse the impact of cyclones on the property market, at least 16% occurred after the cyclone (i.e Yasi). This information is used to create the before and after variable: cyclone. The average house sale price was AUD 280,087 with an average of between 3 and 4 bedrooms, and 1.4 bathrooms (see, Table 4a and 4b). The land size varied from 414 m^2 to 2000 m^2. The year-dummy variables depicted the number of transitions occurring in each year (e.g. D2012).

Panel 'b' of Table 4 compares the descriptive statistics 'before and

Table 4a
Descriptive statistics of a selected sample for measuring the impact of cyclones.

Variable	Mean	Std. dev.	Minimum	Maximum
Sale price	280,087.2	196397.4	24900	1600000
Bedroom	3.104	1.044685	1	13
Bathroom	1.432	0.755326	1	8
Garage	1.848	0.981235	1	6
LandSize	946.304	204.193	414	2000
School	2571.96	1245.882	160	8900
Park	1333.696	1285.787	44	7700
Cyclone	0.16	0.366973	0	1
D2004	0.108	0.310691	0	1
D2005	0.072	0.258747	0	1
D2006	0.154	0.36131	0	1
D2007	0.152	0.359381	0	1
D2008	0.068	0.251998	0	1
D2009	0.118	0.322931	0	1
D2010	0.084	0.277666	0	1
D2011	0.092	0.289315	0	1
D2012	0.068	0.251998	0	1

Table 4b
Comparison of descriptive statistics before and after the cyclone.

Variable	Mean	Std. dev.	Minimum	Maximum
Before				
Sale price	280143.3	204723.3	24900	1600000
Bedroom	3.085	1.051098	1	13
Bathroom	1.411	0.700733	1	8
Garage	1.845	1.00231	1	6
LandSize	947.354	209.0196	414	2000
School	2613.05	1232.46	160	8900
Park	1345.648	1283.791	44	7700
After				
Sale price	279792.5	146106.8	70000	930000
Bedroom	3.2	1.011328	1	8
Bathroom	1.537	0.992933	1	8
Garage	1.862	0.867759	1	5
LandSize	940.787	177.7857	473	1534
School	2354.375	1300.469	210	6800
Park	1269.375	1302.454	180	5600

after' cyclone Yasi. As the results show, the selected variables are not different before and after the cyclone. However, the average sale price is less after the cyclone.

Property transaction data from four cyclone-affected suburbs (by cyclone Yasi) were considered as a case study. In line with previous literature, the impact of the disaster was captured by before and after analysis (Athukorala et al., 2016). First, before and after HP models were estimated and tested for spatial dependency. The OLS estimation is statistically significant and shows a high explanatory power (*Adj-R sq* 0.4 and 0.5). Most of the explanatory variables are as expected and significant at the 1% level (Table 5). Similar to our previous analysis, a test for spatial interaction and *LM statistics* imply the presence of a spatial lag effect. We corrected for spatial impacts by using a spatial lag model. We specified the impacts of cyclone Yasi in two different ways – as a dummy variable and using time dummies. The model 2 in Table 5, includes year dummy variables instead of cyclone variable to observe property price dynamics.

Despite slight changes in coefficients, most of the variables in ML estimations also are as expected. For instance, *Bedroom* and *Bathroom* were statistically significant at the 1% and 5% levels respectively. Either an additional bedroom or bathroom will increase property values by 8%. The second model shows that an additional garage space exerts a positive impact on property value – increasing property values by 4%. Unlike the first case study, land size does not show any significant impacts on property values. In terms of the neighbourhood explanatory variables, *LogSchool* is statistically significant and the coefficient sign positive. This implies that the level of competition for school admission

Table 5
Impacts of cyclones.

	Model 1		Model 2	
	OLS	ML	OLS	ML
Bedroom	0.0818***	0.0799***	0.0661***	0.0637***
	(0.021)	(0.0208)	(0.0195)	(0.019)
Bathroom	0.0802**	0.0793**	0.0770**	0.0753**
	(0.0309)	(0.0305)	(0.0284)	(0.0276)
Garage	0.0328	0.0298	0.0432**	0.0387**
	(0.0207)	(0.0205)	(0.0191)	(0.0187)
LogLandSize	0.0809	0.0853	0.0389	0.0423
	(0.0968)	(0.0955)	(0.0887)	(0.0864)
LogBeach	−0.129***	−0.158***	−0.141***	−0.184***
	(0.011)	(0.0204)	(0.0102)	(0.019)
LogSchool	0.147***	0.169***	0.106**	0.138***
	(0.0412)	(0.0427)	(0.0379)	(0.0388)
LogPark	0.0929***	0.116***	0.105***	0.139***
	(0.0267)	(0.0296)	(0.0244)	(0.0269)
LogRealMed˜n	0.151	0.205*	0.167	0.244**
	(0.119)	(0.121)	(0.109)	(0.11)
Cyclone (Yasi)	−0.203***	−0.204***		
	(0.0518)	(0.0511)		
D2004			0.310***	0.309***
			(0.0789)	(0.0769)
D2005			0.385***	0.405***
			(0.0888)	(0.0868)
D2006			0.564***	0.573***
			(0.0743)	(0.0725)
D2007			0.690***	0.704***
			(0.0747)	(0.0729)
D2008			0.628***	0.633***
			(0.0891)	(0.0868)
D2009			0.559***	0.569***
			(0.0795)	(0.0775)
D2010			0.496***	0.527***
			(0.0846)	(0.0832)
D2011			0.291***	0.299***
			(0.0821)	(0.08)
D2012			0.238**	0.248**
			(0.0892)	(0.087)
Constant	9.930***	12.94***	10.01***	14.40***
	(1.02)	(2.033)	(0.932)	(1.874)
rho		−0.275*		−0.399**
		(0.161)		(0.149)
adj. R-sq	0.398		0.500	
Robust LM Error	0.182			
Robust LM Lag	3.082**			
N	500	500	500	500

Note: *, ** and *** denote significant variables at 10%, 5% and 1% levels of significance, respectively. The standard error value for each variable is found in parentheses.

in selected suburbs is low and hence, residents do not value living within close proximity to schools. The coefficient sign for *LogPark* is also positive and significant, implying people are willing to reside away from parks.

The impact of the cyclone is most severe close to the beach but also exerts an amenity value to the property. In relation to the environmental explanatory variable in the estimated regression, the coefficient sign for *LogBeach* was negative and statistically significant at the 1% level. For every one-unit increase in the direct distance in metres to the beach, residential property values decrease by 15%–18%. The estimated regression results therefore show that residents are willing to pay a price premium to live within close proximity to the beach despite the risk of the impacts of storm surge and cyclones. The estimated results are different to the first model – the value for beach is comparatively low. The amenity value depends on the beach quality (i.e. beach width) (see, Halkos and Matsiori, 2018; Gopalakrishnan et al., 2011).

As the focal research question in this study was to determine the impacts of cyclones on residential property values, it needs to be asked whether residential property values would decrease sharply after a major cyclone. The answer to this research question can be found in the *Cyclone* variable. We hypothesised that residential property prices would fall following the event of a major storm or cyclone.

As estimated, the coefficient sign of *Cyclone* in the HP regression models was found to be negative, which confirmed the hypothesis in this study. The results show that after cyclone Yasi, real property values decreased by 20% (Model 1). As an alternative, we included year dummies instead of the cyclone variable in Model 2. Although all dummy variables show positive and significant coefficients, the value of coefficients is comparatively small after the cyclone (2011 and 2012). This then adds to the evidence that Cyclone Yasi did exert an influence on residential property values. To be noted is that the magnitude of Cyclone Yasi, which was the second major cyclone in five years to hit Northern Queensland after Cyclone Larry (in 2006), was significantly larger than the latter.

5. Conclusions

Public's concern about climate change is relatively low although having an experience of an extreme weather event such as a flood elevates their concern about the effects of climate changeand produces a greater willingness to undertake adaptive measures (Spence et al., 2011). This study examined public's response to beach erosion and extreme weather events in terms of property market behaviours, particularly when governments intervene to mitigate climate change impacts. Property buying is a long-term investment decision and here we explored individuals' long-term decision making in response to climate change and extreme weather events. In line with existing research, this study confirms that property prices decrease considerably (approximately 20%) after a severe cyclone, while the impact of beach erosion on property values is less.

This is in spite of the fact that the selected suburbs in the survey are those highly vulnerable to beach erosion. Beaches lying between Kawana and Alexandra Headland are shown to have already been affected, with up to 10 m of sand being swept out to sea. In an effort to mitigate beach erosion, the Sunshine Coast Council has been monitoring several locations and is also incurring expenditure to pump sand onto the beaches between Alexandra Headland and Maroochydore. One possible reason for the low level of responsiveness in property prices to beach erosion is this sort of intervention. However, it is quite possible in the long-run that the detrimental effects of beach erosion will eventually adversely affect residential property values. Furthermore, the method we adopted in this analysis is not perfect in distinguishing amenities and disamenities of being close to a beach. Future research in this area, therefore, needs to address some of the shortcoming of this analysis.

The Sunshine Coast Council has adopted both adaptation and mitigation approaches in its climate change action plan. This includes strategies such as environmental protection, beach nourishment, and building community resilience to natural hazards (Zeppel, 2011). In addition, the Sunshine Coast Council has announced that future infrastructure projects, including housing development plans, need to incorporate adaptation to minimise natural hazard impacts (Sunshine Coast Council, 2011; Zeppel, 2011). These positive measures indeed help to stabilise property market values.

As extreme weather events are difficult to forecast under certain circumstances, residents living in cyclone prone areas need to prepare for cyclones by having safety precautionary measures ready at all times. These measures can include checking with local council and/or the building control authority to see if residential properties in cyclone prone areas have been built to cyclone standards, knowing the nearest safe high ground and safest access route to it and ensuring the walls, roofs and eaves of residential properties are secure (Bureau of Meteorology, 2013). The use of a natural experimental approach can be used for precise estimation of disaster impacts. In this research we could not capture the public's adaptation strategies (if any) to climate change and extreme weather events.

References

Anning, D., Dominey-Howes, D., Withycombe, G., 2009. Valuing climate change impacts on Sydney beaches to inform coastal management decisions: a research outline. Manag. Environ. Qual. 20 (4), 408–421.

Anselin, L., 2013. Spatial Econometrics: Methods and Models, vol. 4 Springer Science & Business Media.

Athukorala, W., Martin, W., Neelawala, P., Rajapaksa, D., Wilson, C., 2016. Impact of wildfires and floods on property values: a before and after analysis. Singapore Econ. Rev. 61 (01), 1640002.

Atreya, A., Ferreira, S., Kriesel, W., 2013. Forgetting the flood? An analysis of the flood risk discount over time. Land Econ. 89 (4), 577–596.

Baranzini, A., Ramirez, J., Schaerer, C., Thalmann, P., 2008. Hedonic Methods in Housing Markets: Pricing Environmental Amenities and Segregation. Springer, New York, New York.

Bin, O., Landry, C.E., 2013. Changes in implicit flood risk premiums: empirical evidence from the housing market. J. Environ. Econ. Manage. 65 (3), 361–376.

Bin, O., Kruse, J.B., Landry, C.E., 2008. Flood hazards, insurance rates, and amenities: evidence from the coast housing market. J. Risk Insur. 75 (1), 63–82.

Bird, E.C.F., 1987. The modern prevalence of beach erosion. Mar. Pollut. Bull. 18 (4), 151–157.

Bureau of Meteorology, 2013. Surviving Cyclones: Preparation and Safety Procedures. Canberra, Australia. Retrieved from. http://www.bom.gov.au/cyclone/about/tcchecklist.shtml.

Capstick, S., Whitmarsh, L., Poortinga, W., Pidgeon, N., Upham, P., 2015. International trends in public perceptions of climate change over the past quarter century. Wiley Interdiscip. Rev. Clim. Change 6 (1), 35–61.

Colgan, P., Vaughan, O., Davidson, H., 2011. Cyclone Yasi: How It Unfolded. Retrieved from. http://www.news.com.au/breaking-news/floodrelief/north-queensland-braces-forcyclone-anthony-as-cyclone-yasi-brews-behind-it/story-fn7ik2te-1225998711771.

CSIRO, 2013. Understanding the Causes and Impacts of Extreme Weather Events. Retrieved from. http://www.csiro.au/en/Outcomes/Environment/Australian-Landscapes/Extreme-Weather-Events.aspx.

Department of Climate Change and Energy Efficiency, 2010. Developing a National Coastal Adaptation Agenda: A Report on the National Climate Change Forum. Retrieved from. . http://www.climatechange.gov.au/sites/climatechange/files/documents/03_2013/developing-national-coastal-adaptation-agenda.pdf.

Department of Climate Change and Energy Efficient, 2009. Climate Change Risks to Australia's Coast: A First Pass National Assessment. Retrieved from. . http://www.climatechange.gov.au/sites/climatechange/files/documents/03_2013/ccrisks-full-report.pdf.

Department of the Environment, 2013. Queensland: Climate Change Impacts in QLD. Retrieved from. http://www.climatechange.gov.au/climatechange/climate-science/climate-change-impacts/queensland.

Du, X., Huang, Z., 2018. Spatial and temporal effects of urban wetlands on housing prices: evidence from Hangzhou, China. Land Use Policy 73, 290–298.

El-Nahry, A.H., Doluschitz, R., 2010. Climate change and its impacts on the coastal zone of the Nile Delta Egypt. Environ. Earth Sci. 59 (7), 1497–1506.

Energy & Climate Intelligence Unit, 2017. Heavy Weather: Tracking the Fingerprints of Climate Change, Two Years After Paris Summit. retrieved from. https://eciu.net/reports/2017/heavy-weather.

Ford, J.D., Berrang-Ford, L., Paterson, J., 2011. A systematic review of observed climate change adaptation in developed nations. Clim. Change 106 (2), 327–336.

Gopalakrishnan, S., Smith, M.D., Slott, J.M., Murray, A.B., 2011. The value of disappearing beaches: a hedonic pricing model with endogenous beach width. J. Environ. Econ. Manage. 61 (3), 297–310.

Halkos, G., Matsiori, S., 2018. Environmental attitudes and preferences for coastal zone improvements. Econ. Anal. Policy 58, 153–166.

Holznagel, C., 2008. Action Needed to Halt Coast Beach Wipeout. Retrieved from. Sunshine Coast Newspaper Company. http://www.sunshinecoastdaily.com.au/news/action-needed-halt-coast-beachwipeout/334393/.

Intergovernmental Panel on Climate Change (IPCC), 2014. Climate change 2014: impacts, adaptation, and vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press.

Islam, M., Kotani, K., Managi, S., 2016. Climate perception and flood mitigation cooperation: a Bangladesh case study. Econ. Anal. Policy 49, 117–133.

Kummu, M., De Moel, H., Ward, P.J., Varis, O., 2011. How close do we live to water? A global analysis of population distance to freshwater bodies. PLoS One 6 (6), e20578.

Landry, C.E., Hindsley, P., 2011. Valuing beach quality with hedonic property models. Land Econ. 87 (1).

Malpezzi, S., 2002. Public hedonic pricing models: a selective and applied review. In: O'Sullivan, T., Gibb, K. (Eds.), Housing Economics and Public Policy. Blackwell Publishing, Oxford, UK.

Managi, S., Guan, D., 2017. Multiple disasters management: lessons from the Fukushima triple events. Econ. Anal. Policy 53, 114–122.

Mei, Y., Hite, D., Sohngen, B., 2017. Demand for urban tree cover: a two-stage hedonic price analysis in California. For. Policy Econ. 83, 29–35.

Munro, A., Managi, S., 2017. Going back: radiation and intentions to return amongst households evacuated after the great Tohoku earthquake. Econ. Disasters Clim. Chang. 1 (1), 77–93.

Niles, M.T., Lubell, M., Brown, M., 2015. How limiting factors drive agricultural

adaptation to climate change. Agric. Ecosyst. Environ. 200, 178–185.
Ortega, F., Taşpınar, S., 2018. Rising sea levels and sinking property values: hurricane Sandy and New York's housing market. J. Urban Econ. 106, 81–100.
Poudyal, N.C., Hodges, D.G., Merrett, C.D., 2009a. A hedonic analysis of the demand for and benefits of urban recreation parks. Land Use Policy 26 (4), 975–983.
Poudyal, N.C., Hodges, D.G., Tonn, B., Cho, S.H., 2009b. Valuing diversity and spatial pattern of open space plots in urban neighborhoods. For. Policy Econ. 11 (3), 194–201.
Rajapaksa, D., Wilson, C., Managi, S., Hoang, V., Lee, B., 2016. Flood risk information, actual floods and property values: a quasi-experimental analysis. Econ. Rec. 92 (S1), 52–67.
Rajapaksa, D., Islam, M., Managi, S., 2017a. Natural capital depletion: the impact of natural disasters on inclusive growth. Econ. Disasters Clim. Chang. 1 (3), 233–244.
Rajapaksa, D., Zhu, M., Lee, B., Hoang, V.N., Wilson, C., Managi, S., 2017b. The impact of flood dynamics on property values. Land Use Policy 69, 317–325.
Rajapaksa, D., Wilson, C., Hoang, V.N., Lee, B., Managi, S., 2017c. Who responds more to environmental amenities and dis-amenities? Land Use Policy 62, 151–158.
Ray, A., Hughes, L., Konisky, D.M., Kaylor, C., 2017. Extreme weather exposure and support for climate change adaptation. Glob. Environ. Chang. Part A 46, 104–113.
Rehdanz, K., 2006a. Hedonic pricing of climate change impacts to households in Great Britain. Clim. Change 74 (4), 413–434.
Rehdanz, K., 2006b. Hedonic pricing of climate change impacts to households in Great Britain. Clim. Change 74 (4), 413–434.
Rey-Valette, H., Robert, S., Rulleau, B., 2018. Resistance to relocation in flood-vulnerable coastal areas: a proposed composite index. Clim. Policy. https://doi.org/10.1080/14693062. 2018.1482823.
Samarasinghe, O., Sharp, B., 2010. Flood prone risk and amenity values: a spatial hedonic analysis. Aust. J. Agric. Resour. Econ. 54 (4), 457–475.
Short, A., 2009. Impact of Coastal Erosion in Australia. Retrieved from. http://www.coastalwatch.com/news/article.aspx?articleId=4524.
Sirmans, S., Macpherson, D., Zietz, E., 2005. The composition of hedonic pricing models. J. Real Estate Lit. 13 (1), 1–44.
Spence, A., Poortinga, W., Butler, C., Pidgeon, N.F., 2011. Perceptions of climate change and willingness to save energy related to flood experience. Nat. Clim. Chang. 1 (1), 46–49.
Tyrvainen, L., Miettinen, A., 2000. Property prices and urban forest amenities. J. Environ. Econ. Manage. 39 (2), 205–223.
van Aalst, M.K., 2006. The impacts of climate change on the risk of natural disasters. Disasters 30 (1), 5–18.
Wheeler, S., Zuo, A., Bjornlund, H., 2013. Farmers' climate change beliefs and adaptation strategies for a water scarce future in Australia. Glob. Environ. Chang. Part A 23 (2), 537–547.
Zhang, K., Douglas, B.C., Leatherman, S.P., 2004. Global warming and coastal erosion. Clim. Change 64 (1-2), 41.