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To move or stay? A cellular automata model to predict urban growth in coastal regions amidst rising sea levels

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ABSTRACT
Low-lying coastal cities are widely acknowledged as the most densely populated places of urban settlement; they are also more vulnerable to risks resulting from intensive land use and land cover change, human activities, global climate change, and the rising sea levels. This study aims to predict how urban growth is affected by sea level rise (SLR) in the Australian context. We develop an urban cellular automata model incorporating urban planning policies as potential drivers or constraints of urban growth under different SLR scenarios and adaption strategies. Drawing on data capturing the socioeconomic and environmental factors in South East Queensland, Australia, our model is positioned to address one core research question: how does SLR affect future urban growth and human resettlement? Results show that urban growth in coastal regions varies depending on the extent to which the sea level rises and is affected by a combination of factors relating to urban planning and human adaptation strategies. Our study demonstrates the complexity of urban growth in coastal regions and the nuanced outcomes under different adaptation strategies in the context of rising sea levels.

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Climate change; Cellular automata; Sea level rise; Urban growth; Human settlement

1. Introduction

Climate change has been acknowledged as one of the most significant phenomena in the twenty-first century; it also has a profound impact on all aspects of human societies and the natural environment (Hay et al. 2017; Dangendorf, Hay, and Calafat 2019). Globally, many of the world's large cities are developed in coastal regions with dense population and intensive economic activities (Becerra, Pimentel, and De Souza 2020). The majority of these coastal cities are low-lying, susceptible to the ravage of climate change and climate disasters such as tsunami, hurricane, storm surge, submergence, flooding and coastal erosion (Kulp and Strauss, 2019). The impact of climate change on the low-lying coastal cities has been increasing throughout the twenty-first century and beyond (Church, Clark, and Cazenave 2013). It is estimated that between 145 and 565 million people living in coastal regions will face potential inundation from rising sea levels by 2100 (Watts, Amann, and Arnell 2020, 130). Considering the total population living in the low-lying coastal regions around the world exceeding one billion by this century (Neumann, Vafeidis, and Zimmermann 2015; Hauer, Fussell, and Mueller 2020), the concentration of economic activities and the high value of coastal lands, there are urgent needs for developing adaptation strategies and policy intervention

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to ensure the long-term sustainability of the region (Neumann, Vafeidis, and Zimmermann 2015; Mills, Leon, and Saunders 2016; Storch and Downes 2011).

Methodologically, there exists a large number of studies on modelling and predicting urban growth using cellular automata (CA) and CA-derived models (e.g. the LSUM model by Stimson, Bell, and Corcoran 2012; the UrbanSim by Waddell 2002; the CLUE model by Verburg, Soepboer, and Veldkamp 2002; the SUSTAIN model by Love, Medin, and Gureckis 2004; and the SLEUTH model by Mahiny and Clarke 2012). Most of these models focus on urban expansion, and overlooking the impact of SLR and the responding adaptation strategies. Existing urban modelling research is also limited in considering the impact of urban planning policies on future urban growth, especially when the Markov Chain or similar methods are used in the estimation of land demand for growth which may lead to unrealistic outcomes. As such, there is a pressing need to model and predict urban growth in coastal regions that are affected by the collective effect of SLR, different adaptation strategies, as well as urban planning policies.

This study aims to address the research question on *how SLR affects future urban growth and human resettlement* by taking into consideration urban planning policy as well as different climate change adaptation strategies. Using South East Queensland (SEQ), Australia as a case study region, we first drew on the population and planning data and a digital elevation model to identify areas that are potentially being affected by SLR, and estimated the size of population living in these areas. We then constructed and calibrated an urban CA model to simulate urban growth from 1991 to 2016, and used the model to predict the spatial patterns of future urban growth from 2016 to 2041 under current planning policy as well as different SLR scenarios and adaptation strategies. Our study contributes to predicting how climate change will reshape future urban growth and human resettlement; it also offers tools to assist local government to plan for areas to accommodate residents who may be affected by climate hazards in future.

The rest of this paper is organised as follows. A description of the study background relating to SLR and its adaptation strategies, and urban modelling is presented in the next section. Then, the study context, data and modelling methods are introduced, followed by the results showing areas and size of population potentially being affected under different SLR scenarios, and predicted urban growth to 2041. The policy implications, study limitations and future research are then discussed, followed by a concluding remark at the end.

2. Background

SLR is generally considered as the most critical consequence of global climate change, causing coastal inundation and erosion, and other coastal hazards (Stive, Ranasinghe, and Cowell 2010; Spencer, Schuerch, and Nicholls 2016). These hazards, together with the growing number of population living in coastal regions, would affect hundreds of millions of people by the end of twenty-first century (Geisler and Currens 2017; Neumann, Vafeidis, and Zimmermann 2015; Hauer, Fussell, and Mueller 2020). Consequently, various coastal hazard adaptation strategies have been proposed in response to climate change hazards and to ensure long-term sustainability of coastal cities (Biagini, Bierbaum, and Stults 2014). There are many different approaches for coastal hazard adaptations, which can be grouped into three broad categories: (1) protection/defence, (2) accommodation/management; and (3) retreat/migration (Black, Bennett, and Thomas 2011; Hauer, Fussell, and Mueller 2020). The first and second categories—protection/defence and accommodation/ management—both refer to hard engineering approaches to protect human settlement by installing hard armouring like seawalls, groyne, and boulder barriers to keep waters at the bay, elevating buildings and road networks, or strengthening sewage and stormwater drainage in areas endangered by SLR to direct water flow (Torabi, Dedekorkut-Howes, and Howes 2018). Thus, urban development would continue under these strategies, and residents would remain in areas that may be subject to risk of coastal hazards (Sutton-Grier, Gittman, and Arkema 2018). The challenges of these strategies include the high construction costs of defence structures as well as the associated negative impact on the environment (Hauer, Fussell, and Mueller 2020). The third category—retreat/migration—is an approach that aims to regulate new development and relocate people to areas away from the coast or in higher elevation hinterland (Dyckman, John, and London 2014). This type of adaptation strategy is especially advocated by environmentalists as an optimal solution given the opportunity to protect the coastal ecosystems, release coastal squeeze and limit the cost of building hard armouring structures (Krolik-Root, Stansbury, and Burnside 2015). However, the implementation of retreat/migration strategy can be challenging and usually involves the negotiation among multiple stakeholders, including politicians, urban planners, property developers and local residents to ensure that all stakeholders' interests are compensated in the relocation process (Rulleau and Rey-Valette 2017). In this study, we re-group the three adaptation strategies into two types—*stay* strategy which includes both protection/defence and accommodation/management where people stay in areas potentially being affected by SLR, and *move* strategy which includes retreat/migration that relocate people from coastal to inland areas—to set up scenarios for modelling future urban growth in coastal regions.

A common approach to simulate and predict urban growth is cellular automata (CA) modelling (Liu 2008). This modelling approach enables researchers to predict where land use and land cover changes are likely to occur and how such changes might be distinct in different locations or under different conditions. CA modelling is a bottom-up approach where land is represented on a lattice of cells with each cell indicating the predominant land use (Wu 2002). The evolution of land use is modelled at individual cell scale as a response to the state of the cell itself and the states of nearby land cells under a series of driving factors which function in complex ways and their effects on urban growth are non-linear in nature (Batty 2007). However, several limitations are observed in the existing CA models. First, most research focus on modelling urban expansions and use Markov Chain or similar methods to calculate land demand for future urban growth; such methods can lead to unrealistic outcomes without considering the impact of urban planning policies. In reality, strategic urban and regional planning policies may be implemented by the state and local governments to legislate the growth of urban footprint and/or to promote high-density land development, resulting in urban densification and the reduction of land demand for future urban growth. Second, most CA modelling work consider land use, socioeconomic and built environment factors to define land transition rules, whereas limited studies consider the impact of climatic events on urban growth, such as tropical cyclones, storm surges and SLR. The exceptions include Hauer (2017) who modelled the spatial distribution of population in the United States that might be induced by sea level rise, and Mills, Leon, and Saunders (2016) who developed four models including a CA-based urban model to explore the impact of SLR on the Moreton Bay region in Australia under different adaptation strategies. A more recent work by Lu et al. (2019) used a fuzzy CA-based Markov Chain model to simulate the impact of climate change on urban growth in New York City, but also overlooked the impact of planning policy in the model prediction.

There is also a pressing need to develop models to enhance our understanding of the impact of climate change on urban growth in the Global South such as Australia (Hansen 2007, 2010; Barredo and Delgado 2008). According to the projection of SLR by Australian Government Bureau of Meteorology (2016), it was estimated that Australia would be exposed to SLR of 0.28–0.61 m for low emissions of greenhouse gas or 0.52–0.98 m for high emissions of greenhouse gas by 2100. Given that over 85% of Australians live within 50 km of the coastlines and all except for one capital cities of the Australian States/Territories are located along the coasts (Australian Bureau of Statistics 2016a), the risk of unprecedented SLR poses severe threat to the human settlement and urban development in this continent. As such, our study aims to simulate and predict urban growth in the coast region in South East Queensland under the impact of SLR and different adaptation strategies to address such pressing needs.

3. Study context, data and methods

3.1. Study context

We choose the SEQ coastal region as the case study as it is one of the fastest growing coastal regions in Australia, and it also has a long history of being affected by various coastal hazards, including flood, tropical cyclone, and land slide (Bureau of Meteorology 2016). SEQ inhabits over 3.6 million people (which accounts for 71% of the total population, 5.1 million in the State), and contains Queensland's three largest cities: Brisbane as the state capital city, and Gold Coast and Sunshine Coast that are world-class tourist destinations (Queensland Government 2016). SEQ covers 22,420 square kilometres of land extending 240 kilometres from Noosa in the north to Gold Coast in the south, and 140 kilometres west to Toowoomba (Queensland Government 2017). This region has experienced significant population growth since the early 1990, and is predicted to have 5.3 million people by 2041 (Australian Bureau of Statistics 2016a). There are 12 local government areas (LGAs) in this region (including part of Toowoomba); six of them, including (from north to south) Noosa, Sunshine Coast, Moreton Bay, Brisbane, Redland, and Gold Coast, are located along the coast. Our study area consists of these six coastal LGAs together with two LGAs off the coast—Logan and Ipswich—given that these two LGAs are closely connected with the state capital city of Brisbane and are part of the Brisbane Metropolitan Area. The total size of our study area is 10,430 km^2 (Figure 1).

SEQ coastal region has a long history of being affected by various types of coastal hazards. It was estimated that about 328,158 ha of land in SEQ was subject to potential inundation induced by SLR, storm surge and other extreme climatic events, affecting approximately 15,200 and 5400 residential buildings located within 110 and 55 metres of soft erodible coastlines (Department of Climate Change 2011). Historically, Cyclone Mahina occurred in Cape York Peninsula, Queensland in March, 1899 as the largest storm surge on record, generating a 13m-high surge. The most recent severe storm surge was Cyclone Yasi, occurred in 2011, generating a 7m-high surge along the coast (Bureau of Meteorology 2016).

According to the Intergovernmental Panel on Climate Change (IPCC), the global mean sea level will rise between 0.43 and 0.84 m (0.29–1.10 m likely range) by 2100 (Oppenheimer, Glavovic, and Hinkel 2019, 324). Building on this estimate and considering the historical record of coastal hazards in the region, we hypothesised three SLR scenarios, that is, SLR of 0.8, 3.5 and 7 m, with 0.8 m being a baseline scenario for modelling future urban growth. We adopted 7 m as a maximum extreme considering the historical storm surge caused by Cyclone Yasi in 2011 (Bureau of Meteorology 2016). The 3.5 m SLR was adopted based on the understanding that the flood level in the hours after a storm's passage was estimated to be half of the highest storm surge (Frazier, Wood, and Yarnal 2010; Möller, Kudella, and Rupprecht 2014). Under these three SLR scenarios, two SLR adaptation strategies were considered: the *move* strategy that residents would move to areas away from the risk of SLR, compared to the *stay* strategy that residents would stay in the coast areas where hard engineering approaches would be in place to protect the rising sea level; this *stay* strategy is therefore considered as SLR 0 m in our model. Nevertheless, we acknowledge that the decisions people make to stay or move in response to SLR are more complex (McMichael, Dasgupta, and Ayeb-Karlsson 2020), but this is beyond the scope of the current study.

For the modelling timeframe, we selected a 25-year window from 1991 to 2016 to construct and calibrate our urban CA model. This timeframe was considered suitable in the Australian context given that Australia has entered into a more mature phase of urbanisation with a relatively slow-pace urban development compared to other more rapidly developing countries such as China, and the 25-year interval would enable our model to capture the subtle land use change over the period. We then used the model to predict future urban growth from 2016 to 2041; this projection timeframe is also in alignment with the gazetted regional plan by Queensland Government – *ShapingSEQ: South East Queensland Regional Plan 2017* (henceforth referred to as *ShapingSEQ*) (Queensland Government 2017).

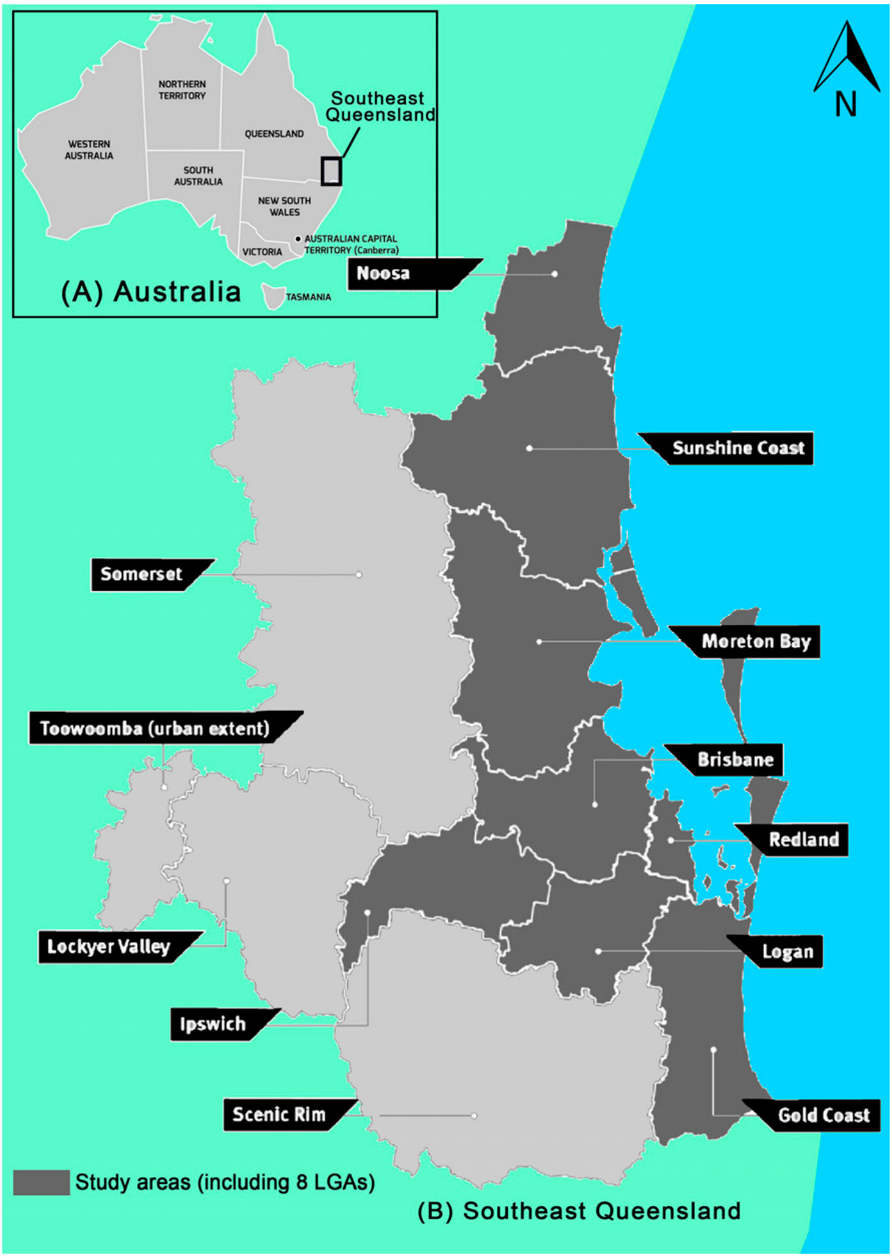


Figure 1. South East Queensland and our study area is shown in dark grey colour.

3.2. Data

We utilised a series of socio-spatial data and environmental data from multiple data sources to build the CA model. Population data in 2016 were retrieved from the Census of Population and Housing through the TableBuilder, an online data portal provided by the Australian Bureau of Statistics (ABS 2016b); land use maps in 1991 and 2016 were collected from the digital cadastral database provided by the Queensland Government (2019a); digital elevation models (DEM) in 1990 and 2016 at 100 m spatial and 0.25 m vertical resolutions were retrieved from the LiDAR remote sensing imageries hosted by the Queensland Government (2019b); the spatial data of major transportation network, city centres, townships, green space, waterbodies (including lakes and rivers, excluding seasonal creeks) and protected areas for biodiversity in 1990 and 2016 were retrieved from the Queensland Spatial Data Catalogue—QSpatial—an online spatial data portal created by Queensland Government (2019c); the proposed urban footprint by 2041 was extracted from the *ShapingSEQ* (Queensland Government 2017); a coastal hazard map which delineates the areas of land along the coast that are subject to coastal erosion under 0.8 m SLR and associated storm impacts was also retrieved from QSpatial (Queensland Government 2019c). All spatial datasets were converted to 100 m grids in GeoTiff format as input for model construction. Considering the large size of the study area over 10 thousand square kilometres, the 100 m spatial resolution was considered sufficient to compromise amongst data availability, computational complexity, and the ability of the model to capture the land use transition in this region.

3.3. Method

3.3.1. CA urban model incorporating SLR scenarios

We constructed a CA urban model that incorporates the SLR scenarios for modelling of future urban growth (henceforth referred to as a SLR-CA model). A critical component of the SLR-CA model is its transition rules, which decide how the state of a cell changes in the next time step as a consequence of being affected by the current state of the cell itself and its neighbouring cells under a set of driving factors and constraints. Conceptually, the transition rules of the SLR-CA model can be expressed as (Feng and Tong 2018):

$$State_{i,\,t+1} = F[State_{i,\,t},\ Dri_i,\ NeiEff_{i,t},\ Con_{i,t},\ CN]_t \tag{1}$$

where F is the overall land use transition function which decides the change of a cell i from the state ($State_{i,\,t}$) at time t to the state ($State_{i,\,t+1}$) at time $t+1$; Dri_i represents the impact of the driving factors on land use transition; $NeiEff_{i,t}$ is the neighbourhood effect of cells around the central cell i on the transition of the state of cell i; $Con_{i,t}$ represents the constraints on land development; and CN is the total number of sampling cells used in the model in order to reduce the computational load.

Mathematically, the transition rule of the model is transformed to a land transition probability measured at each cell location i, defined as (Feng and Liu 2013):

$$P_i = (LPro_i \times Pro_{\mathrm{Scale}} + NeiEff_i \times NeiEff_{\mathrm{Scale}}) \times Con(S_i, S_{\mathrm{land}}, S_{SLR})/2 \tag{2}$$

where P_i represents the model's overall transition probability; $LPro_i$ is a local land transition probability of cell i, which is detailed in Equation (3); Pro_{Scale} is a time parameter ranging from 0.0 to 0.1 to scale the land transition probability; $NeiEff_i$ is the neighbourhood effect on land transition which is explained in Equation (4); $NeiEff_{Scale}$ is a local parameter ranging from 0.5 to 1.0 to scale the neighbourhood effect $NeiEff_i$; Con (S_i, S_{land}, S_{SLR}) represents three sets of constraints: $Con(S_i)$ denotes the constraints of urban development (e.g. waterbodies and conservation land); $Con(S_{SLR})$ denotes the constraints related to the risk of SLR (e.g., inundated areas at a certain level of SLR); $Con(S_{land})$ denotes the constraints of available land for construction within the urban footprint.

$LPro_i$ is a local land transition probability of cell i, written as (Feng and Liu 2013):

$$LPro_i = \frac{\exp\left(a_0 + \sum_{k=1}^{N} a_k D_{k,\mathrm{envi}} + \sum_{h=1}^{N} a_h D_{h,\mathrm{urban}} + \lambda W_i + \varepsilon\right)}{1 + \exp\left(a_0 + \sum_{k=1}^{N} a_k D_{k,\mathrm{envi}} + \sum_{h=1}^{N} a_h D_{h,\mathrm{urban}} + \lambda W_i + \varepsilon\right)} \tag{3}$$

where a_0 is a constant; $D_{k,envi}$ ($k = 1, 2, \ldots, 1$) represents a series of driving factors of future urban growth related to the natural environment and topography (e.g. slope and elevation); $D_{h,urban}$ ($h = 1, 2, \ldots, 1$) represents a series of driving factors of future urban growth related to urban infrastructures and facilities (e.g. distances to urban centres and railway stations); N is the number of driving factors; W_i is a 5×5 spatial adjacency weights matrix to reflect the relationships among neighbouring cells to cell i, with 1 for adjacent cells and 0 for diagonal cells; λ is the coefficient of the spatial adjacency weights; ε is the regression residual; a_k ($k = 1, 2, \ldots, \mathrm{l}$) and a_h ($h = 1, 2, \ldots, \mathrm{l}$) are the coefficients for each of the driving factors, indicating the extent each driving factor affects the land transition. These coefficients were calculated using a spatial-lag regression, given the advantage of this method that can minimise the spatial autocorrelation among the driving factors and improve the simulation accuracies (Bihamta, Soffianian, and Fakheran 2015).

$NeiEff_i$ represents the effect of existing urban cells around a non-urban cell i within the neighbourhood on the state of the cell i towards urban state, which can be written as (Dahal and Chow 2015):

$$NeiEff_i = \frac{\sum_{m \times m} [Cell_i(S = Urban) - Cell_i(S = SLR)]}{m \times m - 1} \tag{4}$$

where $m = 5$, representing a 5×5 neighbourhood size.

Finally, with P_i being measured as land transition probability of a cell i at a current time, its next status at a subsequent time $t + 1$ can be determined by comparing the overall probability with a threshold value P_θ ranging from 0 to 1 (Feng and Liu 2013). The value of P_θ was defined by adjusting the parameter settings of the model to achieve an optimal configuration of the model's transition rules; it was calibrated by comparing the disagreements between the simulated land-use pattern generated by the model and the actual land-use pattern derived from remotely sensed imageries (Feng and Liu 2013). If the overall probability (P_i) is larger than P_θ, the state of cell i will be converted from non-urban to urban at time $t + 1$; otherwise, its state remains unchanged.

3.3.2. Defining the driving factors

Similar to existing work on urban CA modelling (e.g. Sakieh, Amiri, and Danekar 2015; Wu, Ren, and Che 2015, 2019; Babak and Abbas 2017), we defined the driving factors in the SLR-CA model based on past land use changes as well as the socio-economic and environmental conditions of the area, including elevation, land slope, road density, and distances to coastlines, roads, railway lines and stations, green space, city centres and waterbodies (Table 1 and Figure 2). Among these driving factors, elevation and distances to coastlines and waterbodies are factors reflecting the impact of SLR.

3.3.3. Estimating land quantities needed for future urban growth

To predict future urban growth, we took on board the estimated land demand from the SEQ regional plan, *ShapingSEQ* (Queensland Government 2017). According to this plan, future urban growth to the year 2041 can be achieved through two main processes: *urban consolidation* (or

Table 1. Driving factors used in the SLR-CA model

Driving factor	Definition	Measurement
Distance to coastlines	Euclidean distance to coastlines	Measured from the coastline layer
Distance to water bodies	Euclidean distance to waterbodies	Measured from the land use data layer
Distance to city centres	Euclidean distance to urban centres	Measured from the urban centre data layer
Distance to roads	Euclidean distance to road network	Measured from the transport network data layer
Distance to green parks	Euclidean distance to conservation and parks	Measured from the land use data layer
Distance to railway lines	Euclidean distance to railway lines	Measured from the transport network data layer
Distance to railway stations	Euclidean distance to railway stations	Measured from the transport network data layer
Road density	Road areas over the total area in a cell	Measured from the transport network data layer
Neighbouring urban areas	Number of the neighbouring urban areas	Measured from the land use data layer
Elevation	Land elevation	Extracted from the DEM
Slope	Land slope	Extracted from the DEM

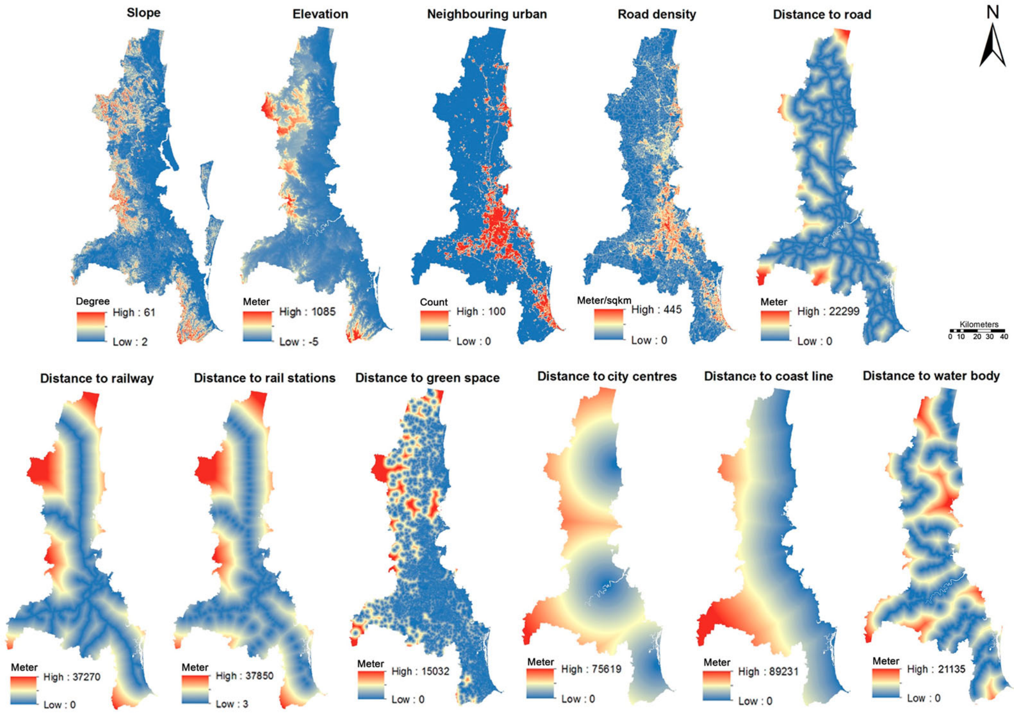


Figure 2. Driving factors to urban land use change.

infill development) and *urban expansion* (or greenfield development). Urban consolidation is defined as development that occurs on land within existing urban footprint, which can occur in the form of high- or medium-density development in areas with good access to public transport, employment and public services. On the other hand, urban expansion is development that occurs on land outside the existing urban footprint, and is characterised by low-density residential housing, single-use zoning, and increased reliance on private automobile for transportation, and usually occurs in regional and remote inland areas.

To achieve the overall sustainable development goal of the region, the official planning document specifies an overall consolidation-to-expansion ratio of 60:40 for future urban development. Given the difference in population size, land demand, current land use status as well as the different future development goals of each LGA, this consolidation-to-expansion ratio was specified differently for each LGA. Table 2 presents the current (2016) and projected (2041) population of each LGAs together with the expected population and dwelling growth according to the consolidation-to-expansion ratio of each LGA.

3.3.4. Defining constraints

To simulate urban growth from 1991 to 2016, we defined a number of constraints to urban growth, including large waterbodies and biodiversity-protected areas (Figure 3). To predict future urban growth from 2016 to 2041, we added other constraints which include the areas outside the planned urban footprint as defined in *ShapingSEQ* (Figure 4) and areas that are subject to potential impact under different SLR scenarios (Figure 5). Using the planned urban footprint data, we estimated the total amount of urban space needed to support urban development and human and economic activities. While in principle urban growth should be confined within the planned urban footprint boundaries, this is not always the case in reality; development can go beyond the confined boundaries, as is the case in some of the existing urban areas in the 2016 land use map. To control for the

Table 2. Estimated population and dwelling growth from 2016 to 2041

	Population in 2016	Projected Population in 2041	Population growth from 2016–2041	Expected dwelling growth			Persons per dwelling	Consolidation-to-expansion ratio
				Consolidation	Expansion	Total		
LGAs included in our urban model								
Brisbane	1,184,200	1,571,000	386,800	176,800	11,400	188,200	2.06	94/6
Gold Coast	576,900	928,000	351,100	127,900	31,000	158,900	2.21	80/20
Moreton Bay	438,300	656,000	217,700	48,200	40,100	88,300	2.47	55/45
Sunshine Coast	303,400	495,000	191,600	53,700	33,300	87,000	2.20	62/38
Logan	313,800	586,000	272,200	19,900	70,000	89,900	3.03	22/78
Ipswich	200,100	520,000	319,900	27,900	83,800	111,700	2.86	25/75
Redland	152,000	188,000	36,000	12,500	4,700	17,200	2.09	73/27
Noosa	54,000	63,000	9,000	4,800	1,600	6,400	1.41	75/25
Other LGAs in SEQ (not included in our model)								
Scenic Rim	41,000	62,000	21,000	0	10,000	10,000	2.10	0/100
Somerset	25,200	38,000	12,800	0	6,200	6,200	2.06	0/100
Lockyer Valley	39,500	61,000	21,500	0	9,600	9,600	2.24	0/100
Toowoomba	134,000	180,000	46,000	3,200	17,100	20,300	2.27	16/84
SEQ	**3,462,400**	**5,349,000**	**1,886,600**	**474,900**	**318,800**	**793,700**	**2.38**	**60/40**
Expected urban land growth in all LGAs in SEQ (ha)					45,543			
Expected urban land growth in LGAs covered in our urban model (ha)					40,843			

Data source: *ShapingSEQ: South East Queensland Regional Plan 2017* (Queensland Government 2017)

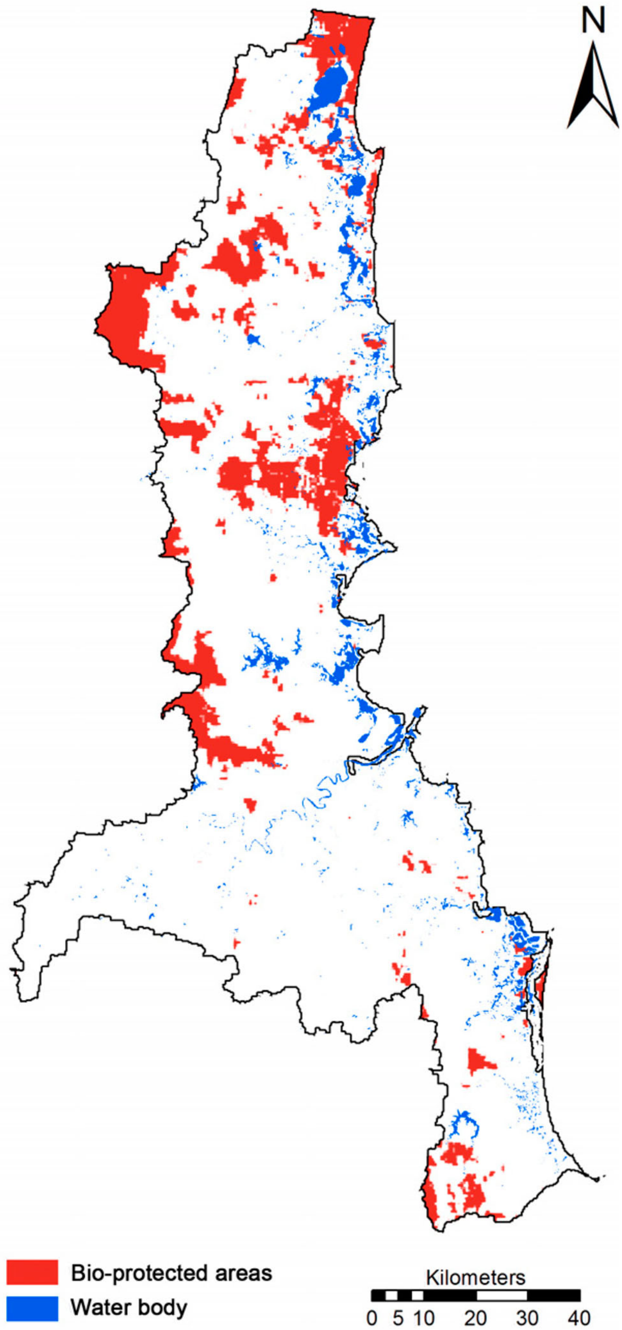


Figure 3. Constraints used in the simulation of urban growth from 1991 to 2016.

future growth of existing urban land in areas beyond the planned urban footprint, we assigned these areas with a low probability of 10% to be developed to urban in the model prediction. The 10% probability was set based on multiple experiments and the overall distribution of land transition probability, as well as a certain degree of randomness to be tolerated in the model.

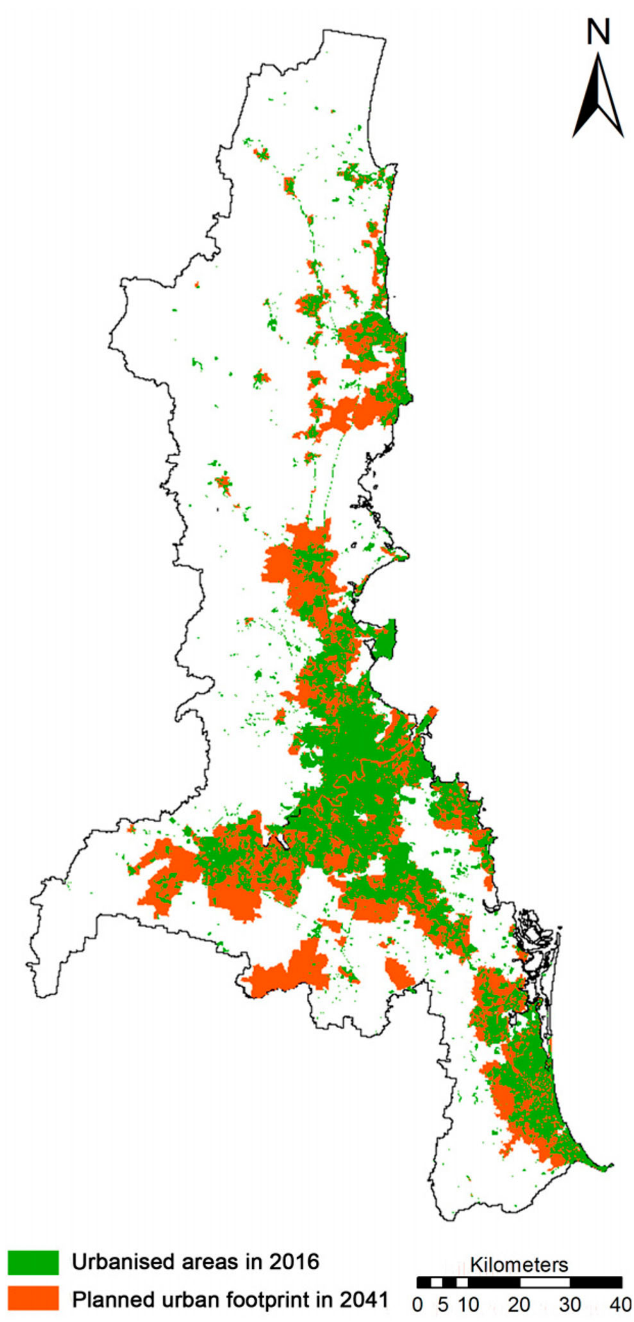


Figure 4. Planned urban footprint in 2041 adopted from *ShapingSEQ* (Queensland Government 2017).

3.3.5. Model calibration

Model calibration was conducted by overlaying the simulated land use map in 2016 with the observed land use map in 2016 for a cell-by-cell comparison. Rather than using the commonly applied error matrix approach to assess the simulation accuracy of the whole study area, we conducted the accuracy assessment focusing on areas with land use change occurred in the model by using seven key indices proposed by Pontius, Peethambaram, and Castella (2011): *Initial*

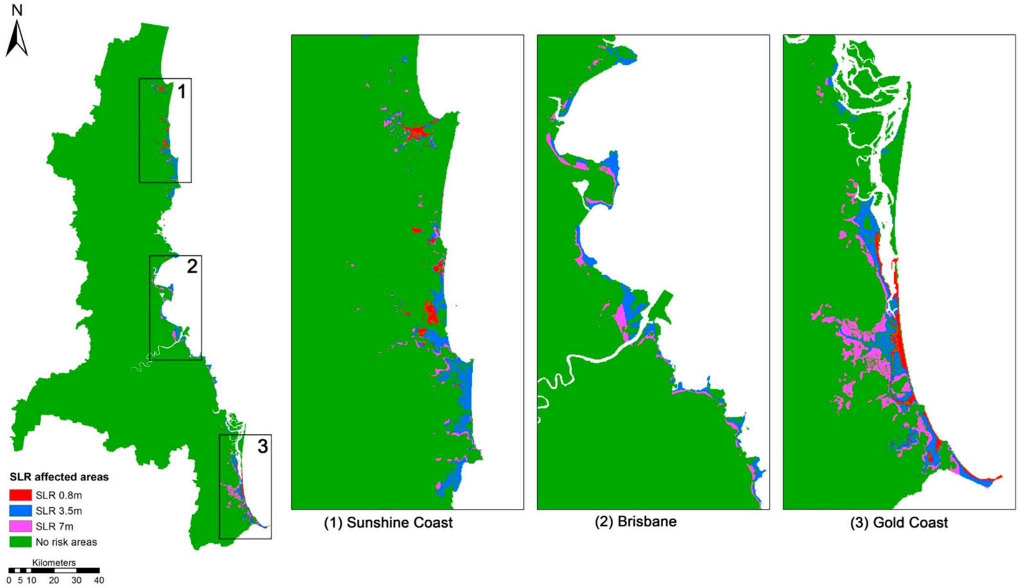


Figure 5. Areas potentially being affected under different SLR scenarios, with three enlarged figures showing parts of the Sunshine Coast, Brisbane and Gold Coast areas.

urban, Hits, Misses, False alarms, Correct rejection, and Figure of Merit (*FOM*). Specifically, *Initial urban* were the observed urban areas at the initial time of modelling; *Hits* were the observed urban growth areas being correctly captured by the model; *Misses* were the observed urban growth being incorrectly simulated as non-urban; *False alarms* were the observed non-urban areas being simulated as urban growth; and *Correct rejection* were the observed non-urban areas being correctly simulated as non-urban (Feng, Yang, and Tong 2019). Accordingly, *FOM* was calculated as:

$$FOM = \frac{\text{Hits}}{\text{Hits} + \text{Misses} + \text{False alarms}} \tag{5}$$

3.3.6. Modelling process

Utilising the UrbanCA software developed by Feng and Tong (2018), we constructed the SRL-CA model following the workflow illustrated in Figure 6. The simulation process consists of three parts: model construction, calibration and prediction. For model construction, we selected a total of 10,000 sampling cells from the 1991 land use map, and the corresponding cells in the 2016 land use map and the driving factor maps. We used systematic sampling to ensure that all cells sampled were evenly distributed in the entire study region; this sampling approach has been applied in other studies to reduce the computational load (e.g. Feng, Yang, and Tong 2019; Wu 2002; Feng and Liu 2013), and the samples were then used to retrieve the CA parameters and build the CA model. The calibration process of the modelling commences by using input data from 1991, with each iteration representing one year, and stops after 25 iterations to 2016. Through extensive computational experiment, calibration and simulation accuracy assessment, the model generates an output map illustrating the land transition probability of each cell in the region from non-urban to urban land over the simulation period. This probability map was then used to predict land use change from 2016 to 2041. For model prediction, we used the 2016 land use map as input to define the initial state of the cells, and we took on board the land use change probability map as well as the projected land demand for future growth and SLR scenarios as constraints to generate future urban growth patterns to the year 2041.

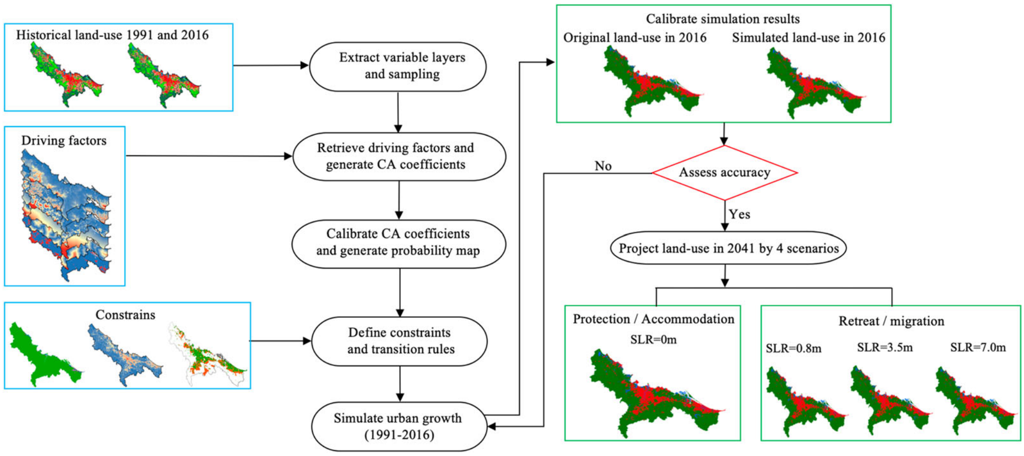


Figure 6. The SLR-CA modelling process.

4. Results

4.1. Land conversion probability and model's simulation accuracy

Table 3 shows that five driving factors (distance to green parks, distance to railway stations, distance to roads, distance to coastlines and road density) were positively correlated with urban growth; the remaining factors were negatively correlated with urban growth. Among these driving factors, the coefficients of distances to green parks, distances to railway stations, and road density were larger than other driving factors, indicating stronger influence (the absolute value of coefficients larger than 0.1) of these three driving factors on urban growth. The probability map (Figure 7) shows the likelihood of each cell being converted to urban land from 1991 to 2016 under the defined transition rules; this probability map was then used to predict future land use change from 2016 to 2041. According to this map, higher land transition probabilities tend to appear in the inland areas of Brisbane and Gold Coast, and appear along the coasts in the Sunshine Coast, Moreton Bay, and Redlands LGAs.

Table 4 presents the accuracy of the SLR-CA model, with FOM being 41.15%. This indicates that our model has correctly predicted 41.15% of the total land conversion; this level of accuracy is similar to other work in early literature (e.g. Feng, Yang, and Tong 2019). The areas of *Hits, False alarms*, and *Misses* are illustrated in Figure 8.

Table 3. Coefficients of the driving factors and its effect on urban growth

Driving factors	Type	a_k[1]	Strength of impact on urban growth[2]
DEM	Surface	−0.032	Moderate
Slope	Surface	−0.008	Weak
Distance to coastlines	Distance	0.011	Weak
Distance to city centres	Distance	−0.024	Weak
Distance to road	Distance	0.048	Moderate
Distance to green parks	Distance	−0.108	Strong
Distance to waterbodies	Distance	−0.066	Moderate
Distance to railway lines	Distance	−0.063	Moderate
Distance to railway stations	Distance	0.150	Strong
Neighbouring urban	Distance	−0.167	Strong
Road density	Density	0.648	Strong

Note:
[1] a_k is the coefficient of each driving factor as shown in Equation (3) produced by the spatial-lag regression;
[2] This is defined based on the absolute value of a_k of each driving factor: strong ($|a_k| > 0.1$); moderate ($0.05 < |a_k| < 0.1$); weak ($|a_k| < 0.05$).

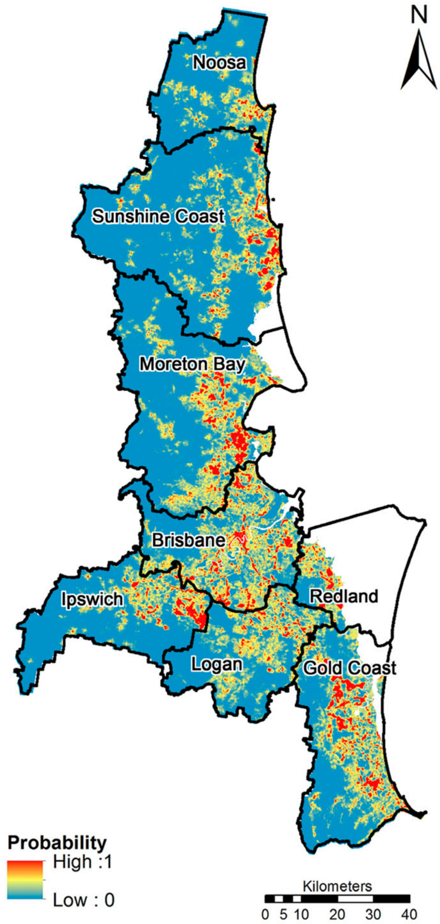


Figure 7. Probability of land being converted to urban from 1991 to 2016.

4.2. Predicted areas potentially being affected by SLR

Table 5 shows the predicted quantity of areas that would potentially be affected by SLR under three different scenarios in 2041. Under the 0.8m-SLR scenario, 0.85%, 0.39% and 0.3% of the land areas in the Gold Coast, Noosa and Sunshine Coast LGAs would be affected, respectively. These areas tend to be located along the coast in the Gold Coast but more towards the inland areas in Noosa and the Sunshine Coast. Under the 3.5m-SLR scenario, more areas would be affected, including Gold Coast (3.44%), Sunshine Coast (1.87%), Redland (1.3%), Brisbane (1.11%) Noosa (0.87%) and Moreton Bay (0.62%). When the SLR increases to 7 m, more land areas in these six LGAs would be affected, with the largest quantity of land on the Gold Coast being affected and the areas being affected extend further towards inland along the cannels and rivers, and may affect the highly valuable waterfront properties. The two inland LGAs of Ipswich and Logan would not be affected directly by SLR under all three scenarios.

Table 4. The model's simulation accuracy indicators (%)

Initial Urban	14.86	Miss	1.10
Correct Rejection	45.19	False Alarm	0.75
Hit	1.29	Excluded	36.81
FOM	**41.15**		

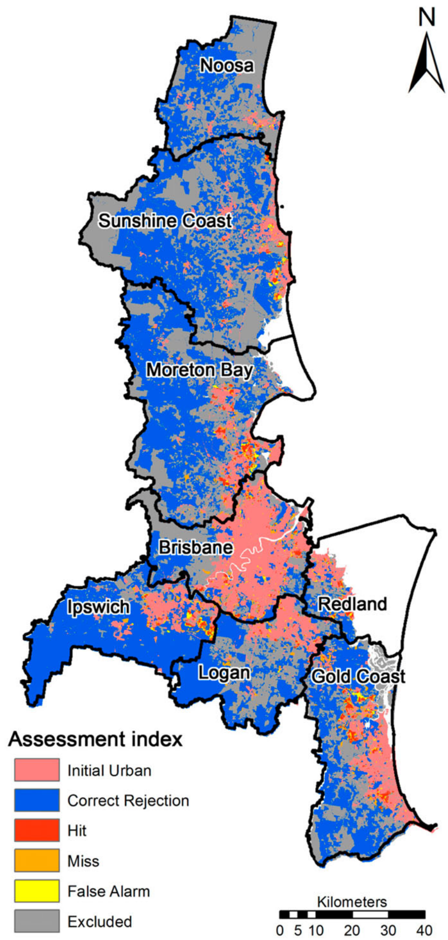


Figure 8. Model's simulation accuracy outcome.

4.3. Predicted urban expansion to 2041

Table 6 shows the predicted urban expansion from 2016 to 2041 under four different SLR scenarios (0, 0.8, 3.5 and 7.0 m). We included the 0 m SLR scenario to indicate the *stay* strategy, that is, any rise in sea levels would be protected through hard engineering approaches; therefore, no SLR impact would be considered in predicting future urban growth. Under this scenario, our model predicted a total of 203,970 ha of urban areas for the whole region, an increase of 24.21% compared to

Table 5. Predicted areas potentially being affected under three SLR scenarios in 2041

LGA (ha)	SLR=0.8 m (%)*	SLR=3.5 m (%)	SLR=7.0 m (%)
Brisbane	0 (0)	1488 (1.11)	2,373 (1.77)
Gold Coast	1,136 (0.85)	4589 (3.44)	8,275 (6.21)
Moreton Bay	0 (0)	1268 (0.62)	2,072 (1.02)
Sunshine Coast	679 (0.30)	4208 (1.87)	5,140 (2.28)
Logan	0 (0)	0 (0)	0 (0)
Ipswich	0 (0)	0 (0)	0 (0)
Redland	0 (0)	698 (1.30)	1,129 (2.10)
Noosa	338 (0.39)	756 (0.87)	1,123 (1.29)
Total	2,153 (0.21)	13,008 (1.25)	20,113 (1.93)

Note: *: % in brackets indicates the percentage of the area potentially being affected by SLR over the total area in that LGA.

the urban areas in 2016 (Table 6). Ipswich would have the highest percentage increase in urban areas to the year 2041 by 59.05% under 0m-SLR scenario, given its geographical position off the coast and its proximity to the state capital city of Brisbane; its urban areas would increase even more under the other SLR scenarios (the *move* strategy), with a higher percentage increase when SLR is higher in order to accommodate more urban population that might be relocating from the coast. Similarly, Logan City LGA would also have a substantial increase in urban areas under the *move* strategy, although its overall increase in urban areas would be smaller compared to Ipswich LGA. On the other hand, the LGAs with long coastlines, such as Gold Coast, Sunshine, Moreton Bay, Redland, and Noosa, would have moderate urban growth by 23.74% to 28.63% under the 0m-SLR scenario; this percentage increase would reduce in various scales across under the *move* strategy, with an exception for Moreton Bay due to its large hinterland to accommodate the need for urban expansion. The capital city of Brisbane would have moderate urban expansion to 2041 by around 15%, and slightly smaller under the 7m-SLR scenario. This can possibly reflect the tight urban planning policy where over 94% of its urban growth would be achieved through consolidation and infill development rather than expansion (Brisbane City Council 2014; Gallagher, Sigler, and Liu 2019). The larger quantity of urban areas overall under the *move* strategy compared to the *stay* strategy may be due to an opportunity to occupy bigger house when relocating from the higher density apartment living in the coastal areas to lower density inland areas (Table 6).

New urban growth was also predicted in areas outside the planned urban footprint, with Noosa having over 10% of new urban growth in these areas under the 0 m SLR scenario, and this proportion was substantially lower under the 0.8 m to 7 m SLR scenarios, with the 0.8 m SLR scenario having the lowest proportion of urban growth outside the planned urban footprint across all LGAs, and various across LGAs under the 3.5 and 7 m SLR scenarios.

Furthermore, we compared the predicted urban areas potentially being affected by SLR with the predicted urban areas in 2041 under different SLR scenarios, both of which were quantified as a proportion over the total area of each LGA (Figure 9). No potential impacts by SLR were projected for Logan and Ipswich given their location off the coast. Redland, Noosa and Sunshine Coast sit on the lower value side of the X-axis (representing the percentage of predicted urban areas in total area of the LGA), with a lower proportion of urban areas, and a relatively lower proportion of urban areas being affected by SLR (Y-axis). On the far east side of the X-axis sits Brisbane LGA given its higher proportion of urban areas, and the proportion of urban areas potentially being affected by SLR is relatively low (Y-axis). In between the two extremes sits Moreton Bay and Gold Coast LGAs, with Gold Coast having a high proportion of urban areas being affected by SLR and the proportion of urban areas in its total area also reduces under higher SLR scenarios (3.5 and 7 m).

The spatial distribution of the projected urban areas in 2041 is shown in Figure 10. The areas being affected by SLR along the coast (Figure 10(A)) increase with the increase in sea levels from 0.8 m to 7 m; this is accompanied by the expansion of existing urban areas further inland (Figure 10(B)). While most new urban growth may occur along the fringe of existing urban areas in each LGA, the patterns of such growth vary. For instance, substantial urban expansion would be observed in Logan, Ipswich and Moreton Bay LGAs (Figures 10B-5, 7&8), however, this would not be the case in Brisbane and Gold Coast given the impact of both SLR and the urban consolidation policies (Figure 10B-6&11). In the Sunshine Coast and Moreton Bay LGAs urban growth would occur along main transport routes such as the M1 Highway (Figure 10B-5&10). Such growth patterns across different LGAs can be attributed to the collective effect of SLR, urban consolidation or expansion policies as well as the adaptation strategies to SLR.

5. Discussion and conclusion

SLR has been regarded as one of the most costly and permanent future consequences of climate change, exerting profound impact on urban development, and settlement trajectory of urban residents (Hauer 2017; Formetta and Feyen 2019; Hauer, Fussell, and Mueller 2020). Herein, our study

Table 6. Project urban expansion to 2041 under different SLR scenarios.

		Projected percentage increase in urban areas in 2041 (%)							
		SLR=0 m		SLR=0.8 m		SLR=3.5 m		SLR=7 m	
	Urban areas in 2016 (ha)	Percentage increase[1]	Outside urban footprint[2]	Percentage increase[1]	Outside urban footprint[2]	Percentage increase[1]	Outside urban footprint[2]	Percentage increase[1]	Outside urban footprint[2]
Brisbane	56,192	15.38	4.19	15.45	0.73	15.33	2.02	14.31	0.56
Gold Coast	28,353	26.35	4.87	25.70	1.09	21.48	4.48	9.68	2.14
Moreton Bay	21,608	22.44	3.44	24.05	0.78	26.78	4.15	26.46	1.51
Sunshine Coast	16,454	28.63	6.91	24.28	-	10.22	4.71	8.96	3.88
Logan	15,319	16.12	5.39	18.85	1.61	30.77	5.36	39.63	4.25
Ipswich	15,228	59.05	3.13	64.78	1.18	88.32	4.63	103.78	3.88
Redland	7,468	23.74	6.29	25.43	1.87	20.43	3.21	16.78	1.86
Noosa	3,589	23.85	10.46	15.13	-	7.05	0.99	0.14	0.53
Total urban areas (ha)	164,211	203,970		204,569		206,328		205,322	

Note:
[1]Percentage increase: This is calculated as a percentage of the projected increase in urban areas in 2041 to the urban areas in 2016;
[2]Outside urban footprint: This is calculated as a percentage of the projected urban areas outside the planned urban footprint in total projected urban areas in 2041.

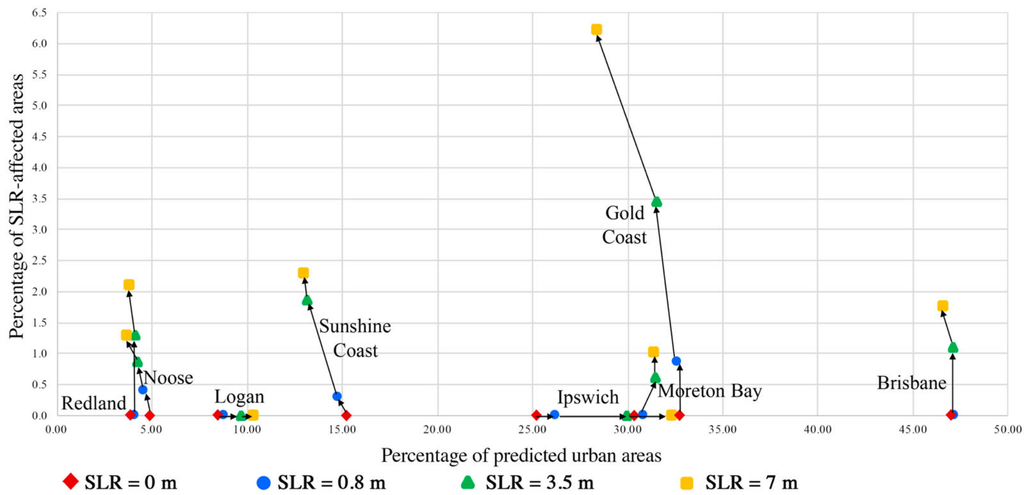
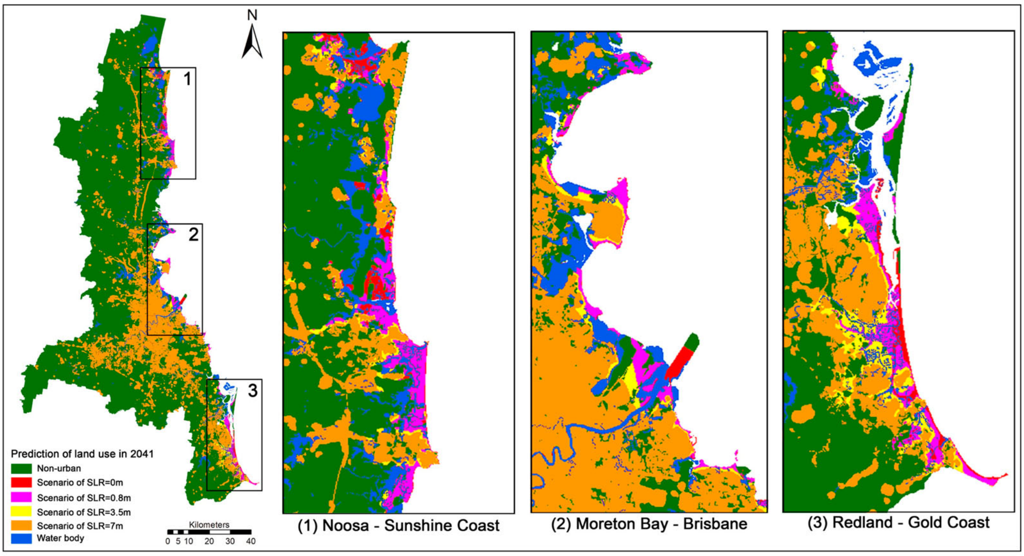


Figure 9. The proportion of areas potentially being affected by SLR versus the proportion of predicted urban areas of each LGA under different SLR scenarios

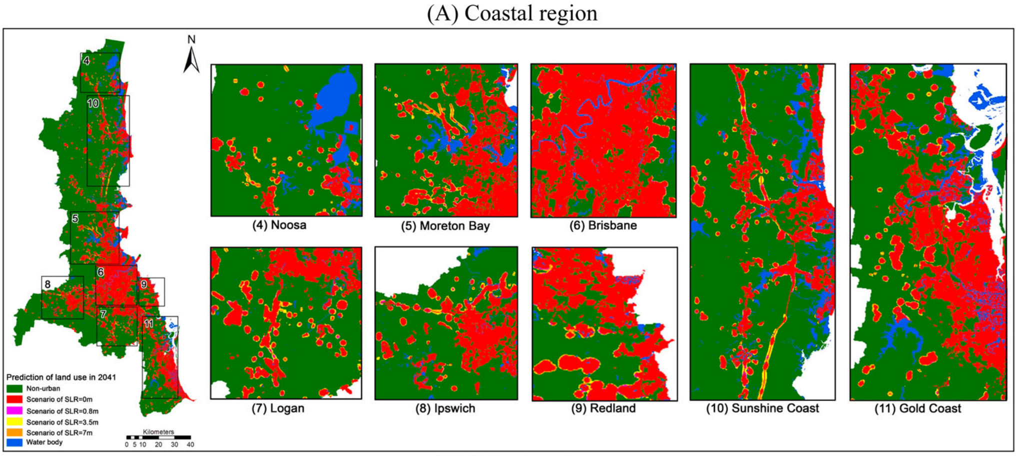
provides a modelling approach to predict future urban growth under different SLR scenarios by considering factors driving or constraining urban growth, SLR adaptation strategies, and urban planning policies. Our results show that under the *stay* strategy where people remain in place with the risks of rising sea levels being prevented through physical engineering approaches, a relatively smaller size of urban expansion would be expected compared to the *move* strategy where people at risk would be relocated from the coast to inland areas. This is possibly due to the opportunity for people to occupy bigger house when relocating from the higher density apartment living along the coast to lower density inland areas, an opportunity to realise the 'great Australian dream' (Maginn 2016).

This study modelled urban growth by considering both SLR and urban planning strategies as proposed by the Queensland Government (2017). On one hand, the implementation of different planning controls in the form of urban consolidation or expansion affects the land demand for future urban growth in different parts of the region. While the importance of urban planning has been demonstrated in various studies (e.g. Ramm, Watson, and White 2018; Michell and Wadley 2004; McCrea and Walters 2012), its impact on urban growth under different SLR conditions has yet to be operationalised through the spatially explicit modelling as we demonstrated in this study. On the other hand, the implementation of SLR adaptation strategies offers different opportunities for future urban growth. Such adaptation strategies can be diverse within the target region to minimise the impact of SLR on urban growth. For example, the *stay* strategy may be more applicable to highly-developed areas such as Brisbane with higher population density and intensive urban infrastructure already in place; while the *move* strategy may work better for less populated rural areas such as Moreton Bay coastal region given the large quantity of land available for urban expansion in its hinterland. As such, it would be more beneficial to implement different SLR adaptation strategies across the metropolitan, regional and rural areas.

Furthermore, it has been acknowledged that the impact of SLR is more than a coastal issue on people living in the coastal region, as the migratory effects of SLR could ripple far inland (Hauer 2017; Hauer et al., 2020). While the coastal regions are likely to be affected directly by the rising sea levels, the inland areas are also likely to be affected indirectly through the inflow of people from the coasts or through the hydrological systems such as underground water and surface waterbodies (i.e. rivers, lakes, cannels and creeks) to affect inland areas potentially available for urban growth. By taking into account both the coastal region and the inland areas, our model



(A) Coastal region



(B) Inland region

Figure 10. Projected urban land use patterns in SEQ in 2041. (A) Coastal region. (B) Inland region.

demonstrates the collective effect of SLR to the whole region; it reduces the potential bias of modelling urban change in the small-scale coastal areas without considering the migrant effect in its hinterland, as the migrant effect would challenge the infrastructure and configuration of inland municipalities if unprepared (Norman and Gurran 2017). Our study fills a critical gap in understanding the scale of population potentially being affected by SLR and possible locations of where these population would likely to resettle which can offer guidance to urban planners and local governments to reconcile urban growth and prevent climate change induced hazards (Hauer 2017).

Nevertheless, our SLR-CA model has certain limitations. First, while some previous studies acknowledged urban growth as a continuous process from non-urban to urban state (Wu, 2002; Liu, 2008), our model was configured using binary states of non-urban and urban to consider the land conversion process. We also did not consider the multiple land use functions that may occur on the same piece of land when defining the cell state in the CA model (Li and Yeh 2002). How to more accurately reflect the status (or multi-functional status) of land cells in CA modelling is a challenging task, but is important for future research to capture the trajectory of urban growth under the impact of SLR given different types of land use are subject to distinct vulnerability and resilience and thus response variously to SLR (Reece, Noss, and Oetting 2013; Martínez, Mendoza-Gonzalez, and Silva-Casarín 2014). Second, our model predicting the future urban growth in response to SLR is dependent on the assumption that the driving factors to urban growth and the land transition probability would hold over the simulation process. However, some of these driving factors may change over time. For example, the road network is subject to change and become more complex in tandem with urban growth. While the UrbanCA model is capable of capturing the dynamics of urban growth over time by updating the driving factors with new data when it becomes available, the challenge remains on the uncertainty how such changes may occur, especially in future term. Furthermore, we used Euclidean distance to quantify the driving factors in the model; these measures can be improved by a road network-based distance or by time based on real-time traffic systems, although this may be more computationally intensive and needs to be supported by real-time traffic data. It is also possible to employ different approaches to measure distances in the areas with complex geographic conditions.

Third, and most importantly, in the current model we regarded areas potentially being affected under different SLR scenarios as hard constraints in predicting future urban growth from 2016 to 2041. However, the impact of SLR on these areas can be considered at a gradually changing scale over time, although this may require more accurate data on SLR and intensive computation. Furthermore, we also treated the impact of SLR to the coastal regions as permanent under the *move* strategy, that is, no urban growth would occur in those areas possibly being affected by SLR. It is possible that some of the areas under SLR impact may be temporary, and people living in such high-risk areas may choose to leave only temporarily rather than permanently. As such, future research would be needed to understand how people living in coastal regions may choose to stay or move under the impact of SLR over different hazard periods (McMichael, Dasgupta, and Ayeb-Karlsson 2020).

In sum, this study provides a useful approach to model and predict future urban growth in the coastal region in SEQ under the impact of SLR. This modelling approach can be employed by urban planners, governments and scholars to predict urban growth and human resettlement in the face of SLR in different geographic contexts or in the face of different environmental stressors (e.g. urban heat). It can be adapted to account for different climate change adaptation strategies and planning policies in order to predict where and how many people will be affected and how human adaptation strategies can alter the distribution of urban growth, and to assist with the long-term planning process for human settlement, hazard prevention, and land use decisions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Data availability statement

The following data sources that we used in this paper are publicly available and provided by different governments:

TableBuilder from Australian Bureau of Statistics: https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by%20Subject/2071.0~2016~Main%20Features~Population%20Shift:%20Understanding%20Internal%20Migration%20in%20Australia~69.

Queensland spatial catalogue – QSpatial: http://qldspatial.information.qld.gov.au/catalogue/custom/search.page?q=coastal+hazard+ma.

ShapingSEQ: South East Queensland Regional Plan 2017: https://www.data.qld.gov.au/dataset/south-east-queensland-regional-plan-2017-shapingseq-series.

Digital cadastral database: https://data.qld.gov.au/dataset/cadastral-data-queensland-series.
LiDAR remote sensing imageries: https://data.qld.gov.au/dataset/digital-elevation-model-3-second-queensland.
The software (UrbanCA) is available in the public repository at 10.6084/m9.figshare.14391902.

Geolocation information

The study area in this paper is South East Queensland, Australia.

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