A Spatial Temporal Decision Framework for Adaptation to Sea Level Rise[1]

Oz Sahin[a, b] and Sherif Mohamed [a]

[a] *Griffith School of Engineering, Griffith University, QLD, Australia (o.sahin@griffith.edu.au)*

[b] *South East Queensland Climate Adaptation Research Initiative (www.csiro.au/partnerships/seqcari)*

Abstract

There is a strong link between decision making and environmental stresses. Two dilemmas confront decision makers: how and when to adapt to sea level rise, due to complexities of environmental systems and the changing nature of the decision making process. This process is inherently complex and often involves many stakeholders with conflicting views. Considering the complexity and dynamic nature of coastal systems, this paper introduces a Spatial Temporal Decision framework to assess coastal vulnerability, and the adaptation alternatives to SLR. The STD is based upon a combination of: System Dynamics modelling; Geographical Information Systems modelling; and multicriteria analyses of stakeholders' views using the Analytical Hierarchy Process. For case study analyses, the City of the Gold Coast located in Southeast Queensland, Australia has been selected. The results of the vulnerability assessment indicate that, at the end of a 100 year simulation period, approximately 6 % of the landscape in the study area will be gradually inundated over time, with 0.5 cm rise per year. However, the percentage of the vulnerable area leapt to about 34 % for Scenario 2, and 56 % for Scenario 3, which represent 1 cm and 1.5 cm rise per year. Using the information obtained from vulnerability assessments, three stakeholder groups (*Politicians, Experts and Residents*) were consulted to determine the goal, criteria and adaptation alternatives for the multicriteria analyses. Analyses of survey data reveal that across the three stakeholder groups, *Effectiveness* and *Sustainability* are the criteria of highest priority.

Keywords: Decision Making; Dynamic Modelling; Sea Level Rise; Vulnerability; Adaptation.

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1. Background

There is overwhelming scientific consensus over the causes and impacts of climate change (IPCC, 2007). Sea level rise (SLR) is one of the most recognized possible impacts of changing climate. Coastal areas are economically productive and three times more densely populated than the global average (Small and Nicholls, 2003). Clearly, while communities have benefited from the many advantages of living in these areas, inevitably they also face the threat of natural disasters and specifically from SLR via permanent inundation of low-lying regions, inland extension of episodic flooding, increased beach erosion and saline intrusion of aquifers (McLean *et al.*, 2001).

Coastal communities have been adapting to changing conditions throughout history. However, faced with increased threats due to SLR, coastal communities must act faster to develop more effective management policies. Moreover, the impacts of SLR are not expected to be spatially uniform across the world (Nicholls *et al.*, 2007). It is, therefore, essential for decision makers (DM) to consider the dynamic and spatial characteristics of these changes in assessing the impacts of SLR when making decisions about the future.

There is a range of analytical tools available to improve decision makers' (DM) ability to understand and evaluate environmental management problems such as simulation models, GIS, and experts systems. However, although these tools provide invaluable information for decision making, each tool addresses only one aspect of a management problem. Therefore, effective decision making, in a dynamic complex environment, requires the expansion of the mental modelling boundaries and the development of additional tools to help DMs better understand how complex systems behave. Thus, DMs need to integrate each tools' analytical results into a rational choice about what to do, where to do it, and when to do it (Schmoldt, 2001).

1.1 Addressing the Vulnerability

The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as: "*the degree to which a system is susceptible to, and unable to cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity*" (Parry *et al.*, 2007).

This definition incorporates three main variables: (1) exposure; (2) sensitivity; and (3) adaptive capacity. Thus, vulnerability is a function of the exposure, sensitivity and adaptive capacity of a system. Based on the IPCC definition, many researchers (Dongmei and Bin, 2009; Eriyagama *et al.*, 2010; Rosenzweig and Tubiello, 2006; Webersik *et al.*, 2010; Yusuf and Francisco, 2009) present vulnerability in the form of the following function:

$$V = f(E, S, AC)$$

<div align="right">Eq. 1</div>

Where, *V*=Vulnerability, *E*=Exposure, *S*=Sensitivity, and *AC*=Adaptive Capacity.

In Eq. 1, changes over time and space are not explicitly taken into account. Hence, vulnerability assessments, based on the above definition, have assumed that vulnerability is a static process and, so, have been conducted with reference to a target year and sea level rise prediction (DCCEE, 2009; Wang *et al.*, 2010; Wu *et al.*, 2009). However, vulnerability is a dynamic process and should be considered as a dynamic continuum. Further, as the three elements constituting vulnerability interact with each other and change in time and space, so does the vulnerability. To include the dynamic and spatial aspects of vulnerability, by considering the time and space dependency, vulnerability can be expressed as:

$$V(t,s) = f\{(E(t,s), S(t,s), AC(t,s)\}$$

<div align="right">Eq. 2</div>

Where; *t*: Temporal dimension, *s*: Three spatial dimensions (x,y,z).

V (*t,s*), in the above definition (Eq. 2), represents four dimensions in describing the vulnerability of a particular system, region or group with respect to time and space; it changes as time passes. The ultimate goal of vulnerability assessment is to predict the vulnerability and provide information and guidance to DMs. Therefore, the use of an appropriate assessment approach would strengthen the DMs' abilities to take appropriate action with speed and accuracy. Evidently, dealing with environmental problems requires an approach that can take into account human decision making processes, as well as time and space. Therefore, integrating vulnerability assessments with decision making process would constitute the fifth dimension of vulnerability and adaptation analyses and, as a result, enhance DMs ability to take concrete action towards adaptation to climate change.

2 Approach

In the light of the above discussion, this paper introduces a Spatial Temporal Decision (STD) framework to assess coastal vulnerability, and the adaptation alternatives to SLR. The STD approach takes into account five dimensions of the decision process in coastal areas (Figure 1). Space (x,y,z) and time (t) constitute the first four dimensions, and provide a common base where all natural and human processes occur. This approach is crucial in generating adequate information from which DMs can devise realistic adaptation strategies. For this reason, it is essential to incorporate the first four dimensions into the fifth dimension, the element of human decision making (h).
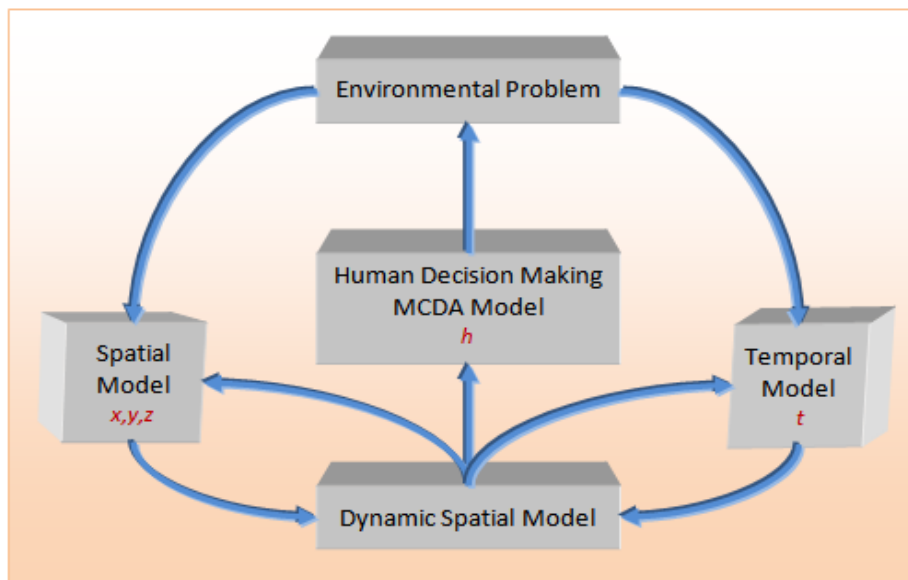

Figure 1 Five dimensional STD framework.

Thus, developing STD is based upon a combination of: System Dynamics (SD) modelling; Geographical Information Systems (GIS) modelling; and multicriteria analyses of stakeholders' views using the Analytical Hierarchy Process (AHP) (Saaty, 1980). The cyclic STD process consists of: 1) Identification of the problem; 2) Vulnerability assessment by using Dynamic Spatial Model (DSM) which combines a spatial model (GIS) and a temporal model (SD); 3) Evaluating potential adaptation strategies by using a Multiple Criteria Decision Aid (MCDA) approach, based on information obtained from the previous step; 4) Test the solution using the dynamic simulation model to see if the preferred adaptation strategies are adequate

enough to provide an effective solution; and 5) Refine the model to eliminate or reduce any weakness in the solution.

2.1 Understanding and Treatment of Uncertainties

There is a range of uncertainty types, often resulting from incomplete scientific understanding of the various processes. Indeed, some uncertainties are caused by the processes themselves, which function in space and time, and so cannot be captured by the models. As a consequence, the uncertainties cannot be reduced. The adequate treatment of uncertainties is a crucial aspect in the development and application of integrated assessment models. According to Robinson (2003), uncertainty about the future stems from three sources: 1) The lack of knowledge about system conditions and underlying dynamics; 2) The prospects for innovation and surprise, and 3) The nature of human decision-making.

From a positivist perspective, the first two sources of uncertainty can be overcome and reduced by progressively improving the models and including more variables (Mannermaa, 1991). However, system theorists question the validity of the positivist approach, arguing that it is theoretically impossible to pre-state all possible future outcomes for most real systems. According to them, behaviour of complex systems is non-linear, chaotic, and sensitively dependent on the initial conditions and contexts, which are not fully known (Kay *et al.*, 1999).

Swart *et al.* (2009) provide a useful review of how uncertainty has been treated in the assessments of the IPCC, and how this treatment has evolved over time. Firstly, uncertainty, as described in the IPCC Third Assessment Report, occurs as a result of problems with: The data (i.e. errors in the data, random sampling errors, and biases); The models (i.e. the processes are known, but the functional relationships or errors in the structure of the model are unknown; the structure is known, but the values of some important parameters are unknown or are erroneous; the historical data and model structure are known, however, the reasons for believing in the parameters or the model structure will change over time); and Other sources of data or information (i.e. the use of inappropriate spatial/temporal units; uncertainty due to projections related to human behaviour; and the ambiguously defined concepts and terminology, etc.).

Although uncertainty is an essential aspect in policy and decision making processes, a formal treatment of uncertainty is difficult to achieve. Hence, in recognising the potentially

critical influence of uncertainties, the authors have adopted a variety of measures in designing the model in a two phase step. In the first phase, uncertainties surrounding the vulnerability assessment models have been addressed through the use of scenarios, sensitivity analysis, and performance tests. In the second phase, to address the temporal and spatial uncertainties surrounding the decision process, the model output of vulnerability analysis was incorporated into the MCDA analysis, then a sensitivity analysis is conducted to further minimise the uncertainties.

2.2 Model Development

Depending on the rate of the SLR, an area that is now subject to a 1 in 100 year flood risk may, in time, and with a high enough SLR, face more frequent flood events, or become permanently inundated (McInnes *et al.*, 2000). As a result, the boundary of the coastal flood plain will shift inland over time. Thus, the ability to identify low-lying areas is a crucial factor in any coastal region vulnerability assessment. Further, coastal inundation and flooding, stemming from SLR and associated extreme events, can be modelled by establishing the interactions between time and space to capture the changes in a coastal system. Importantly, the physical processes such as overland flow, and proximity to and connectivity of the area with neighbouring areas should be considered essential for modelling inundation. The direction of the flooding, between the adjacent grid-cells, depends on the difference in elevation between them.

In order to capture the fundamental dynamic processes of inundation the area under consideration is subdivided into a cellular (*i* x *j*) grid to simulate how flood water spreads between adjacent cells. Each cell represents a specific area corresponding to one of four cover types: *Sea*, *Waterways*, *Pond*, or *Land*. The transition rules, which describe the relationships between the cells and the criteria showing how the states of a cell are to change, regulate the behaviour of the system. Based on the following equation, the flood water diffusion from one cell to another is projected:

$$F(X_{i,j}) = \begin{cases} 1, & CT(X_{i,j}) = L \ and \ \exists x CT(X_{n,m}) = W, and \ CE(X_{i,j}) \leq \exists x CE(X_{n,m}) \\ 0, & otherwise \end{cases}$$

Eq. 3

Where, *F* is, either flooded (1) or not flooded (0); *CE* is the cell elevation; *CT* ($x_{i,j}$) is the cover type, either inundated *L* or not inundated *W*; *CT* ($x_{n,m}$) is the adjacent cells cover types,

either *L* land (or other cover types other than sea) or *W* sea (or became sea due to inundation); *X* represents a grid cell; (*n,m*) refers to all adjacent cells to *i,j* (i.e.: *i,j-1, i,j+1, i+1,j and i-1,j*).

2.2.1 Dynamic Spatial Model (DSM): Linking GIS with SD

SD allows us to model, describe and better understand the behaviour of complex systems, and thus, to identify and manage the information related to these systems. GIS are spatial data processing systems capable of storing, retrieving and displaying various type of data. Given the strength of SD in representing the temporal processes, especially with restricted spatial modelling capabilities, the association of SD and GIS produces a synergy effect. As a result, addition of a spatial dimension to SD would enable modellers to explicitly; 1) simulate system structure that is heterogeneous over space, as well as 2) consider how spatial interactions affect systems themselves (BenDor and Kaza, 2012). As spatial detail improves model accuracy, visualisation and usability for simulating changes in time and space, a number of researchers have proposed the use of a versatile approach, which considers many aspects of the problem by combining GIS with SD (Ahmad and Simonovic, 2004; Gharib, 2008; Grossmann and Eberhardt, 1992; Ruth and Pieper, 1994; Sahin and Mohamed, 2010; Zhang, 2008).

In this paper, therefore, the authors employ a DSM approach by loosely coupling GIS and SD approaches. The DSM approach utilises GIS to reduce the data preparation and processing workloads considerably for use in the SD model, enhance the spatial visualisation, and reveal spatial relationships. Meanwhile, the SD model is employed to deal with the dynamics of the complex system, revealing its causal structure and the relations of the system component while adding temporal dimension to the spatial modelling capability of GIS. The DSM consists of three components: SD (temporal) model, GIS (spatial) model, and the data convertor (Figure 2). The DSM captures the changes in time and space by obtaining and processing the temporal data from the SD and the spatial data from the GIS by exchanging data through the data convertor.

There are three common approaches for coupling GIS and SD; loose coupling, moderate integration and tight integration (Gimblett, 2002; Maguire *et al.*, 2005). There are trade-offs that are unique to each of the coupling strategies, since each approach has its advantages and disadvantages. Although the loose coupling approach has some disadvantages, such as slow

execution speed and low simultaneous execution capability, this approach is adopted to link

SD and GIS in this study by considering some of its overpowering advantages, such as (Fedra,

2006): ease of use, both in GIS and SD can be modified and run without any complication;

data structures do not have to be matched; data can be transformed to each other's

formats through a converter; users are able to make on-the-fly changes more rapidly, and It is

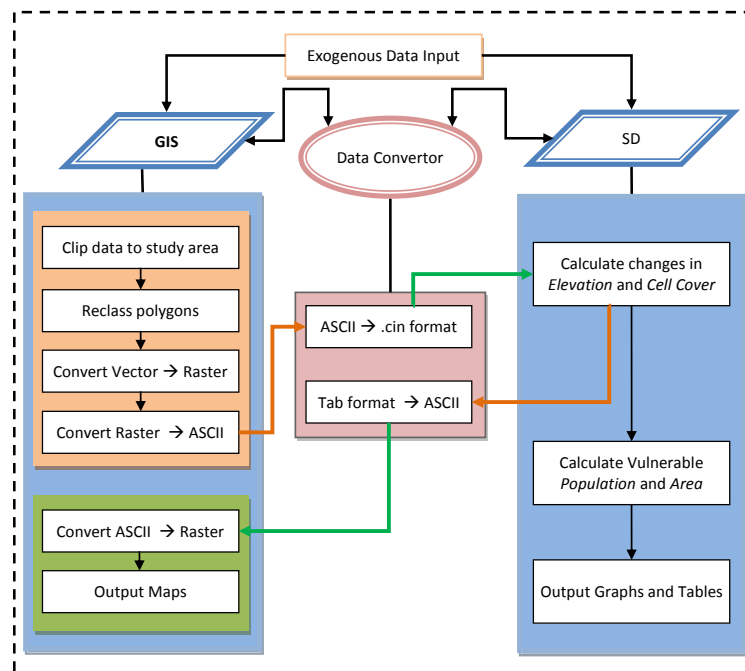fast and portable; the SD model can be used with different GIS.

Figure 2 Dynamic Spatial Model Structure

2.2.1.1 Temporal Model Component:

The temporal modelling segment consists of the building, integration and running of two

types of models: an *Inundation Model* and a *Vulnerability Model*. Figure 3 illustrates the overall

model structure and its submodels.

These submodels of the temporal components interact with each other through feedback

links. The *Sea level* and *Population* variables are the two key drivers affecting *Inundation* and

Vulnerability Models. For the model, a hundred year time horizon is considered as from the

2010 through to 2110; this scale is consistent with most SLR scenarios developed by the IPCC
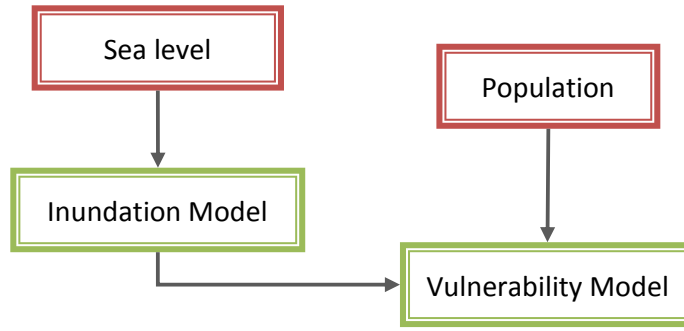
(Meehl, 2007).

Figure 3 Model Structure and its submodels

For building the temporal model, the Vensim DSS (Decision Support System) software was chosen because of its flexibility when representing continuous or discrete time, a graphical interface, or performing causal tracing, optimization, and sensitivity analysis (Ventana Systems, 2012).

2.2.1.1.1   Inundation Model

Figure 4 shows the inundation model structure and some of the variables assumed to be important in a coastal system, and their interactions. As seen in Figure 4, the system comprises three state variables; *Cell Cover*, *Elevation* and *Sea Level*. The *Sea Level* is an exogenous variable causing changes in both the *Elevation* and *Cell Cover* variables, over time. The model assumes a linear increase in the *Sea Level* over time, based on a range of SLR projections ranging from 0.5 m to 1.5 m. The SLR, at a given time, is calculated by:

$$SL_t = \int dR * dt + SL_0$$

Eq. 4

Where: SL_t represents the linear *Sea Level* at time *t*, *dR* is the rate of rise at each time step *dt,* and SL_0 denotes the initial *Sea Level* at the beginning of the simulation.

For modelling purpose, the study area is subdivided into a cellular grid to simulate how flood water spreads between adjacent cells, based on the conceptual framework for inundation. This grid is then superimposed over the coastal area. Each cell represents a specific area corresponding to one of four cover types: *Sea*, *Waterways*, *Pond*, or *Land*. At each

simulation step, the state of each cell is determined by the condition of its neighbours to the north, east, south, and west.
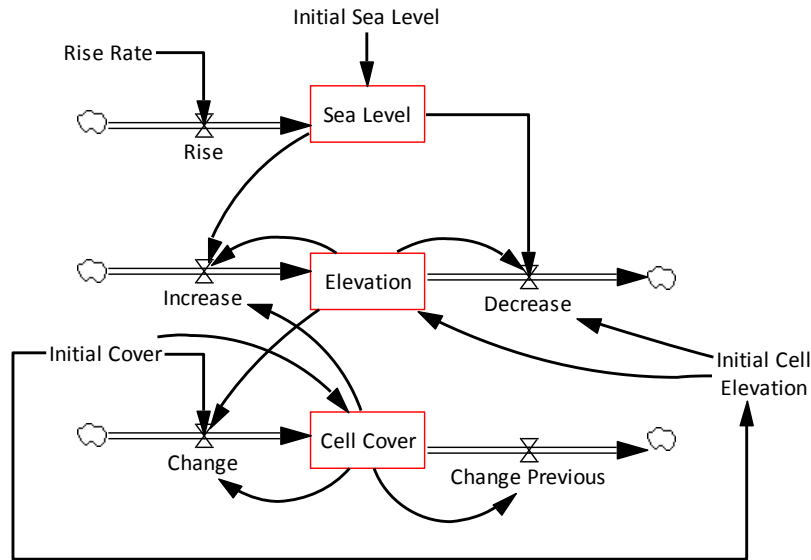

Figure 4 Inundation model based on cell elevation and cover types

At each simulation step, as the sea level rises, the elevation of a cell is determined by its condition at the previous time step, its border conditions with its neighbours, and the cover type of its neighbours (*Land, Waterways, Sea,* or *Pond*). The elevation of a cell is determined by adjusting the elevation, at the previous time steps, by the flow-in (*Increase*) and the flow-out (*Decrease*) of the cell, according to the properties of the adjacent cells. The *Elevation* is the integral of the net flow of *Increase* and *Decrease*, which is mathematically represented by the following equation:

$$E_t(x,y) = \int_0^t \left(I_t(x,y) - D_t(x,y) \right) * dt + E_0(x,y)$$

Eq. 5

Where: $E_t(x,y)$ denotes cell elevation at location (x,y) at a given time; $E_0(x,y)$ represents initial cell elevation at location (x,y); $I_t(x,y)$ shows the rate of elevation increase at location (x,y); and $D_t(x,y)$ indicates the rate of elevation decrease at location (x,y).

The changes in cell elevation occur when only the *Cover Type* of a cell is *Land, Waterways,* or *Pond*, at time step t_n, and it is transformed into *Sea* at the next time step, t_{n+1}. Here, the cell

is assumed to be inundated from the rising sea level and, therefore, the elevation of the cell is updated, and said to be equal to the *Sea Level* at the time period t_{n+1}. The *Cell Cover* is the integral of the net flow of *Change* and *Change Previous*. Based on the following equation, the type of Cell Cover in any given time is determined.

$$CT_t(x,y) = \int_0^t \big(C_t(x,y) - CP_t(x,y)\big) * dt + CT_0(x,y)$$

Eq. 6

Where: CT_t *(x,y)* represents cell cover type at location (x,y) at a given time; CT_0 *(x,y)* indicates initial cell cover type at location (x,y); C_t *(x,y)* denotes rate of cell cover type change at location (x,y); and CP_t *(x,y)* denotes the rate of previous cell cover type change at location (x,y).

As the model runs, the state of the each cell is assessed simultaneously. The *Change* flows into the cell (Stock) and updates the *Cover Type* of the cell for the present time step (i.e. t_1). Subsequently, *Change Previous* removes the *Cover Type* of the cell at the previous time step (i.e. t_0). This is necessary to assign only one *Cover Type* value to the cell for each time step. For example, if the *Change* alters the *Cover Type* of a cell from *Land* to *Water* at time step (t_1), then *Change Previous* discards the previous cover type value (*Land*) from the cell.

2.2.1.1.2 *Vulnerability Model*

Vulnerability to SLR results from a combination of various factors, such as high population density along the coast, and the susceptibility of coastal regions to coastal storms, as well as other effects of climate change. Therefore, an accelerated SLR could fundamentally change the state of the coast and, as a result, coastal environments and human populations will be affected significantly. In the final building step of the temporal model component, the Vulnerability model is developed to estimate the potential impacts of SLR (Figure 5). The critical vulnerability of coastal areas to coastal storms (in the short term) and SLR (in the long term) relates to flooding. Therefore, the vulnerability assessment (VA) needs to focus on people and properties. Hence, two VA indicators are selected: 1) *People at Risk* over time due to coastal flooding, and 2) *Area at Risk* (loss of land)due to inundation and coastal flooding

First, the number of people who live in the area is calculated based on two stocks in the model: The *Population* (P_0) that resides in the area at the beginning of simulation, and the

Residents (R_t), which is the integral factor of the *Population Increase* (P_t). The model determines the changes in the population living in the area using the following equation:

$$R_t(x,y) = \int_0^t P_t(x,y) * dt + P_0(x,y)$$

Eq. 7

Where: R_t (*x,y*) indicates people reside at location (x,y) at a given time; P_0 (*x,y*) denotes initial number of people reside at location (x,y); and P_t (*x,y*) represents rate of population increase at location (x,y).
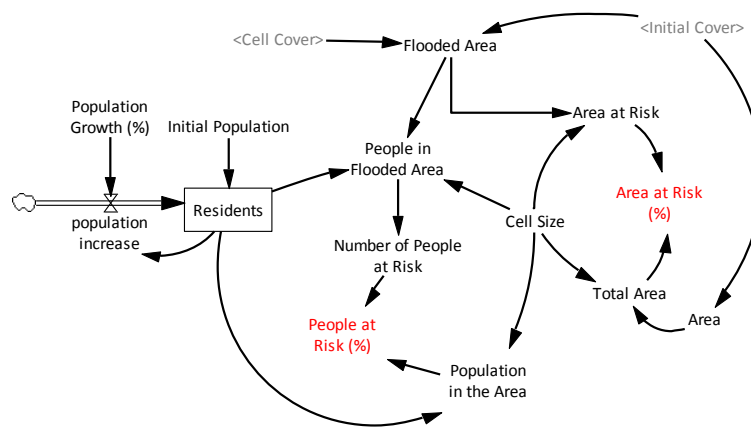

Figure 5 Vulnerability model for people and property at risk

Then, *People at Risk* are calculated by multiplying the sum of *Flooded Cells* with the *Cell Size*:

$$VP_t = \sum R_t(x,y) * FC_t(x,y) * Cs$$

Eq. 8

Where: VP_t (*x,y*) is vulnerable people at a given time; R_t (*x,y*) denotes people residing at location (x,y) at a given time; *Cs* represents a constant value showing size of each grid cell; and FC_t (*x,y*) shows flooded cells at location (x,y)

Then, the *Area at Risk* is calculated by multiplying the sum of the *Flooded Cells* with the *Cell Size*:

$$A_t = \sum_0^t FC_t(x,y) * Cs$$

Where: $A_t(x,y)$ is vulnerable area at a given time; Cs represents a constant value showing size of each grid cell; and $FC_t(x,y)$ shows flooded cells at location (x,y)

2.2.1.2 Spatial Model Component

Spatial analysis is a set of methods whose results change when the locations of the objects being analysed change (Longley, 2005). Importantly, spatial analysis derives information from the data using the spatial context of the problem and the data. Spatial modelling involves the use of disaggregated spatial data and relationships in order to understand spatial forms and process (BenDor and Kaza, 2012). That is, it deals with space. GIS is the main tool used in the spatial analysis. In this study, the ArcInfo 9.3.1 is used to develop the spatial model (ESRI, 2009), which is connected to the simulation model through the data convertor and file monitor application developed for this framework by the authors.

There are two main ways to spatially model sea level rise and subsequent coastal inundation. Geospatial data depicts the real world in two forms, which leads to two distinct approaches: the *object-based* model, and the *field-based* model (Goodchild, 1992). The object-based method uses contour lines; it is usually suitable for a very rapid and simple risk assessment over large areas. However, it does not take into account the presence of intervening topographic ridges or other features (e.g. man-made defences) that can separate a low-lying area from the source of flooding (Brown, 2006). That is, since a contour-line method relies solely on elevation data, inaccuracies arise when deriving a vulnerable zone based on this method because it does not consider connecting cells. The Raster model, as Lo and Yeung (2007) define it, is one of the variants of the field based models of geospatial data modelling. It is best employed to represent spatial phenomena that are continuous over a large area. For

example, the Raster data model uses a regular grid to cover the space; the value in each cell represents the characteristic of a spatial phenomenon at the cell location. In computing algorithms, a raster can be treated as a matrix with columns and rows (x- y coordinates), and its values can be stored into a 2D array. These characteristics hence make integration of GIS and SD easier, especially since SD can easily use array variables for data manipulation, aggregation, and analysis. Therefore, the raster data model was selected for spatial modelling. The basic elements of a raster model include the cell value, cell size, raster bands, and spatial reference (Chang, 2006). Each cell in a raster has a value (integer or floating) representing the characteristic of a spatial phenomenon at the location denoted by its column and row (x,y). Depending on the data type, both integer and floating point rasters are used in spatial modelling. For example, the research considers a sea level rise of 0.5-1.5 cm. Thus, a floating-point raster is more suitable for the elevation data, as rise of sea level represents continuous numeric data with decimal digits, i.e. 10.125 m, 10.124, and so forth. However, the integer values are used for land cover rasters, i.e. 1 for Sea, 2 for Waterways, 3 for Pond, and 4 for Land.

Essentially, the cell size determines the resolution of the raster model. As a larger raster cannot provide the precise location of the spatial features, the model result may not be satisfactory. Nevertheless, the smaller cell size can address these problems; although their use increases the data volume and data processing time, considerably. There are always trade-offs between the quality of the model outcomes and the processing time. In this study, a 5 m cell size is used for the modelling. The elevation data are the most critical elements in assessing the potential impacts of rising sea level. The uncertainty of the elevation data affects the delineation of the coastal elevation zones. Most elevation datasets have vertical accuracies of several meters or even tens of meters (at the 95% confidence level). Gesch (2009) argues that the mapping of submeter increments of sea-level rise is highly questionable, especially if the

elevation data used have vertical accuracy of a meter or more (at the 95 %). That is, the elevation uncertainty is much smaller for the more accurate elevation data. To keep the analysis reasonably manageable, this study has focused on the vertical accuracy. Therefore, to acquire more accurate results, the research used 5 m DEM with 0.1 m vertical accuracy.

A variety of data from different sources is required as inputs to the spatial model. All the data layers needed to be in grid (raster) format, with a resolution of 5 x 5 m cell size. By working at a high spatial resolution, the model is able to reflect, accurately, the spatial changes in inundation resulting from the SLR. This approach provides a convenient way for describing the geo-processing procedure in GIS. Hence, based on this approach, we begin by converting the shape-files to the raster format, then reclassifying, and correcting their projection and, finally, unifying the coordinate system by using the model builder (Figure 6). The vector data are, consequently, converted to a raster format.

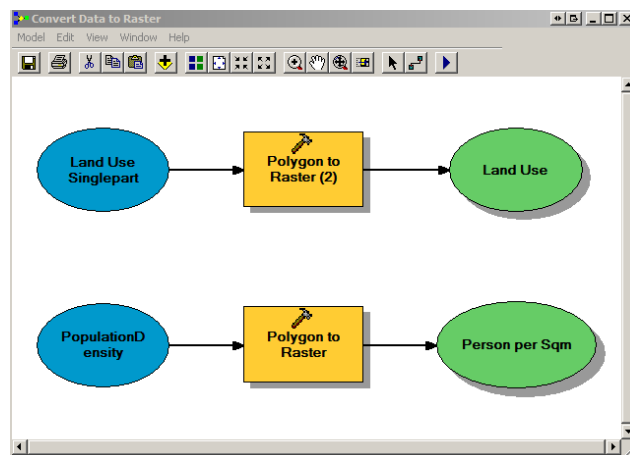Figure 6 Vector to raster conversion using the Model Builder

The Model Builder is a graphical tool for automating a model through the use of a work flow. Spatially, the size of the raster cell generated was based on the minimum mapping unit (5x5m) to match the DEM data. The attribute assignments are based on the centroid of the cell. Australian Bureau of Statistic (ABS) data on dwellings and the Digital Cadastral Database

(DCDB) are also converted to a raster format. Uncertainty, however, exists regarding where the population resides within the census parcel. Therefore, in the current study, the vulnerable population is estimated as a percentage of the census population, based on the inundated parcels.

2.2.2 Data Convertor

The loose coupling approach involves the transfer of data between the GIS and SD. Hence, it is necessary to establish, create and manipulate data files, so that they can be exported or imported between the spatial and temporal components of the model. The data in the files can be stored in several file formats. Different file formats have different characteristics, depending on a range of factors, such as the source of the data, and the software architecture. As the STM combines two different modelling approaches, it is useful to choose a device independent file format which can be usable by both applications, regardless of their hardware or software platforms. Therefore, in the current study, the device independent ASCII file format for GIS, and the *.cin* and *tab* text file formats for SD are chosen for the cross-platform exchange of data. When exchanging data between two applications, it is necessary to convert the data formats into the right file format, as used by the applications (i.e., ASCII → .cin, and/or .cin → ASCII). To assist with this process, a converter program is developed.

The converter program involves two separate applications: the data converter and the file monitor. The data converter software automates the format transition between the ArcGIS and SD data formats. First, it converts the ArcGIS text (ASCII) files to SD text files (.cin), and then it converts the files from the SD .tab files back to the ArcGIS .txt files. All code for the data converter is written in C++ under Visual Studio 2008, using the Microsoft.NET framework version 2.0. As a console application, it takes its commands via program arguments.

2.2.3 Decision Model

Decision making is a process of selecting from among several alternatives, based on various (usually conflicting) criteria. Information on priority alternatives is vital in aiding DMs to design more effective adaptation options and better management plans to reduce the adverse effects of SLR. The current study will use the MCDA technique because it is the most suitable approach by which to identify the priority of adaptation alternatives. Several multicriteria decision aid techniques are suitable for comparing multiple criteria, simultaneously, and for providing a solution to a given problem. While there are no better or worse techniques, some techniques are better suited to a particular decision problem (Haralambopoulos and Polatidis, 2003).

The AHP technique, despite some criticisms, has been selected for the current study. Criticisms of the AHP include; Difficulty of conversion from verbal to numeric scale; Inconsistencies imposed by the 1 to 9 scale; Number of comparisons required may be large (Macharis *et al.*, 2004; Ramanathan and Ganesh, 1995). However, AHP, owing to its flexibility to be integrated with different techniques, enables the user to extract benefits from all the combined methods and, hence, achieve the desired goal in a better way (Vaidya and Kumar, 2006). In addition, the AHP is set apart from other MCDA techniques because of the unique utilisation of a hierarchy structure to represent a problem in the form of a goal, criteria and alternatives (Saaty and Kearns, 1985). This allows for a breakdown of the problem into various parts for pair wise comparisons, which uses a single judgement scale. Thus, the AHP has been widely used to solve various decision problems. Examples of the recent AHP applications include: Awasthi and Chauhan (2011); Bottero *et al.* (2011); Crossman *et al.* (2011); Chen and Paydar (2012); Do *et al.* (2012); and Gao and Hailu (2012).

The underlying concept of the AHP technique is to convert subjective assessments of relative importance to a set of overall scores or weights (Saaty, 1980). When making decisions it is necessary to ensure that the alternatives selected for further consideration/implementation are consistent with the value systems and preferences of the stakeholders (Basson and Petrie, 2007). The large body of the literature emphasises the importance of stakeholder participation in the decision making process on environmental issues, which are complex, uncertain, and vary in time and space (Adger *et al.*, 2007; Lim *et al.*, 2004; van den Hove, 2000; Willows and Connell, 2003). Jakeman and Letcher (2003) also emphasise the importance of stakeholders' involvement in the model validation process. Although there are many definitions, in the literature, for the term stakeholder, in the current

study, the following IPCC definition is used as it refers to (Parry *et al.*, 2007): *'people or organisations, who have an investment, financial or otherwise, in the consequences of any decisions taken'*. Here, three key stakeholder groups, within the study area, were included in the decision making process: *Expert, Residents*, and *Politicians*.

To achieve and facilitate a workable process to reduce the vulnerability of an area and a population to SLR, a hierarchical (AHP) structure was designed (Figure 7). The hierarchical elements, goal, criteria and alternatives are identified and finalised through stakeholders' consultation in the study area. The specific goal used in the AHP structure is *to reduce SLR vulnerability*. To clarify further, this goal implies the identification and evaluation of adaptation alternatives in an attempt to reduce the negative impacts from SLR. It encompasses the idea behind the entire effort to reduce the negative impacts from climate change, specifically SLR. The criteria used in the decision making process to evaluate the alternatives, with respect to the goal, were: *Applicability*, *Effectiveness*, *Sustainability*, *Flexibility,* and *Cost*. The five chosen adaptation alternatives were: *Retreat*, *Improve Building Design*, *Improve Public Awareness*, *Build Protective Structures,* and *Take No Action*.

Figure 7 AHP structure

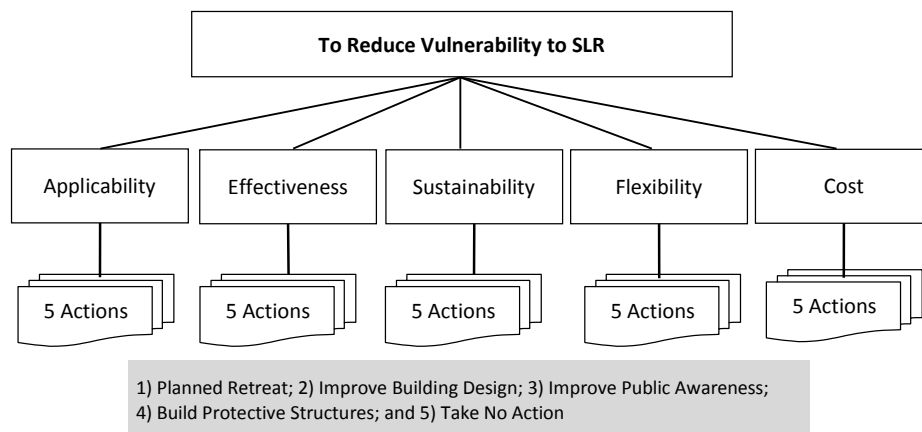## 3   *Implementing the Approach*

For case study analyses, the City of the Gold Coast located in Southeast Queensland, Australia has been selected. The area encompasses a diverse range of features including sandy beaches, estuaries, coastal lagoons and artificial waterways and is highly vulnerable to SLR. In this region, the maximum tidal range is 1.8m, and on average, the coast is affected by 1.5

cyclones each year (Boak *et al.*, 2001). Many of the residential areas in the city are filled to the 1:100 year flood level (Betts, 2002).

3.1   Vulnerability Assessment

To determine the effect of changes in vulnerable populations and land areas over time, the *Cover Type* and *Elevation* data were simulated under a number of SLR. The changes were captured in a SD model and exported to a GIS model for visualisation. The inundation layer was overlayed with the 2001 Australian Bureau of Statistics census data, which was aggregated by census parcel for the area.
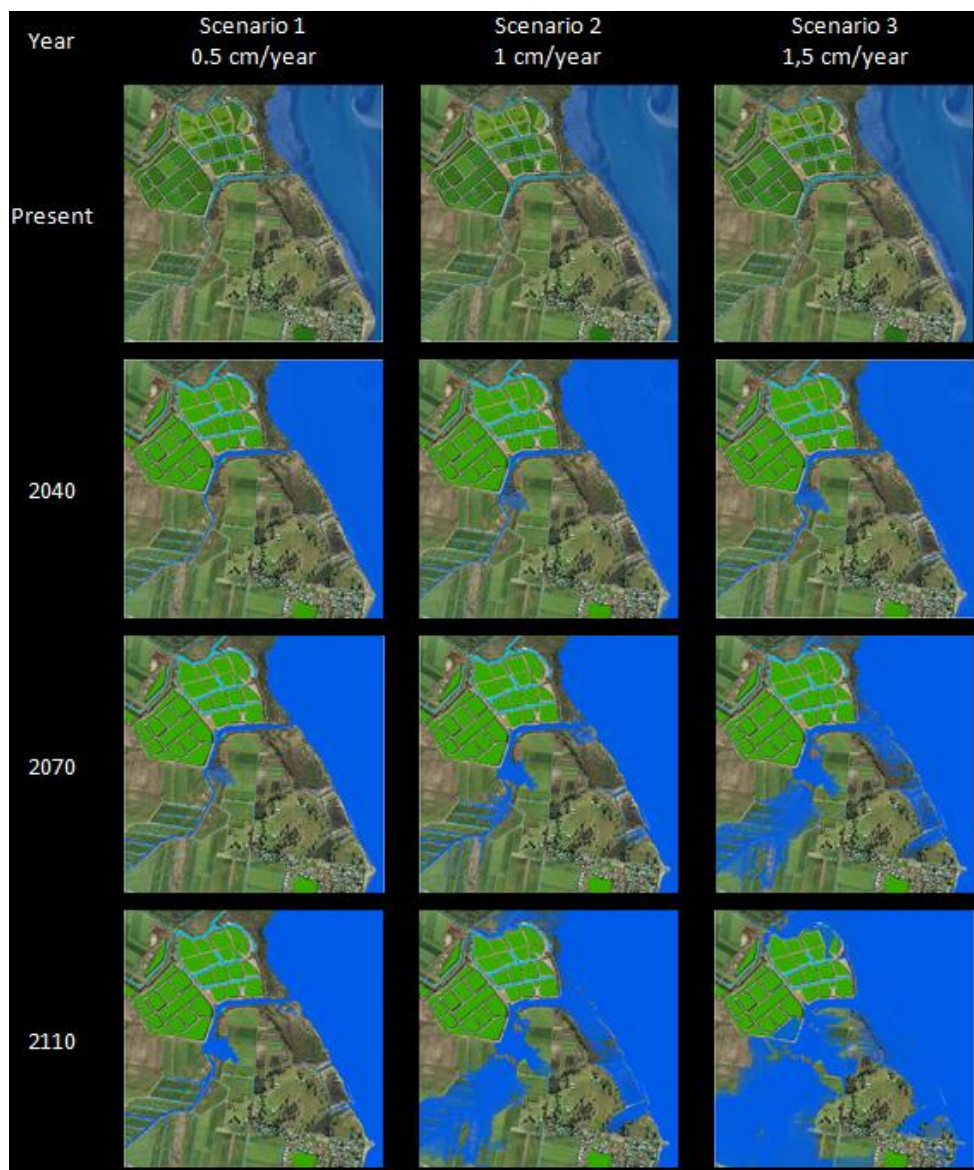

Figure 8 Flood maps generated by the model

Figure 8 presents a series of flood maps generated by the model. It shows the extent of the areas at risk due to rising sea level, over a period of 100 years. Clearly, as inundation occurs at the water – land interface, the land area in close proximity to the sea, and around water bodies, were identified as the most vulnerable areas. The rising sea quickly penetrates inland through waterways and submerges the vulnerable areas around them, thus, putting the people currently living in those areas at risk.

As shown in Figure 9, at the end of a 100 year simulation period, approximately 6 % of the landscape in the study area will be gradually inundated over time, with 0.5 cm SLR per year. Importantly, a 0.5 cm SLR does not pose any significant threats to the local population. However, this situation dramatically changes with scenarios 2 and 3, which represent 1 cm and 1.5 cm SLR per year. Indeed, the percentage of the vulnerable area leapt to about 34 % for Scenario 2, and 56 % for Scenario 3. The most noticeable changes occur after the first 25 years. Further, the rate of inundation becomes much higher after the first 50 years of the simulation period for both scenario2 and scenario3.
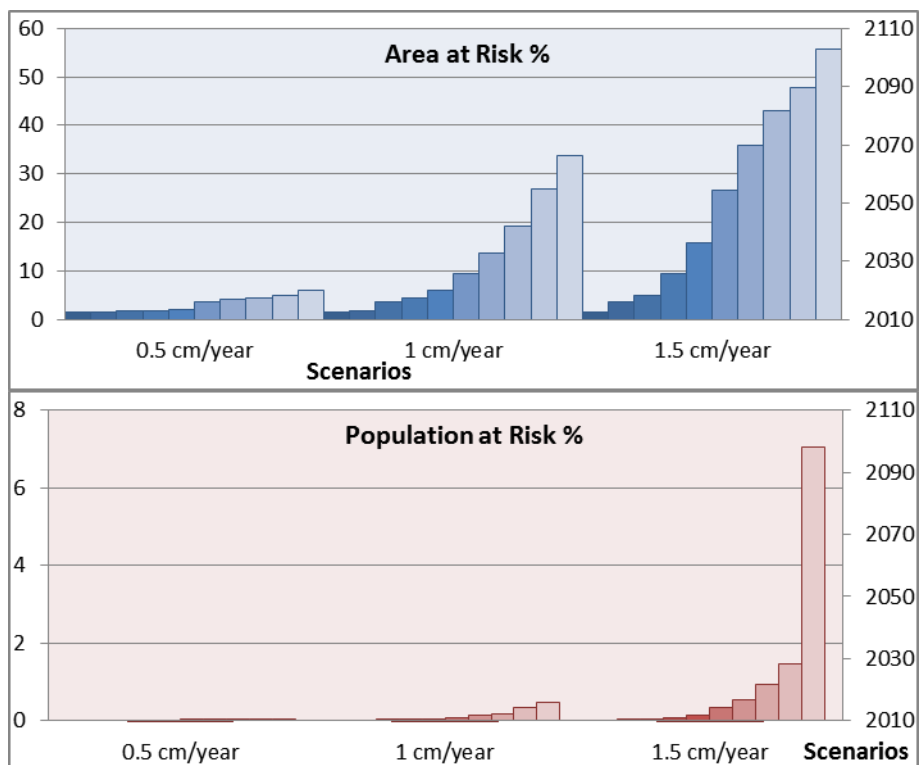

Figure 9 *Area at Risk* and *Population at Risk* under three SLR scenarios

Although a substantial fraction of the landscape is threatened by the rising SLR, the percentage of the population that can be classified as vulnerable is relatively low for Scn2 and Scn3 scenarios, only 0.5 % and 7 %, respectively. The answer lies with most of the population residing at high altitudes. Nevertheless, the population located near waterways and coastal strips was especially vulnerable.

Indeed, about 6% of the study area landscape will be submerged if the sea level rises a 0.5 m by 2110 (Figure 9). Hence, the area at significant risk will be increased, up to 34% and 56% with a 1 m and 1.5 m rise in sea level, respectively. However, the inundation will, generally, be restricted to fringing shorelines and finger waterways margins (Figure 8). Additionally, although, up to 56% of the land area will be facing the risk of inundation, the impacts of the same SLR scenarios on the residential areas are much smaller.

3.2   Multi-Criteria Decision Analysis for Adaptation options

The fifth dimension of the current framework focuses on linking vulnerability assessment with the evaluation of adaptation alternatives through the use of AHP. The implementation of the MCDM models involved: assigning weights and priorities to the criteria by stakeholders; the normalisation of the raw scores to create a common scale of measurement; and the calculation of the decision scores used to generate the final output from the models. By using the questionnaire, the participants were asked to compare the relative importance of the decision alternatives pairwise, with respect to criteria and the goal. The results were obtained through the use of Expert Choice11 package for computing relative weights, consistency ratio and local and global priorities (Expert Choice, 2008). Additionally, the MS Excel 2007 was also been employed for some calculations and data plotting.

The AHP allows the inconsistency of every participant's survey responses to be represented by the consistency ratio (CR). The resulting CRs are 0.02 for *Residents,* 0.02 for *Experts* and 0.06 for *Politicians* – all less than the 10% limit*.* The result indicates that stakeholder groups' judgements with respect to each criterion and the goal are expected to be highly consistent. As seen in Figure 10, regarding the *Residents*, from the five different adaptation alternatives presented in the survey questionnaire, the highest priority alternative was *Improve Building Design* (0.325 priority), closely followed by *Build Protective Structures* (0.285 priority).

The least preferred alternative was *Take No Action*, followed by *Retreat*, with priorities of 0.061 and 0.102 respectively. In contrast, the *Experts* gave their highest priority to *Improve Public Awareness* with priority of 0.289, while *Improve Building Design* and *Retreat* were deemed the next most important alternatives with priorities of 0.278 and 0.203, respectively. While in accord with the *Residents* judgements for their least preferred alternative (*Take No Action* had a 0.089), the experts next least preferred alternative was *Build Protective Structures* (0.141 priority).

Global Alternative Priorities for Stakeholders					
	Retreat	Improve Building Design	Improve Public Awareness	Build Protective Structures	Take No Action
Residents	0.102	0.325	0.227	0.285	0.061
Experts	0.203	0.278	0.289	0.141	0.089
Politicians	0.254	0.457	0.125	0.111	0.052

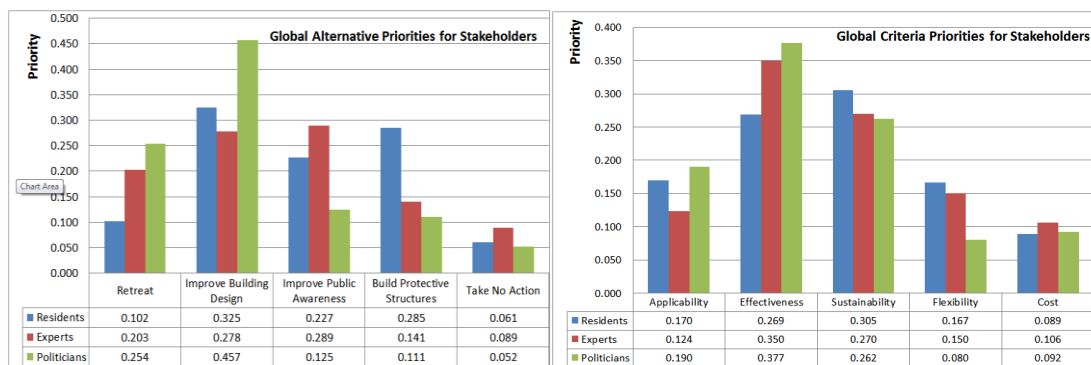| Global Criteria Priorities for Stakeholders					
	Applicability	Effectiveness	Sustainability	Flexibility	Cost
Residents	0.170	0.269	0.305	0.167	0.089
Experts	0.124	0.350	0.270	0.150	0.106
Politicians	0.190	0.377	0.262	0.080	0.092

Figure 10 Global criteria and alternative priorities for stakeholders

The *Politicians* top two preferred adaptation alternatives were *Improve Building Design* with a priority of 0.457 (the *Residents* had this alternative as their top priority, while the *Experts* rated it as their second priority), and *Retreat* with a priority of 0.254, which was one of the *Residents* least preferred alternatives, but the *Experts* third top priority (Refer to the *Politicians*' row in Figure 10). Once again, the least preferred option for all three groups was *Take No Action*; however, the *Politicians* rated, as second to last, the alternative to *Build Protective Structures*, which disagreed with the *Residents* judgement, but agreed with the *Experts* judgement.

The criteria priorities were obtained in the same way as the alternative priorities (Figure 10). From the combined results for each stakeholder group, the two most important criteria to consider when making a judgement to reduce the negative impacts of SLR are *Effectiveness* and *Sustainability.* It appears that the three stakeholder groups uniformly agree about the importance of the criteria. For example, *Applicability* and *Flexibility* generally rank next highest

(with *Politicians the* exception), while *Cost* ranks the lowest (with *Politicians* the exception ranking *Flexibility* last).

3.3 Model Refinement

As there is a strong intersection between human decision making and environmental stresses, due to the uncertainty of the precise behaviour of complex environmental systems, two dilemmas confront DMs: how and when to adapt to SLR. While most decisions inherently are flawed to some degree, the decisions still have to be made. In order to improve the chance of better decision making, therefore, a robust process that considers the range of risks and associated uncertainties is required.

The temporal model, introduced above, takes into account key variables that predict the extent and timing of coastal inundation. However, no variable was available to represent the adaptation alternatives. Thus, the model simulations were conducted under the *Take No Action* strategy. By modifying the model, 14 successive simulations were performed, with various values, to explore the impact of the *Build Protective Structure* and *Improve Building Design* adaptation options on vulnerable people and areas, as seen in Figure 11. To be consistent with the modelling framework, the refined model tested the findings of the decision analysis.
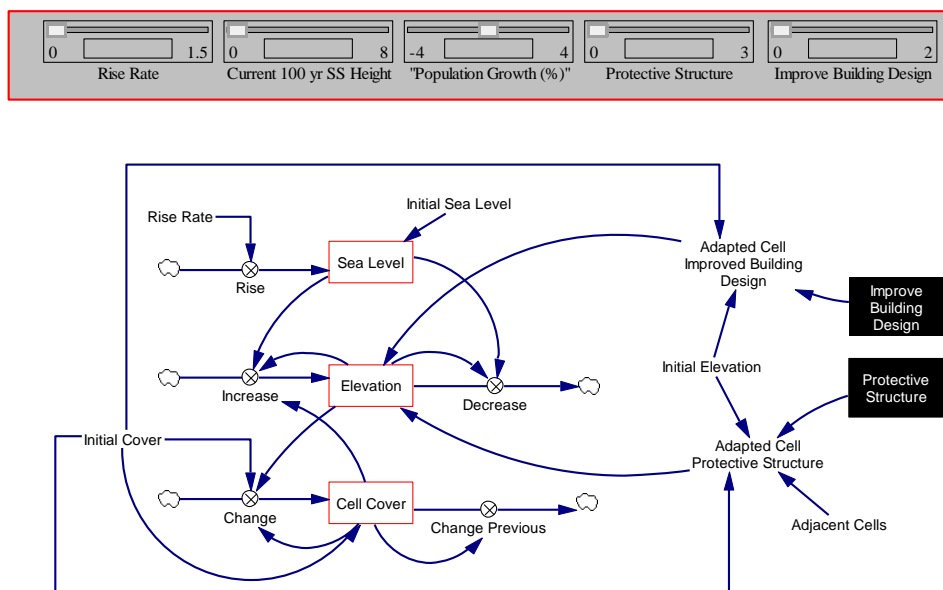

Figure 11 Modified temporal model with *Improve Building Design* variable

First, to test the efficiencies of *Build Protective Structure*, the model was modified by adding a variable to represent an imaginary protective structure along the shoreline. The term "*Build Protective Structure*" refers to coastal engineering activities that reduce the risk of flooding and inundation. The heights of the protective structure varied from 0 to 2.5 m to estimate the most effective height that provided the best protection. The imaginary wall was built by altering the initial elevations of the border cells whose initial cover types were *Land* and adjacent to cells with *Sea.*Secondly, to test the efficiency of the *Improve Building Design* option, the model was further modified by adding another variable (*Improve Building Design*).

A comparison was made of the usefulness of building a 1m or 2m high protective structure to reduce vulnerable areas to a 1.5 cm SLR per year. The results showing vulnerabilities under three adaptation scenarios; *No Action*, 1 m and 2 m *Protective Structure* can be seen in Figure 12. The findings show that building protective structures along the coastline does not have any effect on reducing the extent of the inundation under Scenario 3, and, therefore, does not reduce the vulnerability. Similarly, the overlapping lines also indicate that *Protective Structures* (both, 1m and 2m) will not provide any safeguard for the vulnerable population from rising sea level (Figure 12).

Secondly, to test the efficiency of the *Improve Building Design* option, the model was further modified by adding another variable. The newly added variable, the *Improve Building Design* option covers a wide range of adaptation measures, including (but not limited to) flood proofing, elevated building design, and minimum flood level. As it was not possible to test each adaptation measure under this category, the focus was specifically on two measures: *elevated building design* and *minimum flood level*. Further, it was assumed that new building regulations would be introduced, and that all existing and new buildings would be modified and/or designed accordingly. Based on these assumptions, the initial elevation of each cell with a *Land* cover type was increased by 1 m, and then 2m.

Period	Area @ Risk			Population @ Risk		
2020	1.6%	1.0%	1.0%	0.0%	0.0%	0.0%
2030	3.6%	3.1%	3.1%	0.0%	0.0%	0.0%
2040	4.9%	4.6%	4.6%	0.0%	0.0%	0.0%
2050	9.4%	9.1%	9.1%	0.1%	0.1%	0.1%
2060	16.5%	16.2%	16.2%	0.2%	0.2%	0.2%
2070	26.7%	26.4%	26.4%	0.3%	0.3%	0.3%
2080	35.8%	35.8%	35.5%	0.5%	0.5%	0.5%
2090	42.9%	42.9%	42.6%	0.9%	0.9%	0.9%
2100	47.9%	47.9%	47.6%	1.5%	1.5%	1.5%
2110	55.7%	55.7%	55.4%	7.1%	7.1%	7.1%
	No Action	1m Protective Structure	2m Protective Structure	No Action	1m Protective Structure	2m Protective Structure

Figure 12 Vulnerable area and Population to SLR, with and without *Protective Structure*

In contrast to *Protective Structures,* the *Improved Building Design* adaption option provides the vulnerable population with better protection (Figure 13). As seen in Figure 13, with a 1.5 m SLR over a 100 year period, 56% of the land area would be submerged. However, implementing the option *Improved Building Design* reduced the vulnerability down to 6.5%, and 0.1 % for a 1 m and 2m building elevation, respectively. It is clear that elevating structures by the amount of the SLR, or more, would keep these structures at the same elevation relative to the sea and, thereby, prevent their becoming more vulnerable as the sea level rises.

Period	Area @ Risk			Population @ Risk		
2020	1.6%	0.0%	0.0%	0.0%	0.0%	0.0%
2030	3.6%	0.0%	0.0%	0.0%	0.0%	0.0%
2040	4.9%	0.1%	0.1%	0.0%	0.0%	0.0%
2050	9.4%	0.5%	0.5%	0.1%	0.0%	0.0%
2060	16.5%	0.7%	0.7%	0.2%	0.0%	0.0%
2070	26.7%	1.0%	1.0%	0.3%	0.0%	0.0%
2080	35.8%	1.5%	1.5%	0.5%	0.0%	0.0%
2090	42.9%	1.9%	1.9%	0.9%	0.0%	0.0%
2100	47.9%	4.4%	4.4%	1.5%	0.0%	0.0%
2110	55.7%	6.5%	6.5%	7.1%	0.0%	0.0%
	No Action	Improve Building Design - 1m	Improve Building Design - 2m	No Action	Improve Building Design - 1m	Improve Building Design - 2m

Figure 13 Vulnerable area and Population to SLR with and without *Improved Building Design*

Further simulations were conducted to compare the effectiveness of adaptation options by setting initial values for *Rise Rate* (max 1.5 cm/y) and *Current 100 year SS Height* (max 2.5 m). Using the simulation results, the impacts of the five adaptation options; *No Action*, *Protective Structures* (1m and 2m) and *Improve Building Design* (1m and 2m) were compared.

The outcomes on vulnerable people and areas are shown in Table 1. Firstly, the *Build Protective Structure* adaptation option was not an effective strategy in reducing vulnerability to SLR and associated SS. Secondly, the presence of rivers and canals in the study area nullified the effectiveness of any protective structures against SS and SLR, especially when combined with heavy rainfall and flash flooding. Thirdly, as the sea level rises, flooding penetrates into the same places it has occurred before. However, the *Improve Building Design* option offers a much better option against SS with a 1.5 cm/year SLR. As demonstrated above, this option has the potential to reduce, significantly, the vulnerabilities to a 1.5 m SLR. On the other hand, its shielding power diminishes against a 1.5 m SLR combined with SS.

Table 1 Comparing five adaptation alternatives under two scenarios

Area at Risk (%)										
	Adaptation Alternatives									
	Take No Action		Protective Structure - 1m		Protective Structure - 2m		Improve Building Design - 1m		Improve Building Design - 2m	
	Scenarios									
Simulation Period	1.5 m SLR	1.5 m SLR + Storm Surge	1.5 m SLR	1.5 m SLR + Storm Surge	1.5 m SLR	1.5 m SLR + Storm Surge	1.5 m SLR	1.5 m SLR + Storm Surge	1.5 m SLR	1.5 m SLR + Storm Surge
2020	2%	82%	1%	82%	1%	82%	0%	56%	0%	10%
2030	4%	88%	3%	88%	3%	88%	0%	75%	0%	19%
2040	5%	89%	5%	89%	5%	89%	0%	79%	0%	31%
2050	9%	90%	9%	90%	9%	90%	0%	81%	0%	38%
2060	16%	90%	16%	90%	16%	90%	1%	83%	1%	45%
2070	27%	91%	26%	91%	26%	91%	1%	85%	1%	51%
2080	36%	91%	36%	91%	36%	91%	1%	86%	1%	59%
2090	43%	92%	43%	92%	43%	92%	2%	88%	2%	72%
2100	48%	92%	48%	92%	48%	92%	4%	89%	4%	77%
2110	56%	92%	56%	92%	55%	92%	7%	89%	7%	80%
Population at Risk (%)										
2020	0%	87%	0%	87%	0%	87%	0%	20%	0%	0%
2030	0%	89%	0%	89%	0%	89%	0%	41%	0%	0%
2040	0%	90%	0%	90%	0%	90%	0%	50%	0%	0%
2050	0%	91%	0%	91%	0%	91%	0%	59%	0%	1%
2060	0%	91%	0%	91%	0%	91%	0%	66%	0%	1%
2070	0%	92%	0%	92%	0%	92%	0%	76%	0%	2%
2080	1%	92%	1%	92%	1%	92%	0%	84%	0%	10%
2090	1%	92%	1%	92%	1%	92%	0%	88%	0%	29%
2100	1%	93%	1%	93%	1%	93%	0%	89%	0%	44%
2110	7%	93%	7%	93%	7%	93%	0%	90%	0%	55%

Thus, it can be concluded that the findings of the simulation are consistent with the AHP findings, that is, the *Improve Building Design* was ranked as the most preferred option by the *Residents* and *Politician*, while the *Experts* voted it the second most preferred option.

However, the *Politicians* and *Experts* voted the *Build Protective Structures* as the fourth most preferred option, while the *Residents* ranked it as the second most preferred option.

4   Conclusion

An innovative characteristic of the STD approach is its ability to evaluate the decision choices prior to their implementation. This is achieved by incorporating the DSM simulation results into the decision making process and, then, retesting the information, obtained from this process, using the DSM. The model's ability to pre-evaluate decision choices is an important feature; its legacy is that communities can avoid or minimise their decision error, and increase their chance of obtaining better decisions.

The STD approach, in summary, provides a critical tool for obtaining quantitative information for managing and making choices with the aim of effective decisions. This integrated approach has the capability to: (1) Generate important spatial-temporal information required by decision makers (DMs); (2) Provide new insights into complex coastal systems; (3) Address multicriteria decision problems involving multiple stakeholders; (4) Enable DMs to examine decision alternatives through the use of the Dynamic Spatial Model; and (5) Address uncertainties and generate alternative scenarios, based on different user inputs.

Acknowledgments

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