Sea Modelling of SeaCities: Why, What, and How to model

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Abstract

In order to realise SeaCities as depicted in this book, several individual projects, at a building (e.g. floating houses) and community (e.g. energy-water-food supply, transportation) levels, need to be designed to solve the inherent issues of such relatively unexplored urban concept. In this chapter, the focus is on the importance of modelling in providing a critical set of support tools to better inform SeaCities design and decision-making. The chapter is intended for the reader interested in SeaCities and relatively unfamiliar with the modelling world. The chapter is structured as follows: first, a brief justification of the need for modelling in SeaCities is provided (“WHY modelling”); this is followed by examples of systems, elements or parameters that will require modelling (“WHAT modelling”). Next, different modelling categories are introduced, based on different criteria, such as the type of inputs available or the type of output desired (“HOW modelling”). The chapter concludes with two case studies, selected as examples of an integrated, participatory systems approach which is suggested as being highly applicable to many of the future SeaCities modelling needs.

11.1 WHY Modelling of SeaCities

The ideal “Sea City” would, eventually, fully take advantage of its interface between land and sea, and benefit of the sea for its incredible amount of resources and opportunities that it provides, rather than merely adapting to its relentless rise due to climate change.

Although the ultimate Sea City might be an urban concept which is yet to be realized, examples from past and present cultures and civilisations, as well as from a new influx of research and innovation around the world, provide evidence of beneficial, feasible individual design solutions that a current coastal city can deploy to slowly move towards the Sea City dream. A Sea City cannot be created overnight, however individual solutions can be tested and progressively implemented.

The type of key questions that need to be addressed to ensure that such design solutions are successfully implemented can be:

- What are the benefits, and for whom?
- What are the risks?

New projects typically require a clear understanding and quantification of the benefits. Would the Government have a return of investment, if floating houses are allowed to be built? What are economic costs and benefits of an offshore desalination plant or of a floating solar farm? What about less tangible cost and benefits, such as to society and to the environment?

Moreover, any project, especially unconventional designs, will inherently carry a number of risks. What are the water quality impacts of a floating city? What about a large, modular aquaculture area? What would happen to a floating development during high seas events? What are the social and large-scale economic implications of bringing people away from land to the water? How would the real estate market be affected?

Any individual Sea City - related project will have to properly address all these types of questions, as well as several other issues such as regulatory frameworks and governance

structures. Although seemingly daunting, Government, academic, and industry experts do have a unique opportunity at this time in history: we have unprecedented knowledge, facilities, infrastructures and computational power, to enable us to accurately quantify and account for all the pros and cons, benefits and risks, of any innovative, disruptive research or design project, before final approval and implementation. In other words, we can *model*, and predict, how effective and feasible SeaCities-related projects will be.

As a consequence, this chapter will explore this essential step required to ultimately realise the Sea City objective. The chapter will first look more specifically at why modelling is crucial and what is needed to be modelled, such as engineering, environmental, and socio-economic aspects of a Sea City project. Subsequently, the focus will shift to how it is possible to model and predict such complex behaviours or systems with a certain level of rigour or accuracy. Specifically, an overview of available modelling types will be presented and discussed. The chapter will conclude with a set of recommendations and case studies, especially advocating the need of a participatory, holistic, “system” thinking and modelling approach.

11.2 WHAT Modelling in SeaCities?

Whether a proposed SeaCities project is about floating structures, floating modular aquaculture systems, or amphibious developments for instance, there are a number of common aspects that need to be modelled to comprehensively quantify risks and opportunities. These are described in the sections below.

First of all, it is important to identify and describe the problem, or risk, that SeaCities aim to provide solutions for. The main one is sea level rise and consequently, exacerbated flooding risks for several low-lying coastal cities both in the short, medium and long term. Climate change studies have recently updated their sea level rise estimations (Oppenheimer et al. 2019), dramatically increasing the predicted number of cities and people that in a few decades will be temporarily or permanently under water: such predictions include, for instance, 190 million people occupying land that will be below the projected high tide lines in 2100, under the more conservative low carbon emission scenarios (Kulp and Strauss 2019). Although this should be enough to trigger global attention towards the gravity of this problem and the benefits of potential SeaCities-related projects, modelling is needed, at a

local level, to downscale such predictions and provide a more detailed estimation of costs and benefits for a local council or government. As discussed in Lin et al. (2019), with some of the larger cities in the world such as London, Miami, Tokyo and Jakarta expanding their territory by up to 10% in urban waters in the next few decades, from an urban planning perspective it is important to evaluate which areas of the city must be kept dry, which areas can be changed from dry to wet, and which waters are most suitable for city expansion. Relevant modelling outputs include the specific areas of a city which are likely to be underwater regularly or during storm surges, as well as an economic assessment of related costs for the council and government. The economic assessment should also quantify traditionally more qualitative measurements such as loss of health and wellbeing of locals impacted. Clear, numerical assessment of the expected costs of the do-nothing option is crucial to convince political institutions, which are usually motivated to achieving short-term goals in line with their political mandates, rather than investing heavily upfront in exchange for a long-term benefit.

Once the problem is clear and quantified, it becomes priority for governments and urban planners to assess the different possible solutions. Studies have already shown (Haasnoot et al. 2012) how traditional “protective” projects, such as raising dikes, are orders of magnitude more expensive than solutions such as floating houses, which look at working together with the sea rather than against it. Land reclamation as well, becomes proportionally more expensive with depth, unlike floating developments (Ko 2015). However, modern floating houses/villages are not that widespread as one would expect, and only in the last decade the world has witnessed an increase in floating architectural projects (the curious reader can refer to Lin et al. (2019) for a few examples). A reason for such slow uptake is that, being a relatively unexplored field of research and investment, there is a feeling that potential negative effects have not been comprehensively identified and quantified. As a consequence, such knowledge gaps have not allowed water authorities and councils to develop policy frameworks clearly defining regulations for new similar projects (de Lima et al. 2015a, de Lima et al. 2015b), with often unfounded concerns hindering the implementation of new floating development concepts (de Lima et al. 2015b). As a result, focusing specifically on floating structures, there is an urgent need to model and quantify all the potential risks, so that the project can be either approved, or optimised, or even rejected in favour of an alternative, better one.

Specifically for floating development projects, the first, key element to analyse would be the structural engineering feasibility. The Archimede's principle is a starting point to help with the design of the structure, with tilting and rotation also critical elements to control (Mohamad et al. 2013); strong external loading affecting the structure includes wind and waves, rain, ice and solar radiation (Stopp and Strangfeld 2010) and need to be quantified. Other critical elements to quantify include the centre of gravity, centre of buoyancy, and moment of inertia (Ishaque et al. 2014). Floatability, floodability and stability need to be guaranteed and verified (Shekhorkina 2015) for normal and worst case scenarios for the location and the project in consideration. In general, the height of buildings is quite limited due to stability issues, based on current engineering knowledge, although research and knowledge applied to e.g. floating oil rigs could be relevant in expanding current height constraints. Structural calculations need to be performed to determine the dimensions and the amount of materials (e.g. reinforced steel) required. An issue with materials is that they could get corroded based on salt content and pH of surrounding water (Stopp and Strangfeld 2010, Strangfeld and Stopp 2014), and this could lead to structural issues in the long term. At the same time, floating structures are protected from earthquakes (Ko 2015), so there would be no seismic requirements on the structure, regardless of the location/seismic area. Potentially, it could also deal better with post-earthquakes events such as tsunamis due to their ability to float and follow the sea level variations. If the floating structure is very large, hydrodynamic modelling challenges arise because the structure cannot be modelled as a rigid body, and because the computational power and time required for the model would increase dramatically (Lamas-Pardo et al. 2015, Yeh et al. 2015).

In addition to engineering feasibility, environmental feasibility is also critical, and still relatively understudied (de Lima et al. 2015b). Floating structures (especially when very large, such as houses or buildings) will block sunlight, providing different types of disruption to the marine ecosystem (Ko 2015). This will indirectly cause a change in temperature of the upper layer of water, causing a reduction of dissolved oxygen too, usually produced by photosynthesis (Burdick and Short 1999) which will be also reduced due to the lower amount of incident solar radiation. This can result in large amounts of dead organic material, which decreases dissolved oxygen further through mineralisation and increases turbidity, and in turn further decreases sunlight penetration, through a positive feedback loop. Wind, which

has a significant impact on circulation of water bodies (Ji 2017), will also change its pattern due to compression of air between the houses. If not recycled, wastewater should also be treated before being released in the environment; if this cannot be done on-site, pipelines to the mainland would have to be adequately designed to withstand external forces and moments (Ko 2015).

Finally, social/health aspects need to be considered. It will be more demanding to design for a comfortable indoor climate, especially in warmer months, due to a lack of plants and shade from other buildings, and an increase in reflected radiation and limited use of blinds due to stronger winds (Stopp and Strangfeld 2010). Hence, residents' wellbeing would be affected, unless more energy is used, or new design solutions are applied to guarantee the same indoor comfort that they now enjoy on land. On the other hand, there is potential to improve the outdoor environment with a better connection to water, and with the potential for new urban design solutions which, unlike the "urban sprawl" concept, can improve cohesion, interactions, and physical activities.

All the described potential engineering, environmental and social issues need to be modelled and quantified as best as possible, to provide a holistic assessment of the project and in turn inform the economic assessment to be presented to the stakeholders. Importantly, feasibility must be verified not only for the actual floating structure/buildings, but for all the critical services which must be provided to the residents.

On the bright side, despite the potential risks, there are also considerable opportunities that, through research and innovation, can make floating developments more feasible. Surrounding water could be used for heating and cooling (Lin et al. 2019), using techniques such as evaporation and heat pipes or running water through the building envelope (Stopp and Strangfeld 2010). Rainwater harvesting would help meet the freshwater demand (Bhattacharjee and Mukherjee 2017), with more potential for storage (e.g. underwater), and floating and/or mobile desalination plants have been already designed (Lin et al. 2019). For food production, it is possible to produce hydroponically grown crops, and rely on fishing, especially cage fishing and aquaculture in general (Bhattacharjee and Mukherjee 2017), though the water quality issues mentioned before (e.g. drop in dissolved oxygen and water temperature, potential contamination from discharged treated wastewater) need to be

accounted for. More research into fish aggregating devices could also be beneficial. Wastewater coming from the aquaculture sites can be naturally treated to improve its quality through the use of floating plant bed systems (Nduwimana et al. 2007). Modelling of high frequency water quality sensor data also showed, unexpectedly, a limited negative impact on dissolved oxygen levels under floating houses in Delft (Foka et al. 2015), with abundant marine life still achievable in proximity of the floating structures (de Lima et al. 2015b), thus showing promising signs despite the theoretical water quality concerns mentioned earlier.

Vertical vegetation will reduce the external wall temperatures during warmer months, thus helping to achieve comfortable indoor environment with a lower energy demand. For waste reduction, concepts exist that aim at recycling waste nutrients and carbon dioxide to produce food and biofuels through the use of floating algae systems (Roelfen et al. 2013). For energy production, solar panels, wind turbines and biodigesters have been suggested for floating houses (Bhattacharjee and Mukherjee 2017); solar panels are known to work better if the temperature is not too high, hence placing them in the water would improve their efficiency and thus, provided the perfect orientation and tilt angle can be still guaranteed, it would lower the number of panels (and space) required; floating solar panels would also benefit water quality by reducing algal growth (Sahu et al. 2016) although a comprehensive assessment of the impact on the water environment underneath should be conducted. Floating projects examples around the world summarised by Lin et al. (2019) achieved (1) energy self-sufficiency with wind turbines and solar panels; or (2) no disruption by wind and waves through the use of dampers, cables and springs.

Structurally, as summarised in Lin et al. (2019), floating foundations are usually heavy and stable, also allowing the structure to adapt to sea level moving up and down. As a consequence and as previously mentioned, the effects of extreme events such as tsunamis (Lin et al. 2019) or earthquakes (Lamas-Pardo et al. 2015) are usually much less severe in open waters. From a socio-economic perspective, the direct experience of the natural environment of water would lead to better lifestyle and wellbeing, in turn making the property more attractive and valuable (Stopp and Strangfeld 2010).

Most of the proposed concepts are still in their infancy and need to be modelled and refined. A number of modelling approaches will be described in the next sections, to help the reader

choose the most appropriate technique based on the modelling goal and scope, and to eventually achieve a holistic, comprehensive assessment of a floating development project.

11.3 HOW Modelling? Modelling categories

There are endless distinctions, in the literature, between models based on their unique features. However, what all the models have in common is the need for some type of inputs, and the delivery of some type of outputs. In SeaCities, the type of inputs available for modelling can vary considerably, as well as the desired type of output. Hence, in this book chapter we categorise different models in simple terms based on the inputs and based on the outputs they produce (Figure 11.1).

Figure 11.1 – Types of models based on inputs and outputs. Red arrows imply a negative relationship, green arrows a positive relationship. Dashed blue line separates model categories based on inputs or outputs.

11.3.1 Model choice based on inputs

We first analyse the left-hand side of Figure 11.1, and introduce different modelling categories based on their inputs.

11.3.1.1 Physical models

A physical model is essentially a copy of an object or a system, typically of a different size. For systems and objects investigated in a SeaCity, these are typically large and thus the

physical model would have a smaller scale. The main input to a physical model, following its preliminary design, is material.

Physical models can be used in conjunction and in support of numerical models. For SeaCities, an important combination is between physical models and computational fluid dynamics (CFD) models, i.e. a type of process-based models. Physical models can be placed in wind tunnels or wave tanks to validate the CFD simulation outputs in relation to how flows of fluids might affect the model, and thus in turn they can help in optimising its own design (e.g. shape). Scaling is a critical issue for physical models, in relation to the dimensions of the instrumentation available for experiments (e.g. wave tank). Boundary conditions become very delicate and important to consider. Froude number and Reynolds number scaling approaches are typically used.

Relevant examples include from authors who have proposed 3D numerical models of floating structures to estimate wave drift forces and hydro-elastic responses, and compared the results with experiments conducted with physical models; creating opportunities for comparison of the influence of difference factors (Ma et al. 2001).

11.3.1.2 Mental models

Although there is no clear, agreed definition of mental models across different disciplines (Rook 2013), a robust definition has been provided by Rook (2013): “*a concentrated, personally constructed, internal conception, of external phenomena (historical, existing or projected), or experience, that affects how a person act*”. The curious reader is directed to Rook (2013) for an interesting analysis of different mental model definitions and concepts. The main input for this type of models are assumptions, i.e. conjectures of how and why a certain object, process or system behaves in a certain way in the real world. A mental model has a number of limitations: firstly, a human mind has limited computational power and abilities; mental models are also only qualitative thus not predictive; they do not indicate which parts of the system are active (and which are not), and are reliant on subjectiveness. But, a well-elicited (to avoid cognitive biases) mental model is typically the first step in modelling any new system/process, after problem formulation: hypotheses must be made and verified in the real world, before the mental model can be validated and a more complex and accurate numerical model developed. There are different types of mental models, and

some of them, such as casual loop diagrams, are the foundations of complex system thinking and system dynamics models, described later in this chapter. In the context of SeaCities, mental models as the foundation for more complex quantitative modelling were applied in Australian coastal locations to assess adaptation options (Smith et al. 2015).

11.3.1.3 Mathematical models: empirical and mechanistic models

Mathematical modelling in general has been described as “*the art of translating problems from an application area into tractable mathematical formulations whose theoretical and numerical analysis provides insight, answers, and guidance useful for the originating application*” (Neumaier 2004). The vast majority of models typically developed in contexts relevant for SeaCities are mathematical, and several different types exist. The main distinction, however, can be made between empirical and mechanistic models. Such subdivision resembles what occurred in the field of philosophy when defining the foundational principle of knowledge; in the 17th and 18th centuries, two philosophical schools emerged in Europe: one (the *empiricists*, led by Locke, Berkeley and Hume) asserting that knowledge can be only gained by experience of reality (Priest 2007), and the second one (the *rationalists*, led by Descartes, Leibniz and Spinoza) claiming that meaningful facts about reality can be inferred by use of reason rather than experience (Garrett 1999).

Empirical, or inductive, modelling in general terms relies on observations to develop, and to validate, a model. In most cases, data-driven models can be considered part of this category of models. Data-driven models essentially rely on data (usually quantitative, but also qualitative in some cases) to seek relationships between different variables and processes, and to eventually extrapolate such relationships for different purposes, such as predictions, optimisation, or scenario testing. Clearly, the main input for this type of model is data. Models under this category can be parametric or non-parametric. Parametric models have a fixed number of predictors based on certain assumptions and only coefficients need to be defined. An example is regression models. Non-parametric models do not rely on any assumption and the most suitable “form” of the model, as well as the number and form of each predictor, is entirely learnt from the data. Under this umbrella sit most of artificial intelligence and specifically machine learning models. Several examples relevant to SeaCities exist, and here we will mention a couple of interesting ones. Multi-objective evolutionary algorithms were developed and deployed by Ugurlu et al. (2015) in order to

optimise a floating settlement (e.g. shape, functions) in a way to minimise the need of roads, and to maximise accessibility, wind protection and visibility based on a number of constraints. A very similar multi-objective optimisation model for urban planning was developed in Levi et al. (2019) for a very large floating structure.

Mechanistic, or deductive, modelling instead relies on the systematic application of mathematical formulations of causal mechanisms to explain a process or a system. The main input here is therefore *mathematical expressions* and the assumption that a system can be decomposed and analysed by examining its individual components. Mechanistic modelling is quite commonly applied in different modelling aspects of SeaCities, such as to understand the water-energy nexus as reviewed in Kenway et al. (2011), to predict urban flooding as reviewed in Mignot et al. (2019), or to predict the performance of marine renewable energy devices as reviewed by Day et al. (2015).

Advantages and disadvantages of empirical and mechanistic models are quite distinct, and similarly to the philosophical debates occurring 2-3 centuries ago, with available data increasing dramatically every day, modellers are now more than ever asked to take an informed decision on what type of model would suit best a particular application. In general, the suitability will depend on the amount of relevant data available as well as the goal and features of the model (e.g. scenario analysis, classification, prediction). A number of dedicated scientific resources are available for the interested reader, to be trained to select the best model type, including the specific one within the individual category (i.e. which particular data-driven model). However, due to the increasing development and application of smart technology and sensors able to collect very large amount of data (see e.g. Figure 11.2), coupled with the increasing capabilities to handle them through machine learning and increased computational power, empirical models seem to have more opportunities for large scale deployment in future years.

Figure 11.2 –Vertical profiling systems (VPS) rely on high frequency sensors to monitor in real-time the water quality of lakes and reservoirs, at multiple sites and depths.

11.3.2 Model choice based on outputs

We now analyse the right-hand side of Figure 11.1, and discuss different modelling categories based on their outputs.

11.3.2.1 Deterministic/Stochastic models

A deterministic model is a model that does not include any randomness, and thus the model outputs are fully defined by the initial conditions and applied equations/algorithms. Conversely, a stochastic model inherently includes some degree of randomness, so that even with the same sets of parameters and initial conditions, different results would be obtained in different simulations. Of relevance for SeaCities, a recent review of flood loss models (Gerl et al. 2016) noticed that 96% of existing models were deterministic, seemingly oversimplifying the uncertainties encapsulated in the real systems.

Our world is filled with stochasticity, and also our computers, despite being able to handle large computational loads and calculations, will inherently add an element of randomness to any deterministic model when, for instance, rounding decimals. Some of these minor changes in initial conditions might not affect certain systems, but for complex, chaotic systems, these variations might lead to totally different predictions even in a relative short time horizon. This concept is at the foundation of chaos theory, and was discovered by Edward Lorenz in the field of meteorology, who called this phenomenon the (famous) “butterfly effect” (Lorenz 2000). This also explains why it is so difficult to generate accurate

weather forecasts. In conclusion, whether the model explicitly accounts for some degrees of uncertainty or not, it is important to be able to interpret the modelling outputs correctly, and to fully understand potential assumptions and sources of errors leading to the results. Trust the model, but do not trust it first.

11.3.2.2 Static/Dynamic models

Another way to classify a model is based on whether time is considered in the way modelling outputs are calculated. In the case of static models, they describe a system at a specific point in time, and thus there is no accounting of previous states of the system when calculating the next. Dynamic systems are instead, to some degree, time-dependant and thus they maintain a “memory” of inputs and outputs of the system at earlier, relevant time steps. In SeaCities for instance, assessing the evolution of a heavy rainfall event and potential related dam spilling and river flooding, inevitably lends itself to a dynamic modelling approach due to inherent lags between rainfall, runoff, and flows at different locations. Of relevance for SeaCities research, in a study comparing a static and a dynamic model to evaluate building (and people) vulnerability to impulsive floods, the dynamic model was found to perform better when assessing them against historical data (Pilotti et al. 2016).

11.3.2.3 Discrete/Continuous models

Although a discrete/continuous distinction can also refer to different methods to run temporal simulations in certain models, here we refer to what form the final output of the model takes. If discrete, this means that only a limited number of states can be assigned to the output parameter. An example of a type of discrete model which has seen widespread application in last couple of decades is Bayesian Networks (Fenton and Neil 2013). With Bayesian Networks, even when numerical, continuous variables are used for input, these have to be discretised in relevant intervals. For instance, in case of SeaCities and specifically coastal flooding, the “mean sea level” in metres could be discretised in “low”, “medium” and “high” based on meaningful thresholds. This can be seen as a limitation of such models for most applications, however often a simpler, categorical representation of a model output can facilitate interpretation by a wide interdisciplinary range of stakeholders; in addition, research is rapidly improving the discretisation capabilities of Bayesian Networks (Mayfield et al. 2019). Continuous model outputs would instead not need to be discretised and the precise numerical output would be calculated. The users should be wary, for fully

deterministic models, of such precise estimation and, as discussed previously, make sure to interpret the results correctly. For stochastic models, a number (usually millions) of different simulations are run, and the results can be represented with the help of probability distributions. Although they can be less user-friendly for some, they allow to account for the uncertainty present in the system and in the model. Probabilistic outputs can be summarised in helpful ways; for SeaCities for instance, “risk maps” of e.g. coastal flooding could be generated by elaborating a coastal model’s outputs. An example is given by Mojaddadi et al. (2017) where a complex spatial model’s outputs were effectively summarised by generating flood risk maps.

11.3.3 System thinking and integrated approaches

There exists a range of modelling techniques and the most suitable choice will depend on a range of factors. The advantages and disadvantages of several common techniques were discussed above. The shortcomings of the techniques as discussed above are evidence that individually, most of the time none of them is suitable for meeting all the modelling requirements of any complex system. For example, no single technique can easily incorporate the expert opinions that could be required for predictions, as well as accounting for complex feedback loops and relationships required to analyse the systems’ behaviours. To achieve the required balance of complexity and system transparency, an integrated modelling is needed to eliminate the weaknesses and utilise the strengths of each technique (Voinov and Gaddis 2008). It is easy to envisage the synergy achieved by integrating multiple techniques in order to provide extra dimensional modelling power, as well as enhanced abilities (Sahin 2011). As such, an “integrated modelling approach” is proposed herein, which can effectively help model complex systems embedded within SeaCities.

Behind this modelling approach, *system thinking* forms the underlying foundations. Unlike mechanistic analysis, where the goal is to separate the individual pieces of what is being studied (in fact, the word ‘analysis’ actually comes from the root meaning “to break into constituent parts”), in system thinking the focus is how what is being studied interacts with the other constituents of the system of which it is a part. A human body, or a car, provide good examples of such systems. The purpose of a car can be generally defined as to bring its driver from point A to point B faster than what the driver could achieve on foot. A car is made of an engine, four wheels, a transmission system, and several other individual components. However, if we one puts all these components inside a box at random, the car

will not fulfil its purpose, even if individually, it has the most powerful engine or the tires with the best grip. What is critical, is not only the performance of its individual components, but how such components are connected and interact with each other. The key idea is that a system is not the sum of its components, but the product of its interactions.

Under the system thinking framework, a number of modelling steps are usually completed; as a consequence, such framework cannot be included in some of the specific modelling categories described above. A system thinking-based approach will have a variety of features, dependent on the project-specific directions and approaches used.

In system thinking, the first modelling step is to articulate the problem, and conceptualise the system. Such conceptual models (described earlier in this chapter) can be developed with an integrated, participatory approach where stakeholders' workshops are designed to achieve an agreed common understanding of the system being modelled. The first step in developing such a conceptual model with a participatory approach is to agree upon the project goals and thus key-variables among the stakeholders. A common shortcoming of this conceptual modelling step is the tendency to focus on parameters and connections which are within the domain of expertise of the specific stakeholder; thus, selecting the appropriate "expert" is crucial. In addition, tools and methods previously developed (e.g. Godet (2001)) can facilitate a more rigorous approach to the model conceptualisation process. Of key importance is also a clear definition of the system's boundaries (i.e. scope of the model), based on a fine balance between need for model complexity and demand for data and computational power.

The following step, once the conceptual model has been finalised, is its conversion to a mathematical model. Based on the different modelling needs and thus modelling features required, different types of models can be used. Commonly used ones are either Bayesian Networks, or System Dynamics, models – or a combination of them (e.g. Bertone et al. (2016a), Bertone et al. (2017)).

Bayesian Networks (BN), previously mentioned due to being discrete, are probabilistic, graphical models of the system of interest and use the Bayes theorem as the mathematical framework for updating probabilities based on evidence. A BN consists of variables (i.e. "nodes") interconnected (parent to child node) through arcs. For nodes having "parent"

nodes, the relationships between connected nodes are quantified through Conditional Probability Tables (CPTs). Populating the CPTs is one of the most challenging parts of developing a BN (Druzdel and Van Der Gaag 2000), but at the same time one of its most important. This is because the input data used to populate the CPTs can be empirical, quantitative data, but also qualitative (e.g. based on expert opinions), based on other models' outputs, or spatial (e.g. GIS data), to name a few. Missing data can be appropriately handled with BNs, as this can either be overcome with expert input or by reflecting this in the level of uncertainty behind specific CPTs, which is clearly represented. Additional advantages of BNs are (Uusitalo, 2007), as a consequence, the ability of incorporating inputs of experts from different disciplines (critical for modelling complex systems), fast simulations facilitating rapid feedback to participants when testing different scenarios, thus supporting effective decision-making; and the ability to detect and explore inconsistencies and different perceptions among stakeholders. Moreover, BNs benefit from the key feature of the Bayes theory, i.e. the probability of a hypothesis being true given updated evidence can be inferred, and also that uncertainty can be quantified. The main limitations, instead, include the difficulty to conduct temporal analyses. Furthermore, feedback pathways are not supported in the structure of BNs due to its "directed *acyclic* graph structure" necessary for the Bayes's theorem to be applied, thus restricting them to static analysis or very basic dynamic ones (e.g. Bertone et al. (2019)). Finally, variables are discretised, with discretisation often limited to only a few states per variable (e.g. Richards et al. (2013), Bertone et al. (2020)). This results in a coarsely parameterised model thus potentially reducing its utility or range of applications (Uusitalo, 2007), though recent improvements and potential beneficial applications exist and were mentioned in previous sections.

System dynamics (SD) modelling, in contrast, represents an approach to numerically quantify the dynamics of complex systems, by facilitating the development of computer simulations of such systems (Sterman, 2000). SD, unlike BN, are dynamic (e.g. they include time as a variable, as well as feedback loops). However, they are less flexible when dealing with model inputs and assumptions.

Table 11.1 summarises pros and cons and features of each approach, showing how BN and SD complement each other and a combination of the two would allow to overcome different data availability and output needs. In addition, it must be said that each modelling approach has intrinsic ways to overcome their limitations. For instance, though SD provides

deterministic outputs, sensitivity analysis and Monte Carlo modelling are typically used to quantify uncertainty.

Table 11.1 – Features of Bayesian Networks and System Dynamics

<i>Feature</i>	Bayesian Networks	System Dynamics
<i>Numerical data input</i>	Yes	Yes
<i>Qualitative data input</i>	Yes	No
<i>Handling missing data</i>	Yes	No
<i>Output type</i>	Probabilistic	Deterministic
	Discrete	Continuous
	Static	Dynamic
<i>Feedback loops</i>	No	Yes
<i>Simulation time</i>	Short	Short
<i>Conceptual model needed</i>	Yes	Yes

Recently, attempts have been made to combine BN and SD, in order to merge the benefits of the two approaches. The potential for integrating “fuzzy logic” in SD, thus creating “fuzzy system dynamics” to enhance input flexibility, was already highlighted by Tessem and Davidsen (1994). Such “fuzzy logic” – based approach can be used to quantify relationships and values for a number of nodes wherever empirical evidence is not available. Fuzzy logic was deployed to account (to some extent) for the uncertainty in systems characteristics, as summarised in a review paper by Labadie (2004) in relation to water resource optimisation research, and by Khanzadi et al. (2012) with a coupled fuzzy logic – systems dynamics approach. Bertone et al. (2016b) proposed a fuzzy logic approach with BN node decomposition as an effective way to complete and deploy a SD model whenever several variables do not have empirical data available, and they successfully applied such approach to study future health-related water quality risks for a large Australian reservoir (Bertone et al. 2016a).

11.4 Case studies

Below, we present two case studies demonstrating successful examples of an integrated, system modelling approach relevant for SeaCities.

11.4.1 A hybrid GIS-System Dynamics approach to assess vulnerability to sea level rise

Environmental problems are neither static nor do they exist in isolation; indeed, they are in a series of continuous dynamic interactions, driven by multi-causality. The complexity and interdependencies of their elements define their characteristics. Consequently, as the environment changes in time and space, so do its problems and the solutions to these problems. As a result, the dynamic characteristics of environmental systems must be fully considered to enable them to be addressed effectively. When addressing these problems, it is essential to use an approach that elicits a variety of relevant information. When designing a suitable purpose-specific model, it is necessary to select the most suitable assessment and decision-making techniques. With this in mind, the aforementioned system approach provides a suitable platform in the development of a dynamic model that assesses whole environmental systems and the many interacting components (Sahin and Mohamed 2014).

The world's coastal areas have been a focus when considering adaptation strategies for sea level rise (SLR). To assess coastal vulnerability, and the adaptation alternatives, to SLR, a spatial-temporal decision-modelling framework as illustrated in Figure 11.3 was developed (Sahin and Mohamed 2013). The framework is based on five dimensions of the decision process for environmental dynamics. 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 was important as to model and simulate changes in coastal zones, it is necessary to consider the spatial and temporal dimensions of rising sea-level, as any single approach is deficient in one feature or the other. Therefore, an integrated approach is the most appropriate way of dealing with various complex problems. Combining SD and GIS approaches provides the power to meet these requirements as previously mentioned and also emphasised by several authors (Grossmann and Eberhardt, 1992, Ruth and Pieper, 1994, Ahmad and Simonovic, 2004, Gahrib, 2008).

This approach is crucial in generating adequate information from which decision makers can devise realistic adaptation strategies. For this reason, it is essential to incorporate the first four dimensions into a fifth dimension, i.e. the element of human decision making (h).

Figure 11.3 - Five dimensional (x , y , z , t , h) spatio-temporal decision modelling framework

It must be noted that, in this study, the term vulnerability refers to people at risk and the loss of property due to exposure to SLR and related storm surges. Using the spatio-temporal framework, we analysed the current conditions first; then, these systems were examined further, under various scenarios, so as to identify how SLR will affect the already distressed systems, over time. We used a range of SLR scenarios and sensitivity analyses to address the uncertainty issues associated with the projections of sea-level rise.

This approach facilitates the use of creativity and experience to clearly structure the complex problems and pursue their solution within a systematic framework. In developing the framework and subsequent model, the following modelling steps were adopted:

1. Problem definition: Identifying and classifying the objectives provides a basis upon which to build a model and solve a problem using mathematical solutions.
2. Model development: The model is formulated, and a conceptualised model of the system under question is developed. All essential system variables are identified and processed. The relationships among the variables are also established, with some assumptions being made for the sake of simplification. Subsequently, the

required data about the system is collected. Finally, the equations and functions needed to explain the relationships among these variables are determined.

3. Model deployment: Through the implementation of the model the solutions are achieved.
4. Model validation and optimisation: After obtaining a solution, the results are examined to determine whether the model works effectively and satisfies the problem objectives.
5. Final model results interpretation and communication: The results are interpreted to provide a conclusion and recommendations to the stakeholders.

In this approach, GIS and SD assessed different aspects of the complex problem. While GIS handles spatial data, SD processes the dynamics of the complex system, revealing its causal structure and the relations of the system components. The use of these two methods is appropriate for tackling different environmental problems (both spatial and temporal). This versatile method, firstly, allows the processing of details separately; and, secondly, then, combines the results of the different methods. Therefore, the coupling of these two approaches provides immeasurable potential to solve problems. Importantly, the coupling of SD and GIS provides a hybrid model which can address temporal and spatial aspects of dynamic processes as illustrated in Figure 11.4.

Figure 11.4 - Hybrid GIS-SD architecture

For brevity a detailed discussion of this method is not given here; the interested reader is referred to Sahin (2011), Sahin and Mohamed (2013) for detailed description of the methods and results of the case study.

11.4.2 A spatial BN approach to evaluate future coastal erosion of a Pacific island

The focus of this second case study was on predicting, and planning for, rare or unprecedented coastal erosion events related to longer term climate change effects on coastal regions. As discussed in the previous section, SLR on coastal regions is expected to exacerbate the impact of coastal hazards such as erosion, inundation, land loss, saline intrusion and flooding from storm surge with increasing frequency and intensity. Accordingly, the resulting negative impacts on coastal settlements and infrastructure will be exacerbated. Therefore, identification and assessment of coastal hazards are critical for

planning and developing effective management strategies to protect lives and properties exposed to coastal hazards.

Erosion is the movement of sediments in response to waves, wind and sea levels. Erosion is a naturally occurring coastal process without which many coastal landforms, in particular beaches would not exist. Generally, coastal adaptation planning requires long-term strategies addressing various aspects such as infrastructure, land use planning and flood protection (Wong 2014). Therefore, suitable approaches must encapsulate uncertainty effectively through a range of scenarios considered for long-term adaptation planning. In previous studies, a range of qualitative and quantitative methods were used to assess the impacts of SLR on shoreline change, which include: a bathtub approach that provides simple vulnerability prediction (McGranahan et al. 2007) but not addressing uncertainty (Gesch 2009); and a quantitative coastal erosion assessment (Gornitz et al. 2001) based on Bruun rules (Rosen 1978). However, many of these methods fail to specifically address the considerable uncertainty involved in quantifying how factors influence the shoreline (Gutierrez et al. 2011).

Gutierrez et al. (Gutierrez et al. 2011) developed a Bayesian Network (BN) model to demonstrate the probability of shoreline change rate on the U.S. Atlantic coast, while Dlamini (2011) developed a spatially explicit BN model to assess climate change impact on vegetation in Swaziland. Following the suggested research directions in these two previous studies, we coupled GIS and BN to generate probabilistic risk maps for predictions of coastal erosion in a small Pacific island, namely, Tanna Island, Vanuatu (Figure 11.5).

Figure 11.5 – Tanna Island’s reliance on the sea is affected by sea level rise and coastal erosion

Key distinctive characteristics of the novel approach developed and demonstrated in this study are:

- (a) use of high-resolution raster datasets (10m) for more accurate prediction;
- (b) development of a BN (structure and parameters) from data rather than using expert knowledge; and
- (c) rapid and interactive demonstration of probabilistic predictions through BN and GIS coupling

As illustrated in Figure 11.6, the first step of BN and GIS integration is to define a BN structure to understand the coastal system qualitatively. The structure was created using Netica software package (Norsys 2018). The input data used in the BN is based on GIS layers. Thus, as a second step, all datasets required to populate the BN input variables were converted to spatially explicit raster grids with a resolution of 10m using ArcGIS (ESRI 2014). The next step was to generate ASCII prediction maps using Netica for shoreline mobility.

Figure 11.6 – Hybrid BN and GIS Architecture

The prediction of future shoreline change is a challenging issue due to a range of complex factors contributing to inherent uncertainties and the absence of high-resolution data required for sophisticated physical modelling. The complexity requires integrated robust approaches to understand the causal relationships between the system components. The BN approach provides a robust platform for modelling the complex interactions of these factors influencing the shoreline changes and to quantify the prediction uncertainty. The proposed spatial BN, through the integration of BN with GIS, offered a novel integrated modelling approach to generate probabilistic prediction maps of likely climate change related to erosion impacts.

For further details, the interested reader is referred to Sahin et al. (2019).

11.5 CONCLUSIONS

Modelling is a spontaneous human process to fulfil our need to understand, predict and control the world around us. SeaCities, and in general coastal cities of the future, will disrupt our

current way of living. As such, our ability to predict and control such new living environment will be lower than what we are capable of in traditional coastal, land-based environments. Therefore, the need for modelling will increase even further.

Though other existing books and resources can provide a more in-depth illustration of the modelling techniques described herein, this chapter wanted to introduce the interested reader with limited modelling knowledge, to a range of modelling categories, highlighting pros and cons and their suitability based on available inputs and desired outputs. The two most important conclusions are:

- (a) We are now in the world of smart technology and artificial intelligence. As such, empirical data-driven models will see a surge in their application opportunities. Widespread deployment of high-frequency sensors and surge in computational capabilities of our machines will allow the understanding and modelling of complex environmental or human patterns and behaviours, which will in turn facilitate a better design of SeaCities.
- (b) Although, individually, data-driven models are expected to become by far the leading modelling type to be deployed, an integrated, “participatory” approach is also recommended when modelling complex systems. A step-by-step, hybrid modelling process, where sensor data is merged with experts’ input, and different modelling types are linked together, will likely lead to a more comprehensive, and accurate, understanding and modelling of the system analysed.

Whilst the full concept of SeaCities might not be realised for a while, the increased dangers to coastal cities coming from sea level rise and overall climate change, with predictions continuously updated for the worse, are increasingly making such concept worth of discussion, especially for those coastal cities where adaptation is not even an option anymore and retreating appears the only way forward. Modelling approaches described herein will increasingly become the right-hand man to SeaCities and will assist in understanding, predicting, and improving the economic, environmental and social viability of SeaCities-related projects.

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