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Modelling the effect of sea level on SE Australian coastal wetlands: a multistage model validation and comparison study

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Abstract

As the rate of sea-level rise is set to accelerate, there is increasing concern regarding the long- term sustainability of coastal wetlands. The validity of a model to reliably represent a particular wetland system considered to be vulnerable is crucial to support efficient management. The primary aim of this study was to examine the adequacy of numerical models in predicting the response of a SE Australian wetland to rising sea levels. A multistage validation process was employed to assess the operational and conceptual validity of three models for the Australian context, with specific focus on the Sea Level Affecting Marshes (SLAM) model originally developed for North American wetlands. A second model, the Spatially Applied Adjusted Temmerman (SAAT) model, originally developed for a Northern European wetland was adjusted and applied in this study. Comparison of the two models with a third developed specifically for an Australian context, the Oliver model, provides further insight into the adequacy of each model to predict the evolution of SE Australian coastal wetlands with rising sea levels.

Basic verification of the SLAM model revealed a significant flaw in the model code, whereby the A1T and A1FI maximum SLR scenarios were interchanged. Predictive validation suggested that the SLAM model had the greatest predictive power over decadal timescales. Inaccuracies noted between modelled and observed data revealed the potential inability of the model to capture important variables influencing the evolution of the Minnamurra site, such as rainfall, groundwater and El Niño–Southern Oscillation (ENSO) related environmental factors. Overall, however, projected model results and conceptual validation of the SLAM model revealed potential conceptual flaws regarding vegetation succession, treatment of wetland surface elevation change (SEC) and simulation of tidal water levels, all of which have the potential to decrease the predictive ability of the model and increase uncertainty of simulated results. The SLAM model was most sensitive to sea-level rise (SLR) and parameters pertaining to the inundation of wetlands, such as tidal range. Stochastic uncertainty analysis allowed for a richer understanding of possible future wetland distributions under rising sea levels but also indicated that the data and conceptual errors within the SLAM model propagated a wide range of uncertainty into deterministic model outcomes. Specific focus on the digital elevation model revealed high accuracy, obtained from expertly refining as-received Light Detection and Ranging (LIDAR) data, was crucial for modelling purposes.

Each of the models applied in this study generated plausible wetland distributions for future scenarios. Comparison of the models indicated that differences were primarily a result of model structure and mathematical expression, indicating that the most applicable model to the Australian context could not be definitively identified.

Despite the potentially large error and uncertainty, modelling remains important in a manager’s tool kit, providing an understanding of the potential response of wetlands to anticipated rising sea levels. It is recommended, however, that stochastic uncertainty analysis be conducted so as to encompass a wider range of possible future scenarios in the planning and decision-making processes regarding the protection of wetlands for the future.

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13th April 2016

Modelling is like sin. Once you begin with one form of it you are pushed to others. In fact, as with sin, once you begin with one form you ought to consider other forms . . . But unlike sin – or at any rate unlike sin as a moral purist conceives of it – modelling is the best reaction to the situation in which we find ourselves.

(Morton & Suárez, 'Kinds of models', 2001)

ABSTRACT

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LIST OF ABBREVIATIONS

AHD	Australian Height Datum
CCA	Comprehensive Coastal Assessment
DEM	Digital Elevation Model
HHWSS	High High Water Solstice Springs
IPCC	Intergovernmental Panel on Climate Change
LIDAR	Light Detection and Ranging
MHW	Mean High Water
MSL	Mean Sea Level
NSW	New South Wales
NWI	National Wetlands Inventory
SAAT model	Spatially Applied, Adjusted Temmerman model
SE	Southeast
SEC	Surface Elevation Change
SET	Surface Elevation Table
SLAM model	Sea Level Affecting Marshes model
SLR	Sea Level Rise
SOI	Southern Oscillation Index
RMSE	Root Mean Square Error
RTK	Real Time Kinematic

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1 INTRODUCTION

Observed and predicted increasing rates of sea-level rise have caused considerable concern for the long-term sustainability of coastal wetlands around the world (Reed 1995; Webb *et al.* 2013). Saline coastal wetlands occur in low energy, saline environments and lie within narrow elevation ranges associated with tidal inundation (Rogers & Woodroffe 2014). These environments are essential to the livelihood of many societies around the world and provide a range of critical regulating services many of which are of considerable economic value to society, including shoreline armouring against storms and erosion, nutrient cycling and carbon sequestration (Barbier *et al.* 2011). These important environments occupy a large area globally, with mangroves covering an approximate area of 137 760 -152 308 km^2 (Spalding *et al.* 2010; Giri *et al.* 2011) and saltmarshes occurring over more than 45 000 km^2 (Greenberg *et al.* 2006). However, due to their characteristic position within the intertidal zone, these extensive areas are considered to be one of the most vulnerable to rises in sea level. As coastal wetlands are inextricably linked to sea level and tidal inundation, changes in tidal regimes of coastal environments influenced by sea-level rise (SLR) during the twenty-first Century will likely see a significant influence on the distribution of coastal wetlands and, in turn, the valuable services they provide. In order to effectively plan for such situations and successfully manage the coastal environments so important to many, the spatial and temporal impacts of SLR need to be well understood. The quality and effectiveness of an environment management plan is determined by the ability to accurately project the response of coastal wetlands to SLR (Martin *et al.* 2000).

Over the past few decades, models that attempt to determine the effect of SLR on coastal wetlands have been developed as a response to the evident need in planning and management (Morris *et al.* 2002; Temmerman *et al.* 2005; D'Alpaos *et al.* 2007; Kirwan & Murray 2008). The models are based on the understanding that the persistence of coastal wetlands is dependent upon the system's ability to maintain elevation with respect to rising sea levels (Cahoon *et al.* 2006). Persistence of coastal wetlands is dependent upon a variety of interconnected processes that build the wetland surface, such as sedimentation, and those that decrease the relative surface elevation, such as soil compaction or inundation resulting from rising sea levels. Increases in frequency and duration of inundation caused by SLR disrupts the balanced environment of wetlands, leading to increases in sediment deposition and maintenance of wetland position, landward shifts in vegetation distribution or, in cases of extreme disequilibrium between wetland surface gains and rate of relative SLR, complete submergence of the coastal wetland (Warren & Niering 1993; Kirwan & Murray 2008; Rybczyk & Callaway 2009). It is these responses critical to wetland evolution that are attempted to be captured in modelling efforts to provide a richer understanding of future wetland distributions under accelerated rates of SLR.

Following the pioneering attempts of modelling wetland evolution (Krone 1987; Allen 1990; French 1993), many of the current numerical models are concerned with aboveground, depositional processes that successively increase elevation over time without providing due consideration of erosional processes on changes in wetland surface elevation (Allen 1995; Clough *et al.* 2012). Other models have explicitly considered erosional and depositional processes (Mudd *et al.* 2004; Kirwan & Murray 2007; Marani *et al.* 2007) yet neglected to incorporate belowground processes. The processes incorporated in a model are partly the function of a modeller's abstraction of the dynamic wetland system, considering the processes most important to the particular site under study. However, the manner in which a system is abstracted, conceptualised and incorporated in a model has a distinct effect on the validity and adequacy of the model to simulate the response of wetland systems to rising sea levels.

Indeed concern has arisen regarding the application of models to systems which display distinctly different geomorphic, hydrological and ecological characteristics to the wetland environment in which the model was initially conceptualised and validated. This is most particularly the case for modelling of SE Australian wetlands. Many of the existing models developed to simulate the effect of SLR on coastal wetlands, such as the Sea Level Affecting Marshes Model (SLAM Model), have been conceptualised for, calibrated and applied to North American or European coastal wetlands, where the geomorphic and environmental conditions are somewhat different to those that support coastal wetlands in SE Australia. In spite of this, these models are being applied to SE Australian coasts without due consideration being given to the efficacy of the models for coastal wetlands in Australia. This ultimately affects the understanding of the unique ecosystems gathered from applying such models and impacts the effective management of these vulnerable environments. Given the significant consequences, it is important to ascertain the validity and reliability of applying such models to Australian wetlands in order that managers may more confidently and effectively prepare and plan for the uncertain future.

1.1 Aims and objectives

This study aims to consider three existing models initially developed for different geographical areas and examine their adequacy in predicting the evolution of SE Australian coastal wetlands under accelerating rates of SLR. The Sea Level Affecting Marshes (SLAM) model is one of the most widely used spatial landscape models originally developed for North American coastal wetlands. Applying the SLAM model to SE Australian coastal wetlands, where the geomorphology and ecology differs from that of North America, throws into question the efficacy and reliability of the model results. Many, however, have continued to implement the model to Australian wetlands without considering the potential impact on results obtained. Considering the change in context and the need for reliable information for management, a validation of the model for the Australian context.is overdue

Other numerical models also exist that may be applied to simulate the response of coastal wetlands to SLR, some of which have been specifically designed for the Australian context. Oliver (2011) developed a statistical model that included the most influential factors affecting the evolution of the coastal wetlands of Minnamurra, Australia. Temmerman *et al.*(2003b) proposed a model that described the sedimentation rates over a Northern European wetland. Adjustment of the model to represent surface elevation change (herein referred to as SEC) and inclusion of a sea level rise component produces a numerical model, the Spatially Applied Adjusted Temmerman (SAAT) model, that may potentially be used in describing the evolution of Australian wetlands. Comparison of the Oliver, SAAT and SLAM models, each developed for a different geographic region, provides further insight into the adequacy of each model to predict the evolution of SE Australian coastal wetlands with rising sea levels.

Modelling the effect of SLR on coastal wetland systems is inherently complex. Not only is a natural system inherently unpredictable, but the conceptualisation of the system, structure of the model and input data used to implement the model may all contain errors or limitations that generate uncertainty in model output. Validation of the SLAM model and examination of the adequacy of the three models to simulate the response of Australian wetlands to SLR must, therefore, occur parallel to an investigation into errors and uncertainty within data and model outcomes.

Though difficult to simulate the dynamic nature of the wetland system and impacts of SLR with absolute precision, creating the most reliable and effective model of future environments is critical for planning and management of these vulnerable systems.

To fulfil the primary aim a number of objectives are outlined for this study; To:

1. Examine the importance of expertly generating the highest vertical resolution of elevation data possible to when modelling the response of wetlands to SLR;
2. Ascertain the internal consistency of the SLAM model in a basic verification process;
3. Investigate the validity of the SLAM model for the Australian context;
4. Examine the plausibility of future wetland distributions simulated by the chosen models;
5. Assess the effect of model structural flaws and data error on the uncertainty of model outcomes;
6. Compare model results developed for different wetland systems around the world, examining their performance when applied to an Australian wetland;
7. Examine reasons for differences in simulated output between models applied, considering the conceptual, structural and data requirements of each;
8. Determine the model most applicable to the Australian context;
9. Evaluate the importance of modelling in the management of coastal wetlands.

1.2 Thesis outline and scope

This thesis presents a review of the current literature relating to mangrove and saltmarsh distribution, sea-level rise and the response of coastal wetlands to changes in sea level. It also examines the philosophy and process of modelling and model validation and the numerical models developed to simulate wetland evolution, with specific reference to the SLAM and other models. In Chapter 3, the study site is defined and the processes of data collection and generation for model parameterisation are outlined. In addition, each numerical model applied within this study is described and its application and analysis explained. Verification and validation techniques implemented for the SLAM model and methods of model comparison are also defined. Chapter 4 presents the results of DEMs generated and associated accuracy assessment. Outcomes of the SLAM model verification and validation processes are also reported and model output of the other models within the study are examined. The final section of the chapter presents the results of model comparison of the three models used in this study. The following chapter, Chapter 5, provides a discussion of the results obtained in relation to the appropriate literature and an investigation into the conceptual validity of the SLAM model is conducted. The final chapter integrates and presents the conclusions drawn from the study and provides recommendations for the use of the SLAM model, in particular, and the choice and application of ecological models in general.

2 LITERATURE REVIEW

Modelling the effect of sea level rise on southeast Australian wetlands cannot be effectively undertaken without a thorough understanding of the relevant previous and current literature. Thus, this chapter explores the history of sea level over the Quaternary period, projections of sea level into the future, the distribution of saltmarsh and mangroves and the possible responses of these wetland environments to sea level rise (SLR). Particular attention is placed upon the modelling process and simulating the responses of coastal wetlands relative to future sea level fluctuations.

2.1 Coastal wetlands

2.1.1 Characteristics and global distributions

Saltmarshes and mangroves are coastal wetlands situated within the tidal frame of low energy coasts. A complex interplay of physical, biological and climatic factors affect the distribution, persistence and adaptation of these coastal communities. As intertidal communities, the elevation limits of saltmarsh and mangroves are significantly influenced by the local tidal range, establishing between highest (HAT) and lowest (LAT) astronomical tides. Mangroves are commonly located lower in the tidal frame, with saltmarshes being established in levels higher than mean high water neap tide (MHWNT) (Allen 2000).Where mangrove and saltmarsh communities coexist, saltmarsh is frequently found in the upper intertidal areas on the landward side of established mangrove stands (Wolanski *et al.* 2009).

Mangroves cover approximately 137 760 -152 308 km^2 of the globe and typically develop within the middle latitudes, dominating tropical and subtropical coastlines (Spalding *et al.* 2010; Giri *et al.* 2011). The global distribution of mangroves generally correlates with the 20°C isotherm for sea surface temperature (Duke *et al.* 1998), partly due to the sensitivity of mangrove species to cold and frost. Duke *et al.* (1998) found that factors such as the dispersal and establishment of propagules, availability of suitable habitat and climate and tectonic events may all be contributing factors to the distribution of mangroves. At their latitudinal extreme, in Australia and New Zealand, the productivity and species diversity of mangroves is significantly reduced, which is most likely due to the stress experienced from the lower seawater temperatures.

In contrast, saltmarsh is relatively tolerant of colder seawater temperatures and as such can grow in Arctic and sub-Arctic conditions (Mendelssohn & McKee 2000). The productivity and diversity of saltmarsh communities increases with increasing latitude. Globally, it appears that saltmarsh establishes in areas where mangroves are not present or are not well established (Kangas & Lugo 1990). From such observations, it has been hypothesised that mangroves would dominate the coastlines if not for the temperature limitation of the tropical/sub-tropical vegetation (Kangas & Lugo 1990). However, evidence from the field suggests that salt marsh has encroached upon mangroves in some areas (McKee *et al.* 2004).

Coexistence of saltmarsh and mangrove is observed along coastlines in temperate climates. Admixtures of these tidally influenced environments are present in Asia, Africa, Australia/New Zealand, North America and South America (Saintlan *et al.* 2014).Whilst temperature is certainly a factor influencing the establishment and survival of these wetlands, the distribution of mangroves and saltmarsh within these communities is predominately determined by the local variations in geomorphology, hydrology and climate.

2.1.2 Mangrove and saltmarsh communities of NSW

In southeast (SE) Australia, coexisting mangrove and saltmarsh communities are frequently associated with barrier estuaries and infilling drowned river valleys (Roy 1984). According to Roy *et al.* (2001), river valleys of the SE Australian coast drowned during the postglacial rise in sea level slowly infill, creating intertidal zones appropriate for mangrove and saltmarsh colonisation. Unlike some coastal wetlands, such as those of the northern Gulf of Mexico (Patterson & Mendelssohn 1991), mangroves of SE Australia are typically established at lower elevations of the intertidal zone, with saltmarsh occupying higher elevation sites within the tidal frame (Montague & Wiegert 1990).

The distribution and vegetation succession within these intertidal, estuarine environments has been debated. Contrary to the succession model proposed by Pidgeon (1940), Saintilan (1997) suggests that saltmarsh encroaches upon mangroves in SE Australian wetlands whilst the seaward boundary of the mangrove forest ‘marches’ forward (Saintilan & Hashimoto 1999; Saintilan *et al.* 2009). This is proposed to occur due to successive intertidal zones being developed as the maturing drowned valley infills, causing mangroves to colonise the new intertidal habitat and the predominantly elevation-determined boundary between saltmarsh and mangrove to also prograde seaward. Mangrove peats and root material found beneath current saltmarsh communities of SE Australia provide strong evidence for this geomorphically controlled vegetation succession model (Saintilan & Hashimoto 1999; Saintilan & Wilton 2001).

However, contrary to this model, recent observations and evidence suggest that in many areas mangrove has ‘marched’ landward, encroaching upon upper intertidal saltmarsh (Harty 2004; Rogers *et al.* 2005, 2006; Saintilan & Williams 2000; Saintilan & Wilton 2001; Saintilan *et al.* 2014). In SE Australia, approximately 30% of saltmarsh has been replaced by mangrove vegetation (Mitchell & Adam 1989; Straw & Saintilan 2006). Growth of mangroves in previously saltmarsh-dominated areas is considered to be driven by environmental changes, including elevated levels of atmospheric CO^2, increased rainfall and higher temperatures (Eslami-Andargoli *et al.* 2009; McKee *et al.* 2012). Rises in sea level are also cited to cause changes in the distribution of salt marsh and mangrove in SE Australia (Rogers *et al.* 2006). With increasing awareness of climate change, numerous studies are focusing upon the possible future effects of the environmental changes such as SLR on the distribution and fate of coastal wetlands.

2.2 Sea level

In concert with both physical and biological processes, sea level is integral to the long-term evolution and ultimate survival of saltmarsh and mangroves. The sensitivity of saltmarsh and mangroves to sea level is clearly exhibited in both the geological record and data recorded at shorter temporal scales (Allen 2000). In order to model the future response of these environments to eustatic trends, it is vital to understand past fluctuations in sea level and the change they effected on past environments.

2.2.1 Quaternary sea levels

A series of glacial-interglacial cycles characterise the Quaternary period (Alley & Clark 1999; Lambeck *et al.* 2002). Drawing from both geological data and recent observations, changes in sea level are considered to result from a complex interplay of processes (Van de Plassche 1982; Murray-Wallace & Woodroffe 2014). Climate change is considered to be the major driver of Quaternary glaciations and consequent changes in sea level. The end of the last glacial maximum occurred approximately 20ka and saw a subsequent rise in sea level by some 130 m (Lambeck *et al.* 2002). However, SLR is not recorded to have been uniform across the globe. Compilations and comparisons of data collected at a wide range of locations quickly reveal that the recorded patterns of SLR differed at individual sites throughout the world (Fairbridge 1961; Pirazzoli 1996). These variations in eustatic trends are primarily attributed to changes in land height at local or regional scales. These and other similar observations gave way to the development of the term relative sea level; the position and height of the sea relative to the land. Various processes such as isostatic rebound or land subsidence can cause significant changes in the elevation of the land and, in coastal settings, can substantially affect the position of sea level relative to the land.

Substantial differences in relative sea level are evident in the Quaternary records of past coastal environments around the world (Clarke *et al.* 1978; Figure 1). During the LGM large expanses of Northern Europe were covered by ice. The melting of these ice sheets led to vertical crustal movements due to glacio-isostatic and hydro-isostatic processes. As a result, north and north western Europe experienced a drop in relative sea level (Lambeck *et al.* 1998). However, only a few hundred thousand kilometres to the south, relative sea level in south-southeast Europe rose rapidly, exhibiting a 14 m – 25 m rise from 8ka to 5ka (Lambeck 1997). More gradual increases in relative SLR occurred to bring the relative sea level to its present position.

On the other side of the earth, Australia is a relatively tectonically stable continent and has no record of having being covered by ice sheets during the LGM. As such, falls in sea level due to tectonic processes or isostatic rebound of the earth following the melting of land-based ice are not observed. In fact, since the LGM, sea level around the Australian mainland only reached a level approximately 1m to 2m higher than present (Lewis *et al.* 2013) and has remained close to its current elevation since the mid-Holocene. The differences in patterns

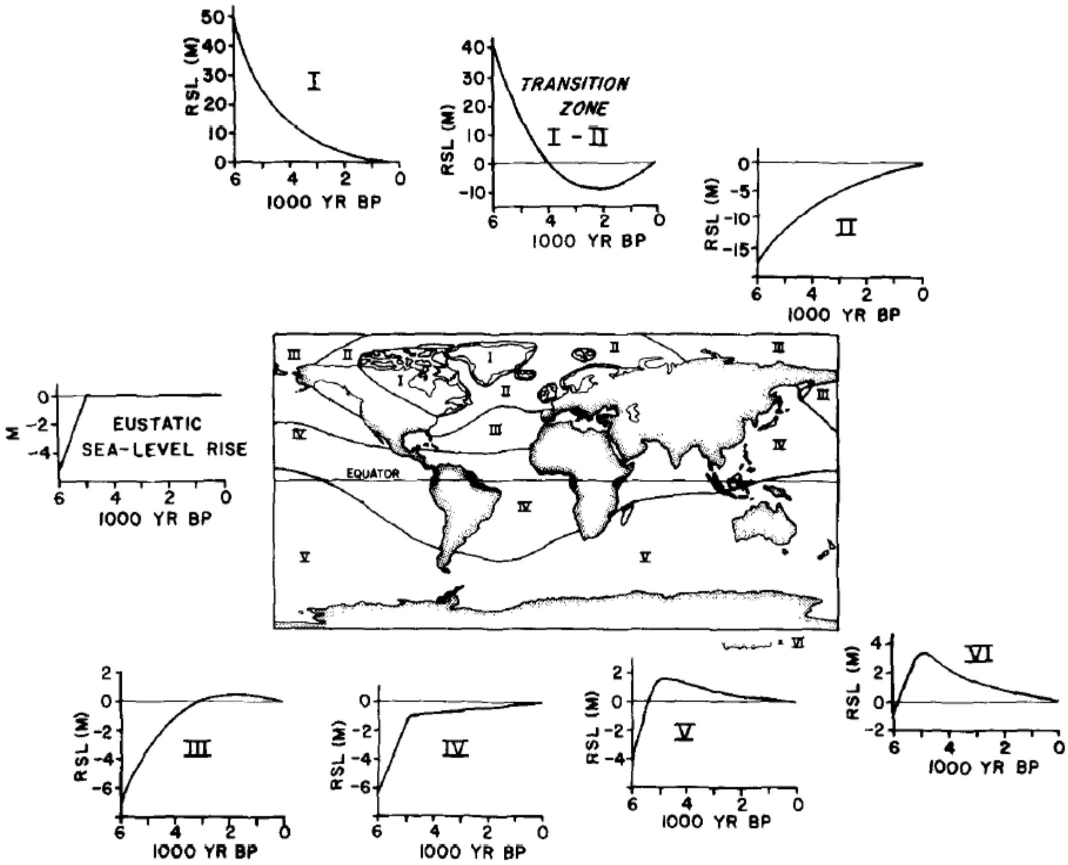


Figure 1:Differences in sea level around the world during the Quaternary are clearly displayed in the sea level curves of six zones delineated by Clark *et al.* (1978). *Zone I* covers formerly glaciated areas that experienced classic glacial isostatic rebound succeeding deglaciation. The *Transition zone* between *Zone I* and *Zone II* experienced a decrease in sea level, as the land emerges from beneath the receding glacier followed by an increase in sea level, as the underlying mantle material constituting the forebulge migrated towards the uplifting centre of the glacier. Sea level in *Zone II* continually rose due to the collapse of the forebulge. *Zone IV* also remains submerged with sea level constantly rising to its present position. In contrast, *Zone V* and *Zone VI* are characterised by a rise in sea level to 2-4m above present sea level approximately 5000 yr BP followed by a gradual decrease in sea level to its present position. The differences in past SLR around the globe affect the present day differences in wetland geomorphology.

and magnitude of SLR have contributed to variations in the geomorphology of natural coastal systems, such as wetlands.

2.2.2 Current and future sea level trends

Relative sea levels recorded in tidal data over the past century suggest that sea level is currently rising at an increased rate and has been doing so since the last glaciation. Records suggest that after the period of relatively stable sea level during the late Holocene a period of more rapid SLR was observed from the mid nineteenth century to present. During the 20th century an average SLR of 1.7mm per year (mm/yr) was observed (Church *et al.* 2013). Global mean SLR is currently estimated at approximately 3.2 ± 0.4 mm/yr (Krauss *et al.* 2013). Rates of SLR are predicted to accelerate in a non-linear fashion (Nicholls & Cazenave 2010) and are expected to again show local and regional variations across the globe (Figure 2).Church *et al.* 2013 suggest that rates of SLR will predominately fall within 20% of the global mean.

The fourth assessment report from the Intergovernmental Panel on Climate Change (IPCC) projected a SLR of 0.59m-0.81m by the year 2100 (IPCC, 2007). Projections of future sea levels are, by nature, uncertain, however rates of SLR have broadly tracked those simulated for scenarios of high sea level changes. Given this, it has been proposed that future sea levels are likely to be closer to the upper edge of the IPCC projections (Church *et al.* 2010), though

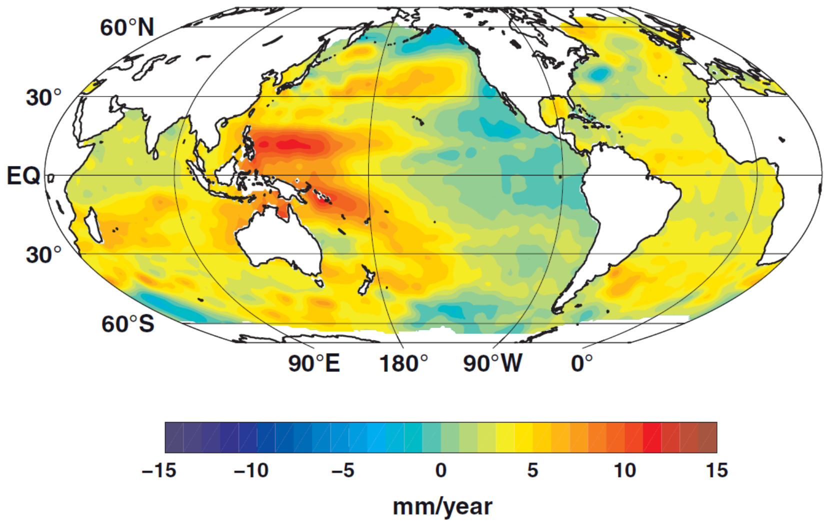


Figure 2: Map of deviations from the global rate of sea level rise for the period 1993-2009. (Source: Church *et al.* 2010). Variabilities in the rates of sea level rise are predicted to continue throughout the 21st Century.

deviations are certainly still considered possible (Rahmstorf 2007; Grinsted *et al.* 2009). Whilst it is generally agreed that sea level will rise over the next century, the degree of change is debated. Vermeer and Rhamstorf (2009) consider the IPCC projections to be too conservative, instead predicting a 0.75-1.90m rise in sea level by the end of the 21stCentury. Grinsted *et al.* (2010) also dispute the rates proposed by the IPCC AR4. Extensive debate continues to surround predicted levels and rates of SLR. Though determining future sea levels remains an active and widely debated area of research, there is general consensus that such rapid rises in sea level could have detrimental effects on coastal wetlands.

2.2.3 Sea Level Trends of the Southeast Australian Coast

The most recent report on the state of the Australian climate jointly prepared by the CSIRO and Bureau of Meteorology reveals that there has been a rise in global mean sea level of some 225 mm since 1880 (CSIRO & BOM 2014).Based upon reliable, relatively continuous data since 1966, SLR along the Australian coast has been broadly analogous to the global average trend (White *et al.* 2014), with some variation observed (Couriel *et al.* 2014).

Similar to global observations, an acceleration in rates of SLR around Australia from the end of the last century is calculated, with a rise of 3.1 ± 0.6 mm/yr from 1993 to 2009 (White *et al.* 2014). However, local and regional departures from the global mean sea level trend have been observed. Based on satellite altimetry data, sea level trends along the NSW coast range from approximately -1mm/yr to +4mm/yr (Couriel *et al.* 2014). Variabilities in sea level trends are attributed to a number of influences working on long term, decadal and inter-annual timescales (Table 1) (BOM 2010; Church *et al.* 2006; Feng *et al.* 2004; Holbrook *et al.* 2011; Kolker & Hameed 2007; Woodworth *et al.* 2009). Such influences are often difficult to isolate from sea level trends when calculating rates of SLR (Monselesan *et al.* 2015; Zhang & Church 2012). Multiple studies have noted that tidal records and altimeter data studied need to cover a sufficient period of time in order to smooth the effects of these meteorological and oceanographic influences and determine the underlying, long-term trends in SLR (Chambers *et al.* 2012; White *et al.* 2014; Zhang & Church 2012).

One of the most significant influences on sea levels measured at the SE Australian coast is the El Niño Southern Oscillation (ENSO) (BOM 2014; Church *et al.* 2013; Holbrook *et al.* 2011). The large-scale, meteorological phenomenon is a three to eight year natural cycle which is characterised by lower sea levels during El Niño events and higher sea levels

Driver	Sea-level response	Indicative timescales
Gravitational attraction of astronomical bodies	Tides	Hours, with some influences extending over multiple years
Wind	Set-up	Days
Changing atmospheric pressure	Inverted barometer	Days
Ocean currents	Variations	Weeks to months
Annual temperature cycle	Annual cycle	One year
El Niño/Southern Oscillation	Interannnual oscillations	Years
Inter decadal Pacific Oscillation	Interdecadal oscillations	Decades
Long-term global temperature changes	Long-term sea-level change	Multiple decades to centuries

Table 1: Factors influencing sea level at different time scales. (Source: OEH 2015)

during La Niña (Boening *et al.* 2012). Along the NSW coast of Australia, differences in sea level of approximately 300mm have been gauged between El Niño and La Niña (Watson 2011). Though these long-term, natural cycles affecting the Australian mainland are distinct from climate change driven sea level fluctuations, their contribution cannot be disregarded when considering future sea levels and their effects on coastal wetlands.

Tide data from Fort Denison, Sydney, provides the longest near continuous tide-gauge record on the SE coast of Australia, with data being collected since 1886 (Couriel *et al.* 2014). Though considered a good indicator of long-term sea level, various rates of relative SLR can be estimated from the Fort Denison gauge depending upon the time frame analysed. You *et al.* (2009) reported a rate of 0.63 ± 0.14 mm/yr for the period covering the first year during which data was collected at Fort Denison until the year 2007. Shortening the time frame analysed to 1914 - 2007 raised the rate of SLR to 0.93 ± 0.20 mm/yr whilst further restriction of the period examined, 1950 to 2007, resulted in a decrease to 0.58 ± 0.38 mm/yr. Some 90km south of Fort Denison at Port Kembla, a substantially higher rate of 2.1 mm/yr SLR was calculated for the period 1991 to 2010 (BOM 2010).

Projections of future sea level trends off SE Australia from the IPCC Fifth Assessment (Church *et al.* 2013) indicate rates of SLR up to 10% greater than the mean global model prediction are to be expected. An understanding of the local trends and future projections is necessary for modelling ecosystems response to changes in sea levels, such as that of coastal wetlands.

2.3 Responses of coastal wetlands to sea level rise

As saltmarsh and mangrove typically establish within a relatively limited range of the intertidal zone, SLR could have a detrimental effect on these coastal communities. The persistence and survival of the coastal wetlands is predominantly determined by their ability to adapt their surface elevations with respect to the rising sea level. During periods of lower SLR, coastal wetlands have historically kept pace with sea levels by accreting sediment and thereby building vertically or by migrating across the landscape (McKee *et al.* 2007; Woodroffe 1988). This pattern of past behaviour observed from sediment records is supported by relatively recent models and field studies that demonstrate a positive relationship between increases in platform water depth and sediment deposition (French 1993; Friedrichs & Perry 2001; Morris 2002). However, it is widely understood that an increase in SLR may result in the drowning of coastal wetlands as accretion within the ecosystems may not be sufficient to maintain their existence. Landward migration of these ecosystems as a response to sea level changes may also not be a viable option for coastal wetlands where anthropogenic transformations and morphology of the surrounding terrestrial landscape prevent any lateral movement of the intertidally bound ecosystems. The survival of both saltmarshes and mangroves are dependent, therefore, upon the rate of SLR, the development of surrounding terrestrial landscapes and the ability of the systems to keep pace with the sea level changes by accreting vertically or migrating laterally.

2.3.1 Principal processes and controls

Elevation changes within saltmarsh platforms and mangrove forests are influenced by a dynamic interplay of physical and biological processes. Sedimentation, erosion, organic-matter accumulation and decomposition, autocompaction, subsidence and groundwater discharge-recharge have been named as the primary processes contributing to wetland elevation change (Cahoon *et al.* 2006). These processes lead to net gains or losses within the coastal wetlands and are fundamental drivers for the evolution and persistence of the respective environments.

One of the most significant factors influencing the persistence or demise of coastal wetland communities is sedimentation. Sediment processes contributing to the positive elevation gain can be further divided into inorganic and organic sediment types. Organic sedimentation is primarily related to litter fall, which can accumulate thick deposits of organic sediment but which varies according to tidal flushing and other site-specific processes (Middleton & Mckee 2001). Inorganic sediment is usually autochthonous in origin. During flooding of the wetland, inorganic sediment carried in the water column may settle and be deposited on the wetland surface (Allen 2000; Marion *et al.* 2009; Temmerman *et al.* 2003a,b). Observations of sedimentation patterns have led to the understanding that rates of sediment deposition are a function of a variety of factors including the frequency and magnitude of inundation (Bricker-Urso *et al.* 1989; Darke & Megonigal 2003; French *et al.* 1995; Temmerman *et al.* 2003b). Sedimentation rates are noted to reduce with increasing wetland surface elevation (Cahoon & Reed, 1995) and decreasing inundation frequency (Temmerman *et al.* 2003b). Increased inundation time and magnitude associated with SLR, therefore, will logically accelerate deposition rates in coastal wetlands (French, 1993; Kirwan & Murray 2007; Morris *et al.* 2002). This fundamental feedback is considered critical to the ability of the wetland to maintain its elevation with respect to rising sea levels (Kirwan & Temmerman 2009). The feedback mechanism, however, is dependent on the sediment supply to a wetland, which is, in turn, related to the local environmental factors and geomorphology (Cahoon *et al.* 2006, 2011; Woodroffe 1990). Wetlands obtaining high inorganic sediment supplies are considered more likely to benefit from the feedback response and therefore survive a rise in sea level. In direct contrast, where biogenic material is the primary contributor to sedimentation in the wetland, only slow rates of SLR are expected to be sustainable.

Biotic processes also play a significant role in wetland elevation change and subsequent survival under rising sea levels. Cahoon *et al.* (2006) discriminated between biologic processes that had a direct and indirect effect on wetland SEC. Direct biotic influences include the formation of algal mats and subsurface root production, where the balance of plant root growth and decay and associated expansion of soil volume have been found in some wetlands to be directly related to elevation change (McKee *et al.* 2007; McKee 2011). Indirect processes of biotic relate to the influence of vegetation on inorganic sedimentation processes. Vegetation may enhance sedimentation via direct capture of sediment (Yang *et al.*

2008). In addition, many studies have shown that with increased vegetation above ground flow velocities, turbulence and erosion across the wetland surface are reduced, all leading to greater sedimentation (Leonard & Luther, 1995; Morris *et al.* 2002; Mudd *et al.* 2010). The combined effect of these interrelating factors and feedback mechanisms further accelerates accretion rates and allows the wetland surface to survive increasing rates of SLR (Kirwan *et al.* 2010; Morris *et al.* 2002).

In addition to the positive gains generated by sedimentation-accretion and vegetation, many processes cause wetland surfaces to decrease in elevation. Though a wetland may accumulate a large body of sediment, autocompaction of the soils can cause the gain to be considerably offset (Cahoon & Reed 1995). Compaction of the soil is influenced by the hydrology of the wetland, where the weight of increased tidal waters results in the compression of aerated soil layers (Cahoon *et al.* 1995, 2011; Nuttle *et al.* 1990). Wetland hydrology has also been found to influence the shrink-swell pattern of soils in coastal wetlands (Nuttle *et al.* 1990; Cahoon & Lynch 1997). Decreases in rainfall runoff and the lowering of the soil water table effectively leads to soil shrinkage and losses in surface elevation (Cahoon & Lynch 1997; Cahoon *et al.* 2006; Smith & Cahoon 2003). Droughts, too, are observed to result in extended periods of soil shrinkage and concomitant losses in wetland surface elevation (van Wijnen & Bakker 2001; Rogers *et al.* 2005). Coastal wetlands of Australia have been found to be particularly effected by ENSO related droughts (Rogers *et al.* 2005). A coastal marsh in Louisiana under severe drought conditions also lead to increased substrate consolidation and loss in wetlands due to lowered groundwater levels (Cahoon *et al.* 2011). In contrast, higher rainfall periods have resulted in increased groundwater levels and expansion of soils, ultimately generating positive elevation changes within the wetlands (Rogers & Saintilan 2009; Rogers *et al.* 2014; Whelan *et al.* 2005). Overall, the changes in water storage and resulting shrink-swell responses have been found to generate rapid and short-term impacts that can display elevation changes up to five times greater than the long-term trend in wetland SEC (Cahoon *et al.* 2011). At longer time scales, such as is the case for ENSO related droughts, these processes may have a lasting impact on the longterm evolution of the coastal wetland.

Subsurface processes have also been demonstrated to contribute to the elevation dynamic in coastal wetlands. Decomposition of organic matter inevitably causes a loss in overall surface elevation. Root structures influences the total soil volume and, thereby, the wetland elevation. The loss of root volume after death therefore causes a collapse of the root structures and further compaction of soils (McKee 2011; Mckee *et al.* 2007). Increases in flooding appear to be linked to an increase in root decomposition rates, most likely a factor of the greater anoxic conditions (Mckee *et al.* 2007). Therefore, accelerating rates of SLR and concomitant increases in flooding frequency and magnitude in coastal wetlands may have potentially debilitating effects.

Storms, floods and pulsing events have been observed to affect both surface and subsurface processes contributing to the net vertical change of a wetland (Nyman *et al.* 1995; Cahoon 2003, 2006). The short-term, high-magnitude perturbations within the system are commonly associated with greater turbidities which may result in significant storm deposits or redistribution of sediments (Cahoon *et al.* 1996; Nyman *et al.* 1995). In contrast, some studies have found that storms may cause erosion due to the disturbance of increased flow velocities and the impact of rainfall (Pethick 1991; Cahoon *et al.* 1995).In some cases, subsurface collapse of the root zone has caused significant decreases in elevation (Cahoon *et al.* 2006). With increased frequency of storms attributed to climate change predicted for the future, the effect of storms may have an increasingly significant impact on the ability of a wetland to persist under accelerating rates of SLR.

Overall, the processes contributing to net elevation changes in wetlands will play a significant role in the persistence of coastal wetlands under rising sea levels. Each of the processes is affected by geomorphic, hydrologic, biotic and climatic controls occurring at different time scales. Examining the ability of wetlands to build vertically, it is apparent that consideration of one process only is not possible to ascertain the response of wetlands to SLR. Ultimately, it is the dynamic equilibrium between forces which contribute to the wetland elevation and controls on its deterioration that govern the long-term evolution of a wetland and drive the response of a wetland to SLR (Rybczyk & Callaway 2009).

2.3.2 Threshold rates of SLR

Despite the processes and feedbacks known to regulate the ability of a wetland to keep pace with rising sea levels (Redfield 1972; Reed 1995; Cahoon *et al.* 2006), observations and modelling of the dynamic system have indicated that there is a limit to the adaptability of coastal wetlands (Kirwan *et al.* 2010; Morris *et al.* 2002; Nicholls *et al.* 2007; Reed, 1995). The threshold rate of SLR at which vegetation is unable to persist and ecogeomorphic feedbacks become inefficient in maintaining wetland surface elevation has been found to vary significantly by site. Depending on factors such as the sediment supply, vegetation, geomorphic inheritance and anthropological interference at a specific wetland, threshold rates of SLR were found to range from 5mm/yr to 20mm/yr (Kirwan *et al.* 2010), with a critical rate of approximately 10mm/yr being suggested by many authors (Morris *et al.* 2002; Kirwan *et al.* 2010).

2.4 Modelling

2.4.1 A philosophical perspective

Modelling in the earth and environmental sciences involves an abstraction of nature such that modelled outcomes may adequately describe the system or process being simulated (Mulligan & Wainwright 2013). Natural systems are a complex combination of chemical, physical and biological processes, often non-linear in nature and operating at a variety of temporal and spatial scales (Young & Leedal 2013). Based on reductionist philosophy that permeates the scientific world, modellers attempt to simplify a complex system to its most influential components in order to achieve the greatest realism.

The principle of parsimony, sometimes referred to as Occam 's razor, applied to a modelling context signifies that a model should be no more complex than absolutely necessary (Lark 2001). Newton, in his first principle of reasoning in philosophy, emphasised the necessity of describing natural systems in no more complex a manner than is "….true and sufficient to explain their appearances." (Newton 1687).This guiding principle can be traced back almost two millennia to the work of Aristotle who wrote:

It is the mark of an instructed mind to rest satisfied with the degree of precision which the nature of the subject permits and not to seek an exactness where only an approximation of the truth is possible.

In a modelling context, not only do the writings of Aristotle drive a modeller to work by the principle of parsimony but also to not seek perfect predictability, where only a representation of the complex system can be achieved. Laplace (1820) further warned of the uncertainty of the future that would limit the ability of a system to be deterministically and accurately defined.

From a philosophical perspective, then, the concept of the model as 'truth' has been repeatedly rejected. Some have even gone as far as to define a model as a work of fiction

(Cartwright 1983). The model, however, can provide the best representation of a system and is considered a powerful tool for developing an understanding of a system in the past, present or future (Baker 1998; Oreskes *et al.* 1994).

2.4.2 Model complexity

The complexity of a system is difficult to simplify and often cannot be captured by modelling techniques applied. Simple models may adequately describe the complex nature of some systems (Mitchell 2009; Scheffer 2009; Waldrop 1992), yet in others fail to sufficiently explain key processes that define the system's appearance (Nihoul 1994). In such cases, further parameters may be defined in order to increase the sufficiency of the model's explanation of the system, thereby increasing the model complexity. With increasing processing power available, the possibility of more complex models has been explored (Perz *et al.* 2013). In theory, the greater complexity allows for a closer approximation of the truth. However, the superiority of more complex models has been questioned, with many suggesting that the greater parameterisation allows for increased potential of additional errors and uncertainty (Fisher *et al.* 2002; Snowling & Kramer 2001). Models of low complexity, however, may also contain much error as a result of structural uncertainty. It is, therefore, debated which type of model is most relevant and useful in modelling of complex environmental systems (Muller *et al.* 2011; Snowling & Kramer 2001).

2.4.3 Verification and Validation

Regardless of model complexity, the modelling process involves processes of *conceptualisation*, in which the working of the system is abstracted by the modeller, *parameterisation*, where the important elements to be included in the model are defined, *calibration*, which generally involves the fine tuning of a model to achieve an optimal output, *sensitivity analysis*, where changes in model output with changing model parameters are examined to evaluate the logic and robustness of the model structure, *verification* and *validation*. Verification was first defined by Fishman and Kiviat (1968) as "…a demonstration that the model formalism is correct". With the explosion of computer use in science, a refined definition of model verification described a model as being verified "…by showing that the computer program is a correct implementation of the logical model" (Hoover & Perry 1989). The manner in which the conceptual model is accurately reflected in the computer code or mathematical formalisms is therefore the primary concern of verification procedures (Rykiel 1996). Some authors, however, have questioned the ability of a model to be verified, indicating that, following the strict sense of the word, a model cannot be proved true (Oreskes *et al.* 1994).

The concept of model validation has been debated ever since it arose in the 1960s (Rykiel 1996). A contributing factor to the problem is the lack of a clear definition of validation as it pertains to the modelling community. Levins (1966) based his definition of validity on the subjective judgment of a modeller, stating that “The validation of a model is not that it is ‘true’ but that it generates good testable hypotheses”. Other authors, however, expound model validation to be a quantitative process, where the predictive ability of a model is determined based upon the agreement of the output data with field data (Goodall 1972; Jørgensen 1986; Mulligan & Wainwright 2013; Power 1993). In an effort to resolve the conflicting perspectives on model validation, Rykiel (1996) and Sargent (1996) specified validation techniques that could be employed in modelling. Three main areas of validation were identified as important, following the work of Sargent (1986). *Operational or whole-model validation* involves the testing of the model’s correspondence with real-world observations. *Conceptual validation* considers the underlying theories and assumptions of the model, testing that they are justifiable and reasonably represented and realised in the logic and mathematical structure of the model. *Data validation* ensures that the data used to parametrise, calibrate and test the model are sufficiently accurate. To complete these validation tests a number of qualitative and quantitative techniques have been noted within the literature (McCarl 1984; Monte *et al.* 1996; Rykiel 1996;Sargent 1996; Senarath 2000). These include:

- *face validation*, where the reasonableness of the model logic and input-output relationships are tested ‘on the face of it’.
- *Turing tests*, in which experts are asked to discriminate between real-world system and model outputs.
- *predictive validation*, where model predictions are compared against real world data.
- *statistical validation*, where the range of model behaviour and its error structure are tested to ascertain the quantitative fit of the data with the real system and whether errors associated with model output fall within certain acceptable limits.
- *extreme conditions tests*, whereby extreme or unlikely conditions are set and the resulting model output is tested for plausibility.

- *comparison to other models,* which involves comparing the results of the model to output from other models.
- *sensitivity analysis,* in which the model parameters are tested to ascertain which produce the greatest change in output with only small variations in parameter value.

It is often assumed the greater number of tests a model is able to successfully pass, the more reliable and credible the model output (Sargent 1984; Mulligan & Wainwright 2013). Model validation is, thus, considered by some to be achieved when all available validation procedures fail to discriminate between real-world and model data (Brown & Kulasiri 1996). Goodall (1972) warned, however, that a model may provide adequate predictions for a certain domain or complex ecosystem but cannot be assumed 'valid' for another. With a change in context or environment, a re-validation of the model would be required.

Contrariwise, according to the Popperian account of falsification, models that fail to correspond to empirical data are to be recreated or disregarded. At the heart of the debate surrounding validation of models is a philosophical argument. Some believe model validation both possible and essential (Gentil & Blake 1981; Rykiel 1996), whilst others suggest that full validation is a logical impossibility (Refsgaard & Storm 1996; Senarath *et al.* 2000). Oreskes *et al.* (1994) argue that it is impossible to establish if a model is 'true'. They suggest that in validating a model problems arise relating to the difficulty of demonstrating the truth of open systems (such as the environment), the erroneous acceptance of a model that fits the observational data for the wrong reasons, the possibility of obtaining the same output from more than one model (non-uniqueness or under determination), the impossibility of determining if a principal or additional hypothesis is incorrect when errors occur, the presence of unknown factors excluded from the conceptual design and, lastly, the fact that assumptions and uncertainty underlie all stages of the observation and measurement of the system being modelled.

Despite the problems in validating a model, many authors maintain that validation remains an important part of the modelling process (Anderson & Woessner 1992; Mulligan & Wainwright 2013; Power 1993). In line with Box and Draper (1987) who stated "*All models are wrong, but some are useful*", Burnham and Anderson (2002) argue that while a model can never be "truth" nor a prediction certain, a model can be ranked from useful to useless, according to its adequacy in describing the system under study. Oreskes *et al.* (1994) also conclude that, while full validation may be a logical fallacy, models can serve as a heuristic, improving understanding and guiding further research or management policies.

2.5 Modelling the response of coastal wetlands to sea level rise

Increasing concern regarding the sustainability of coastal wetlands under rising sea levels has led to the development of numerous models attempting to understand the potential response of these important ecosystems. Most models attempt to incorporate a variety of physical and biological factors affecting the sustainability of coastal wetlands and are built upon general conceptual frameworks of the evolution of mangroves or salt marshes. However, due to the complex, dynamic and generally unpredictable nature of natural processes, modelling the response of coastal wetlands to SLR is quite challenging and inherently incorporates errors and uncertainty. Incomplete knowledge of the natural system, data used within the model building and implementation processes and lack of sufficient measurements in space and time of the coastal wetland all contribute to the difficulties of modelling coastal wetlands.

The evolution of a wetland is the result of numerous interrelating processes operating at a range of spatial and temporal scales, complicating the ability to effectively model the long term evolution and resilience of the coastal wetlands with SLR (Cowell & Thom 1994). Many authors have noted the difficulty of collecting data sufficient in quantity and temporal range to capture the full suite of influences acting on the coastal wetlands (Rybczyk & Cahoon 2002; Woodroffe 1990). For instance, long term processes such as subsidence, and shorter term pulsing events, such as storms, may not be represented in the short-term, measurements used in the modelling process (Rybczy & Cahoon 2002). The incomplete nature of the parameterising and calibrating data leads to an inadequate description of the system's response during the modelling process, in turn resulting in additional error and uncertainty introduced to model predictions (de Vriend 1992). A similar result can occur when the factors influencing the response of the system are not exhaustively understood. Coastal environments evolve as the result of innumerable processes which are not completely understood (de Vriend 1992; Cowell & Thom 1994). The neglect of an influencing variable, understood or not, in the conceptualisation of the system has been suggested to cause significant uncertainty and flaws in resulting data (Sargent 1996; Perz *et al.* 2013). Addition of variables, surrogate parameters or bulk parameters, which can be included even without an exhaustive understanding of all significant processes and interactions within the system, can go some way to reducing the effect of such a problem. However, with increasing parameterisation carried out to mitigate the effect of incomplete system explanation within the model arise the difficulties associated with increasing model complexity (Perz *et al.* 2013;Renard *et al.* 2013; Waldrop 1992).

The influences and feedback mechanisms key to the development and persistence of coastal wetlands also generate difficulties in modelling the response of these important environmental systems to SLR. Phillips (1995) termed systems such as coastal wetlands which include complex feedbacks to be 'state dependent', since the future response of the dynamic system relies upon its prior or initial condition. Furthermore, coastal systems are inevitably non-linear as a result of the same feedback mechanisms and interconnected processes causing wetland evolution to be cumulative and ever-changing (Phillips 1992; Waldrop 1992; Wright and Thom 1977). In examining the effect of SLR on such coastal systems it is also necessary to consider the inherent uncertainty of future sea levels. When modelling coastal wetlands, boundary conditions equate to the environmental conditions influencing the system. SLR thus represents a stochastic boundary condition of the coastal wetland, since the environmental condition, SLR, has many possible outcomes, levels, which may not be predicted precisely. Cowell and Thom (1994) noted that, given the state dependence and non-linearity of the coastal system and the stochastic boundary conditions impacting the environment, the exact manner of coastal evolution is "…unpredictable, unrepeatable and irreversible…" and is "…largely a question of historical accident."

Given such a situation, reducing a system to its component parts and determining a single solution to coastal wetland evolution when modelling does little to describe the possible future response of the dynamic systems to SLR (Schumm 1991; Wright & Thom, 1977). Deterministic methods, however, continue to dominate the modelling of the impact of SLR on coastal wetlands. To mitigate the limitations and reduce the uncertainty associated with deterministic models, sensitivity and uncertainty analyses can be conducted (Perz *et al.* 2013). Sensitivity analyses systematically examine the changes in model output related to the variability of each model parameter and aids in determining the relative importance of each variable in the evolution of the coastal wetland system as defined in the model (Saltelli *et al.* 2000). Uncertainty analyses provide a method of evaluating to what extent parameter uncertainties influence the model output (Monte *et al.* 1996), thus providing confidence intervals for output data and allowing a greater range of potential outcomes to be obtained. Even when conducting the sensitivity and uncertainty analyses, however, the exact nature of the future condition cannot be specifically determined (Renard *et al.* 2013). The analyses, instead, provide a manifold of possible outcomes that serve to provide a richer understanding of the response of the inherently unpredictable wetland systems to SLR.

2.5.1 Numerical models of wetland evolution

Traditionally, rates of accretion within a coastal wetland have been compared to rates of SLR to ascertain the future sustainability of wetlands (De Laune *et al.* 1978; Reed 1995). An accretion value greater than the rate of SLR therefore signifies the persistence of the wetland, whilst equal rates indicate equilibrium and greater rates of SLR with respect to the accretion value suggest eventual submergence of the system (Cahoon 2015; Rybczyk & Callaway 2009). However, the simplicity and inherent uncertainty of comparing rates of SLR with those of sediment accretion in the dynamic, non-linear coastal systems inevitably limits the understanding of future responses of coastal wetlands to SLR. Numerical models have been developed in an attempt to improve upon such simplistic treatment of wetland sustainability and further the understanding of the impact of rising sea levels on coastal wetland (Fagherazzi *et al.* 2012). These models occur at a variety of spatial scales and attempt to account for the most relevant processes and interconnected variables affecting the wetland evolution with varying success.

Among the first to pioneer the use of numerical models in determining the response of wetlands to SLR were Krone (1987), Allen (1990) and French (1993). The models developed were all zero dimensional, signifying that changes were simulated for a single point rather than the entire wetland surface, and were primarily concerned with the sedimentation processes active within the wetland. Conceptualisation of sediment processes influencing coastal wetlands was based upon observations similar to Pethick (1981) who found that sedimentation rates decreased with increasing elevations. Mechanistic models break a system into its physical component parts to examine the behaviour of a system. Krone (1987) mechanistically simulated the change of surface elevation under varying sea levels for a coastal wetland of the San Francisco Bay. The model was calibrated to past accretion rates as determined by ^{14}C data and assumed a steady supply of sediment to the wetland surface. Only accretion of sediment was modelled, with autocompaction processes being ignored. Varying the rates of sea level, Krone (1987) found that with increasing sea levels, an increase in sedimentation occurred.

Allen (1990), working from the model of Krone (1987), developed a model to examine the evolution of a saltmarsh in the Severn Estuary, Great Britain, that allowed the variation of sediment supply and treated autocompaction implicitly. The exploratory model results were used to show the relationship between sea levels and sedimentation processes, the outcomes revealing a steep increase in sedimentation rates in new wetlands and a gradual decrease in rates as the wetland surface increased in height before reaching an approximately stable state at an elevation just below highest astronomical tide (Allen 1990). French (1993) implemented a similar model calibrated to the North Norfolk barrier coast to evaluate changes in wetland surface elevation over time.

Although only constant rises in sea level were simulated, the methods implemented in these first models remain the basis for many current models ofwetland response to SLR. Indeed, drawing from the theory and models available at the time, Allen (2000) proposed a generic equation for the elevation change at a particular time step in a model to be:

$$\Delta \mathrm{E} = \Delta S_{\mathrm{min}} + \Delta \mathrm{S}_{\mathrm{org}} - \Delta \mathrm{M} - \Delta \mathrm{P}$$

where $\Delta \mathrm{E}$ is the change in the wetland surface elevation at a given time step, $\Delta \mathrm{S}_{\mathrm{min}}$ and $\Delta \mathrm{S}_{\mathrm{org}}$ are the inorganic and organic sediment added to the surface respectively, $\Delta \mathrm{M}$ is the incremental change in mean sea level and $\Delta \mathrm{P}$ is the adjustment in surface elevation resulting fromautocompaction of the sediment. Allen (2000) noted that each of the parameters were inherently complex to simulate, especially those that involve the interrelation of other factors in feedback loops.

Modelling the rate at which the marsh builds vertically due to sedimentation has been the focus of most numerical models developed. In line with the initial modelling attempts, many models simulate the addition of inorganic sediment as a function of sediment supply and elevation, the latter being a proxy for the magnitude and frequency of tidal inundation (eg. Allen 1995; Morris *et al.* 2002; Temmerman *et al.* 2003a). Given the interconnectedness of processes affecting sediment flux and deposition in coastal wetlands, different factors and methods of simulating sedimentation have been attempted. Moving from zero-dimensional to two dimensional models, Temmerman *et al.* (2003a) simulated sedimentation rates that were a function of elevation and distance to the marsh edge and channel in recognition of the pattern of decreasing rates of sediment deposition away from the river channel resulting from progressive sediment deposition along flow paths. Others, too, included the distance to the river or tidal source as a factor when modelling wetland evolution (eg. D'Alpaos *et al.* 2007; Mudd *et al.* 2004; Oliver 2011; Rogers *et al.* 2013).

Further attempts at simulating the inorganic sedimentation component of wetland evolution have focused on the dynamic effect of vegetation and tidal flows on sediment supply and deposition. Physical models that simulate the flow paths of sediment and water across the wetland impacted by the presence of vegetation have been initialised for a variety of wetlands around the world (D'Alpaos *et al.* 2007;Marani *et al.* 2004; Mudd *et al.* 2004;Silvestri & Marani 2004; Temmerman *et al.* 2005).Physical models are "…founded on the laws of conservation of energy, momentum and mass and …(have their)…parameters and variable(s) defined by means of equations that are at least partly based on the physics of the problem…" (Favis-Mortlock 2013). Hydrodynamic models are physical models that employ the laws of fluid flow to produce a solution. A number of models utilise the hydrodynamic model of Rinaldo *et al.* (1999), that uses two-dimensional shallow wave equations to simulate flow over a tidal marsh, to develop physical models which simulate sediment transport and deposition on the coastal wetland (Fagherazzi *et al.* 2004; D'Alpaos *et al.* 2006, 2007). These models are distinct from previous modelling attempts in their explicit and detailed treatment of sediment trapping by plant biomass. Inorganic sediment trapping in these models is a function of biomass density, plant stem diameter, height of the plant stems and local flow depth. Deposition of trapped sediment was then dependent on the elevation range for saltmarsh biomass (D'Alpaos *et al.* 2007). Though physical models are, in general, considered more reliable (Kirkby *et al.* 1992), models based upon the shallow flow equations are suggested to best capture the initial stages of inundation prior to the greater influence of sheet flow at higher levels of inundation (Fagherazzi *et al.* 2012). With due consideration of the limitation, results of such studies coupling vegetation, tidal flow and sedimentation indicated the important role vegetation plays in the evolution of coastal wetlands. Given the outcomes of such simulations, it would seem unusual that the impact of vegetation is not consistently considered in modelling efforts. Certainly, more recent modelling of long term evolution of coastal wetlands has seen a focus on the incorporation of biological, hydrological and morphodynamic processes.

Assuming the same impact of vegetation on inorganic sedimentation, Temmerman *et al.* (2005, 2007) attempted to describe the dynamic relationship in a three-dimensional fashion. The model explicitly simulates tidal flow and, in addition to parameters incorporated in earlier physical models simulating the effect of vegetation on sedimentation, further includes the effects of turbulence and friction. Results of the simulations affirmed observations and modelling outcomes that suggested that the vegetation canopy has a critical impact on the spatial pattern of sedimentation rates in a coastal wetland. Though the model served to improve the understanding of coastal wetland evolution and the associated role played by vegetation, the model was not without limitations, signifying that results should be considered carefully in full appreciation of the possible inaccuracies (Fagherazzi *et al.* 2012).

The effect of plant biomass on sedimentation processes has not only been represented by physical models. Morris *et al.* (2002) developed azero dimensional model, the Marsh Elevation Model (MEM), based on empirical observations to relate the sediment accretion within a wetland under rising sea levels. MEM accounts for the effects of elevation, platform inundation and aboveground plant biomass on sedimentation. Morris *et al.* (2002) noted that wetland species *Spartinaalterniflora* was most productive at an optimum elevation below which the productivity of the species declined. To mathematically explain this relationship, biomass productivity was described as a quadratic function of inundation within the MEM model. The simulations of Morris *et al.* (2002) revealed that at an optimal rate of SLR exists where elevation and sea level would be in equilibrium, allowing for maximum plant growth. At higher rates of SLR, inundation depths would be too great and the plant community would submerge. The optimum depth at which the wetland reaches equilibrium with rising sea levels was extrapolated to be a function of vegetation, rate of SLR and concentration of inorganic sediment. Similar to all zero dimensional models, MEM excels in mechanistically simulating processes at a given location but lacks the spatial articulation so important for planning (Rybczyk & Callaway 2009).

The MEM model has formed the basis of several models that simulate the evolution of wetlands on a two-dimensional scale (Mudd *et al.* 2004; D’Alpaos *et al.*, 2005; Morris 2006; Kirwan & Murray 2007;Mariotti & Fagherazzi 2010). Models such as these that account for both physical and biological effects wetland evolution have been termed by some as ecogeomorphic (Fagherazzi *et al.* 2012). The spatial application of the zero-dimensional MEM model is acknowledged by many to provide results primarily exploratory in nature (Kirwan & Murray 2007). Though the MEM model includes both physical and biological processes, it was created and used to predict responses to sea level for an individual wetland species, *Spartina alterniflora*, at one location, reducing the model’s transferability to other wetlands. Interspecific competition among species in a wetland is more commonly present in sites around the world (eg. Marani *et al*. 2010; Silvestri *et al.* 2005).

It is clear that, though the treatment of inorganic sedimentation differs considerably between models, it is the common factor incorporated in all models of wetland evolution. The feedback mechanisms and interrelated processes included in numerical simulations of wetland evolution are considered superior to the simplistic comparisons of SLR and accretion rates, with a greater representation of the system usually being obtained. Despite the obvious advantages of describing a system in greater detail through the use of numerical models, many limitations and sources of error and uncertainty are attributable to each modelling method. With due consideration of these problems, however, the numerical model output provides an understanding of the past or future systems that would otherwise be unattainable.

In addition to inorganic sedimentation, the addition of organic sediment to the wetland surface can have a significant impact on the long term evolution of a coastal wetland (Mckee *et al.* 2007; Mckee 2011; Morris & Bowden 1986). It is interesting to note that, though the organic contribution to wetland elevation change is considered sufficiently significant to include in a generic equation of wetland elevation change Allen (2000), few models actually explicitly account for this component of the system. Where the organic sedimentation is considered, the component is either simulated as a constant rate over time (French 1993; Rybczyk & Cahoon 2002; Stolper 1996) or as a function of elevation (D'Alpaos *et al.* 2007; Pizzuto & Schwendt 1997). The frequent absence of an organic sedimentation component within many models is partially a result of there being limited information regarding the organic sedimentation processes over time (Parkinson *et al.* 1994).

Despite widespread agreement that belowground processes such as organic matter production, decomposition and sediment compaction can significantly influence the evolution of a coastal wetland, few models incorporate these processes. Similar to the problems regarding inorganic sedimentation, a paucity of information regarding belowground processes has resulted in frequent disregard of such influences in modelling efforts (Rybczyk & Callaway 2009). Those models that do explicitly simulate compaction in particular have primarily focused on peat wetlands and are often associated with engineering objectives (Hobbs 1986). Pizzuto and Schwendt (1997) presented a zero-dimensional physical model that simulated compaction on saltmarsh sediments using finite strain theory. Some models have attempted to capture the belowground processes implicitly by applying a constant rate of compaction (French 1993; Allen 1995; Temmerman *et al.* 2003b). However, a greater account of the rate of autocompaction and its mechanistic simulations is required for a more accurate and reliable representation of coastal wetland evolution.

Asmall portion of models explicitly account for both organic sedimentation and belowground processes (Callaway *et al.* 1996; Chmura *et al*, 1992; Day *et al.* 1999; Rybczyck & Cahoon 2002; Rybczyk *et al.* 1998). The majority of these zero-dimensional models adopt a cohort approach, signifying that a given 'cohort' of sediment is tracked over time as it becomesprogressively buried beneath sediment. The cohort approach to modelling wetland dynamics was pioneered by Morris and Bowden (1986) to simulate the belowground processes active in a tidal marsh on North River, Massachusetts, focussing upon decomposition. Following the work of Morris and Bowden (1986), Chmura *et al.* (1992) developed a cohort model for the Barataria Basin wetlands that accounted for organic sedimentation and belowground processes in modelling the evolution of the wetlands with rising sea levels. Callaway (1996) used a mechanistic cohort approach to simulate the belowground production and organic decomposition in wetlands in Mississippi and Great Britain, where decomposition was input as a forcing function (i.e. a variable that is not simulated but input as an independent variable). Drawing from the previous research and modelling, Rybczyk *et al.* (1998) further incorporated aboveground biomass and organic matter production as a function of root biomass and elevation respectively in their model simulating the effect of waste water on soil dynamics. This work further stimulated a variety of models examining the effect of SLR on coastal wetlands (Day *et al.* 1999; Rybczyk & Cahoon 2002).

Cahoon *et al.* (2003) also implemented the model of Rybczyk *et al.* (1998) in their valiant attempt to simulate the effects of storms on coastal wetlands. Simulating storms and pulsing events is inherently difficult due to the natural uncertainty surrounding the frequency, magnitude and impact of the processes. Very few models have attempted to simulate the effects of storms on wetlands, despite empirical data that suggest storms, floods and other pulsing events have significant potential to add, move or remove large amounts of sediment in coastal wetlands (Cahoon *et al.* 1996, 2006; Guntenspergen *et al.* 1995; Nyman *et al.* 1995).

Within the last decade a suite of models have been developed that explicitly account for erosional processes affecting the coastal wetland system (Kirwan & Murray 2008; Kirwan *et al.* 2007; Mariotti & Fagherazzi 2010). These models simulate erosion as a function of bed shear stress, with some also explicitly considering the effect of wave height and water depth (Kirwan & Murray 2008; Mariotti & Fagherazzi 2010). However, following the empirical observations of Christiansen *et al.* (2000), many models assume erosion is negligible within coastal wetlands (D'Alpaos *et al.* 2007; Temmerman *et al.* 2005). Whilst the influence of erosion is possible to be discounted in some coastal wetlands, the influence of erosional processes is significant in others. Especially in process based, landscape-scale models, the absence or simplistic treatment of erosion is often the norm rather than the exception.

Landscape models focus upon simulating trends in a system over large areas allowing the response and spatial interrelationships among different environments to become apparent. Simulations of the relationships between SLR and coastal wetlands at the landscape level are considered important for informing decision and management measures. However, the landscape models often do not simulate in a mechanistic fashion the physical and biological processes that affect the evolution of coastal wetlands, but instead input the processes as forcing functions (Reyes 2000; Clough *et al.* 2012). Due to the complexity of introducing explicit accountability of smaller scale processes to simulations of large areas, influences such as erosion, compaction and belowground processes are, thus, often overlooked, further limiting the reliable representation of coastal evolution provided in model output.

Examining the full suite of numerical models developed over the past half century to simulate wetland evolution at a variety of scales it becomes clear that the processes leading to positive gains in wetland surface elevation have been the primary focus of numerical modelling efforts (also see Appendix A for a simplified overview of numerical models). This may primarily be attributable to the greater availability of information that has enhanced the understanding of the aboveground processes and fulfilled the necessary data requirements for conceptualisation, calibration and validation of numerical models. Nevertheless, the incorporation of processes that only account for sediment deposition and vertical growth of the wetland surface without sufficient consideration of the processes leading to losses in surface elevation results in significant limitations and uncertainties associated with model output. At its most basic, 'deposition-only' models may overestimate the ability of a wetland to increase in elevation and, thus, survive under rising sea levels. Numerical models developed over the past decade go some way to mitigate such an effect through their consideration of erosion. These models, however, neglect to simulate the effects of belowground processes impacting the evolution of coastal wetlands, generating their own uncertainties and limitations. Further parameterisation may enhance the ability of the models to more adequately represent the dynamic wetland systems, though an associated increase in complexity is inevitable. It has also been suggested that the integration of already-developed models may advance the simulations of wetland evolution and improve the understanding of the future conditions of these dynamic coastal environments (Rybczyk & Callaway 2009). Furthermore, simulating the effect of vegetation on wetland evolution is in its infancy, with coupled sediment-vegetation models only being developed since the beginning of the 21st century. As further understanding of the wetland system evolves it is expected that numerical models, too, will change to more accurately incorporate those influences affecting the long-term persistence of the coastal wetland. Certainly, as the greatest possible description of future wetland scenarios is necessary in order for managers to effectively plan for the uncertain future, continued investigation and improvement in modelling of the dynamic system is required.

2.5.2 The SLAM model

The Sea Level Affecting Marshes (SLAM) model is one of the most widely used spatial landscape models originally developed for North American coastal wetlands. The model, created in 1986 and revised numerous times, is a complex, non-hydrodynamic model that simulates six primary processes affecting the survival of coastal wetlands with long term SLR. These processes include inundation, erosion, overwash, saturation, salinity and accretion, of which inundation and accretion are most frequently implemented. The ability of the SLAM model to adequately describe the response of wetlands to SLR has been called into question by Kirwan and Guntenspergen (2009). It is noted that the ensuing discussion between the critics and the creators of the SLAM model related to SLAMM version 5 (Craft *et al*. 2009). Kirwan and Guntenspergen (2009) suggested that the simulation of accretion in the SLAM model was incorrect, with the feedback mechanisms considered so important to the persistence of wetlands with rising sea levels were not being modelled. Constant rates of accretion were simulated where an increase in accretion rates with accelerating SLR has been suggested to more comprehensively explain the response of the wetland. Craft *et al.* (2009) defended their model design by emphasising that the broad-scale nature of the model limited the capacity of such mechanistic detail of feedbacks to be incorporated. However, with further funding, advancements in computer science and renewed model development, successive versions of the SLAM model, versions 6 and 6.2, incorporated an accretion feedback component, which attempted to provide a flexible model for the simulation of accretion dynamics across the wetland under accelerated rates of SLR.

Though used primarily to simulate the changes in wetland boundaries and shoreline modifications with increasing sea level (Clough *et al.* 2015; Galbraith *et al.* 2002; Glick & Clough 2006; Linhoss *et al.* 2015), the SLAM model has been used to simulate the effect of SLR on the natural services and regulatory processes offered by coastal wetlands, such as species habitats and carbon sequestration and denitrification (Craft *et al.* 2009; Glick *et al.* 2007, 2013; Naughton 2007). In addition, the SLAM model has been coupled with ecological models to examine the potential effect of SLR on wetland dependent and threatened species (O'Mara 2012; Traill *et al.* 2011).

Despite its many uses, applying the SLAM model to coastal wetlands, such as those of SE Australia, where the geomorphology and ecology differs from that of North America throws into question the efficacy and reliability of the final output. This ultimately affects the understanding of the unique ecosystems around the world and the management of these vulnerable environments. In applying the SLAM model to wetlands of north-eastern NSW, Akumu *et al.* (2011) acknowledged that model output could be unrealistic due to the differences between North American and Australian wetlands yet continued to conclude that the SLAM model generated data which provided useful insight into the possible impacts of SLR. Further studies on the impacts of SLR on coastal ecosystems of SE Queensland drew unwavering conclusions from the SLAM model output without first examining the reliability of the model to adequately describe the system (Traill *et al.* 2011; O'Mara 2012). Considering the change in context, a re-validation of the model is, thus, overdue for the Australian context.

3 METHODS

In fulfilling the aims and objectives of this study a number of models were implemented. The methods of data preparation for common parameters of the models are first outlined followed by more detailed model description and explanation of parameters specific to individual models.

3.1 Collation and preparation of common inputs for modelling

3.1.1 Empirical data

Modelling the effect of SLR on coastal wetlands requires a comprehensive understanding of past trends in coastal wetlands, which serve to provide insight into past responses to SLR and ultimately guide projections of future wetland scenarios (Woodroffe 1990; Woodroffe & Murray-Wallace 2012). Based upon geological and contemporary observations, it is hypothesised that the ability of a wetland to survive with increasing sea levels is dependent upon its capacity to build vertically, primarily though processes of sedimentation (Redfield 1972; Reed 1990, Reed 1995). Thus, it is crucial that site-specific accretion and wetland elevation change are quantified and temporal trends understood such that more reliable projections of the effect of SLR on coastal wetlands to be produced. For the very same reason, a quantitative understanding of relative SLR as recorded by a tide gauge is required when simulating the changes in coastal wetlands with SLR (Cahoon 2015). Empirical, time-series data recorded at the Minnamurra site regarding wetland surface elevation and sea level were, therefore, obtained and analysed to ascertain past trends that could inform future projections of wetland evolution under rising sea level conditions.

Surface Elevation Table- Marker Horizon data

A Surface Elevation Table (SET) is a portable device that is used in combination with a benchmark pipe fixed in the wetland substrate to obtain surface elevation measurements (Cahoon *et al*. 2002; Callaway *et al.* 2013; Cahoon 2015). At the Minnamurra study site a total of six SETs were established in 2001 by Rogers (2004); three situated within the mangrove community and three within the saltmarsh. Initial measurements were taken on 11 September 2001 and subsequent measurements were taken on 17 October 2002, 5 August 2003, 8 September 2009, 28 April 2010, 6 September 2010, 5 October 2010, 1 November 2010, 1 December 2010, 10 February 2011, 14 March 2011, 11 April 2011, 12 May 2011 and

20 May 2013. Increased frequency of measurements between 2010 and 2011 are the result of diligent data collection by Oliver (2011) for analysis in his honours thesis. All measurements were recorded in millimetres.

Three marker horizons (MH), established around each SET site at the Minnamurra site by Rogers (2004) and Oliver (2011), allow for the calculation of accretion following the methods of Cahoon *et al.* (1995). However, data gaps in the accretion information were recorded at the Minnamurra area, especially within the mangrove zone, bioturbation affecting the marker horizons established at the site.

Rates of SEC were calculated from the SET-MH data according to the method applied by Rogers (2004). An average rate of SEC for each vegetation type, mangrove and saltmarsh, was determined. Considering the data needs for model development (see below), the process of calculating the incremental and accumulative elevation changes and determining an elevation trend was repeated per individual SET.

Accretion values utilised in this study were drawn from the work of Oliver (2011). These values were implemented in modelling efforts conducted here to allow for meaningful subsequent comparison with the simulated data of Oliver (2011) for the Minnamurra site. Furthermore, the lack of sufficient accretion information recorded at the study site precluded the direct calculation of accurate accretion values for this study.

Tidal data

Information on tidal levels over time informs the simulation of wetland evolution impacted by SLR. Tidal information for this study was primarily sourced from the Manly Hydraulics Laboratory's tidal plane analysis of the Minnamurra River (MHL 2012). The automatic water level monitoring station at Minnamurra River was commissioned in March 2003, meaning that tidal data analysed by The Manly Hydraulics Laboratory (MHL) represented an eight-year period between 2003 and 2010. MHL use the Foreman tidal heights and prediction programs (Foreman 1997) to determine tidal ranges and tidal constituents, such as mean high water (MHW). Raw tidal information for years subsequent to 2010 was available from MHL but not included within this study, as a Foreman analysis was considered beyond the scope of the current thesis. Though tidal inundation was a common parameter between the models, individual requirements of tidal information for each model are outlined in the relevant section below.

3.1.2 Digital Elevation Models

Since the topography of the land determines the potential frequency and magnitude of inundation, high-resolution elevation data is arguably the most important component when modelling the effect of SLR on coastal wetlands (Morris *et al.* 2005; Schmid *et al.* 2011). Light Detection and Ranging (LIDAR) data can provide measurements of surface elevation of high accuracy (Hopkinson *et al.* 2004) and have become the most widely used and trusted source of elevation information (Franklin 2008). From such data, which are recorded and distributed as point elevation heights, a Digital Elevation Model (DEM) of high vertical resolution can be potentially derived (Poulter & Halpin 2008). DEMs are a raster or vector-based representation of surface elevation and are the common, base elevation input for spatially applied inundation and SLR models of coastal environments. To explicitly test the importance of the elevation information in modelling the effect of SLR on coastal wetlands, three elevation models were created and used within this study.

The primary LIDAR data utilised in the production of all three DEMs for the Minnamurra site were acquired by Land and Property Information (LPI) during the March of 2011 as part of the Coastal Capture program spanning the coastal area between Nowra and Wollongong. The data were collected with an ALS50-II sensor (Leica Geosystems, Heerbrugg, Switzerland) at a flying height of 2000 m which yielded a nominal nadir point density of 1.03m and an overall vertical and horizontal accuracy of 80cm and 30cm respectively. Data were projected in metres (Geocentric Datum of Australia 1994, Map Grid of Australia Zone 56) with elevation values referenced to the Australian Height Datum 1971 (AHD71). The LIDAR data was distributed in the popular format of the *.las file. At the time of obtainment in 2015, the data had been pre-processed, meaning that ground points had been classified from the raw LIDAR data.

The first DEM created, DEM1, used purely the processed data acquired from LPI as the base ground surface height information. This DEM was produced in a relatively simplistic, standard fashion, assuming that all elevation heights measured and metadata regarding the LIDAR information were accurate and pertinent to the study site. Such an approach was deliberately executed to emphasise the importance of exploring and analysing possible errors prior to modelling as well as to highlight the necessity of expert judgement and analysis for high quality modelling. Within ArcMap (v 10.2), a LAS dataset was created from the four tiles of LIDAR data covering the Minnamurra study site. To maintain a continuous water flow pathway in the DEM, bridges on the Minnamurra River were removed manually using the edit tool of the ‘Las Dataset Toolbar’. The ‘Point File Information’ (3D Analyst) tool was applied to generate an estimate of the point spacing of ground-classified points, a value required to convert the LIDAR data to workable point features in ArcMap. The final ground point features produced by applying the ‘LAS to Multipoint’ tool were input as the height source in a terrain dataset. A terrain dataset builds a Triangular Irregular Network (TIN), multiresolution surface based upon input elevation measurements, 3D features and defined boundaries. It provides the ability to create a ground surface at an appropriate level of detail integrating different sources of information. The terrain dataset used for the derivation of DEM1 was constructed using the point spacing, as calculated above, and surface elevation heights as defined by the ground mass points. The area was constrained by enforcing a ‘hard clip’ to the boundary of the study site. Applying the ‘Terrain to Raster’ tool with a natural neighbour interpolation method, a raster-based DEM was derived from the resulting TIN-based surface of the Minnamurra site. The raster was developed with a five metre horizontal resolution, following the general rule of thumb that the final cell size of a DEM should be approximately four times greater than the point density. The final cell size of DEM1 also reflects a decision to maintain compatibility for comparison between DEMs within the study, DEM3 being an inherited product of five metre spatial resolution. Significant errors were noted along the water course of the area and where dense vegetation occurred, such as in mangrove dominated areas. However, in view of DEM1’s purpose within the study, no further adjustments to reduce the errors were made.

The second DEM used throughout this study, DEM2, was created with the aim of producing an elevation model with the highest possible vertical accuracy from the data available within the given time. The process to create this DEM was, thus, more technically demanding and required greater expert input and decision-making. Possible vertical error was initially explored and identified through the theoretical analysis of the metadata accompanying the disseminated LIDAR product, the exploration of the vertical errors of DEM1 and the manual analysis of the LIDAR data using the ‘Las Dataset’ toolbar in ArcMap.

The LIDAR metadata supplied by LPI reported the vertical accuracy of the dataset as 0.3 metres. Whilst this does provide a submetre accuracy for all elevation measurements, the estimate of accuracy also indicates that each individual LIDAR point is potentially displaced 60cm from its true position. Given that this study is primarily focused upon a low-gradient floodplain where centimetre variations in elevation can significantly affect the frequency and magnitude of tidal inundation, a possible error of this scale within the elevation information could significantly perturb and alter any analysis or inundation modelling of the area. Moreover, the tidal range affecting the intertidal zone of the Minnamurra River has been measured by MHL (2012) to be approximately 1.55m (discussed below). An error of 0.3 metres is effectively increasing or decreasing the elevation of a point by almost one-fifth of the tidal range, potentially erroneously excluding or including a point within the intertidal zone under study. Consideration of these problems and potential sources of error drove the initial effort to increase the vertical accuracy of the elevation model.

Further problems within the elevation data were identified through the visual and expert examination of DEM1. Significant differences in the modelled representation of the surface appeared to be clustered in mangrove-dominated areas. In some areas, elevation errors reached above one metre. Returning to the LIDAR dataset from which the DEM was derived and using the '3D View' and 'Profile View' from the 'Las Dataset' toolbar in ArcMap it was noted that the original, processed las files sourced from LPI contained many vegetation points misclassified as ground, especially where vegetation was dense or positioned directly adjacent to the Minnamurra River.

Given the combination of misclassification and spatially clustered vertical error within the LIDAR data, further post-processing was considered necessary. Filtering is the process of separating ground points from non-ground points and is commonly the first step in post-processing of LIDAR. Collaborating with experts in the field, the FUSION (v 3.5.0) software (McGaughey 2015) was used to post-process the LIDAR data. The 'Catalog' program was used to re-evaluate the internal quality of the data covering the study site. This program provides a report on the important characteristics of the LIDAR data, such as the minimum and maximum elevation, total number of returns and nominal point density. The 'GroundFilter' program was then applied to better identify the points that lie on the ground surface. The filtering algorithm employed in FUSION is based on that of Kraus and Pfiefer (1998). A rough approximation of the surface is first computed using all LIDAR points. From this generated surface the residuals, that is the distance and direction of error at each LIDAR point from the surface, are calculated. Elevation points are then assigned a weight according to their relative residual and a surface is recomputed using the weighted measurements. This process is implemented iteratively until all gross errors are eliminated or the maximum number of iterations have been completed (Kraus & Pfeifer 2001; McGaughey 2015). The final output from the application of the filtering process described above to the LIDAR data of the Minnamurra area was comprised entirely of ground returns and was imported into ArcMap for further analysis and DEM2 creation.

In addition to the filtered ground point data, Real-Time-Kinematic Global Positioning System (RTK-GPS) spot heights collected in the same year as the LIDAR data were utilised to further increase the accuracy of the elevation model. RTK-GPS equipment use complex algorithms that include both differential correction and ambiguity resolution to locate the horizontal (x,y; coordinates) and vertical (z) position of a point on the earth. The RTK-GPS measures elevation within an accuracy of 1 – 5cm vertically and a mean accuracy of 1cm horizontally. The RTK elevation points used in the creation of DEM2 were sourced from data collected by Oliver (2011) in April 2011and referenced to AHD71 (see Oliver (2011) for further information). These surface heights were used rather than elevation data acquired in 2015 so that any possible errors arising from differences in surface elevation over time would be eliminated. The 300 points collected by Oliver were randomly divided into two subsets, a 70% subset to be used in the derivation of DEM2 and a 30% subset to aid in a basic accuracy assessment.

Similar to the method of model creation for DEM1, the point density of the ground-filtered LIDAR data for the entire area was approximated, the points were converted to multipoint features and a terrain dataset was built for DEM2. Both filtered ground points and RTK-GPS spot heights were referenced as surface heights within the terrain dataset. A soft replace of 0m for all elevation heights within the river was defined for the terrain using the Minnamurra River polygon prepared as described in Section 3.3.2.6. This was determined based on the recognition that elevation points within or near the river were almost consistently positioned at 0.5 metres, a value that loosely corresponds to the MHW level at Minnamurra as reported by MHL (2012). Laser pulses of LIDAR systems will often be absorbed or reflected off water bodies, often resulting in gaps or increased surface elevation in the final data respectively.

The terrain built from the input features was converted to a raster following the method outlined for DEM1. The natural neighbours interpolation technique was again employed since it develops a smoother, more continuous surface ideal for the floodplain-dominated study site (Webster & Oliver 2001).

The last DEM used in this study was developed by Oliver (2011) for the floodplain referenced in this study as the western floodplain. As the 2011 LIDAR data was not processed before the completion of the study by Oliver (2011), ground points were selected that fell within set boundaries for the vegetation communities in addition to those points that visually corresponded to ground sites on a high resolution image acquired from Nearmap. These selected points were combined with the 300 RTK-GPS points and an Inverse Distance Weighting interpolation technique to obtain the final, 5m resolution, raster-based elevation surface, here referenced as DEM3. Further explanation of the process of DEM3 derivation can be found in Oliver (2011).

DEM Name	Data input	Interpolation technique	Horizontal resolution
DEM1	LIDAR ground points Study site polygon	Natural Neighbours	5m
DEM2	Refiltered LIDAR ground points RTK-GPS points River polygon Study site polygon	Natural Neighbours	5m
DEM3	Selected LIDAR points RTK-GPS points	IDW	5m

Table 2: Overview of DEMs used within this study and the methods used for their generation. Each DEM was developed with the same spatial resolution to allow for a greater strength and credibility of subsequent comparisons.

Accuracy assessment

An accuracy assessment of LIDAR derived DEMs involves the comparison of modelled elevation with ground-truth data to determine the error associated with individual DEM values. Error within a LIDAR-derived DEM is often the cumulative result of a variety of propagated errors, including LIDAR sensor error, ground classification error and interpolation error (Liu *et al.* 2015). Methods developed to assess this error are commonly based upon theoretical frameworks such as approximation theory (Liu *et al.* 2012) and error propagation theory (Aguilar *et al.* 2010; Höhle & Höhle 2009). In this study, accuracy assessment is conducted following the method of Schmid *et al.* (2011), which separates the vertical elevation error into two main components, offset and level of precision.

The 30% subset (72 points) of the RTK-GPS points collected by Oliver (2011) were used as the ground control points from which elevation errors were measured. As these points lay within the western floodplain only and elevation error will vary through space, it was not logical to compute the DEM vertical accuracy for the entire study area covered by both DEM1 and DEM2. Thus, the aforementioned DEMs were clipped to the boundary of DEM3 in preparation for the accuracy assessment.

Elevation values from DEM1 were extracted based upon the position of the RTK-GPS points using ‘Sample’ in Arcmap. From these values the root mean square error (RMSE) was calculated using the equation:

$$\mathrm{RMSE}_z = \sqrt{\frac{\sum_{i=1}^{n}(z'_i - z_i)^2}{n}} \quad (1)$$

where n is the number of ground control points, z' is the DEM elevation, z is the elevation of the ground control point at the same position, and i is an integer from 1 to n. The maximum, minimum, mean and skewness of the errors were also calculated to provide a greater understanding of the distribution of error.

The RMSE calculated estimated the vertical accuracy for the western floodplain. This value, however, represents a global accuracy for the area, masking the spatial variation of error. It is well understood that the vertical accuracy of LIDAR data is often dependent upon the land cover and vegetation of a particular area (Flood 2004; Schmid *et al.* 2011). Thus, the RTK-GPS points were split according to vegetation type, mangrove, mixed, saltmarsh and casuarina, and statistical analysis of the error recalculated according to the methodology described above.

The process of DEM sampling and subsequent statistical analysis was repeated for DEM2 and DEM3. Thus, an understanding of overall and vegetation-specific vertical error was gained for each elevation model used in this study.

3.1.3 Vegetation information and land classification maps

The spatial distribution of vegetation, wetlands and land use is a common requisite component when modelling the effect of SLR on coastal wetlands (Akumu 2011). Models used in this study displayed basic differences in the delineation of vegetation type and approach to wetland vegetation switching with inundation. However, common to each model were the land types principally identified within the land classification, which included:

- Mangrove
- Mixed
- Saltmarsh
- *Casuarina* (swamp oak)
- Undeveloped land and
- the Minnamurra River (river channel)

A mixed zone, consisting of both mangrove and saltmarsh was incorporated in the vegetation map where it was considered pertinent given the available data. Further description of wetland vegetation identification and modelling are described in the relevant sections below.

3.1.4 SLR Scenarios

Though not the only factor affecting the distribution of mangrove and saltmarsh, sea level plays a crucial role in the persistence of wetlands over time (Saintilan *et al.* 2013). In particular, the rate and magnitude of SLR has been observed as critical to the question of the wetland's persistence or demise (Boesch *et al.* 1994; Reed 1995).

In this study, three projected sea level scenarios were used, representing low, intermediate and extreme rates of SLR by 2100 (Table 3). Low and intermediate projected sea levels were based upon the emission scenarios produced for the fourth IPCC assessment report (AR4). IPCC emission scenarios are developed from predictions of future political and

Scenario	Source	IPCC (2007) emission scenario	Implemented in model	Projected sea level rise by 2100 (m)
Low	IPCC AR4 (2007)	B1 5%CI	Oliver model SAAT model SLAM model	0.185
Intermediate	IPCC AR4 (2007)	A1F1 95%CI	Oliver model SAAT model SLAM model	0.819
Extreme	Vermeer and Rahmstorf (2009)	n/a	SAAT model SLAM model	1.9

Table 3: SLR scenarios used throughout this study.

socio-economic trends from which SLR is modelled. Though the observed, eustatic SLR has exceeded the lowest limit predicted by the IPCC AR4 (2007), the B1 5% confidence interval (CI) SLR was used to defined the low SLR scenario utilised in this study. This scenario was primarily chosen for comparison purposes and to investigate the flexibility and validity of models examined. Following the same reasoning for scenario choice, the upper limit of SLR of the AR4 IPCC (2007), corresponding to the A1FI 95%CI, was also used across all models applied in this study. A last scenario, suggested by Vermeer and Rahmstorf (2009), was used to examine the validity of the models under extreme conditions whilst also providing information on possible coastal wetland evolution effect of extreme rates of SLR on wetland communities.

Time-series data of projected AR4 IPCC sea levels calculated at 10-year increments were sourced from Hunter *et al.* (2010). Decadal data were not readily available for the sea level projection by Vermeer and Rahmstorf (2009). In the absence of data, the SLAM model was used to simulate a eustatic SLR of 1.9 metres by the year 2100. Output data of the SLAM model include the incremental SLR for a given time step. As such, a SLR of 1.9 metres was specified, relative SLR was set as zero, 10-year time steps were defined and a mock simulation conducted from the year 1990 to 2100, corresponding to the temporal period of Vermeer and Rahmstorf's (2009) projection of SLR. Modelled SLR values could only be visually compared with the graphed data from Vermeer and Rahmstorf (2009) due to the lack of exact projected values. It is noted that the SLAM model scales the A1B 95% CI IPCC scenario of the third assessment report (TAR) to estimate a specified SLR, in this case the 1.9 metres. Therefore, output values of SLR would not exactly correspond to those of Vermeer and Rahmstorf (2009). However, for this study the values were considered sufficient to model the effect of extreme SLR on coastal wetlands.

Any further SLR information gathered and analysed for individual model verification, calibration or application is discussed within the relevant section below.

3.2 Modelling wetland evolution

The previous sections of this chapter outlined the process of preparing input data common to models applied within the study. Model description, additional parameter preparation and model implementation are further outlined below.

The first model under investigation in this study was the SLAM model, a model developed and calibrated in the United States of America. The second model applied, adjusted from that developed by Temmerman *et al.* (2003b), was selected due to its relative simplicity, empirically based structure, non-hydrodynamic and deterministic nature and broad similarity to the SLAM model in parameterisation. Comparison of the simulated results from the two models was, thus, both possible and justifiable due to the many similarities between the two models which, in assessment, also serve to highlight the differences in the model performance.

The third model, only briefly explained in this section, was implemented for the Minnamurra site by Oliver (2011). The statistical model is empirically based and developed specifically for the Australian context. It, thus, represented the most locally-derived, site-specific model of the three chosen for this study.

3.3 The Sea Level Affecting Marshes model

3.3.1 Model description

The SLAM model is a complex, non-hydrodynamic model that attempts to simulate the response of wetlands to SLR (Clough *et al.* 2012). Abstraction of the wetland system response resulted in the development of six processes being included in the latest version of the SLAM model (SLAMM v.6.2, Clough *et al.* 2012). Inundation, accretion, overwash, soil saturation, accretion and salinity are all included as the primary processes that affect wetland fate under scenarios of SLR. Certain processes are optionally incorporated in simulations, such as overwash and soil saturation, and still others remain in their formative stages and have been recommended not to be utilised, such as the salinity module.

The basic conceptual model upon which the SLAM model is designed is quite simplistic and is based on the assumption that wetland categories only inhabit a certain elevation range that are a function of tidal range or salinity. The model can simulate changes in 25 different landcover categories under rising sea levels. Wetland categories are based on the National Wetland Inventory prepared for the United States of America (Cowardin *et al.* 1979). The structure of the model can be broken into two broad areas pertaining to the wetland elevation change with rising sea levels and the subsequent conversion of elevation-defined vegetation.

The SLAM model divides an area into cells of a custom-defined size and carries out calculations and conversions on a cell-by-cell basis. The change in wetlands surface elevation of a single cell is a function of SLR and accretion and is defined mathematically as:

$$E_t = E_{t-\Delta t} + \Delta t.A - SLR_t \qquad (2)$$

where E is elevation, A is the site-specific accretion or sedimentation rate, SLR is the SLR for a given time step and t is time. The accretion rate can be characterised by vegetation-specific values or may be defined as a function of elevation using the accretion module. The magnitude of SLR follows the IPCC scenarios of the TAR or a custom-defined SLR. In addition to the global SLR, the local SLR is simulated from the deviation of the local historic SLR trend from the eustatic SLR trend, assuming a linear relationship remains over time. The SLR is therefore calculated at each time step as:

$$\mathrm{SLR_t} = \mathrm{GSLR}_t + (t_n - t_0)(H_L - H_G) \qquad (3)$$

where GSLR is the global mean SLR over a certain time step as custom defined or following the TAR (IPCC 2001) scenarios, H_L is the local historic trend of SLR and H_G is the eustatic trend of SLR. The combination of estimated SLR and accretion responses thus drives the elevation change of a wetland with respect to mean sea level.

Subsequent conversion of a wetland category in a cell is driven by the cell's elevation. Each category is assigned a specific elevation, salinity or tidal range within which the particular wetland can exist. In any given simulation, if the elevation of the cell falls below the elevation range defined for the wetland category contained in the cell, then a fraction of the cell is converted to a lower-elevation habitat. The fraction of the cell lost is a function of the slope of the land and the magnitude of the fall below the wetland-category's lowest elevation. The lower the cell falls, the greater the fraction converted to a lower wetland category. Conversions, thus, occur in one direction only, from one wetland vegetation type to another of a lower elevation range. The lower vegetation type to which a category is converted is governed by a decision-tree process programmed into the SLAM model from which site-specific deviations cannot occur.

3.3.2 Model setup

The SLAM model requires a variety of spatial and site-specific parameters to be determined prior to its implementation. Figure 3 provides a general overview of the processes followed and information gathered for the most accurate implementation of the SLAM model at the Minnamurra study site.

Elevation data and terrain derivatives

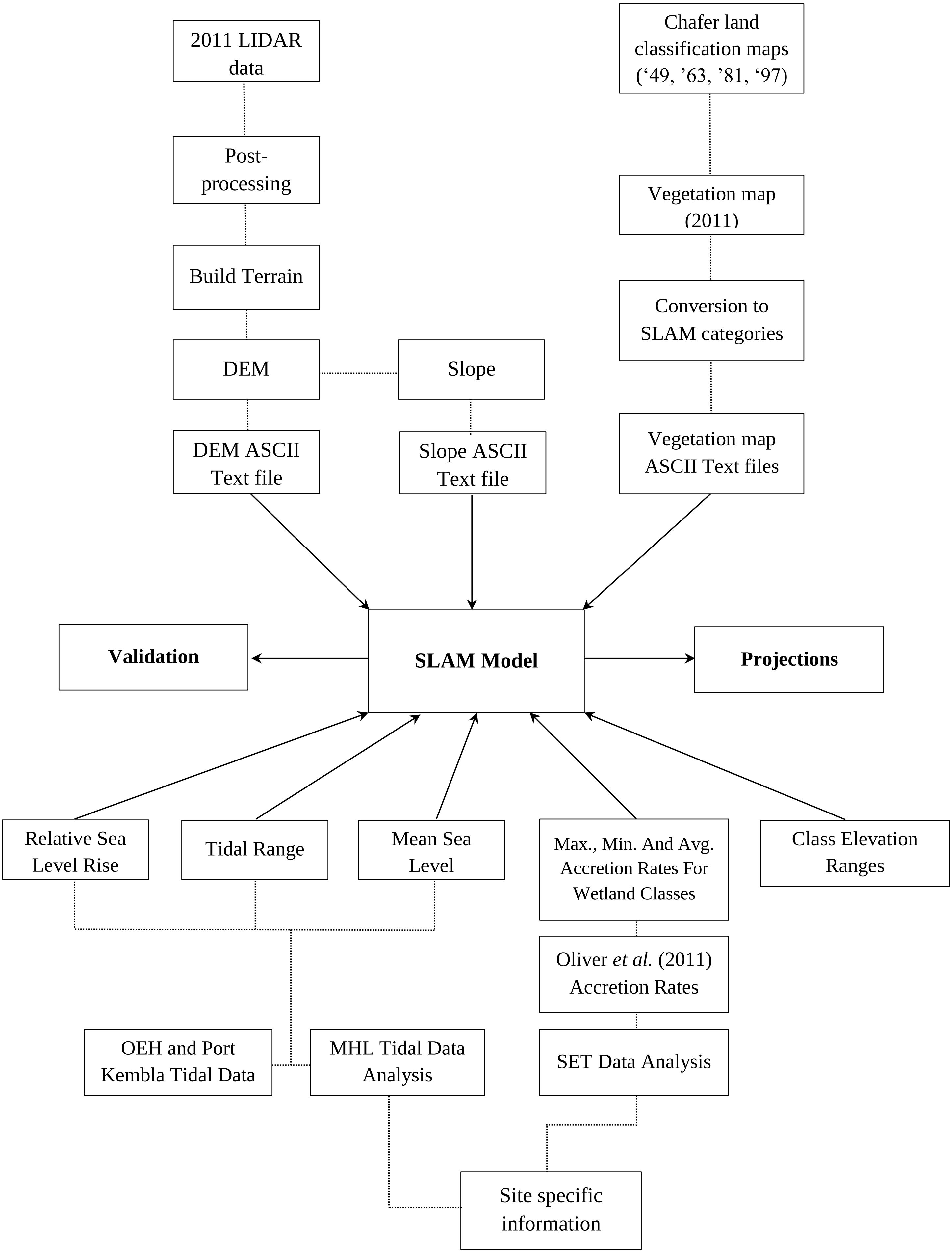
The importance of elevation data within the SLAM model is not to be disregarded. The input elevation information is at the heart of almost all constituent modules within the model, signifying that high-vertical resolution is critical to the model's application. DEM1, DEM2 and DEM3, developed as outlined above, were used as elevation input data for simulations in THE SLAM MODEL. The main elevation model used in this study for model validation, verification and calibration was DEM2, with subsequent projections being implemented for all three DEMs, as described below.

The SLAM model also requires a layer that represents the slope of the land in degrees, which in this study was derived from each DEM using the 'Slope' tool in ArcMap. Spatial resolution of slope layers corresponded exactly to that of the DEMs, with 5mx5m cells. In the SLAM model these slope layers are used in determining the percentage conversion of an inundated cell from wetland type to another during model projections. All DEMs and their respective slope layers were converted to text layers using the 'Raster to ASCII' tool in ArcMap as required for the SLAM model.

Identification of model subsites

Within a region, or even within an individual estuary, site characteristics, such as tidal range and accretion rates, can vary. Such variation can be partially accounted for in the SLAM model by dividing a study area into subsites and applying site-specific parameters to each. Though this method is not without its limitations, it was used in this study to maintain the effects of tidal attenuation along the Minnamurra River. Division of the entire study area into subsites also served to simplify the calibration process.

Figure 3: Broad overview and schematic representation of the processes and data collection required for the implementation and use of the SLAM model in this study.



Foulsham *et al.* (2012) emphasise the importance of tidal attenuation along estuaries when modelling SLR. The significance of following the suggestion was fully realised within this study when a singular tidal range value was applied to the entire study site. Tidal levels demarcate areas of inundation and therefore, are inextricably linked to the distribution of wetland vegetation over time. Thus, to account for variance in tidal ranges along the Minnamurra River, eight subsites were identified based upon attenuated tidal range values derived from Office of Environment and Heritage(OEH) (2014). Subsites approximately correspond to those defined in the study by Chafer (1998) (Figure 4). The western floodplain lies completely within subsite four. Subsite parameters set for each defined section are discussed in successive sections below.

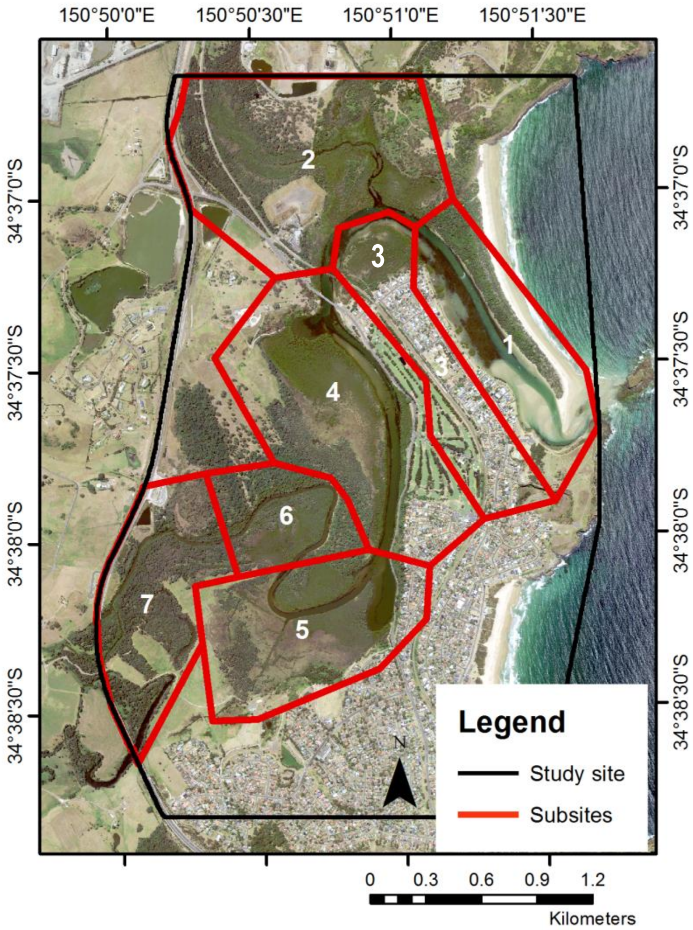


Figure 4: Subsites defined for the study site following Chafer (1998). Subsites were utilised to partially account for spatially varying parameters, such as the tidal range.

Tidal data

The SLAM model required a range of diverse tidal information for model setup, calibration and projection. Tidal information was sourced from MHL (2012), as described in Section 3.1.1.2. and combined to data drawn from OEH (2014) and the Port Kembla and Fort Denison tide gauges.

Historical sea level rise

A past trend in SLR, nominated as historical sea level rise in the SLAM model, is used in the model currently under discussion to determine the differential rise in local sea level with respect to the established eustatic SLR of 1.7mm/yr (IPCC 2007) and to account for the effect of local factors on projected SLR. The latter aim is fulfilled by simply summing any difference between local and eustatic sea level trends to the global SLR projections being used. In this way, a historical sea level rise of 1.8mm/yr being set for a simulation being conducted for the period 2000-2100 results in an additional 10mm (0.1mm x 100) of SLR by 2100. This basic method of accounting for local variations in SLR assumes that any differences between local and eustatic trends derive purely from the effect of local subsidence, even though other/further/a combination of local factors are commonly cited when considering spatial variations of local or relative SLR.

Local variations in sea level along the NSW coast have been noted by many and are considered to be the response of tides to influences such as the local bathymetry, barometric effects, changes in hydrodynamic conditions and land subsidence (MHL 2012; Couriel *et al.* 2014). Thus, when considering the effect of SLR at a local to regional scale, the most relevant, site specific tidal information is required. Minnamurra tidal range and constituent data was thus utilised throughout this study, as outlined above. However, as the temporal period of tidal data collection did not extend over a full 18.6 year tidal epoch, the typical regression of mean sea level over time to establish an approximate relative SLR was not completed for the Minnamurra tidal data. Instead, sea level trends calculated for the Port Kembla tide gauge, situated approximately 20km South of Minnamurra, and the long-established Fort Denison tide gauge, located within Sydney Harbour, were used as representative values of SLR for the study site. During validation and calibration stages, the historical SLR most appropriate was identified and subsequently utilised in projections to 2100.

Tidal range and tidal attenuation

As discussed above, tidal range and tidal attenuation are significant factors to consider when simulating SLR and its effect on coastal wetlands. Most particularly within THE SLAM MODEL, assignment of accurately quantified tidal range vales is crucial to the modelling process and for the production of informative and logical results. Not only does the tidal range define areas of potential inundation, it is also used to establish the distribution of wetland vegetation. Based upon the work by McKee and Patrick (1988), individual wetland vegetation classes are considered to be a function of their position within a tidal range. Thus, a particular vegetation type will only occur within a particular elevation range with respect to the tide.

Given the importance of tidal range in the model, specific attention was paid to assigning the most accurate and appropriate tidal ranges for the Minnamurra site. The singular value of great diurnal tidal range sourced from MHL (2012) was used but not considered to be representative of the parameter throughout the entire study site. Subsites, primarily identified for their variations in tidal range, were thus each assigned a tidal range based upon the extrapolation of data from OEH (2014) and MHL (2012) (Table 4).

OEH (2014) developed and documented information regarding tidal planes in NSW estuaries as a function distance from the ocean. Analyses were based upon tidal level data from MHL (2012), tidal limit data reported in MHL (2006) and ocean tide levels modelled by the authors of the OEH risk assessment report (OEH 2014). As tide ranges recorded at ocean gauges can be greater than those recorded at estuary entrances MHL (2005), OEH (2014) used the Oregon State University Tidal Inversion Software (OTIS 2013) to obtain the tidal water levels and ranges at the coast. For the Minnamurra site, the OTIS derived value for the river’s entrance represented the greatest tidal range and was assigned to the first subsite. The tidal gauge, from which the MHL (2012) data was measured, is situated in Rocklow Creek, subsite 2, and thus the tidal range for the site was assigned to subsite 2. Subsequent subsites were assigned a tidal range value between 1.8m and 1.5m, successive sites decreasing at a rate equal to that documented in OEH (2014). In this way, tidal range was set to approximately attenuate along the Minnamurra River.

	Global	Subsite1	Subsite2	Subsite3	Subsite4	Subsite5	Subsite6	Subsite7
Tidal range	1.8	1.8	1.8	1.65	1.62	1.615	1.56	1.5
Salt elevation boundary	0.974558	0.974558	0.974558	0.942625	0.936238	0.935217	0.923465	0.910692

Table 4: Tidal range and value of salt elevation boundary assigned to each subsite in an attempt to account for varying water levels throughout the estuary.

Salt elevation

Within THE SLAM MODEL, the salt elevation parameter defines the boundary between inundated and dry lands (Clough *et al.* 2012) and is often obtained by approximating the greatest land elevation that is inundated once every 30 days. Similar to the tidal range discussed above, the salt elevation boundary is yet another parameter that is significant in the delineation of coastal wetlands and requires accurate, site-specific data in order to maximise the performance of the model. In this study the High High Water Solstice Springs (HHWSS) reported for the Minnamurra area by MHL (2012) was used to determine the elevation of the salt boundary. HHWSS is here used as a proxy for the Highest Astronomical Tide, the highest level a tide may reach given any combination of influential factors.

Logically, as the tide range attenuates, so too does the salt elevation boundary. The standard deviation of HHWSS (MHL 2012) was used to determine an estimate of the upper and lower limit of the salt elevation boundary. The highest value was assigned to the first subsite, closest to the ocean, and the lowest to the final subsite with areas in between being set a value proportional to their distance from the ocean (Table 4).

Accretion rates/ rates of surface elevation change

The ability of a wetland to maintain elevation with respect to a rising sea level defines its ability to survive over time. Though net wetland SEC over time is controlled by a number of dynamic processes, including accretion and compaction (Cahoon 2006), only accretion is modelled within the SLAM model. To investigate the manner in which SEC is captured within the SLAM model, three different methods of defining the accretion parameter were used. The first two utilised the vegetation-specific accretion parameter in which a single, constant accretion trend was assigned to a vegetation class. Rates of SEC and accretion rates as determined from analysis of the SET data used for respective validation runs and projections using the SLAM model (Table 5). The process of defining the parameter in the different manners was aimed at determining which parameter, SEC or accretion, best modelled the evolution of the Minnamurra wetlands.

A third method of defining the accretion parameter was applied to test the ability of the SLAM model to simulate wetland elevation dynamics, namely the accretion module. After severe criticism of earlier SLAMM versions regarding the ability of the SLAM model to successfully capture fundamental feedback systems influencing accretion rates (Kirwan & Guntenspergen 2009), SLAMM version 6.2 includes a model-based approach that attempts to account for the important, spatially variable feedbacks between accretion and SLR, herein called the accretion module.

The accretion module consists of three main components; accretion, distance to tidal channel and salinity. The salinity component of the model was not considered sufficiently robust for use at the Minnamurra site (discussed below). Given the distance to tidal channel component is still in its formative stage and required data was not available to inform parameterisation, this component too was disregarded. Thus, only the accretion component of the module was parametrised and applied.

The accretion component is composed of a flexible cubic equation that relates accretion rates within a given wetland type to elevation. The key input parameters required are the maximum and minimum accretion rates for the wetland vegetation type and equation coefficients that define the curve relating varying accretion rates to elevation. Maximum and minimum accretion values assigned to mangrove and saltmarsh communities for this study are summarised in Table 5. The lowest accretion rate of the mangrove zone was assigned as the highest for saltmarsh to allow a smooth and continuous decrease in accretion rates to be modelled. A zero accretion rate was assumed for *Casuarina* zones.

A relationship between elevation and accretion rates was derived by calibrating the SLAM model accretion curve to the SAAT model equation developed in this study (equation outlined in Section 3.4.1). The use of the SAAT model for calibration was attractive for two reasons. Firstly, the model defines spatial variability of SEC across a wetland, aligning almost perfectly with the purpose of the accretion component of the module. Secondly, similarity between the models used in this study allows for more meaningful comparisons.

Treatment of SEC	Accretion/module defined by:	Mangrove (mm/yr)	Mixed (mm/yr)	Saltmarsh (mm/yr)
Vegetation-specific accretion parameter	Constant rate of SEC	0.93	0.76	0.45
	Constant rate of accretion	8.2	5	1.8
Accretion module	Maximum accretion rate	10	n/a	5
	Minimum accretion rate	5	n/a	0
	Cubic coefficients; a, b, c	0.8, 0.8, 0	n/a	0.8, 0.8, 0

Table 5: Summary of the methods of treating SEC and the values used to define the parameters for mangrove, mixed and saltmarsh vegetation within the SLAM model utilised in this study. The mixed values were utilised for those projections in which a mixed zone was delineated within the input vegetation map (outlined below).

Vegetation information and mapping

In THE SLAM MODEL, explicit information on the spatial distribution of wetlands is required for model runs. Several data sources were used in this study to establish the land cover types at the Minnamurra site (Table 6). To satisfy the spatial data requirements of the model for validation, calibration and projection purposes, vegetation maps were prepared for the years 1949, 1963, 1986, 1997 and 2011, the former four being primarily based upon the work by Chafer (1998) and the latter on the work of Owers *et al* (2015) and Department of Primary Industries (DPI 2006) for the Comprehensive Coastal Assessment (CCA).

Vegetation map source	**Use in vegetation mapping for this study**	**Mapping technique**
Chafer (1998)	1949, 1963, 1986, 1997, 2011	Digitised aerial photography
CCA (2006)	2011	Digitised aerial photography
Owers et al. (2015)	2011	Spectral classification of remotely sensed imagery

Table 6: Sources of vegetation information for the development and adjustments of vegetation maps used for projection and validation runs in the SLAM model.

Modification of historical vegetation maps

'Historical' vegetation maps for the Minnamurra area were developed by Chafer (1998) to analyse the temporal habitat change of the Minnamurra River estuary. The maps displaying wetland vegetation over time were produced by scanning, georectifying to the Australian Map Grid, Zone 56 (1966 Australian Geodetic Datum) and digitising aerial photography of a 2m spatial resolution. Vegetation zones were classified implementing the scheme defined in Table 7 and spatially delineated based on an area-based rule that a particular class polygon must contain at least 90% of the relevant vegetation. Chafer (1998) acknowledged that this method introduced a degree of error, since the natural distribution of vegetation communities is not characterised by abrupt, linear changes in plant type as indicated by the vegetation maps produced for the Minnamurra River estuary (and indeed all vegetation maps). Rather, boundaries between communities are mostly gradual, with one vegetation type coexisting with another, producing an ecotone, such as is the case for saltmarsh and mangrove at the Minnamurra site. Such boundary interpretation error in addition to the potential error associated with digitising areas from aerial photography must be understood and deemed appropriate or within a defined error limit before any modelling occurs.

Using the method described above, Chafer (1988) developed eight vegetation maps for certain years between 1938 and 1997. Of these, four were chosen for use in this study, primarily to validate the SLAM model as described in Section 3.3.4. Classes defined by Chafer (1998) were reclassified for this study as displayed in Table 7. Reclassification rules were formulated in response to the requirement of the greatest possible similarity between diversely derived vegetation maps for conducting any subsequent comparison or analysis. A mixed zone was not demarcated by the author for the historical vegetation maps as aerial photography used in the initial analysis by Chafer was not obtained. Furthermore, validation of a model logically requires both the input data and comparison data to be created in exactly the same manner, signifying that any attempt to create polygons representing ecotones would only serve to increase the error inherent in the vegetation data but also decrease the reliability of the model validation.

Chafer (1998) vegetation class	Vegetation classification definition	Vegetation class for this study
Supratidal sands	Permanently exposed sediments of sandy constitution associated with ocean beach and river shoals	Beach Sands
Mangrove	Tidally inundated substrates vegetated by *Avicennia marina* and *Aegiceras corniculatum*	Mangrove
Saltmarsh	Semi-intertidal substrates vegetated in zones with *Sarcocornia quinqueflora*, *Sueada australis*, *Sporobulus virginicus* and *Juncus krausii*	Saltmarsh
Sedgeland/Reedland	Seasonally inundated poor soils generally vegetated with *Juncus krausii* and *Cumbungi Typha orientalis*	Saltmarsh
Swamp Oak	Forested land on seasonally inundated poor soils, primarily vegetated by *Casuarina glauca*	Casuarina
Seagrass	Submerged aquatic vegetation growing in water generally at a height less than one metre depth	River
Channel	Low water channel of Minnamurra River and Rocklow Creek	River
Intertidal Flats	Muddy or sandy substrates periodically exposed with tidal fluctuations.	River

Table 7: Reclassification of the categories defined by Chafer (1998) for this study.

2011 vegetation map creation

The final vegetation map used within this study was developed to reduce boundary interpretation error, test the flexibility and comprehensive nature of THE SLAM MODEL and provide a vegetation distribution map which covered the entire study site which was temporally consistent with the LIDAR-derived elevation model. Spatial vegetation information used to characterise wetland cover was sourced from Chafer (1998), CCA (2006) and Owers *et al.* (2015).

To decrease the potential error in vegetation mapping and test the flexibility of models in predicting future distributions of ecotones, the mixed vegetation community saltmarsh-mangrove was delineated and classified as a mixed zone within the final vegetation map. Both Oliver (2011) and Owers *et al.* (2015) produced spatial layers that incorporated a defined mixed zone in addition to mangrove and saltmarsh. The spatial extent, methodologies and final vegetation maps were compared to identify the layer that displayed the most accurate spatial delineation of the wetland communities and ecotone.

Oliver (2011) discriminated between vegetation types, mangrove, mixed, saltmarsh and casuarina, based on the wetland vegetation mapping protocols outlined in Wilton (2002). Whilst the protocols provide convenient guidelines for spatial delineation of wetland communities, their application to the Minnamurra area caused certain areas to be misclassified as mangrove, where they would be better described as a mixed zone. This may be partially due to the protocols being based on canopy gaps, which are not necessarily indicative of the presence or absence of saltmarsh. Indeed, in some areas, saltmarsh has been observed thriving beneath mangrove stands. In such locations, the mapping protocols fall short of accurate vegetation classification. Thus it was that the vegetation mapping by Oliver (2011) was not utilised within this study. The relatively small spatial extent of the map produced a further reason for its exclusion from this study.

Owers *et al.* (2015) used a complex, spectral analysis of remotely sensed imagery coupled with a decision tree process to identify and spatially demarcate three vegetation zones, namely the mangrove, mixed and saltmarsh communities. Resulting boundaries between vegetation categories were distinct and canopy based. The Owers *et al.* (2015) vegetation map covers the western floodplain and almost a third of the entire wetland area for the Minnamurra site. Whilst the method does potentially introduce uncertainty in boundary identification, the final output from the classification process was considered to provide the greatest accuracy within the primary study area and to be more suitable for the purposes of this study.

The Owers *et al.* (2015) vegetation map was combined with wetland vegetation spatial data developed for the CCA (2006) to determine the vegetation distribution within the entire Minnamurra study site. Seagrass, mangrove and saltmarsh boundaries were digitised for the CCA from aerial photographs at a consistent scale of 1:1500, producing a positional accuracy of less than 10m. For this study, the seagrass zones were reclassified to river. The CCA wetland vegetation map was clipped to that produced by Owers *et al.* (2015) and merged to create a wetland vegetation layer for the study area.

Working from the casuarina polygon developed by Chafer (1998) for the 1997 vegetation map, a casuarina zone was produced and incorporated in the final 2011 vegetation map for this study. The casuarina area was extracted from Chafer, edited to represent casuarina distribution displayed in the aerial photography and merged with the wetland vegetation layer to create one final, continuous spatial layer of wetland distribution at the Minnamurra site.

In addition to the vegetation distribution, spatial representation of the Minnamurra River was required. The polygon feature of this water course developed for the CCA (2006), however, was incorrectly positioned. To better identify the river boundary for the study area, adjustments to the river shapefile were made during an edit session in ArcMap at a scale of 1:1000.

It was deemed a priority to maintain the spatial delineation of the Minnamurra River when combining the wetland vegetation and river layers. Therefore, areas of the combined wetland vegetation map overlapping the river polygon were erased. Any gaps between vegetation and river were removed using the topology tool during an edit session, efficiently filling the small voids with the nearest habitat. All areas in the study site that had not been assigned a class were defined as undeveloped land. Those areas that were in fact developed were not considered in the modelling phase but rather removed after simulations to determine the percentage loss of vegetation growth due to coastal squeeze.

Reclassifications for an Australian setting

The SLAM model designates wetland vegetation type based upon the Cowardin classification system used by NWI (Cowardin *et al.* 1979; Clough *et al.* 2012), a system developed specifically for the North American context. Alignment of Australian vegetation types with those of NWI classifications was necessary before application of the model to the Minnamurra site. Assignment of NWI classes to the Australian vegetation for this study was also conducted in consideration of any wetland type conversions in the SLAM model.

Based on the work by Traill (2011), the Chafer (1998) vegetation maps and 2011 vegetation map were reclassified to correspond to NWI wetland classes, as shown in Tables 8 and 9 respectively. Adaptations were made to the suggested classifications of Traill (2011) for the wetlands of SE Queensland in consideration of the decision-tree programmed within the SLAM model. The changes were necessary a) to ensure the Minnamurra wetland system was not immediately classified as a tropical system within the model and b) to allow the mixed zone to move across the land. The SLAMM ID code, used as the vegetation reference within the model, relevant to individual class types was assigned to the 'dissolved' class polygons of each vegetation map in ArcMap. Final, reclassified Chafer (1998) and 2011 vegetation maps were then converted to raster layers with identical spatial resolution to the DEMS (5m x 5m cells). Rasters were converted to text files using the 'Raster to ASCII' tool in ArcMap, prepared, as required, for import into the SLAM model.

Chafer (1998) vegetation class	NWI vegetation class	SLAMM ID code	Under inundation, converts to
Mangrove	Regularly flooded marsh	8	Mudflat (tidal flat)
Saltmarsh	Irregularly flooded marsh	20	Regularly flooded marsh
Casuarina	Transitional salt marsh	7	Regularly flooded marsh
Undeveloped land	Undeveloped dry land	2	Nearest transitional salt marsh, mangrove, ocean or estuarine beach
Minnamurra River	Riverine tidal open water	16	Estuarine water
Ocean	Open Ocean	19	n/a
Sandy beach	Ocean beach	12	Ocean

Table 8: Reclassification of the Chafer (1998) vegetation classes as defined in this study to match NWI vegetation classes coded within the SLAM model.

2011 Vegetation map class	NWI vegetation class	SLAMM ID code	Under inundation, converts to
Mangrove	Regularly flooded marsh	8	Mudflat (tidal flat)
Mixed	Irregularly flooded marsh	9	Regularly flooded marsh
Saltmarsh	Tidal swamp	20	Irregularly flooded marsh
Casuarina	Transitional salt marsh	7	Regularly flooded marsh/mangrove
Undeveloped land	Undeveloped land	2	Nearest transitional salt marsh, mangrove, ocean or estuarine beach
Minnamurra River	Riverine tidal open water	16	Estuarine water
Estuarine Beach	Estuarine beach	10	Open water
Ocean	Open ocean	19	n/a
Beach	Ocean beach	12	Ocean
Rocky Intertidal	Rocky intertidal	14	Ocean

Table 9: Reclassifications of the wetland and landcover classes of the 2011 vegetation map to correspond with the NWI classes required for the SLAM model.

Vegetation elevation ranges

As previously described, the SLAM model is based on the assumption that wetland vegetation classes will exist at a certain elevation or position within the tidal frame. Vegetation classes within the SLAM model are each assigned elevation ranges within which the class exists. Whenever a cell containing that class falls below the lower boundary of its assigned range it is converted to a lower-elevation vegetation class. Given that the elevation ranges therefore drive the conversion and evolution of a wetland under rising sea levels, it is vital that most accurate delineation of elevation ranges for each vegetation is determined for a

	Lower boundary (m)	Lower boundary with respect to MSL (m)	Lower boundary as a function of tidal range (HTU)
Mangrove	0	-0.1125	-0.125
Mixed	0.567	0.4545	0.505
Saltmarsh	0.684	0.5715	0.635
Casuarina	0.877	0.7645	0.8494

Table 10: Lower elevation boundary of each vegetation type with respect to the local mean sea level (MSL) and tidal range (represented by the HTU).

given site. Within the SLAM model, it is possible to define the elevation ranges for a site by elevation, as a function of the tidal range or as a function of salinity.

Allowing for model comparison, elevation boundaries for wetland categories in this study were based on those demarcated for the Minnamurra site by Oliver (2011). As elevation ranges of wetland vegetation often change with decreasing tidal levels and differences in physiochemical conditions, elevation boundaries relative to the local tidal datum were converted to half tide units (HTU). Such a treatment of elevation ranges caused boundaries of wetland elevation to vary proportional to defined tidal ranges for each subsite. Table 10 shows the lower elevation boundaries of each vegetation class defined by Oliver (2011) and the method by which they were converted to HTU for the SLAM model. The boundaries were first expressed relative to the MSL measured at the Minnamurra site as required for the model prior to defining the elevations as a function of the tidal range. Given the tidal range defined for the entire study site, one HTU for the Minnamurra site was 0.9m. The elevation boundaries were originally defined with respect to this value with the SLAM model automatically applying the same proportional definitions of the boundaries to each subsite.

The final elevation ranges assigned to vegetation classes are displayed in Table 11. Vegetation maps created by Chafer (1998) did not include a mixed zone. Therefore, in order to partially account for the mixed zone when the Chafer maps were incorporated in the SLAM model, the upper value of the mangrove zone and lower boundary of the saltmarsh

	Lower boundary (HTU)	Upper boundary (HTU)
Mangrove	-0.125	0.635
Mixed	0.505	0.635
Saltmarsh	0.635	0.849
Casuarina	0.635	1.083

Table 11: Final elevation ranges assigned to each vegetation type. For validation runs, the lower elevation boundary of saltmarsh was extended to the lower boundary of the mixed zone as outlined above.

zone were defined to overlap such that the mangrove and saltmarsh elevation ranges extended to the upper and lower limits of the mixed zone respectively. Such a method was applied for all validation runs outline below.

3.3.3 Basic verification of the SLAM model

Verification of models as defined in this study denotes the process of testing the internal consistency of a model algorithm and checking that the inbuilt computer code performs as it should (Mulligan & Wainwright 2013). Testing of the SLAM model code in the traditional, computer science manner was beyond the scope of this study. However, based on the final output of models run using default parameters over the entire 1990 to 2100 period, a basic verification of the SLAM model was conducted.

Of particular interest was the verification of projected SLR in the SLAM model. The model is programmed to simulate eustatic SLR according to the decadal values reported in the third IPCC assessment report (IPCC 2001) or based upon user-defined values. To check the correct projection of SLR was occuring, historic SLR was set to 1.7mm/yr, effectively confining any changes in sea level to eustatic factors, default settings were applied and the model was run from 1990 to the end of the current century at decadal time steps. The process was repeated for each of the TAR IPCC (2001) sea level projections. Model output from individual runs was examined for any deviations from the correct, reported values.

3.3.4 Model validation

In this study, validation of models refers to the process of testing that modelled results are in agreement with a known reality and confirming that the model output can indeed be considered plausible and reliable (Fishman & Kiviat 1968). It is generally understood amongst modellers that it is logically impossible to achieve full validation of any model (Oreskes *et al.* 1994; Senarath *et al*. 2000; Mulligan & Wainwright 2013) yet validation must be attempted and is still considered an integral part of the modelling process (Gentil & Blake 1981; Power 1993). With a full appreciation of this, this study attempted to validate the SLAM model employing a multistage validation process, which included:

- *conceptual validation,* in which the underlying theories and assumptions are examined

- *operational or whole-model validation,* where model output is tested for its agreement with real-world observations and
- *data validation*, where data used to parametrise and/or test the model is evaluated (Rykiel 1996).

Conceptual validation was conducted by examining the model's structure, logic and treatment of component parameters. Operational or whole-model validation of the SLAM model conducted for the Minnamurra site incorporated a variety of validation procedures to provide a more robust and comprehensive understanding of the model's validity. The first procedure employed was a *predictive validation,* which involved utilising historical data to test if the predicted output from the model corresponded to real-world observations. As it is difficult to force changes in system behaviour within the code of the SLAM model, predictive validation based on historical data was performed, working with the predefined structure of the model. Of the methods trialled, the most successful predictive validation procedure was based upon a hindcasting process employed by Geselbracht *et al.* (2011). Historical vegetation maps by Chafer (1998) were used as the input vegetation information for validation runs and final, real-world, vegetation distributions for model comparison. Given the lack of accurate elevation information for the relevant input years, DEM2 was adjusted within the SLAM model using the NAVD88 correction parameter to produce an elevation surface representative of the required initial year of validation runs. The NAVD88 correction parameter is included in the SLAM model to adjust elevation data from a height datum to a tidal datum (Clough *et al.* 2012). With rising sea levels there is logically a corresponding rise in the local tidal datum. Thus, based on the observed SLR at Port Kembla of 2.1mm/yr and Minnamurra MSL (MHL 2012), elevation adjustments were defined for each validation run using the equation:

$$\mathrm{MTL} - \mathrm{NAVD88} = \bar{\mathrm{S}} - \left((2011 - T_0) * \left(\frac{2.1}{1000} \right) \right) \tag{4}$$

where NAVD88-MSL is the final correction value input into SLAMM to adjust elevations and account for SLR, $\bar{\mathrm{S}}$ is mean sea level at 2011 in metres and T_0 is the year of the Chafer vegetation map used and consequently the initial year of a validation run.

Elevation ranges were defined for validation runs as defined above. Site parameters were defined for validation runs as displayed in Table 12. Parameters were calibrated for the year

1986, with modelled variations less than 10% considered acceptable for validation runs. The first validation run was from 1986 to 1997, with years of simulated output set as 1990

Parameter	Validation runs		
	1949-1997	1963-1997	1986-1997
NWI Photo Date (yr)	1949	1963	1986
DEM Date (yr)	1949	1963	1986
Direction Offshore	East	East	East
Historic Trend (mm/yr)	2.1	2.1	2.1
MTL-NAVD88 (m)	-0.01745	0.01195	0.06025

Table 12: Parameters defined for each validation run.

and 1997. The modelled output was then visually and statistically compared with the ‘true’ 1997 vegetation map by Chafer (1998) to determine the validity, reliability and predictive capacity of the model. As the SLAM model may project more than 100 years into the future based on user-defined parameters, the ability of the model to project at longer time scales was tested by repeating the predictive validation process for the periods 1963-1997 and 1949-1997, holding all other parameters constant. Each validation run was set to produce simulated output for the years 1986, 1990 and 1997 to allow for comparison with Chafer vegetation maps and subsequent statistical validation. Confusion matrices were created for 1997 for each of the validation runs to examine more closely the performance of the model with respect to the observed data.

Statistical validation was performed to evaluate the fit of the modelled data to the available historical data and to test if errors associated with model output were within acceptable limits. Deviations of less than 10% from observed vegetation distribution were considered statistically valid. Errors were examined in this manner for the final year of modelling, 1997, for all validation runs. In addition to analysis for the final year, simulations initiating from 1949 and 1963 repeated the statistical analysis at the year 1986 to increase the robust nature of the validation procedure. Since these statistical tests were based purely on numerical deviations in area, further visual analysis accompanied any statistical analysis to ensure that modelled spatial distributions of vegetation were indeed similar to those observed.

Extreme condition tests were also used for validation purposes at the projection stage of this study to determine the model’s ability to produce valid, reliable and plausible output under an extreme SLR scenario (outlined further below).

Perhaps most germane to this study was the validation of the SLAM model based on its *comparison to other models*. In this validation procedure, output of the SLAM model was conceptually, visually and statistically compared with that of another two models, as defined in Section 3.6.

3.3.5 Calibration of the SLAM model for projection

In modelling, calibration is the tuning of defining parameters within acceptable limits to enhance the performance of the model. Calibration for the SLAM model before simulations were conducted using a process of optimisation, whereby parameters were iteratively altered to optimise the goodness of fit between modelled results for the initial year of a simulation and a vegetation map of the same year. Calibration of parameters focussed primarily on the tuning of elevation ranges and definition of salt elevation, whilst the measured input rates of accretion or SEC were held constant.

Projections were performed from the 2011 until the year 2100. A calibration procedure was implemented for the initial year of projection runs, using the 2011 vegetation layer as the calibration dataset for simulations. A time zero step was simulated in the SLAM model to produce modelled data for initial years of projections. Statistical analysis was again used to test the goodness of fit between the model output at time zero and the relevant calibration dataset. A 10% variance from the calibration dataset was considered to be within acceptable limits for projection. In certain instances, where, under visual analysis, the SLAM model output appeared to provide refinement to the initial wetland vegetation layers when compared to aerial photography, a variance slightly greater than 10% was accepted. The calibration process was repeated iteratively until the interplay between tidal ranges, elevations and coastal habitat maps at time zero were deemed satisfactory.

3.3.6 Implementation of the SLAM model – deterministic projections

Deterministic projections using the SLAM model were conducted for three main purposes within this study; to test the flexibility of the model, to evaluate the plausibility of predictive outcomes and, lastly, to simulate data that would allow comparison of models for validation purposes. Information regarding the vulnerability of wetlands at the end of the century was, therefore, simply a useful by-product of the primary aims.

Model projections were run using the prepared spatial layers (DEM, slope and relevant vegetation map) and calibrated model parameters. Simulations were conducted from 2011, corresponding to the year of input vegetation map layers. The 2011 vegetation layer was used for projections rather than Chafer's 1997 vegetation map to increase projection accuracy as a result of greater temporal correspondence between vegetation and elevation data. Projections were conducted to test the model's ability to simulate mixed zones for Australian contexts and to produce data suitable for comparison purposes.

Primary projections used the IPCC AR4 SLR scenarios outlined above. The SLR scenario proposed by Vermeer and Rahmstorf (2009) was used in projection runs as an extreme condition test, examining the ability of the model to behave reasonably under extreme scenarios.

Projection procedure followed for each SLR scenario was repeated for both DEMs to examine the importance of accurate data and expert judgement in the application of the SLAM model. All model output was saved as a raster layer, compatible for GIS analysis, and the areal extent of vegetation for simulated years was saved for further statistical analysis.

3.3.7 Sensitivity analysis

Sensitivity analysis is the process of examining how changes in parameter values affect the variance in model output (Saltelli 2000). A parameter is considered sensitive if small changes in its value cause significant variation in the model output (Tibshirani & Wasserman 1988). A sensitivity analysis also provides information on the approximate contribution of parameters to model uncertainty (Chu-Agor *et al*. 2011). Within this study, a sensitivity analysis for the SLAM model was performed by iteratively varying selected parameters by ±10%, keeping all other parameters unaltered (Clough *et al.* 2012). The magnitude of variation was chosen such that changes in parameters analysed did not exceed appropriate or plausible values for the wetland system. Parameters chosen for analysis included great diurnal tidal range, historic trend in SLR, NAVD88-MSL value, salt elevation, mangrove and saltmarsh accretion or SEC rates and amount of SLR by 2100. Since all IPCC SLR projections could not be tested in the one sensitivity analysis, the process was repeated for each SLR scenario examined in this study. A sensitivity statistic for individual parameters analysed was calculated by relating the percentage change in the parameter (10%) to the proportional change in individual vegetation types modelled for the year 2100. Results were used to investigate the robustness of simulations, to further an understanding of the behaviour of the model and contribution of parameter error or variation to model uncertainty.

3.3.8 Uncertainty analysis – stochastic analysis of results

The SLAM model is a deterministic model that produces a single, time-dependent simulation according to the set of input parameter values utilised. Any uncertainties or error in the original input, therefore, introduces potential sources of error and uncertainty in the final output. Uncertainty analysis provides a method of assessing to what extent parameter uncertainties influence the model output (Monte *et al.* 1996), thus providing confidence intervals for output data and allowing a full range of potential outcomes to be obtained.

The SLAM model employs a Monte Carlo analysis to test uncertainty, where uncertainty surrounding a chosen parameter is characterised by a probability distribution (normal, log-normal, triangular and uniform) related to key statistics for the variable (eg. mean, standard deviation etc.). Using the Latin Hypercube method (McKay *et al.* 1979), sample values are drawn from the probability distribution and a defined number of runs are simulated to obtain an array of likely projections.

Uncertainty is associated with the measured, site-specific data required by the SLAM model, including the elevation data, wetland vegetation distribution, tidal range, rates of accretion or SEC and local historic sea level rise. Since errors or uncertainty in any one of these errors can propagate into model simulations and output, an uncertainty analysis was conducted for each parameter to gain insight into model behaviour, test the effect of potential measurement errors on final output and establish whether a sufficient degree of belief in the validity of the model could be obtained given the uncertainty, such that the model could be applied in research-based decision-making.

Eight parameters were identified to be incorporated in the Monte Carlo analysis, seven of which were identified from the sensitivity analysis to have the greatest effects on the modelled areas of wetland vegetation. In addition, a spatially autocorrelated error field was generated for DEM2 based on the $RMSE_z$ of the elevation layer. This was then used to generate a number of equally likely DEMs from which 500 iterations were run to assess the effects of elevation errors and uncertainties possibly incorporated and propagated throughout the model. For each parameter used in the uncertainty analysis an uncertainty distribution was defined based upon the available data (see Appendix B). Given the temporal restrictions, an uncertainty analysis was not conducted for all SLR scenarios, DEMs and characterisations of the accretion parameter. Instead different SLR scenarios were incorporated in the probability distribution function for the SLR and accretions rates were utilised to characterise the accretion parameter and its related error distribution.

3.4 The SAAT Model – a spatio-temporal, empirical model

3.4.1 Model description and adjustment for long-term wetland evolution

Based on empirical data, the original Temmerman model was developed to explain the relationship between sedimentation rates and a number of controlling, morphometric parameters on saltmarsh platforms along the Scheldt Estuary situated in the northwest of Belgium and southwest of The Netherlands (Temmerman *et al.* 2003b). The point-based, empirical relationships were applied spatially to simulate the varying patterns of sedimentation over the entire platform. Based on the common understanding that environmental processes are interconnected and can act synergistically, the sedimentation rate of each cell-defined point on the saltmarsh platform was calculated using the equation:

$$\mathrm{SR} = \mathrm{k} \times \mathrm{e}^{\mathrm{lH}} \times \mathrm{e}^{\mathrm{mD_c}} \times \mathrm{e}^{\mathrm{nD_e}} \tag{5}$$

where SR is the sedimentation rate, H is the intensity of tidal inundation estimated as the surface elevation with respect to the mean high tidal water, D_c is the linear distance to the nearest tidal channel, $\mathrm{D_e}$ is the distance to the marsh edge measured along the closest tidal creek and k, l, m, and n are parameters estimated by a multiple non-linear regression procedure, as explained further in Section 3.4.2.

The basic conceptual structure and form of Temmerman model was used in this study to aid in simulating wetland evolution at Minnamurra. Initial adjustments to the structure of the model were made based upon availability of site-specific data and its overall applicability to the final objective of this study. Lack of data regarding the volume of sediment supply and deposition at the study site rendered the calculation of the Temmerman model's dependent variable illogical. Measurements of wetland SEC at Minnamurra, calculated from SET data, were, however, available for statistical analysis. Since sedimentation is a process that contributes to the overall change in wetland surface elevation, it was considered justifiable to replace the original dependent variable of the Temmerman model, sedimentation rate, with SEC. This substitution altered Equation 5. to:

$$\mathrm{SEC} = \mathrm{k} \times \mathrm{e}^{\mathrm{lH}} \times \mathrm{e}^{\mathrm{mD_c}} \times \mathrm{e}^{\mathrm{nD_e}} \tag{6}$$

where SEC is the surface elevation change of the wetland. The slight modifications to the model effectively increased its applicability in simulating long-term wetland evolution. Modelling of coastal wetland evolution is fundamentally complex and requires a full appreciation of the numerous, interconnected processes acting on the system and the resulting feedback loops between form, surface topography, and process that drive the change in coastal wetlands (Cowell & Thom 1994).The combined effect of these numerous processes culminates in topographic changes, be they positive or negative in nature. Therefore, wetland SEC, which captures both surface and subsurface processes influencing the system (Cahoon 2015), is an appropriate variable to be incorporated when modelling wetland evolution, more so than a simple sedimentation rate that accounts for but one morphodynamic process attributable to the long-term change.

As coastal wetlands of SE Australia are comprised of both saltmarsh and mangrove communities, the exponential relationships observed on the saltmarsh platforms along the Scheldt Estuary are not necessarily present along the Minnamurra River. To counteract this potential problem, empirical relationships between model variables were examined and analysed prior to the application of the adjusted Temmerman model. Furthermore, unlike the saltmarsh environment of northwestern Europe (Belgium/The Netherlands), the SE Australian coastal wetlands do not characteristically have channel networks that act as conduits for water flow to the main tidal channel. Instead, ebb and flow of tides occur in a relatively sheet flow manner. This being the case, the parameter, distance to edge, used by Temmerman *et al.* (2003b) in the original model is set to zero in its application here, effectively excluding the variable from the model.

The adjusted Temmerman model resulting from the above modifications was used as a parameter in modelling the wetland surface evolution to the end of the century. Evolution of coastal wetlands is inherently time dependent and is the natural result of the system's response to changes in external conditions (Wright & Thom 1977; Cowell & Thom 1994) Changes in sea level, itself a response to changing external conditions, therefore has a significant influence on the evolution of coastal wetlands. The adjusted Temmerman model, as a surrogate of the system's response to change, was thus used in combination with estimated sea level changes modelled by the IPCC (2007) to simulate wetland evolution to the year 2100. Following the zero-dimensional models of Allen (1990, 1995, 1997), French (1993) and Cowell and Thom (1994) and maintaining wetland surface heights relative to mean high water (MHW) as required by the adjusted Temmerman model, elevations at a given time step were calculated as:

$$\mathrm{E_T} = \mathrm{E_{T-1}} + \mathrm{SEC} - \Delta\mathrm{M} \tag{7}$$

where E_T is the elevation at a given time step, E_{T-1} is the elevation at the previous time step, SEC is the surface elevation change as estimated by Equation 6 and ΔM is the incremental rise in sea level.

Based on the relationship of surface elevation with wetland evolution and work by Oliver (2011), a simple vegetation model calibrated to site-specific data was used in this study to delineate between wetland communities at any given time step thereby simulating the time-dependent evolution of coastal wetland vegetation. Surface elevation can be said to control coastal wetland evolution in two important ways. Firstly, it determines the spatial boundary of tidal inundation and hence the boundary conditions of the responding, interconnected morphodynamic processes (Cowell & Thom 1994). Secondly, it governs the accommodation space within the wetland that, in turn, allows further sedimentation to occur and the surface to build upward (Allen 2000). The combined effect of these dynamic, interrelated processes represented in wetland surface elevation determines the development, distribution and persistence of vegetation communities within the coastal wetland environment. Working from an understanding of this relationship between morphodynamic changes and vegetation persistence, the simple vegetation model applied within this study was achieved by assigning a wetland vegetation type based on vegetation-specific elevation ranges to each cell of the surface elevation layer developed from the cell-based, spatial application of equation 6. In applying the entire model as described above, the resulting spatially applied adjusted Temmerman (SAAT) model simulated the process of wetland evolution, effectively determining the morphodynamic evolution (represented by surface elevation) and subsequent vegetation change at each time step until the year 2100.

3.4.2 Model setup

Model input parameters and coefficients for the SAAT model were based on the preparation, assessment and statistical analyses of relatively short-term field measurements recorded at the study site. Empirical data used for analysis included the eleven-year SET record introduced above, tidal plane data documented by MHL (2012) and RTK-GPS spot heights measured in 2011 by Oliver (2011).

Data preparation

'True' surface elevation heights through time were needed for model parameter calculation and subsequent time-series analysis. As the primary elevation information for the site was derived from LIDAR collected in March 2011 (as outlined in Section 3.1.2), RTK-GPS elevations as recorded by Oliver in the same year at each of the SETs were used as the basis for determining 'true' surface elevations through time. Incremental changes in surface elevation recorded by SETs between the years 2001 and 2011 were calculated relative to 2011 and subtracted from the RTK spot heights at the respective SET. Changes in surface elevation for years subsequent to 2011 were summed to the base RTK elevation height.

The SAAT model requires surface elevation heights to be expressed relative to the local MHW level. To produce such time series elevation information, the local MHW level recorded at the Minnamurra River was subtracted from the final elevation values calculated at the SETs. To capture the tidal conditions of each year as truly as possible, the yearly-averaged MHW levels of the Minnamurra River as reported by MHL (2012) were used for the period 2003-2010, a temporal period corresponding to the establishment of the tidal gauge at the Minnamurra River and final year analysed in the MHL (2012) report. For years not within the 2003-2010, an eight-year time-averaged MHW level as reported by MHL (2012) was used. Given that the small variabilities in MHW data displayed no significant trend over time, the constant, averaged value was considered to be sufficiently representative of the mean high water level at the Minnamurra site. To ensure this was the case, further analysis was conducted at relevant stages during model preparation, as discussed below.

To obtain the distance to tidal channel parameter required for the SAAT model, the distance from each SET to the Minnamurra River was calculated using the 'Euclidean Distance' tool in ArcMap. Final elevation and distance to channel information were recorded before being exported to JMP Pro (SAS v.11).

Exploratory data analysis and temporal patterns of elevation change

Exploratory analysis of site-specific data was conducted to understand the primary processes at work in the Minnamurra wetlands, verify parameter relationships used in the SAAT model and ensure model parsimony. Given the modifications to the original model and its application to an area displaying obvious differences in site characteristics to that of the Scheldt estuary, statistical analysis was necessary to ensure the exponential relationships remained between the environmental variables used in the original model and wetland surface elevation changes, the new dependent variable of the adjusted Temmerman model.

Using the same method employed in Section 3.1.1, trends in SEC were calculated for each individual SET. Further factors calculated to test their significance in explaining SEC over time included values of HHWSS, elevation values with respect to HHWSS, time in years since the previous SET measurement and since the initial SET measurement. All data was collated with the time series elevation data and distance values in Excel and imported to JMP for further statistical investigation and determination of model coefficients.

To ensure model parsimony, the relationships of all measured parameters with surface elevation trends were examined in JMP. Those parameters that displayed a weak or non-existent relationship with SEC were disregarded. Non-linear regressions were conducted and a goodness of fit examined to ensure an exponential relationship existed between SEC and absolute elevations relative to MHW and distance to channel values respectively.

Statistical analysis for model coefficients

Coefficients for the SAAT model were determined using a non-linear regression in JMP. Each regression model was set to iterate 1 000 000 times or until convergence was reached. The fit of the modelled data to the established elevation trends was calculated using a linear-regression. Factors for analyses included absolute elevations relative to MHW and distance to channel values.

Non-linear regression analyses were completed for the entire period of SET data, 2001-2013, and for the period in which real-world, non-averaged observations of elevation and tidal data were coincident, that is 2003-2010. This method was employed to evaluate the variation in model fit caused by the introduction of averaged data. Modelled data for both the entire and coincident period regression analyses were linearly regressed against the established elevation trends to calculate the fit of the model to the real world. A coefficient of determination, r^2, greater than 0.85 was deemed to provide a sufficient explanation of the observed data. Given the method of evaluating the 2003-2010 period significantly reduced the amount of data from which the relationship was being extrapolated yet did not produce a considerable difference in model fit, the averaged data was considered suitable for the determination of the coefficients to be used in the modelling process.

Spatial data preparation

Elevation layers covering the western floodplain and entire study area were prepared as described in Section 3.1.2.The eight year time-averaged MHW level (MHW=0.50825) calculated by the MHL (MHL 2012) was subtracted from each cell of the DEMs using the ‘Raster Calculator’ tool in ArcMap to create an elevation layer relative to MHW, effectively producing the spatial representation of parameter *H*.

The ‘Euclidean Distance’ tool in ArcMap was implemented to create a spatial layer that established the distance from each point in the landscape to the nearest tidal water source, as required by the SAAT model. A polygon of the Minnamurra River, developed following the methods of section), was used as the basis for the derivation of this 5mx5m cell-based spatial layer. The position of the tidal channel, Minnamurra River, was assumed to be constant over the period modelled. Though the river is likely to change slightly over the course of the next century, the simplistic abstraction of the river system for this model was considered relatively justifiable based on the small variation in channel position observed for the 62 years captured by vegetation maps used in this study.

3.4.3 Spatial application of the adjusted Temmerman model

The SAAT model was spatially implemented in ArcMap to simulate wetland elevation change as a response to SLR for the period 2011-2100. SLR scenarios used in model projections were equivalent to those outlined in Section 3.1.4. In keeping with the original Temmerman model, the Minnamurra River was extracted from the initial elevation layer, thereby excluding it from model simulations. The model variables, elevation, distance to channel and incremental SLR for a given time step, were used to simulate wetland surface elevation at annual or decadal time steps. The resulting elevation layer at a specific time step was input as the temporally-adjusted elevation layer, parameter *H*, for the subsequent calculation of wetland surface elevation. The process was repeated iteratively for individual DEMs at decadal time steps until the year 2100.

As decadal time steps were implemented in this study, the annually-based SEC parameter was multiplied by ten to simulate elevation changes at the appropriate temporal scale. As the initial elevation layer represents wetland surface heights at 2011, calculation of the surface elevation at 2020 utilised a nine-year SEC and SLR value, with subsequent time steps following the method defined above.

For each time step to the year 2100, the wetland vegetation distributions were modelled based on the approximate elevation references of each wetland community type at the Minnamurra site. Wetland elevation boundaries defined by Oliver (2011) were implemented in the classification process, further aiding in subsequent model comparability. For DEM1, classifying vegetation based on elevation ranges produced significantly disparate wetland distributions to that observed from 2011 aerial photography and vegetation map. A calibration process was therefore employed to allow a modicum of increased model performance. The vegetation classification process was conducted for each simulated elevation layer using the ‘Reclassify’ tool in ArcMap.

3.5 The Oliver model

3.5.1 Model description

The model implemented by Oliver (2011), herein referred to as the Oliver model, is an empirically based spatial model that simulates wetland surface elevation and vegetation distributions under conditions of rising sea levels. Based on the significance of factors in an initial stepwise regression, a factorial analysis of variance was conducted to develop a numerical model that provided the best fit with site-specific accretion trend data. Factors considered significant to the dependent variable and employed in the model include time (days from first SET measurement), average rainfall for the previous month, 6-month average water level , distance to shore, 3-month averaged Southern Oscillation Index value and the mean sea level. Full description of the model is reported in Oliver (2011).

3.5.2 Model implementation

The model was implemented by Oliver in 2011 and results documented in his honours thesis (Oliver 2011). Simulations of wetland evolution under SLR were conducted at decadal time increments from 2011 until the end of the current century. SLR increments were in accordance with the IPCC AR4 projections, namely the A1FI 95%CI and B1 5%CI. The initial elevation surface utilised was that named DEM3 for this study. Subsequent elevation surfaces were calculated using the equation derived from factorial analysis and relevant values for each significant factor at given time steps. The distance to shore was adjusted during model runs according to the SLR scenario investigated.

Elevation layers developed were used to model the response of wetland vegetation to SLR. The same simple vegetation model described above for the SAAT model was employed to demarcate wetland categories. Elevation boundary values were adjusted proportional to the SLR scenario used for each model projection.

3.6 Comparison of models

Comparisons between model outputs provide a means of evaluating the validity and performance of models. Focusing upon the western floodplain common to all the models output, the similarities and differences between the areal extent of wetland vegetation and flooded areas simulated by the SLAM, SAAT and Oliver models were analysed. To obtain the greatest strength in comparison results, those SLR scenarios common to output of all three models were utilized, namely the B1 and A1FI SLR scenarios. Using the same reasoning, only predictions based upon DEM3 elevation information were utilised in the comparison process.

Visual and statistical comparison of the simulated output of the different models was conducted. Variations in model results by overall output, vegetation and SLR scenario were tested for significance using a factorial analysis of variance (ANOVA) in JMP. Where an effect was noted between models, a one-way ANOVA was applied to determine more precisely where the variance occurred.

Differences and similarities between model output identified, both visual and statistical in nature, were examined closely to determine the source of variations. In doing so, the scientific principles and assumptions upon which each model was based were considered. In addition, the treatment of influential factors, the mathematical definition and conceptual abstraction of the wetland system were examined and compared in attempt to evaluate the performance of the models and determine if a specific model were more appropriate for the simulation of Minnamurra wetland evolution with rising sea levels.

4 RESULTS

4.1 Digital Elevation Models and Vertical Accuracy

Baseline elevation information is essential to all models applied within this study. The validity of model output, therefore, partially relies upon the input elevation information being sufficiently accurate. The accuracy of the three DEMs utilised within this study are presented below, accounting for the source of vertical errors identified within the spatial layers.

DEM1

DEM1, generated using the ground points from the as-received, vendor-supplied LIDAR data, was produced to explicitly display the need for accurate, expert-derived elevation information when modelling the effect of SLR on wetlands. Results indicated that, as expected, hasty and unconsidered generation of a DEM yielded elevation information insufficiently accurate for the production of valid model results.

Errors within DEM1 were primarily a result of propagated inaccuracies from the LIDAR data. Visual inspection of the elevation surface revealed stark inaccuracies where dense mangrove vegetation predominated. Inspection of the original LIDAR data confirmed that DEM1 elevation errors corresponded with misclassified LIDAR points, most specifically where low vegetation or dense mangrove canopies had been classified as ground. These errors are considered to be a manifestation of both physical limitations of LIDAR systems and classification errors attributable to the data processing stage.

Inaccurate representation of the main water body in the study site is also considered attributable to such limitations and errors. DEM1 elevations within the river channel ranged from 0.472 m to 3.195 m AHD with an average elevation of 0.822m. Investigation of the errors revealed three potential sources of the inaccuracies. Firstly, low mangrove vegetation fringing the river had been misclassified as bare earth points, causing significant problems when interpolating elevations across the river. This was particularly the case in the upper reaches of the Minnamurra River, where overhanging vegetation obstructed LIDAR signals from reaching the bare earth or water surface. Secondly, given the lack of elevation data within the river zone, accuracy of interpolation decreased in these areas as a result of decreased point resolution. Thirdly, water surfaces may have been misclassified as ground, erroneously increasing ground surface heights where water was inundating the land. Considering the mean height of the water channel in DEM1 approximately corresponds to the high water level recorded for the Minnamurra River, it is possible that the LIDAR was collected during high tide. No metadata was provided on the LIDAR collection time, therefore this particular source of error can only be considered as a valid hypothesis.

Global descriptive statistics of the LIDAR data indicate an overall vertical accuracy of 0.3m. In the absence of ground control points for the entire study site, this statistic was considered to be the most approximate vertical accuracy of the DEM able to be determined. However, in light of the significant errors in the representation of surface elevation discussed above, it is understood that the reported value does not provide a comprehensive assessment of DEM accuracy.

Elevation errors in the western floodplain were quantified from 72 RTK-GPS points. It was considered important to understand the spatial variation of vertical errors according to species type, allowing for a comprehensive appreciation of possible errors per vegetation type when modelling. Table 13 reports the vertical accuracy statistics for the ground control points as grouped by vegetation class type. The $RMSE_z$ and standard deviation of errors for all land cover types in the western floodplain suggest that the overall vertical accuracy is less than that reported for the LIDAR data. As expected, the greatest elevation errors occurred within the mangrove area, with the largest overall accuracies in both the positive (maximum) and negative (minimum) direction occurring in mangrove dominated locations. Skewness of measured errors in mangrove areas indicates vertical inaccuracies are predominately greater than the mean value, with most errors being the result of overestimation in surface elevation. The $RMSE_z$ values are similar to the calculated averages, indicating the significant bias in LIDAR data collected.

Land Cover	No. of Points	$RMSE_Z$ (m)	Mean (m)	Minimum (m)	Maximum (m)	Skew	Standard Deviation (m)
All	72	0.42	0.27	-0.62	1.21	0.96	0.32
Mangrove	22	0.68	0.54	-0.62	1.21	-0.63	0.42
Mixed	30	0.23	0.16	-0.28	0.81	1.44	0.17
Saltmarsh	12	0.20	0.15	-0.01	0.51	1.80	0.13
Casuarina	8	0.24	0.14	-0.15	0.54	0.95	0.21

Table 13: Vertical accuracy statistics by vegetation for DEM1.

The mean of elevation errors in swamp oak zones were the smallest of all classes in the western floodplain. However, considering the small sample, the calculated values are not thought to be fully representative of the vegetation class.

Greatest vertical accuracy was measured for saltmarsh areas, with $RMSE_z$, standard deviation and range of errors all calculated as being considerably less than other classes such as mangrove. The overall vertical accuracy of DEM1 and error statistics by species type were used in the considered development of DEM2. Full awareness and appreciation of the significant vertical errors within DEM1 also contributed to understanding sensitivity of models applied in this study.

DEM2

DEM2, derived from the combination of 2011 LIDAR data and RTK-GPS points, was used to assess the importance of accurate input elevation information when modelling coastal wetland evolution under SLR and to stress the significance of expertly refining as-received data for valid model application.

Applying a filtering algorithm to the LIDAR dataset prior to the generation of DEM2 resulted in a considerable increase in the accuracy of surface elevations within wetland areas (Figure 5). Visual inspection of DEM2 revealed a notable decrease in elevation errors within mangrove zones, most particularly within the western floodplain. Furthermore, a significant increase in vertical accuracy was observed at each meander bend of the Minnamurra River (subsites 3, 5 and 6), indicating DEM2 provides a more realistic representation of the floodplain and wetland areas at these sites. Though elevations of wetland areas included fewer errors, some inaccurate representations of surface elevation remained, particularly along the river bank within subsites 5 and 6. Again, the limitations of LIDAR systems and classification algorithm applied are considered primarily responsible for the propagated errors evident within DEM2.

Water bodies were more clearly defined in the elevation model with respect to DEM1. Misrepresentation of surface elevation within the river resulted primarily from the interpolation technique applied. Interpolation errors along the tidal channel decrease proportional to the width of the Minnamurra River.

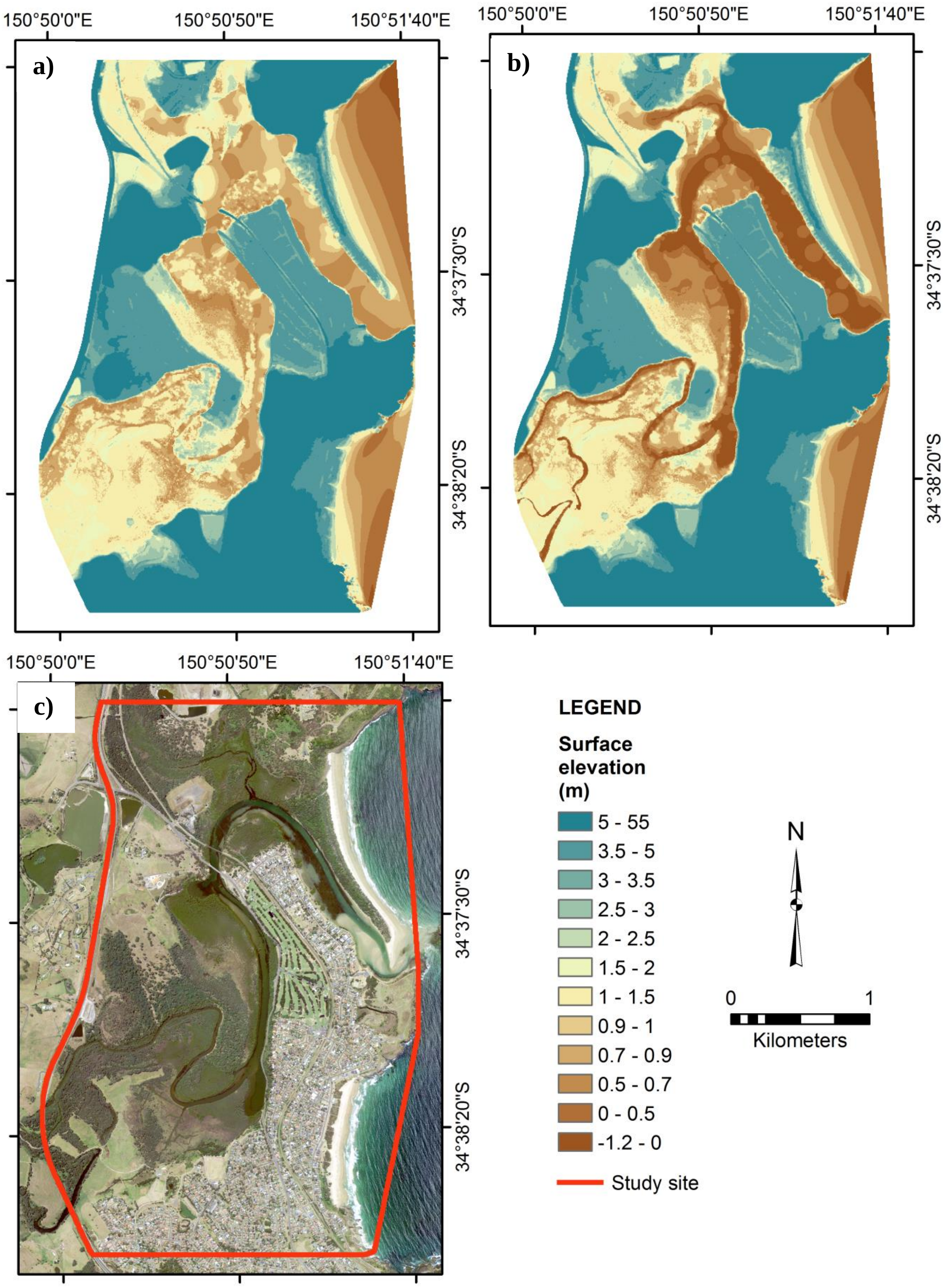


Figure 5: Digital Elevation Models of the entire study site: **a)** DEM1 and **b)** DEM2. The two models represent the surface elevation of the site outlined in **c)**. A considerable increase in the vertical accuracy can be observed in the river and floodplains of the Minnamurra river represented in DEM2.

Quantifying the accuracy of DEM2 was conducted using the 72 RTK-GPS ground reference control points. Similar to DEM1, values describing elevation error derived from the accuracy assessment provide relative confidence in vertical accuracy for the western floodplain only. Extrapolation of the error statistics to the entire site was therefore not a reliable method of quantifying vertical error for the study site. Instead, vertical error statistics were considered to provide a basic understanding of the spatial variation of inaccuracies throughout the area.

Statistics regarding the magnitude of elevation error associated with the western floodplain within DEM2 is reported in Table 14. Elevation error for all land cover types and for each vegetation zone was characterised by calculating the $RMSE_Z$. The author acknowledges that the explanatory power of the RMSE is limited given the error metric requires stationarity of variance within the data.

The overall vertical accuracy within the western floodplain was approximately consistent with that reported for the LIDAR dataset and indicated a 14cm increase in vertical accuracy when compared to DEM1. Of particular note was the reduction in elevation error within the mangrove zone, with an $RMSE_Z$ of 45cm. The largest elevation errors were recorded again where mangrove vegetation predominated.

Measured inaccuracies of surface elevation in saltmarsh zones remained the same as DEM1, suggesting that the errors were more likely a result of LIDAR system limitations rather than from classification or interpolation techniques applied. Whilst the magnitude of surface elevation errors in saltmarsh zones are commonly less than within mangrove forests, potential elevation errors arise from the resolving threshold of the LIDAR being at or near the elevation of the short saltmarsh vegetation, meaning that the bare earth surface cannot be

Land Cover	No. of Points	$RMSE_Z$ (m)	Mean (m)	Minimum (m)	Maximum (m)	Skew	Standard Deviation (m)
All	72	0.31	0.15	-0.62	1.65	2.51	0.28
Mangrove	22	0.45	0.20	-0.62	1.65	2.06	0.42
Mixed	30	0.22	0.12	-0.30	0.80	1.34	0.19
Saltmarsh	12	0.20	0.15	-0.01	0.51	1.80	0.13
Casuarina	8	0.26	0.13	-0.29	0.54	-0.06	0.24

Table 14: Vertical accuracy statistics by vegetation for DEM2.

clearly distinguished from the top of the saltmarsh within the LIDAR system. Given the magnitude of the saltmarsh $RMSE_Z$, it is likely the errors are a consequence of a situation.

DEM3

As the subset of RTK-GPS points used in accuracy assessments of DEM1 and DEM2 were in fact used for the generation of DEM3, it was not logical to characterise elevation errors based on the 72 point dataset. Instead, the 9.3cm RMSE reported by Oliver (2011) for DEM3 was treated as the vertical accuracy of the elevation model. This measurement of error is significantly less than that calculated for either DEM1 or DEM2.The lowest elevation of DEM3 was recorded at -0.255m and the highest at 2.704m, the greatest elevation being approximately two metres less than that of DEM1 and DEM2.

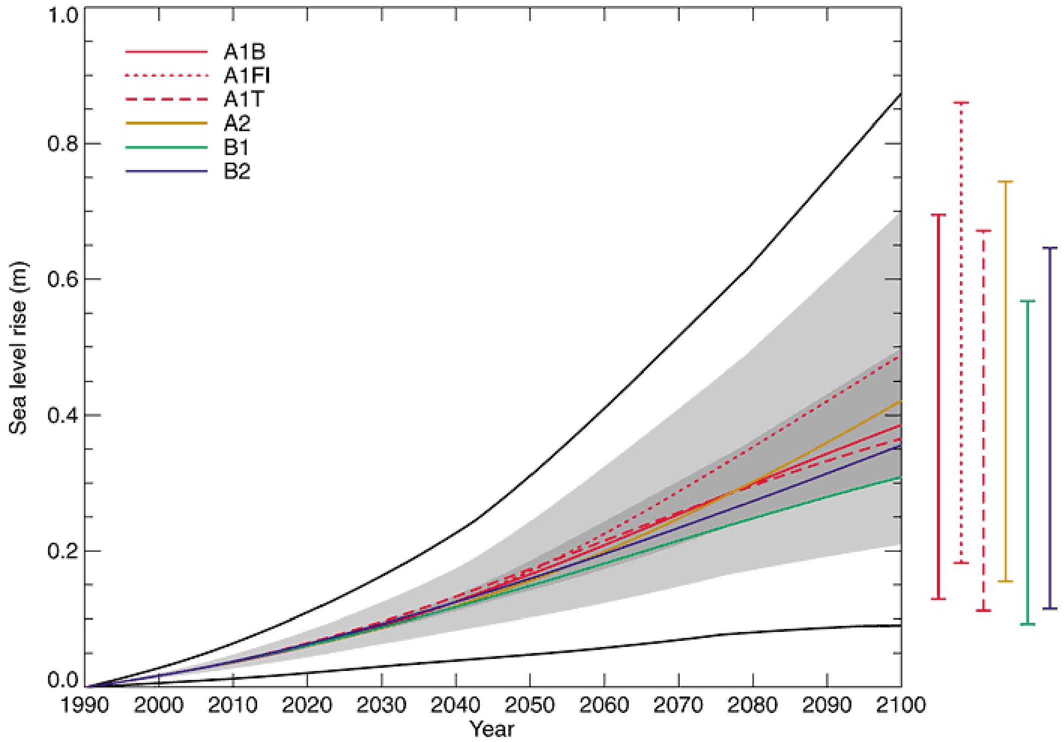
Spatial variation of error in DEM3 based on vegetation type was not quantifiable, however the elevation layer was examined visually to gather useful supplementary information on DEM3 elevation error by vegetation. Based on in-field observations, it appears that the floodplain is well represented, with few elevation errors occurring in the mangrove zone. Given the use of selected LIDAR ground points in the generation of DEM3, it is likely that similar errors of DEM1 and DEM2 in this zone are also present. Significant differences between DEM3 and the other two DEMs generated for this study occur in surface elevations for areas populated by *Casuarina*. Variations between DEMs in this zone commonly fall within 0.3m of each other at any given point, an error equal to the vertical accuracy reported for the LIDAR data used to generate the surface elevations of the *Casuarina* zone for all elevation models.

4.2 The SLAM model

4.2.1 Model Verification

Verification is an important process in assessing the performance of a model. The simplistic process applied in this study to verify the SLAM model focussed on ensuring that the computer programming and implementation of SLR scenarios within the model were correct.

SLR scenarios incorporated in the SLAM code are based on the IPCC TAR (2001) emission scenarios. SLR is programmed at 25 year increments within the model, despite the accumulative SLR values for each scenario being reported at decadal time steps in the TAR. Applying the model for the period 1990 - 2100 at 25 year increments confirmed that the eustatic SLR is modelled as it is designed according to the computer code. However, closer inspection of model output and related programming revealed a significant systematic error in the code design. The maximum magnitude of SLR modelled for the A1T and A1FI emission scenarios were incorrectly identified in the code or, more specifically, the timeseries data of these two SLR scenarios had been interchanged. This systematic error appears to have occurred during SLAM model development and programming due to an unquestioning use of SLR timeseries data presented in the TAR. That is, the error within the SLAM model corresponds exactly to an inexplicable error in reporting on the part of the IPCC, whereby the upper limit timeseries data of SLR under the A1T emission scenario has been erroneously replaced by A1FI values and vice versa. The timeseries data of A1T and A1FI reported in IPCC TAR table II. 5.1 do not correspond with either the within text discussion or the graphical representation (figure 11.12; IPCC, 2001) of projected SLR for the same scenarios (Figure 6). Furthermore, the TAR table of SLR values and hence the programmed SLR scenarios in the SLAM model would suggest an increase in sea level of 0.859 metres and 0.671metres for the A1T and A1FI scenarios respectively over the period 1990-210 0. However, logically, a future scenario in which there is a technological emphasis on fossil fuels (A1FI) would be associated with a greater rise in sea level than a scenario in which non-fossil energy sources predominate (A1T).



Year	A1T SLR (m)	A1FI SLR (m)
1990	0	0
2000	0.029	0.029
2010	0.063	0.065
2020	0.104	0.110
2030	0.153	0.164
2040	0.214	0.228
2050	0.291	0.299
2060	0.386	0.375
2070	0.494	0.453
2080	0.612	0.529
2090	0.735	0.602
2100	0.859	0.671

Figure 6: Table II.5.1 and Figure 11.12 of the IPCC TAR (IPCC 2001). Projection results reported in Table II.5.1 (presented on the right) do not correspond with the in text discussion or graphical presentation of the same results (graph presented to the right). It is clear the A1T and A1FI maximum SLR scenarios (corresponding to the upper limit of the coloured bars in the figure) have been interchanged. The reporting error is transferred as an error in the SLAM model, which directly sourced values from table II.5.1 to define the SLR scenarios programmed within the model.

The SLAM model code was not tested for further errors as computer science methods of verification were beyond the scope of this study. It was therefore assumed that required model verification conducted by the model development team was sufficient.

4.2.2 Predictive validation

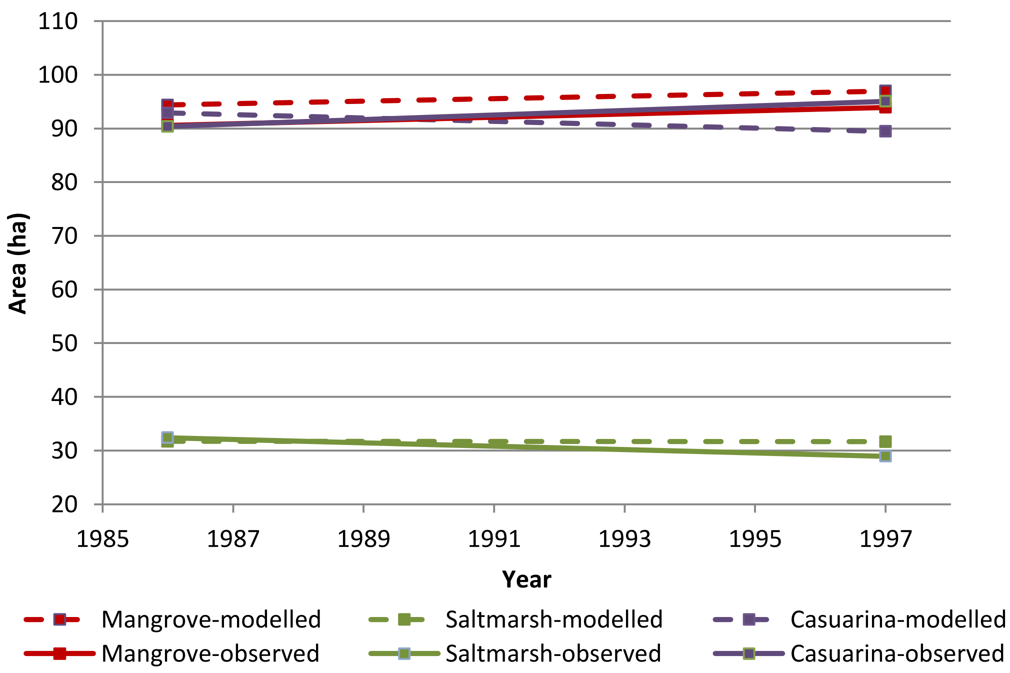
Predictive validation involves modelling a system's behaviour and comparing the output with the real system to determine if they are the same (Sargent 1996). This validation technique was implemented utilising the Chafer vegetation maps as the comparison data. Validation runs were conducted at three time scales, namely 1986-1997, 1963-1997 and 1949-1997. In testing the predictive validity of the SLAM model at each temporal period, two methods of simulating elevation changes were applied. The first utilised accretion rates specified for each wetland vegetation type and the second used rates of SEC set per land cover type. A selection of the data is presented herein.

Validation run: 1986-1997

Validation runs over this temporal period resulted in a generally good fit of model output with real world observations (Figure7; Table 15). Characterising vertical increases in wetland surface heights by vegetation-specific rates of SEC resulted in less than 10% error in the areal extent of almost all wetland classes. Of the wetland vegetation classes modelled, saltmarsh areas produced the least fit with observed, 1997 vegetation data. Areal extent of saltmarsh zones was underestimated at time zero, 1986, and overestimated in the final year simulated. Visual analysis and interpretation of the confusion matrix generated for the final year suggested that overestimation was a result of mangrove areas being erroneously simulated as saltmarsh zones. For this period, a larger decrease in the distribution of saltmarsh was noted in the observed data than in that modelled.

Mangrove areas were simulated relatively well by the SLAM model, with model errors associated with this class falling below 5% (Table 15). Statistically, the small errors in modelled mangrove areas were the result of consistent overestimation in the spatial extent of mangrove zones. Visual analysis suggests that, with respect to the Chafer vegetation comparison data, mangrove zones were indeed overestimated within subsite 8, especially along the banks of the river. In other areas, however, the distribution of mangrove vegetation was considerably underestimated, such as within the western floodplain (Figure 8). This

Figure 7: Modelled and observed total areas of mangrove, saltmarsh and *Casuarina* for the period 1986-1997.



		Mudflat	Mangrove	Saltmarsh	*Casuarina*	Undeveloped land
1986	Observed Area (ha)	0.00	90.60	32.41	90.38	538.08
	Modelled Area (ha)	0.44	94.37	31.72	92.89	526.84
	Percentage error	43.99	4.16	-2.12	2.78	-2.09
1997	Observed Area (ha)	0.00	93.92	28.93	95.06	536.62
	Modelled Area (ha)	1.70	96.98	31.64	89.45	525.93
	Percentage error	169.64	3.26	9.37	-5.90	-1.99

Table 15: Total areas modelled and observed for each vegetation type and respective error statistics. Results are drawn from the validation run utilising rates of SEC to define the accretion parameter over the period 1986-1997.

observation is confirmed by interpretation of the confusion matrix, where the greatest errors in simulated output occur within the mangrove zone (Table 16)

Modelled *Casuarina* zones were slightly overestimated at time zero and underestimated for the final year of simulation (Table 15). *Casuarina* zones were observed to increase between 1986 and 1997 yet a decrease in area was simulated by the SLAM model. Greatest errors in model simulation of *Casuarina* zones occurred in subsite 8 where the vegetation had been replaced by mangrove zones in model output.

Areas of undeveloped land were relatively well simulated by the SLAM model, being associated with an approximately consistent underestimation of its area by 2% (Table 15).

	Mudflat (ha)	Mangrove (ha)	Saltmarsh (ha)	*Casuarina* (ha)	Undeveloped land (ha)	Total observed area (ha)
Mangrove	0.21	88.16	2.47	0.88	0.25	91.97
Saltmarsh	0.05	1.16	26.98	0.65	0.07	28.90
Casuarina	0.00	4.53	1.85	84.18	4.28	94.85
Undeveloped land	0.03	2.79	0.37	3.48	521.23	527.90
Total modelled area (ha)	0.29	96.65	31.66	89.19	525.83	

Table 16: Confusion matrix of modelled (vertical) vegetation at the year 1997 against observed (horizontal) data of the same year showing areas that are accurately simulated. More than the simple error statistic, the matrix also provides an understanding of where vegetation has been inaccurately simulated with respect to observed distributions. The greatest overall errors are observed for the mangrove zone.

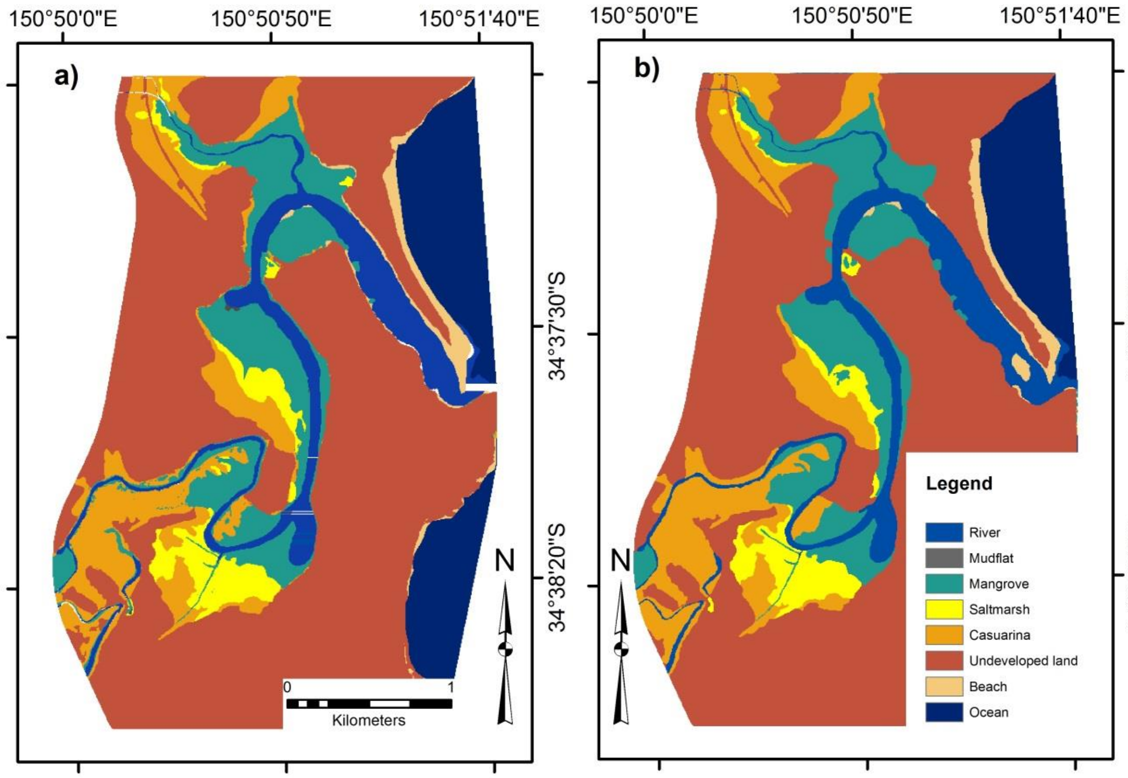


Figure 8: **a)** Modelled and **b)** observed wetland distributions for the year 1997. Modelled data was generated for the validation period 1986-1997 utilising rates of SEC.

The small percentage error is partially due to the initial extent of the land cover class being considerably large. The greatest loss in hectares between modelled and observed data in fact was calculated for the undeveloped land. Visual analysis suggests this is a result of beach areas being correctly simulated in the southernmost land extent of the study site (Figure 8). The rate of decrease in the area of undeveloped land is approximately equal for both the modelled and observed undeveloped land zones.

Mudflat areas were simulated in the model output of the validation run. For the year 1997, 1.694 hectares of mudflat were modelled, resulting in a 169% increase in mudflat area. Though a substantial error statistic, it should be noted that a mudflat class was not included in the Chafer vegetation maps utilised in this study. Simulated mudflats occurred primarily in the areas of lower elevation within the mangrove zone of the western floodplain.

Characterising vertical increases in wetland surface heights by vegetation-specific accretion rates resulted in relatively similar statistical and spatial patterns of error in modelled output. Use of accretion rates marginally decreased the ability of the model to simulate mangrove and saltmarsh zones (Table 17). Use of accretion rates also significantly reduced the area of

		Mudflat	Mangrove	Saltmarsh	*Casuarina*	Undeveloped land
1986	Observed Area (ha)	0.00	90.60	32.41	90.38	538.08
	Modelled Area (ha)	0.44	94.37	31.72	92.89	526.84
	Percentage error	43.99	4.16	-2.12	2.78	-2.09
1997	Observed Area (ha)	0.00	93.92	28.93	95.06	536.62
	Modelled Area (ha)	0.98	97.23	31.68	89.86	525.93
	Percentage error	98.10	3.53	9.54	-5.47	-1.99

Table 17: Total areas modelled and observed for each vegetation type and respective error statistics. Results are drawn from the validation run utilising rates of SEC to define the accretion parameter over the period 1986-1997.

mudflat simulated by the year 1997 (Table 17), thereby decreasing the error statistic associated with this class.

Validation run: 1963-1997

Validation runs for the longer temporal period 1963-1997 using both accretion and SEC rates produced greater errors overall in the model output. At time zero, 1963, errors associated with modelled distributions of saltmarsh, *Casuarina* and undeveloped land all fell below 5% for both predication validation runs (Table 18 and Table 19).Mangrove and mudflat areas were less accurately simulated at time zero, resulting in an error of 10.9% and 17.75% respectively.

Characterising vertical increases in wetland surface heights by vegetation-specific rates of SEC resulted in underestimation of mangrove, *Casuarina* and undeveloped land and a considerable overestimation of saltmarsh zones within the model output for both 1986 and 1997 (Table 18; Figure 9.). Considerable errors in modelled data first occurred at 1986, where the SLAM model did not simulate the observed increase in mangrove areas and corresponding decrease in saltmarsh zones between 1963 and 1986.Visual comparison of modelled and observed vegetation distributions for 1986 suggest that the error statistics associated with each class do not entirely account for the distribution of error across the study site. Overall mangrove error indicates an underestimation of the class at 1986. However, overestimation of mangrove areas with respect to the 1986 Chafer vegetation map was observed in subsites 5, 6and 8 and mangrove zones were underestimated within the western floodplain in subsite 4 and nearby Rocklow Creek in subsite 2. *Casuarina* zones simulated for 1986 were underestimated, with saltmarsh being simulated in its place.

		Mudflat	Mangrove	Saltmarsh	*Casuarina*	Undeveloped land
1963	Observed Area (ha)	0.00	66.37	57.20	78.66	538.73
	Modelled Area (ha)	0.18	73.59	54.37	80.16	529.70
	Percentage error	17.75	10.88	-4.95	1.91	-1.67
1986	Observed Area (ha)	0.00	90.60	32.41	90.38	538.08
	Modelled Area (ha)	0.62	77.09	53.85	77.26	528.54
	Percentage error	61.74	-14.92	66.17	-14.51	-1.77
1997	Observed Area (ha)	0.00	93.92	28.93	95.06	536.62
	Modelled Area (ha)	1.21	77.97	53.21	76.96	527.47
	Percentage error	120.58	-16.98	83.97	-19.04	-1.54

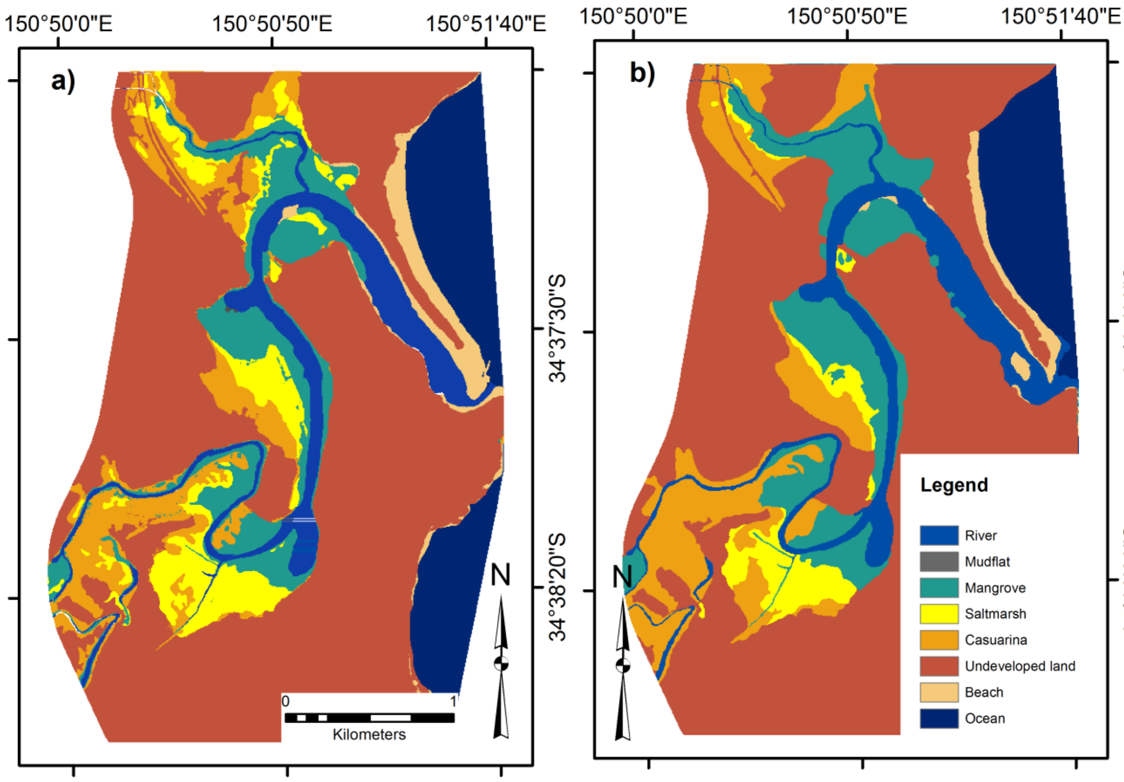
Table 18: Total area, observed and modelled, and error statistics associated with each vegetation/land cover type of the validation run 1963-1997 utilising rates of SEC.

Similar errors to those reported above occurred within the model output for the final year of simulation, 1997. All errors in the areal extent of classes were greater than 10%, excepting the undeveloped land class which saw only a marginal underestimation of 1.54% (Table 18) Though an increase in mangrove and *Casuarina* zones was simulated between 1986 and 1997, the magnitude of area increase did not reflect that observed in the real system, resulting in a further underestimation of these two vegetation zones at 1997. Spatially, approximately 73% of mangrove vegetation was modelled in the correct position. Inaccuracies of mangrove areas with respect to the observed data occurred within subsite 8 where mangrove vegetation was simulated in place of *Casuarina* (Figure 9).Further visual inspection and interpretation of the confusion matrix revealed that underestimation of mangrove areas was directly related to an overestimation of saltmarsh zone, especially within subsites 2, 4 and 6 (Figure 9).

Simulated saltmarsh zones replaced areas observed to be covered by mangrove, *Casuarina* and undeveloped land and were associated with the greatest error. Whilst the total area observed for saltmarsh zones almost halved over the period 1963-1997, simulated distributions indicated a loss of only 1.15 ha, equating to an approximately 2% change in areal extent.

Mudflat zones simulated produced a large error in model output at the final year of the validation run. Areas of mudflat were simulated in place of certain mangrove vegetation and zones of undeveloped land (Figure 9).

Figure 9: Comparison of **a)** modelled and **b)** observed data for the year 1997 for the validation period 1963-1997. Modelled distributions were simulated utilising rates of SEC.



Characterising vertical increases in wetland surface heights by accretion rates very slightly improved the fit of the modelled data to the observed wetland distributions (Table 19). Marginal variations in each class with respect to the model output when implementing rates of SEC were produced at both 1986 and the final year, 1997. Though the magnitude varied, spatial patterns of error were congruent to those generated in modelled data when utilising vegetation specific rates of SEC.

Mangrove zones were consistently underestimated, more so than when SEC was used as a parameter in the model. This was particularly notable in the western floodplain and surrounding Rocklow creek (Figure 9). The confusion matrix indicated that approximately 72% of modelled mangrove vegetation was situated in the correct position, a positional accuracy slightly less than that calculated for simulations utilising rates of SEC (72%).

Inaccuracies in the simulation of saltmarsh areas were greater when using accretion rates than for the first validation run reported here for the temporal period 1963-1997. Saltmarsh was again significantly overestimated, with the SLAM model only simulating a change of 0.6% by 1997, where a loss of almost 50% had been observed and mapped by Chafer. Analysis of the confusion matrix and vegetation distributions at 1997 suggested that a significant proportion of this error was attributable to the inaccurate simulation of mangrove zone growth over the temporal period 1963-1997.

Casuarina zones modelled using accretion rates rather than rates of SEC displayed greater fit with the observed vegetation distribution data, though errors greater than 10% still occurred (Table 19). Errors associated with mudflat zones were almost a quarter of those in model output simulated using rates of SEC, indicating a significantly greater increase in model fit for these zones.

With respect to the SLAM model's performance for the first predictive validation period, 1986-1997, greater errors were associated with mangrove, saltmarsh and *Casuarina* zones of the simulated vegetation distributions over the period 1963-1997. Comparing model output of simulations using the same characterisation of vertical increases between the two validation periods suggested that the longer temporal period produced a more accurate representation of mudflat zones, but that all other wetland vegetation was more accurately represented at shorter time scales.

		Mudflat	Mangrove	Saltmarsh	*Casuarina*	Undeveloped land
1963	Observed Area (ha)	0.00	66.37	57.20	78.66	538.73
	Modelled Area (ha)	0.18	73.59	54.37	80.16	529.70
	Percentage error	17.75	10.88	-4.95	1.91	-1.67
1986	Observed Area (ha)	0.00	90.60	32.41	90.38	538.08
	Modelled Area (ha)	0.23	76.47	54.16	77.87	528.64
	Percentage error	22.67	-15.60	67.11	-13.84	-1.75
1997	Observed Area (ha)	0.00	93.92	28.93	95.06	536.62
	Modelled Area (ha)	0.39	76.82	54.03	77.90	527.69
	Percentage error	38.62	-18.20	86.78	-18.06	-1.53

Table 19: Total area, observed and modelled, and error statistics associated with each vegetation/land cover type of the validation run 1963-1997 utilising accretion rates.

Validation run: 1949-1997

Predictive validation runs for the period 1949-1997 produced model output that varied in its fit with the comparison data for the simulated years, 1963, 1986 and 1997. However, at time zero, 1949, errors in the modelled output for validation runs using SEC and accretion rates respectively were congruent. Error statistics evaluated by land cover type were consistently less than 10% for all validation runs (Table 20 and Table 22). Saltmarsh and undeveloped land zones were underestimated but the simulated land cover types displayed the greatest fit with the available observed data. Simulated areas of the *Casuarina* zone at time zero were greater than those observed and mapped by Chafer for the year 1949, with incorrectly simulated areas of *Casuarina* appearing in subsite 2, near Rocklow Creek, and subsite 8, at the back of the already extensive *Casuarina* zone. Modelled mangrove zones, too, covered a greater area at 1949 than those observed due to the simulation of mangrove vegetation within the *Casuarina* zone of subsite 8. Mudflat zones presented the greatest positive error in modelled output at time zero, yet represented the smallest areal extent of mudflat generated throughout all validation runs. Subsequent model output for the

Examining the model output for validation runs which characterised the vertical increases of wetland surface over time by rates of SEC revealed a good fit of simulated data for the succeeding time step of the validation run, 1963, with all errors between modelled an observed data falling below 10%. The mangrove zone at 1963 was the most accurately modelled, displaying a 1.13% variance from the observed data. The inaccuracies associated with modelled saltmarsh zones changed from negative at 1949 (an underestimation) to positive at 1963(an overestimation) due to a greater rate of observed saltmarsh zone change

		Mudflat	Mangrove	Saltmarsh	*Casuarina*	Undeveloped land
1949	Observed Area (ha)	0.00	58.30	65.16	80.39	541.13
	Modelled Area (ha)	0.11	63.72	62.45	85.41	530.79
	Percentage error	11.39	9.29	-4.17	6.25	-1.91
1963	Observed Area (ha)	0.00	66.37	57.20	78.66	538.73
	Modelled Area (ha)	0.36	67.32	62.32	81.96	530.19
	Percentage error	36.43	1.43	8.94	4.20	-1.58
1986	Observed Area (ha)	0.00	90.60	32.41	90.38	538.08
	Modelled Area (ha)	0.74	67.85	62.06	81.77	529.11
	Percentage error	74.27	-25.12	91.50	-9.52	-1.67
1997	Observed Area (ha)	0.00	93.92	28.93	95.06	536.62
	Modelled Area (ha)	0.99	68.86	61.56	81.50	528.06
	Percentage error	99.01	-26.68	112.82	-14.26	-1.59

Table 20: Error statistics of the modelled data for the validation period 1949-1997. Total areas modelled are derived from simulations conducted when characterising the accretion parameter by rates of SEC. Considerable errors in the simulated data are calculated for the mangrove and saltmarsh zones.

in comparison to that modelled. *Casuarina* zones in the observed data decreased over this period at a slower rate than that modelled, producing a reduced error statistic for this simulated zone at 1963 (Table 20)

Excepting undeveloped land zones, considerable error was noted in the model output for the succeeding time step, 1986(Table 20). The mangrove and *Casuarina* zone within the comparison data increased significantly over the 23-year period, 1963-1986, however a corresponding increase in the simulated vegetation areas was not observed. As a result, considerable overestimations of the zones were noted at 1986, the greatest of which measured within the mangrove zone. Similarly, the error associated with modelled saltmarsh zones was an order of magnitude greater than the previous time step due to the SLAM model's not capturing the observed substantial decline in saltmarsh areas.

The final modelled output for the predictive validation run involved considerable visual and statistical errors. Whilst areas of undeveloped land remained well modelled, all other simulated land cover type sat 1997 exhibited significant variations from the 'true' system. Further reduction in mangrove zones was simulated from 1986 to 1997, during which time an opposite trend in mangrove distribution was noted in the comparison data. Thus, a significant, overall underestimation of mangrove areas occurred within the final model output, as is evident in Figure10. Visual analysis indicated that model errors were spatially distributed throughout the study site. Overestimated mangrove zones in subsite 8 were, however, outweighed by the substantial underestimation of the vegetation type in all other subsites of the study area. Analysis of the confusion matrix for the validation run confirmed this visual observation, with incorrect modelling of mangrove within *Casuarina* zones and large errors resulting from saltmarsh simulated in place of mangroves.

More than a third of simulated saltmarsh areas (37.8%) were located within observed mangrove zones, predictably causing the vegetation type to be associated with a significant degree of model error (Table20). Only 43.1% of saltmarsh simulated was accurately simulated in space. These errors were blatantly apparent when visual comparison of modelled and observed reference data was conducted (Figure 10).

The overall error statistic relevant to modelled *Casuarina* zones at 1997 revealed the model's underestimation of the vegetation type (Table 20). Similar to mangrove areas, the error in simulated *Casuarina* zones is greatest at 1997 with the observed change in the comparison data not being accurately modelled. Visual analysis indicates that modelled *Casuarina* zones

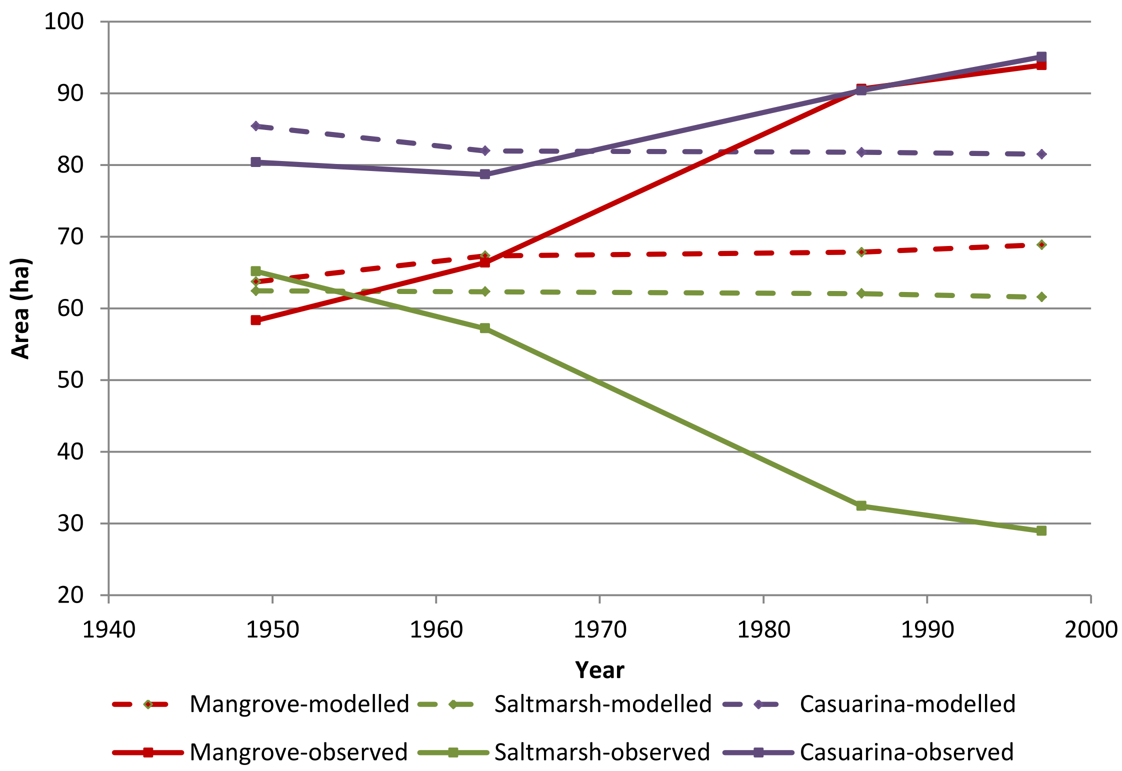


Figure 10: Observed and modelled data over the period 1949-1997. Similar to the validation runs 1986-1997, at short temporal periods (1949-1963) the modelled data displays a relatively good fit with the observed data. However, at larger temporal scales the modelled data shows significant deviations from the 'real-world' data. The SLAM model was unable to capture the large increase in mangrove vegetation and loss of saltmarsh. (Data pertains to the validation run in which accretion rates were used to define the accretion parameter. Similar deviations, however, were noted when accretion rates were utilised).

have exceeded the area displayed in the 'true' data for 1997 within subsite 8. This is reflected in the confusion matrix, where 10.6 ha of observed undeveloped land were recorded as being simulated as *Casuarina*.

An increase in predicted mudflat areas in the 1997 model output caused a directly proportional rise in the overall model error statistic for this vegetation type (Table 20). Spatially, these errors are situated in areas which, within the observed comparison data, are defined as mangrove or undeveloped land (Table 21).

Examining the model output for validation runs which characterised the vertical increases of wetland surface over time by accretion rates revealed very similar results to those simulated when using rates of SEC. Time zero simulations were congruent to that of the SEC validation run as described above. A good fit of modelled data to the available reference data was again noted at 1963, with overall errors in simulated areas of vegetation being within 5% of the observed data. In comparison to the 1963 simulated output for the validation run using rates of SEC, undeveloped land, *Casuarina* and mudflat zones were more accurately modelled. In contrast, errors associated with mangrove and saltmarsh zones were greater when accretion rates were used as a parameter within the SLAM model.

Significant errors in model output at 1986 again occurred as a result of the considerable growth of mangrove and *Casuarina* areas and substantial reduction in saltmarsh zones not being accurately modelled. The large error associated with simulated mangrove vegetation did in fact decrease slightly when the SLAM model utilised accretion rates. Conversely, saltmarsh and *Casuarina* zone simulation errors increased marginally with respect to model output from the validation run using rates of SEC.

Final simulated output at 1997 when implementing accretion rates as a factor within the model presented significant errors, most especially within the mangrove and saltmarsh zones (Figure 11.; Table22).Though modelled mangrove areas increased at a greater rate over the period simulated when using accretion rates, the total area simulated as being covered by mangrove vegetation remained substantially underestimated with respect to available reference data. Furthermore, of the mangrove area simulated, only 85% was accurately modelled. The remaining 15% of simulated mangrove zone was incorrectly modelled in place of *Casuarina*, undeveloped land and, in a few instances, saltmarsh zones. Visual analysis and interpretation of the confusion matrix indicated that a significant proportion of mangrove zone (25.4%) has been modelled as saltmarsh (Figure 11), especially within

	Mudflat (ha)	Mangrove (ha)	Saltmarsh (ha)	*Casuarina* (ha)	Undeveloped land (ha)	Total observed area
Mangrove	0.11	59.48	23.09	4.50	0.45	87.64
Saltmarsh	0.00	0.68	26.66	0.72	0.77	28.83
Casuarina	0.00	3.18	9.60	65.46	16.26	94.50
Undeveloped land	0.02	2.44	2.23	10.58	510.34	525.61
Total modelled area	0.13	65.78	61.59	81.25	527.82	

Table 21: Confusion matrix of the observed and modelled data for the year 1997 when rates of SEC were utilised. Significant errors in simulated position of wetlands can be identified from the matrix, such as the a significant proportion of mangrove area erroneously simulated as saltmarsh (23.09ha).

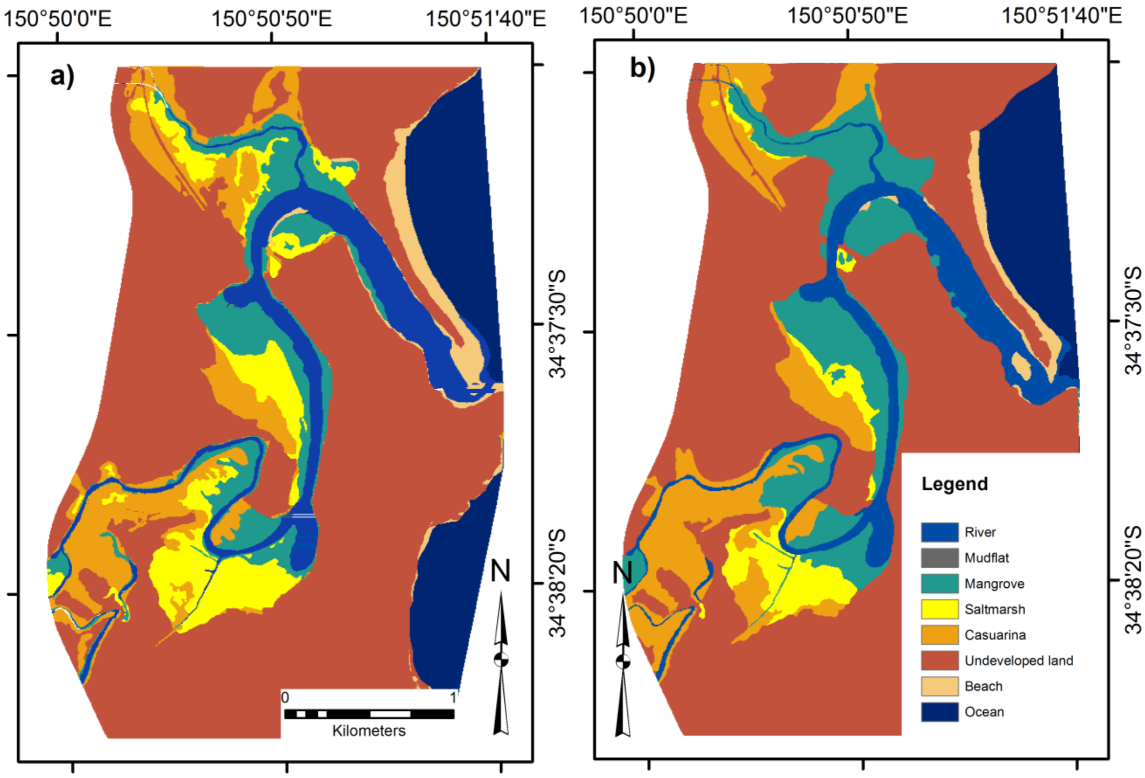


Figure 11: a) Modelled and **b)** observed distributions of the Minnamurra wetlands at 1997 for the validation period 1949-1997. Modelled distributions represent the final output from simulations using accretion rates to define the accretion parameter. Distinct differences can be quickly identified between the modelled and observed data, most particularly in subsites 2 (Rocklow Creek) and 4 (the western floodplain). Similar deviations from the observed data were noted when rates of SEC characterised the accretion parameter.

subsites 2, 4, 5 and 6. This model error was reflected within the error associated with simulated saltmarsh zone, where 38.2% of simulated saltmarsh was erroneously modelled as mangrove. Subsequently, modelled saltmarsh zones at 1997 were more than double that observed and mapped by Chafer (1998). In comparison to the predictive validation run utilising rates of SEC, simulated saltmarsh areas when implementing accretion rates included marginally greater inaccuracies.

Casuarina zones at 1997 were underestimated when accretion rates were used to characterise vertical increases in the wetland surface (Table 22). The error statistic describing the inaccuracy of modelled *Casuarina* zones was greater than that calculated of the respective vegetation type for the validation run in which rates of SEC were implemented. This appears to be the result of a greater decrease in the area of modelled *Casuarina* with respect to the increased *Casuarina* zone observed in the comparison data.

Mudflat areas modelled using accretion rates were almost a fifth of those simulated when utilising rates of SEC. This corresponded with a significant decrease in the error statistic noted for the land cover type. Once again, mudflats were simulated in position of a small proportion of the mangrove and undeveloped land zones.

Comparing model output generated from prediction validation runs utilising rates of SEC with those implementing accretion rates indicated that neither method of characterising vertical increases over time produced a consistently greater fit of simulated data with the comparison data.

Simulations using accretion rates produced greater accuracy in undeveloped land, *Casuarina* and mudflat zones with respect to those modelled using rates of SEC as a parameter. However, greater accuracy was obtained in mangrove and saltmarsh zones when rates of SEC were defined as a parameter for predictive validation runs at each temporal period. Visual analysis and comparison of model output generated using the different methods indicates rates of SEC were able to more accurately produce spatial distributions of wetland vegetation, especially within the western floodplain. Despite the greater accuracies or inaccuracies attributable to output using different methods of calculating wetland surface change,

		Mudflat	Mangrove	Saltmarsh	*Casuarina*	Undeveloped land
1949	Observed Area (ha)	0.00	58.30	65.16	80.39	541.13
	Modelled Area (ha)	0.11	63.72	62.45	85.41	530.79
	Percentage error	11.39	9.29	-4.17	6.25	-1.91
1963	Observed Area (ha)	0.00	66.37	57.20	78.66	538.73
	Modelled Area (ha)	0.18	67.16	62.42	82.20	530.19
	Percentage error	17.96	1.19	9.12	4.51	-1.58
1986	Observed Area (ha)	0.00	90.60	32.41	90.38	538.08
	Modelled Area (ha)	0.24	67.23	62.38	82.53	529.15
	Percentage error	23.70	-25.80	92.49	-8.68	-1.66
1997	Observed Area (ha)	0.00	93.92	28.93	95.06	536.62
	Modelled Area (ha)	0.23	67.55	62.29	82.59	528.31
	Percentage error	23.49	-28.07	115.36	-13.12	-1.55

Table 22: Error statistics of the modelled data for the validation period 1949-1997 when accretion rates are used to define the accretion parameter. Considerable errors in the simulated data are calculated for the mangrove and saltmarsh zones.

significant model errors remain in all modelled data.

In comparing all six predictive validation runs across the three simulation periods, it was evident that, with the exception of mudflat zones, errors in model output increased with increasing temporal periods of simulations. Greatest errors for each validation run were consistently associated with overestimated saltmarsh vegetation, which, in turn, was linked to underestimated areal extents of modelled mangrove zones. In contrast, simulated areas of undeveloped land varied little from the observed data, with errors across all validation runs never exceeding 2%. Increased errors over time associated with *Casuarina* zones appeared to be primarily related to the incorrect trend of areal change being simulated by the SLAM model. That is, where *Casuarina* zones were observed to increase over each temporal period, the model simulated a loss in the vegetation type over the same period. Spatial distributions of vegetation-specific inaccuracies were relatively similar within model output of each validation run. The magnitude of these errors, however, varied according to the input data and temporal period simulated.

4.2.3 Projections: 2011-2100

Simulations of the effect of SLR on wetland distributions from the year 2011 to the end of the century were conducted to examine the plausibility of the output under extreme conditions, to produce output suitable for comparison with other models, to investigate the ability of the SLAM model to simulate plausible distribution of wetlands under varying SLR scenarios and to consider the effects of using different input elevation information or method of characterising the accretion parameter within the model. For these purposes, 18 different runs were performed producing 180 maps. Selected model output and associated data are presented herein. See Appendix C for model output for all model projections.

Calibration

The SLAM model required calibration before projections were initiated so as to ensure the initial wetland distribution as defined by the model coincided with the available wetland vegetation map and aerial photography of the same year. The SLAM model immediately converts cells that fall below the minimum elevation range to a lower wetland category. Due to this definition of vegetation switching functions within the model, certain vegetation types were misclassified at time zero. The elevation ranges of wetland vegetation were required to remain as similar as possible to those utilised for the Oliver and SAAT model. Thus, only minor adjustments of minimum elevations of wetland categories were made to correct the errors within the simulated vegetation map for the initial year of modelling. Adjustments resulted in significantly refined time zero model output, as reported in Table 23. Variations greater than 10% were accepted for the mixed zone due to the simulated area more accurately representing the distribution at 2011 distinguished from the aerial photography. By default,

Table 23: Results of calibration at time zero (2011).

Land cover type	Initial coverage (ha)	Modelled coverage (ha)	Change (ha)	% Change
Mudflat	0	1.39	1.39	139.43
Mangrove	90.67	90.66	-0.01	-0.01
Mixed	7.22	8.35	1.14	15.75
Saltmarsh	26.59	25.42	-1.18	-4.43
Casuarina	89.62	95.62	6.00	6.69
Undeveloped Dry Land	523.89	514.73	-9.16	-1.75

any mudflat simulated by the SLAM model resulted in a large percentage error being calculated for the class as the original vegetation map had not included mudflats as a category. The small area of mudflat modelled in subsite 4 at time zero was accepted as the sole method for reducing the zone was by adjusting the minimum mangrove elevation boundary to an unrealistic value. To preserve the plausibility of the modelling, it was considered prudent to accept the minor deviation in model output from the original vegetation map.

Model output under various scenarios of SLR

Examination of the model output for projections from the year 2011 to 2100 showed that the magnitude of change in the areal extent of each vegetation or land cover type increased with increasing predicted levels of SLR (Table 24). For all SLR scenarios, undeveloped land and saltmarsh classes decreased in coverage by the year 2100. In general, a loss in *Casuarina* zones and increases in mixed zones were also predicted by the same year. Modelled vegetation and associated change in vegetation areal extent compared to the year 2011 varied according to the DEM utilised and the method used to define the accretion parameter within the model. General trends and differences between SLR scenarios are, therefore, noted within this section, with a further focus on differences between projections attributable to treatment of the accretion parameter and original input elevation data being reported in greater detail below.

Vegetation Type	Percentage change (%)		
	Low SLR	Intermediate SLR	Extreme SLR
Mudflat	4.48	-4.77	-7.99
Mangrove	4.83	82.85	-54.61
Mixed	0.01	17.87	137.48
Saltmarsh	-4.84	-24.13	-25.72
Casuarina	2.85	-36.18	-80.24
Undeveloped	-7.93	-37.60	-67.10

Table 24: The magnitude of change by the year 2100 when characterising the accretion parameter by rates of SEC. The pattern of greater change with increasingly larger rises in sea level is observed in each of the projections conducted for this study even with the changes in the definition of the accretion parameter or variation in the input elevation information. Positive values indicate an increase in area covered by the vegetation whilst negative values indicate a loss of the vegetation type.

Variations in areal extent of each vegetation type modelled under the SLR scenarios were evident by the year 2100. Total areas of mangrove zones reduced with increasing SLR and produced significant differences in its distribution within the final model outputs ($F_{(2,5)} = 31.3$, $p < 0.0098$). Though saltmarsh suffered losses across all modelled SLR scenarios, the variation of the vegetation distribution was also significant by the year 2100 ($F_{(2,5)} = 494.23$, $p < 0.0001$). The significance of differences in modelled mudflat zones was also great by the final year ($F_{(2,5)} =114.95$, $p < 0.0001$).

The distribution of simulated wetland vegetation under the low scenario of SLR, B1, was little altered by the year 2100 compared to that at 2011 (Figure 12a), with changes less than 10 hectares (ha) being calculated for all model output. Of these, the greatest changes in areal extent were losses recorded for zones of undeveloped dry land due to an encroachment inland of *Casuarina* modelled in subsites 6 and 7. Increases in mangrove areas were a result of marginal landward migration being simulated, causing concomitant losses in saltmarsh and *Casuarina* zones (Appendix C). Mixed and mudflat zones increased at approximately the same rate until the year 2100 (Figure 12a).

The general patterns modelled under a low SLR scenario were magnified when an intermediate level of SLR, A1FI, was simulated. *Casuarina* zones decreased due to encroaching mixed and mangrove areas. Approximately 36ha of undeveloped land were lost to *Casuarina* or mangrove zones. The large loss was not reflected in the percentage change recorded in the areal extent of undeveloped zones, where the considerable original area reduced the significance of the almost entire loss of undeveloped zones in subsites 6 and 7 by the year 2100.

Under the intermediate scenario of SLR a loss of greater than 90% was modelled for saltmarsh zones, with little more than 1 ha left throughout the study site by 2100. The rate of saltmarsh loss was greatest over the period 2030-2080, the same temporal period over which a substantial increase in mangrove zones was modelled (Figure 12b). Visual analysis indicated that this relationship was due to a landward growth of the mangrove zone at the expense of upland wetland classes, such as saltmarsh.

Simulated mangrove proliferated throughout the study site under the A1FI SLR scenario and recorded the largest areal extent of all wetland vegetation by the year 2100 (Figure 12b) Small changes were noted in the distribution of the mangrove zone over the first half of the

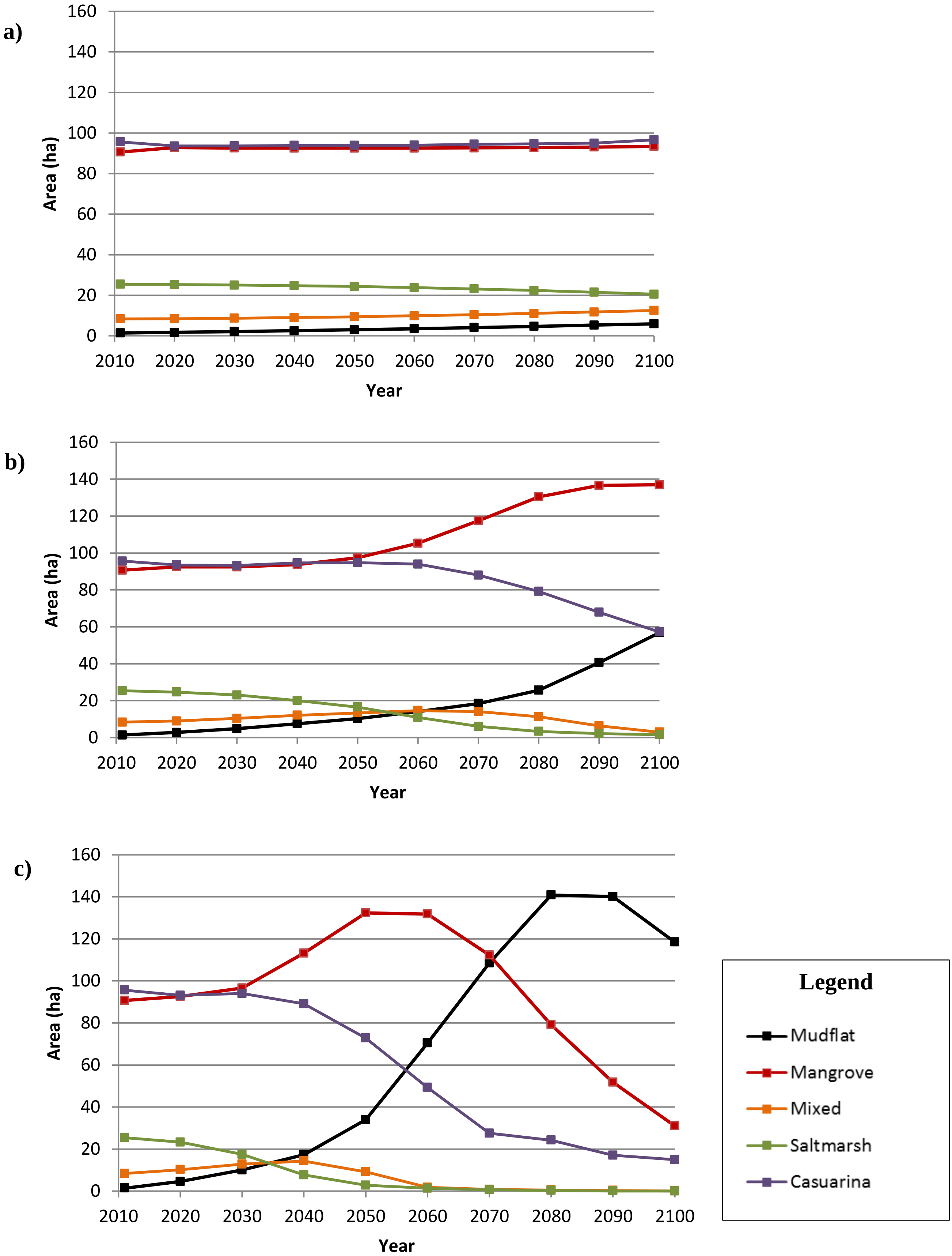


Figure 12: Patterns of wetland change under varying rates of SLR: **a)** low (B1) **b)** intermediate (A1FI) and **c)** extreme (Vermeer and Rahmstorf 2009) rates of SLR. Distinct difference in wetland areas can be seen between the three scenarios of SLR. Graphs presented here are derived from the timeseries data generated by using DEM2 as the input elevation information and rates of SEC defining the accretion parameter in the projections of wetland change from 2011 to 2100. The general patterns, however, were similar throughout all projections. With increasingly greater rates of SLR, an increase in the areal extent of mudflats and loss of wetland vegetation is observed.

century followed by a significant increase in the rate of mangrove growth and resulting areal extent from approximately 2050 or 2060.

An increase of mixed zone until the latter half of the century was associated with the A1FI scenario. Visual analysis indicated that a growth in the vegetation class at subsite 6 was primarily responsible for the increase in areal extent recorded, especially since the zone was lost to mangrove vegetation at subsite 4 over the same period. The predicted decrease in the distribution of the mixed zone was attributable to the proliferation of mangroves across all subsites. The final change in areal extent by the year 2100 varied according to the treatment of the accretion parameter (outlined below).

Under the extreme SLR scenario all simulated wetland vegetation was predicted to suffer significant losses (Figure 12c). Saltmarsh and mixed zones covered close to no area by the year 2100. Saltmarsh zones were quickly lost over the first 50 years, whereas an initial increase was simulated for mixed zones before its demise. A growth in mangrove zones was also simulated, reaching a maximum areal distribution of the category in the middle of the century (2050-2070 depending on the method of characterising the accretion parameter) before it too was simulated to experience a significant and rapid decline until the year 2100.

Loss and growth of zones were the result of the same relationships and patterns of distribution noted for simulated wetlands under the A1FI SLR scenario. It is noted, however that the patterns of growth and decline and the rate of wetland conversions were significantly increased under the extreme SLR scenario. In fact, the wetland change and distribution up to the year 2060 associated with the 1.9m rise in sea level is similar to that modelled over the entire period of simulations under the A1FI SLR scenario (Figure 12b and 12c) indicating that, with respect to the latter SLR scenario, the wetland change almost doubled under the extreme SLR scenario.

The mudflat zone was the only land cover category simulated to increase in extent by the end of the century. A significant increase in mudflat zones was associated with the decline of mangrove zones in the study area. The rate of change was observed to increase with even greater rates of SLR modelled for the second under the extreme SLR scenario.

The extent of inundation increased with increasing SLR. Under the B1 SLR scenario, little to no inundation was simulated in the study site. The increased level of SLR associated with the A1FI scenario also produced only a small area of land being inundated within all model output. In contrast, widespread flooding and inundation of wetland zones was simulated under the extreme SLR scenario (Figure 13).

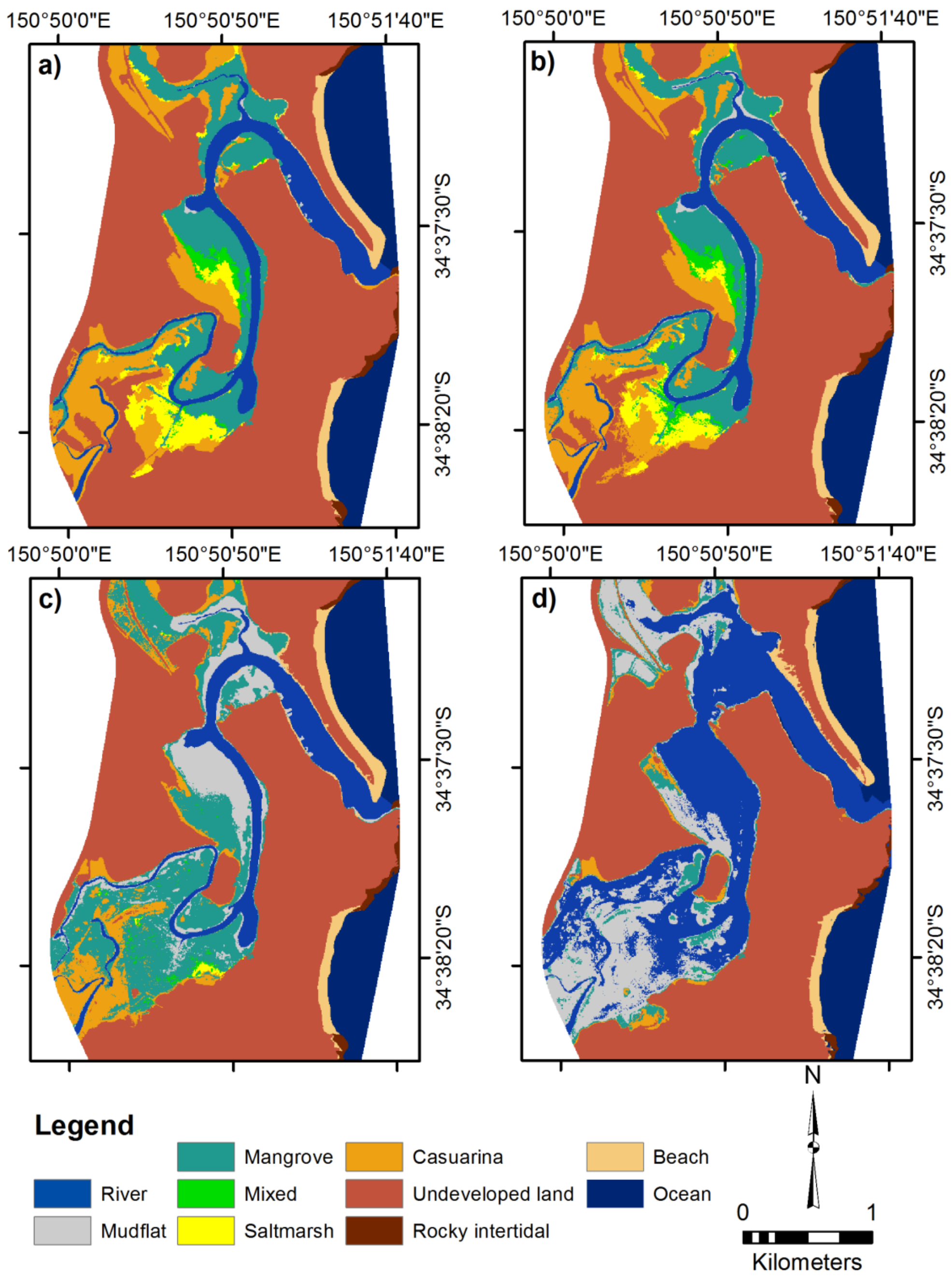


Figure 13: **a)** Initial wetland distribution at 2011 and modelled wetland areas for 2100 under **b)** low (B1), **c)** intermediate (A1FI) and **d)** extreme rates of SLR. An increase in the level of SLR produced successively larger areas of land to be inundated. (Note: results presented in this figure relate to the projection run in which rates of SEC defined the accretion parameter. The trend of increasing rates of sea level leading to increased loss of vegetation and greater inundation is, however, noted in each projection [Appendix C]).

Comparison of simulations modelled using different treatment of the accretion parameter

Three different methods were used to characterise the accretion parameter in this study, two of which involved applying individual values of SEC or accretion rates to entire areas of wetland categories and the last defined by the use of a numerical model to simulate spatially varying rates of accretion. The latter method will be referred to as the accretion module.

Assessment of visual and numerical model output indicated that, though patterns of simulated wetland distribution over time between SLR scenarios were similar, the magnitude and rate of wetland vegetation change varied with differing treatment of the accretion parameter. Landward migration of mangroves occurred at a faster rate when utilising rates of SEC within the SLAM model and low wetlands were rapidly converted into mudflat zones. For the same reason, under extreme SLR scenarios, a larger area of the vegetated floodplain was inundated with respect to that modelled using accretion rates or the accretion module. The difference in utilising rates of SEC to define the accretion parameter is clearly demonstrated by considering the mudflat zone modelled under the intermediate SLR scenario. By the year 2100, 56.86 ha of mudflat were modelled using rates of SEC in comparison to 1.9ha and 0.6ha simulated using accretion rates and the accretion module respectively.

Defining the accretion parameter for each vegetation type by an individual accretion rate resulted in an overall greater persistence in the upper wetland categories, a related decrease in the rate of mangrove landward migration and significantly less inundation by the year 2100. Mudflat zones were greatly reduced when accretion rates were utilised (Figure 14a). Similarly, accretion rates applied in the mixed zone reduced the rate of mangrove proliferation and simulated a greater persistence of upland wetland vegetation. Indeed, in applying accretion rates the greatest growth in the mixed zone was simulated. Under the intermediate SLR scenario, the SLAM model simulated a growth in the mixed zone of 100.4% when accretion rates were used in complete contrast to a simulated 64.7% loss when rates of SEC were applied and a 45.5% reduction in the zone's area when the accretion module was utilised. Under an extreme rate of SLR, the same pattern was observed, with model output simulated using rates of SEC producing the only growth in the mixed zone.

The greatest effect of applying the accretion module within the SLAM model was the increased persistence and proliferation of the mangrove zone. The varying accretion rates defined by the module were based on the elevation and accretion ranges of each wetland

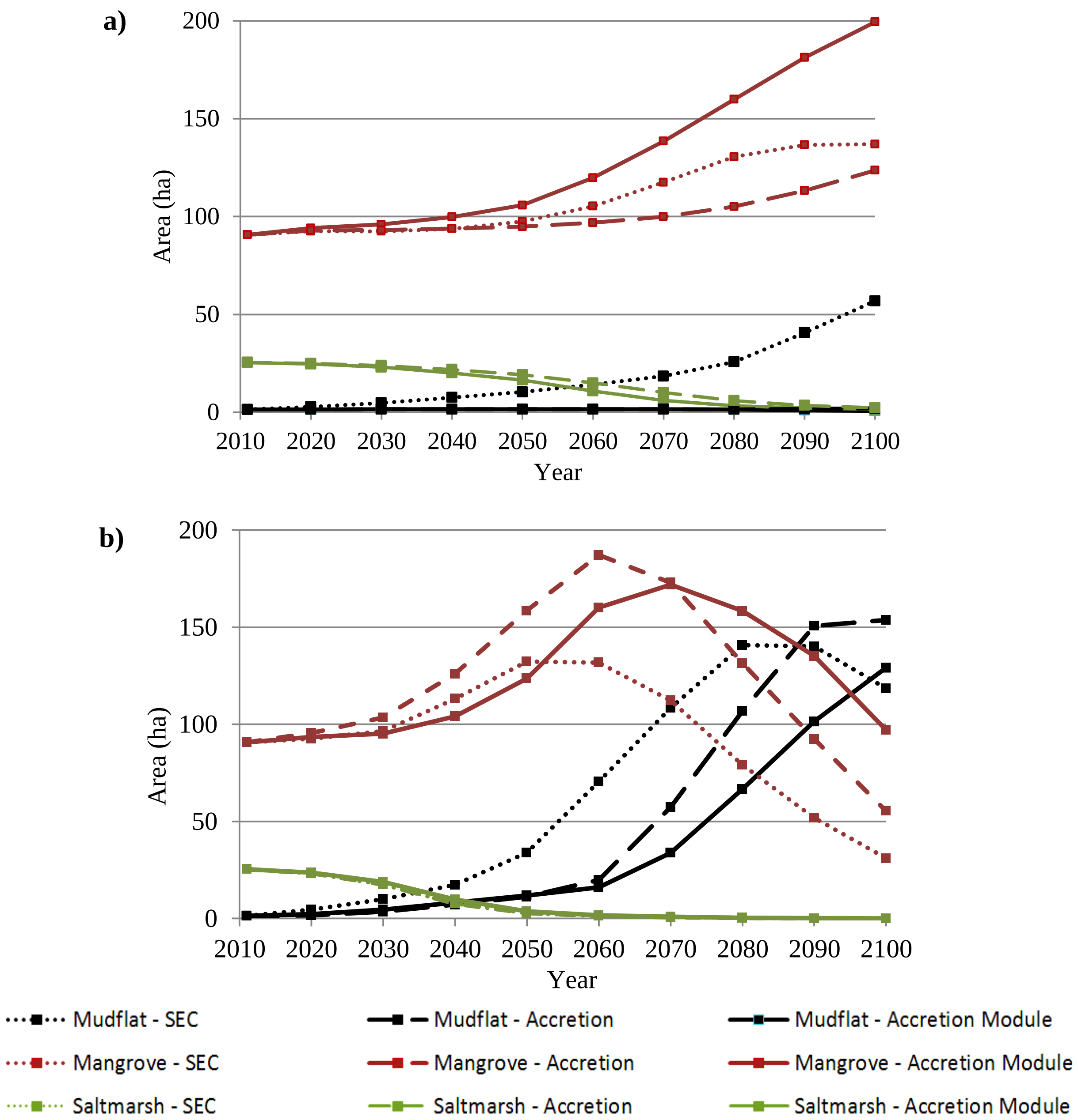


Figure 14: Areal extent of certain vegetation types modelled when using different methods to define the accretion parameter under **a)** intermediate (A1FI) and **b)** extreme SLR scenarios. Distinct differences can be seen in the modelling of mangrove and saltmarsh when the accretion parameter is characterised differently. In contrast, saltmarsh areas simulated are relatively similar regardless of the definition of the accretion parameter.

vegetation type and, when applied, produced a decrease in accretion rates with decreasing distance from the Minnamurra River. Under an intermediate SLR scenario (A1FI), such a definition of the accretion parameter generated a substantial increase in the mangrove area (119.9%) with respect to that simulated when applying rates of SEC (51.1% change) or vegetation-specific accretion rates (36.3%) . Application of the accretion module under the intermediate SLR scenario produced the only loss in mudflat zones simulated for all combinations of SLR scenarios and accretion parameter definitions. This was a result of the largest defined accretion rate at the river causing elevations of the mangrove zone's lowest boundary to be maintained with respect to the modelled SLR, thus allowing no conversion of mangrove to mudflat to occur and little inundation of the land to be simulated.

Flooding of the land was greatest when rates of SEC were used, most noticeable in model output for 2100 under extreme SLR scenarios (Figure 15). Rates of SEC applied under a simulated SLR of 1.9m generated an almost complete loss in wetland extent of subsites 3 and 4. In contrast, when accretion rates characterised the accretion parameter, flooding associated with extreme SLR was less extensive, with simulated areas of inundation using rates of SEC remaining as mudflat when accretion rates were applied. Similar patterns of inundation were observed in model output produced from runs in which the accretion module was applied (Figure 15). For the extreme SLR scenario, a relationship was evident between inundated lands simulated when using rates of SEC and areal extent of mudflat zones when using accretion rates. Differences in mudflat zones, and thereby areas inundated, when the accretion parameter was defined in a different manner were significant under extreme sea level scenarios.

Wetland vegetation distributions within each scenario generally displayed significant variation. As is clearly shown in Figures 14 and 15, mangrove distributions varied significantly under different scenarios of SLR according to the manner in which the accretion parameter was defined. Simulated mudflat zones, too, showed distinct variation within each SLR scenario modelled as described in detail above. Though variations occurred between modelled areas of upland vegetation under the extreme SLR scenario, no statistical difference was found for the overall or final model output generated utilising different accretion parameter definitions. This is primarily a result of upland wetland vegetation being significantly reduced in all model output for the extreme scenario, regardless of the definition of the accretion parameter.

Varying the method by which the accretion parameter was characterised produced no statistical difference in modelled areas of saltmarsh zones within all SLR scenarios. This is also evident in considering the percentage area change calculated for the saltmarsh zone under the extreme SLR scenario where a 99.9% loss was recorded since 2011 when rates of SEC were utilised, a 99.85% reduction in area was simulated when accretion rates were applied and a 99.91% decrease in saltmarsh areal extent was modelled when the accretion module was implemented.

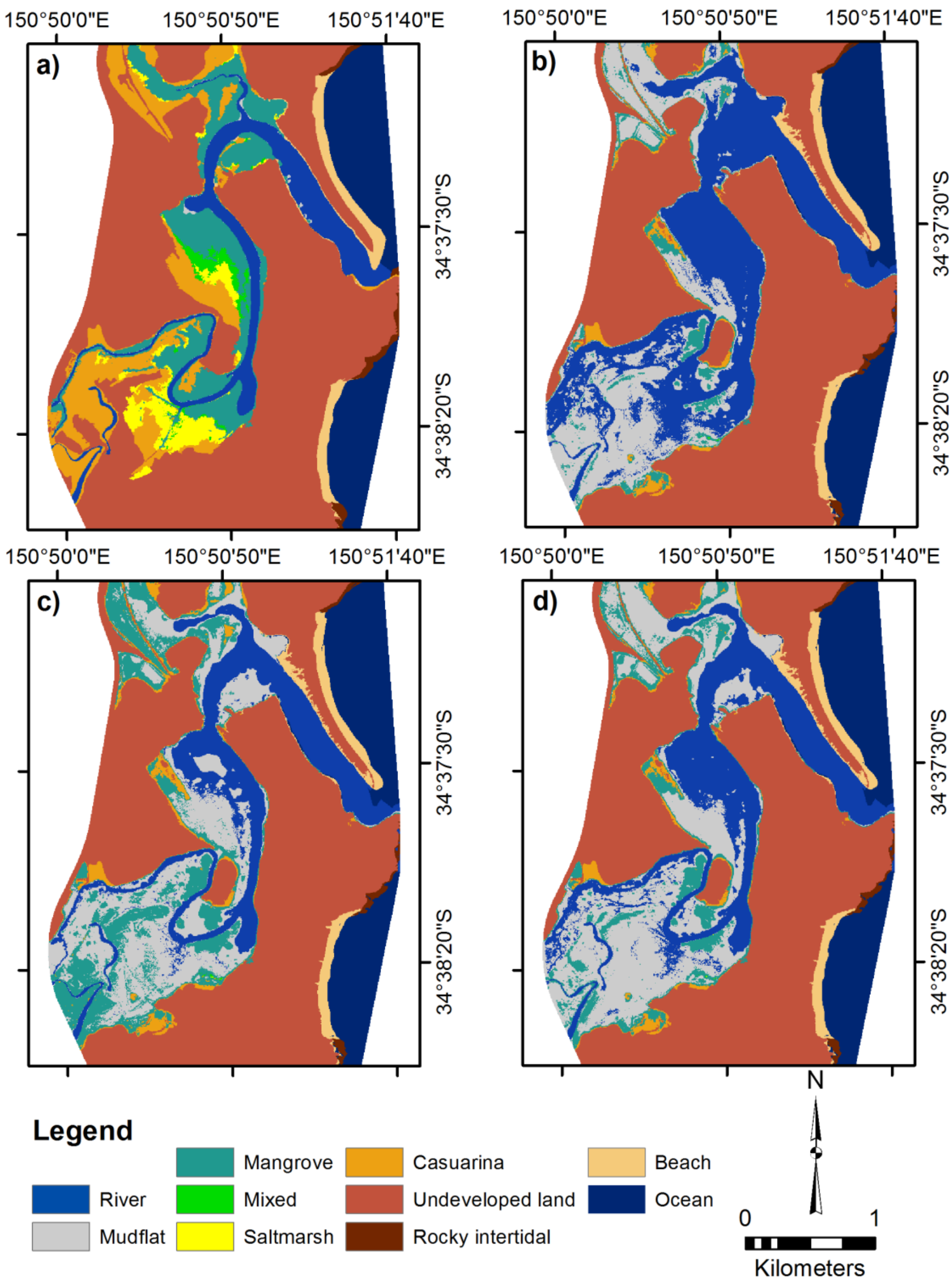


Figure 15: **a)** Initial wetland distribution and vegetation extent at 2100 under an extreme SLR scenario when utilising **b)** rates of SEC **c)** accretion rates and **d)** accretion module to define the surface elevation change in the SLAM model. Differences in the magnitude and spatial pattern of inundation can be seen between figures b) – d).

Analysis of model output defined by differing input elevation information

Projections which utilising DEM1 as the base input elevation information produced varying model output with respect to that generated when DEM2 was utilised within the SLAM model. Assessing the percentage change in areal extent of each vegetation type within individual SLR scenarios indicated that the lower wetland areas were most affected by the use of the two different input elevation layers. In addition, variations in model output from projections defined by different elevation information were most noticeable when rates of SEC or accretion rates characterised the accretion parameter. This was most evident under the extreme SLR scenario. Mangrove areas modelled utilising accretion rates saw a 26.5% change by the year 2100 when DEM1 was used as the input elevation with respect to a 7.1% growth in the mangrove area when DEM2 was utilised. Visual analysis of the model output indicated that the difference in simulated mangrove areas was a result of greater persistence of mangrove vegetation in subsites 2, 4 and 6. It was noted that areas where vegetation was observed to persist in projections using DEM1 coincided with distributions of dense mangrove vegetation in 2011. Specifically within subsite 4, the additional mangrove zones simulated using DEM1 were located in areas calculated to contain the greatest elevation errors. An analysis of model output indicated that the variations in the areal extent of mangrove simulated using DEM1 and DEM2 were significant within all SLR scenarios and projections utilising different accretion parameters.

As elevations of lower wetlands were generally greater within DEM1 than DEM2, slower conversion and landward migration of the mangrove zone was noted in projections utilising DEM1 as the base elevation layer. As a result, a significant difference in the spatial distribution of simulated mangrove and *Casuarina* zones were observed, the latter vegetation type simulated to persist in subsites 6 and 7 by the year 2100 when using DEM1 in comparison to the proliferation of mangroves in the same areas modelled when utilising DEM2 as the base elevation information. Across all scenarios the total areal extent modelled for the *Casuarina* vegetation was significantly different when different elevation information was used ($F_{(1,16)} = 110.41$, $p < 0.001$).

Utilising different elevation information resulted in significant variation in mudflat areas being simulated, especially under extreme SLR conditions. Comparing model output from DEM1 to that of DEM2 indicated that under the extreme SLR scenario a further 19ha were simulated when utilising rates of SEC and a 25 ha increase was calculated from output produced from using the accretion module. Similar to the locations of persisting mangrove vegetation, additional mudflat zones simulated using DEM1 were situated in areas associated with significant elevation errors (Figure 16).

Areas of mudflat simulated are related to the extent of inundation and conversion of wetland to estuarine water. Therefore, it is not unsurprising that simulations utilising DEM2 as the base input elevation information produced substantially greater areas of wetland inundation for all SLR scenarios.

It is noted that, although variation in output was statistically significant when utilising different base elevation information, simulations of the effect of SLR on wetland vegetation did not greatly vary in subsite 7 (Figure 16).

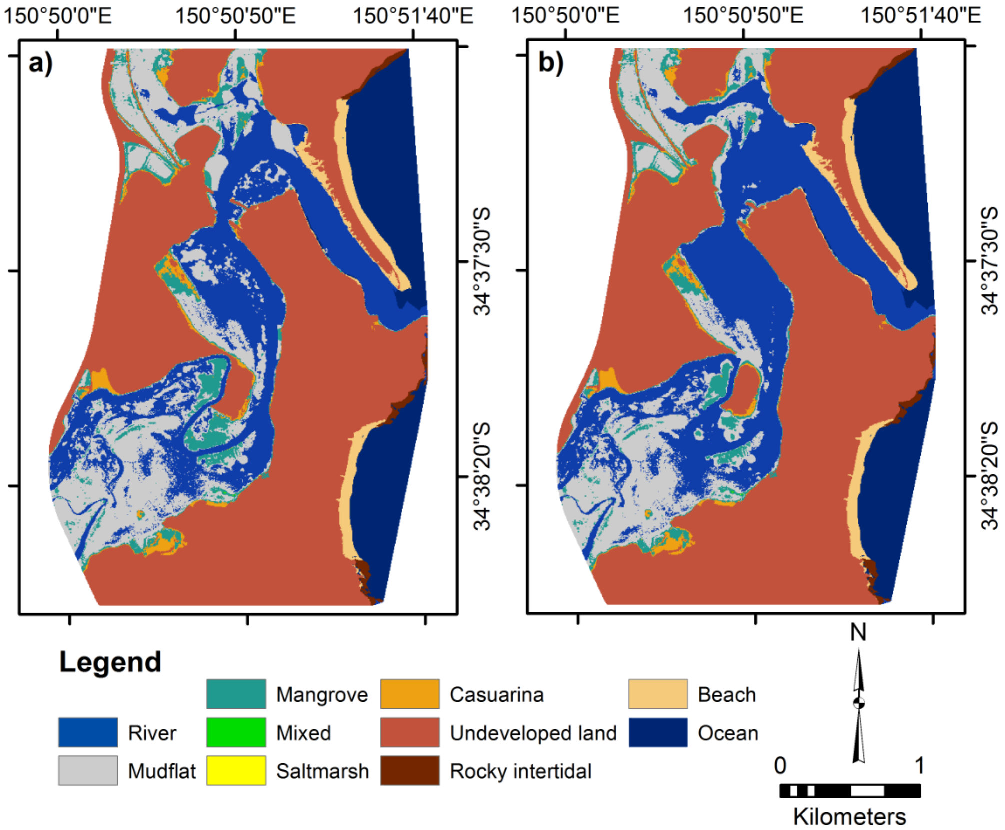


Figure 16: Modelled wetland distributions for the year 2100 when simulating the effect of extreme SLR using **a)** DEM1 and **b)** DEM2 as the input elevation information while holding all other parameters constant. Mudflat areas simulated on the western floodplain when utilising DEM1 approximately correspond to the position of vertical errors within the elevation layer. In comparison, when using DEM2, these same areas are simulated as being inundated. It is apparent that the base elevation information has a distinct impact on final projections.

4.2.4 Sensitivity

Running models in which parameters were individually varied by 10%, whilst holding all other parameters constant provided insight into the sensitivity of the SLAM model. From the multiple outputs of sensitivity runs, a sensitivity statistic was calculated such that a 100% sensitivity was defined if the 10% change in a particular parameter resulted in a 10% change in the areal extent of simulated vegetation (Clough *et al.* 2012). Results showed that, of the parameters tested, SLR, tidal range, salt elevation boundary, NAVD88-MTL and historic sea level rise trend were the most sensitive factors of the SLAM model. Accretion rates were also calculated to be sensitive parameters regardless of the manner in which they were defined. Numerical results of the sensitivity analysis are presented in Appendix D and reported within this section.

The SLAM model was most sensitive to the SLR defined in any projection run. An increase in the magnitude of SLR resulted in a greater sensitivity of the model when simulating the areal extent of each vegetation type considered in this study. Evaluating the sensitivity of the model to SLR, when different methods were used in characterising the accretion parameter, indicated that the model was least sensitive to SLR when the accretion module was utilised, whilst the greatest sensitivity to the factor occurred when the accretion parameter was defined by rates of SEC.

The great diurnal tide range and salt elevation boundary also produced significant variation in model output . The tidal range was used in this study to define the elevation ranges of vegetation classes, which also defines the point at which one class will switch or convert to another. A 10% variation in the great diurnal tidal range, therefore, produced a considerable effect on all vegetation classes whose elevation ranges were defined in half tide units, namely mudflat, mangrove, mixed, saltmarsh and *Casuarina*. The salt elevation boundary defines the highest elevation that is regularly inundated by water. It follows, therefore, that the upland vegetation class, *Casuarina*, was most sensitive to changes in the salt elevation parameter. The greatest effects of changes in the salt elevation boundary occurred when high levels of SLR were defined, regardless of the treatment of the accretion parameter. Variations in the salt elevation boundary had no effect on mixed and saltmarsh zoned for all SLR scenarios and accretion parameter method utilised.

Within the SLAM model, the historic sea level trend parameter contributes to determining the magnitude of inundation over time. Unlike the effects of altering the salt elevation boundary, the lower elevation vegetation zones were most sensitive to variations in the historic sea level trend, specifically the mudflat, mixed and saltmarsh zones. The sensitivity to the parameter within saltmarsh and mixed zones increased with increasing magnitude of SLR by 2100.

Overall sensitivity of the model to SLR, great diurnal range and salt elevation boundary parameters indicated that the definition and magnitude of inundation were the most important factors affecting the model output. Errors in the characterisation of these parameters would, therefore, cause possibly significant inaccuracies in model output. Further investigation of the potential errors was conducted within the uncertainty analysis reported below.

Variations in the accretion parameters, characterised either by rates of SEC, accretion rates or the accretion module, resulted in variations of areal extent for certain wetland vegetation zones modelled within the SLAM model. Simulations of mangrove and mudflat were most effected by the 10% variation in the mangrove accretion parameter in all SLR scenarios, whereas the sensitivity statistics associated with the defined mixed accretion rates indicated that modelled mixed and mangrove zones were most affected by this variable.

Focusing upon the model's sensitivity, when the accretion module was utilised indicated that the maximum mangrove accretion parameter of the module caused the greatest variation in model output, especially under high levels of SLR. In contrast, the model was not as sensitive to variations in the mangrove minimum accretion rate defined. Sensitivity statistics associated with the mangrove elevation coefficients, b and c, indicated that the SLAM model was little affected by their definition even under extreme scenarios of SLR. A similar pattern of sensitivity was noted for the mixed accretion module, whereby the maximum value defined showed the greatest sensitivity, the minimum value had little effect and the coefficients produced marginal to non-existent variations in the model output. Compared to the mangrove accretion module, however, the mixed and mangrove zones simulated by the SLAM model were most affected by variations in the mixed accretion module, most specifically by the defined maximum accretion rate.

4.2.5 Uncertainty

The Monte Carlo uncertainty-analysis provides confidence statistics for model results whose accuracy and precision are proportional to the number of iterative simulations completed. For this study, 500 uncertainty simulations were thus run in order to increase the confidence of statistical elements derived from the model output. A conservative treatment of the results is reported herein, with all graphical representation of model output being bound by the 5% (lowest) and 95% (highest) confidence intervals.

Results are representative of the errors and uncertainties introduced to the model from input, defined parameters, namely the elevation information, great diurnal tide range, salt elevation boundary, NAVD88-MTL, mangrove accretion, mixed accretion and saltmarsh accretion parameters. It is noted that uncertainties resulting from the model structure itself are not incorporated in the stochastic, time series data produced from the uncertainty model runs.

Assessment of uncertainty analysis results suggested that, when utilising accretion rates, mangrove and *Casuarina* areas were the most uncertain categories modelled overall. Analysing the statistics associated with the iterated model output for the year 2050 (Table 25) and 2100 (Table 26) clearly indicated that the error associated with simulated vegetation zones increased over time, with uncertainty intervals widening by 2100 (Figure 17).Based upon the uncertainty analysis statistics, saltmarsh and mixed zones were least effected by errors and uncertainties incorporated in the SLAM model.

Analysing the deterministic output with respect to the uncertainty prediction, time series data indicated that modelled mangrove areas were below the overall mean for the vegetation

Land cover type	Minimum	5% CI	Mean	95%CI	Maximum	Standard Deviation
Mudflat	1.53	4.32	6.63	10.44	14.97	1.89
Mangrove	89.73	92.41	103.48	120.67	140.51	8.56
Mixed	6.96	9.06	12.83	16.88	18.71	2.37
Saltmarsh	5.57	10.15	15.87	21.46	24.41	3.49
Casuarina	71.62	85.72	95.34	103.82	107.73	5.64

Table 25: Uncertainty results for the year 2050 for simulations utilising accretion rates. Statistics are calculated in hectares.

Land cover type	Minimum	5% CI	Mean	95%CI	Maximum	Standard Deviation
Mudflat	0.02	0.88	13.09	43.89	70.88	14.07
Mangrove	88.22	97.99	138.95	185.41	207.26	27.53
Mixed	0.56	2.02	10.05	21.20	28.11	5.98
Saltmarsh	0.11	0.58	5.19	14.13	21.16	4.33
Casuarina	21.40	42.36	83.93	113.31	122.91	22.31
Undeveloped Land	453.80	459.33	475.22	490.13	499.49	9.46

Table 26: Uncertainty results for the year 2100 for simulations utilising accretion rates. Errors associated with simulated vegetation zones increased with respect to those at 2050 reported in Table25, indicating an increase in uncertainty associated with simulations of greater temporal periods

category calculated from the uncertainty analysis (Figure 17). Errors and uncertainty propagated through the model over time produced a variation of 119.04 ha, from 88.22 ha to 207.26 ha, by the year 2100.

Similar to the mangrove category, positioning of deterministic output within the possible extents to be modelled was generally observed below or only slightly above the mean for each vegetation and land cover category (Appendix E). A special case was observed for

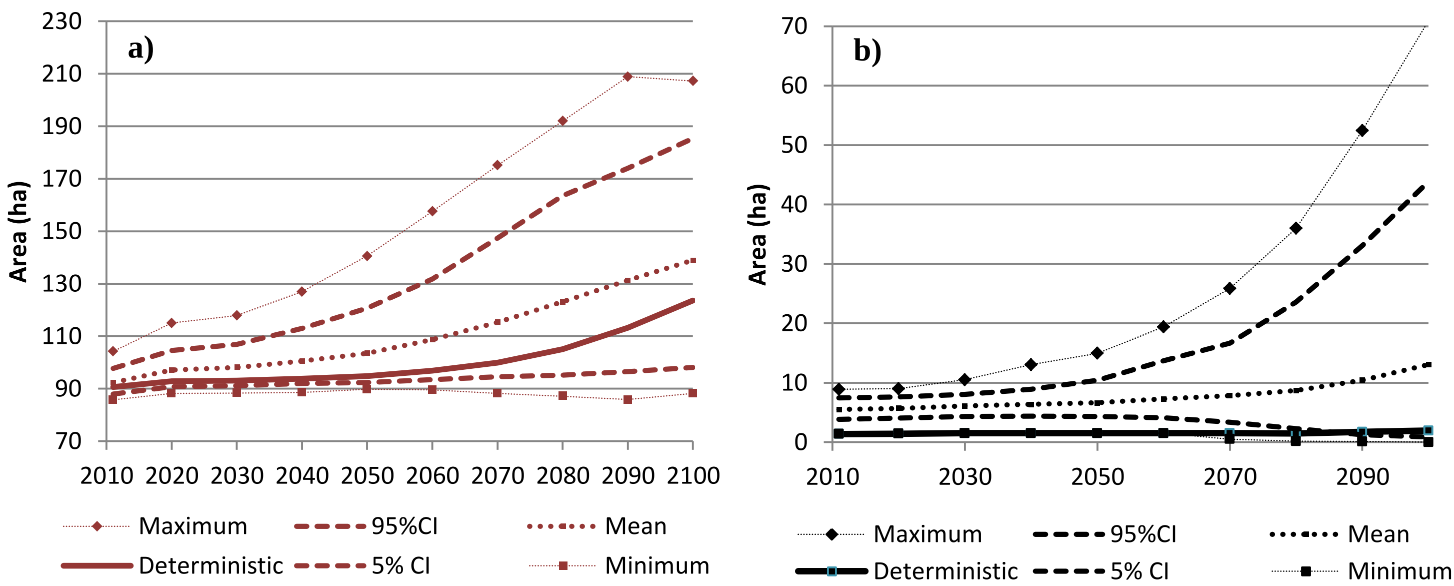


Figure 17: Results of the uncertainty analysis for **a)** mangrove and **b)** mudflat zones. Descriptive and inferential statistics of model output from the 500 iterations provide an indication of the possible outcomes and display the uncertainty associated with future projections.

simulated mudflat zones whereby deterministic output lay at or only slightly above the minimum values simulated within the uncertainty runs (Figure 17b).

Distributions of model output generated from the 500 iterations of the uncertainty analysis provided additional information about the areal extent of each vegetation type by the year 2100. From Figure 18a.it can be understood that large areas of mangrove are likely to be modelled and present in the study site by the year 2100. Similar distributions are observed for the *Casuarina* zones, whilst the likelihood of retaining only a fraction or no saltmarsh zone by the year 2100 is indicated in Figure 18c.

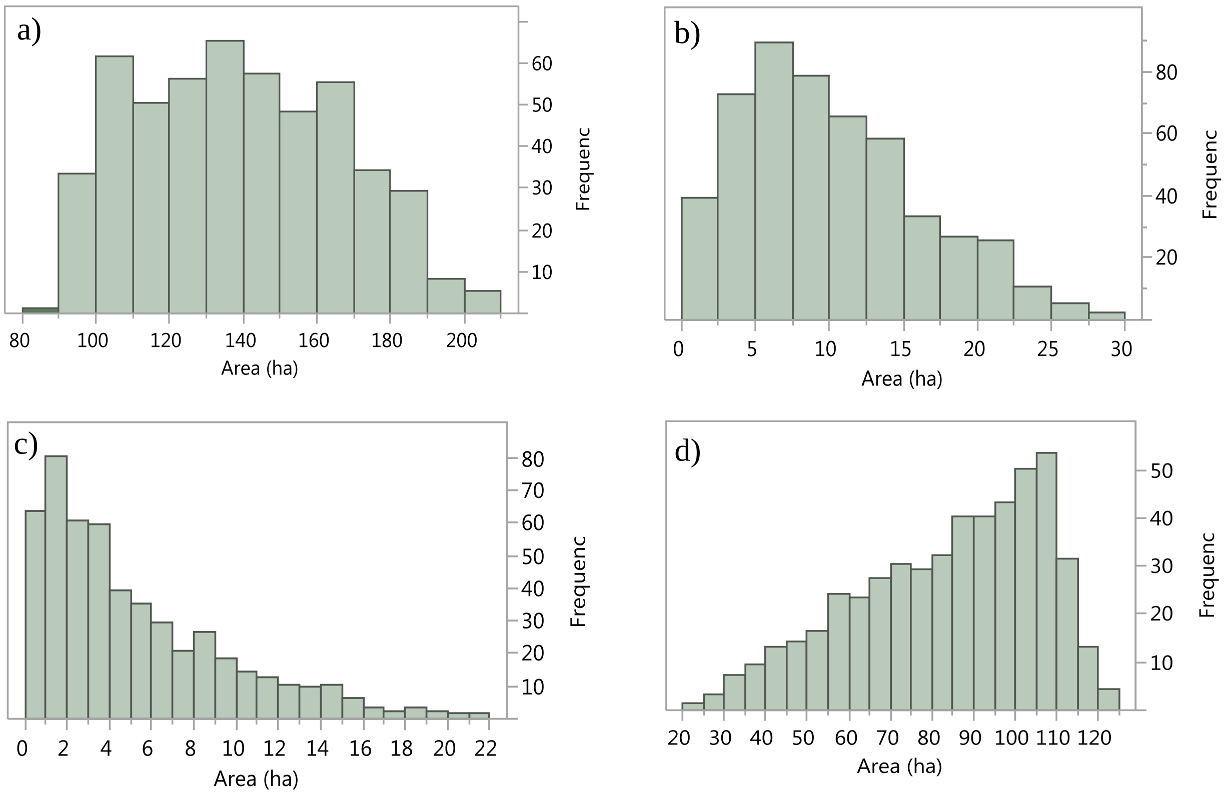


Figure 18: Histograms for **a)** mangrove, **b)** mixed, **c)** saltmarsh and **d)** *Casuarina* for the year 2100. The distributions of results from the uncertainty analysis provide insight into the likelihood of certain areal extents occurring by the year 2100. The skewness of saltmarsh areas simulated by the SLAM model suggests that the vegetation zone is most likely to be represented by low acreages in 2100.

4.3 The SAAT model

4.3.1 Numerical equation and basic model validation

The final equation developed and implemented in this study was derived from the entire available SET dataset and the combined true and averaged tidal data from MHL (2012). Values of SEC modelled using this equation compared relatively well to those calculated from SET data ($R^2 = 0.862122$). The fit of the modelled data was slightly less than that obtained when only true, non-averaged numerical information for the years 2003, 2009 and 2010 was used to develop the equation ($R^2 = 0.86304$). However, given the small difference in the fit of the data and the problems associated with defining an equation and system utilising only a small dataset, effectively three, non-consecutive years, the equation derived from the full SET dataset and averaged data was considered to provide the most suitable representation of wetland SEC over time. Thus, the numerical equation derived from non-linear regression and deemed to provide the most adequate explanation of the wetland system was:

$$\mathrm{SEC} = 0.00112762606907659 * e^{-5.12615410987054*\mathrm{H}} * e^{-0.00378438213262039*D_c} \qquad (8)$$

where SEC is surface elevation change (m/yr), H is the elevation with respect to local mean high water (m) and D_c is the distance to the most proximal tidal source (m). It was to the value calculated from this equation that wetland surface elevation was added and incremental SLR subtracted to determine the wetland elevation at a given time step during the implementation of the SAAT model.

Basic validation of the SAAT model was conducted by comparing surface elevations modelled for singular points in space with the observed SET based data. Repeating the process of modelling and comparison at each SET location confirmed that the model simulated wetland elevation change relatively well (Figure 19). It was noted that, for the particular points modelled, variations were perceptible in comparison to observed data. Greatest variations occurred in modelled surfaces within the mangrove zones, where simulated elevations were underestimated by 2 - 10mm (Figure 19). However, simulated surfaces in saltmarsh zones obtained a relatively good fit with the observed data, modelling within millimetre variations. The differences, or errors, noted in saltmarsh and mangrove zones at individual points in space provided a basic understanding of the performance of the model within respective zones. Such errors were considered when examining and interpreting surfaces developed from the spatial application of the model.

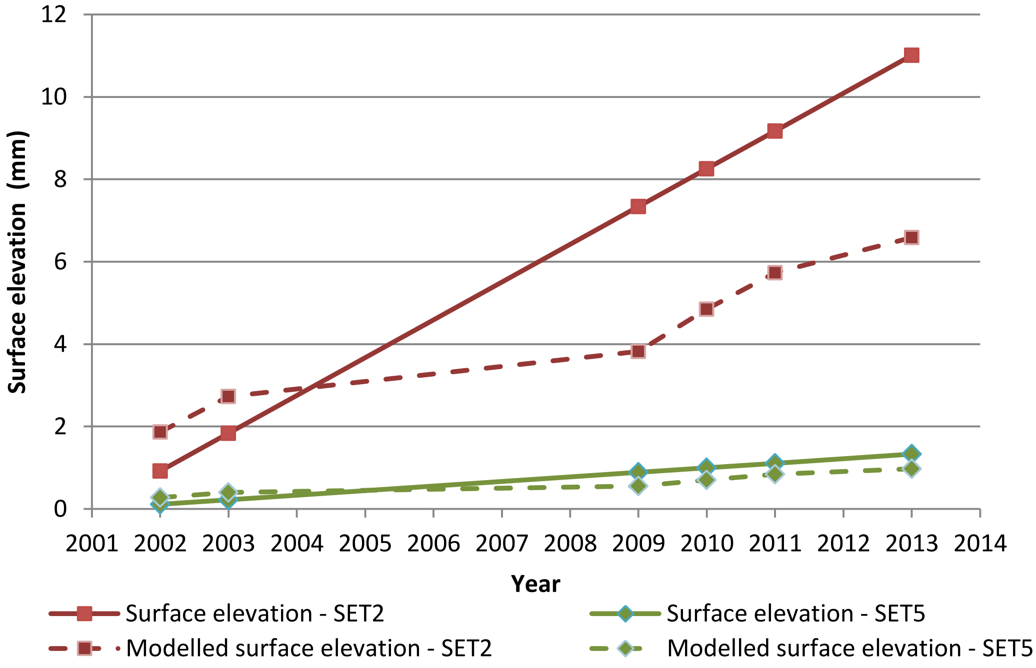


Figure 19: Comparison of observed and modelled trends in SEC for two points in space; SET2 and SET5. The former SET is situated amongst mangrove vegetation, whilst SET5 is located within the saltmarsh zone. Deviations and similarities of the modelled and observed data are indicative of the goodness of fit and validity of the SAAT model for the study site.

4.3.2 Projections under varying SLR conditions: 2011-2100

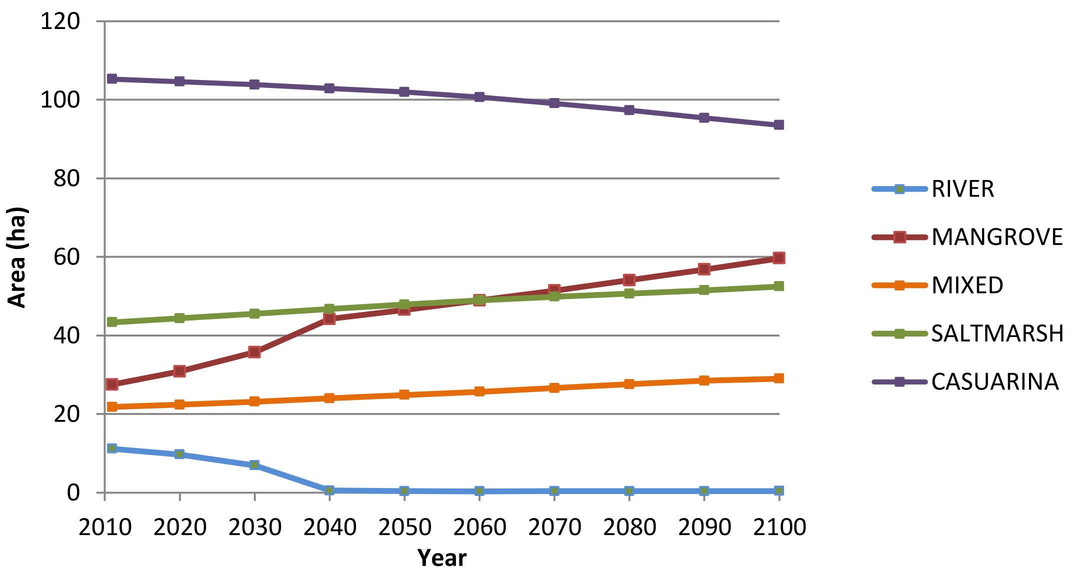
General patterns of wetland vegetation distribution under varying conditions of SLR were similar across projections utilising different base elevation information. This section, therefore, discusses the patterns with respect to those modelled using DEM2.Variations between model output utilising DEM1 and DEM2 are discussed in detail below.

B1 5%CI sea level rise scenario

Dramatic changes in distribution of wetland classes were not observed for model output over the period 2011-2100. The small growth or decline of classes that was simulated occurred in an almost linear fashion (Figure 20), indicating an almost constant, low rate of wetland change for this SLR scenario. Mangrove, mixed and saltmarsh zones increased in areal extent by the year 2100, the greatest growth being associated with mangrove vegetation (116% change). By contrast, the *Casuarina* zone was predicted to be subjected to minor losses over the same temporal period (-11%).

Under the low SLR scenario, only 0.39 ha of land was simulated to be inundated by the year 2100, representing an overall decrease in inundated areas with respect to 2011 (-96.5%). Between 2030 and 2040, a perceptible decrease in river areas appeared to be directly related to an increase in mangrove zones. Closer examination of spatial layers generated by the model indicated that the loss in river area was indeed due to the establishment of mangrove vegetation in previously inundated areas (Figure 21). It should perhaps be noted here that, based on preliminary investigations, if the model were to include the Minnamurra River in its

Figure 20: Areal extent of each vegetation class simulated for the period 2011-2100. The small growth or decline in each class can be seen to occur in an almost linear fashion.



simulations, the same pattern of mangrove establishment in river zones would likely occur.

An examination of the spatial patterns of mangrove growth indicated both a landward encroachment and internal expansion (for example, on the western floodplain) of mangrove clearly reflected in the large percentage change and increase in areal extent of the vegetation type (Table 28; Figure 21). Though simulated mangrove saw the greatest overall increase in area, *Casuarina* remained the wetland class whose distribution across the study site was greatest.

Mixed zones were predicted to increase by the end of the 21stcentury. A growth in mixed areas was only evident when modelling the lowest level of SLR used for this study.

Vegetation/Land cover type	Areal extent of vegetation (ha)		
	2011	2100	%Change
River	11.17	0.39	-96.53
Mangrove	27.49	59.64	116.91
Mixed	21.80	29.00	33.03
Saltmarsh	43.36	52.48	21.03
Casuarina	105.25	93.53	-11.14

Table 27: Percentage change in the total area of each vegetation or land cover type by the year 2100 under low rates of SLR.

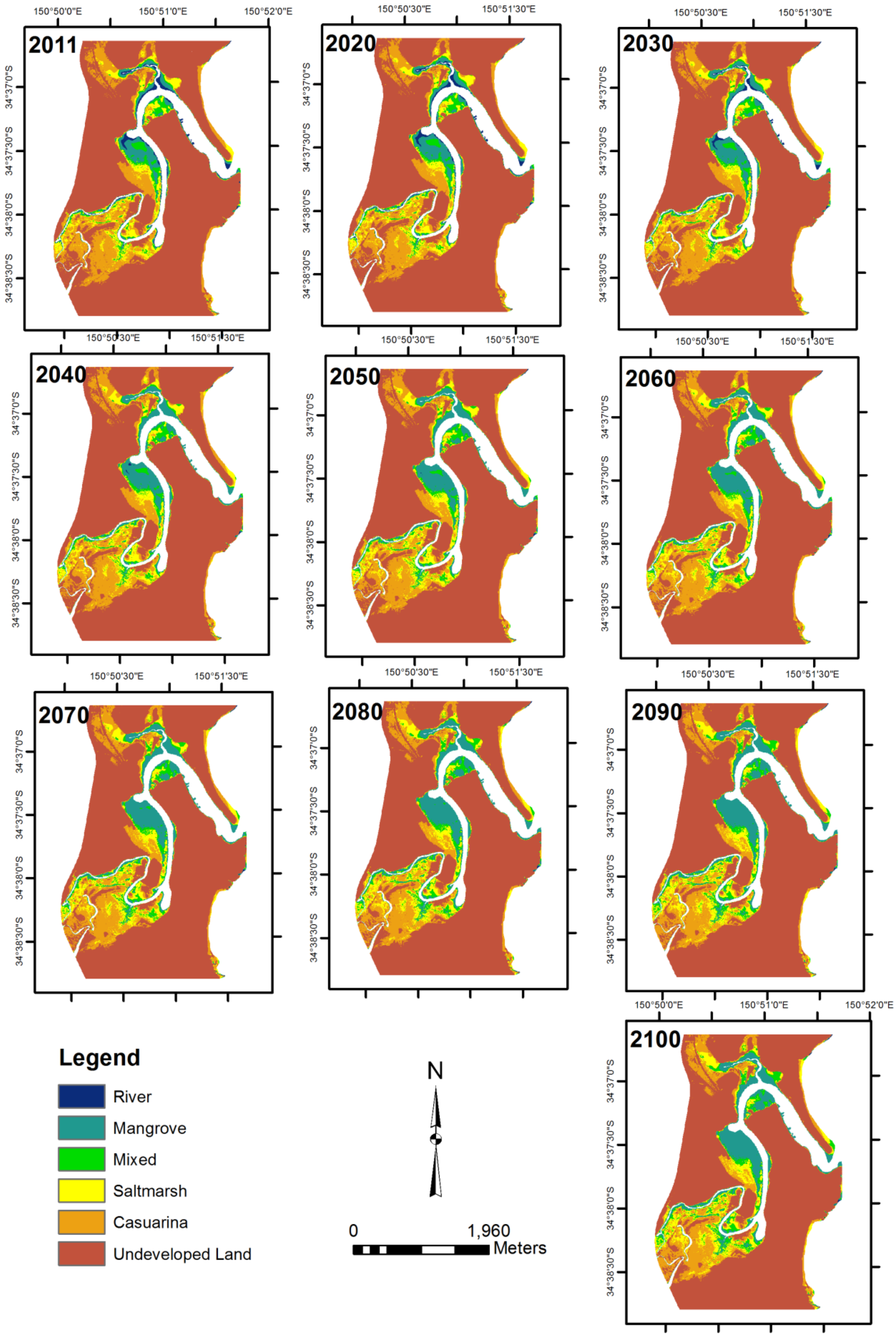


Figure 21: SAAT model output for the period 2011-2100 under a low SLR scenario (B1). Note: all main waterbodies were excluded from analysis.

A1FI 95% CI SLR scenario

Under the intermediate scenario of SLR distinct changes in vegetation distribution were modelled throughout the site. Assessment of vegetation change over time indicated that, by the year 2100, substantial losses of saltmarsh and *Casuarina* areas would be sustained (34% and 70.3% respectively). In contrast, the areal extent of inundated land (river), mangrove and mixed zones increased by the final year of model output.

With respect to its initial distribution, areas dominated by mangrove vegetation more than tripled over the period modelled, 2011-2100. Spatially, this related to the landward growth of the zone at the expense of both *Casuarina* and saltmarsh zones located behind mangrove forests (Figure 22). A peak areal extent of mangrove vegetation (98.9ha) was simulated at the year 2090 prior to lower ranges of the vegetation zone being inundated at a relatively fast rate, amounting to an overall decrease in the total area of mangrove over the last decade. An examination of numerical and spatial data of model output indicated that a significant proportion of land was inundated under a SLR of 0.819 m. The rate of inundation of land began to increase substantially at 2060, with a dramatic, exponential increase of river areas modelled for subsequent years until 2100. Flooding of land was particularly apparent at subsites 2, 3 and 4.

Decreases in areal extent of saltmarsh zones occurred from 2050. Simulated mixed zones replaced the areas once covered by saltmarsh, resulting in an overall growth of the mixed vegetation zone between 2050 and 2070. The decline-growth relationship between saltmarsh and mixed zones was visually evident in subsites 6 and 7, where the presently undeveloped, pastures were slowly converted to *Casuarina*, which was followed by saltmarsh, in turn replaced by mixed vegetation and finally populated by mangrove vegetation before certain areas were inundated as a result of rising sea levels. A limited zone of *Casuarina* remained in these subsites by 2100. Within subsites 2, 3 and 4, inundation and conversion of wetlands to mangrove predominated by the final year modelled, with little persistent saltmarsh, mixed and *Casuarina* zones.

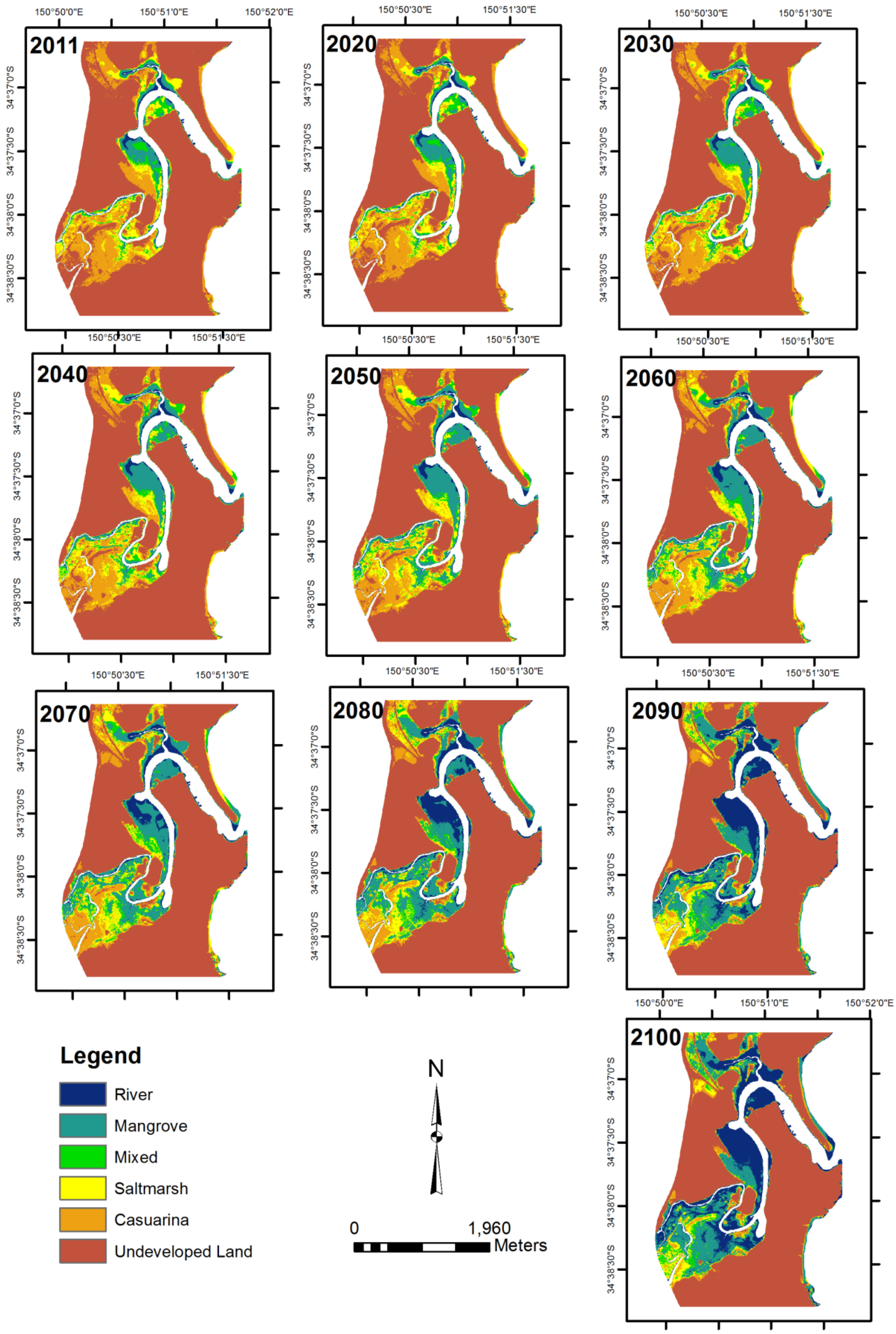


Figure 22: SAAT model output for the period 2011-2100 under an intermediate SLR scenario (A1FI). Note: All main waterbodies as delineated for 2011 were excluded from analysis. River areas simulated are, in most cases, an extension of the river zone.

Extreme SLR scenario- Vermeer and Rahmstorf (2009)

Modelled output indicated that with an extreme rise in sea level there was widespread flooding in all subsites by the year 2100 and a concomitant loss in wetland vegetation (Figure 23 and Figure 24f). Mangrove areas initially gained in area, replacing saltmarsh, *Casuarina* and mixed zones, until the peak areal extent of mangrove vegetation at 2050. Simulated mangrove zones decreased in area over subsequent years as a result of a significant rise in the rate of flooding, recording only 18.77ha of persistent mangrove areas remaining by the end of the century. Hence, only under the extreme condition was a decline in mangrove areas simulated.

By the year 2100, all wetland vegetation was simulated to sustain significant losses (Table 29). In contrast, inundated areas increased by 2326.86% by the end of the century. It should be noted that the large percentage change is partly a function of there being only a small area of river zone accounted for at 2011, water bodies being excluded from analysis of the SAAT model.

Figure 23 clearly show a significant and consistent loss of *Casuarina* zones in simulated output for the entire projection period. A similar pattern was recognised for saltmarsh and mixed zones following an initial increase in the respective areas. Considering rates of change for each wetland type for the period 2011-2100, it was apparent that rates of conversion from one class to another were accelerated under conditions of extreme SLR.

Modelling vegetation distribution under a 1.9-metre rise in sea level doubled as an extreme condition validation for the SAAT model. It was concluded that, as much as is possible to understand, given the characteristically unpredictable nature of the future, the vegetation distributions modelled using the SAAT model were plausible and in keeping with expected outcomes.

Vegetation/ Land cover type	Areal extent (ha)		Percentage change (%)
	2011	2100	
River	11.17	271.08	2326.86
Mangrove	27.49	18.77	-31.73
Mixed	21.80	5.09	-76.63
Saltmarsh	43.36	9.41	-78.30
Casuarina	105.25	19.76	-81.23

Table 28: Percentage change in the total area of each vegetation or land cover type under intermediate rates of SLR.

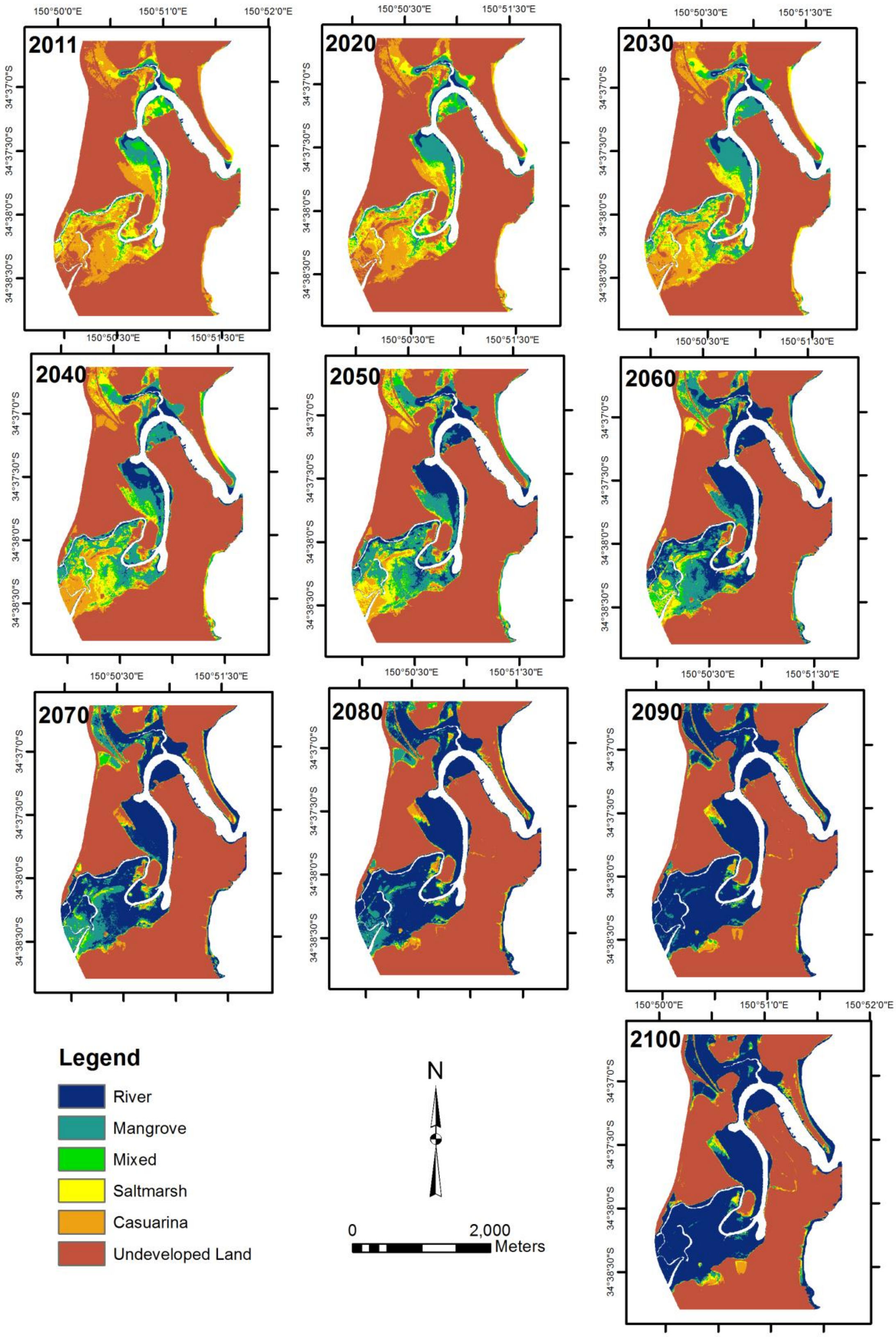


Figure 23: Simulated changes in the Minnamurra wetland under an extreme SLR scenario as modelled by the SAAT model. Significant losses are sustained by all vegetation types by the year 2100.

Brief comparison of vegetation distribution patterns under varying SLR scenarios

The effect of different sea level rises on wetlands is clearly demonstrated by considering the change in areas simulated to be flooded, represented by the river class included in the model output. By the year 2100, the SAAT model simulated a decrease in inundated areas of 96.5% associated with the B1 scenario, an increase of 856.6% under an intermediate SLR scenario (A1FI) and, with a 1.9m rise in sea level, a dramatic 2326.9% increase in inundated areas. The effect of different SLR scenarios on model output was further noted from the values of percentage change calculated for each vegetation type.

Within all scenarios, a relationship was observed between mangrove growth and decline and simulated river zones. Increases in mangrove and the maximum areal extent of vegetation in all SLR scenarios were observed to precede greatest increases in flooded areas (i.e. increases in simulated river zones). An examination of patterns of growth and decline for all vegetation under different rates further indicated a common pattern in the succession of vegetation decline whereby *Casuarina* zones declined from the year 2011, saltmarsh began to decline a few years after, followed by the mixed zone and, finally, mangrove vegetation. The pattern held true for vegetation under intermediate and extreme SLR conditions (Figure 24).

Analysis of SAAT model output generated from different basal elevation information

Analysis of model output of the initial year simulated using DEM1 was necessary to identify potential problems, 2011 being a year at which real world observations can be compared to the simulated output. Comparison of vegetation distributions simulated for the year 2011 using DEM1 with aerial imagery and the vegetation layer previously derived for the same year indicated a significant overestimation of saltmarsh and *Casuarina* areas, most especially in subsites 2, 3 and 4. These inaccuracies in modelled data were directly related to elevation errors and resulted in an underestimation of mangrove areas. Further upstream, at subsites 5, 6 and 7, simulated saltmarsh zones appeared to be modelled in place of observed mangrove zones. These errors in the initial information were most likely responsible for many of the variations noted between model output using different basal elevation information.

Modelled vegetation distribution generated using DEM1 as the initial surface elevation information varied significantly to that produced using DEM2. Figure 24 clearly displays the differences in total areal extent of wetland vegetation modelled when utilising different basal information. Though the initial extent of vegetation varied between simulations for the year

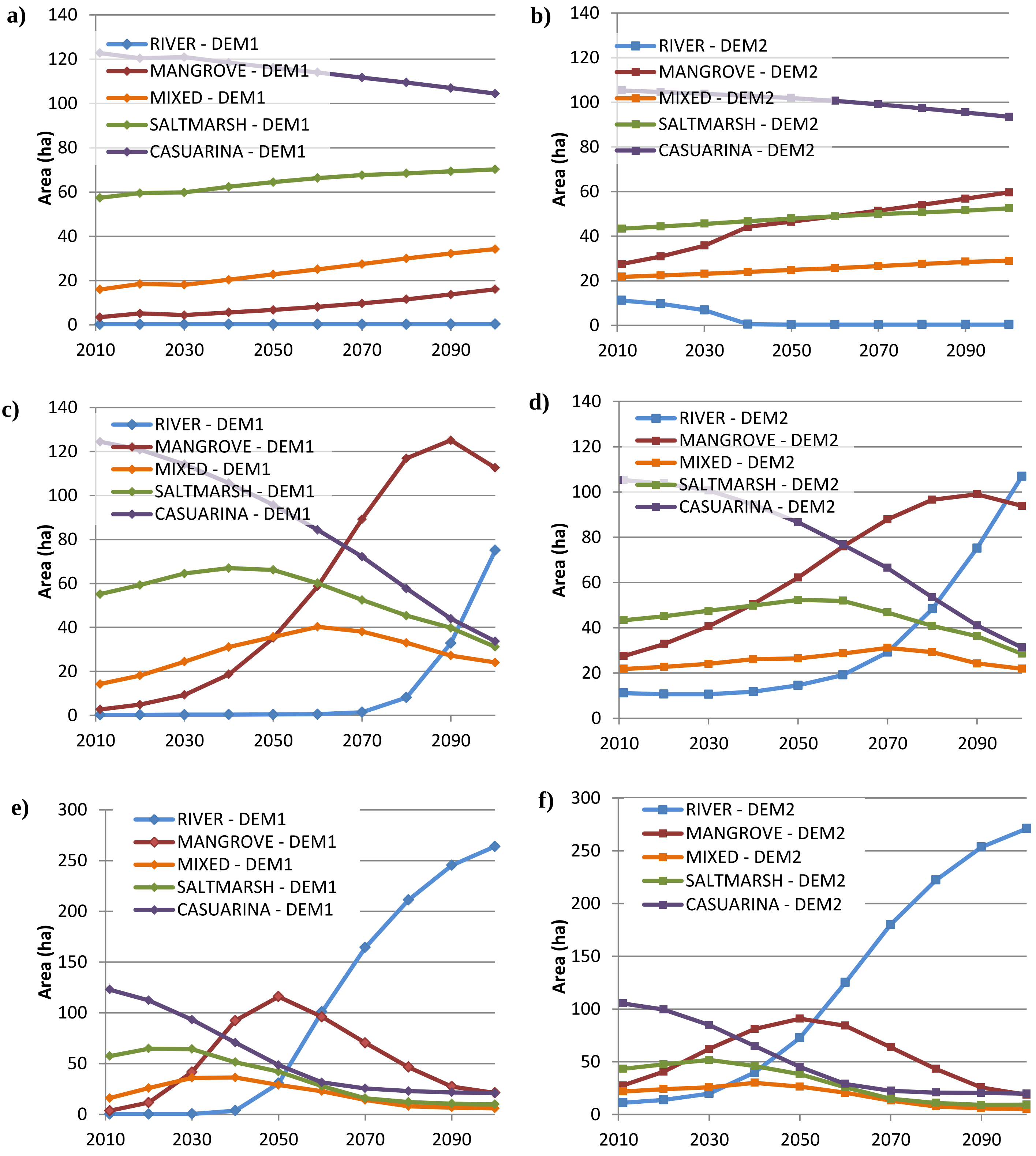


Figure 24: Areal extent of vegetation in hectares modelled under varying rates of SLR utilising different elevation information. The time series data represent simulated results under **a)** a low SLR using DEM1 as base elevation information, **b)** a low SLR using DEM2 as base elevation information, **c)** an intermediate SLR (A1FI) using DEM1 as base elevation information, **d)** an intermediate SLR (A1FI) using DEM2 as base elevation information, **e)** an extreme SLR using DEM1 as base elevation information and **f)** an extreme SLR using DEM2 as base elevation information.

2011, model output incorporating DEM1 revealed almost consistently greater distributions of each wetland vegetation under all SLR scenarios. Of particular note was the significant difference in mangrove areas (Figure 25). For intermediate and extreme SLR

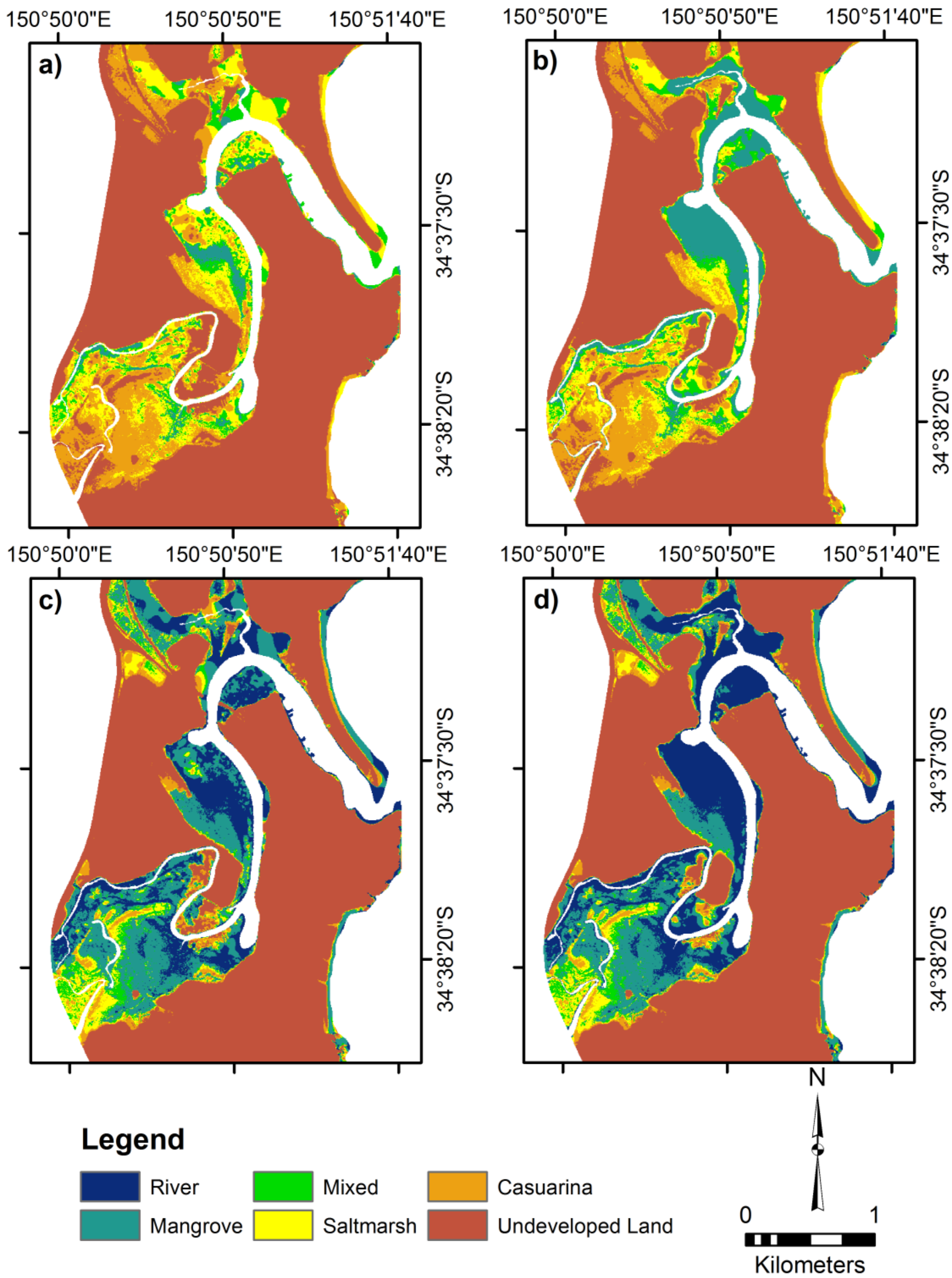


Figure 25: Modelled vegetation distributions at 2100 when utilising different elevation information in the SAAT model. Modelled output presented here represent the simulated wetland distributions when utilising **a)** DEM1 under a low SLR scenario, **b)** DEM2 under a low SLR scenario, **c)** DEM1 under an intermediate SLR scenario and **d)** DEM2 under an intermediate SLR scenario. Large discrepancies between simulations utilising DEM1 and those using DEM2 as the base elevation information can be clearly seen on the western floodplain and in the vicinity of Rocklow Creek. In most cases, the discrepancies are a result of mangrove and saltmarsh being simulated to persist when using DEM1 yet modelled as inundated areas when using DEM2. The persisting vegetation correlates almost exactly with the position of large vertical errors within DEM1.

scenarios, output derived from DEM1 saw greater rates of increase and decline in the mangrove areas and the maximum area simulated was consistently higher than that found when utilising DEM2 in the modelling process, as can be quickly understood from Figure 24.

By the year 2100, under the low SLR scenario mangrove areas were 43.52 ha less when using DEM1, 124.5 ha greater under an intermediate SLR scenario and a slight, 2.34 ha difference when modelling the effect of an extreme SLR on wetland vegetation with DEM1 input as the initial elevation data. The pattern of the greatest differences occurring within the intermediate scenario held for all vegetation types. Under an extreme scenario of sea level rise widespread flooding was modelled to occur when either DEM was utilised as the base information, thereby reducing the variation in respective model output in the final year of simulation.

In contrast to the increased vegetation areas simulated when using DEM1, river areas were less under all sea level scenarios. Where flooding had been simulated to occur in DEM 2, model output from DEM1 generated mangrove, saltmarsh or *Casuarina* zones, contributing to the greater areal extent of wetland vegetation generated when using DEM1 as the basal elevation information.

4.4 Model comparison

An analysis of deterministic results from each of the models indicated that the models produced different areal extents of vegetation for different scenarios and different vegetation types ($F_{(8,25)}$ = 3.3742, p = 0.0092). Restriction of analysis to the final year of model output, however, revealed that no significant variation was detected between modelled vegetation distributions overall ($F_{(8,25)}$ = 1.1884, p = 0.3449).

Under the B1 SLR scenario, simulated extents of wetland vegetation were affected by the model used ($F_{(8,5)}$ = 27.57, p = 0.001). Further testing by vegetation type, however, indicated that no wetland vegetation type differed greatly between the model output for the SLAM, SAAT and Oliver models. Differences existed between modelled saltmarsh zones under the low SLR scenario (Table 29), however they were not calculated to be statistically significant (($F_{(2,1)}$ = 167.38, p = 0.0546).

Though, statistically, there was no significant variation between model outputs under the B1 SLR scenario, visual analysis suggests otherwise. The SLAM model predicts a proliferation of mangrove into the *Casuarina* zones where both the Oliver and SAAT models have predicted a slow encroachment of predominately mixed and saltmarsh areas. This primarily arose as a result of the differences in the programming of vegetation conversion incorporated in each mode. Variations in the modelling of inundated areas were also noted and are outlined further below.

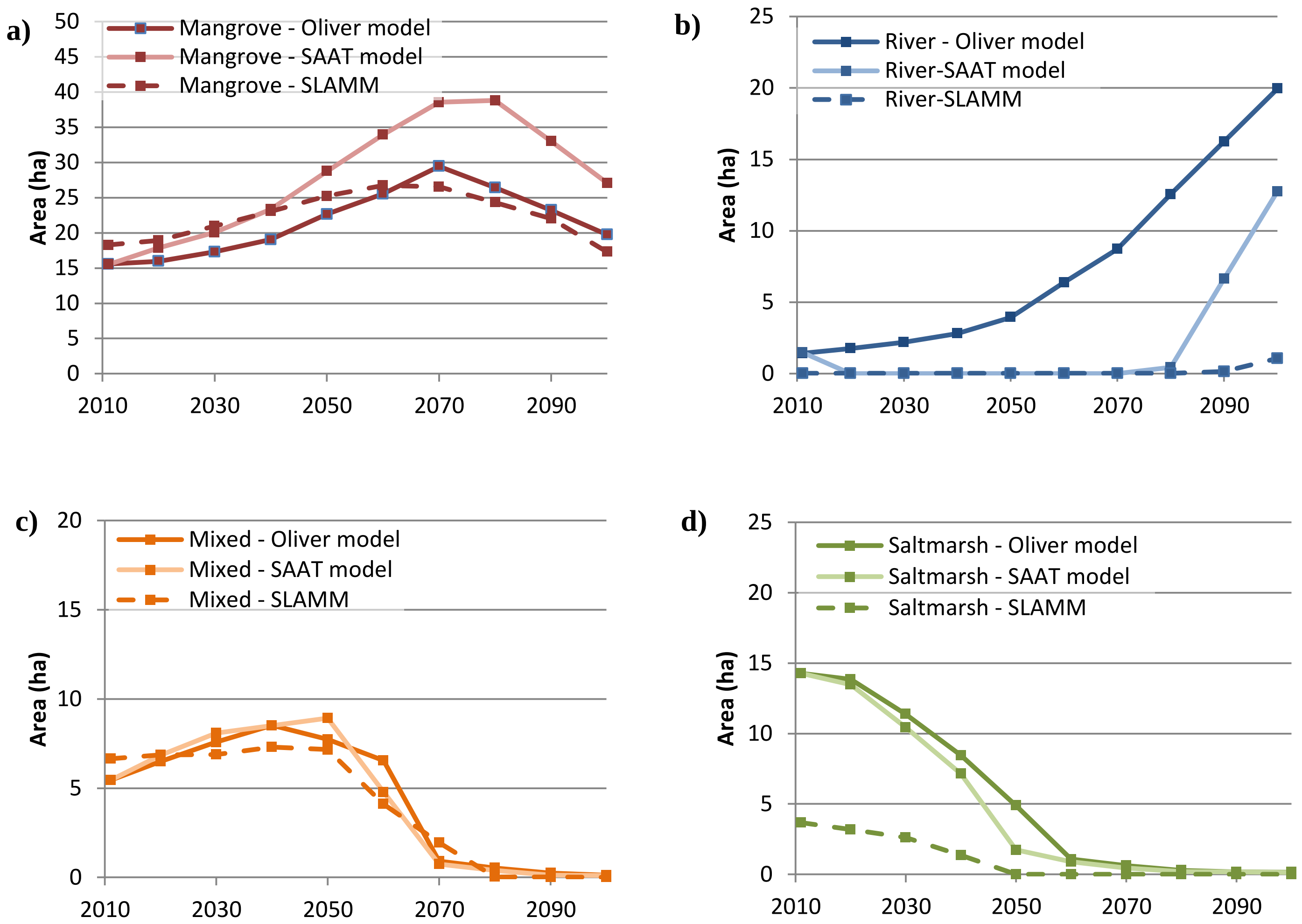
Scenario	Model	Areal extent (ha)				
		River	Mangrove	Mixed	Saltmarsh	Casuarina
B1	Oliver model	2.04	17.32	7.91	11.27	1.70
	SAAT model	0.00	23.05	9.21	6.85	1.11
	SLAM model-accretion	0.02	18.31	7.17	3.17	10.08
	SLAM model -rates of SEC	0.02	22.48	7.40	1.68	5.58
A1FI	Oliver model	19.95	19.75	0.13	0.16	0.24
	SAAT model	12.75	27.06	0.11	0.13	0.18
	SLAM model-accretion	1.07	35.58	1.49	0.00	1.18
	SLAM model -rates of SEC	1.07	17.29	0.01	0.00	0.32

Table 29: Total areal extent of each vegetation type by the year 2100 as simulated by each model incorporated in this study for the low (B1) and intermediate (A1FI) SLR scenarios. SLAM model-accretion and SLAM model- rates of SEC refer to modelling of wetland distributions within SLAM when utilising accretion rates and rates of accretion respectively.

Under the A1FI SLR scenario, the choice of model had a significant effect on vegetation distribution ($F_{(8,5)} = 5.6250$, $p = 0.0366$). Considering each vegetation type separately it was found that simulated saltmarsh and flooded (river) zones were, overall, significantly different according to the numerical model applied. ($F_{(2,1)} = 766.28$, $p = 0.0255$ and ($F_{(2,1)} = 6.521e^{15}$, $p < 0.0001$ respectively). *Casuarina*, mixed and mangrove areas simulated, in comparison, were not significantly affected by the model used.

Figure 25 provides further insight into the differences in vegetation distribution between the SLAM, SAAT and Oliver model output under the A1FI future scenario. As is clearly shown in Figure 25c simulated mixed zones were relatively similar between models. By the year 2100, *Casuarina* zones, too, covered similar areal extents regardless of the model applied. Though variation in saltmarsh was significant, when considering the entire time series data of each model, it is noted that all three models predicted between a 95% and 100% loss of the saltmarsh zone by the year 2100. By the year 2060, only small variations were evident between the models. The considerable initial difference recorded for the saltmarsh zone is a result of the mode in which vegetation distributions were defined for the year 2011, the SLAM model utilising a vegetation map as the base vegetation information, whilst the SAAT and Oliver model simulated initial wetland distributions based on vegetation-specific elevation ranges. *Casuarina* areas, too, were affected by the differences in initial definition of the input vegetation layer. Similar to saltmarsh zones, *Casuarina* areas displayed significant variation at the year 2011 yet simulated *Casuarina* distributions of each model converged by the year 2100 (Figure 25e).

Further investigation into the variance between model outputs suggested that, though no significant variance was calculated for the mangrove zones under the A1FI SLR scenario, differences in vegetation distributions did occur (Figure 25a). An examination of percentage change in mangrove vegetation distributions showed that under the intermediate SLR scenario the SAAT model simulated a loss in mangrove areas (18.6%) by the year 2100, the Oliver model predicted a moderate increase in the zone (26.9%) and the SLAM model using accretion rates modelled a 94.7% growth. In contrast, the SLAM model, characterising the accretion parameter by rates of SEC, produced a loss of 5.4% by the year 2100 (Table 30). From this it was clear that the simulation of mangrove vegetation varied considerably according to the numerical model applied.



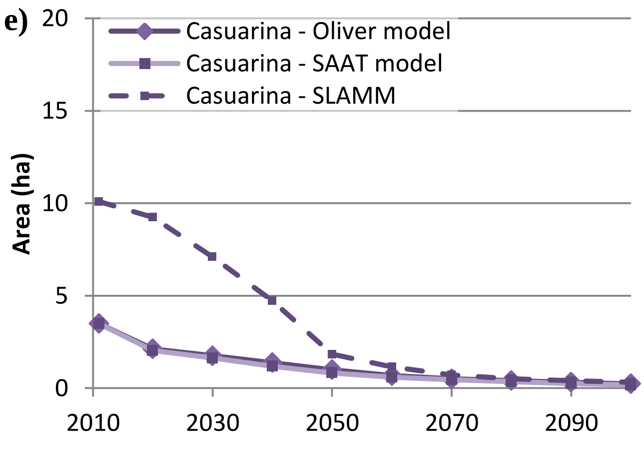


Figure 26: Areal extent of **a)** mangrove, **b)** river, **c)** mixed, **d)** saltmarsh and **e)** *Casuarina* zones simulated by the Oliver, SAAT and SLAM models using an intermediate rate of SLR (A1FI) for the period 2011-2100.

Simulation of wetland flooding and conversion to open water over the period 2011-2100 differed between models under all SLR scenarios examined. Under the B1 SLR scenario, where inundated land was predicted by the Oliver model, mangrove was simulated using the SAAT model and mudflat areas coincided exactly when the SLAM model was applied (Figure 26). The similarity in the spatial position of inundated areas in the Oliver model

Vegetation/land cover type	Percentage change (%)			
	Oliver Model	SAAT model	SLAM model-accretion	SLAM model-rates of SEC
River	1297.4	1508.5	4660.4	4660.4
Mangrove	26.9	-18.6	94.7	-5.4
Mixed	-97.7	-95.9	-77.6	-99.8
Saltmarsh	-98.9	-95.8	-100	-100
Casuarina	-93.3	-95.6	-88.3	-96..9

Table 30: Percentage change in areal extent by the year 2100 of each vegetation class within the Oliver, SAAT and SLAM model output. SLAM model accretion denotes the simulations complete using accretion rates to define the accretion parameter, whilst the final column of the table reports percentage change in vegetation extent of the model output when rates of SEC were utilised. Negative values indicate an overall loss of the vegetation by the year 2100 whilst positive values indicate an overall gain.

output and predicted mudflat areas in the SLAM model output was particularly apparent with a greater rise in sea level. The pattern of conversion for each model was similar over time, with changes from mangrove to mudflat (SLAM) or mangrove to river (Oliver) initiating at the far northeastern border of the western floodplain and spreading throughout the area in a southerly direction.

River areas derived from the SAAT model did not follow the same pattern of conversion over time. Under the A1FI scenario, no river was simulated until the year 2080. Initial conversion of mangrove to river areas was not observed from the northeastern boundary but rather at a point approximately 100m from the river. Simulated inundated areas expanded until the year 2100, yet a mangrove stand, on average 40m wide, remained between the original position of the river and the predicted inundated wetland (Figure 26). This was distinctly different to the flooded areas generated in both the SLAM and Oliver models.

Despite the differences in flooded wetlands simulated, the SAAT model generated output that was similar to data produced by the Oliver model, with no significant difference found between the overall means of modelled vegetation zones ($F_{(4,10)} = 0.7304$, $p = 0.5914$). Figure 25 shows that only small variations in simulated mixed, saltmarsh and *Casuarina* zones occurred between the SAAT and Oliver models. The larger differences displayed in the mangrove and river areas are related to the distribution of flooded areas

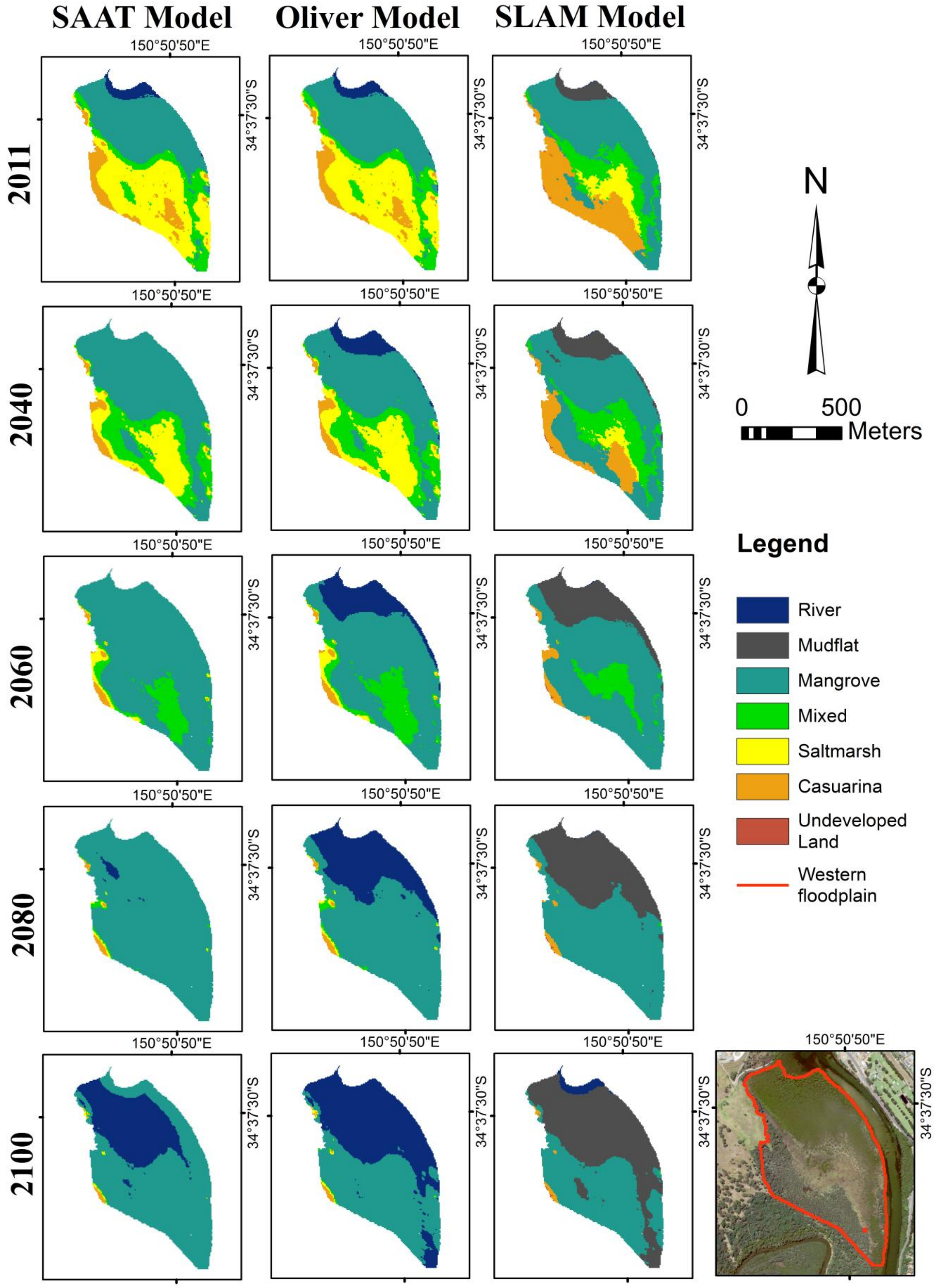


Figure 27: Model output from the SAAT, Oliver and SLAM models under the intermediate SLR scenario clearly showing the similarities and differences in simulated vegetation zones at discrete points in time for the period 2011-2100.

noted previously. It can be observed that the differences between the mangrove and river areas simulated using the two models are approximately equal, with overestimation in simulated mangrove areas when using the SAAT model with respect to the Oliver model being almost identical to the underestimation of river areas.

Analyzing the growth and demise of wetland vegetation over time within SLR scenarios revealed a common pattern between models. Though the magnitude and temporal occurrence of losses varied between models, in all model output *Casuarina* was the first wetland vegetation to experience substantial losses sequentially followed by saltmarsh, mixed and mangrove zones. It was further noted that at the greater level of SLR mangrove areas consistently reached a maximum total areal extent between 2060 and 2080 before decreasing until the year 2100.

5 DISCUSSION

The current study has incorporated a wide range of validation techniques for models that predict the effect of sea-level rise on coastal wetlands, with the understanding that the greater number of tests a model successfully passes, the greater the validity and reliability of that model for the context under study. It is emphasised here that the validation of the SLAM model conducted and discussed in this study is specific for the Australian context, and more particularly for the Minnamurra coastal wetlands. It therefore does not indicate a validation or invalidation of the model for the context in which it was originally conceptualised. Rather, given the change in context, the process could be considered a re-validation of the model to ascertain the usefulness and applicability of the model in SE Australian wetlands.

The discussion of the multistage validation procedure presented in this chapter follows the basic structure of the results section. The accuracy of elevation information is first discussed, followed by in depth examination of the SLAM and SAAT model validity. The conceptual and operational validity of the SLAM model is examined, with reference to the predictive validation test, extreme conditions tests and model output under varying sea levels. The final section of this chapter compares the structure and output of the SLAM model to that of the SAAT and Oliver models, investigating the usefulness of each model in simulating the effect of SLR on the coastal wetlands of SE Australia.

5.1 Digital Elevation Models

The validity of any model or prediction is related to the accuracy of the input information. As the old adage warns, ‘garbage’ input will produce ‘garbage’ output. Thus, it follows that the accuracy of the input elevation information is essential for determining the ability of a model to simulate the effect of SLR on coastal wetlands, especially as small errors in elevation for a low-lying, shallow gradient area can propagate significant errors in wetland inundation simulations (Gornitz *et al.* 2002; Pugh 2004).

Uncertainty is inherent in spatial data (Leon *et al.* 2014), therefore it was not unexpected that each DEM utilised in this study was found to be subject to some elevation error. The greatest vertical accuracy was obtained by DEM3, with an $RMSE_z$ of approximately 9.3cm. The small overall error calculated for the elevation layer is likely a result of the method used for DEM generation. Unlike DEM1 and DEM2, the third elevation layer used in this study was predominately created from the interpolation of point elevation data collected at very high vertical resolution (Oliver 2011). Theoretically, the vertical accuracy of DEM3 suggests the elevation model is the most suitable for modelling purposes. However, in practical terms, this is not the case, as DEM3 did not provide elevation information for the entire study site. Furthermore, generation of an elevation surface at the scale required by certain models applied in this study was not practically possible, given that the method of rigorous RTK-GPS sampling of elevations used for the derivation of DEM3 could not be efficiently employed at landscape or even estuary-scales.

LIDAR data provided the opportunity to determine wetland surface elevations at the larger spatial scale. DEM2 and DEM1 were both primarily derived from LIDAR data and contained considerably greater error than DEM3. The overall vertical accuracy calculated for each of the elevation layers was above that reported by the LIDAR data provider. This finding is in accordance with a large body of literature, which report global error statistics accompanying disseminated LIDAR data to not necessarily reflect the accuracy of a specific study area due to vertical accuracy being calculated from the best-performing ground reference areas within an entire dataset (Flood 2004; Hohle & Potockova 2006; Aguilar & Mills 2008; Coveney & Fotheringham 2011).

Further to this, local variation and spatial dependency in elevation errors is not reflected within the overall error statistics as calculated by either the LIDAR producer or by the author within this study (Flood 2004; Bater & Cooper 2009; Schmid *et al.* 2011). Calculation of vertical accuracy by wetland vegetation for both DEM1 and DEM2 revealed vegetation-specific variations in elevation error. These inaccuracies were primarily related to limitations of the LIDAR system, errors in the separation of ground points from non-ground points and uncertainties generated during the interpolation process; three errors commonly associated with DEMs derived from LIDAR data (Liu *et al.* 2015).

Greatest vertical errors were calculated for mangrove areas, proposed to result from both systematic limitations of LIDAR and ground filtering errors. Arguably the greatest vertical inaccuracies associated with the mangrove areas were propagated from the filtering process applied to the LIDAR data. The filtering process involves identifying the bare-earth points from non-ground points in a LIDAR dataset and is considered one of the most critical steps for DEM generation from LIDAR data (Liu 2008; Meng *et al.* 2010; Liu *et al.* 2015;). Misclassifications of LIDAR points have been proposed to have the greatest impact on DEM accuracy (Liu *et al.* 2015). The error statistics associated with mangrove areas for DEM1 and DEM2 affirm such suggestions. Application of a more stringent filtering algorithm to the LIDAR data resulted in a significant reduction in vertical errors in mangrove zones of DEM2 in comparison to DEM1, subsequently generating a greater overall accuracy for DEM2.

Though a significant reduction in error was calculated for DEM2 after the application of the filtering algorithm, inaccuracies in derived elevations remained. These are partially attributable to the limitations of the LIDAR system. Coastal wetlands are, by definition, heterogeneous mixtures of vegetation species that are typified by varying degrees of dense vegetation cover (Lotze *et al.* 2006). Intuitively, as the vegetation density increases, the ability of the LIDAR laser pulse to penetrate the vegetation is reduced, increasing the associated elevation error. An examination of this relationship, through the quantification of vertical errors by vegetation, indicated that mangrove areas, presenting the densest canopy of the vegetation types, were consistently associated with the largest elevation errors. In contrast, saltmarsh areas, commonly populated by low-growing herbs, grasses and sedges interspersed with non-vegetated patches, displayed the lowest $RMSE_z$, reflecting the greater opportunity of LIDAR pulses reaching the true ground surface.

Though saltmarsh zones were associated with the least vertical error, measured inaccuracies of surface elevation in saltmarsh zones remained the same in DEM2 as DEM1, suggesting that the errors were more likely a result of LIDAR system limitations rather than from classification or interpolation techniques applied. Whilst the magnitude of surface elevation errors in saltmarsh zones are commonly less than within mangrove forests, potential elevation errors arise from the resolving threshold of the LIDAR being at or near the elevation of the short saltmarsh vegetation, meaning that the bare earth surface cannot be clearly distinguished from the top of the saltmarsh within the LIDAR system (Wagner *et al.* 2004). Populus *et al.* (2001) also found that errors increased due to difficulties in separating LIDAR pulses reflected from saltmarsh vegetation in the saltmarshes of the Baie del'Aguillion, France.

In addition to systematic limitations and ground-filter derived errors, interpolation errors were also associated with the DEMs generated. This was most evident in the representation of water bodies in DEM1, where the limited point density of the Minnamurra River resulted in interpolation of surrounding higher ground points and subsequent overestimation of the river's elevation. Effective application of a breakline reduced this error within DEM2.

Moreover, in accordance with the work of Lichtenstein and Doytsher (2004) and Worstell *et al.* (2014), the inclusion of the soft breakline appeared to increase the reliability of the DEM and improved the accuracy with which hydrological pathways or waterways were defined in the study area. It is noted that some error may have been introduced with the assignment of a new elevation value for the Minnamurra River. In some cases, the assigned elevation fell substantially lower than the surrounding terrain, possibly introducing errors into the data (Worstell *et al.* 2014) and likely misrepresenting the elevation.

Evaluation of the accuracy assessments for each elevation layer demonstrates the need for expert, or at least closely considered, use of LIDAR data for generating DEMs. Time limitations, budget constraints and difficulties associated with LIDAR acquisition and expert processing often result in 'as-received' data being used in DEM creation (Flood 2004; Coveney *et al.* 2010; Liu *et al.* 2015). Vertical errors associated with DEM1, however, warn against such an imprudent use of LIDAR data. By comparison, DEM2 provides a more reliable and accurate elevation surface, with respect to vegetation type and the intertidal zone of the Minnamurra River. The considerable reduction in error associated with the mangrove zone, increased accuracy in the representation of water bodies and greater overall accuracy of wetland surface elevations of DEM2 suggest that application of a more technically demanding process in the derivation of a DEM is necessary to obtain reliable, morphologically correct and hydrologically enhanced elevation information. An expertly conducted process to reduce elevation error is most especially required when modelling the effect of SLR on shallow-gradient coastal wetlands, where even small elevation errors can propagate error and uncertainty through model output, significantly impacting the validity of models.

5.2 The SLAM model

5.2.1 Verification

In the development and dissemination of any computer-based model, a verification process is undertaken to ensure the conceptual model has been accurately translated into computer code (Rykiel 1996). Results from further verification of the complex code of the SLAM model conducted in this study revealed a significant error in the mechanical realisation of the SLR scenarios within the model. It is noted that, with strictest adherence to the definition of verification, the SLAM model passes the verification test as the model does indeed perform in the manner in which it is coded to do. However, broadening the term verification to include how "…faithfully and accurately *ideas* are translated into computer code…" (Rykiel 1996) indicates that the model was not verified under certain circumstances, namely when the maximum A1T or A1FI SLR scenarios are utilised. Within the SLAM code, the A1T Max SLR projection corresponded to the A1FI Max reported in the IPCC TAR and vice versa. The systematic error within the SLAM model appears to be a result of erroneous reporting of SLR in Table II.5.I of the IPCC TAR.

To the author's knowledge, no other research or project-based findings have recognised the error inherent within the model, though the reversal of the SLR values for the two scenarios appears to have been coded within the SLAM model since the release of version 4.1 in 2005. The inversion of SLR values between the A1T and A1FI maximum SLR scenarios may have far reaching effects on any conservation project or management plan formulated on the basis of SLAM model output utilising these scenarios.

As the SLR scenarios are based on the findings of the TAR (IPCC 2001) and the current version of the SLAM model allows for SLR values to be defined, it is less likely that this error will affect research being conducted using site-specific values. As neither the A1T nor A1FI scenarios of the TAR (IPCC 2001) were utilised in this study, validation tests conducted remain unaffected by the errors coded within the SLAM model.

5.2.2 Validation

Predictive validation

Predictive validation involves modelling a system's behaviour and comparing the output with the real system to determine if they are the same (Sargent 1996). Outcomes of such validations are indicative of the predictive ability of models. Results from predictive validation runs in this study suggest that at decadal timescales the SLAM model is able to simulate system behaviour reasonably well, with only small errors pertaining to model output over the periods 1949-1963 and 1986-1997. At longer timescales exceeding 10 years, it appears that the predictive power of the SLAM model is significantly reduced. The substantial errors associated with final model output, from simulations spanning approximately half a century (1949-1997), cast doubt upon the SLAM model's ability to reliably predict the behaviour of a system over even longer-term periods of 100 years or greater and contrasts with the perceived capacity of the SLAM model to simulate SLR effects to the end of the 21st century.

Potential data errors affecting model performance

Given the implications of the predictive validation results, it is pertinent to examine the potential reasons for which the model appears to be inefficient at explaining the wetland system for periods greater than a decade. Errors between modelled and observed data, such as that noted for the mangrove and saltmarsh areas during validation runs, are often attributed to the model's failure to adequately describe aspects or processes acting on the system in the real world (Mulligan & Wainwright 2013). Such a case is made here in addition to giving due consideration to possible errors inherent to input data.

It is incorrect to assume that observed data accurately represents the real system as all data, being an abstraction of reality, contains a degree of error and uncertainty (Monte *et al.* 1996; Mulligan & Wainwright 2013). Inaccuracies and imprecision of data used in the predictive validation process most likely contributed in some manner to the poor performance of the SLAM model. Spatial data, elevation and vegetation layers, and measurements used to characterise the model parameters all contain some error and uncertainty. While the errors associated with each input data or variable may be small, the resulting error and uncertainty propagated through the model may cause significant deviations of model output from the 'true' system (Oreskes *et al.* 1994; Monte *et al.* 1996).

The base elevation layer utilised in predictive validation runs must be first cited as a source of potential error in the predictive validation runs. Elevation data specific to the initial years of validation runs were not accessible, signifying that an alternative method of obtaining an input elevation layer was needed. The method chosen within this study follows that of Geselbracht *et al.* (2011), which adjusts elevations of the 2011, LIDAR-based elevation layer (DEM2) to approximate wetland surface elevations at initial years of validation runs.

However, adjustments were made based on assumptions of constant SLR and steady-state of wetland environments. As it is known that SLR accelerated during the last century (Church & White 2006) and much evidence suggests wetlands tend towards but generally do not obtain equilibrium with SLR (Cahoon *et al.* 2006; Kirwan & Murray 2008), it is questionable whether the elevation surface generated for predictive validation runs indeed represent the wetland surface heights for the relevant years. Furthermore, the 2011 elevation layer used in the adjustment process is known to contain vertical errors (as discussed above). Thus, the substantial differences noted between observed and modelled data of predictive validation runs may be largely due to propagated error from input elevation data.

Vegetation layers are an additional source of error. Input vegetation layers and comparison data alike were developed from the interpretation and digitisation of aerial photography (Chafer 1998). The derivation of the maps, therefore, incorporated interpretation errors, spatial errors and inaccuracies associated with the abrupt delineation of vegetation types where a gradual gradient between habitat types occurs in the real system (Chafer 1998). Such errors associated with mangrove, saltmarsh and *Casuarina* zones of each map utilised were, however, all estimated by Chafer (1998) to fall below 5%. Thus, though both the initial and comparison vegetation data contain a degree of error and uncertainty which contributes to the error associated with predictive validation runs, it is unlikely that it accounts for the substantial underestimation of mangrove areas and overestimation of saltmarsh areas determined from SLAM model output.

Perhaps of greater import, the input data used to characterise the accretion parameter may have affected the ability of the model to describe the behaviour of the wetland under rising sea levels. Not only do natural errors in measurement impact the accuracy of accretion or elevation values extrapolated from the SET dataset, rates of SEC and accretion rates were derived from relatively short-duration datasets which do not necessarily capture longer-term processes or the range of conditions possible in the wetland system (Rybczyk & Callaway 2009). In addition, the short-term datasets do not correspond to the temporal scale at which the SLAM model operates. Therefore, whilst the rates derived from the SET data are relatively high precision for the timescale and period over which the data was collected, extrapolation of the short-duration datasets to larger time frames limit the ability of the model to describe the natural variations in the dynamic wetland environment, with unanticipated changes and infrequent events being poorly incorporated. The potential implications of such data limitations are observed in the predictive validation runs. It is noted that the timescale over which (the) predictive model output (or outputs) displayed adequate agreement with observed data approximately corresponded to that of SET measurements and observations of SEC, yet at larger temporal scales model predictions were poor. Such observations are noted in a number of studies across many disciplines, where the use of data describing system behaviour over short temporal scales has led to a reduction in the predictive reliability of models (Anderson & Woessner 1992; Konikow 1995; Weaver *et al.* 1996).

Potential errors in applying the SLAM model to the SE Australian context

The inadequacy of models to reliably extend into the future often signifies that the conceptualisation of the system within the model is flawed (Oreskes *et al.* 1994; Rykiel 1996; Sargent 1996). We, thus, turn now to the possibility of errors in predictive validation runs resulting from the inadequacy of the model to describe the Australian site. Over the period 1949-1997, a considerable increase of mangrove area (61%) and substantial loss of saltmarsh (56%) was observed in the Minnamurra wetlands as a result of mangrove zones expanding landward, displacing saltmarsh in doing so (Chafer 1998). Significant discrepancies between modelled and observed vegetation distributions are primarily related to these vegetation dynamics, with the model underestimating mangrove extent and overestimating saltmarsh extent. In order to understand the flaws within the conceptualisation of the model, it is necessary to inspect the possible factors contributing to the changes in wetland vegetation not accounted for within the SLAM model. Numerous possible reasons have been posited to contribute to the trend of mangrove encroachment on saltmarsh observed within NSW (Saintilan & Williams 2000).

Clarke and Hannon (1967) linked changes in coastal wetlands to changes in rainfall patterns. Increases in rainfall were directly related to decreases in soil and surface water salinity in wetlands which, in turn, increased the ability of mangroves to survive and expand into previously-hypersaline saltmarsh zones. Though some have found no link between rainfall and mangrove encroachment (Wilton 2002; Saintilan 2004), many studies have related the proliferation of mangrove to increases in rainfall along the SE Australian coast (Saintilan & Wilton 2001; Eslami-Andargoli *et al.* 2009, 2010; Rogers *et al.* 2014). With full appreciation of this fact, the 10-14% increase in rainfall along eastern Australia observed over the period 1946-1978 (Pittock 1984) may have contributed to the proliferation of mangrove vegetation at the Minnamurra site between 1972 and 1981 (Chafer 1998). As it is the considerable growth of mangrove vegetation that the SLAM model was unable to simulate, it is feasible to suggest that model is unable to capture the importance of increased rainfall or freshwater inputs on the evolution of SE Australian wetlands. This suggests the existence of a conceptual flaw within the model, where the exclusion of rainfall as a significant parameter in modelling decreases the adequacy with which it describes and simulates SE Australian wetlands.

The inability of the SLAM model to account for compaction in wetland soils is posited to also have been a source for the major discrepancies between modelled and observed output. Measurements from the SET network established along the NSW coastline have highlighted the frequent differences between SEC and accretion rates (Rogers *et al.* 2006), which can be attributed to the processes of compaction, and organic matter decomposition (Cahoon 2006, 2015; Rogers *et al.* 2006; Lovelock *et al.* 2011). Amongst many site specific factors, compaction of wetland soils in SE Australia has been associated with groundwater fluctuations and the Southern Oscillation Index (Rogers *et al.* 2008). These factors are, in turn, affected by ENSO-related drought conditions, which cause greater soil shrinkage and compaction (Rogers *et al.* 2006; White *et al.* 1997). As compaction affects the wetland surface elevation, it can also be considered an important factor in the distribution of wetland vegetation, wetland habitats often being limited to certain ranges within the tidal frame (Clarke & Myerscough 1993; Kim *et al.* 2010). The absence of a compaction parameter or module within the SLAM model, therefore, may have added to the significant errors being simulated during the validation runs. An addition of a compaction parameter, even simply defined within the model, would result in elevations calculated at each time step being slightly lower than currently simulated within the SLAM model. With repeated application of the hypothetical compaction model, however, the final wetland surface elevation at larger time frames would possibly be significantly different to that currently modelled. This is particularly pertinent to the validation runs conducted within this study, where an overall lower wetland surface would have allowed greater conversion of saltmarsh zones to mangrove. The outcomes of the thought experiment would be a greater predictive ability obtained by the SLAM model. As it stands, the behaviour of the Minnamurra wetlands over time appear to be inaccurately described by the SLAM model, possibly as a result of no compaction parameter being included. It is noteworthy, that included in the factors affecting compaction are processes specific to the Australian and the central and eastern Pacific context, such as ENSO related factors. Addition of such variables within the SLAM model would likely increase the validity of the model for the Australian context.

Continuing in this vein, it is pertinent to consider the influences of pulsing events or sudden, infrequent sediment deposition events from major storms and floods that are not considered within the SLAM model. It is inherently difficult to model such events, their unpredictability in terms of frequency, duration, return interval and intensity being a defining characteristic. Storms and floods have the potential to greatly affect coastal wetlands, disrupting and redistributing sediment within the wetland (Cahoon *et al.* 1995; Guntenspergen *et al.* 1995) or even depositing large quantities of sediment, as a result of increased runoff and erosion instigated by the extreme precipitation associated with storms (Cahoon *et al.* 2003). The influence on the wetland forms part of a negative feedback process, whereby the greater sedimentation may result in a change in elevation which affects patterns of inundation, which in turn influences the rate of sedimentation, decomposition and wetland surface elevation and so the cycle continues. The extreme scenarios (storms and floods etc.) and related feedback mechanisms are suggested to play a possibly significant role in the development and dynamics of wetlands and their ability to survive with rising sea levels (Rybczyk & Cahoon 2002; Cahoon 2006). Over the period 1949 – 1997, floods and associated increases in rainfall are recorded to have occurred in the Minnamurra study site in the late 1950's and throughout the 1970's. Presumably, an increase in sediment deposition and freshwater flows would have accompanied such events, changing the dynamics of the wetland system and possibly facilitating the colonisation and growth of saltmarsh areas by mangrove vegetation. Flooding events and their effects were not, however, modelled within the predictive validation runs, further increasing the error associated with the model output. Though an overwash parameter is included in the SLAM model, its conceptualisation and realisation within the model is not pertinent to the Australian context. Thus, the inability of the model to capture well significant flood and storm events remains a limitation of the conceptual SLAM model.

Coastal wetlands are a complex dynamic system in which numerous processes are continually at play. Adequate description of the wetland systems within numerical models is difficult to obtain as can be seen by the limitations of the already complex SLAM model in predicting the evolution of Australian wetlands over time. However, perhaps the greatest introduction of error to the predictive validation runs is the influence of humans themselves. Ironically, anthropological influences can be one of the most unpredictable influences on coastal wetlands. Chafer (1998) reports clearing of land in subsite 2 of the Minnamurra study site for grazing, development of a railway and the introduction and expansion of the Kiama Waste Disposal Depot. These activities resulted in an overall loss of mangrove and *Casuarina* areas for significant periods of time. By 1972, however, mangrove and *Casuarina* had begun to expand into former saltmarsh and grazing areas, with a significant increase in their total area being noted by 1981. The considerable increase of mangrove at this subsite at the expense of saltmarsh may be a major contributor to the substantial increase in mangrove zones unable to be replicated in predictive validation runs. Due to the unpredictable and complex nature of human influence on coastal wetlands, it is not suggested here that the SLAM conceptual model should be adjusted to include anthropogenic influences. It is noted, however, that such influences were unable to be captured within the SLAM model output and, by extrapolation, could cause significant problems in any predictive output.

Capturing the response of wetlands to SLR by considering all the relevant processes operating at the appropriate time scales and incorporating all feedback mechanisms working within the system causes an explosion of complexity in the model structure and mechanical expression of the relevant concepts (Mulligan & Wainwright 2013). The exclusion from the SLAM model of certain factors commonly observed to play a role in vegetation distribution dynamics along the NSW coastline has been proposed here to contribute to the inadequacy of the model's predictive ability displayed in the validation runs. A hypothetical solution to such limitations in the predictive power of the model would be the addition of parameters or modules pertaining to factors such as soil compaction or ENSO-related processes. However, further parameterisation of the model, though it may increase its predictive power over a certain domain, may cause further uncertainty and possible failure over other domains. Furthermore, it would make the model even more complex than currently and, in so doing, further reduce the comprehensibility of the model.

The question remains, though, as to how reliable the predictive output of the SLAM model actually is. Based purely on how well the observed data was modelled in the predictive validation runs, it could be concluded that the SLAM model has the potential to predict responses of wetlands at decadal timescales but has little predictive power at greater time frames. Furthermore, given the limitations posited in this discussion, possible underlying conceptual problems could be said to reduce the validity of the model for the Australian context, specifically, the Minnamurra site. However, though these conceptual problems remain, the considerable errors identified within the input data of the validation runs make it difficult to disentangle the inaccuracies due to model flaws from the uncertainty attributable to data error. Thus, for this study, a complete predictive validation of the model is not possible, a result not uncommon within the modelling community, where it is generally understood that absolute validation of a model is virtually impossible (Refsgaard & Storm 1996; Senarath *et al.* 2000). Even for those models whose agreement of output with past observational data would suggest a strong predictive ability, post-audits of model predictions often determine that predictive validation of the model was essentially invalid (Anderson & Woessner 1992, Konikow 1995). Such findings cast doubt on the validity of predictive validation tests and emphasises the fact that there is no guarantee that a model will perform in the same manner that is indicated by a validation tests. Therefore, rather than a test of predictive power, the predictive validation tests of the SLAM model conducted in this study effectively served as a means to identify potential conceptual problems and closely examine input data error.

5.2.3 Plausibility of model outcomes – projections under varying SLR scenarios

Determining the accuracy of a prediction is a logical impossibility (until the time modelled comes to pass, at which point it is no longer a prediction). By invoking the principle of uniformitarianism, however, some idea as to the plausibility and reliability of model output can be obtained. Relying heavily upon this principle and despite the poor performance of the model in predictive validation tests, SLAM model outputs generated in this study could be said to be plausible.

With increased rates of SLR observational and modelled evidence suggests that there is a limit to the wetlands ability to adjust to rising sea levels (Kirwan & Murray 2008). The modelled output of SLAM under varying SLR scenarios is in step with the current understanding of the response of coastal wetlands to increasing sea levels and as such can be considered to provide plausible representations of wetland vegetation until the end of the century. Under low rates of SLR, the SLAM model simulates little change in the wetland distribution indicating the system's ability to maintain surface elevation with respect to the increasing water level. At intermediate and extreme rates, however, a greater proportion of wetland was inundated. Such model results reflect the findings of numerous studies suggesting that increasing rates of SLR lead to deepening of the wetland surface elevation, increasing soil anaerobia and a decline in plant productivity past the point at which vegetation can survive (Kearney & Stevenson 1991; Reed 2002; Kirwan *et al.* 2008, 2010).

In considering the threshold of wetland resilience with rising sea levels, Kirwan *et al.* (2010) found that though threshold rates of SLR varied according to the sediment availability and geomorphic characteristics of the individual site. SLR projections indicate that increases greater than 10mm/yr may be experienced by the end of the century (Vermeer & Rahmstorf 2009; Grinsted *et al.* 2010). At such rates, despite the feedback mechanisms that allow coastal wetlands to increase elevation with rising sea levels, many models indicate that most wetland systems will begin to be submerged, their threshold rate of SLR being reached. The extreme conditions test conducted in this study utilised such projections to test the plausibility of model outcomes under such extreme rates of SLR. Model output affirmed the findings of many, displaying significant losses to wetland by the year 2100 under high rates of SLR (Kearney & Stevenson 1991; D'Alpaos *et al.* 2007; Kirwan & Murray 2008; Kirwan *et al.* 2008, 2010). Furthermore, the maximum wetland resilience and threshold rate of SLR were simulated by the SLAM model to occur in the middle of the century when rates of SLR are projected to accelerate. It could be argued that, by considering the point at which the threshold occurred with the time at which the rate of SLR surpassed 10mm/yr, the SLAM model output records a potential geomorphic lag of approximately 30 - 50 years in the response of the wetland system to the threshold SLR conditions, in keeping with many modelling results previously reported (see Fagherazzi *et al.* 2012 and references therein).

Modelled results of wetland vegetation distribution simulated by the SLAM model indicate a proliferation of mangroves and a concomitant reduction in saltmarsh and *Casuarina* zones by the year 2100 under all SLR scenarios. Observations of wetland vegetation patterns over the past century along the SE Australian coastline indicate a landward encroachment of mangrove and decline of saltmarsh vegetation extent (Saintilan & Hashimoto 1999; Saintilan & Williams 1999; McLoughlin 2000; Rogers *et al.* 2005) As previously discussed, many potential causes for the landward incursion have been posited, with a growing body of evidence suggesting SLR plays a significant role in the pattern of vegetation change (Rogers *et al.* 2006; Gilman *et al.* 2007; Williamson *et al*. 2011). The combination of SLR, increased temperatures, atmospheric CO_2, rainfall, and frequency of storm events all associated with projected climate change may cause the current trend of mangrove proliferation into saltmarsh zones to be exacerbated (Adam 2002; McKee *et al.* 2012). The results of the SLAM output under each SLR scenario tested, therefore, correspond to observational evidence of mangrove expansion over the 20th century and predicted patterns in vegetation change for the next century (Lovelock *et al.* 2015).

Despite the plausibility of SLAM model outcomes, a potential problem in model structure is recognised in examining the decadal model output. The SLAM model implements switching functions, whereby the vegetation of a cell is converted to a lower wetland class when it falls below the elevation range assigned to its vegetation type. A cell must pass through each sequentially lower wetland category according to a pre-defined succession sequence programmed within the decision-tree of the SLAM model. It is this predefined succession and conversion which could cause potential problems in modelling Australian coastal wetlands. In this study, significant areas of saltmarsh were lost with simulations of rising sea level. Whilst this trend is in step with many studies heralding the demise of saltmarsh (Adam 1990; Chafer 1998; Saintilan 1998; Saintilan & Williams 1999; Adam 2002; Rogers *et al.* 2005, 2006) the magnitude of the decline may be severely overestimated. Due to the set decision tree controlling conversion in the SLAM model, saltmarsh, as defined in this study, is unable to migrate upland. This is in contrast to many observations of wetlands along the NSW coast, where evidence of saltmarsh occurring beneath *Casuarina* and *Casuarina* dieback in saltmarsh zones suggest a landward shift of saltmarsh sometime in the past (Rogers, 2015, pers.comm). The SLAM model, however, is unable to adjust its programmed vegetation succession to allow such changes to be simulated for wetlands within the Australian, nor indeed any other, coastal wetlands.

The problems in defining succession relate to the long-standing debate regarding wetland successional changes over time (Vaughan 1909; Davis 1940; Thom 1967; Spackman *et al.* 1969; Lugo 1980; Grindrod 1985). The SLAM model could be said to conceptually follow the proposed succession of Bird (1988), where a retrogression of zones (i.e. more seaward zones replacing land zones) is seen with transgressing sea levels. The distinct flaw in the SLAM model, however, is that diversion from such succession as required by a particular site is not possible. The structure of the model precludes conversion of water to any vegetation class, signifying that any sites in which mangroves are observed to expand in a seaward direction or 'build land' are inadequately simulated by the SLAM model. Such a problem is particularly pertinent to wetlands of Northern Australia, where more landward zones have replaced lower wetlands (Grindrod 1985; Woodroffe 1990).

5.2.4 Treatment of surface elevation change in the SLAM model

The SLAM model provides two different methods for characterising the accretion dynamics within a wetland system. The first is defined by applying an empirically-based measurement of accretion to the entire area of each vegetation type. The second is a model-based approach, the accretion module, where a relationship between elevation and accretion rates is defined for each vegetation type in order to approximate the spatial variability of accretion in coastal wetlands (Clough *et al.* 2012). This section first discusses the conceptual validity of the accretion parameters programmed within the SLAM model before discussing the model output resulting from their use within this study.

The first treatment of the accretion parameter programmed within the SLAM model is conceptually simple and has been noted to inadequately describe the dynamics within a wetland system with rising sea levels (Kirwan & Guntenspergen 2009). Coastal wetlands are dynamic systems that are expected to adjust to rising sea levels, as they have been observed to do in geological records (Reed 1995). With increased inundation, greater sediment supply is anticipated for systems where sediment supply is not constant, leading to higher rates of sedimentation and accretion (Morris *et al.* 2002). This feedback mechanism so important to the evolution of wetlands under rising sea levels is not, however, accounted for within the first method of defining the accretion parameter in the SLAM model. The method of assigning constant, empirically-based accretion rates to each vegetation type therefore leads to underestimation of wetland persistence with fluctuating sea levels. Furthermore, using individual rates of accretion to represent an entire vegetation type neglects to account for the spatial variation in sedimentation and accretion that has been commonly observed to occur within coastal wetlands (Morris *et al.* 2002; Temmerman *et al.* 2003b).

The accretion module was introduced in version 6 of the SLAM model in an attempt to account for the spatial distribution of accretion rates and the ecogeomorphic feedbacks within wetlands that contribute to the persistence of wetlands over time (Kirwan *et al.* 2010; Clough *et al.* 2012). The accretion module defines accretion in a given cell as a function of elevation, salinity and distance to the mouth of the nearest river. The distance to river parameter of the module assumes a linear relationship between sedimentation and the distance of a point from the sediment source, the river channel. Though the basic concept behind such an assumption is not unfounded, it does not hold true for all coastal wetlands where marine influences are greater than riverine. Indeed, sediment input in an estuary, and thereby accretion rates, can vary according to whether riverine, wave or tidal energy dominates the system (Roy *et al.* 2001; Rogers *et al.* 2012). Thus, use of the distance to channel parameter in the accretion module is questionable, especially when modelling accretion rates for estuaries such as that at Minnamurra.

The SLAM model attempts to simulate the effect of turbidity maximum zones on accretion rates in an estuary by inclusion of the salinity parameter within the accretion module. The salinity parameter remains an experimental variable as the data required to validate the model have not been available (Clough *et al.* 2012). However, the theory behind its inclusion is that maximum turbidity zones are often associated with high concentrations of sediment and sediment deposition. As the maximum turbidity zone is related to the position in the estuary where fresh and salt water interact, it was assumed that the influence of the zone on accretion could be related to the salinity level at which the interaction and maximum accretion rate occurs. Most likely for simplicity, the numerical expression of the concept is developed assuming a salt-wedge estuary. However, many estuaries of the NSW coast are mixed rather than salt-wedge estuaries meaning that a turbidity maximum zone as defined in the model is not relevant to these environments. This, in addition to the hypothetical nature of the model, all indicate that the salinity parameter within the SLAM model does not adequately describe accretion dynamics of coastal wetlands in NSW estuaries and should be excluded from use in the Australian context until such time that the model has been improved and validated based on empirical evidence.

The final parameter included in the accretion module relates accretion rates to elevation ranges of vegetation zones in an attempt to account for feedback mechanisms active within coastal wetlands such as that previously discussed. The SLAM model expresses this numerically as a cubic equation which can be calibrated to site-specific data. The relationship between elevation and accretion based on biomass and sedimentation observations created in Morris' Marsh Elevation Model (MEM) can, thus, be reproduced in the SLAM model. Clough *et al.* (2012) have emphasised the greater applicability of the SLAM model with respect to MEM due to the accretion module's ability to simulate elevation-accretion curves for sites that do not follow the assumptions and characteristics of Morris' model (2002). Furthermore, where site-specific data, such as suspended sediment concentration or biomass density, is not available the more theoretical approach to the elevation-accretion relationship in the SLAM model is advisable. However, attached to any theoretical definition of a parameter in modelling is the possible introduction of considerable uncertainty. Even in areas where accretion rates and surface elevation changes have been well documented, the point-based measurements used to define the theoretical elevation-accretion relationship do not necessarily capture the spatial variation of accretion characteristic to a particular site (Mulligan & Wainwright 2013). In addition, the strength of the feedback mechanism attempting to be modelled by the accretion module may vary over time depending upon a number of interconnected factors such as the availability of sediment, nutrients and fresh water pulses to the system (Day *et al.* 1999). The temporal and spatial variability of accretion patterns within the wetland under SLR may, thus, be inefficiently modelled. Despite the limitations of the module, the elevation-accretion relationship simulated has the potential to improve the modelling of the response of coastal wetlands to SLR. However, given the possibility of introducing even greater uncertainty to the model, expert judgement and an in depth understanding of the wetland system in general and the spatial pattern of accretion in particular is required before the accretion module can be applied with reasonably agreement with the module assumption.

A flaw in the conceptualisation of the SLAM model arises in both treatments of SEC. The definition of accretion in the model appears to assume that accretion equates to SEC within a wetland system. Numerous studies have shown that incremental changes in the elevation of wetland surfaces often do not follow the accretion trends of the system (Nuttle *et al.* 1990; Cahoon *et al.* 1995, 1999, 2006, 2011; Rybczyk & Cahoon 2002; Cahoon 2015). Processes such as compaction and erosion and influences of short-term perturbations are cited as possible causes for the deviation of elevation change from vertical accretion trends. Yet, despite the considerable evidence to the contrary, the SLAM model disregards the numerous processes contributing to negative vertical changes in the coastal wetland, accounting only for processes of accretion. It is noted that an erosion parameter is coded within SLAM, but is only implemented when there is a 9km fetch for a particular cell, an attribute not applicable to SE Australian wetlands within estuaries. The flaw that arises, therefore, in which only depositional processes are incorporated would imply that the SLAM model commonly overestimates the ability of coastal wetlands to build vertically under rising sea levels. Using rates of SEC derived from SET time-series data may potentially ameliorate the conceptual flaw by implicitly accounting for autocompaction and other processes contributing to decreases in wetland surface elevation.

It is interesting to note that the basic numerical expression of the vertical growth of a wetland under rising sea levels was defined by Allen (2000) to be the net effect of sedimentation, both organic and inorganic, sea level and *autocompaction*. While some models account for erosion and compaction mechanistically (Kirwan & Murray 2008; Mudd *et al.* 2009) and others implicitly, as in the initial models developed to simulate wetland response to rising sea level by Krone (1987), Allen (1990) and French (1993), most attempt to make allowances for the negative elevation changes observed to occur in coastal wetlands. The absence of a compaction parameter within the SLAM model is, therefore, all the more conspicuous.

The limitations of the treatment of SEC in the SLAM model must be considered when interpreting any model output. Three different methods were applied in this study to characterise the accretion parameter, two of which utilised the vegetation-specific accretion rates and the last implementing the accretion module. In utilising the various methods of characterising the accretion parameter the magnitude and rate of wetland vegetation change varied considerably. This could be said to attest to the differences in the mechanical structure of the various methods used to define vertical accretion trends within the SLAM model and to show the limitations of their conceptualisation.

Characterising the vegetation-specific accretion parameter by rates of SEC is a method by which both positive and negative components of elevation change can potentially be incorporated in the SLAM model, with the rate of SEC implicitly incorporating site-specific compaction processes. Model output for the Minnamurra site indicates that when compaction processes are incorporated significantly greater inundation and loss of wetlands occurs than if accretion only is simulated to affect the elevation change in wetlands under rising sea levels. Furthermore, the rate of wetland loss is substantially increased. Though the rates of SEC determined from the SET dataset may contain a degree of uncertainty and potentially be an inaccurate representation of wetland elevation change through time, it could be concluded that the neglect of compaction within the accretion parameter results in an underestimation of wetland loss under rising sea levels. However, the strength of this conclusion is affected by the limitations inherent in the structure of the model. That is, the constant rate of SEC simulated when using the vegetation-specific accretion parameter is an inadequate description of the response of the dynamic wetland system to rising sea levels, as previously discussed.

If the values used to define the accretion parameter and their mathematical realisation in the SLAM model are considered, results obtained in this study using different methods of characterising the accretion parameter are quite logical and consistent with a large body of literature pertaining to the resilience of wetlands with increasing sea levels (Cahoon *et al.* 2006; Kirwan *et al.* 2010; Rogers *et al.* 2014). Application of sub-centimetre rates of SEC to each vegetation type effectively reduces the ability of the simulated wetland to build vertically over time in comparison to when accretion rates, almost an order of magnitude greater than rates of SEC, are utilised. Kirwan *et al.* (2010) proposed that when wetlands receive relatively low levels of sediment and, by extension, experience potentially low rates of accretion, even under low rates of SLR the resilience of a wetland would be significantly reduced. Rybczyk and Cahoon (2002) also found that lower rates of SEC critically increased the potential for wetland submergence with rising sea levels. Moreover, abundant empirical and modelled evidence suggest that higher rates of sedimentation and associated rates of SEC increase the ability of wetlands to persist under scenarios of increasing SLR (Allen 2000; Cahoon *et al.* 2006; Kirwan *et al.* 2010; Fagherazzi *et al.* 2012).The results of this study are, thus, in accordance with previous observations within the literature, where model output using rates of SEC suggest a significant loss in wetland area in comparison to simulated results utilising higher rates of 'elevation change' (i.e. accretion rates).

Given the limitations of the vegetation-specific accretion parameter discussed previously it is pertinent to compare the output of the SLAM model when the vegetation-specific accretion parameter is utilised with that when the accretion module is calibrated and applied. Within this study, only the accretion variable was utilised within the accretion module, the salinity and distance to channel parameters being considered to contain too many flaws and uncertainties to be applied to the Minnamurra site. Applying the module resulted in significant differences in the modelling of some wetland vegetation, whilst simulations of other zones, such as saltmarsh, remained relatively similar regardless of the treatment of SEC. The similarities and differences can mostly be related to the manner in which the accretion rates were characterised and defined within the SLAM model. The single accretion rate values applied to the entire area of a wetland vegetation category effectively produced a large elevation change per year, with respect to applying rates of SEC. The lower boundary of the mangrove area, therefore, was not modelled to fall below the lowest elevation of the defined mangrove elevation range, greatly reducing the area of mudflat zone simulated. A similar trend was seen when the accretion module was used. The maximum accretion rate defined in the module for the mangrove zone, being larger again than that of the accretion value, similarly caused greater elevation change in the mangrove zone, signifying a reduction in mudflat zones in model output associated with the accretion module in comparison to that simulated when the accretion parameter was utilised. Proliferation of the mangrove zone and greater persistence of the mixed zone can also be attributed to the progressively greater accretion rates of each method of SEC used within this study. In contrast, the similarities of the areal extent of saltmarsh by the year 2100 were not a function of the different treatment of

SEC but rather a product of the decision tree programmed within SLAM to characterise the conversion between wetland vegetation, as discussed above.

The greatest perceptible difference in applying the accretion module was the increased persistence and proliferation of the mangrove zone and, thereby, an overall greater ability of the wetland to maintain its elevation with respect to rising sea levels. If the uncertainties and potential errors associated with calibrating the accretion module for a particular site are disregarded, the results indicate that the accretion parameter potentially underestimates the ability of wetlands to build vertically under SLR. This would suggest that it is important to model the feedback mechanisms, in SLAM included within the accretion module, in order to gain a fuller understanding of the potential persistence or demise of a wetland with fluctuating sea levels. However, given the uncertainty involved in the calibration process, a greater quantity of site-specific empirical data would be needed to better understand the spatial and temporal variability of the feedbacks being modelled before the use of the accretion module in the SLAM model could be reliably supported. Such conclusions affirm those drawn from observations and modelling recorded in the literature (Murray *et al.* 2008).

Considering the conceptual and mathematical limitations and sources of uncertainty contained within each treatment of SEC in the SLAM model, it is likely that the ability of a wetland surface to build vertically and vegetation to change accordingly under rising sea levels is overestimated, especially when site-specific accretion values are used. Nevertheless, the possibility of SEC being underestimated within the model cannot be discounted. As extreme climatic conditions, such as flooding and storms, are not incorporated in the model, the substantial influence such large magnitude, short-term perturbations have on the wetland elevation is not being simulated. Storms can have a significant impact on geomorphic change in coastal wetlands (Cahoon *et al.* 2003; Cahoon 2006; Smith *et al.* 2009; Rogers *et al.* 2013). As mentioned previously, a variable effect of storms can be observed in coastal wetlands (Rogers *et al.* 2013) where storm events have the potential to cause erosion and further compaction of sediments (Pethick 1991; Cahoon 2006) or deposit or redistribute large quantities of sediment within the wetland (Cahoon *et al.* 1996; Whelan *et al.* 2005). Exclusion of the former elevation changes resulting from storm events would exacerbate the overestimation of wetland change suggested above in reference to compaction processes. Exclusion of significant storm deposits in modelling, however, may result in an overall underestimation of wetland persistence with time. Given that high-magnitude storm events are projected to occur more frequently with climate change over the next century, the inclusion of storm events is increasingly relevant to modelling the response of wetlands to SLR.

Overall, examination of the treatment of SEC and associated results of this study indicate that there are many conceptual flaws in the definition of wetland elevation change that would indicate that the SLAM model may more typically overestimate changes in wetlands. However, use of rates of SEC may mediate these inaccuracies to some degree. In addition, use of the accretion module, theoretically, allows for a greater description of wetland evolution with rising sea levels as feedback mechanisms are simulated, accounting for the spatial variability of accretion trends. However, limitations and considerable uncertainty and error are associated with the definition and use of each model. Caution should be exercised, therefore, in the choice and characterisation of SEC as it is conceptualised within the SLAM model. Moreover, any model output should be interpreted with a full understanding of the limitations and associated uncertainties of the treatment of SEC used within the SLAM model.

5.2.5 Error and uncertainty in the SLAM model

Errors inevitably occur in all processes and the modelling process is no exception (Monte *et al.* 1996; Saltelli *et al.* 2000; Renard *et al.* 2013). Similar to many other numerical models attempting to simulate the complexity of dynamic environments, the SLAM model contains considerable error and uncertainty generated as a result of conceptual flaws, measurement and data errors and, of course, the complexity of predicting a system that is inherently complex, evolving over time and continuing to do so into the future.

Conceptual flaws and limitations of the SLAM model each have the potential to generate uncertainty within simulations and resulting model output. When the conceptual model does not contain certain variables or processes considered to be crucial to the system under study, the chance that the system is adequately described and simulated in the model is considerably decreased (Renard *et al.* 2013). The absence of the parameters or incomplete expression of the processes within the model therefore can produce significant uncertainty in model output. Of the conceptual flaws and limitations of the SLAM model the greatest contributors to error and uncertainty in model output are most likely the treatment of SEC and the programmed switching functions associated with wetland conversion within the SLAM model, as discussed in detail in previous sections.

In addition to the conceptual realisation of the system, model output is only as reliable and valid as the input information used to define the SLAM model. Numerous limitations and errors exist in association with the input data of the SLAM model.

For the most part, the SLAM model is characterised by empirical data collected over a relatively short time period. Based on the principle of uniformitarianism, simulations are then conducted over larger time scales. However, the factors and interrelated processes driving wetland evolution over time and, by extension, under rising sea levels occur over a broad range of temporal and spatial scales (Wright & Thom 1977; Cowell & Thom 1994; Woodroffe 2002; Rybczyk & Callaway 2009). For instance, eustatic SLR adjustments influencing the geomorphic changes of coastal wetlands operate at geological timescales whilst pulsing events, such as storms and floods, occur at event scale temporal periods. Both processes, however, are known to affect the evolution of coastal wetlands over time. It is unlikely that the short-duration data used to characterise, and indeed initially parametrise and calibrate, the SLAM model is thus able to capture the full suite of interrelated processes influencing the response of wetlands to rising sea level. Measurements utilised in characterising model variables, such as the accretion parameter or degree of historic sea level, which only represent subsamples of the real-world coastal wetland system result in a certain amount of error being inherently contained within the SLAM model output.

Considering the inherent heterogeneity of the wetland system, further problems arise in the characterisation of spatially and temporally variable processes represented within the SLAM model (disregarding for the moment those processes that have been overlooked in the conceptualisation of the model). This is particularly pertinent to the definition of the accretion parameter. In this study, accretion rates and rates of SEC were generated from SET measurements, which represent discrete point data in time. However, the extrapolation of the point measurements to the entire study area may be a poor estimate of the true spatial representation of the accretion parameter (Mulligan & Wainwright 2013; Li & Heap 2014).

Moving from the problems associated with the spatial and temporal variability of data, the accuracy and precision with which measurements are recorded may significantly affect the error and uncertainty in the SLAM model output. The SLAM model is a deterministic model and as such provides unique output for a given set of unique input parameters (Renard *et al.* 2013). Small differences in the initial values of parameters can lead to considerable variation in the model output. In this way, even small errors contained within the measurements used to define the SLAM model can produce large errors in output. Considerable care is required, therefore, in obtaining the most reliable and accurate site-specific data before the application of the SLAM model.

Accuracy of elevation layers used within the SLAM model, for instance, can have a large impact on the simulated wetland distributions and response to rising sea levels. Using a DEM known to have significant elevation errors, model output under all sea level scenarios was observed to overestimate the persistence of wetland over time. Similar to the findings of Chu-Agor *et al.* (2011), modelled results showed that the lower wetlands were most affected by the differences of the input elevation data. The importance of utilising a superior representation of wetland surface elevation when modelling was clear when considering the areas inundated and wetland lost by the end of the century. When utilising the elevation model that displayed considerable vertical inaccuracies in the lower wetlands, DEM1, considerably less wetland area was inundated. Given that mudflat and lower wetland areas simulated when utilising DEM1 almost exactly corresponded with the spatial distribution of significant vertical errors in the DEM, it is suggested that utilising inaccurate elevation data results in underestimation of inundation risk. Indeed, though it is impossible to ascertain the absolute accuracy of the prediction, it could be concluded that the accuracy in representation of the present allows for greater reliability of simulated representations of the future. Such results and conclusions mirror those drawn by Coveney and Fotheringham (2011) who found significant advantages in higher accuracy DEMs for the prediction of land inundation. Leon *et al.* (2014) also concluded that vertical errors inherent in DEMs propagate into inundation mapping.

Examining results from the sensitivity analysis, it becomes even more imperative that certain parameters do not contain considerable error. Sensitivity analyses conducted in this study revealed that SLR, tidal range, salt elevation boundary, NAVD88-MTL and historic SLR trend were the most sensitive factors of the SLAM model. Accretion rates also had a vegetation-specific effect on modelling outcomes. As slight changes to these parameters results in proportionally larger variations in model output, it is important that they be defined as accurately as possible. Within this study, however, a degree of error could be attributable to each of the sensitive parameters identified, no doubt increasing the uncertainty of model output.

Similar to most models simulating wetland change (Kirwan & Murray 2008; Mariotti & Fagherazzi 2009), sea-level rise was found to have the greatest impact on the SLAM model output. Considering inundation is a driving function of wetland change within the SLAM model, such a finding is to be expected. However, given the sensitivity of the model to the SLR defined, results suggest that, if possible, SLR projections determined for a particular region or site should be applied rather than the global SLR value defined by the IPCC. This is especially true for areas that are experiencing rates of SLR significantly above or below the global eustatic trend. Modelled projections by Church *et al.* (2013) suggest that SLR for NSW deviate from the global mean by 0 - 10%, therefore choice of SLR projection to be used in the SLAM model should occur on a site by site basis according to the requirements of the project or study. Despite the increase in accuracy of model output if local SLR projections are utilised, uncertainty is not eliminated from the model parameter and simulated results. Indeed, all projections are uncertain (Oreskes *et al.* 1994; Church *et al.* 2010) and use of the uncertain projections in further modelling processes may simply amplify the uncertainty within the end modelled product (Monte *et al.* 1996; Mulligan & Wainwright 2013).

Uncertainty amplification may also occur according to the characterisation of the tidal range and salt elevation boundary parameters within the SLAM model. Erroneous definition of these sensitive parameters may result in considerable error within the final output. Within this study, vegetation-specific elevation ranges were defined as a function of subsite tidal ranges. Therefore, conversions of wetland vegetation were based on these two parameters and any uncertainty in the input tidal data potentially propagated error throughout the entire modelling process. The ability within the SLAM model to define the tidal range on a subsite basis rather than applying the one value to an entire, landscape-scale area allows spatial variation of tides within estuaries to be incorporated in a rudimentary manner. Tidal levels in NSW estuaries are observed to attenuate or amplify according to estuary type and shape (Roy *et al.* 2001; Foulsham *et al.* 2012; OEH 2014). The variation in tidal levels influences the magnitude of inundation and distribution of wetland vegetation in the estuary. Use of subsites, as applied in this study, simply accounts for tidal attenuation. However, applying a spatial average to a subsite describes poorly the true tidal levels within the estuarine-wetland system. Following encouraging results from previous studies and modelling (Foulsham *et al.* 2012; OEH 2014), it is posited that incorporating a model of the site-specific tidal plane in the SLAM model may improve the reliability and accuracy of model output. Addition of the spatial parameter may increase the complexity and computational load of the model however the advantages of reduced uncertainty and increased accuracy may outweigh these disadvantages.

Historic levels of sea-level rise were found to greatly affect the model output. Within the SLAM model this parameter defines the deviation of the site-specific rate of SLR from the global mean, assuming that all deviations are a result of geological subsidence specific to the study area (Clough *et al.* 2012). Conceptually, such an assumption is incorrect, with many studies clearly citing a number of different factors influencing the rate of relative sea-level rise (Woodroffe & Murray-Wallace 2012). Mathematical expression of the concept, however, is simplistically defined. In addition to the errors introduced from the model structure, definition of the parameter for a site is also difficult as described previously. A record of at least 18 years is required for a reliable trend in SLR to be defined. In this study, the lack of adequate data at this temporal scale precluded the use of site-specific tidal data to characterise the historic SLR. The value, instead, is drawn from trends in the region, which may not represent those of the system under study. The error introduced from the data combined with the conceptual errors suggest the historic SLR has the potential to propagate additional error within the modelling process.

The expression of error and uncertainty within model output is clear when considering the stochastic data generated from the Monte-Carlo uncertainty analysis. Most of the sensitive parameters and potential sources of error, both conceptual and data related, affect the magnitude of inundation and thus the persistence or demise of wetlands under rising sea levels. Mangrove areas, being the lowest wetland vegetation and the first greatly affected by inundation, were found in this study to be associated with the greatest errors and uncertainty in model output. Though areal extent of mangrove vegetation was found to vary considerably in the final year of output, statistical distribution of possible mangrove areas suggested that it is likely greater areas of mangrove zones could exist by 2100 than is indicated by deterministic model output. Similarly, conclusions could be drawn for the simulated mudflat zone. In contrast, stochastic data from the uncertainty analysis suggest that the uncertainty and errors within the model do not significantly affect the mixed and saltmarsh zones. The combined interpretation of the uncertainty analysis indicates that the deterministic SLAM model output should always be accompanied by an uncertainty analysis, with results being analysed in full appreciation of the possible error and uncertainty inherent within the data. Many have suggested and promoted the need for uncertainty analysis or stochastic investigation into the error associated with model output (Monte *et al.* 1996; Hunter & Goodchild 1997; Saltelli *et al.* 2000; Clough *et al.* 2012; Renard *et al.* 2013; Zhang *et al.* 2013). This study simply adds to the combined voices of these many before that question the trust placed in deterministic models, especially considering the constant presence of uncertainty in defining and describing the dynamic wetland system. It is important to note, however, that such a conclusion does not negate the plausibility of the deterministic SLAM model output. It simply implies that the model results are but one possibility of wetland distributions under rising sea levels and the flaws, limitations and uncertainties should be considered and treated with due care when interpreting simulated outputs from the SLAM model.

5.3 The SAAT model

5.3.1 Model outcomes

As much as is possible to understand given the characteristically unpredictable nature of the future, the vegetation distributions modelled using the SAAT model were plausible and in keeping with expected outcomes. Under low levels of sea-level rise, little vegetation loss was simulated for the Minnamurra wetlands. Indeed, mangrove zones were projected to translate both landward and seaward over the century, leading to a significant increase in their modelled extent. A similar trend of landward migration was noted in all sea-level scenarios, with mangrove vegetation replacing saltmarsh over time. This trend of mangrove encroachment into saltmarsh zones follows that observed for the past few decades along the SE Australian coast (Saintilan & Williams 1999, 2000).

The overall patterns of vegetation loss associated with each modelled SLR scenario also follow the observations and modelling outcomes of previous studies (Reed 1995; Rybczyk & Cahoon 2002; Temmerman *et al.* 2004; Marani *et al.* 2007; Kirwan *et al.* 2008). Kirwan *et al.* (2010), using simulations from five different models applied to various sites around the world, found that by increasing accretion rates wetlands were able to persist under conservative sea level acceleration scenarios. At increased rates of SLR, however, submersion and widespread demise of wetlands was simulated, with vegetation unable to maintain elevation with respect to the accelerating sea levels. The same trends were observed in this study, where simulated vegetation loss increased with increasing rates of SLR. This is particularly noticeable under the extreme SLR scenario where high inundation rates resulted in a substantial portion of the coastal floodplains being permanently inundated and a concomitant loss or, in some cases, migration of wetland vegetation being simulated for the Minnamurra area. The output of the SAAT model reported here could be said to affirm the conclusions of many studies that suggest a critical threshold in the rate of SLR exists past which accretion rates will not be able to compensate for the effects of SLR on the survival of wetland vegetation (DeLaune *et al.* 1994; Fagherazzi *et al.* 2006; Kirwan *et al.* 2010).

In further consideration of simulated wetland distributions, model output of the intermediate SLR scenario, A1FI, showed a shallow waterbody developing behind a mangrove stand on the western floodplain. It had been assumed that, with rising sea levels, wetland inundation would increase, forcing vegetation to migrate landward, each zone replacing the others as it translated upland. By 2100, therefore, the sequence of zones from seaward to landward would approximately mirror that of the present day zonation. Vegetation distributions under the A1FI SLR scenario modelled in this study, however, displayed a deviation from such expectations. It has been proposed that the long-term evolution of a wetland may be controlled by the geomorphological features of a wetland (Thom *et al.* 1975; Thom 1984; Cowell & Thom 1994; Woodroffe 1995). Simulation of a lake within the mangrove zone on the western floodplain, therefore, is potentially a reflection of the underlying geology and geomorphology of the area. Alternatively, the mangrove stand may be indicative of a flaw within the conceptualisation, calibration or mechanical realisation of the SAAT model. Further simulations at the Minnamurra and other sites would need to be conducted to clearly ascertain the true source of the interesting deviation from expected vegetation distributions in model output.

5.3.2 Model uncertainty and limitations

Many limitations exist in the implementation of the SAAT model, some of which pertain to the underlying assumptions of the model design and others attributable to the information used to calibrate and apply the model. Errors and uncertainty within this model may thus be significant.

Similar to most numerical models simulating the effect of SLR on coastal wetlands, the SAAT model in this study was based on the assumption of uniformity. Though such assumptions have been observed to be relatively robust (Woodroffe & Murray-Wallace 2012) and has allowed for great progress in the field, with changing environmental conditions over the next century the assumption does not necessarily hold true. This is particularly problematic when the measurements used to calibrate and apply the model are only based on a short-term, sub-sample of real events, as has occurred in this study. In such a case, the timescale of the data collection is not sufficient to allow a full understanding of past wetland behaviour under rising sea levels which in turn reduces the reliability of any extrapolation of past events in determining future responses. The issue of timescales of influencing factors not being captured by SET data has been discussed previously in relation to the error and uncertainty attributable to the SLAM model output. This same problem arises in the use of the SAAT model.

Model calibration using only six points within the study area is also flagged as a potential problem of the SAAT model as implemented in this study. Though accurate, the SET timeseries data all pertained to the western floodplain. The assumption that the sparse data could explain the spatial and temporal variation of SEC may, therefore, be unfounded and the model output a potentially inaccurate representation of the dynamic system and its response to sea level. A greater number of SET sites situated throughout the site would be ideal to improve the understanding of the patterns of elevation change, their strength and variability over time.

The SAAT model is not a hydrodynamic model and as such does not mechanistically take into account the influence of complex flows of water and suspended matter over the wetland surface. Many models simulating the response of wetlands under changing conditions, including the SLAM model, are not hydrodynamic in nature. However, the potential problem of surface flow not being included in the numerical model cannot be disregarded. The impact of the flows not being incorporated may be said to be expressed in the modelling of river zones and immediately surrounding areas, potentially evidenced by the persisting mangrove zone of the A1FI scenario modelled.

In this study, the river boundary was assumed stable over time, resulting in little loss of wetland at the shoreline. However, it is possible that the shoreline will change over time with adjustments of wetland distribution to environmental influences. Inclusion of a changing shoreline, such as in the Oliver model, may simulate wetlands that better represent future conditions.

Turning to error and limitations introduced by the input data, the basal elevation information data (the DEM) plays a considerable role in producing reliable output and could be said to be a sensitive parameter of the model. Experimentation with inaccurate elevation data when applying the SAAT model showed that inaccurate basal elevation information significantly amplifies the error in model output. Perceptible errors in model output directly related to vertical errors within the DEM. The significant positive errors in vertical elevation information precluded the cell from being inundated and falling within a lower wetland vegetation range. Thus, where errors occurred, vegetation conversion and associated migration or inundation was underestimated. It is noted that under extreme conditions the differences in model output when accurate or inaccurate DEMs were used is not significant. Under extreme sea-level rise, the rate of inundation was such that even the erroneously higher elevations were inundated, causing less impact on modelling when extreme rates of sea-level rise were simulated.

Perhaps the greatest limitation of applying the SAAT model in this study was the lack of stochastic analysis of model error and uncertainty. All stages of the data collection, statistical analysis, model calibration and model implementation for scenarios of increasing SLR inevitably contained error. Failure to incorporate an uncertainty analysis therefore reduces the understanding of the workings of the model and the wetland distributions simulated for the end of the century.

5.4 Comparison of numerical models

The numerical models compared within this study, the SAAT, Oliver and SLAM models, are all deterministic models that attempt to simulate the response of wetlands to rising sea levels by accounting for the major physical processes considered to be most influential in its evolution. As the models were conceptualised by different people and for different environments, namely the Australian (Oliver), Northern European (SAAT) and American (SLAM) wetlands, the factors considered crucial to the wetland system vary somewhat. The effects of these differences in system abstraction within respective models are examined here, further comparing the ability of each to adequately describe an Australian wetland system and its evolution over time.

Analysis of model output suggests that differences occur according to the numerical model applied. Simulations of some vegetation types were more significantly different than others when different modelling approaches were implemented. This may be attributable to the varying expression of accretion within each model affecting the pattern of SEC simulated, in turn impacting the height of vegetation and conversion over time within the study area. The Oliver model implements a linear model to describe the spatial pattern of SEC in the wetland, whereas the SAAT model defines an exponential relationship between inundation and SEC and the SLAM model applies constant rates by vegetation or simulates the spatial variation of accretion within a site.

Application of rates of SEC to an entire vegetation zone within the SLAM model produced relatively similar output to the Oliver model by the year 2100. In contrast, applying accretion rates by vegetation and as spatially varying values defined by the accretion module in the SLAM model generated output that varied significantly from the Oliver and SAAT model. Though the predicted outcome using accretion rates cannot be disregarded, the deviation from the other model may affirm conclusions drawn earlier regarding the importance of including compaction processes when modelling the response of wetland systems to rising sea levels. In consideration of both these findings and the numerous studies indicating the importance of compaction processes, it is strongly suggested that rates of SEC be utilised when implementing the SLAM model.

The initial definition and modelling of vegetation change within each model also appeared to cause differences to be observed in the model output. Significant differences calculated for the initial year of modelling, 2011, were the result of initial vegetation distributions being simulated in different styles. The Oliver and SAAT models define vegetation by discrete elevation ranges from the initial year, whereas the SLAM model utilises a vegetation map to ascertain the initial distribution of vegetation. For time zero, vegetation distributions of the SLAM model could therefore be considered the most accurate. By extrapolation, this would indicate the final output from the SLAM model also obtains the highest accuracy, however such an assumption can certainly not be made. Error and uncertainty propagated throughout the complex modelling process may in fact generate data that does less accurately represent the wetland by the year 2100. This could equally be considered for the Oliver and SAAT models, especially as the accuracy of any future prediction cannot logically be obtained.

The conversion of wetlands in the Oliver, SAAT and SLAM models are all based on the concept that specific vegetation types thrive within certain elevation ranges. Considering the work by Clarke and Myerscough (1993), Clarke (1995), Adam (2002) and comments by Saintilan and Rogers (2009), an assumption of a vegetation-elevation relationship for modelling purposes is somewhat justified in the Australian context, though other factors, such as physiochemical characteristics, may be more relevant to the wetland distribution in some wetlans.

The style of conversion within the models examined in this study may, however, not be adequate for coastal wetlands of SE Australia. The SAAT and Oliver models allow conversion to occur in the same simplistic manner. Any cell within the entire study site that falls within a certain range is classified as the associated wetland type. In this way, output of the two models displayed vegetation zones expanding landward and, in some cases, seaward. This is consistent with observations of vegetation change within SE Australian coastal wetlands (Chafer 1998; Saintilan & Williams 1999). In contrast, the SLAM model does not allow the conversion of any water to wetland vegetation as a result of the decision-tree based conversion set within the SLAM code, as discussed above. Furthermore, conversion of vegetation types occurs in a set succession, resulting in saltmarsh zones being unable to expand upland. As discussed previously, the combined effect of this one-way succession and set conversion of vegetation based on a defined decision-tree potentially causes problems in the modelling of vegetation distributions, especially for those sites where a seaward translation of mangrove areas is observed with rising sea levels. Within the comparison process, the differences in model output are particularly obvious over the first half of the century.

Simulation of wetland flooding and conversion to open water over the period 2011-2100 differed between models under all SLR scenarios examined. This is partially a function of the differences in vegetation conversions as described above. Within the SLAM model, the lowest vegetation (mangrove) must pass through a mudflat class before being converted to river. In contrast, the Oliver model does not simulate mudflats, with mangroves being simulated as river following irreversible inundation. In comparing model output it was noted that the SLAM model simulated mudflat that corresponded almost exactly with the spatial proliferation of inundated land in the Oliver model. Though this could be considered evidence of a significant difference, due to the style of vegetation conversion realised in the two models such a conclusion cannot be legitimately drawn as within the inundated land of the Oliver output, mudflats may be present. Inundated areas of the SAAT model were different again from the Oliver and SLAM models. Reasons for the development of a small lake in the western floodplain under study have been discussed previously.

Comparison of model output revealed that, under the intermediate SLR scenario, mangrove consistently reached a maximum total area by 2060 to 2080 before decreasing until the year 2100. As the rate of SLR increases exponentially after the middle of the century (Church *et al.* 2013), the modelled maximum likely corresponds to the critical threshold of SLR at which mangrove begin to decline.

Interestingly, other than slight variations in mangrove and river simulations, model output from the SAAT and Oliver models are relatively similar. Such similar results may be partially due to the respective model structures. In the abstraction of the system, both models attempt to account for the feedback mechanisms that increase the capacity of the wetland system to adjust to changes in SLR. In addition, in the calibration of the model, almost identical time-series data were implemented. Furthermore, the treatment of vegetation and conversion between wetland classes was performed in precisely the same manner. The main difference, it appears, between the Oliver and SAAT model is in the processes included in the mathematical realisation of the respective conceptual models. The Oliver model, incorporates factors such as rainfall, SOI values (relate to ENSO events), distance to the river, surface elevation and accretion derived from factorial analysis of empirical data. In contrast, the SAAT model is derived from and implements fewer parameters, not incorporating the site-specific variables such as rainfall or ENSO related factors. However, examination of the SOI and rainfall values implemented within the Oliver model indicated that the average rainfall and SOI from the past record was used due to their being a lack of reliable information on future projections for the SOI and rainfall along the SE Australian coast. The SOI and rainfall values were therefore, in effect, kept constant though time. Thus, upon proper consideration, it could be inferred that the variables included in the SAAT and Oliver models are relatively similar. With such an understanding, the similarities between model outputs are more likely a function of the effective similarities in the mathematical structure of the models than an indication of underdetermination. This conclusion is supported by the primary difference between the SAAT and Oliver models. That is, the SAAT model, defining accretion by an exponential relationship as a function of the distance from the channel, simulates greater SEC near the rivers before tapering at progressively greater distances from the channel. This causes areas nearby the river to accrete more quickly and thereby allows greater persistence of mangrove areas with rising sea levels whilst areas further inland are more susceptible to inundation, as can be seen by the development of a lake like structure behind a mangrove stand in the SAAT model output. In comparison, the Oliver model simulates accretion as a linear function with distance from the channel, allowing areas further inland to build vertically at a faster rate. As noted, then, the differences between the SAAT and Oliver models could also be attributed to the mathematical structure.

In comparing the three models, it becomes clear that each contains error and uncertainty that affect the final realisation of vegetation distributions under rising sea levels. Given the uncertainty of the future and general unpredictability of the dynamic coastal wetland system (Carter & Woodroffe 1995) it is difficult to ascertain which model is most valid and which most accurately describes wetlands in the Australian context. In some cases, the SLAM model is not appropriate for the Australian context, yet in others the three models may perform in an equally plausible manner. Thus, it could be that expertise is the deciding factor in which model to apply. The SLAM model is quite complex and requires a large amount of accurate data to be generated and collected to obtain a reliable output. The SAAT and Oliver models, though comparatively more simplistic, require a greater statistical skill in their application. It may be that subjectivity in the choice of a model for wetlands of a particular site along the SE coastline plays a more important role than would generally be acknowledged in scientific research. In all cases, however, the limitations of each model, as has been presented throughout this study, characteristics of the study site, availability and accuracy of site-specific data and the final purpose of the project should all be considered before a decision is made. In all cases, however, stochastic analysis of the error and uncertainty associated with deterministic model is crucial to ensure a more holistic understanding of future wetland conditions is obtained.

6 CONCLUSIONS

With projections of accelerated SLR for the twenty first century, there is increasing concern regarding the long-term sustainability of coastal wetlands. Managers are tasked with the responsibility of planning for future scenarios, responding to the potential vulnerability of the important coastal environments. Models provide opportunities to explore future scenarios under varying levels of SLR and thereby become an important instrument in a manager's toolkit. However, the validity of a model used to support decision-making is crucial for a plausible and more reliable representation of the future system to be obtained.

Elevation data is the basis of all spatial modelling techniques used to examine the impact of SLR on coastal wetlands. Results of this study emphasise the importance of generating the most accurate DEM possible for modelling purposes. This is especially true in modelling of low-lying wetlands where small errors in the surface representation result in large variations in the hydrological properties, geomorphic adjustments and simulation of wetland persistence or demise. Given the necessity of accurate elevation information, this study strongly advocates the expert processing of as-received LIDAR data and considered derivation of the elevation model in order to obtain an elevation surface that best represents the initial conditions of the system to be modelled. Furthermore, given the inherent uncertainty of spatial data, an accuracy assessment of a DEM generated is required so as to obtain an understanding of potential error and uncertainty in subsequent modelling efforts.

Modelling efforts of this study were conducted to examine the adequacy of three models in predicting the evolution of SE Australian coastal wetlands under accelerating rates of SLR. A specific focus was placed on validating the SLAM model, originally developed for North American wetlands, for the Australian context.

Basic verification of the SLAM model revealed a significant flaw in the model code, whereby the A1T and A1FI maximum SLR scenarios were switched. This disrupts the internal consistency of the model and has potential impacts on previous studies and management plans that have implemented these IPCC TAR scenarios.

The multistage validation technique employed suggested that simulations of the wetland response to SLR were plausible, however certain conceptual limitations and error and uncertainty are associated with the application of the model to the Minnamurra site and, by extrapolation, to coastal wetlands of SE Australia. Predictive validation results suggest that the SLAM model is most effective at simulating wetland responses to SLR at decadal time scales. Though model projection results were plausible, even under extreme conditions, conceptual flaws identified during the multistage validation process potentially limit the efficiency with which the SLAM model simulates the responses of Australian wetlands. These flaws include:

- *potential problems of vegetation succession.* The inability to diverge from the predefined, successional conversions of the SLAM model result in saltmarshes, as defined for the Australian context, being unable to convert or expand upland in contrast to real-world evidence. Inclusion of a mixed zone in simulations may mitigate the effect of the conceptual limitation. Furthermore, the inability to invert vegetation succession programmed within the model make it inadequate for sites in which seaward translation of mangrove areas is observed with rising sea levels.
- *inadequate treatment of wetland SEC*. The SLAM model accounts for accretion processes only, without due consideration of processes that may lead to the loss of wetland elevation, such as compaction. This potentially results in the overestimation of wetland persistence under the impact of rising sea levels. Use of rates of SEC that implicitly account for compaction processes may go some way to ameliorate this problem.
- *insufficient simulation of tidal water levels.* The variation of tidal waters within Australian estuaries in which coastal wetlands are situated is not efficiently captured by partitioning discrete tidal values to subsites delineated in the SLAM model. Incorporation of a modelled tidal plane that accounts for tidal attenuation or propagation could potentially improve the theoretical accuracy and reliability of model output.
- *potential failure to include factors influencing the Australian wetland system.* Inaccuracies noted between modelled and observed data during the predictive validation runs potentially indicate the inability of the model to capture important variables influencing the evolution of the Minnamurra site, such as rainfall, groundwater and ENSO related environmental factors.

The conceptual flaws identified within this study limit the efficiency of the SLAM model to describe not only Australian wetlands, but also coastal wetlands around the world.

Conceptual flaws and limitations of the SLAM model each have the potential to generate uncertainty within simulations and resultant model output. In addition to these, the input data contains numerous limitations and errors that may significantly affect the model output. Indeed, similar to all modelling efforts, the accuracy of the data used is paramount when applying the SLAM model for the prediction can only be as good as the data upon which it is based. It is critical, therefore, that, if the model is to be applied, the most accurate, site-specific data that captures an appropriate temporal period is collected and utilised.

Results of the sensitivity analysis of the SLAM model further highlight the importance of the recommendation for high accuracy of input data. The SLAM model was found in this study to be most sensitive to errors and variations in SLR in addition to those parameters affecting the magnitude of inundation and thus the persistence or demise of wetlands under the influence of rising sea levels. Errors, therefore, contained within these parameters amplify the uncertainty inherent in the SLAM model output. The uncertainty analysis conducted in this study captures the impact of some of this error and reveals the wide range of possible wetland distributions responding to SLR simulated by the deterministic SLAM model.

Given the plausibility of output data, the SLAM model can be said to provide an understanding of the response of wetland systems to rising sea levels. However, application of the model to an Australian wetland system must be conducted with full appreciation of the possible errors and limitations inherent in the model output. Inclusion of an uncertainty analysis is critical when implementing the SLAM model, in order to understand and communicate the possible uncertainty associated with the deterministic output.

A similar process is necessary when applying the SAAT model to the Australian wetlands. For the Minnamurra wetlands, the SAAT model simulated plausible responses of the wetland to rising sea levels. However, similar to the SLAM model, error and uncertainty are propagated through the modelling process. The stochastic analysis of error and uncertainty, therefore, would ensure that a more holistic understanding of future wetland conditions was obtained.

Determining the accuracy of predictions is logically impossible, therefore, in comparing the SAAT, Oliver and SLAM models, it is not possible to conclude that one model is definitively better than another at simulating the response of the Minnamurra coastal wetlands to SLR, nor that one model is more valid than another. However, the results of this study show that the differences and similarities between the models were primarily a result of the conceptualisation and mathematical realisation of each of the models. The decision, then, of researchers and modellers alike is to ascertain which model should be applied in simulating the response of a wetland to SLR. The author advocates that a multimodel approach would be a most appropriate solution, where trends and patterns can be explored from a variety of different methods. In addition, inferences would be more robust and a more holistic understanding of the future wetland would be gained. However, where time and resources do not permit such an approach, some guidelines on model choice and application are proposed:

- Determine the availability and accuracy of data for the chosen system, ensuring that the temporal range of the empirical information is sufficient for modelling purposes.
- Consider the site-specific factors most influential on the long-term evolution of the particular wetland system under study.
- Examine the suite of models available.
- Select the model whose conceptual basis and parameter requirements best fit the data determined as available and the informed understanding of processes influencing the dynamic system under study.
- Validate the chosen model for the specific site under examination, following techniques outlined by Sargent (1996) or Rykiel (1996).
- Apply the model according to the various scenarios needing to be explored.
- Conduct sensitivity and stochastic uncertainty analyses to provide an understanding of error and uncertainty associated with deterministic results. Considering the inherent uncertainty of the future and large uncertainty associated with natural systems, this step is particularly important to capture the myriad of possible outcomes for effective understanding and management of the coastal wetland environments.

If time and resources permit, a repetition of the process is recommended for a multimodel approach.

Overall, given the great uncertainty associated with much of the data and model outcomes, an argument could be made surrounding the futility of modelling the dynamic wetland systems and, indeed, if any worthwhile information is obtained from the modelling process. These same arguments, however, are not constrained to the modelling of the impact of SLR on coastal wetlands but could be extrapolated to encompass any modelling effort. Whilst the argument is not unfounded, managers need to plan for the uncertain future and models provide one way of assisting the process. Modelling, therefore, appears to be the best response to explore an uncertain future and examine the possible scenarios for which we need to prepare.

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APPENDIX A – Brief overview of models

The following table provides a brief overview of some models available to model wetland evolution.

Year	Model/ Modeller[s] (Author[s])	Dimension/ Scale	Sedimentation-accretion	Organic sedimentation	Erosion	Autocompaction	Vegetation	Other	SLR	Physical base	Hydro-dynamic	Cohort model	Initialised for vegetation type	Application	Zone
1987	Krone	1D	Yes -sediment supply; constant value	No	No	No	No	No	Constant trend	Yes- mechanistic	No	No	Saltmarsh	San Francisco Bay	North America
1990	Allen	1D	Yes -SSC and settling velocity	Yes- as a function of elevation	No	Implicit	No	No	Constant trend	Yes- mechanistic	No	No	Saltmarsh	Severn Estuary	Great Bri
1992	Chmura et al	0D	Yes- accretion rate-diectly coupled with SLR to determined limit	No	No	Explicitly - function of depth of cohort	No	Subsidence- constant rate	Constant trend	No	No	Yes	Saltmarsh	Barataria Basin, Louisiana	North America
1993	French	1D	Yes - sediment supply; function of elevation	Yes - constant rate	No	Treated implicitly- Constant rate of autocompaction	No	Explicit treatment of eustacy	Constant trend	Yes- mechanistic	No	Yes	Saltmarsh	North Norfolk barrier coast	Great Bri
1995	Allen 1995	0D	Yes -SSC and settling velocity	Yes- as a function of elevation	No	Treated implicitly	No	No	Fluctuating		No	No	Saltmarsh	Severn estuary	Great Britain
1996	Callaway et al 1996	0D	Yes -sediment supply; function of elevation	Yes	No	Treated explicitly- function of depth below surface	No	No	Constant trend	Yes- mechanistic	No	Yes	-	Mississipi; Great Britain	North America, Great Bri
1996	Stolper	1D	Yes- sedimentation rate; function of elevation and tidal range	Yes- rates as a function of elevation	No	No	No	No	Constant trend	No	No	No	Mangrove	Hunter River, NSW	Australia
1997	Pizzuto and Schwendt	0D	Yes -sediment supply; function of elevation	Yes - function of elevation	No	Treated explicitly- finite strain theory	Yes- perrenial aboveground biomass	No	Constant trend	Yes	No	Yes	Freshwater wetlands and saltmarsh	Delaware	North America
1998	Rybczyk et al 1998	0D	Yes -sediment supply; function of elevation	Yes- function of elevation	No	Treated explicitly- function of density of sediment above cohort	Yes- function of root biomass	No	Constant trend	Yes- mechanistic	No	Yes	Saltmarsh	Pointe au Chene , Louisiana	North Americz
2000	Reyes et al 2000	2D- landscape	Yes - SSC - function of elevation and settling velocity	Yes - volume of belowground organic	Yes- function of bottom shear stress and wave action	Treated implicitly - part of soil volume value	Yes- function biomass production (aboveground and belowground)	Subsidence- constant rate; wind stress; friction; diffusion wave; salinity, function of elevation; waterlogging	Constant trend	Yes- mechanisitic	Yes	No	Saltmarsh, brackish marshes, forested wetlands	Barataria Basin, Louisiana	North America
2002	Morris et al 2002 (MEM)	1D	Yes- SSC; constant can be varied mechanically	Yes- Empirical	No	Treated implicitly	Yes- function of biomass density and inundation	No	Constant (vary manually)	No	No	No	Saltmarsh	North Inlet estuary, S Carolina	North America
2002	Rybczyk and	0D	Yes - sediment supply -	Yes -	No	Treated explicitly-	Yes- function	No	Constant	Yes-	No	Yes	Saltmarsh	Bayou	North

	Cahoon		function of elevation	function of elevation		function of density of sediment above cohort	of root biomass		trend	mechanistic				Chitigue; Old Oyster Bayou, Louisiana	America
2003a	Temmerman et al	1D	Yes- sedimentation rate; function of SSC, settling velocity and elevation	No	No	Treated implicitly - constant rate	No	No	Constant trend	Yes	No	No	Saltmarsh	Scheldt Estuary, Belgium	Northern Europe
2003b	Temmerman et al	2D	Yes- sedimentation rates, function of elevation, distance to tidal channel	No	No	No	No	No		No			Saltmarsh	Scheldt Estuary, Belgium	Northern Europe
2004	Mudd et al 2004	1D	Yes- function of SSC, settling velocity, sedimentation rate; related to biomass density, plant stem diameter and flow dynamics	Yes- function of biomass	No	Treated implicitly - constant rate	Yes-function of depth below spring high tide	No	Constant trend	Yes	Yes	No	Saltmarsh	North Inlet estuary, South Carolina	North America
2005	Temmerman et al 2005	3D	Yes- sedimentation rates; function of elevation and friction force	No	No	No	Yes-	Friction force, function of flow velocity and vegetation stem diameter, height and density	Constant trend	Yes	Yes	No	Saltmarsh	Scheldt Estuary, Belgium	Northern Europe
2007	D'Alapos et al 2007	2D	Yes- SSC, trapping rates	Yes- constant net production	Yes- function of bottom shear stress	No	Yes-function of elevation	Depth averaged flow velocities	Constant trend	Yes	Yes	No	Saltmarsh	San Felice, Venice	Mediterranean
2007	Kirwan and Murray 2007	2D	Yes- function of SSC and biomass	No	Yes- function of bottom shear stress	No	Yes- function of biomass productivity	No	Constant trend; fluctuating	Yes	Yes	No	Saltmarsh	Hypothetical	-
2008	Kirwan et al 2008	2D	Yes- function of SSC, distance to channel and biomass	No	Yes- function of bottom shear stress	No	Yes- function of biomass productivity	No	Constant trend; fluctuating	Yes	Yes	No	Saltmarsh	Wesham Island, British Columbia	North America
2008	Kirwan and Murray 2008	3D	Yes- SSC; function of elevation	Yes-function of elevation and biomass	Yes - function of wave height, water depth and bed shear stress	No	Yes-function of depth below spring high tide	No	IPCC projections	Yes	No	No	Saltmarsh	Fraser River Delta, British Columbia	North America
2010	Mariotti and Fagherazzi 2010	1D	Yes- sediment supply; function of elevation and biomass	Yes - function of biomass	Yes - function of bottom shear stress, biomass, and waves	No	Yes- function of elevation	No	Constant	Yes	Yes	No	Saltmarsh, Tidal flat	Hypothetical	-
2011	Oliver et al	2D	Yes - accretion rates; function of elevation, rainfall, sea level, SOI value and distance to channel	No	No	No	No	SOI, Rainfall	Fluctuating	No	No	No	Mangrove and saltmarsh	Minnamurra River	Australia
2012	Clough et al (The SLAM model v.6.2)	2D	Yes-accretion rates	No	Yes- constant rate (conditional	No	No	Salinity, Overwash	Fluctuating ; IPCC projections	No	No	No	NWI wetland types	Numerous	North America

					9km fetch)										
2012	Rogers et al 2012	2D	Yes - accretion rates; function of elevation, rainfall, sea level and distance to channel	No	No	No	No	Rainfall	Fluctuating	No	No	No	Mangrove and saltmarsh	Hunter River, Australia	Australia

APPENDIX B - Uncertainty analyses and probability distribution functions

The uncertainty analysis drew from the results of the uncertainty analysis to delineate those parameters that caused the greatest variations in model output. Errors in such parameters have the ability to greatly affect the final outcome of modelling projections, with errors propagating through the simulations. Model parameters naturally contain a degree of error and uncertainty. For each chosen input parameter an uncertainty distribution was defined based on the measured and literature-based information available, as described below.

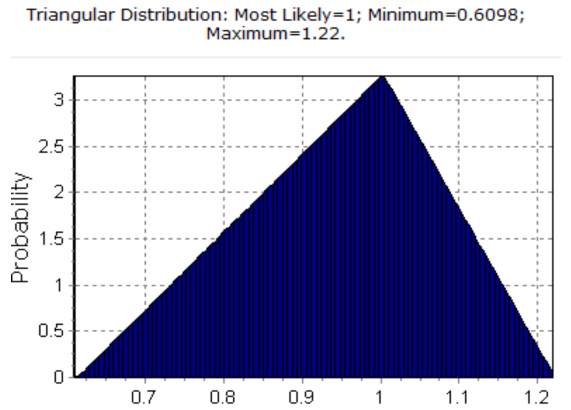
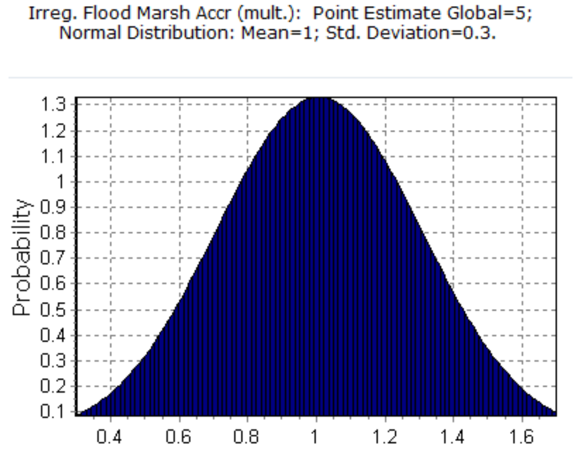
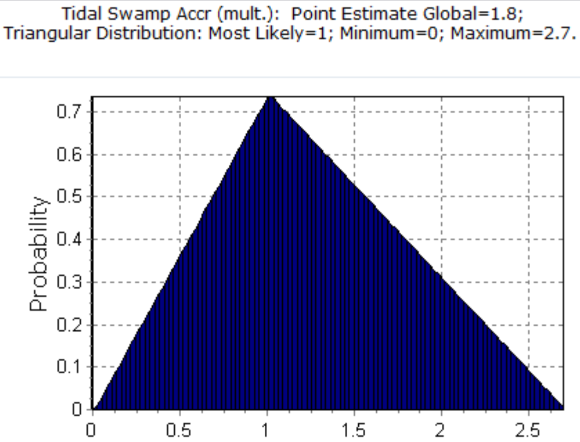
Uncertainty analyses were undertaken for simulations that utilised rates of SEC and those that used accretion rates to define the accretion parameter. Model parameters, such as the DEM error, tidal range, salt elevation and NAVD88-MTL, are common to both modelling methods. The uncertainty distribution derived for these parameters were used in the uncertainty analysis of projections utilising rates of SEC as those utilising accretion rates. Distributions of the accretion parameter, however, were altered according to the method used to define the parameter as outlined in Table A1 and A2.

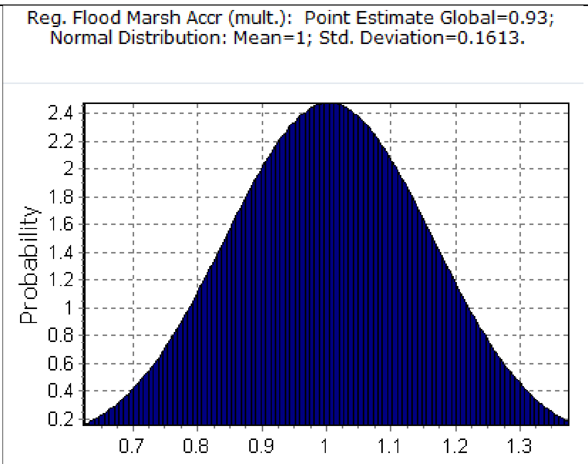
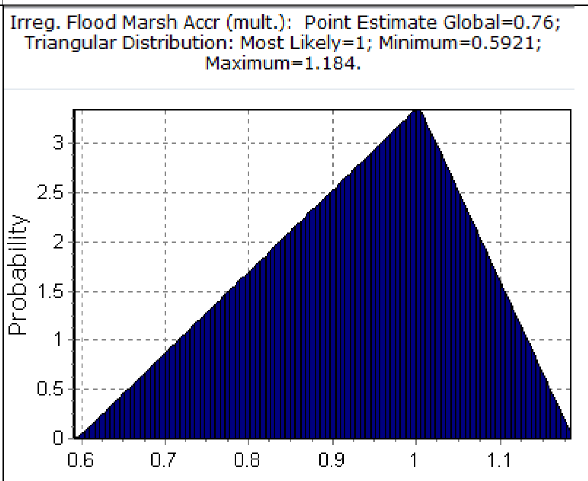
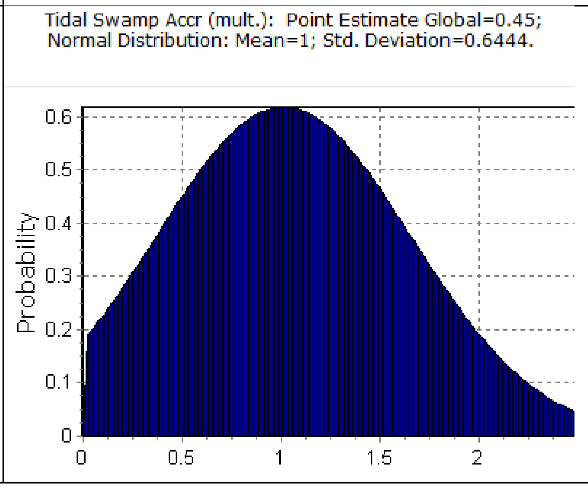
Choices of uncertainty distribution were confined to normal, uniform or triangular distributions within the SLAM model.

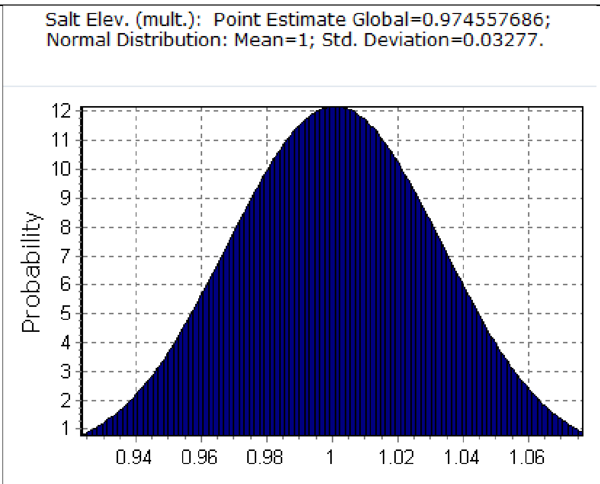
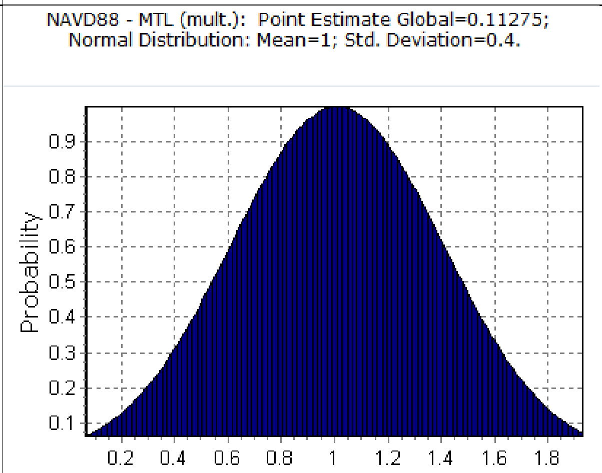
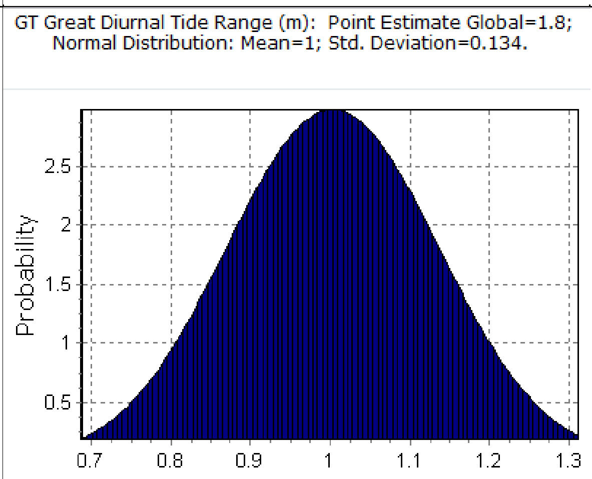
Parameter	Distribution	Global value	Minimum	Mean	Maximum	Standard deviation
Mangrove accretion rates	Triangular	8.2 mm/yr	0.609756	1	1.21951	
Mixed accretion rates	Normal	5 mm/yr		1		0.3
Saltmarsh accretion rates	Triangular	1.8 mm/yr	0	1	2.7	
Mangrove rates of SEC	Normal	0.93 mm/yr		1		0.1613
Mixed rates of SEC	Triangular	0.76 mm/yr	1.184	1	0.5921	
Saltmarsh rates of SEC	Normal	0.45mm/yr		1		0.644
Salt elevation boundary	Normal	0.97156 m		1		0.032765
NAVD88-MTL	Normal	0.11275 m		1		0.20112
Great Diurnal Tidal Range	Normal	1.8 m		1		0.13403
SLR by 2100	Triangular	0.819 m	0.4884	1.089	1.9158	

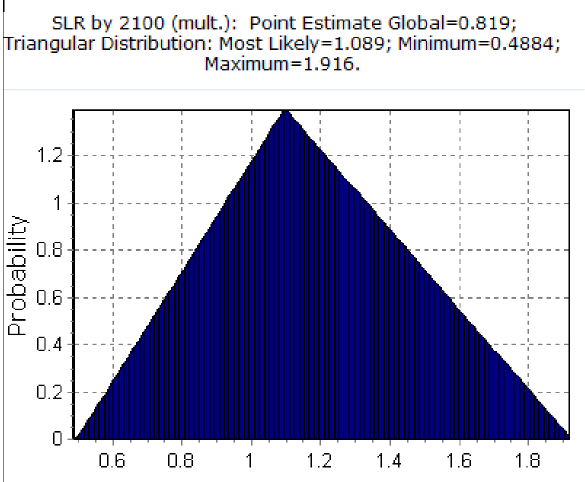
Table B1: Overview of uncertainty distributions defined for each parameter. The global value represents the value used in deterministic projections to define the given parameter. The mean, minimum, maximum and standard deviations used to describe the uncertainty distribution of the parameter are calculated with respect to the global value as required by the SLAM model. Derivation of the values is further described in Table B2 below.

Table B2: Uncertainty distributions of each parameter with explanations regarding its derivation.

Parameter	Uncertainty distribution	Explanation and description of values defining the uncertainty distribution
Mangrove accretion rates		A triangular distribution was chosen for the mangrove accretion parameter to allow the available data to be described. The accretion rate as defined by Oliver (2011) was set as the most likely outcome. An upper value of accretion selected as a plausible maximum accretion rate based on the literature. The lower value of the pdf corresponds to the accretion rate of the mixed zone where mangrove vegetation is still present.
Mixed accretion rates		The mixed zone was assumed to have a large range of possible accretion rates given its typical position on the tidal floodplains and variable vegetation coverage. The mean accretion value is derived from accretion value reported by Oliver (2011). A large standard deviation was calculated in order to incorporate sedimentation rates of both saltmarsh and mangrove zones.
Saltmarsh accretion rates		A triangular distribution was chosen for the saltmarsh accretion rates, where the most likely value was set as that from the Oliver (2011) thesis. The minimum value was assigned a value of zero in the assumption that little accretion would occur at the back of saltmarsh zones, where the saltmarsh transitioned into *Casuarina*. The maximum value for the distribution was set to the most likely accretion within the mixed zone.

Mangrove rates of SEC		A normal distribution was chosen for the uncertainty associated with the mangrove accretion rates as the measured rates were coupled with standard error calculations. Therefore, the mean rate of SEC was defined as that calculated from the SET data and the standard deviation followed the standard error calculated for the same data.
Mixed rates of SEC		A triangular distribution was chosen, where the mean value remained that assigned in the model. Considering the mixed vegetation of this zone the maximum value was set to the average mangrove accretion and the minimum set to the average rate of SEC for the saltmarsh zone.
Saltmarsh rates of SEC		Similar to the mangrove uncertainty distribution, a normal distribution was chosen which was defined by a mean value equal to the rate of SEC calculated from the SET data. The associated error of the measurement was used to define the standard deviation of the uncertainty distribution.

Salt elevation boundary		The salt elevation was partially defined by the MHL (2012) MHW data. Therefore, the standard deviation of the yearly averaged MHW value was used to describe the uncertainty distribution.
NAVD88-MTL		The NAVD88-MTL is defined by the MTL of the study site. As likelihoods of tidal levels were not reliably known, a normal distribution was assumed, whose standard deviation was defined by the standard deviation of the yearly-averaged tidal data reported by MHL (2012).
Tidal range		The tidal range in this study was defined using a variety of sources, each with their own error. A normal distribution was chosen for the uncertainty distribution of the tidal range due to data limitations. The standard deviation of the tidal range as reported by MHL (2012) was scaled up to include the errors developing from assigning subsite tidal levels. the final value was used as the standard deviation of the uncertainty distribution.

<table>
<tr>
<td>SLR</td>
<td>
</td>
<td>Future SLR is inherently uncertain. Given the information available, a triangular distribution was chosen to define the uncertainty. The most likely value was set as 0.9m, drawing from the Climate Impact Profile for NSW (DECCW 2010) developed by the OEH The minimum value for the PDF was drawn from the lowest SLR projection of the same report. The maximum value was sourced from modelling by Hunter (2011), which simulated SLR for a number of points around the world. Simulations for Sydney defined the maximum value of the pdf.</td>
</tr>
</table>

Accounting for uncertainty associated with the input elevation information

The input elevation information also contained a degree of error. However, the uncertainty associated with DEM2 was not defined by a probability distribution function. Instead, the SLAM model follows Heuvelink's method of assessing the effects of elevation data uncertainty (Heuvelink 1998) whereby a host of equally likely elevation maps are developed on the basis of a given error statistic and autocorrelation strength defined by a p-value. For this study, the elevation uncertainty was defined by the overall $RMSE_z$ calculated for DEM2 and a p-value of 0.2495, suggesting a strong autocorrelation of errors. An error field is created that is applied to the DEM in successive simulations. Applying the process iteratively, an understanding of the range of uncertainty generated by elevation error can be gained.

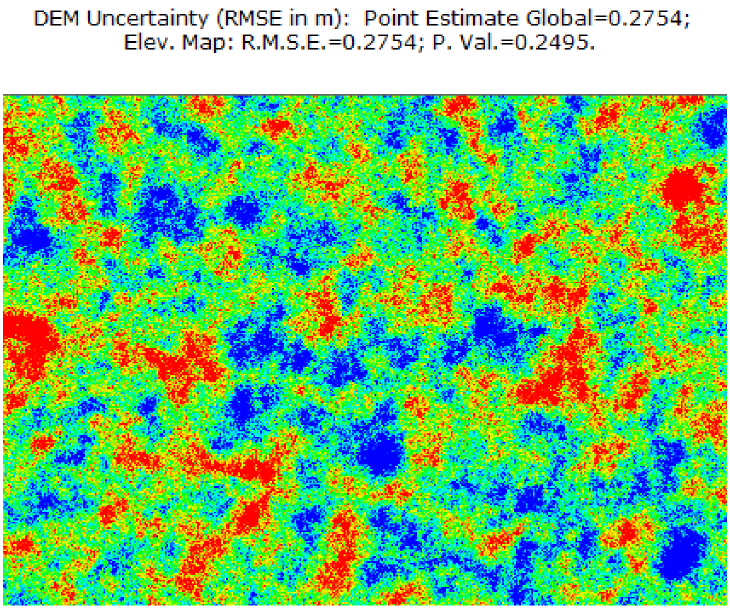


Figure B1: An error field generated in the SLAM model using the $RMSE_z$ and p-value representing the strength of autocorrelation of errors.

APPENDIX C – All SLAM model output for projections 2011-2100

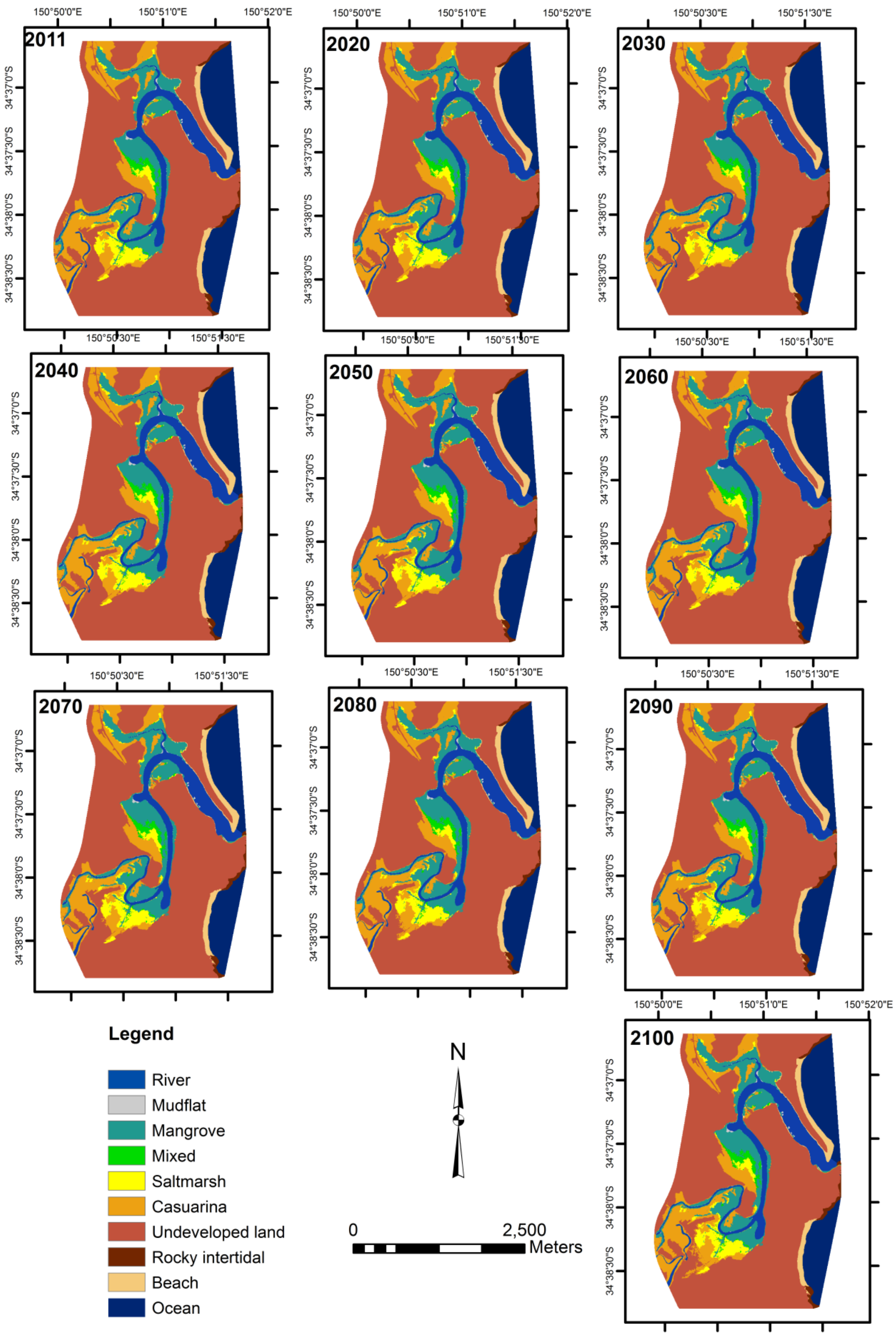


Figure C1: SLAM model output under a low rate of SLR, utilising accretion rates and DEM2 as the base input elevation information

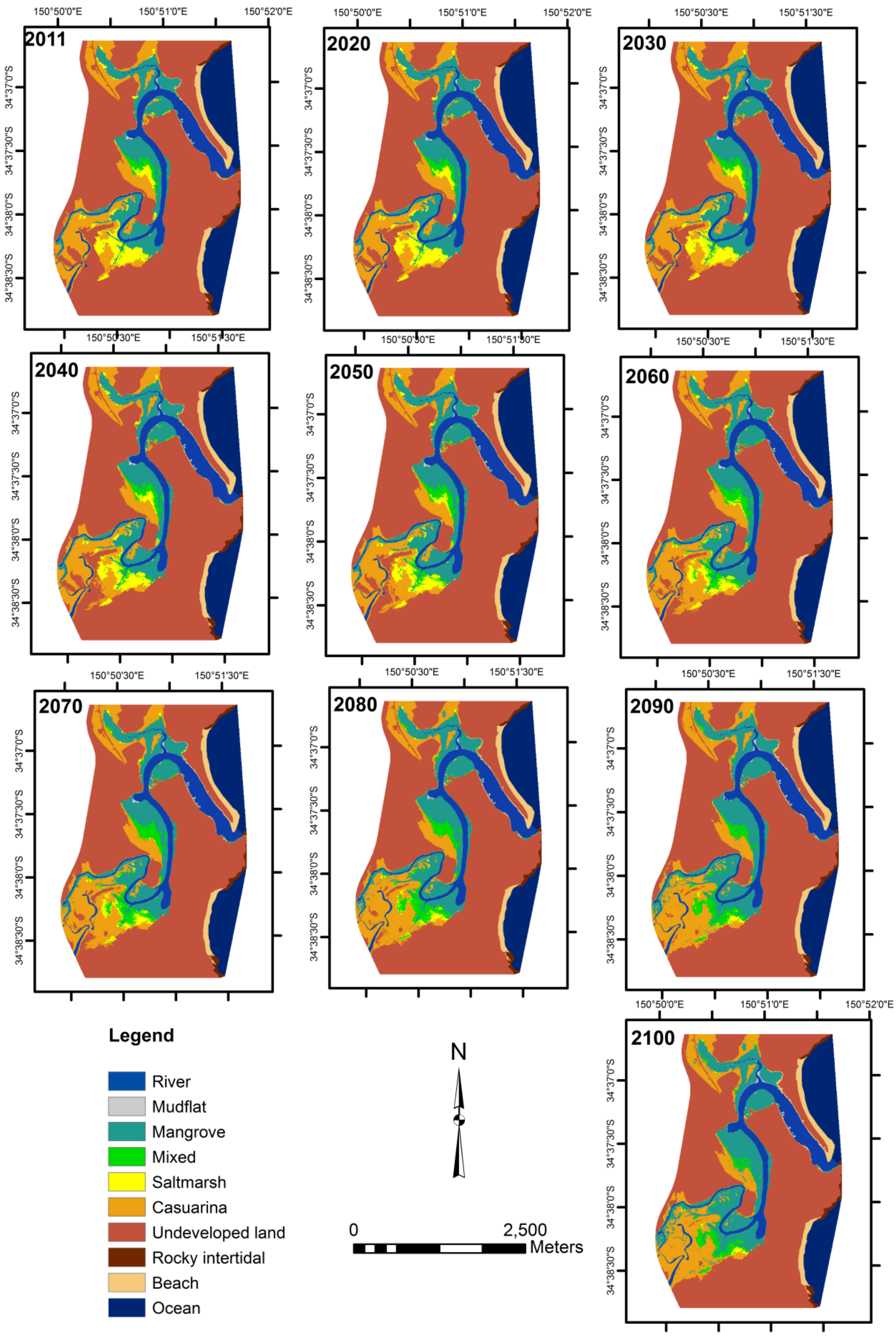


Figure C1: SLAM model output under an intermediate rate of SLR, utilising accretion rates and DEM2 as the base input elevation information

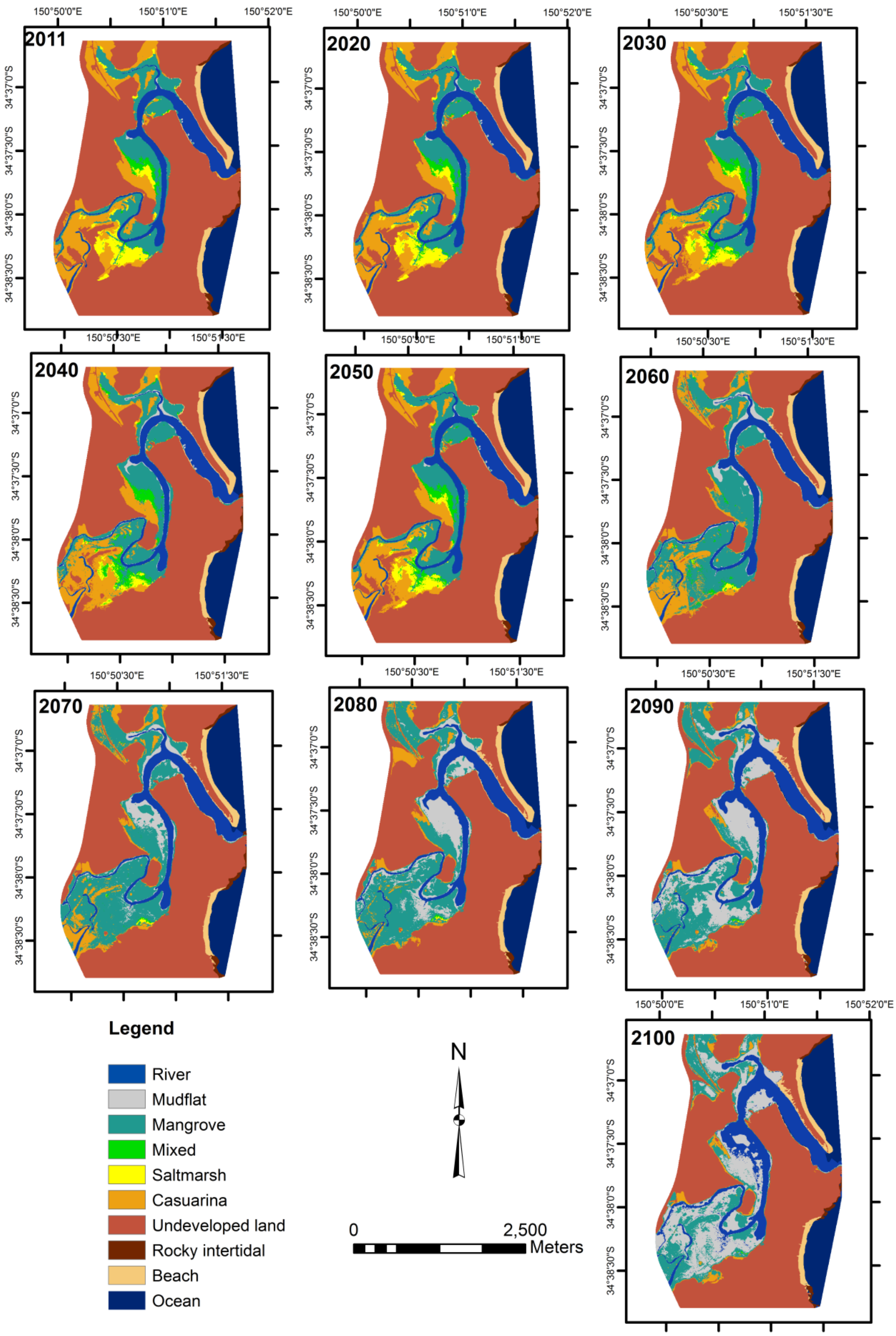


Figure C2: SLAM model output under an extreme rate of SLR, utilising accretion rates and DEM2 as the base input elevation information.

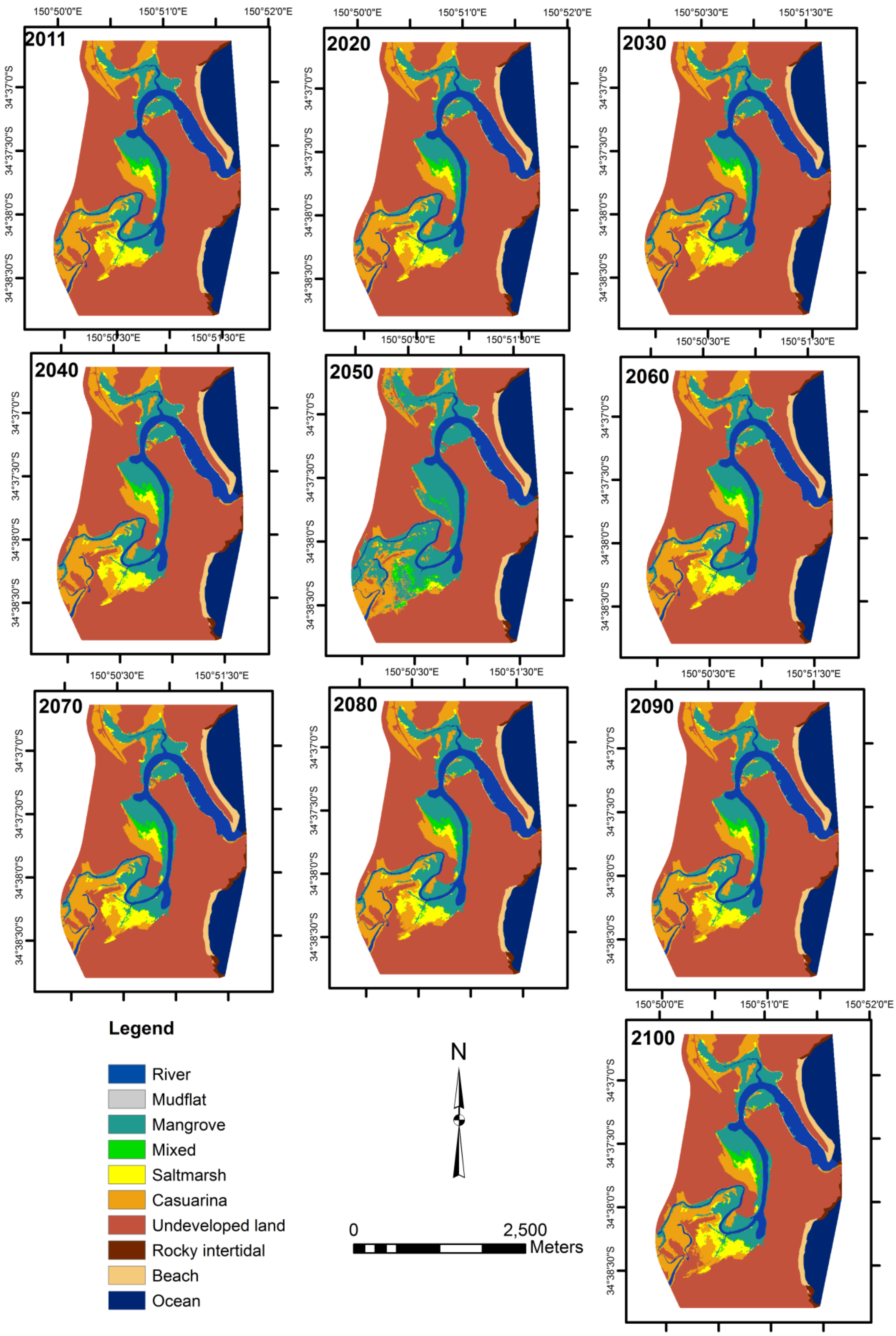


Figure C3: SLAM model output under a low rate of SLR, utilising accretion rates and DEM1 as the base input elevation information.

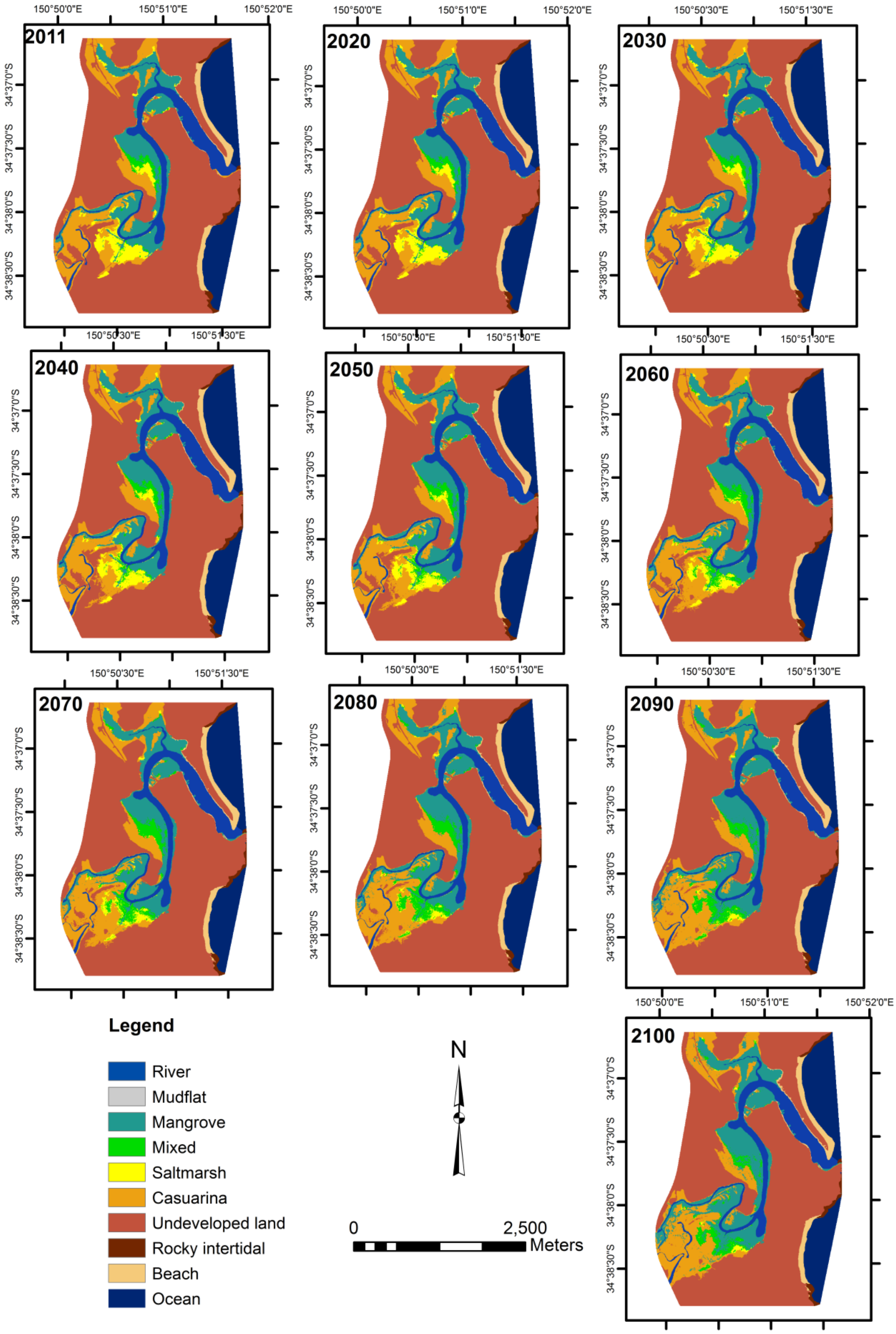


Figure C4: SLAM model output under an intermediate rate of SLR, utilising accretion rates and DEM1 as the base input elevation information

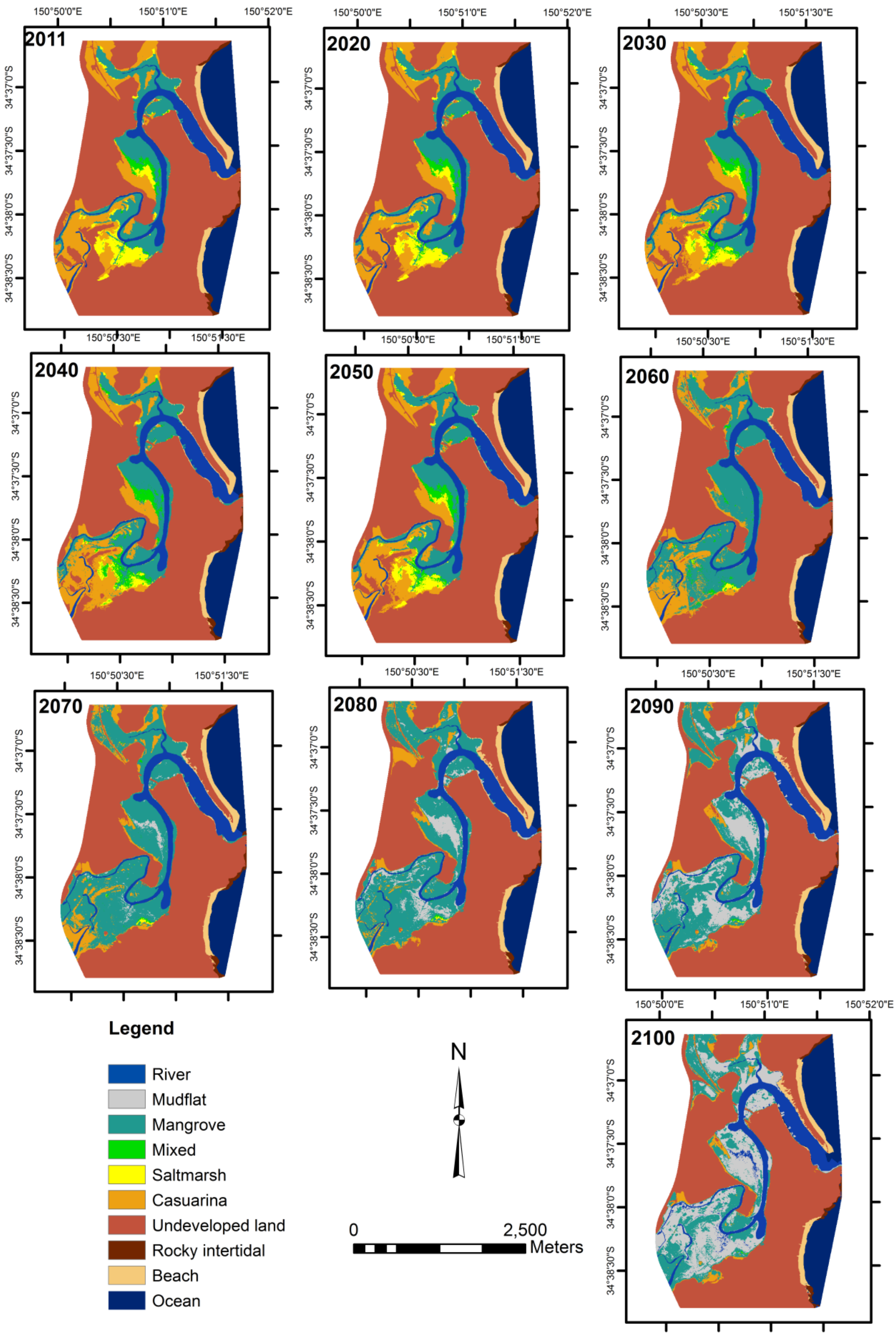


Figure C5: SLAM model output under an extreme rate of SLR, utilising accretion rates and DEM1 as the base input elevation information

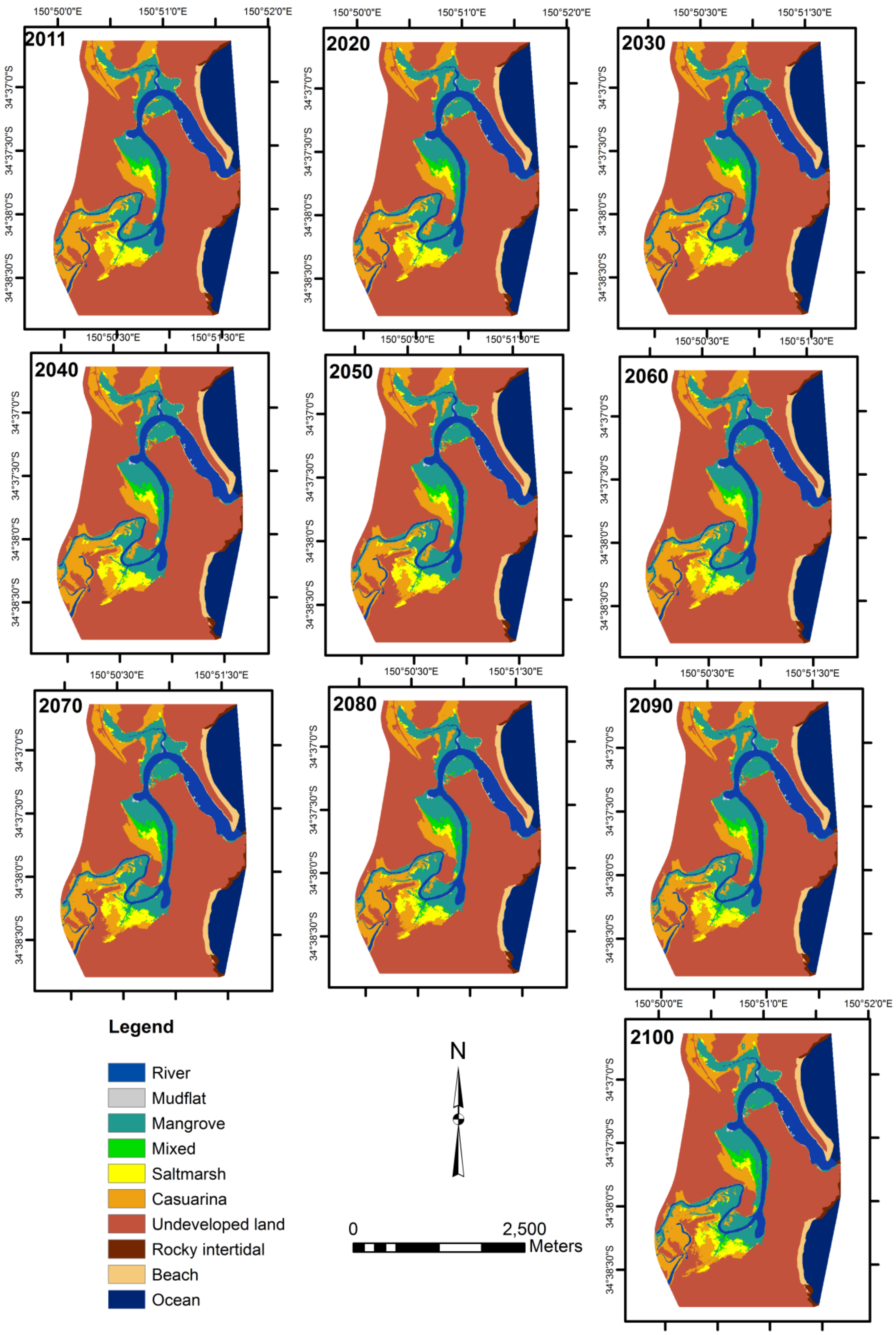


Figure C6: SLAM model output under a low rate of SLR, utilising the accretion module and DEM2 as the base input elevation information.

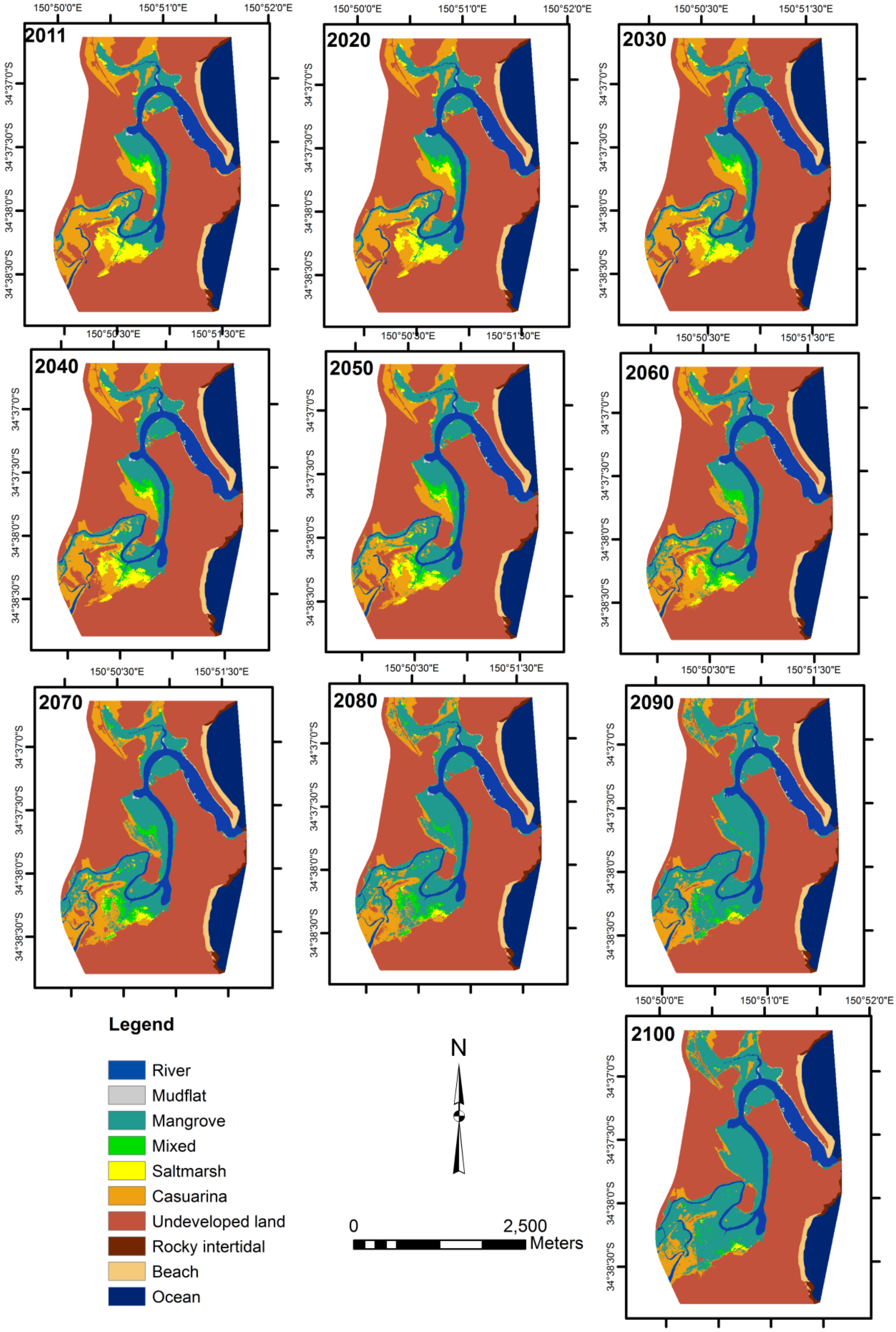


Figure C7: SLAM model output under an intermediate rate of SLR, utilising the accretion module and DEM2 as the base input elevation information.

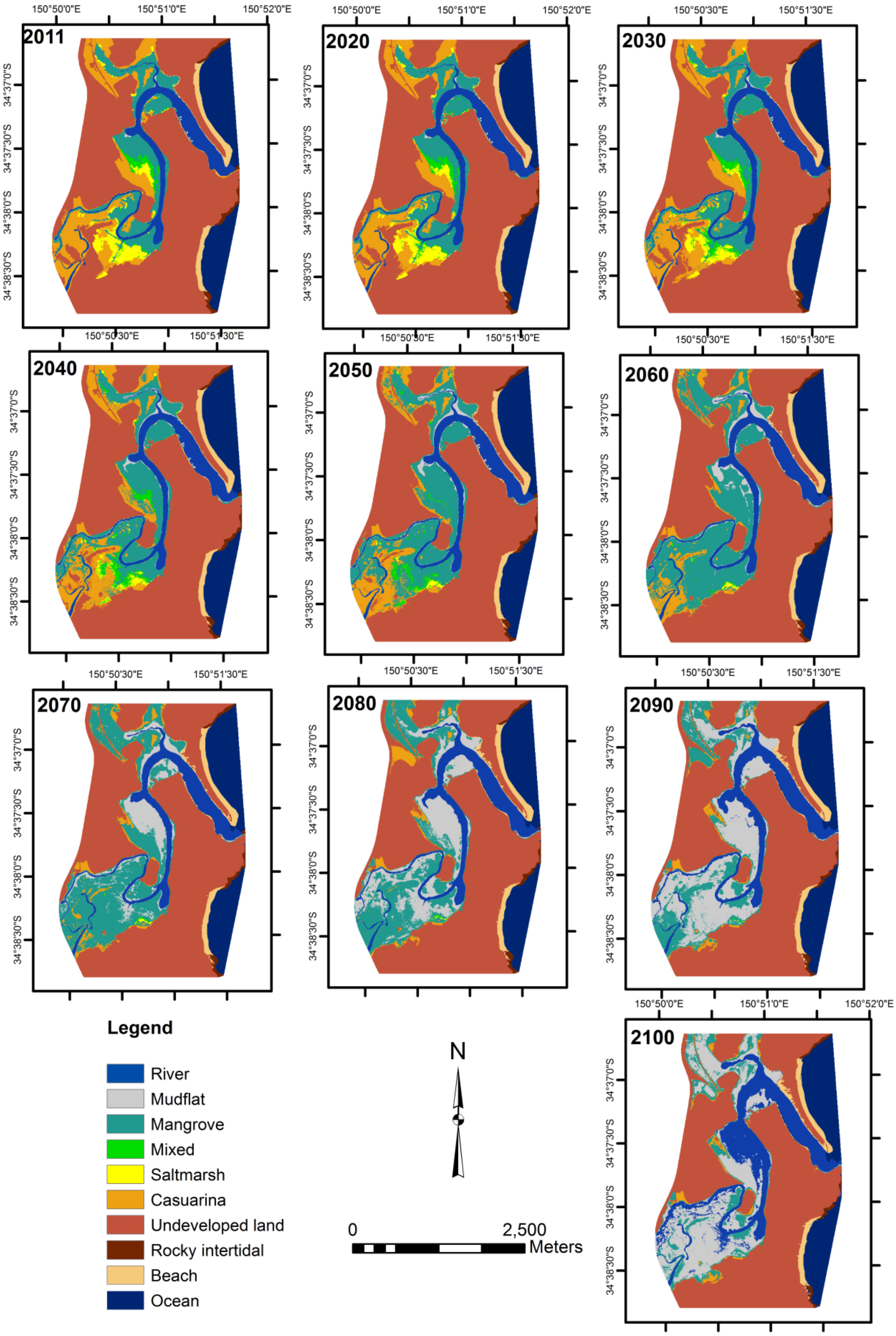


Figure C8: SLAM model output under an extreme rate of SLR, utilising the accretion module and DEM2 as the base input elevation information.

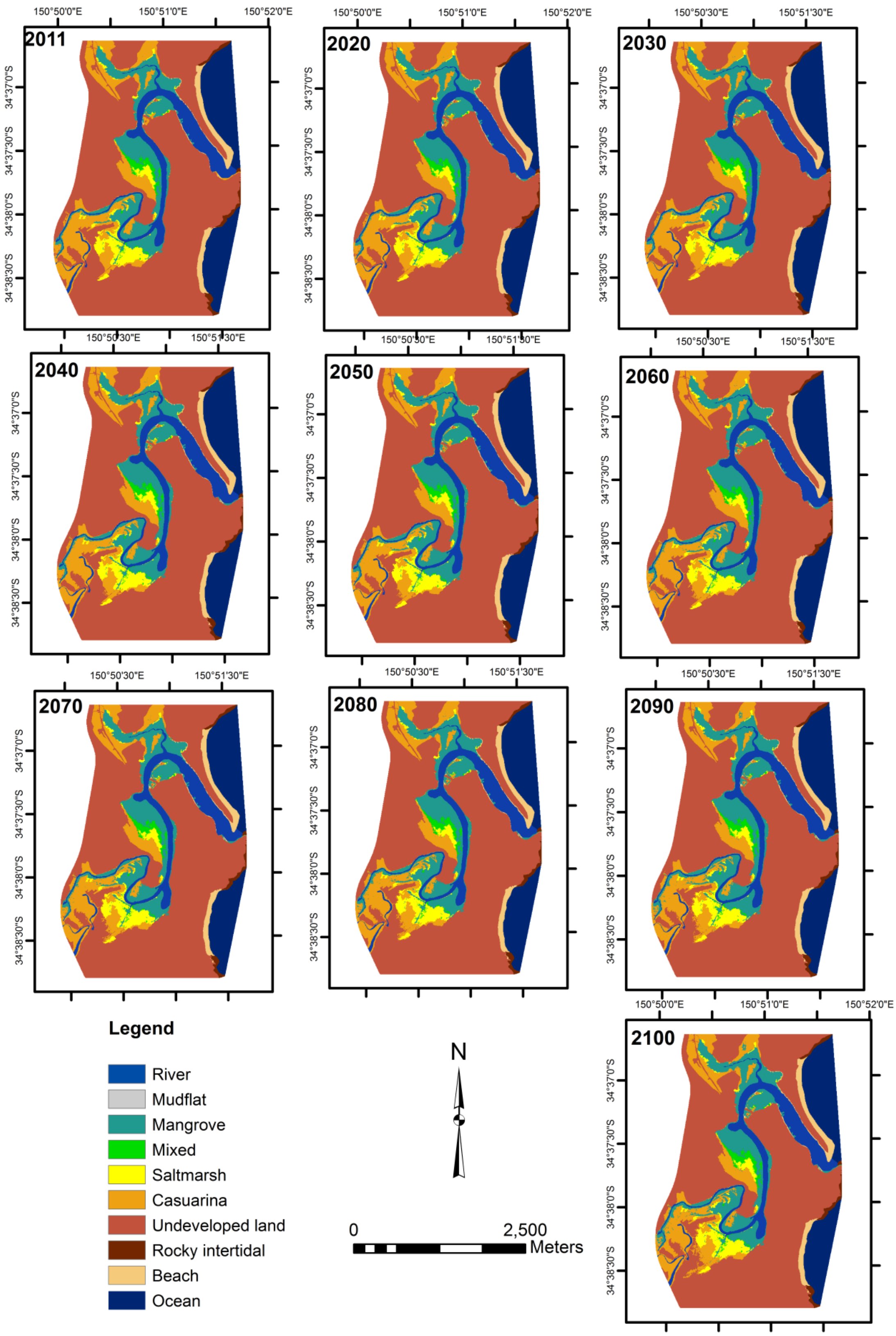


Figure C9: SLAM model output under a low rate of SLR, utilising the accretion module and DEM1 as the base input elevation information.

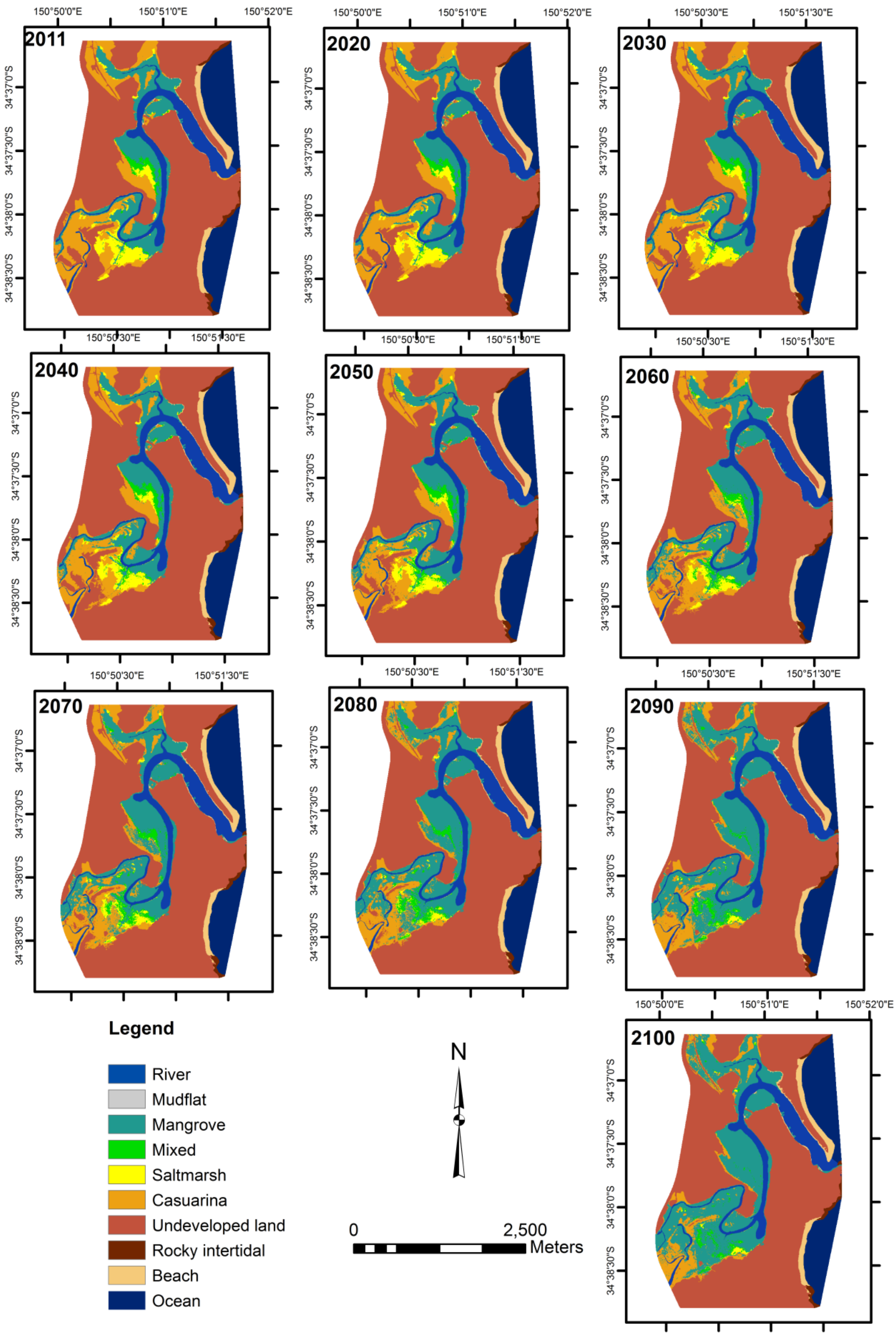


Figure C10: SLAM model output under an intermediate rate of SLR, utilising the accretion module and DEM1 as the base input elevation information.

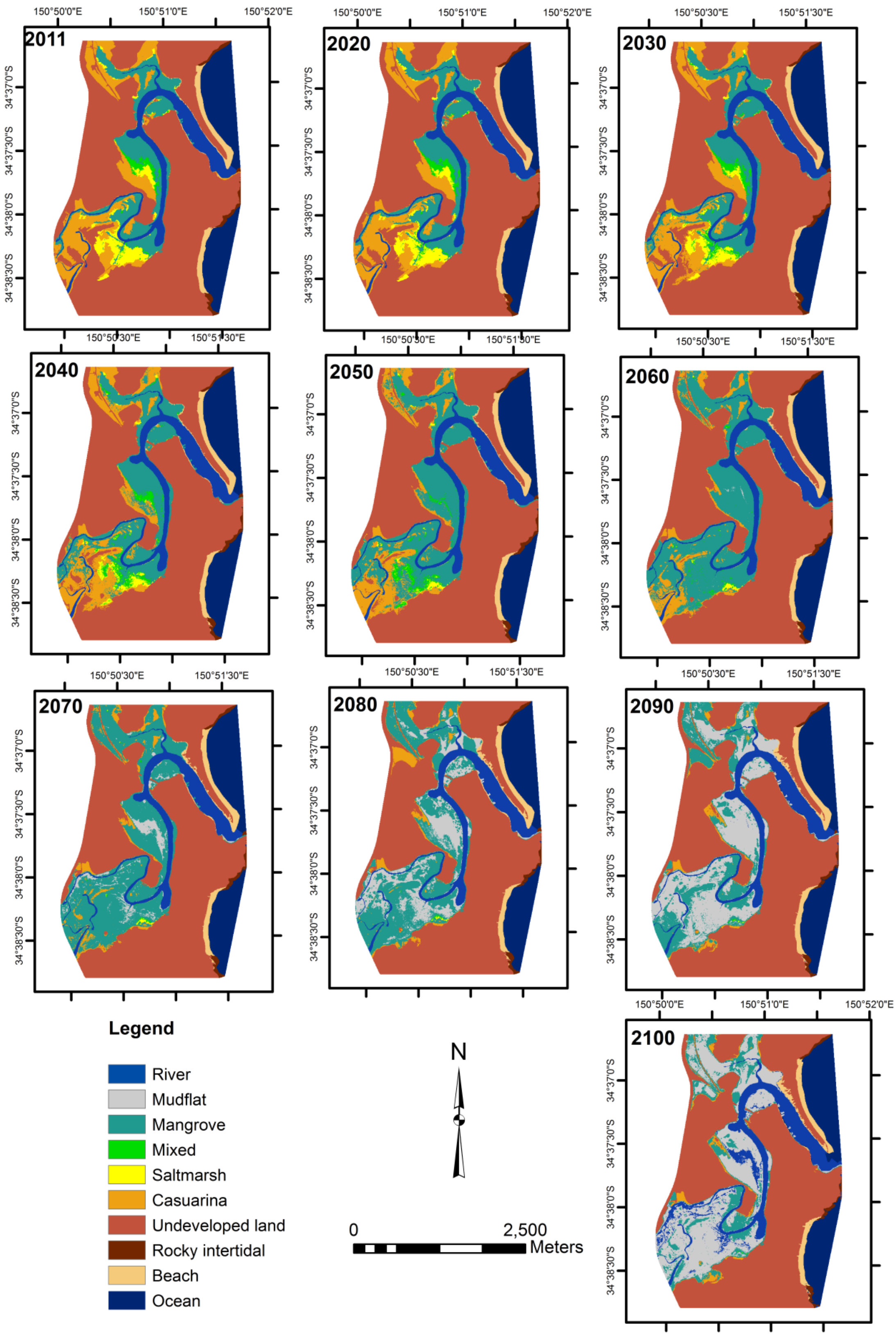


Figure C11: SLAM model output under an extreme rate of SLR, utilising the accretion module and DEM1 as the base input elevation information.

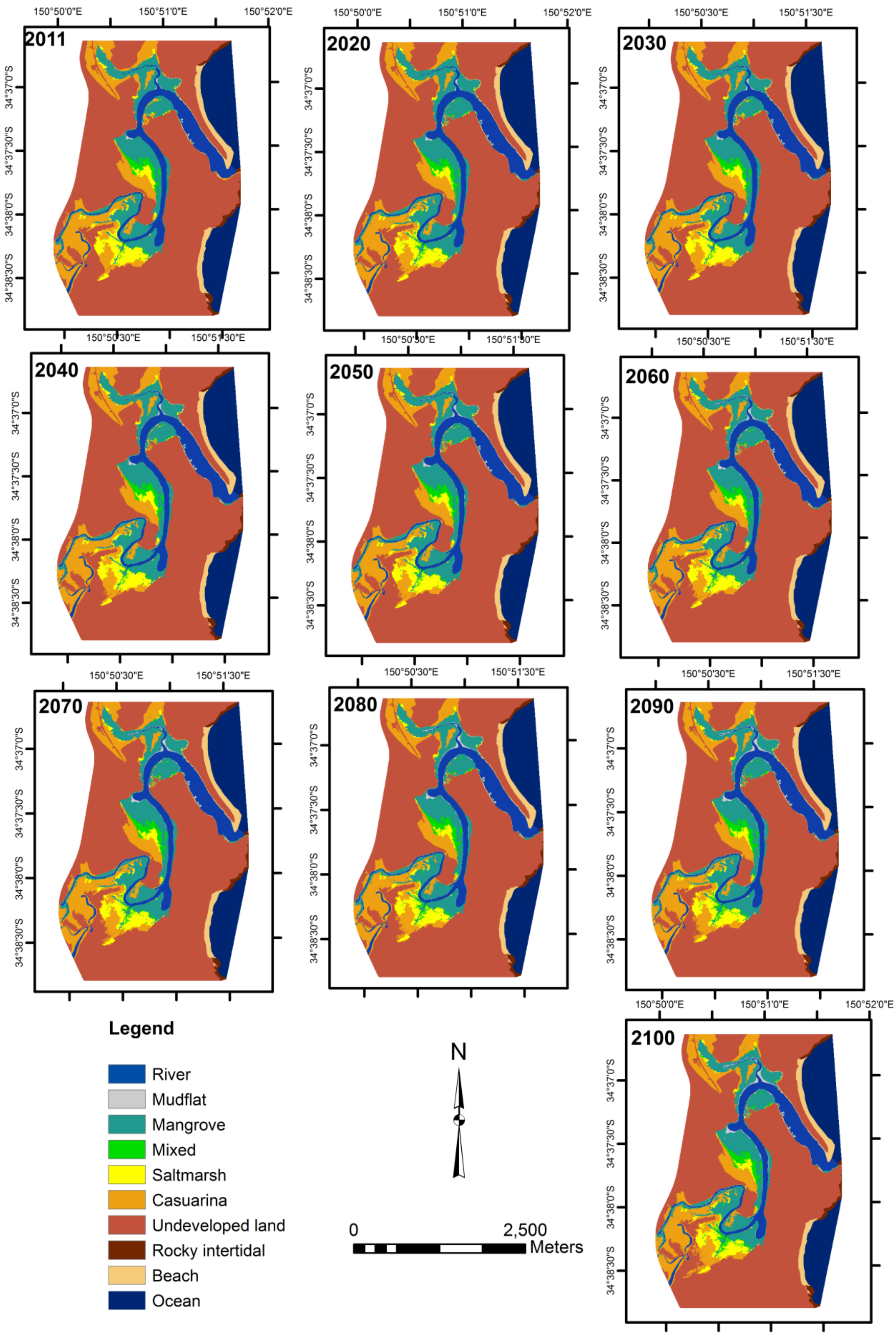


Figure C12: SLAM model output under a low rate of SLR, utilising rates of SEC and DEM2 as the base input elevation information.

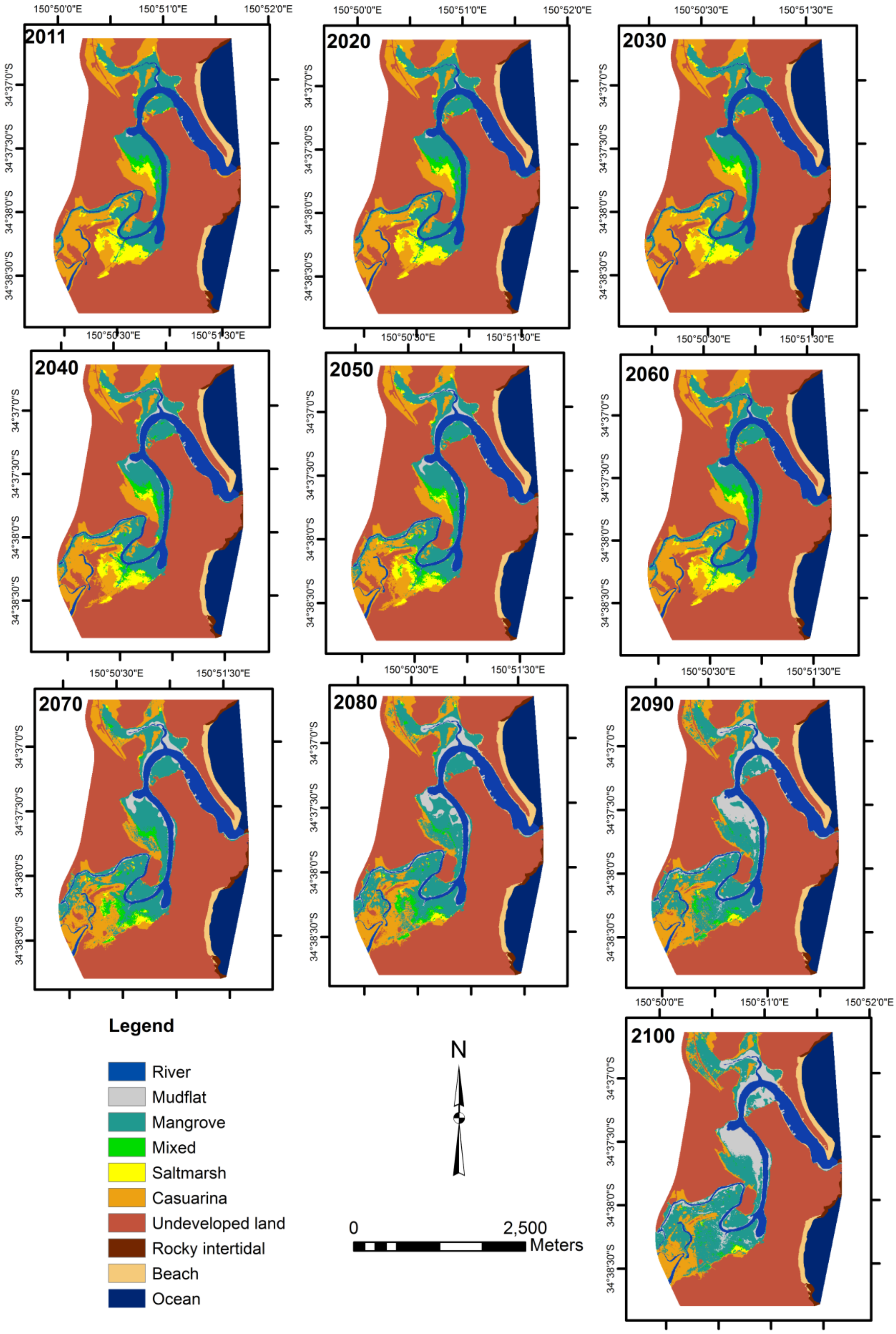


Figure C13: SLAM model output under an intermediate rate of SLR, utilising rates of SEC and DEM2 as the base input elevation information.

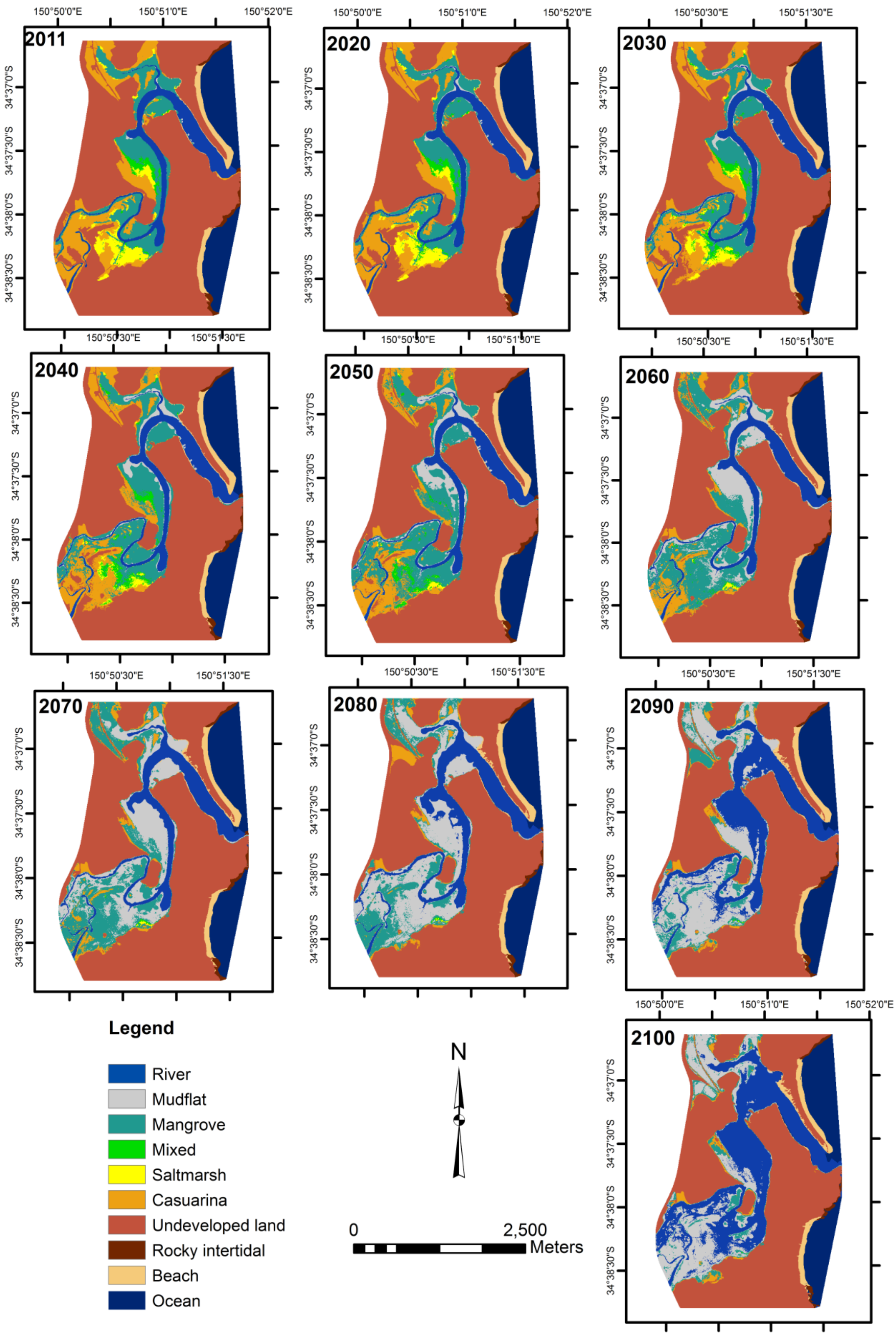


Figure C14: SLAM model output under an extreme rate of SLR, utilising rates of SEC and DEM2 as the base input elevation information.

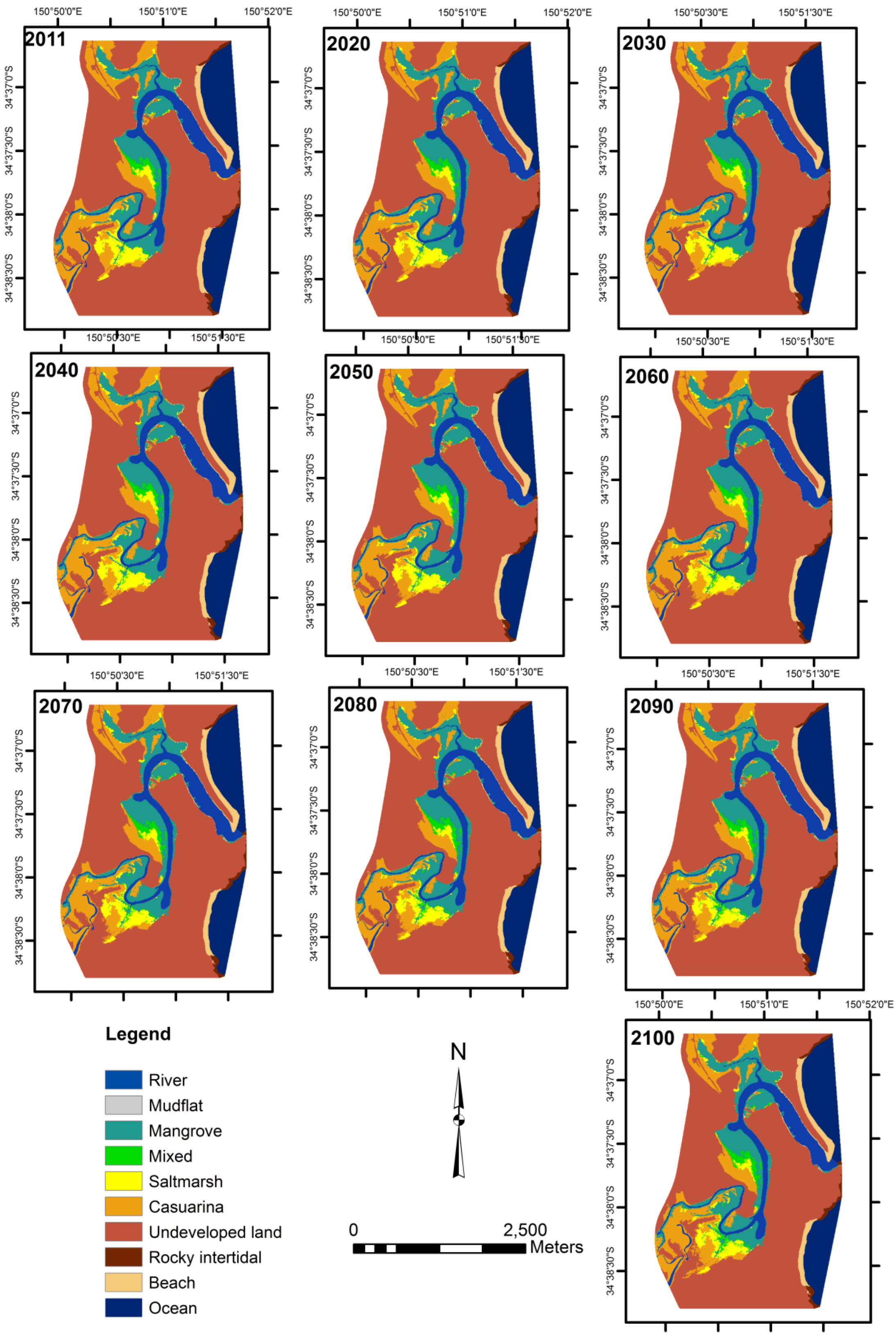


Figure C15: SLAM model output under a low rate of SLR, utilising rates of SEC and DEM1 as the base input elevation information.

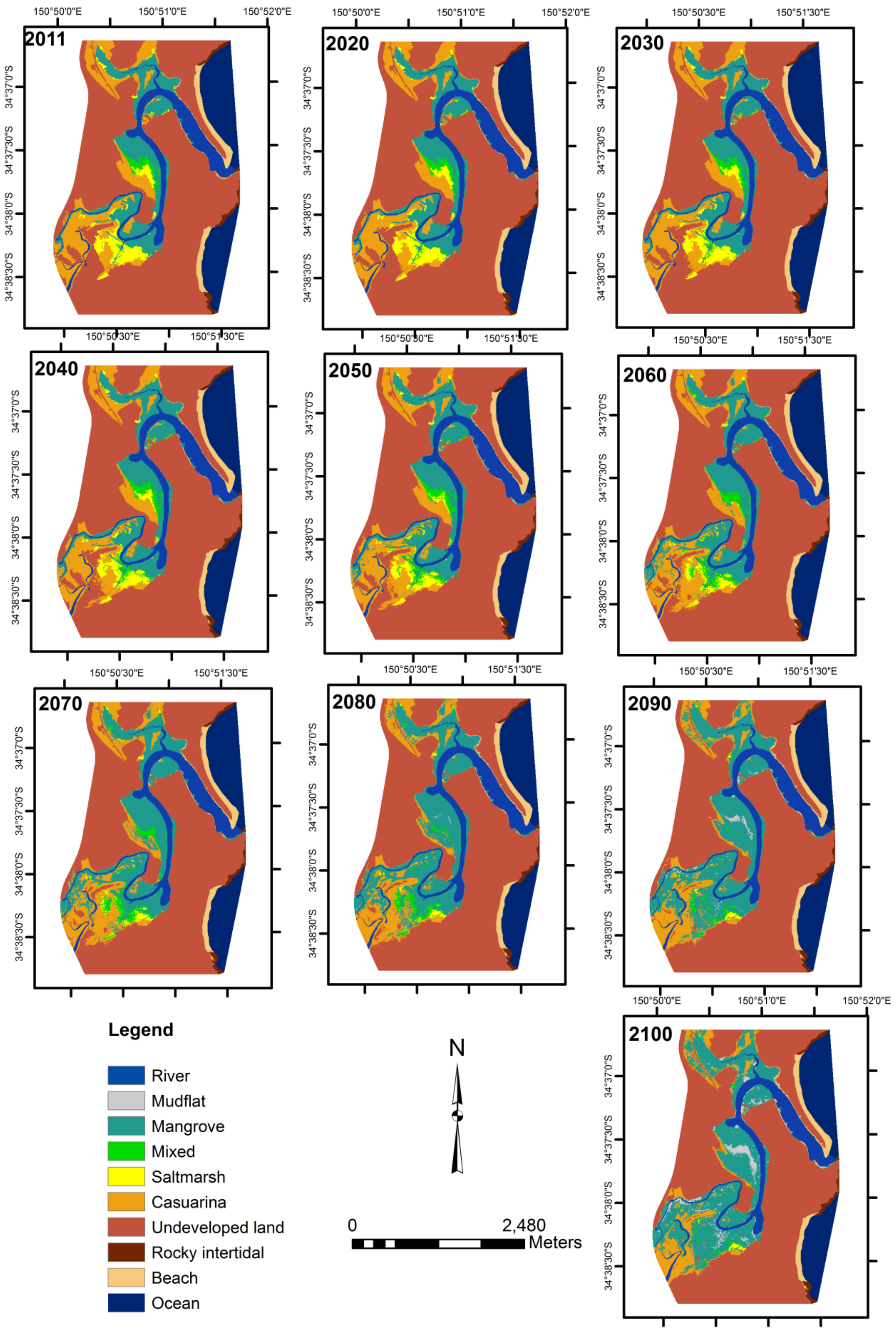


Figure C16: SLAM model output under an intermediate rate of SLR, utilising rates of SEC and DEM1 as the base input elevation information.

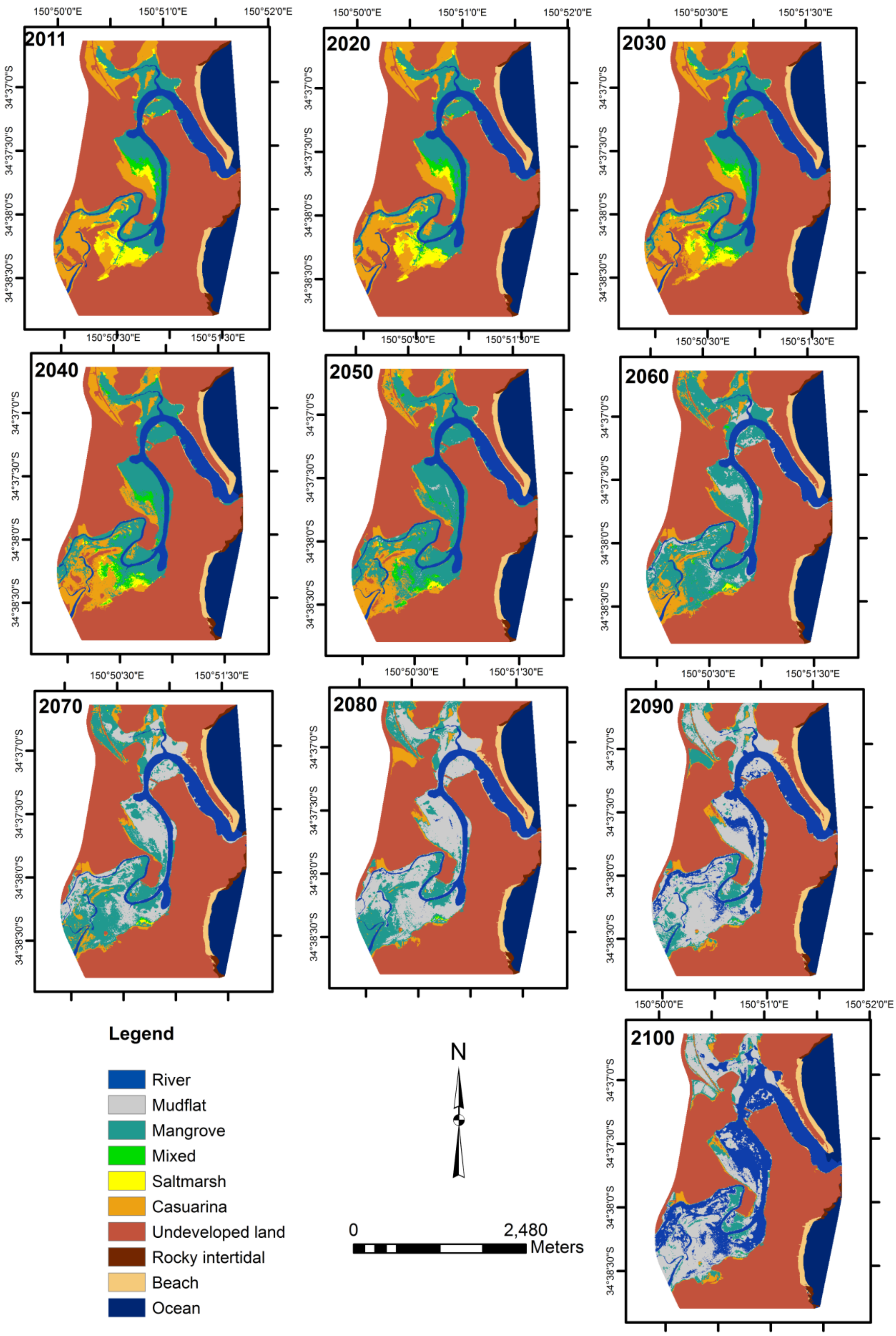


Figure C17: SLAM model output under an extreme rate of SLR, utilising rates of SEC and DEM1 as the base input elevation information.

APPENDIX D – Further sensitivity analyses results

Results presented herein are the derived sensitivity and associated descriptive statistics for the sensitivity analyses. Results are presented first for sensitivity analyses conducted when utilising rates of SEC to characterise the accretion parameter, followed by accretion rates and projections using the accretion module. Within each group, the three SLR scenarios and associated sensitivity statistics are reported. All values reported are percentages, where 0 indicates no effect occurs with variation in the parameter, positive values indicating a gain in vegetation areas and negative values indicating a loss. It is noted that SLR is consistently calculated to have a significant effect on model output, with 10% variation in the parameter resulting in significant losses or growth of certain vegetation zones.

Sensitivity results when rates of SEC were utilised

Parameter	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	4	-4	-8	-253	-76	82	-253	82	-43	114
NAVD88 - MTL	2	-1	-5	-151	-49	49	-151	49	-26	69
Salt Boundary Elevation	22	-110	0	-1	0	0	-110	22	-15	47
Mangrove Accretion	0	0	-7	109	0	0	-7	109	17	45
Mixed Accretion	0	-6	8	0	-19	0	-19	8	-3	9
GT Great Diurnal Tide Range	0	44	-67	140	-272	220	-272	220	11	172
SLR by 2100	3	-3	-7	-222	-68	72	-222	72	-37	101

Table D1: Sensitivity statistics for projections utilising rates of SEC under a low rate of SLR (B1).

Parameter	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	2	72	9	-117	299	118	-117	299	64	140
NAVD88 - MTL	1	42	5	-69	175	71	-69	175	38	82
Salt Boundary Elevation	11	-97	7	-1	0	0	-97	11	-13	41
Mangrove Accretion	0	0	-19	46	0	0	-19	46	4	22
Mixed Accretion	0	-25	9	7	-39	0	-39	9	-8	19
GT Great Diurnal Tide Range	0	243	-145	0	369	313	-145	369	130	206
SLR by 2100	9	287	28	-430	1228	448	-430	1228	262	560

Table D2: Sensitivity statistics for projections utilising rates of SEC under an intermediate rate of SLR (A1FI).

Parameter	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	2	23	68	48	220	315	2	315	113	125
NAVD88 - MTL	1	13	41	30	127	174	1	174	64	70
Salt Boundary Elevation	11	-256	-3	-1	0	0	-256	11	-42	105
Mangrove Accretion	0	0	-16	-8	10	28	-16	28	2	15
Mixed Accretion	0	-10	-9	-3	-29	0	-29	0	-8	11
GT Great Diurnal Tide Range	0	206	-160	-295	446	581	-295	581	129	344
SLR by 2100	19	212	624	389	3006	2026	19	3006	1046	1197

Table D3 Sensitivity statistics for projections utilising rates of SEC under an extreme rate of SLR.

Sensitivity results when accretion rates were utilised

	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	4	-18	0	-6	-96	35	-96	35	-13	44
NAVD88 - MTL	2	-5	8	-867	-59	22	-867	22	-150	352
Salt Boundary Elevation	22	-105	0	-2	0	0	-105	22	-14	46
Mangrove Accretion	0	1	0	7	0	0	0	7	1	3
Mixed Accretion	0	1	1	2	0	0	0	2	0	1
GT Great Diurnal Tide Range	0	24	-39	844	-259	96	-259	844	111	378
SLR by 2100	3	-15	0	-5	-85	31	-85	31	-12	39

Table D4: Sensitivity statistics for projections utilising accretion rates under a low rate of SLR.

	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	3	25	-63	160	201	146	-63	201	79	105
NAVD88 - MTL	1	16	-21	-1428	87	88	-1428	88	-209	599
Salt Boundary Elevation	12	-70	21	-1	0	0	-70	21	-6	32
Mangrove Accretion	0	0	0	38	0	0	0	38	6	16
Mixed Accretion	-2	-79	120	-2	-331	0	-331	120	-49	152
GT Great Diurnal Tide Range	0	103	-119	-274	75	409	-274	409	32	231
SLR by 2100	10	110	-244	1252	765	610	-244	1252	417	557

Table D5: Sensitivity statistics for projections utilising accretion rates under an intermediate rate of SLR (A1FI).

	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	2	30	77	-64	242	164	-64	242	75	112
NAVD88 - MTL	1	17	39	-31	154	89	-31	154	45	67
Salt Boundary Elevation	11	-242	-43	56	0	0	-242	56	-36	105
Mangrove Accretion	0	0	-273	209	-1	17	-273	209	-8	153
Mixed Accretion	0	-81	-48	59	-129	1	-129	59	-33	67
GT Great Diurnal Tide Range	0	210	-156	8	261	538	-156	538	143	246
SLR by 2100	19	308	694	-570	1609	2326	-570	2326	731	1067

Table D6: Sensitivity statistics for projections utilising accretion rates under an extreme rate of SLR.

Sensitivity results when the accretion module was utilised

	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	4	1	-20	-6	-96	35	-96	35	-14	44
NAVD88 - MTL	2	1	0	-860	-59	22	-860	22	-149	349
Salt Boundary Elevation	22	-113	-2	-1	0	0	-113	22	-16	49
GT Great Diurnal Tide Range	0	61	-69	836	-259	96	-259	836	111	377
SLR by 2100	3	2	-18	-5	-85	31	-85	31	-12	39
Mangrove maximum accretion	0	0	0	9	0	0	0	9	1	4
Mangrove minimum accretion	0	0	0	0	0	0	0	0	0	0
Mangrove elevation b coefficient	0	0	0	0	0	0	0	0	0	0
Mangrove elevation c coefficient	0	0	0	0	0	0	0	0	0	0
Mixed maximum accretion	0	0	0	0	0	0	0	0	0	0
Mixed minimum accretion	0	0	0	0	0	0	0	0	0	0
Mixed elevation b coefficient	0	0	0	0	0	0	0	0	0	0
Mixed elevation c coefficient	0	0	0	0	0	0	0	0	0	0

Table D7: Sensitivity statistics for projections utilising the accretion module under a low rate of SLR

	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	2	81	-37	162	255	146	-37	255	102	108
NAVD88 - MTL	1	49	-15	-1420	146	88	-1420	146	-192	605
Salt Boundary Elevation	11	-87	-1	0	0	0	-87	11	-13	36
GT Great Diurnal Tide Range	0	264	-91	-297	302	409	-297	409	98	271
SLR by 2100	8	320	-143	1223	940	610	-143	1223	493	532
Mangrove maximum accretion	0	0	0	87	0	0	0	87	14	36
Mangrove minimum accretion	0	0	0	0	0	0	0	0	0	0
Mangrove elevation b coefficient	0	0	0	0	0	0	0	0	0	0
Mangrove elevation c coefficient	0	0	0	0	0	0	0	0	0	0
Mixed maximum accretion	0	0	5	0	-133	0	-133	5	-21	55
Mixed minimum accretion	0	0	-2	0	61	0	-2	61	10	25
Mixed elevation b coefficient	0	0	0	0	9	0	0	9	1	4
Mixed elevation c coefficient	0	0	0	0	-9	0	-9	0	-1	4

Table D8: Sensitivity statistics for projections utilising the accretion module under an intermediate rate of SLR.

	Undeveloped Dry Land	Casuarina	Mangrove	Mudflat	Mixed	Saltmarsh	Minimum	Maximum	Mean	Standard Deviation
Historic sea level trend	2	23	100	26	239	164	2	239	92	94
NAVD88 - MTL	1	14	48	8	146	88	1	146	51	57
Salt Boundary Elevation	11	-263	-31	11	0	0	-263	11	-45	108
GT Great Diurnal Tide Range	0	210	-216	-246	393	531	-246	531	112	320
SLR by 2100	19	192	920	134	2029	2314	19	2314	935	1013
Mangrove maximum accretion	0	0	-120	-28	-9	10	-120	10	-24	49
Mangrove minimum accretion	0	0	-86	-18	-2	4	-86	4	-17	35
Mangrove elevation b coefficient	0	0	5	2	-5	-4	-5	5	0	4
Mangrove elevation c coefficient	0	0	-5	-2	5	4	-5	5	0	4
Mixed maximum accretion	0	0	0	-4	-37	4	-37	4	-6	15
Mixed minimum accretion	0	0	0	2	20	0	0	20	4	8
Mixed elevation b coefficient	0	0	0	0	4	0	0	4	1	2
Mixed elevation c coefficient	0	0	0	0	-4	0	-4	0	-1	2

Table D9: Sensitivity statistics for projections utilising the accretion module under an extreme rate of SLR.

APPENDIX E – Further uncertainty analysis results

Uncertainty analysis results for projections utilising accretion rates to characterise the accretion parameter. Figure F1 and F2 are discussed in the main body of the thesis and clearly display a significant uncertainty associated with the lower wetlands. Figures F1 – F5 present the uncertainty associated with simulations of each vegetation type over the period 2011-2100.

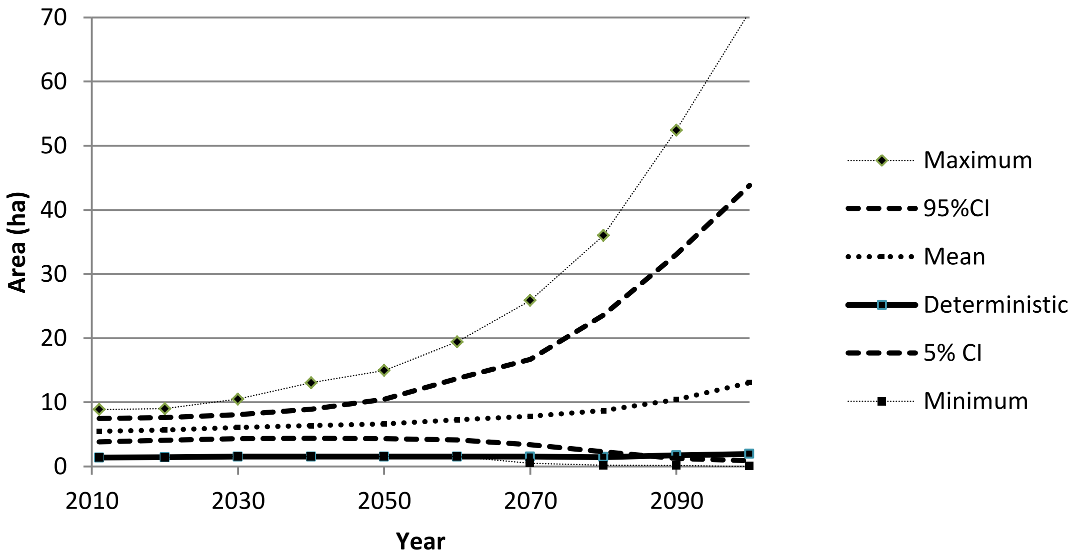


Figure E1: Results of the uncertainty analysis for mudflat zones. It is noteworthy that the deterministic run is situated at or near the very minimum of the possible mudflat distributions over the simulated period.

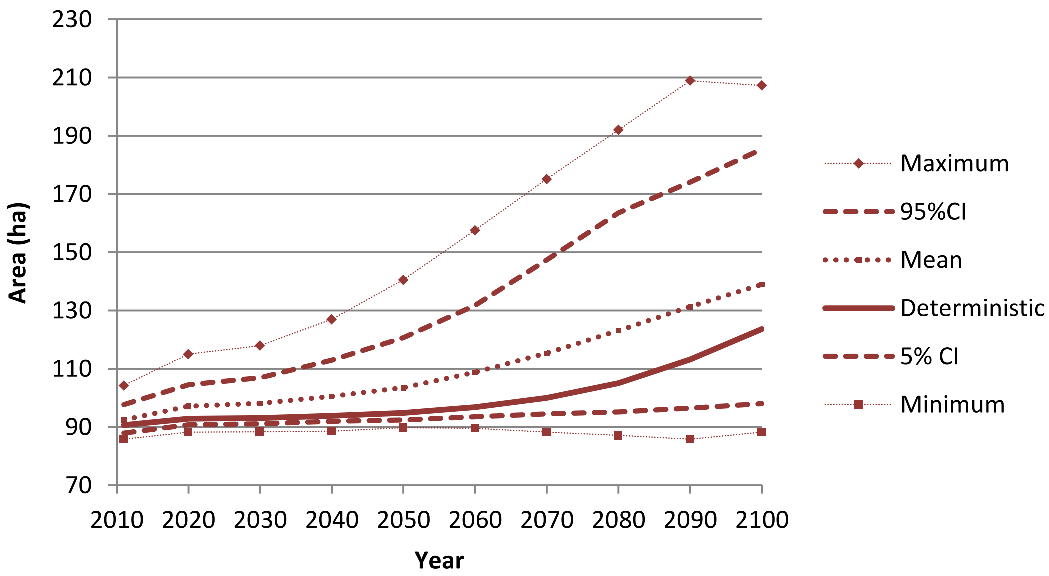


Figure E2: Results of the uncertainty analysis for mangrove zones. Significant uncertainty in output can be observed by the year 2100.

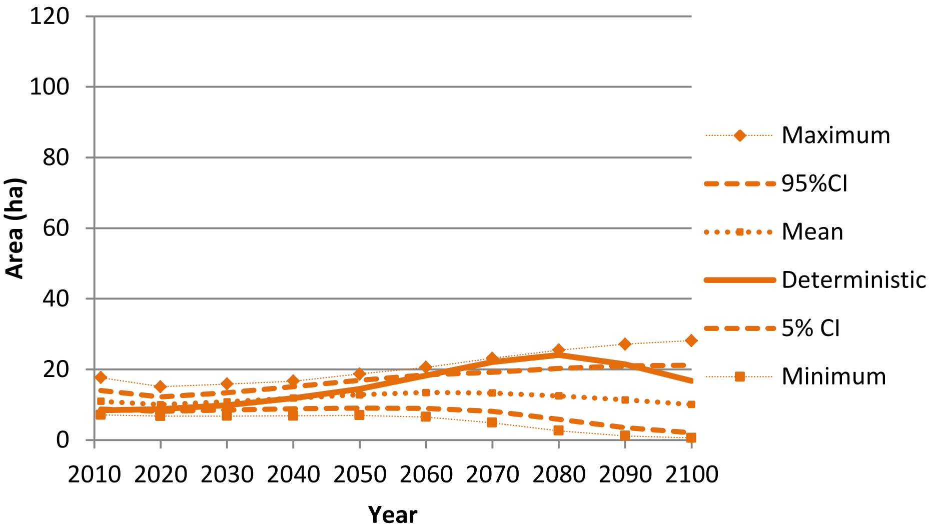


Figure E3: Uncertainty results for the mixed zone. Some uncertainty is associated with the model output. It is noteworthy that the results of the uncertainty analysis suggest that the mixed zone may increase or decrease by the year 2100.

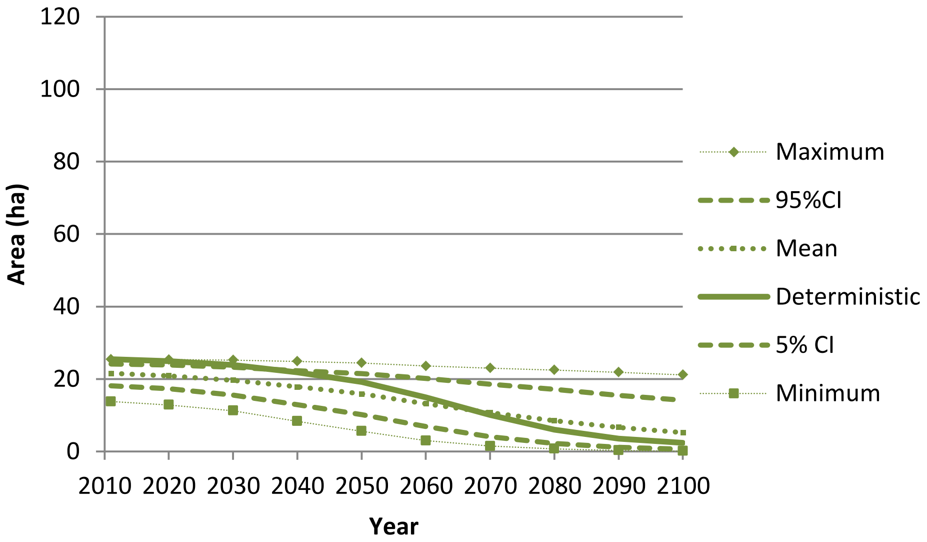


Figure E4: Results of the uncertainty analysis for the saltmarsh zone. The distribution of possibilities for the simulated period 2011-2100 suggest that a loss in saltmarsh is more than likely.

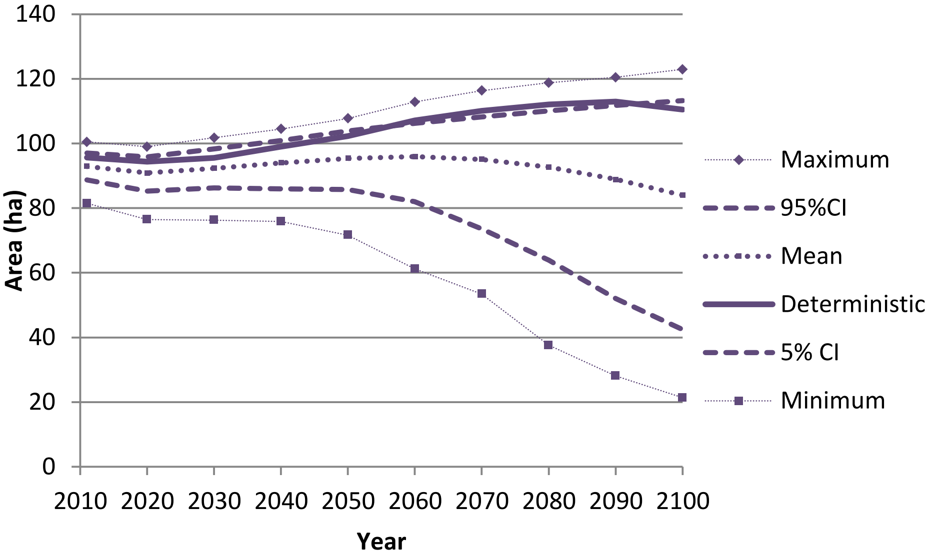


Figure E5: Results of the uncertainty analysis for the *Casuarina* zone. Considerably greater uncertainty is associated with this class than with the saltmarsh or mixed zones. However, similar to the mixed zones, simulated *Casuraina* zones may increase or decrease by the end of the century.

Uncertainty results for projections utilising rates of SEC

Greatest uncertainties are associated with lower wetlands (mudflat and mangrove areas) and Casuarina zones. Descriptive and inferential statistics derived from the 500 iterations of the uncertainty analysis are presented in Figures F6-F10.

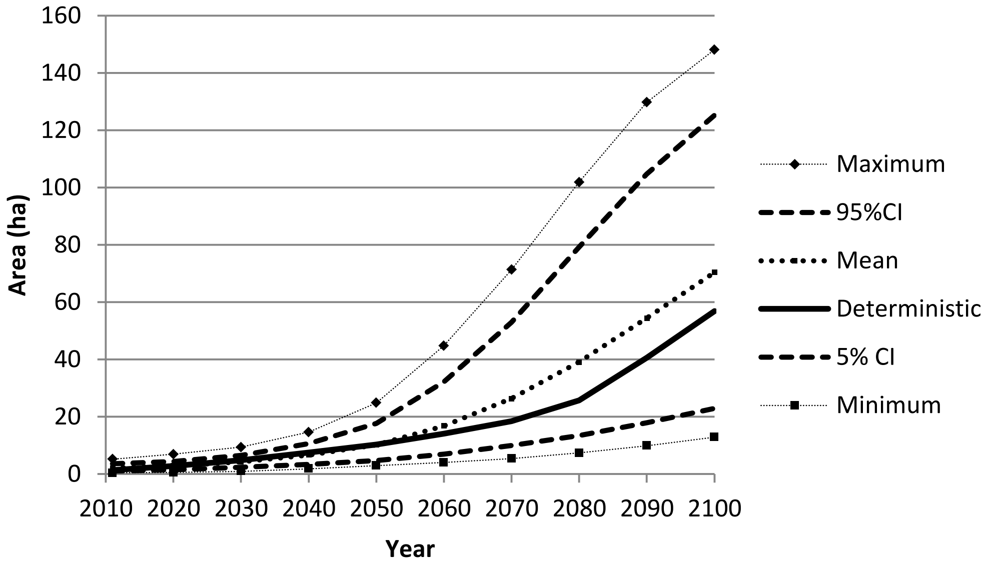


Figure E6: Results of the uncertainty analysis for mudflat zones. A large amount of uncertainty is associated with simulated mudflat zones, especially by the year 2100. Unlike when accretion rates are utilised, the deterministic projection is only slightly below the mean value calculated for possible mudflat zones.

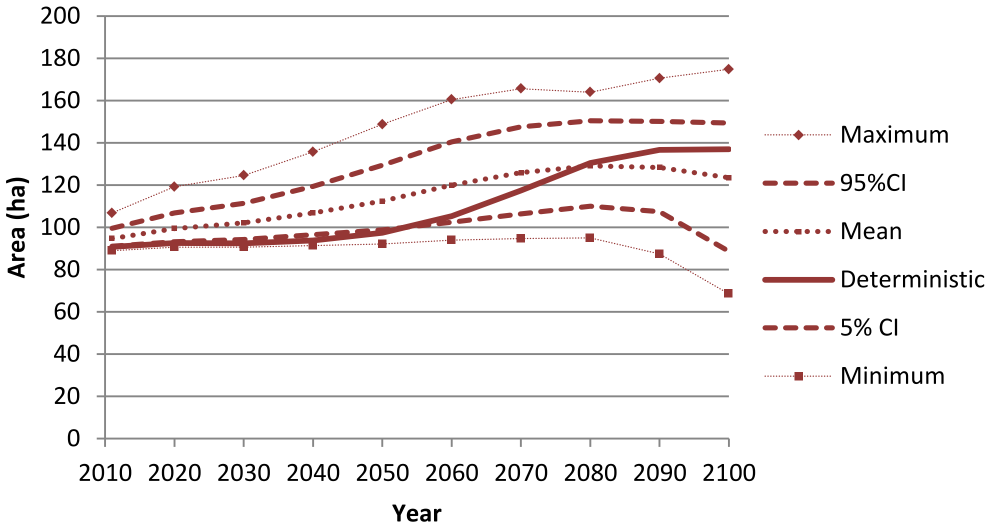


Figure E7: Results of the uncertainty analysis for mangrove areas. Uncertainty associated with mangrove zones when utilising rates of SEC are slightly less than when accretion rates are utilised.

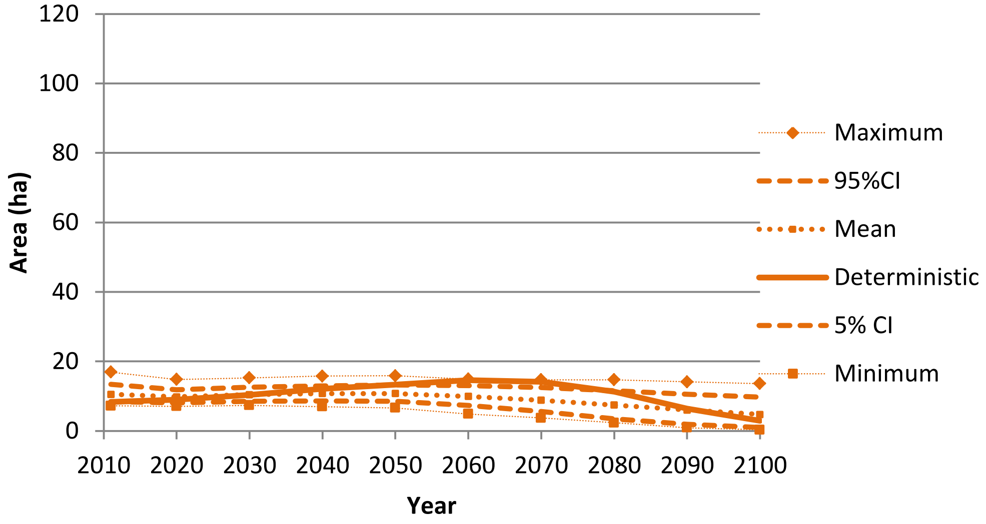


Figure E8: Results of the uncertainty analysis for mixed vegetation zones. Little variation can be seen in the simulation of this zone by the year 2100.

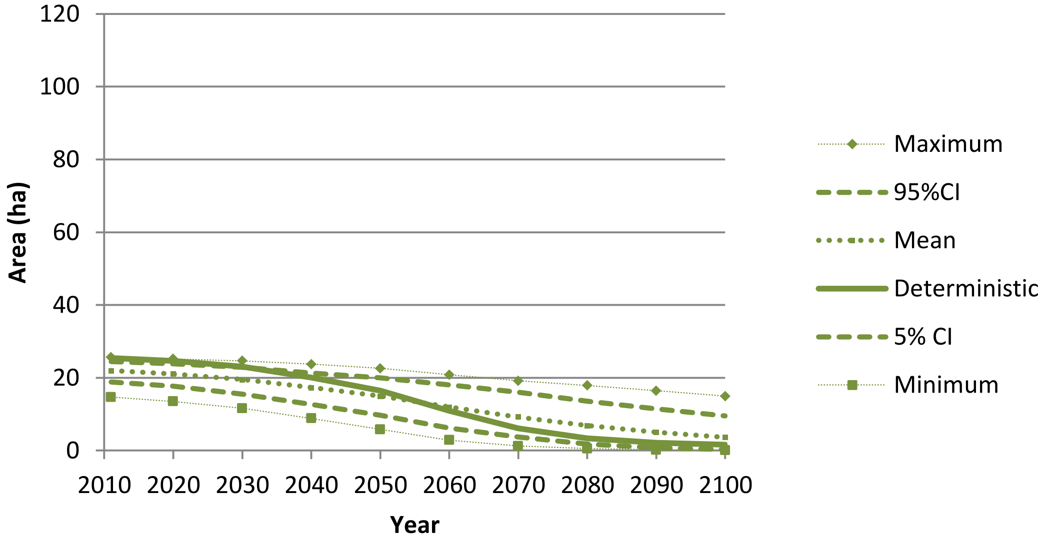


Figure E9: Results of the uncertainty analysis for saltmarsh. A loss of saltmarsh can be inferred to be most likely to occur by the year 2100 given almost all possible areas simulated for in this uncertainty analysis for the year 2100 are below the initial vegetation distribution. The vegetation succession defined in the SLAM model, however, may also affect the ability of the saltmarsh zone to be sustained over time, as considered in the discussion of this study. Error in the framework of the SLAM model may increase the uncertainty associated with simulated saltmarsh zones, more so than is depicted here.

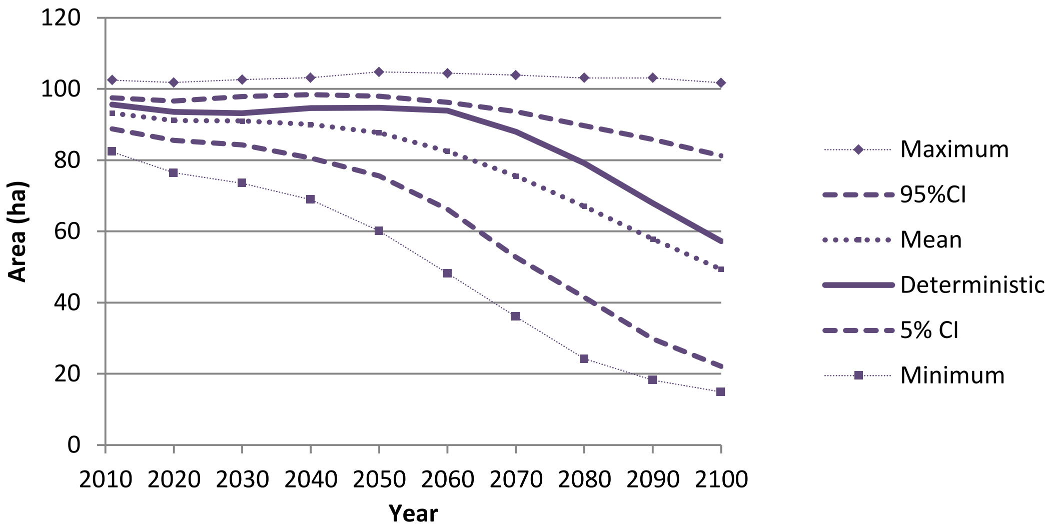


Figure E10: Results of the uncertainty analysis for Casuarina zones. Greater uncertainty is associated with this vegetation class than the saltmarsh and mixed zones. Considering the statistics calculated from the uncertainty results, it appears that a loss in wetland is most likely to occur.