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Integrating Uncertainty Theories with GIS for Modeling Coastal Hazards of Climate Change

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Prediction of coastal hazards due to climate change is fraught with uncertainty that stems from complexity of coastal systems, estimation of sea level rise, and limitation of available data. In-depth research on coastal modeling is hampered by lack of techniques for handling uncertainty, and the available commercial geographical information systems (GIS) packages have only limited capability of handling uncertain information. Therefore, integrating uncertainty theory with GIS is of practical and theoretical significance. This article presents a GIS-based model that integrates an existing predictive model using a differential approach, random simulation, and fuzzy set theory for predicting geomorphic hazards subject to uncertainty. Coastal hazard is modeled as the combined effects of sea-level induced recession and storm erosion, using grid modeling techniques. The method is described with a case study of Fingal Bay Beach, SE Australia, for which predicted responses to an IPCC standard sea-level rise of 0.86 m and superimposed storm erosion averaged 12 m and 90 m, respectively, with analysis of uncertainty yielding maximum of 52 m and 120 m, respectively. Paradoxically, output uncertainty reduces slightly with simulated increase in random error in the digital elevation model (DEM). This trend implies that the magnitude of modeled uncertainty is not necessarily increased with the uncertainties in the input parameters. Built as a generic tool, the model can be used not only to predict different scenarios of coastal hazard under uncertainties for coastal management, but is also applicable to other fields that involve predictive modeling under uncertainty.

Keywords GIS, coastal hazard, climate-change, uncertainty, random-simulation, fuzzy set, differential-method, DEM-remapping

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Predicting coastal geomorphic hazard due to climate change is important to society, given that many cities around the world are concentrated on the coastal fringe. Although assessment of the coastal-hazard zone helps in managing the coasts effectively, especially in mitigating the coastal impacts of climate change, the assessment itself can also have a great impact on property values (Smith 1994). Conservatism in predicting impacts thus pertains not only to precautionary practices in sustaining environmental heritage, but also to limiting the opportunity costs that result when land is quarantined through planning controls (set-back limits) flowing from coastal hazard assessments.

The coastal impact of climate change includes three significant aspects (Cowell and Thom 1994): (a) mean sea-level rise caused by the thermal expansion of ocean water (Church et al. 1991; Douglas et al. 2000; GSC 1990; IPCC 2001; Woodroffe and Nash 1995); (b) the intensifying and greater frequency of storm surge (Vellinga 1983, 1986; Weggel 1979); and (c) the changes in wave climate and wave patterns (Gordon 1987, 1988; Roy et al. 1994; Short et al. 1996; Thom and Hall 1991). Predicting the coastal hazard involves handling uncertainties in each of these aspects (Zeng et al. 1997). The uncertainties stem from (a) the nonlinear and highly complex nature of the coastal processes that are driven across different scales in time and space (Cowell and Thom 1994; Stive et al. 1995); (b) the projections of climate change itself (Cardwell and Ellis 1996; Henderson-Sellers 1993), including available estimation of sea-level rise (Gornits 1995; Gregory 1993); and (c) error in the digital elevation model (DEM) and wave-climate changes at a regional level. Therefore, assessing the coastal hazard should be probabilistic rather then deterministic (Cowell et al. 1996).

This article reports the development of a modeling tool for predicting coastal hazard by integrating an existing coastal-response model with the differential approach and random simulation, implemented within the framework of a geographic information system (GIS). The GIS-based model is applied in a case study (Fingal Bay Beach, two hundred kilometres north of Sydney, SE Australia) to illustrate how coastal-impacts of climate change can be predicted with quantification and management of the uncertainty.

Methodology

Predicting coastal change with GIS has, for the most part, previously involved a deterministic, vector-based approach to coastline change (e.g., Daniels 1996; Granger 1995; Hennecke 2000; Hickey et al. 1999; Lee et al. 1992; Li et al. 1999). Despite being easy to implement, it is difficult to handle the uncertainties using this approach. Furthermore, it is difficult to map the transitional phenomena of coastal hazards caused by climate change. Grid (raster-based) modeling techniques are better alternatives in this respect.

Cowell et al. (1996) outlined a probabilistic method for estimating and mapping the coastal-recession hazard due to climate-change impacts. The method used GIS procedures that delineate three zones in which the probability of the coastal erosion increases from $P(x_i) = 0$ to $P(x_i) = 1$ along shore-normal profiles in a seaward direction across the subaerial portion of a coastal sand barrier (Figure 1). Where $P(x_i) = 1$, impacts are certain because they occur already under present conditions, due to the effects of storms, or will occur based on existing trends in shoreline recession. These effects also must be added to predicted climate impacts in the domain $0 < P(x_i) < 1$. Probabilities also vary as $P(y_j)$ along the coast in relation to a range of environmental factors, as well as with variations in the cross-sectional sand volume.

The coastal-hazard probabilities, P_{ij}, for each grid cell in the DEM can be obtained from a stochastic generator based on a simplified relationship for coastal recession (R) as a function of sea-level rise, the onshore sand-body volume (i.e., dune height) and offshore

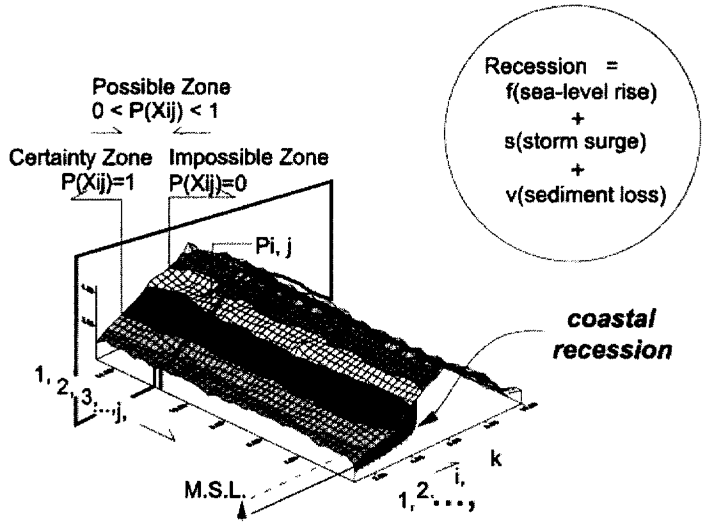

FIGURE 1 A probabilistic approach to modeling coastal hazard due to climate change (from Cowell et al. 1996).

seabed slope, an erosion volume associated with design storm events (or storm sequences), and net losses or gains in the littoral sediment-transport budget. Each of these factors is subject to varying degrees of uncertainty. Based on this concept, we constructed the GIS-based model schematized in Figure 2. The model consists of four main components: (a) *Random-Input Simulation Model*; (b) *Recession Model*; (c) *Storm-Erosion Model*; and (d) *DEM Remapping Module*. The *Random-Input Simulation Model* is designed to manage input uncertainty (terrain, sea level, sediment budgets). The *Recession Model* involves a 2D-vertical (2DV) alongshore-averaged, cross-shore profile that predicts deterministic recession within a defined littoral subcell (section) with allowance for uncertainty based on a differential approach. The *Storm-Erosion Model* operates on the shoreline in plan form (2DH) to predict the erosion volume associated with the design storm or sequence of storms, with allowance for uncertainty managed through a fuzzy set approach applied to the overall hazard estimate (recession and storm erosion combined).

In the *DEM Remapping Module*, outputs from the 2DV and 2DH modules are combined as continuous shoreline-change along the coast, together with associated coastal hazard contours. Each module is described below.

Random Simulation of Inputs

Like all other complex systems, coastal systems consist of many subsystems, each of which can vary freely to some degree. The changes in boundary conditions of the system cannot be predicted exactly. For example, estimates of sea-level rise due to the Industrial Greenhouse Effect are constantly under review, subject to much debate, and expressed as a range of future scenarios (IPCC 2001). Random simulation (Rubinstein 1982) can be used to deal with uncertainty in inputs, which in the context of coastal-response to sea level includes (a) predicted sea-level rise, (b) errors in the DEM, and (c) sediment budgets (ignored herein).

Handling Uncertainty in Sea-Level Rise

Sea-level rise is modeled as an exponential distribution because the uncertainty is assumed to be completely random and highly variable (in the absence of information to indicate systematic uncertainty), and expected to be greater for predictions over longer time

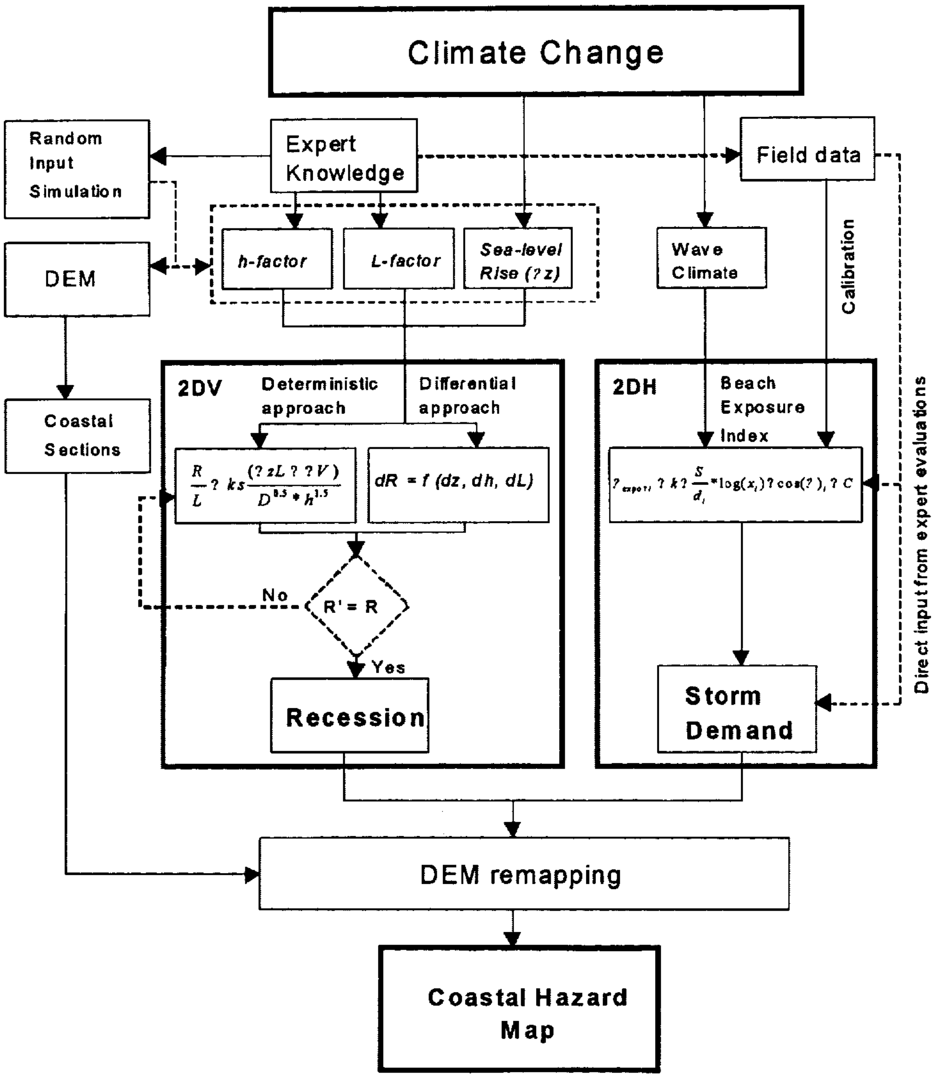

FIGURE 2 A GIS-based model for modeling coastal hazard.

spans (IPCC 2001). Thus, sea-level rise is expressed as

$$z = k^{\lambda} e^{t}, \tag{1}$$

where z is the sea-level, k is a scale factor, λ is a correlation factor (as used here, an estimated rate of sea-level rise), and t is the time horizon for which the prediction is required (Figure 3). Empirical fit to the IPCC (1995) best-estimate sea-level curve gives $k = 0.378$ and $\lambda = 0.009804$.

Our random-simulation techniques follow the methods described by Banks and Carson (1984) and are based on the assumption that the trend of sea-level rise is as given by IPCC (IPCC 1995). Our calculations were made before IPCC (2001) revised the rates downward, but the methodology is unaffected and the case study remains valid for the purpose of illustration. Moreover, the difference of the predicted sea-level rise between IPCC 1995 and 2001 is only 2 mm (0.86 m and 0.88 m, respectively). The difference is insignificant

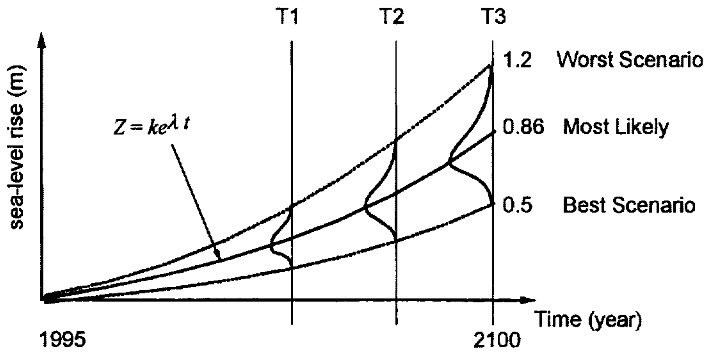

FIGURE 3 Simulation of sea-level rise.

with respect to the final model output because the impact of storm erosion is 5–8 times greater than the impact of sea-level rise. The cumulative-distribution function (CDF) is determined by integrating Equation (1) to obtain

$$F(z) = \begin{cases} 0 & t < 0 \\ \int_0^t Ke^{\lambda t} dt & t \geq 0 \end{cases}. \tag{2}$$

Handling DEM Uncertainty

Accuracy of the DEM is another problem in determining the inundation and erosion impacts on the coast, because it affects the calculation of sediment volume, based on which the coastal hazard is assessed. DEM uncertainty has been an important issue in geosciences since the 1970s. Much work has been done in developing methodologies for DEM interpolation and accuracy assessment (Li 1993, 1994; Lpez 1979; Polidori and Chorowicz 1993; Schut 1976).

Experiment shows that a "minimum curve" algorithm is more appropriate for the sandy beach on open coasts (Zeng et al. 1997). Hence, it is adopted in interpolation of the DEM from 10 m interval contour lines (1:25,000 scale), with additional contour lines at −5, 2, and 5 m height. The resultant DEM is used as 1:25,000.

DEM accuracy depends on many factors (Li 1993), such as accuracy, density and distribution of spot-height samples, characteristics of the terrain, and the method used for construction of the DEM. Thus, DEM uncertainty is complex and since most of the above effects generally remain unknown; uncertainty in the DEM cannot be specified other than by assuming that the error is inherently random. Thus, we assume that the overall error can be characterized through random simulation, so sensitivity analysis of random errors can be conducted using a normal distribution implemented in the ArcInfo GRID module.

Recession Model (2DV)

Deterministic Component

To predict geomorphic-impact hazard within a coastal region, we built a three dimensional model by dividing the coast into alongshore sections and then incorporating the 2DV model into each section. Each section is thereby aggregated internally through alongshore averaging into a single cross-shore profile representation, a common approach in coastal-change modeling. The profile section is used to calculate the mean-trend recession distance based on trends estimated from a practical model (Cowell et al. 1995) based on a sediment

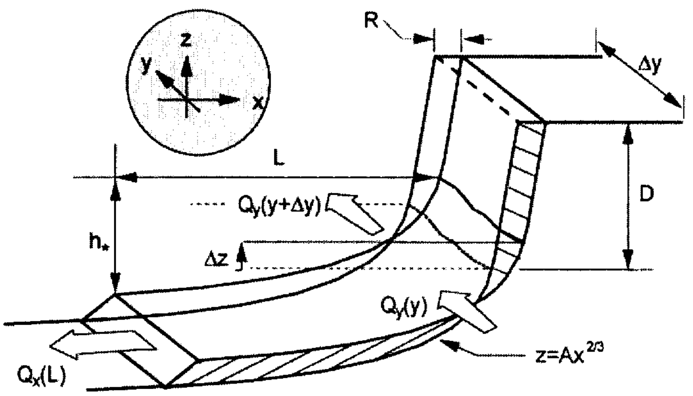

FIGURE 4 Definition of parameters of the coastal recession model (after Cowell et al. 1996).

mass balance approach (Bruun 1962; Dean 1990; Dean and Maurmeyer 1983; Edelman 1970; Komar et al. 1991) but with the ability to incorporate net sediment transport in the littoral zone and the possibility of cross-shore sand losses from the beach through either washover of sediments into the lagoon or displacement of beach sand offshore or both, depending on site-specific conditions. The model expresses the recession distance, R (defined in Figure 4), as

$$\frac{R}{L} = ks\frac{(\Delta zL - \Delta V)}{D^{0.5}h^{1.5}}, \tag{3}$$

where L is the distance seaward to the limit of significant sand exchange with the beach, h is the water depth at distance L, Δz is the sea-level rise relative to the land, ΔV is net sand loss or gain in the littoral sediment budget (generally associated with alongshore transport), and D is the average elevation of the backshore (e.g., dune).

We refer to Equation (3) as the Coastal Recession Model (CRM) which we derived through analysis of results from Cowell et al. (1996), who ran 202 simulations using 28 different initial profile configurations, various littoral sediment budgets, and a range of scenarios for sea-level rise. The simulations collectively cover the range of geographically varying conditions found in nature (Cowell et al. 1996). The simulations were conducted using a more elaborate computer model, known as the *Shoreface Translation Model* (STM), developed by Cowell et al. (1992, 1995). The STM is capable of handling the above-mentioned factors, based on conventional principles of mass balance along the coastal profile. In a narrow sense, D in Equation (3) refers to dune height; but in a general sense, it represents the available sediment volume that maintains mass balance in a coastal section. The mass balance varies in response to change in external forcing, such as sea-level rise.

The sediment-budget term, ΔV, in Equation (3) must be determined from other studies, such as coastal-survey monitoring or separate modeling results. Results on ΔV from these other studies may include previous rise in relative sea level. Care should be taken therefore not to compound such sea-level effects by including them in both Δz and ΔV. The procedures outlined in Figure 2 evaluate the recession (R) for each coastal section for given conditions (e.g., IPCC $\Delta z = 0.86$ m) using the CRM programmed in Arc/Info AML (Arc Macro Language) and remapping onto DEM in GRID.

Uncertainty Component

Like most of 2DV coastal models, the CRM requires exact values for input parameters in order to obtain the output recession rate, R. The uncertainty can be addressed using the differential approach (Pritchard and Adelman 1991). For instance, the long-term closure-depth variable is estimated to be about $h = 25$ m for the NSW coast, although it could range between 20 to 30 meters (Cowell et al. 1999). Therefore, the distance from the beach to the closure depth is about $L = 1500$ m, depending on the slope of the seabed.

Similar uncertainty in each of the other input parameters also affects the predicted recession R. The effect of this uncertainty can be investigated through the differential

$$\frac{dR}{dx} = \frac{d(f(x))}{dx}, \tag{4}$$

where x is the across-shore distance. Putting Equation (3) into (4), the modeled uncertainty in output can be represented as a function of the uncertainties of input parameters:

$$dR = \frac{ks}{D^{0.5}h^{1.5}}\left(\Delta z dL + L dz - 1.5\frac{\Delta z L}{h}dh + 1.5\frac{\Delta V}{h}dh\right). \tag{5}$$

The resulting uncertainty, dR, due to the three variables $(\Delta z, h, \Delta V)$ is added to the predicted recession R to give a contingent recession, $R + dR$.

Storm-Erosion Model

Storm demand is the erosion volume, Q_e, resulting from wave action during and/or following a storm (or series of storms). It can be defined as a function of beach exposure, μ_e: $Q_e = f(\mu_e)$. The magnitude of storm demand is determined by wave characteristics, physical condition of the beach, and rip-current effects, as well as human interaction. We introduce a practical but gross representation using the concept of a Beach Exposure Index (BEI), based on analysis of the first two factors; the later two factors are beyond the scope of this article.

The rationale for the BEI is that wave characteristics are the main contributing factor to the storm demand (Couriel et al. 1993; Dean 1990; Nairn 1991). Thus, storm demand varies along the beach due to the degree to which the beach is exposed to the open ocean, which we characterize by the BEI, μ_e. Exposure may be indexed by the ratio of S/d, where d is the distance from beach perpendicular to the line of length S that links two headlands. The effect of headlands is to attenuate wave height within a coastal embayment through the effects of wave refraction, which can be scaled roughly with the incident wave angle relative to the cross-shore profile, cos(α.) Based on these considerations, μ_e is expressed for variables defined in Figure 5 as

$$\mu_{exposure-i} = k\frac{S}{d_i} * \log(x_i)\cos(\alpha)_i + C, \tag{6}$$

where S is distance between headlands, d_i the perpendicular distance from the shoreline at profile i to S, x_i is distance of shoreline from profile i to the nearest headland, α_i is angle between wave direction and the cross-shore profile i, and C is a constant.

DEM Remapping Module

The storm demand, $Q_e = f(\mu_e)$, is calculated for each coastal section (Figure 5). Shoreline retreat due to storm erosion extends landward from the point of coastal recession, R, induced

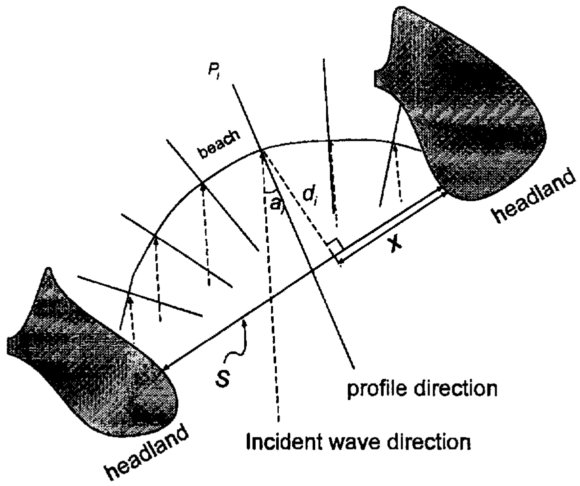

FIGURE 5 Definition of parameters of beach exposure index.

by sea-level rise and is calculated based on the sediment volume obtained from the DEM following random simulation. Uncertainty is further addressed by expressing the probable degree of the coastal hazard as a fuzzy membership (Zimmermann 1991), F, for each pixel along the coast:

$$F(x_{ij}) = P_{ij} = \begin{bmatrix} P_{ij} \geq 1 & x_i = R \\ 0 < (P_{ij}) < 1 & \frac{\sum_{i=1}^{n} v_i}{V_{R+dR}+Q_e} < 1, \\ P_{ij} = 0 & \frac{\sum_{i=1}^{n} v_i}{V_{R+dR}+Q_e} \geq 1 \end{bmatrix} \tag{7}$$

where $\sum_{i=1}^{n} v_i$ is the accumulated sediment volume from present shoreline to the pixel n, and V_{R+dR} and Q_e are the sediment volumes due to inundation R and storm erosion, respectively.

A Case Study

The study area, Fingal Bay Beach, is located two hundred kilometers north of Sydney (Figure 6). It was selected because it is typical of beaches in SE Australia. The beach is 1.5 km long. A DEM was generated from 1:25,000 contour and bathymetric maps with a grid of 10 m × 10 m cells, using a minimum-curve algorithm.

Two aspects of coastal hazards are investigated: (a) the effect of uncertainties in the input parameters on output uncertainties of the Coastal Recession Model (CRM) model; and (b) the combined effect of recession and storm erosion. The first part was examined for one section of the beach only, whereas the second was assessed for the whole beach.

Combined Effect of Storm Erosion with Recession

Equation (6) is a generalized form for calculating storm demand. It can be determined for a specific site based on the historical data. The k-factor is calibrated to achieve a storm demand of $Q_s = 250$ m^3 per meter of beach; which is regarded as the average of storm demand for SE Australia. Therefore Equation (6) as expressed for Fingal Bay Beach and becomes

$$Q_e = f(\mu_{exposure-i}) = 130\frac{S}{d_i}\log(x_i)\cos(\alpha)_i + 150. \tag{8}$$

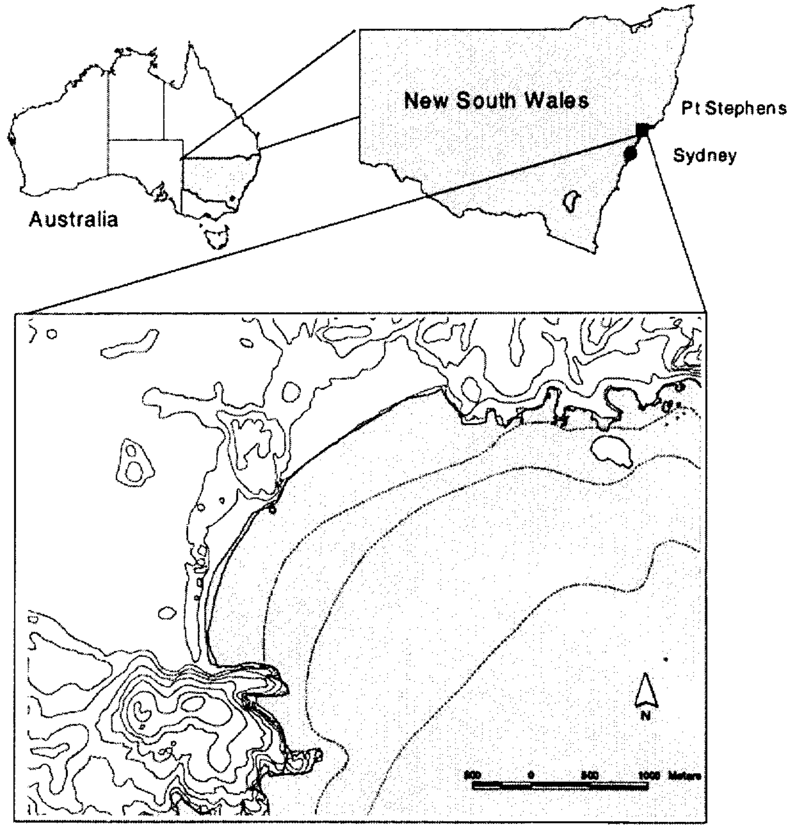

FIGURE 6 Location of the case study.

The total volume loss from the DEM per meter of beach is the sum $Q_e + V_{R+dR}$ along each meter of shoreline, and this total sediment volume is used to assign the probability of coastal hazard via Equation (7). In a modeled scenario of 0.86 m sea-level rise, the predicted recession caused by sea-level rise is only about 10% of the total shoreline retreat when recession and storm-erosion effects are combined: $\bar{R} = 12$ m averaged along the beach (52 m maximum). However, combined with storm erosion, the effect can be as great as 120 m, with an average of $Q_e + V_{R+dR} = 90$ m (maximum 120 m) (Figure 7).

Effect of Random Errors in the DEM

Sensitivity analysis was carried out to assess the effect of the error in the DEM by applying 10%, 15%, 20%, 25%, 30%, 35%, and 40% error to the DEM through random simulation. The results show that the output uncertainty decreases slightly with application of larger random errors to the DEM (Figure 8). This can be explained by the fact that the random errors can be either positive or negative, thus tending to cancel each other. As random errors increase, the "residual error" decreases because the output uncertainty is an algebraic sum of the individual, projected uncertainties (Zeng and Cowell 1999).

Effect of Uncertainties in the Input Parameters on Output Uncertainty

Results of differential analysis on how uncertainties in the input parameters affect output uncertainty indicate that increase in sea-level rise and decrease in closure depth contribute

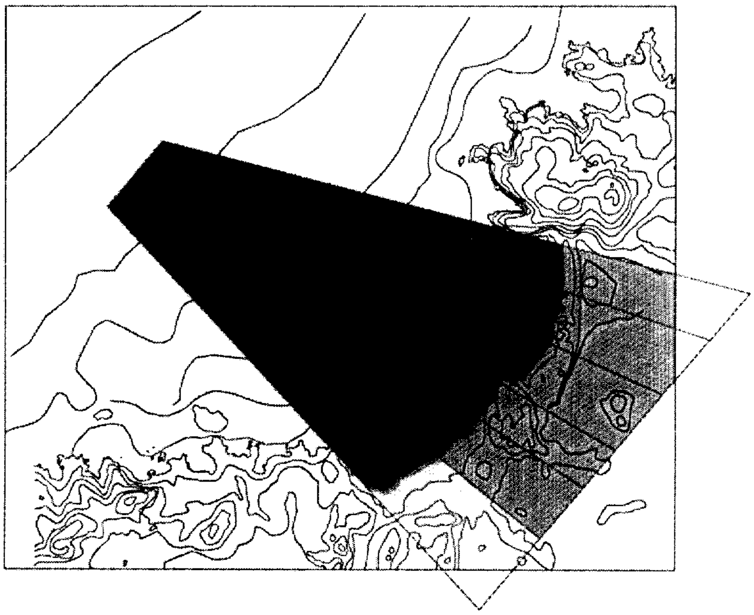

FIGURE 7 Modeled coastal hazard area (recession + storm erosion) for all directions of incident waves.

the largest portion of uncertainty in predicting coastal hazard (Figure 9). Uncertainty associated with sea-level rise (z) and closure-depth (h) are amplified along the profile-length (L) axis because the effects of both variables are mediated by the width of the submarine profile responding to sea-level rise. That is, for a given closure depth and sea-level rise, lower bed slope gives a longer submarine profile over which sand is displaced from the dune, amplifying not only the offshore sand demand and hence predicted shoreline recession, but also its uncertainty (Figure 9).

Output uncertainties relate closely to single variables and their combination as multivariables. The results confirm that the projection of the multivariable uncertainty onto the output uncertainty equals the algebraic sum of the output uncertainties for respective single variables (Zeng and Cowell 1999).

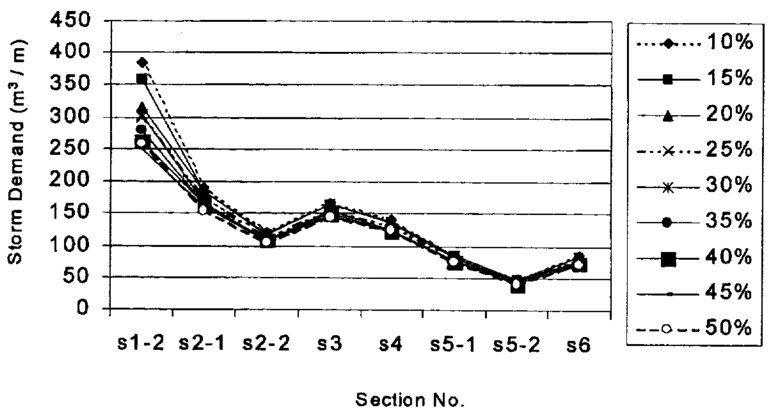

FIGURE 8 Simulation of DEM errors.

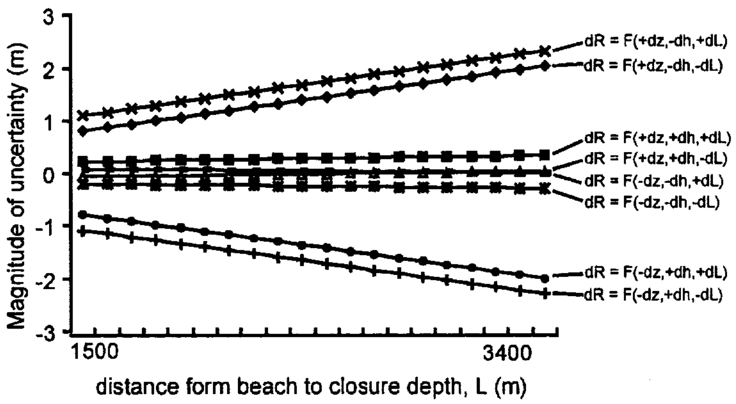

FIGURE 9 Projection of multivariable uncertainty.

Discussion and Conclusions

In this study, different uncertainty handling methods were used to address different aspects of uncertainties, integrated into the overall modeling framework as a series of modules. Inputs for successive modules derive from outputs from preceding modules in the series: specifically, the results of (a) random simulation can be averaged into values of an interval ($-Z - +Z$), which can be used as input to (b) the differential approach, from which results can be translated into (c) a fuzzy term and combined with the result from (d) the storm erosion module. Regarding the fuzzy term, the fuzzy-membership function can be constructed using the nature of the random uncertainties: that is, the shape of the cumulative probability curve can be used as a guide in deciding the form of the membership function (e.g., sigmoidal form and transition rate).

Theory and results from the case study demonstrate that differential, fuzzy set, and random simulation methods can be combined with a simplified coastal-response model to predict geomorphic-hazard probability due to coastal impact of climate change. The case study indicates the method of integration is robust in assessing spatial distribution of the hazard along the coast and cost-efficient for hazard assessments of extensive coastal areas.

Sensitivity analysis confirms that the projection of the multivariable uncertainty onto the modeled output uncertainty equals the algebraic sum of the output uncertainties of respective single variables. This means that the magnitude of modeled uncertainty is not necessarily increased due to larger uncertainties in the input parameters: it can be increased or reduced. The reduction is most likely due to a "compensation-effect" among the input uncertainties, contrary to conventional opinion that greater uncertainty in input parameters results in greater uncertainty in modeled output (shown mathematically by Zeng and Cowell 1999). Although the modeled multivariable uncertainty is aggregated in the worst scenario, they are more typically reduced by the compensation-effect.

It is impossible to verify and validate environmental models since they apply to open systems (Oreskes 1994). Moreover, environmental prediction is based on the unprovable assumption that "the future will like the past" (Simon 1996). The model presented in this article is not an exception. Nevertheless, the practicality of the GIS-based model presented here can be assessed through sensitivity analysis and used to supplement empirical analysis, common sense, and expert knowledge in coastal-hazard assessment and scenario evaluation.

References

Banks, J., and J. S. Carson. 1984. *Discrete-event system simulation.* New Jersey: Prentice-Hall.

Bruun, P. 1962. Sea level rise as a cause of shore erosion. *J. of Waterways Harbour Division*, American Society of Civil Engineering 88:117–130.

Cardwell, H., and H. Ellis. 1996. Model uncertainty and model aggregation in environmental management. *Applied Mathematical Modelling* 20(2):121–134.

Church, J. A., J. S. Godfrey, D. R. Jackett, and T. J. McDougall. 1991. Model of sea level rise caused by ocean thermal expansion. *J. of Climate* 4:438–456.

Couriel, E. D., R. J. Cox, J. T. Carley, and B. Build. 1993. Methods for storm cut estimation: A review. *Proceedings of NSW Coastal Management Conference.* Kiama, NSW, 1–9.

Cowell, P. J., P. S. Roy, and R. A. Jones. 1992. Shoreface translation model: Computer simulation of coastal-sand-body response to sea level rise. *Mathematics and Computers in Simulation* 33:602–608.

Cowell, P. J., and B. G. Thom. 1994. Morphodynamics of coastal evolution. In *Coastal evolution: Late quaternary shoreline morphodynamics*, edited by R. W. G. Carter and C. D. Woodroffe, pp. 33–86. Cambridge: Cambridge University Press.

Cowell, P. J., P. S. Roy, and R. A. Jones. 1995. Simulation of large-scale coastal change using a morphological behaviour model. *Marine Geology* 126:45–61.

Cowell, P. J., P. S. Roy, T. Q. Zeng, and B. G. Thom. 1996. Relationships for predicting coastal geomorphic impacts of climate change. *Proceedings of International Conference on Ocean and Atmosphere Pacific*, Adelaide, October, 1995. Adelaide: National Tidal Facility, 16–21.

Cowell, P. J., D. J. Hanslow, and J. F. Meleo. 1999. The shoreface. In *Handbook of beach and shoreface morphodynamics*, edited by A. D. Short, pp. 37–71. Chichester: Wiley.

Daniels, R. C. 1996. An innovative method of model integration to forecast spatial patterns of shoreline change: A case study of Nags Head, North Carolina. *Professional Geographer* 48(2):195–209.

Dean, R. G., and E. M. Maurmeyer. 1983. Models for beach profile response. In *CRC handbook of coastal processes and erosion*, edited by P. D. Komar, pp. 151–166. Boca Baton, FL: CRC Press.

Dean, R. G. 1990. Beach response to sea level change. In *Ocean engineering science*, edited by B. Le Mehaute and D. M. Danes, pp. 869–887. New York: Wiley.

Douglas, B. C., M. S. Kearney, and S. P. Leatherman, eds. 2000. *Sea level rise: History and consequences.* San Diego: Academic Press.

Edelman, T. 1970. Dune erosion during storm conditions. *Proceedings 12th International Conference on Coastal Engineering*, American Society of Civil Engineering, pp. 1305–1307.

Gordon, A. D. 1987. Beach fluctuations and shoreline change—NSW. *Proceedings of the 8th Australiasian Conference on Coastal and Ocean Engineering*, Lauceston, 30 Nov.–4 Dec. 1987, pp. 103–107.

Gordon, A. D. 1988. A tentative but tantalizing link between sea-level rise and coastal recession in New South Wales, Australia. In *Greenhouse planning for climate change*, edited by G. Pearman, pp. 121–134. CSIRO Australia.

Gornitz, V. 1995. Sea-level rise: A review of recent past and near-future trends. *Earth Surface Processes and Landforms* 20:7–20.

Granger, K. 1995. Measuring Vulnerability. *GIS User* 13:29–30.

Gregory, J. M. 1993. Sea level changes under increasing atmospheric CO_2 in a transient couple ocean-atmospheric GCM experiment. *J. of Climate* 6:2247–2262.

GSC (Geophysics Study Committee). 1990. *Sea-level change.* Washington, DC: Commission on Physical Sciences, Mathematics and Resources, National Research Council, National Academy Press.

Henderson-Sellers, A. 1993. An antipodean climate of uncertainty? *Climate Change* 25:203–224.

Hennecke, W. G. 2000. *GIS-based modelling of potential sea-level rise impacts on coastal re-entrants and adjacent shorelines.* PhD Thesis, School of Geosciences, University of Sydney.

Hickey, R. J., D. Bush, and R. Boulay. 1999. GIS applications in coastal risk assessment. *Cartography* 28(2):11–20.

IPCC. 1995. *Climate change 1995: The science of climate change*. Intergovernmental Panel on Climate Change. New York: Cambridge University Press.

IPCC. 2001. *Climate change 2001: The scientific basis*. Contribution of Working Group I to the third assessment report of the Intergovernmental Panel on Climate Change. Cambridge: Cambridge University Press.

Komar, P. D., N. Landfredi, M. Bada, R. G. Dean, K. Dyer, T. Healy, N. Ibe, J. Terwindt, and B. G. Thom. 1991. The response of beaches to sea level changes: A review of predictive models. Scientific Committee on Ocean Research (SCOR) Working Group 89. *J. of Coastal Research* 7:895–921.

Lee, J. K., R. A. Park, and P. W. Mausel. 1992. Application of geoprocessing and simulation modeling to estimate impacts of sea level rise on the northeast coast of Florida. *Photogrammetric Engineering and Remote Sensing* 58:1579–1586.

Li, R., J. K. Liu, and Y. Felus. 1999. Spatial modeling and analysis for shoreline change detection and coastal erosion monitoring. *J. of Marine Geodesy* 24:1–12.

Li, Z. 1993. Theoretical models of the accuracy of digital terrain models: An evaluation and some observations. *Photogrammetric Record* 14(82):651–660.

Li, Z. 1994. A comparative study of the accuracy of digital terrain models (DTMs) based on various data models. *Photogrammetry and Remote Sensing* 49(1):2–11.

Lpez, C. 1979. Locating some types of random errors in Digital Terrain Models. *Int. J. Geographical Info. Sci.* 11(7):677–698.

Nairn, R. B. 1991. Problems associated with deterministic modelling of extreme beach erosion events. *Proceedings of Coastal Sediments' 91*, pp. 588–602.

Oreskes, N., K. Shrader-Frechette, and K. Belitz. 1994. Verification, validation, and confirmation of numerical models in the earth sciences. *Science* 263:641–645.

Polidori, L., and J. Chorowicz. 1993. Comparison of bilinear and Brownian interpolation for digital elevation models. *Photogrammetry and Remote Sensing* 48(1):18–23.

Pritchard, J. I., and H. M. Adelman. 1991. Differential equation based method for accurate model approximations. *AIAA J.* 29:484–486.

Roy, P. S., P. J. Cowell, M. A. Ferland, and B. G. Thom. 1994. Wave dominated coasts. In *Coastal evolution: Late quaternary shoreline morphodynamics*, edited by R. W. G. Carter and C. D. Woodroffe, pp. 121–186. Cambridge: Cambridge University Press.

Rubinstein, R. Y. 1982. *Simulation and the Monte Carlo method.* New York: Wiley.

Schut, G. H. 1976. Review of interpolation methods for digital terrain model. *The Canadian Surveyor* 3(5):389–412.

Short, A. D. 1979. Three-dimensional beach-stage model. *J. of Geology* 87:553–571.

Short, A. D., P. J. Cowell, M. Cadee, W. Hall, and B. van Dijk. 1996. Beach rotation and possible relation to the Southern Oscillation. *Proceedings International Conference on Ocean and Atmosphere Pacific*, Adelaide, October 1995, pp. 329–334.

Smith, B. H. 1994. Coastal setback and the impact of water amenities. *Geographical Analysis* 26(4):364–369.

Simon, H. A. 1996. *The sciences of the artificial*, 3rd ed. Cambridge, MA: MIT Press.

Stive, M. J. F., H. J. De Vriend, P. J. Cowell, and A. W. Niedoroda. 1995. Behavior-oriented models of shoreface evolution. *Proceedings of Coastal Dynamics' 95*, ASCE, pp. 998–1005.

Thom, B. G., and W. Hall. 1991. Behaviour of beach profiles during accretion and erosion dominated periods. *Earth Surface Processes and Landforms* (16):113–127.

Vellinga, P. 1983. Predictive computational modelling for beach and dune erosion during storm surges. *Proceedings of ASCE Specialty Conference Coastal Structure '83*, pp. 806–819.

Vellinga, P. 1986. *Beach and dune erosion during storm surge*. PhD Thesis. Delft University of Technology (Publication No. 131), Delft Hydraulics, Delft, The Netherlands.

Weggel, R. J. 1979. *A method for estimating long-term erosion rates from a long-term rise in water level. Coastal Engineering Technical Aid 97-2.* U.S. Army Corp. Coastal Engeering.

Woodroffe, C., and D. Nash. 1995. Sea level. *Progress in Physical Geography* 19(3):391–398.

Zeng, T. Q., P. J. Cowell, B. G. Thom, and Z. X. Zeng. 1997. Modeling the coastal impact of climate change under uncertainties. *Tropical Geomorphology* 18(1):36–53.

Zeng, T. Q., and P. J. Cowell. 1999. Assessing uncertainties in modeling coastal recession due to sea level rise. In *Spatial accuracy assessment—Land information uncertainty in natural resources,* edited by K. Lowell and A. Jaton, pp. 79–88. Michigan: Ann Abor Press.

Zimmermann, H. J. 1991. *Fuzzy set theory and its applications,* 2nd ed. MA: Kluwer Academic Publishers.