ELSEVIER

Geomorphology 40 (2001) 253–269

GEOMORPHOLOGY

www.elsevier.com/locate/geomorph

Coastal cliff recession: the use of probabilistic prediction methods

E.M. Lee [a,*], J.W. Hall [b], I.C. Meadowcroft [c]

[a] *Department of Marine Science and Coastal Management, University of Newcastle, Ridley Building, Newcastle-upon-Tyne NE1 7RU, UK*
[b] *Department of Civil Engineering, University of Bristol, Bristol, UK*
[c] *Environment Agency, National Centre for Risk Analysis and Options Appraisal, Steel House, 11 Tothill Street, London SW1H 9NF, UK*

Received 20 July 2000; received in revised form 6 February 2001; accepted 6 February 2001

Abstract

A range of probabilistic methods is introduced for predicting coastal cliff recession, which provide a means of demonstrating the potential variability in such predictions. They form the basis for risk-based land-use planning, cliff management and engineering decision-making. Examples of probabilistic models are presented for a number of different cliff settings: the simulation of recession on eroding cliffs; the use of historical records and statistical experiments to model the behaviour of cliffs affected by rare, episodic landslide events; the adaptation of an event tree approach to assess the probability of failure of protected cliffs, taking into account the residual life of the existing defences; and the evaluation of the probability of landslide reactivation in areas of pre-existing landslide systems. These methods are based on a geomorphological assessment of the episodic nature of the recession process, together with historical records.

Keywords: Cliff recession; Landslides; Landslide modelling; Historical records; Geomorphological mapping

1. Introduction

Recession of coastal cliffs presents significant risks to people and property. For example, Sunamura (1992) reports that problems of average cliff recession rates in excess of 1 m/year are experienced at coastal sites in Denmark, Germany, Russia, Japan, New Zealand, Canada, the UK and the USA. Although individual failures generally tend to cause only small amounts of cliff retreat, the cumulative effects can be dramatic. For example, the Holderness coast, England, has retreated by around 2 km over the last 1000 years, destroying at least 26 villages listed in the Domesday survey of 1086. Average recession rates are around 2 m/year, although up to 20 m may be lost in a single year at a particular site (Valentin, 1954; Lee, 1997a). Large sums of money have been invested in erosion control schemes in an attempt to prevent the loss of cliff top properties, services and infrastructure and to mitigate the risk to public safety and the distress associated with coastal landsliding. In England, for example, there are some 860 km of coast protection works, with over £20 million spent each year on maintaining and improving these defences, and providing new schemes.

An awareness of the possible cliff position at some future date is fundamental to coastal planning and management. Reliable predictions of future recession rates are needed to support the formulation of land-use planning policies that avoid locating new

* Corresponding author. Tel.: +44-191-222-5607; fax: +44-191-222-5095.
E-mail address: e.m.lee@ncl.ac.uk (E.M. Lee).

0169-555X/01/$ - see front matter
PII: S0169-555X(01)00053-8

development in areas where erosion is likely to occur during the lifetime of the building. In those situations where coast protection works or improvements may be required, estimates of future recession rates are needed to evaluate options for the installation or replacement of erosion control measures. The economic justification of capital schemes for controlling cliff erosion depends crucially on the accurate prediction of cliff recession rates both with and without the scheme in place (Hall et al., 2000).

Various approaches to predicting cliff recession have been adopted, ranging from extrapolation of historic recession data to methods which rely on understanding of the cliff recession process, for example methods which relate incident wave energy and cliff strength parameters to recession rate (e.g., Gelinas and Quigley, 1973; Thornton et al., 1987; Kamphuis, 1987; Mano and Suzuki, 1998). Bray and Hooke (1997) presented a variety of empirically based methods, including the modified Bruun Rule (Bruun, 1962) for predicting recession rates with accelerating sea-level rise. On the whole these approaches provide deterministic predictions of cliff recession and do not reflect the potential uncertainty and variability in the cliff recession process.

This paper presents a number of examples of the way in which probabilistic prediction methods have been developed by the authors during the course of a UK Ministry of Agriculture, Fisheries and Food research project (Hutchison et al., 1998; Rendel Geotechnics, in press) to address a range of cliff recession problems, including:

- A probabilistic model for the simulation of recession on eroding cliffs;
- the use of historical records and statistical experiments to model the behaviour of cliffs affected by rare, episodic landslide events;
- the adaptation of event tree approaches to assess the probability of failure of protected cliffs, taking into account the residual life of the existing defences;
- methods for evaluating the probability of landslide reactivation in areas of pre-existing landslide systems.

A key feature of these methods is the recognition of the episodic nature of cliff recession at many coastal sites. In other words, cliff recession proceeds primarily via occasional landslide episodes followed by periods of relative inactivity, which may last for more than 100 years on some coastlines (Lee, 1998). This is very different from the continuous process that has been implicit in many previous approaches to predicting cliff recession. The process is complex and far from random. Recession is not an inevitable consequence of the arrival of a storm that removes material from the cliff toe or raises groundwater levels in the cliff. In order to fail the cliff must already be in a state of deteriorating stability, which makes it prone to the effects of an initiating storm event. At other sites there may be an ongoing 'base flux' of erosion of the cliff on a day-to-day basis, on which occasional major landslide episodes (the 'event flux') are superimposed.

2. Example 1: an eroding cliffline

Although the projection of historical rates into the future is the most obvious approach to prediction, there can be significant limitations to this method. The historical record consists of a series of measurements made, typically, five times or less over the last 100 years or so and, as such, is often insufficient to explain the pattern of recession events (probably of different size) that led to the cumulative land loss between the measurement dates or the sequence of preparatory and triggering events that generated the individual recession event. The historical record can, at best, reveal only a partial picture of the past recession processes. This may be adequate in some circumstances, but in many others there will be a need to expand this picture through an understanding of the contemporary cliff behaviour (Lee, 1997b). Of particular importance is an awareness of how a cliff has responded to past weather and wave conditions, notably the size and style of the range of recession events that can occur (i.e., the retrogression potential), and the timing and sequence of recession events (i.e., the recurrence interval).

The scarcity of historical cliff position data can limit the usefulness of many conventional statistical methods, such as linear regression. One approach to addressing this problem is the development of probabilistic models to simulate the recession process,

based on Monte Carlo sampling and considering cliff recession as an episodic random process (Hall et al., in press). In other words, cliff recession is assumed to proceed by means of a series of discrete landslide events, the size and frequency of which are modelled as random variables. A discrete model for the probabilistic cliff recession, X_t during duration t is

$$X_t = \sum_{i=1}^{N} C_i$$

where N is a random variable representing the number of cliff falls that occur in duration t, and C_i is the magnitude of the ith recession event.

This model can be used to simulate synthetic time series of recession data, which conform statistically to the cliff recession measurements. Three typical realisations of the model are shown in Fig. 1. The time series are stepped reflecting the episodic nature of the cliff recession process. Multiple realisations of the simulation are used to build up a probability distribution of cliff recession.

The model is defined by two distributions.

1. An *event timing distribution* describes the timing of recession events. The model incorporates physical understanding of the cliff recession process by representing the role which storms have in destabilising cliffs and initiating recession events. Note that in this example it is assumed that recession is driven by storm events; in other instances, groundwater and other factors will be important. The approach has links to renewal theory (Cox, 1962) inasmuch as the cliff is considered to be progressively weakened by the arrival of storms. The arrival of damaging storms is assumed to conform to a Poisson process, i.e. successive storms are assumed to be independent incidents with a constant average rate of occurrence. After a number of storms of sufficient severity, a cliff recession event occurs. The time between successive recession events can therefore be described by a gamma distribution. The shape of this distribution is defined by a scaling parameter λ (the reciprocal of the return period of the significant storm event) and a shape parameter k (the number of storms above a certain threshold which cause damage to the toe of the cliff that is sufficiently severe to trigger failure).

2. An *event size distribution* describes the magnitude of recession events in terms of the mean size and their variability. The form and parameters of this distribution should reflect the frequency distribution of actual cliff failures and is likely to be site specific. The model developed here uses a log-normal distribution, following the conclusions of the wave basin tests on a model cliff undertaken by Damgaard and Peet (1999). A log-normal distribution is non-negative which corresponds to the non-existence of negative cliff recession events. The probability density rises to a maximum value, and then approaches zero as the recession distance becomes large, i.e. very large cliff recession events are unlikely. Under specific geomorphological circumstances it may be possible to justify the use of another distribution. Sel-

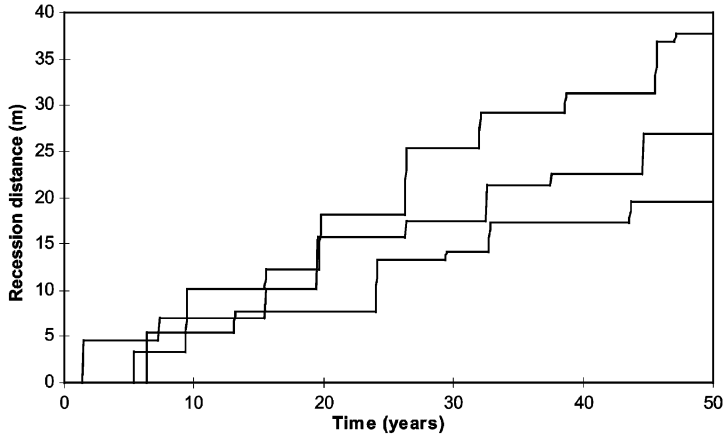


Fig. 1. Typical realisations of the two-distribution simulation model (see text for explanation of the model).

Table 1
Historic recession data for sample site in Kent, southern England (average annual recession rates expressed in m/year)

	1907–1929	1929–1936	1936–1962	1962–1991	1907–1991
Cliff section 1	0.09	1.50	1.31	0.00	0.57
Cliff section 2	2.09	2.00	0.31	0.06	0.83
Cliff section 3	1.63	0.57	0.00	0.34	0.57
Cliff section 4	0.91	0.57	0.23	0.31	0.48
Cliff section 5	0.64	0.28	0.31	0.28	0.50
Cliff section 6	0.00	0.28	0.15	0.34	0.19
Cliff section 7	0.09	0.00	0.54	0.18	0.24
Cliff section 8	1.27	0.00	0.54	0.00	0.26
Mean	0.84	0.65	0.42	0.19	0.45
Standard deviation	0.72	0.68	0.38	0.14	0.20

dom is there sufficient historic data to conclusively identify a preferred distribution on the basis of data alone.

The cliff recession model is therefore characterised by four parameters, λ and k from the gamma distribution, and the mean, μ and variance, δ of the log-normal distribution. The model is fitted to historic data at the site up to the second moment, leaving two remaining degrees of freedom which have to be established from geomorphological analysis of the cliff site. There is, therefore, scope to include geomorphological knowledge of event size and timing, which may not necessarily be revealed by the historic data record.

Table 2
Two realisations of the two-distribution simulation model, giving cliff recession in m/year (compare the mean and standard deviations with historical data in Table 1)

	1907–1929	1929–1936	1936–1962	1962–1991	1907–1991
Realisation 1					
Cliff section 1	0.00	0.00	0.18	0.37	0.18
Cliff section 2	0.26	0.36	0.75	0.88	0.63
Cliff section 3	0.85	0.60	0.68	0.36	0.61
Cliff section 4	0.23	0.90	0.20	0.77	0.46
Cliff section 5	0.40	0.43	0.51	0.39	0.44
Cliff section 6	0.05	0.07	0.30	0.40	0.25
Cliff section 7	0.76	0.00	0.70	0.45	0.57
Cliff section 8	1.34	1.64	0.24	0.54	0.75
Mean	0.49	0.50	0.45	0.52	0.49
Standard deviation	0.43	0.52	0.23	0.19	0.18
Realisation 2					
Cliff section 1	0.34	0.60	0.42	0.42	0.42
Cliff section 2	0.58	0.74	0.90	0.69	0.73
Cliff section 3	0.53	0.94	0.38	0.53	0.52
Cliff section 4	0.97	0.00	0.46	0.67	0.63
Cliff section 5	0.50	0.51	0.08	2.53	1.07
Cliff section 6	0.13	0.00	0.28	0.13	0.17
Cliff section 7	0.20	0.39	0.31	0.24	0.27
Cliff section 8	0.54	0.19	0.22	0.97	0.56
Mean	0.47	0.42	0.38	0.78	0.55
Standard deviation	0.24	0.32	0.23	0.71	0.26

This method has been tested using historical recession data for 20-m high cliffs, in Sussex, southern England, developed in sandstones overlain by Wadhurst Clay. The position of the cliff top was obtained from 1:2500 scale historical maps at years 1907, 1929, 1936, 1962 and 1991. Cliff top locations were extracted at eight positions along the coast, covering a total length of about 400 m. For each 'epoch' between map dates, the mean recession rate (m/year) was calculated for each of the eight locations. In addition, overall recession rates from 1907 to 1991 were calculated. For each of the five measurement periods, the standard deviation of recession rate between the different locations was calculated as well as the mean rate (Table 1).

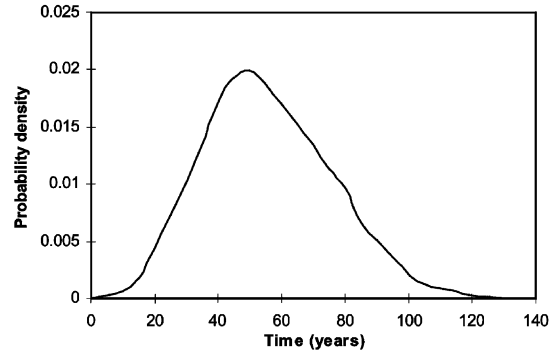
Geomorphological assessment highlighted the characteristics of cliff-fall events, averaging around 3 m in size. The event-size distribution was, therefore, set as a log-normal distribution with a mean value of 3 m. A standard deviation of 3 m was required to generate sufficient variability within the simulated data sets.

The event timing distribution was chosen using a maximum likelihood parameter estimation model (Hall et al., in press), with parameters $k = 2$ and $\lambda = 0.3$, i.e. two storm events each of a return period of 3.33 years will cause a recession event. With more frequent events, the statistical model would not generate sufficient variability as compared with the data. Furthermore, the number of zero recession rates in the data record indicated that the characteristic time between recession events was quite long. For example, during the 7-year period from 1929 to 1936, two of the locations showed no recession at all, indicating a significant probability (about 0.25) that the interval between recession rates could be greater than 7 years. This type of reasoning was used to constrain the simulation model parameters.

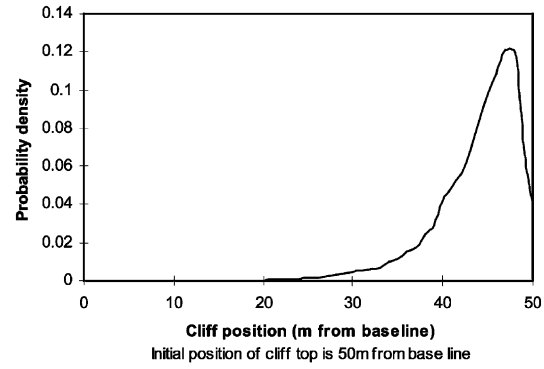
Table 2 shows results of two simulations from the calibrated model. These were obtained by simulating the time period 1907–1991 and extracting results at the relevant years so that these could be compared directly with the measured values. As this is a sampling approach, different simulations give different results, so the two example simulations shown in Table 2 give different individual values. Nevertheless, the general characteristics of the model results are similar to the measured values in Table 1.

The statistical model was then used to make probabilistic predictions of:

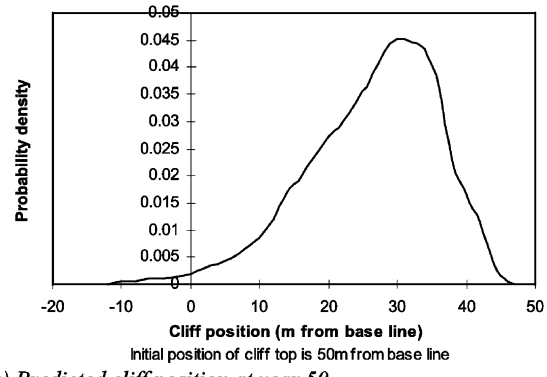
- the time for the cliff to undergo recession of a certain distance, to assess when in the future a hypothetical fixed asset currently 29 m from the cliff top will be lost (Fig. 2a);



a) Predicted time to recess by 29m



b) Predicted cliff position at year 10



c) Predicted cliff position at year 50

Fig. 2. Sample results from the two-distribution model. (a) Predicted time to recess by 29 m. (b) Predicted cliff position at Year 10. (c) Predicted cliff position at Year 50.

- the cliff position after 10 and 50 years (Fig. 2b and c). Cliff position is measured relative to a fixed baseline. The baseline is 50 m landward of the initial cliff position, so greater than 50 m recession appears as a negative value (i.e., it is landward of the baseline).

Since these are numerical simulation results the final distribution is not completely smooth.

The stochastic simulation model has a number of fundamental advantages over conventional regression analysis. The method incorporates an episodic model of recession events, which can be closely related to known cliff behaviour. In addition, knowledge about cliff behaviour can be included in the model, in terms of the frequency and magnitude of events and the observed of variability in these aspects.

3. Example 2: a rare major coastal landslide event

On some coastlines the recession process is dominated by rare, single landslide events, rather than the repeated sequences of regular events modelled in the previous example (although from a short-term perspective all recession occurs through single episodic events). In these cases, the historical frequency of landslides can provide an indication of the future probability of such events and the basis for modelling the "survival probability" of the cliffline. For example, Lee et al. (1998a) used this historical frequency approach to assess the landslide risk on the South Cliffs at Scarborough, on the northeast coast of England. The cliffs had been protected by seawalls, drained and landscaped around 100 years ago. However, they were the scene of the dramatic and unexpected Holbeck Hall landslide in 1993, which led to the destruction of a large hotel (Clements, 1994; Clark and Guest, 1994; Lee, 1999). The landslide raised concerns about the level of risk on adjacent parts of South Cliff and the threat that such events pose to the coastal defences and cliff-top property.

South Cliff comprises 50- to 60-m high cliffs developed in glacial till (25–40 m thick) over sandstones, siltstones and mudstones of the Scalby Formation. The 1-km long cliffline can be subdivided into eight separate cliff sections dominated by two contrasting geomorphological units: large landslide features and the intervening intact (i.e., unfailed) steep slopes. The history of landsliding in both of these settings was established through a search through journals, prints, reports, records and local newspapers (held on micro-fiche) archived at the Scarborough local library, and charts held at the Hydrographic Office, Taunton (Lee and Clark, 2000).

The historical frequency of failure of the intact steep slopes was estimated to be four events in 400 years (i.e., 1 in 100). Thus, the annual probability of failure (P_f) of any one of the eight original intact slopes was estimated to be: $P_f = 4/(8 \times 400) = 0.00125$ (1 in 800). The survival probability of the remaining four intact coastal slopes was modelled by Meadowcroft et al. (1999) as a series of repeated statistical trials involving only two possible outcomes: success (i.e., survival) or failure (i.e., landslide). The binomial distribution was used to estimate the probability that 1 or more cliff sections will survive in a particular time period. This distribution can be used for problems when:

- there is a fixed number of trials (i.e., cliff sections);
- the trials (cliff sections) are independent;
- the outcome (i.e., recession scenario) of any trial is either success or failure;
- the probability of failure is constant for each trial (i.e., each cliff section).

Fig. 3 presents the results of the simple binomial experiment undertaken to model the future behaviour of the four remaining intact slopes, over the next 250 years. It has been assumed that once one of the sections fails, it does not fail again. The experiment gives the probability of the number of successes (i.e., the number of cliff sections surviving) in a given number of trials (i.e., cliff sections) for each year. For example, the experiment suggests that, at Year 250, there is a 42% chance that three cliff sections will have survived (i.e., one failure) and a 23% chance that only two sections will survive. The method also predicts that there is a 0.5% chance that all four sections will have failed over this time period.

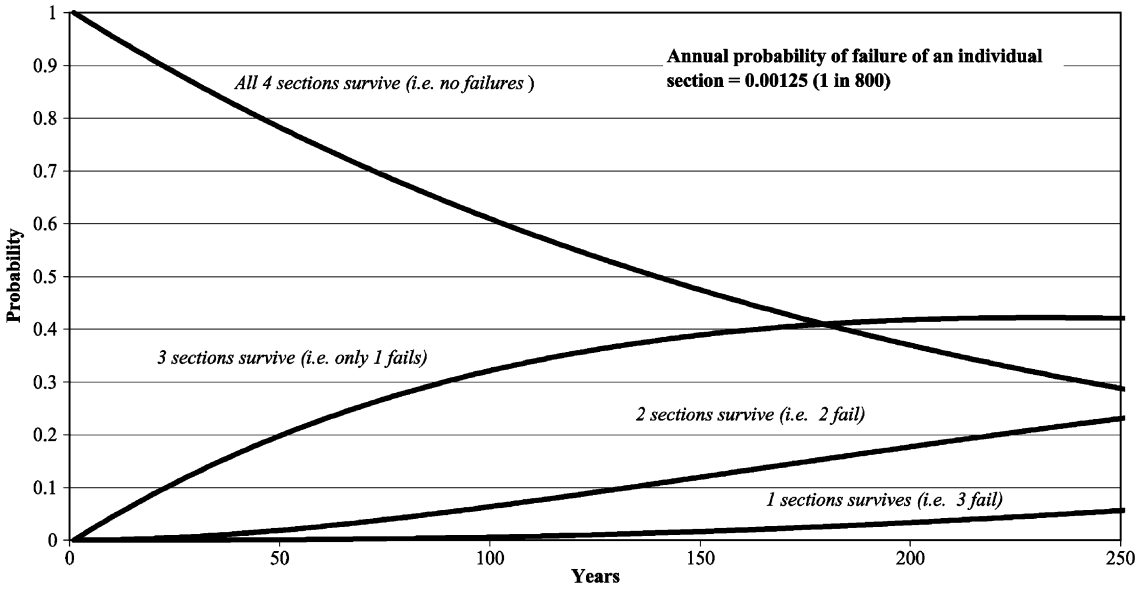


Fig. 3. Modelled survival probability of cliff sections, South Cliff Scarborough.

Although this is essentially a statistical prediction method, the key input parameters—the number of independent cliff sections and the annual failure probability—can best be obtained through an awareness of the historical cliff behaviour. The failure probability can also be obtained or verified through use of stability analysis (e.g., Bromhead, 1986).

4. Example 3: a protected cliff

Over the last 100 years, there has been a shift in the focus of cliff recession priorities in the UK away from providing defences for unprotected communities towards the maintenance and improvement of both the existing defences and the protected slopes behind (Lee, 1997a). It has become increasingly apparent that whilst the prevention of marine erosion at the cliff foot has reduced the potential for cliff recession and landsliding, it has not eliminated it. The internal slope processes of weathering, strain-softening, creep and the recovery of depressed pore water pressures can cause delayed failures many years later. Thus, long lengths of cliff in urban areas which are currently defended by toe protection works will not necessarily remain stable over the design lifetime of these structures. Problems may also be experienced as a result of the deterioration of the toe protection and associated slope stabilisation works.

This type of problem does not lend itself to conventional methods of extrapolating past recession rates, because defences may have prevented erosion for a long period. An alternative strategy is required, and it is suggested that the structured use of expert judgement and subjective probability assessment using event trees can be a useful tool in this context. Lee et al. (2000) present an example of such an approach developed to assess landslide risks at Lyme Regis on the south coast of England.

The coastal slopes at Lyme Regis are relict landslide systems which form the seaward part of larger coastal landslide systems. The slopes were covered with landslide debris and head deposits, probably formed during past phases of slope instability. The area is currently protected against marine erosion by concrete seawalls and promenades and a series of groynes that hold low shingle and sand beaches. However, the landslides have been experiencing progressive reactivation and future movements present a significant hazard to the local community. As part of a wider programme of studies of the landslides and coastal geomorphology (Clark et al., 2000; Sellwood et al., 2000; Fort et al., 2000), an assessment was made of possible landslide reactivation scenarios.

These scenarios provided a framework for assessing landslide risk and for testing the economic viability of different coast protection and landslide management options.

A range of landslide reactivation scenarios were identified (Fig. 4), each involving an inter-related sequence of events driven by an *initiating event* (i.e., seawall failure or high groundwater levels) and *propagating conditions* (e.g., high groundwater levels, progressive removal of toe support). These scenarios are based on an understanding of the causes and mechanisms of landslide behaviour, particularly the likely reactivation sequences and an in-depth appreciation of the stability of the landslide systems and the interrelationships between adjacent landslide units. In general, each scenario involves the progressive inland expansion of the zone of active instability, as pre-existing landslide units are unloaded, in turn, by the movement of the downslope landslide units (which provide passive support to the upslope units); each phase of reactivation is promoted by the occurrence of high groundwater levels.

Whilst these sequences of events might be expected at some time within the next 50 years (or not), the precise timing of the initiating events and subsequent responses will be controlled by the almost random occurrence of potential initiating events and the antecedent conditions at that time. In addition, the cliff conditions are progressively deteriorating, with the chance of failure expected to increase over time, due to a combination of the decline in structural integrity of the seawalls and the increased storminess and increased winter rainfall predicted to be associated with climate change.

The event tree approach involves tracing the progression of the various combinations of scenario components using logic tree techniques to identify a range of possible outcomes (e.g., Cox and Tait, 1991). The individual probability of achieving a certain outcome is the product of the annual probability of the causal factor and the conditional probabilities of subsequent responses and outcomes. For example, suppose an initiating event (E) has a probability $P(E)$. Given that this event occurs, the failure mechanism, M, has the probability $P(M|E)$. Likewise, the outcome O has a conditional probability $P(O|M)$. The probability of this scenario, or chain of events, occurring is:

$$\text{Scenario Probability} = [P(E)][P(M|E)][P(O|M)].$$

For each landslide system along the coastal frontage, a series of event trees (reflecting different initiating events) and associated estimates of scenario probabilities were established as follows:

1. *Identification and characterisation of landslide systems*. Detailed geomorphological mapping of the coastal slopes highlighted a series of discrete landslide units within broader landslide systems. Within each system there is a complex arrangement of individual landslide units which reflect the wide variety of landslide types and processes. The recognition of these units and systems formed a framework for

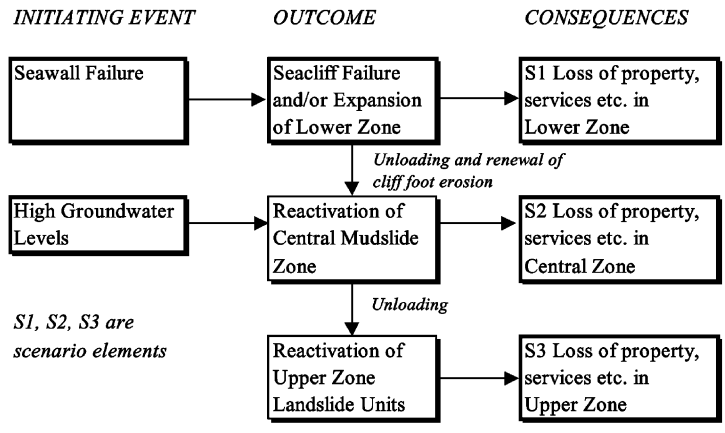


Fig. 4. Landslide reactivation scenario: East Cliff, Lyme Regis (after Lee et al., 2000).

understanding the contemporary ground behaviour of the Lyme Regis area which was later revised as a result of a detailed ground investigation (Sellwood et al., 2000).

2. *Identification of landslide reactivation scenarios*. Understanding of the contemporary ground behaviour of the landslide systems (i.e., surface mapping and subsurface geotechnical data), recent monitoring data (ground movements and piezometric levels; Fort et al., 2000), together with an analysis of past events was used to develop a range of credible reactivation scenarios at each site. Each scenario was developed from an initiating event (e.g., seawall failure, wet years/high groundwater levels), with subsequent responses and outcomes as the effects of the initiating event were transmitted through the adjacent landslide units. It should be noted that these scenarios are "do nothing" scenarios, in the sense that nothing is done to prevent an initiating event or to control the subsequent responses, i.e., landslide problems are allowed to develop unchecked.

3. *Development of event trees*. Each scenario comprised an initiating event followed by a response (Response 1). In turn, this response may act as an initiating event for a second response (Response 2) and so on. Ultimately the combination of initiating event and the responses will lead to a particular outcome (Scenario elements S1, S2, etc.). Each sequence of initiating event–response–outcome was simplified to a series of simple event trees (Fig. 5), with responses to a previous event either occurring or not occurring (i.e., yes/no options).

4. *Estimation of the annual probability of initiating events*. This involved the estimation of the likelihood of seawall failure and wet years/high groundwater levels in each year from Year 1 to Year 50. These initiating events were considered to be "once only" events in the sense that they would only initiate the sequence of events defined in the event tree once (i.e., once the slopes have been destabilised and affected by widespread movement, they could not be destabilised again). The annual probability of seawall failure was assessed at individual seawall sections by the local authority, West Dorset District Council, who also estimated an expected annual rate of increase in the chance of failure to reflect the

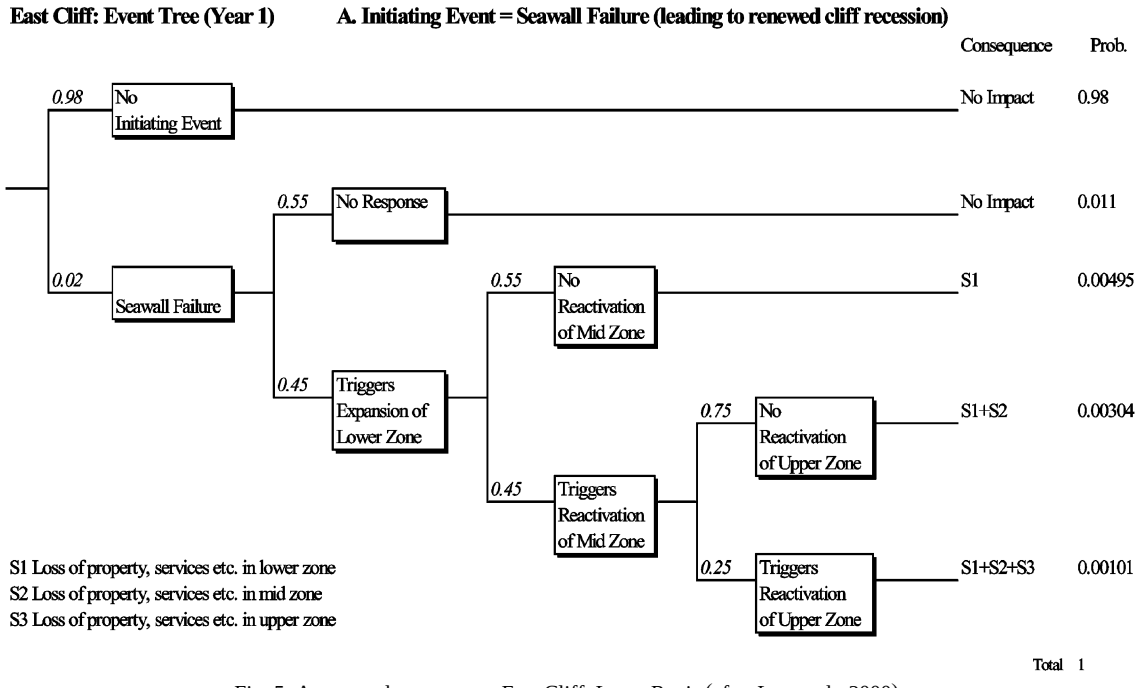


Fig. 5. An example event tree: East Cliff, Lyme Regis (after Lee et al., 2000).

gradual deterioration of the structures (under a do nothing scenario). There have been eight "wet year" sequences in 130 years, suggesting an annual probability of around 1 in 16 (0.06), with duration of 3–6 years. The frequency of these sequences (and possibly the duration) appears to have increased over the last 3 decades, suggesting a current annual probability of around 0.1 (1 in 10).

5. *Estimation of the annual probability of responses*. Annual probabilities were assigned to each of the event tree "branches" at each site, mindful that the sum of probabilities at each branch must equal 1.0. This was achieved by the "expert judgement" of the individual project team members and discussions to reach consensus on the "best-guess" figures.

Whilst expert judgement can be an effective tool it is important to stress that there can be problems in using this type of subjective approach, especially where it is undertaken by single individuals (see Roberds, 1990; Rendel Geotechnics, in press). A range of techniques are available for eliminating or reducing the effects of these potential problems, involving more rigorous individual assessments or group consensus. These techniques will help ensure that the judgements are defensible. The approach used to develop convergence or agreed consensus in this study were *open forum* and the so-called "*Delphi panel*". Open forum relies on the open discussion between team members to identify and resolve the key issued related to the recession problem. Delphi panel is a systematic and iterative approach to achieve consensus and has been shown to generally produce reasonably reproducible results across independent groups. In this example, each individual in the project team was provided with the same set of background information and is asked to conduct and document (in writing) a self-assessment. These assessments were then compiled to identify areas of disagreement and discussion. Typically, the individual assessments tended to converge after discussion. Such iterations were continued until consensus was achieved.

It was found through discussions that the most acceptable approach to identifying annual probabilities at "branches" was to identify a time period over which the team believed there was a 95% chance of the "failure" route being realised. This was used to identify a corresponding annual probability that would deliver this cumulative probability over the agreed time period (this assumes a *normal* distribution of events). The estimated annual probability, cumulative probability and the time by which an event is almost certain to have occurred are related as follows, assuming a normal distribution:

$$\text{Probability of Occurrence in } x \text{ years} = 1 - (1 - \text{annual probability})^{x}$$

6. *Calculation of conditional probabilities for each scenario*. For Year 1 (the initiating event and response occur in Year 1), the conditional probability associated with each "branch" of an event tree (i.e., a unique combination of scenario elements e.g., S1 + S2 + S3, etc.) was calculated as follows:

$$\text{Scenario Prob.} = [P(\text{Initiating Event})][P(\text{Response 1})] \times [P(\text{Response 2})][P(\text{Response } n).$$

For subsequent years (the initiating event and response occur in the same year), the calculation is essentially the same at the above, with the exception that the annual probability of the initiating event is changing over time (e.g., the estimated probability of seawall failure increases at 5% per year). In addition, the probability of a combination of scenario elements occurring in Year 2 needs to take into account the possibility that the scenario actually occurred in Year 1 and, hence, could not occur in Year 2. Thus, the annual probability for Year 2 (and subsequent years) was modified as follows:

$$(\text{Probability of failure in Year } i = \text{Annual Probability of failure Year } i) \times (\text{Prob. failure not occurred in year } i - 2 - \text{Prob. failure occurred year } i - 1).$$

However, a response might occur in any year after an initiating event, i.e. if the initiating event occurred in Year 1 the response could be in Year 1, Year 2 or any year up to Year 50. Thus, the combined probability of a response occurring in a particular year is a more complex problem. For example, the probability of the response occurring in Year 4 involves the combination of four possibilities: P(seawall failure in Year 1 and the response 3 years later) + P(breach

Site East Cliff: Failure Scenario A

Model Probability of Response 1 (Lower zone failure) following seawall failure

1 minus Probability S1 not occurred year 2

Year of Response	Annual Prob. Initiating Event	Prob. Response 1 Lower zone Event	Combined Probability: Initaiting event (Seawall failure) and Response 1 (lower zone reactivation) Year of Initiating Event 1	2	3	48	49	50	S1 Loss of Property Total Probability	Prob. S1 Year i	Prob. S1 Not Occurred	Cumulative Prob. S1
1	0.020	0.450	0.009						0.01	0.01	0.99	0.01
2	0.021	0.248	0.005	0.009					0.01	0.01	0.98	0.02
3	0.022	0.136	0.003	0.005	0.010				0.02	0.02	0.96	0.04
4	0.023	0.075	0.001	0.003	0.005				0.02	0.02	0.94	0.06
5	0.024	0.041	0.001	0.002	0.003				0.02	0.02	0.92	0.08
45	0.171	0.000	0.000	0.000	0.000				0.16	0.01	0.04	0.96
46	0.180	0.000	0.000	0.000	0.000				0.17	0.01	0.04	0.96
47	0.189	0.000	0.000	0.000	0.000				0.18	0.01	0.03	0.97
48	0.198	0.000	0.000	0.000	0.000	0.089			0.19	0.01	0.02	0.98
49	0.208	0.000	0.000	0.000	0.000	0.049	0.094		0.20	0.00	0.02	0.98
50	0.218	0.000	0.000	0.000	0.000	0.027	0.051	0.098	0.21	0.00	0.02	0.98
			0.020	0.021	0.022	0.165	0.145	0.098				

Prob(Initiating event year1) x Prob(Response 1 year3)

Prob(Initiating event year2) x Prob(Response 1 year4)

The Cumulative Probability of Response 1 occurring over next 47 years if the Initiating event occurs in year 3. Sum of column.

Probability of Scenario S1 occurring in Year 47 (Sum of row).

Probability of Scenario occurring in Year 48 x Probability that Scenario has not already occurred by previous year (year 47)

Probability Scenario 1 not occurred in Year 46 - Probability Scenario 1 occurs in Year 47

Fig. 6. An annotated example of the worksheet used to define the conditional probability of an outcome (scenario element S1) following an initiating event (seawall failure) and subsequent response (lower zone landslide reactivation) after Lee et al. (2000).

in Year 2 and response 2 years later) + P(breach in Year 3 and response 1 years later) + P(breach in Year 4 and response 0 years later). For the probability of the response in Year 50, there would be 50 combinations of probabilities.

The analysis has involved the development of a sequence of related worksheets for each landslide system. Each worksheet comprises a 50×50 matrix of probabilities derived from multiplying P(Initiating event) by P(Response) for all possible combinations of timings. Fig. 6 presents an annotated worksheet, which illustrates how the analysis was built up. The example produces the probability of Response 1 following the occurrence of an initiating event. The results from this sheet (the total probability column) then form the input data (along with the probability distribution for Response 2) to the next sheet, and so on. The results give an indication of the possible consequences of landslide reactivation within the various landslide systems along the Lyme Regis coast. They are not predictions about what will happen, rather they are plausible projections about what might happen if a particular combination of adverse conditions occur and are allowed to develop. As such, the results were important in supporting the economic evaluation of different coast protection options.

5. Example 4: coastal landslide reactivation

Many pre-existing landslide systems are sensitive to variations in groundwater levels and hence, sequences of wet and dry years. An assessment of the climatic influence on landslide activity can, therefore, be used to assess the probability of reactivation. Lee et al. (1998b) describe how a combination of landslide systems mapping, historical records and rainfall analysis provided a pragmatic tool for assessing the annual probability of significant ground movement events in different parts of a 12 km long ancient landslide (the Undercliff) on the south coast of the Isle of Wight. The relationship between landslide reactivation and rainfall was established as follows.

(i) Identification of landslide systems. Detailed geomorphological mapping, at 1:2500 scale, of the Undercliff has highlighted a series of discrete landslide units within broader landslide systems (Lee and Moore, 1991; Moore et al., 1995).

(ii) Analysis of historical records. Reports of past landslide events were identified by a systematic review of available records, including local newspapers (from 1855 to present day). Over 300 reported incidents have occurred over the last two centuries.

(iii) Analysis of rainfall records; a composite data set was derived from the various rain gauges that have operated within the Undercliff since 1839. The antecedent effective rainfall was calculated for 4-month periods between August and March (the wet period of the year), from 1839/1840 to present day —this being previously identified as a good measure of the prolonged periods of heavy rainfall that appear to control landslide activity in the Undercliff (Lee and Moore, 1991).

This data series was used to calculate the likelihood of different 4-month antecedent effective rainfall totals (4AER) occurring in any single year (i.e., the return period). Fig. 7 shows the winter rainfall totals that may be expected to be equalled or exceeded, on average, for particular recurrence intervals.

(iv) Assessment of threshold conditions. This involved relating the historical record for each landslide system to the 4AER data series to identify the minimum return period rainfall that is associated with landslide activity in a particular area. For example, in the westernmost system, Blackgang, significant movements are a frequent occurrence, and the minimum rainfall threshold needed to initiate significant movement appears, in the past, to have been 1 in 1.1 year event. The winter rainfall associated with recorded ground movement events in particular areas are indicated on Fig. 7 to highlight the varying degrees of sensitivity of different parts of the Undercliff.

(v) Assessment of the probability of landsliding. That ground movement does not always occur when the winter rainfall thresholds shown on Fig. 7 are exceeded highlights the importance of other factors in controlling landslide activity, i.e. preparatory and triggering factors. An assessment was made, therefore, of the annual probability of a 4AER of a particular magnitude actually triggering landslide activity. An estimate was made of the number of times a 4AER over a threshold value initiated landsliding

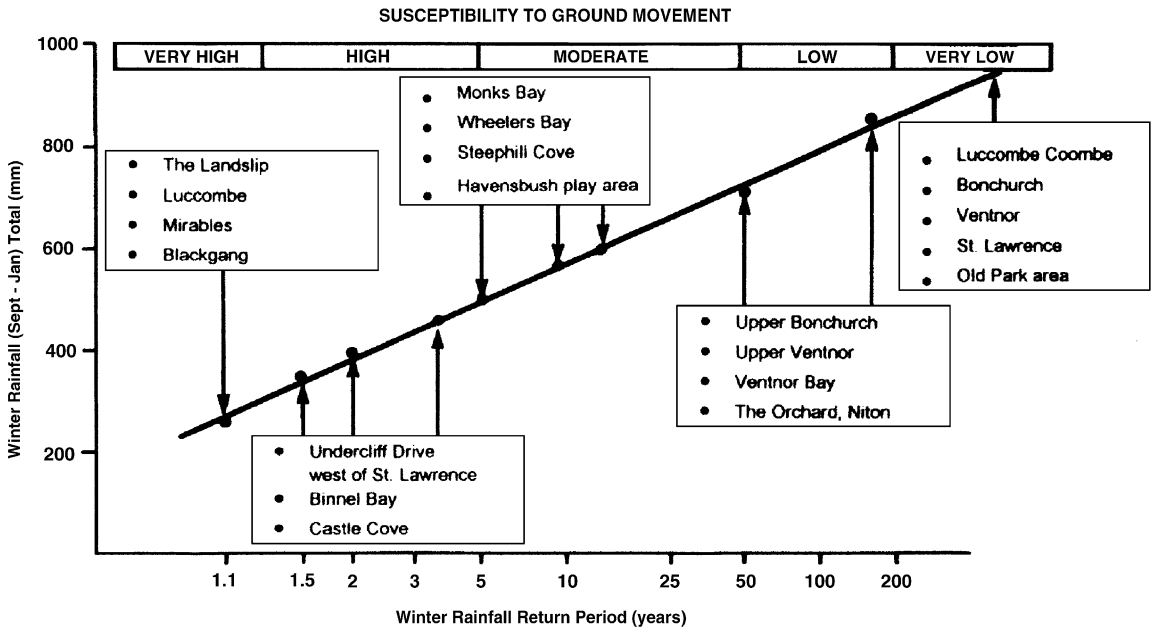


Fig. 7. Landslide sensitivity within the Isle of Wight Undercliff (after Lee et al., 1998b).

in a particular system, compared with the number of times this threshold had been exceeded over the last 150 years.

The conditional probability of significant ground movement in a particular landslide system was calculated as follows:

$$P_m = [P(4AER)][P(O \mid 4AER)]$$

P_m = the annual probability of ground movement in a system; $P(4AER)$ = the annual probability of a threshold 4AER being equalled or exceeded in a particular year; $P(O \mid 4AER)$ = the annual probability of an event given the occurrence of the threshold 4AER being equalled or exceeded.

Table 3 provides an indication of the estimated probabilities of significant movement in a number of parts of the Undercliff.

This assessment of the probability of significant movement has formed the basis for a pragmatic approach to landslide forecasting by the Isle of Wight Council. An understanding of the relationship between ground movement and rainfall has assisted the local authority in improving its landslide management response and advice that it can give to local

Table 3
An indication of the estimated annual probabilities of significant movement in a number of parts of the Isle of Wight Undercliff (after Lee et al., 1998b)

Location	Annual probability of threshold 4AER	Annual probability of threshold 4AER triggering movement	Estimated conditional probability of significant movement
Blackgang	0.9	0.1	0.09 (1 in 11)
Luccombe	0.25	0.2	0.05 (1 in 20)
Upper Ventnor	0.02	0.5	0.01 (1 in 100)
St. Lawrence	0.005	0.5	0.0025 (1 in 400)

residents as part of its "Landslide Management Strategy". Information available to date is used by the local authority staff to prepare for instability events at sensitive sites, taking account of continuous rainfall and ground movement readings which are linked to alarms by telemetry. This information, combined with the many years of practical experience and local knowledge of site staff, enables decisions to be made with respect to safety measures involving emergency response, evacuation and engineering works.

6. Discussion

Cliff recession is a complex process, involving minor events; small-scale losses associated with water and wind erosion, weathering and spalling off a cliff face, and episodic events; associated with the periodic failure of cliffs in response to preparatory factors, such as slope-profile steepening and triggering factors, such as large storms or periods of heavy rainfall. For example, at Black Ven, Dorset, there is an estimated 50- to 60-year "cycle" of major activity associated gradual increases in slope angle (Chandler and Brunsden, 1995; Brunsden and Chandler, 1996).

When a cliff fails, the displaced material moves to a new position so that equilibrium can be reestablished between the destabilising forces and the strength of the material. Landsliding, therefore, helps change a cliff from a less stable to a more stable state with a margin of stability. No subsequent movement or recession will occur unless the cliff is subject to processes that, once again, affect the balance of opposing forces. In many inland settings, cliffs and landslides can remain dormant or relatively inactive for thousands of years. However, on the coast, marine erosion removes material from the cliff foot, reducing the margin of stability, and promotes further recession. Thus, on any coastal cliff the margin of stability will vary through time; from a peak immediately after a recession event to progressively lower levels as marine erosion or other slope processes (e.g., weathering) affect the cliff stability (Fig. 8; Brunsden and Lee, 2000).

This perspective makes it possible to recognise two categories of factors that are active in promoting cliff recession:

(i) Preparatory factors which work to make the cliff increasingly susceptible to failure without

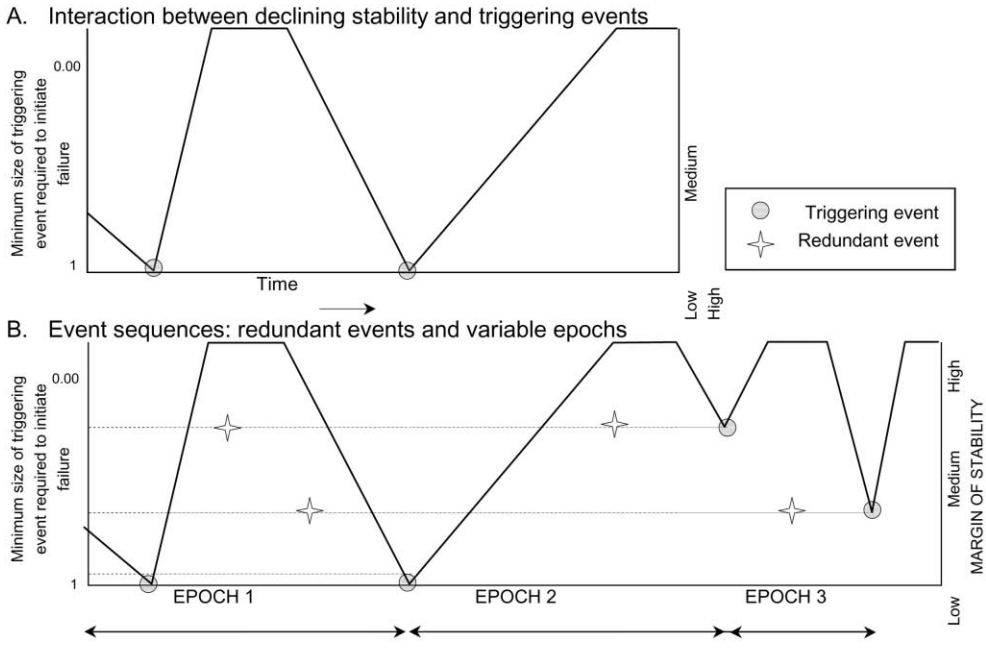


Fig. 8. A schematic illustration of the variable interaction between potential triggering events and landslides (from Brunsden and Lee, 2000).

actually initiating recession (e.g., the long-term effect of marine erosion at the cliff foot, weathering, etc.);
(ii) Triggering factors which actually initiate recession events (e.g., storm events).

Fig. 8 highlights the complex relationship between preparatory and triggering factors. There are rapid temporal changes in the margin of stability of coastal cliffs due to the superimposition of triggering factors on the trends imposed by relatively steady erosion at the base of the cliff. As the margin of stability is progressively reduced by the operation of preparatory factors, so the minimum size of triggering event required to initiate recession becomes smaller. Thus, triggering events of a particular magnitude may be *redundant* (i.e., do not initiate cliff recession) until preparatory factors lower the margin of stability to a critical value. As Fig. 8 indicates, this can mean variable time periods (epochs) between recession events, depending on the sequences of storm or rainfall events. In addition, the same size triggering events may not necessarily lead to recession events. The response of a cliff to storms of a particular size is controlled by the antecedent conditions. Cliff recession, therefore, does not conform particularly well to either the deterministic or the random model. Recession events are not independent but are influenced by the size and location of previous recession events. In other words cliff recession is a process with a 'memory' (insofar as the current and future behaviour is influenced by the effects of past events on the system) which means that it is not amenable to most common statistical models.

Cliff recession often appears to be a highly variable process, with marked fluctuations in the annual recession rate around an average value. From the short-term perspective, cliff recession is usually an uncertain and episodic process. However, as the outcomes are relatively certain (internal controls tend to limit the range of potential event sizes), the recession process becomes more predictable over time (i.e., as the sample time period increases). A time period will be reached over which an average recession rate will be delivered, reflecting a balance between the event size distribution of the cliff system and the almost-random wave energy inputs. However, the chaotic nature of the short-term forcing (e.g., Essex et al., 1987) and of geomorphological systems in general (e.g., Hallet, 1987; Furbish, 1988) suggests that there is a limit to the predictability of the recession process.

The pattern of past recession events is the result of a particular and unique set of wave, weather and environmental conditions. A different set of conditions could have generated a different recession scenario. The inherent randomness in the main causal factors (e.g., wave height, rain storms, etc.) dictates that future recession cannot be expected to be an accurate match with the historical records; it could, however, deliver a similar overall recession rate with comparable variability between measurements, trends and periodicity. Adopting a probabilistic framework for prediction can accommodate this uncertain relationship between past and future. Probabilistic methods, of the type highlighted in this paper, may be viewed as offering an improvement on conventional deterministic predictions because they aim to represent the variability and uncertainty inherent in the recession process.

7. Selection of appropriate probabilistic prediction methods

From the preceding text, it is clear that different probabilistic methods are suited to different cliff settings. The key influences on the choice of method are:

1. the nature of available information on cliff recession;
2. the cliff recession process at the site in question;
3. whether future conditions at the site are expected to resemble past conditions;
4. the amount of investigation and analysis which can be justified.

The nature of the cliff recession process influences the type of information that is available, so the first two determinants are closely related. For example, at a site characterised by very rare recession episodes followed by long periods of stasis, the historic record, which may include only one landslide event, will be of little value in statistical terms. Under those circumstances the recession prediction

will be guided by information about the recession potential at the site and similar sites, and will include an important element of expert judgement. By contrast, at a site with rapid cliff recession there may well be an informative time series of cliff recession data for statistical prediction, which can be combined with expert knowledge and perhaps modelling of the recession process.

The amount of investigation and analysis that can justifiably be invested in the prediction is a function of the stage in the decision-making process (e.g., strategy planning, feasibility study, detailed design of erosion control measures, etc.) and the level of risk at the site. Coastal zone management planning decisions will need to be supported by a general indication of probable future trends whilst engineering of scheme options will require more detailed analysis. Detailed probabilistic predictions are likely to be best suited to situations where there is a clear but uncertain risk to property or public safety.

Wherever possible, more than one method should be adopted to provide and indication of the robustness of the predictions. In some situations, it will be appropriate to undertake progressively more sophisticated predictions as and when additional information or resources become available.

References

Bray, M.J., Hooke, J., 1997. Prediction of soft-cliff retreat with accelerating sea-level rise. J. Coastal Res. 13, 453–467.

Bromhead, E.N., 1986. The Stability of Slopes. Surrey Univ. Press, London.

Brunsden, D., Chandler, J.H., 1996. Development of an episodic landform change model based upon the Black Ven mudslide, 1946–1995. In: Anderson, M.G., Brooks, S.M. (Eds.), Advances in Hillslope Processes, vol. 2, Wiley, Chichester, pp. 869–896.

Brunsden, D., Lee, E.M., 2000. Understanding the behaviour of coastal landslide systems: an inter-disciplinary view. In: Bromhead, E.N., Dixon, N., Ibsen, M.-L. (Eds.), Landslides: In Research, Theory and Practice. Thomas Telford, London.

Bruun, P., 1962. Sea-level rise as a cause of shore erosion. J. Waterw. Harbours Coastal Eng. Div., Am. Soc. Civ. Eng. 88, 117–130.

Chandler, J.H., Brunsden, D., 1995. Steady state behaviour of the Black Ven mudslides: the application of archival analytical photogrammetry to studies of landform change. Earth Surf. Processes Landforms 20, 255–275.

Clark, A.R., Guest, S., 1994. The design and construction of the Holbeck Hall landslide coast protection and cliff stabilisation emergency works. Proceedings of the 29th MAFF Conference of River and Coastal Engineers, Loughborough, UK, pp. 3.3.1–3.3.6.

Clark, A.R., Fort, D.S., Davis, G.M., 2000. The strategy, management and investigation of coastal landslides at Lyme Regis, Dorset, UK. In: Bromhead, E.N., Dixon, N., Ibsen, M.-L. (Eds.), Landslides: In Research, Theory and Practice. Thomas Telford, London, pp. 278–286.

Clements, M., 1994. The Scarborough experience—Holbeck landslide, 3–4 June 1993. Proceedings of the Institution of Civil Engineers, Municipal Engineers 103, 63–70.

Cox, D.R., 1962. Renewal Theory. Methuen, London.

Cox, S.J., Tait, N.R.S., 1991. Reliability, Safety and Risk Management: An Integrated Approach. Butterworth-Heinemann, Oxford.

Damgaard, J.S., Peet, A.H., 1999. Recession of coastal soft cliffs due to waves and currents: experiments. Proceedings of Coastal Sediments '99. 4th International Symposium on Coastal Engineering and Science of Coastal Sediment Processes, Long Island, NY, pp. 1181–1191.

Essex, C., Lookman, T., Nererberg, M.R.H., 1987. The climate attractor over short time scales. Nature 326, 64–66.

Fort, D.S., Clark, A.R., Savage, D.T., 2000. Instrumentation and monitoring of the coastal landslides at Lyme Regis, Dorset, UK. In: Bromhead, E.N., Dixon, N., Ibsen, M.-L. (Eds.), Landslides: In Research, Theory and Practice. Thomas Telford, London, pp. 573–578.

Furbish, D.J., 1988. The river meandering process: evidence for nonlinear chaos. Geol. Soc. Am. Abstr. Progr. 20, A362–363.

Gelinas, P.J., Quigley, R.M., 1973. The influence of geology on erosion rates along the north shore of Lake Erie. Proceedings of the 16th Conference of Great Lakes Research, pp. 421–430.

Hall, J.W., Lee, E.M., Meadowcroft, I.C., 2000. Risk-based benefit assessment of coastal cliff recession. ICE/IAHR J. Water, Marit. Energy 142, 127–139.

Hall, J.W., Meadowcroft, I.C., Lee E.M., van Gelder P.H.A.J.M., in press. Stochastic simulation of episodic soft cliff recession. Proc. Inst. Civ. Eng.

Hallet, B., 1987. On geomorphic patterns with a focus on stone circles viewed as a free-convection phenomenon. In: Nicolis, C., Nicolis, G. (Eds.), Irreversible Phenomena and Dynamic Systems Analysis in Geosciences. NATO ASI. Kluwer, Dordrecht, pp. 533–553.

Hutchison, J., Lee, E.M., Meadowcroft, I.C., 1998. Recession of soft cliffs: prediction and control. Proceedings of the 33rd MAFF Conference of River and Coastal Engineers, Keele, pp. 3.1.1–3.1.10.

Kamphuis, J.W., 1987. Recession rate of glacial till bluffs. ASCE J. Waterw., Port, Coastal Ocean Eng. 113, 60–73.

Lee, E.M., 1997a. Landslide risk management: key issues from a British perspective. In: Cruden, D., Fell, R. (Eds.), Landslide Risk Assessment. Balkema, Rotterdam, pp. 227–237.

Lee, E.M., 1997b. The investigation and management of soft rock cliffs. Proceedings of the 31st MAFF Conference of River and Coastal Engineers, Keele, pp. B.1.1–B.1.12.

Lee, E.M., 1998. Problems associated with the prediction of cliff

recession rates for coastal defence. In: Hooke, J.M. (Ed.), Coastal Defence and Earth Science Conservation. Geological Society Publishing, Bath, pp. 46–57.

Lee, E.M., 1999. Coastal planning and management: the impact of the 1993 Holbeck Hall Landslide, Scarborough. East Midlands Geogr. 21, 78–91.

Lee, E.M., Clark, A.R., 2000. The use of archive records in landslide risk assessment: historical landslide events on the Scarborough coast, UK. In: Bromhead, E.N., Dixon, N., Ibsen, M.-L. (Eds.), Landslides: In Research, Theory and Practice. Thomas Telford, London, pp. 904–910.

Lee, E.M., Moore, R., 1991. Coastal Landslip Potential: Ventnor, Isle of Wight. Department of the Environment, London.

Lee, E.M., Clark, A.R., Guest, S., 1998a. An assessment of coastal landslide risk, Scarborough, UK. In: Moore, D., Hungr, O. (Eds.), Engineering Geology: The View from the Pacific Rim. Balkema, Rotterdam, pp. 1787–1794.

Lee, E.M., Moore, R., McInnes, R.G., 1998b. Assessment of the probability of landslide reactivation: Isle of Wight Undercliff, UK. In: Moore, D., Hungr, O. (Eds.), Engineering Geology: The View from the Pacific Rim. Balkema, Rotterdam, pp. 1315–1321.

Lee, E.M., Brunsden, D., Sellwood, M., 2000. Quantitative risk assessment of coastal landslide problems, Lyme Regis, UK. In: Bromhead, E.N., Dixon, N., Ibsen, M.-L. (Eds.), Landslides: In Research, Theory and Practice. Thomas Telford, London, pp. 899–904.

Mano, A., Suzuki, S., 1998. A dimensionless parameter describing sea cliff erosion. Proceedings of the 26th International Conference of Coastal Engineers, Copenhagen.

Meadowcroft, I.C., Hall, J.W., Lee, E.M., Milheiro-Olveira, P., 1999. Coastal cliff recession: development and application of prediction methods. HR Wallingford Report SR 549, Wallingford.

Moore, R., Lee, E.M., Clark, A.R., 1995. The Undercliff of the Isle of Wight: a review of ground behaviour. South Wight Borough Council.

Rendel Geotechnics, in press. The Investigation and Management of Soft Rock Cliffs in England and Wales. Thomas Telford, London.

Roberds, W.L., 1990. Methods for developing defensible subjective probability assessments. Transp. Res. Rec. 1288, 183–190.

Sellwood, M., Davis, G.M., Brunsden, D., Moore, R., 2000. Ground models for the coastal landslides at Lyme Regis, Dorset, UK. In: Bromhead, E.N., Dixon, N., Ibsen, M.-L. (Eds.), Landslides: In Research, Theory and Practice. Thomas Telford, London, pp. 1361–1366.

Sunamura, T., 1992. The Geomorphology of Rock Coasts. Wiley, Chichester.

Thornton, E.B., McGee, T., Tucker, S.P., Burych, D.M., 1987. Predicting erosion of the recessive Monterey Bay shoreline. Proceedings of Coastal Sediments '87, New Orleans. American Society of Civil Engineers, New York, pp. 1809–1825.

Valentin, H., 1954. Der landverlust in Holderness, Ostengland von 1852 bis 1952. Die Erde 6, 296–315.