

Predicting coastal cliff erosion using a Bayesian probabilistic model

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ABSTRACT

Regional coastal cliff retreat is difficult to model due to the episodic nature of failures and the along-shore variability of retreat events. There is a growing demand, however, for predictive models that can be used to forecast areas vulnerable to coastal erosion hazards. Increasingly, probabilistic models are being employed that require data sets of high temporal density to define the joint probability density function that relates forcing variables (e.g. wave conditions) and initial conditions (e.g. cliff geometry) to erosion events. In this study we use a multi-parameter Bayesian network to investigate correlations between key variables that control and influence variations in cliff retreat processes. The network uses Bayesian statistical methods to estimate event probabilities using existing observations. Within this framework, we forecast the spatial distribution of cliff retreat along two stretches of cliffed coast in Southern California. The input parameters are the height and slope of the cliff, a descriptor of material strength based on the dominant cliff-forming lithology, and the long-term cliff erosion rate that represents prior behavior. The model is forced using predicted wave impact hours. Results demonstrate that the Bayesian approach is well-suited to the forward modeling of coastal cliff retreat, with the correct outcomes forecast in 70–90% of the modeled transects. The model also performs well in identifying specific locations of high cliff erosion, thus providing a foundation for hazard mapping. This approach can be employed to predict cliff erosion at time-scales ranging from storm events to the impacts of sea-level rise at the century-scale.

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1. Introduction

Coastal erosion is a worldwide societal issue and problems associated with it are expected to increase with rising in sea levels. With the recognition of the hazards facing coastal development, there is an increasing interest in models that forecast or predict where the highest hazards will be, whether from the gradual sea-level rise or large storm events. Existing models that forecast coastal response to sea-level rise or high water levels (i.e. storm surge or swell) are typically geometric models that focus mainly on sandy and dune-backed coasts (Bruun, 1962; Komar et al., 1999). Along geologically and geomorphically variable coasts such as are found along the U.S. west coast, there is a need to model both sandy beaches and coastal cliff systems. Existing geometric models for predicting erosion rates on bluff or cliffed coasts typically apply a modified Bruun Rule (Bray and Hooke, 1997), whereas similar but empirically driven models rely on historical water level data in conjunction with cliff toe elevations (Ruggiero et al., 2001) to establish potential erosion hazard zones. Sunamura (1982) combined empirically derived data from wave tank experiments with measurements of cliff geometry, material strength and wave frequency distributions to

predict cliff erosion rates. More simplistically, hazard zones are delineated by a linear forward projection of historic rates (Moore et al., 1999; Priest, 1999). All of these models and methods focus on climatologically averaged predictions but generally do not account well for the spatial and temporal variability and uncertainty of cliff retreat processes.

Recently, there has been a focus on the development of statistical and probabilistic models of coastal cliff retreat of which Lee et al. (2001) provide detailed examples. A conclusion they reach is that cliff retreat is not amenable to statistical forecasting models because each retreat event is not independent (i.e. each event is influenced by previous events) but that a probabilistic model can accommodate the spatial and temporal uncertainty inherent to the process of cliff retreat. Hall et al. (2002) utilized probabilistic models to predict the maximum likelihood distributions of cliff failure based on a time series of historic cliff retreat data, and additionally developed a Bayesian probabilistic model based on historical retreat rates, recent observations and expert assessments of the expected recession frequencies. They generated a probability density function of cliff retreat for various future time periods (22 to 84 yr), but the output was not in the form of geospatial data suitable for generating hazard maps, nor do they provide a verification of the model output.

The Bayesian approach is well-suited to the prediction of cliff retreat due to its ability to include prior (e.g., historic) information and to address the complexity of the feedback mechanisms inherent

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in cliff failure processes. In addition it addresses the existing difficulties in correlating the multiple variables that influence the process and is able to infer the relationships between them. As noted previously, cliff retreat is not a continuous process; it occurs episodically and is difficult to predict. A model must track the cliff evolution to account for the fact that a cliff must have an unstable geometry to fail, but after failure it may be in a stable configuration for a long period of time. In a Bayesian network, variables such as cliff geometry can be updated as changes occur, and more information can be added to the model as it becomes available.

Bayesian statistics have been used in the geosciences for several decades, mainly in the seismic and landslide hazard communities. The heavy computational requirements of calculating joint probability distributions using Bayesian methods limited its application until recently with the accessibility of fast and powerful computers and availability of software compatible with most standard desktop computers. Examples of seismic applications include the use of Bayesian statistics to generate extreme-value distributions of earthquake occurrences (Cambell, 1982; Stavrakakis and Drakopoulos, 1995) in California and Greece, respectively. Additionally, Oh et al. (2008) apply Bayesian methods to develop early warning systems for earthquakes, and Amiri and Tabatabaei (2008) use a Bayesian approach in earthquake risk assessment studies. Gritzner et al. (2001) employ a Bayesian probability model to help identify which variables are most important in watershed-scale landslide risk assessments. Lee et al. (2002), Demoulin and Chung (2007), and Miller et al. (2007) develop geospatial landslide susceptibility models based on Bayesian statistics. Dahal et al. (2008) assessed the predictive performance of Bayesian statistics to map landslide hazards and found a prediction accuracy greater than 88%.

Coastal cliff failure and accompanying cliff edge retreat are similar in behavior to earthquakes and landslides, exhibiting nonlinear behavior with occurrences that are episodic in both time and space. Few studies have been conducted that explore the use of Bayesian methods to predict future behavior of coastal systems (Hall et al., 2002; Plant and Holland, in press). In this study, we apply a Bayesian network to model the probability of coastal cliff retreat in two study areas located in Southern California. Cliff retreat within a study area along the San Diego coast (Fig. 1) is modeled over a 3-yr time period and a study area in Santa Barbara is modeled over a 7-yr time period.

2. The Bayesian model

An advantage of a Bayesian inference approach is that it can be used to combine multiple parameters to make statistically robust forecasts. Additionally, unlike more classical inferential models, Bayesian models permit the incorporation of prior knowledge, and a Bayesian network allows the utilization of conditional probabilities in the predictive model.

Bayes rule is expressed as:

$$p(F_i|O_j) = p(O_j|F_i)p(F_i) / p(O_j), \tag{1}$$

where the left-hand term is the updated conditional probability (or 'posterior probability') of a forecast, F_i , given a particular set of observations, O_j . In the case of this study, we are forecasting the probability distributions of cliff erosion on a number of transects

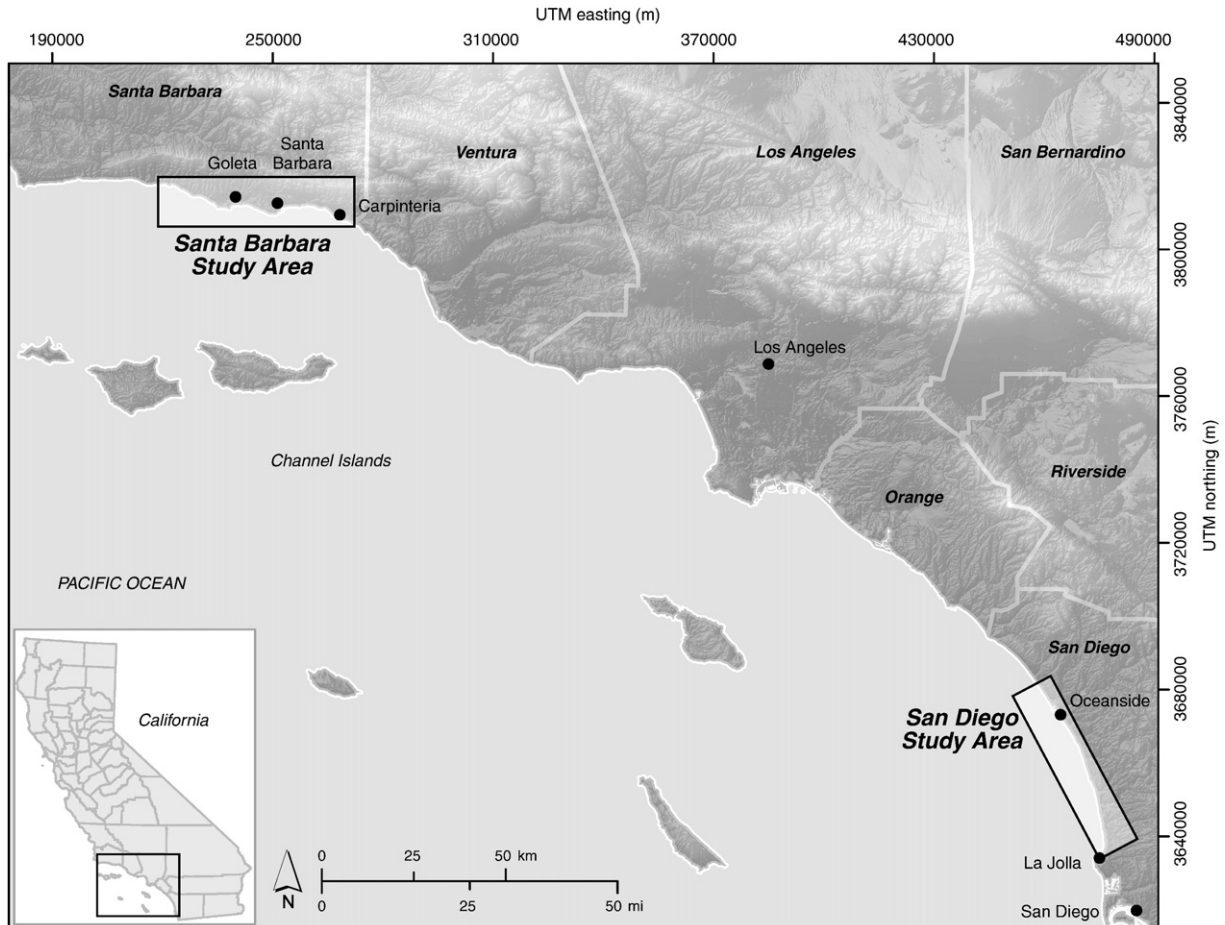


Fig. 1. Location map of study areas in Southern California.

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