



Brief communication

“Evaluating European Coastal Evolution using Bayesian Networks”

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Abstract. The coastal zone is a complex environment in which a variety of forcing factors interact causing shoreline evolution. Coastal managers seek to predict coastal evolution and to identify regions vulnerable to erosion. Here, a Bayesian network is developed to identify the primary factors influencing decadal-scale shoreline evolution of European coasts and to reproduce the observed evolution trends. Sensitivity tests demonstrate the robustness of the model, showing higher predictive capabilities for stable coasts than for eroding coasts. Finally, the study highlights the need to update and expand large-scale coastal data sets, particularly by including local scale processes and anthropogenic impacts.

1 Introduction

The evaluation of coastal vulnerability has received increasing attention in recent years due to observations of coastal erosion, pressure from coastal urbanization, and increased concerns about the impacts of sea-level rise and climate change (Nicholls et al., 2007). In a review of physical coastal vulnerability studies, Cooper and McLaughlin (1998) concluded that the majority of these studies were designed to improve local coastal management or to characterize the potential future response to climate change or sea-level rise (e.g. Nicholls and Klein, 2005; Nicholls and de la Vega-Leinert, 2008; Hinkel and Klein, 2009).

Evaluating coastal evolution on large spatial scales and incorporating the effects of a variety of factors requires integrating knowledge of coastal landforms and processes (Finkl, 2004; Pearson et al., 2005). Coastal vulnerability indices have been developed to aggregate factors such as sea-level rise, coastal elevation, historical shoreline movement,

geology, geomorphology, wave height, tide range, beach slope, vegetation, and coastal defenses (e.g. Gornitz et al., 1994; Shaw et al., 1998; Coelho et al., 2006). However, one challenge is to evaluate the relative importance of each factor.

The objective of the current study is to make statistical predictions of European shoreline evolution with a Bayesian network (BN) approach and to identify the most important factors contributing to the predictions. The BN approach has been used in a variety of different applications, from studies of artificial intelligence to ecological systems (Berger, 2000), and recent work has applied this approach in the coastal domain (Hapke and Plant, 2010; Gutierrez et al., 2011; Plant and Holland, 2011). The current article, following Gutierrez et al. (2011), presents the construction of a BN model (Sect. 2) evaluating European shoreline evolution trends (Sect. 3), the derived model and its sensitivity (Sect. 4), and a summary of the study implications (Sect. 5).

2 Bayesian network design

The BN approach is based on the application of Bayes’ theorem (Bayes, 1763), which relates the probability (p) of an event (F_i) to the occurrence of another event (O_j):

$$p(F_i|O_j) = p(O_j|F_i)p(F_i)/p(O_j). \quad (1)$$

In this study, a BN was constructed using six variables (Fig. 1) similar to those used in previous coastal vulnerability studies (e.g. Thieler, 1999; Coelho et al., 2006; Gutierrez et al., 2011). The causal relationships (black arrows, Fig. 1) were predetermined based on physical knowledge of coastal systems. The geology, mean significant wave height (H_s), relative sea-level rise rate (SLR), and mean tidal range impact the geomorphology through the erodibility of

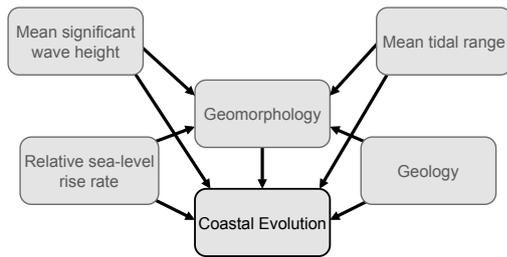


Fig. 1. Bayesian network: the black arrows indicate causal relationships linking the forcing factors (gray) and the response variable (coastal evolution, black).

the sediments and underlying substrata, wave action causing sediment transport, and profile adjustments to the current mean sea level. Additionally, all five factors are also considered to impact directly the coastline evolution.

3 Data

The coastal database developed during the EUROSION project¹ divided the European coastline into segments with uniform geology, geomorphology, and shoreline evolution characteristics. They estimated shoreline evolution using available maps, reports, aerial photographs, and observations to calculate trends over a five to ten-year period. The database also includes offshore wave, tide, and relative sea-level rise data. The wave and tidal data were calculated from ARGOSS databases. Relative sea-level rise estimations were made by extrapolating values estimated from tide gauge data by Douglas et al. (2001) and Lambeck et al. (1998).

In this study, the EUROSION data were preprocessed for use in the Bayesian network. The offshore data were interpolated alongshore to correspond to the coastline segments. Due to data quality issues, coastline segments designated as having man-made structures or lacking complete data were removed. The geomorphology was divided into four classes: rocky cliffs and platforms, erodible (e.g. chalk) cliffs, beaches, and wetlands; the geology was divided simply into two categories: hard and soft sediments (depending on the erosion potential). The shoreline evolution data were classified as eroding, stable, or accreting. The continuous data variables were discretized by quantiles into four bins. These observations were then used to calculate the conditional occurrence probabilities of a given shoreline evolution for each combination of variables using the Netica software package (Norsys Software Corp., v4.16).

¹Data and further details available from the European Environment Agency (<http://www.eea.europa.eu/data-and-maps/data/>)

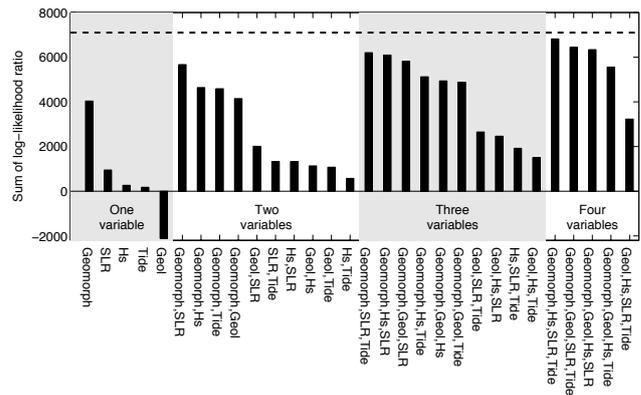


Fig. 2. The sum of the log-likelihood ratio (LR) for tests using between one and four variables. The horizontal dashed line indicates the sum of the LR when all five variables are used.

4 Model performance

A predictive model was created by assigning to each combination of variables the event (erosion, stability, or accretion) with the maximum probability (p), resulting in both a prediction and a level of uncertainty (p ranges from 36 to 99 %). No model prediction is made when no data are available or when all events have the same probability. This simple model correctly reproduces 65 % of the observations.

The log-likelihood ratio (LR) is a second way of estimating the model performance by measuring the improvement in the prediction probability when using the model (Gutierrez et al., 2011):

$$LR = \log[p(F_i | O_j)] - \log[p(F_i)]. \quad (2)$$

The LR is positive when the updated prediction is greater than the prior prediction, indicating that the updated distribution is either more accurate (the distribution corresponds to the observations) or more precise (the distribution is narrower). The LR ratio is positive for approximately 70 % of all observations in this study.

4.1 Sensitivity tests

The sensitivity of the BN was tested by comparing the percentage of correctly reproduced observations ($P_{\text{corr}} = 65\%$) and the percentage of observations with a LR greater than zero ($P_{\text{LR}>0} = 70\%$) of the original model with model variations. In the first test, from two to ten bins were used to discretize the continuous data. P_{corr} ranged from 57 to 69 %, and $P_{\text{LR}>0}$ ranged from 60 to 75 %, showing that the model is relatively insensitive to the number of discretization bins. A second test comparing different discretization methods (quantiles, the mean plus or minus one to two standard deviations, and manual discretization) showed no significant differences in the model results (P_{corr} and $P_{\text{LR}>0}$ varied by approximately 5 %). A third set of tests evaluated the

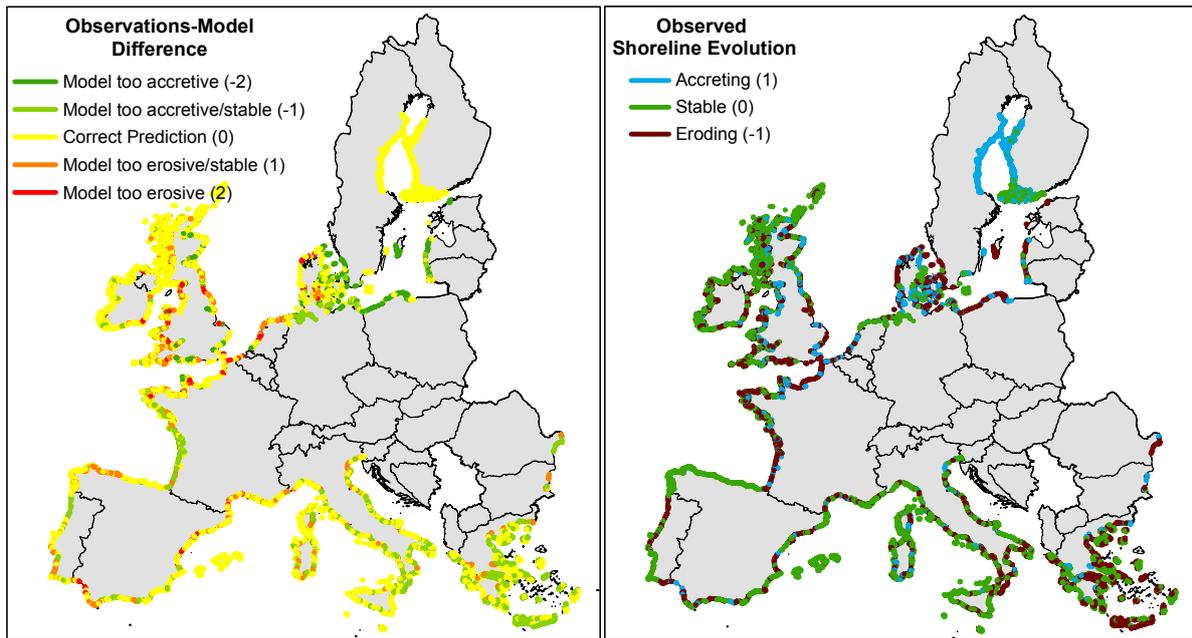


Fig. 3. Spatial distribution of (left) the difference between the Bayesian Network model “prediction” and the observations of coastal shoreline evolution, and (right) the observed shoreline evolution.

significance of the predictions by randomizing the shoreline evolution outcomes (eliminating any physical explanation of the trends) and by creating an entirely randomized data set (with the same range of values as the observations). P_{corr} dropped to 30 % and 10 %, and $P_{\text{LR}>0}$ dropped to 25 % and 10 %, for these two tests, respectively, defining the significance level of the model.

To evaluate the importance of each variable, individual models were created using all combinations of between one and four variables to predict the coastline evolution. The model performance was compared by evaluating the sum of the LR of each model. With a one-variable model, the LR sum is greatest when using the geomorphology (by a factor of three or four), and with two to four-variable models, the LR sum decreases rapidly within each category when the geomorphology is excluded (Fig. 2). In the one and two-variable models, sea-level rise is the second most important variable, with only slight differences between adding the wave height, tide level, or geology. P_{corr} only increases from 72 to 76 % with two to five-variable models, and the relative increase in the LR sum is small (Fig. 2), suggesting that the BN can identify the most likely outcome with relatively few variables. However, a reduction in the number of variables would also decrease the outcome probabilities and thus the reliability of the model.

4.2 Predictive ability

In the previous examples, all of the observations (> 17 000) were used to determine the model probabilities, and the

model skill was evaluated by reproducing the observed shoreline evolution. A more relevant test of a coastal management model is its predictive ability. Ten random samples of varying percentages (0.5, 1, 5, 10, 20, 30, 50, 70, and 90 %) of the observations were used to determine the model probabilities, and each model was then tested with the data not used in the calibration. The overall results show little variability in P_{corr} and $P_{\text{LR}>0}$ once the percentage of observations used to train the model exceeds 10 to 20 % of the total number of observations, defining the minimum data requirement for constructing the BN.

4.3 Spatial distribution of results

The spatial distribution of the results highlights areas in which the model is successful (Fig. 3). By analysing the modelled probability as a function of the input variables, the highest probabilities are in areas with rocky cliffs or platforms (with mostly stable shorelines), and the lowest probabilities are in areas with wetlands (with eroding, stable, and accreting shorelines). For example, the northern coast of the United Kingdom shows regions with accurate model predictions due to the stability of the rocky coastline, whereas regions with pocket beaches and erodible cliffs are less well predicted. The eastern coast of Sweden and western coast of Finland are primarily undergoing accretion, and the model reproduces accurate predictions at these sites due to the relative sea-level fall caused by post-glacial rebound. However, the model over predicts erosion along the coast of Holland and Belgium since the majority of the coastline is affected

by coastal management policies and is primarily stable or accreting (EUROSION, 2004). The French Atlantic coastline is primarily eroding, but the model was unable to predict this trend, likely due to the importance of longshore transport caused by oblique waves (Castelle et al., 2007). The model is able to reproduce the stability observed along the coastline of northern Spain and western Portugal but is unable to identify the zones experiencing erosion. Finally, in the Mediterranean Sea, the tide range, sea-level rise, and wave height are rather small, and the geomorphology is the most variable. However, the coastline shows significantly more variability in shoreline evolution than in the broad categories of geomorphology, and the model is unable to explain this variability.

The model reproduces better the evolution of stable coasts (90 % correct predictions) than of accreting (68 %) or eroding (47 %) coasts. The reduced predictive ability for eroding coasts suggests that the variables in this model are insufficient for determining erosive behavior. Additional factors that are important on local scales, such as coastal structures, shoreline orientation, longshore transport, sediment budgets, or other human impacts may significantly improve predictions of sites experiencing coastal erosion.

5 Summary and conclusions

In summary, a predictive model using a BN accurately reproduced more than 65 % of decadal shoreline evolution trends from the EUROSION database. By evaluating the model behaviour using from one to four variables, the geomorphology was identified as the most important model parameter determining coastal evolution trends. In a study of the US Atlantic Coast, Gutierrez et al. (2011) concluded that sea-level rise was the primary model parameter affecting shoreline stability, which encourages future study of the differences between and the broad applicability of such predictive models.

Although the development of the BN model is limited by data availability, the model demonstrates skill in predicting shoreline evolution trends with a restricted set of variables, with more successful predictions for stable shorelines than for eroding shorelines. Future work requires the improvement of the data quality as well as an increase in coastal observations to update and expand existing databases. Future BN models could benefit from the inclusion of additional model parameters such as alongshore transport, sediment budgets, and the impacts of anthropogenic activities (i.e. coastal structures, beach nourishments, etc.). The development of BN models for coastal applications can enhance knowledge about regional scale coastal evolution, as well as provide a tool for estimating the future evolution of coastlines undergoing shifts in the wave regime or sea-level rise.

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