National evaluation of Chinese coastal erosion to sea level rise using a Bayesian approach

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Abstract. In this paper a Causal Bayesian network is developed to predict decadal-scale shoreline evolution of China to sea-level rise. The Bayesian model defines relationships between 6 factors of Chinese coastal system such as coastal geomorphology, mean tide range, mean wave height, coastal slope, relative sea-level rise rate and shoreline erosion rate. Using the Bayesian probabilistic model, we make quantitative assessment of china's shoreline evolution in response to different future sea level rise rates. Results indicate that the probability of coastal erosion with high and very high rates increases from 28% to 32.3% when relative sea-level rise rates is 4~6mm/a, and to 44.9% when relative sea-level rise rates is more than 6mm/a. A hindcast evaluation of the Bayesian model shows that the model correctly predicts 79.3% of the cases. Model test indicates that the Bayesian model shows higher predictive capabilities for stable coasts and very highly eroding coasts than moderately and highly eroding coasts. This study demonstrates that the Bayesian model is adapted to predicting decadal-scale Chinese coastal erosion associated with sea-level rise.

1. Introduction

The accelerated SLR will exert widely impacts on physical environment and human society in coastal zones [1]. As a main physical long-term effect, increased coastal erosion associated with such large rate of SLR will exacerbate coastal vulnerability [2]. To reveal the relationship between rising sea level and coastal physical vulnerability including erosion, several methods have been developed. A typical quantifying method is Bruun Rule of erosion [3], which is a geometric model to predict shoreline erosion response to SLR focusing on sandy coasts. Based on the Bruun Rule, a modified model has been developed to estimate erosion rate for cliffed coasts [4]. Likewise, the approach of historical trend analysis predicts shoreline response to local sea level change based on historical observed data [5]. Since coastal response to SLR is a complex morphodynamic issue, process-based numerical models have been advanced to modelling rock-shore recession, such as Trenhaile's model [6] and the SCAPE model [7, 8]. However, not accounting well for the spatial and temporal variability and uncertainty of coastal erosion processes, all of these mentioned approaches are not suitable for large-scale evaluation of coastal erosion. Alternatively, coastal vulnerability indices can integrate multiple factors to calculate comprehensive risk index as a measure of potential impact for SLR [9, 10], but this model does not take relative importance and uncertainty of factors into account.

Due to its ability to quantify uncertainty of multiple variables and infer causal relationships between them by integration prior information, The Bayesian network (BN) approach has been used in a variety of different applications, especially in artificial intelligence and ecological systems. Recently, this approach has been employed in studies relevant to coastal systems [11-13]. In this paper, we apply BN approach to make quantitative assessment of china's decadal-scale shoreline evolution in response to SLR based on prior knowledge relevant to coastal physical environment.

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Following the description of study area in Section 2, Section 3 demonstrates the construction of a BN model and historic data used during parameters learning. Section 4 evaluates Chinese coastal erosion trends response to different SLR rates and analyzes performance of the derived model. Section 5 discusses the results and summarizes our conclusions.

2. Study area

Chinese coast is located in the transitional zone of Eurasia and the Pacific Ocean. With global climate change and urbanization in late 20th century, it becomes more and more vulnerable influenced by natural and anthropogenic factors. The Chinese coastline starts from the Yalu River Mouth in Liaoning Province and extends to Beilun Estuary in Guangxi Zhuang Autonomous Region along the West Pacific coast, with a total length of 1.8×10^4 km approximately, as shown in Figure 1. Considering the geomorphic characteristics, Hangzhou Bay can divide the whole coastline into northern part and southern part. Although some of the mountains and hills of Northeast China and the Shandong Peninsula extend to the coast, most of the coastal regions are very flat and low-lying land in the northern part, with an average altitude of 2~5m above sea level, protected by seawall or embankments. In the southern part, the coasts are more irregular, along which hills, mesas and low mountains scattered especially in Zhejiang and Fujian provinces.

China's coastal region plays an important role in national social and economic progress. Since the mid- to late 20th century, several economic belts along the coasts have been developed. These areas have experienced particularly rapid economic and population growth during the past 30 years because of the government's "reform and opening-up" policy. With area of about 1.3×10^6 square km which is just 14% of China's land area, China's coastal area has 41% of the total population of the nation and makes more than 60% of gross domestic product (GDP) of the whole country [14]. There is no doubt that the increasing vulnerability resulting from the accelerated SLR will exert a significant influence on natural environments and social-economic activities of the coastal zones.

3. Methods

3.1. Bayesian network construction

A BN is essentially a directed acyclic graph (DAG), together with the associated condition probability distributions. The DAG in a BN is used to represent the dependency relationships between random variables qualitatively by a set of nodes and a set of directed edges. A node represents a random variable and a directed edge represents dependency relationship between two nodes. The condition probability distributions associated with nodes represent conditional dependency relationship quantitatively between nodes.

The key of Bayesian approach is Bayes' theorem which relates the probability of one event to the occurrence of another event [15]:

$$p(R_i|O_j) = \frac{p(O_j|R_i)\cdot p}{p(O_j)} \quad (1)$$

In which, $p(R_i|O_j)$is the conditional probability of a particular response, R_i, given a set of observations O_j, also called posterior probability. R_i is one of a finite number of scenarios of event R. Likewise, O_j is an observation set which represents one of many possible observations sets denoted by event O. $p(O_j|R_i)$ is the likelihood of R_i given O_j. $p(R_i)$ denotes the prior probability of R_i. $p(O_j)$ is a normalization factor to account for the likelihood of the observations.

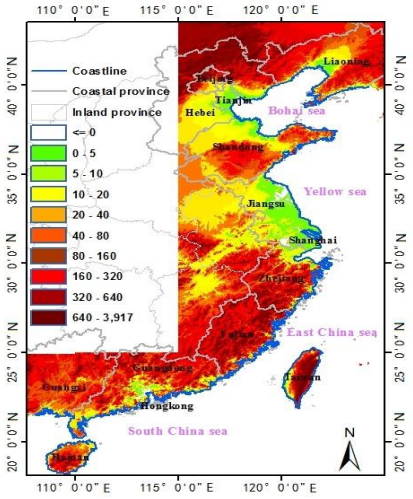


Figure 1. Chinese coastline and DEM.

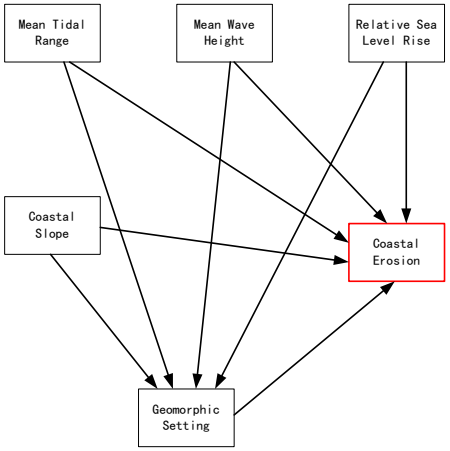


Figure 2. Structure of the BN model.

In this paper, we construct a Causal BN model similar to that used in [11] based on coastal physical knowledge, as exhibited in Figure 2. In the BN model, there are six variables including mean tidal range, mean wave height, relative sea-level rise rate, coastal slope, geomorphic setting and coastal erosion rate denoted as nodes. The coastal erosion rate is response variable which depends on the other variables, denoted by the red lined node.

3.2. Data reprocessing

In this paper, the six variables of China's coast are used to learn the parameters in the BN model and predict coastal erosion in response to different future sea level rise rates. The whole shoreline is divided into 4054 segments by 5 km. Based on the vulnerability categories described in Table 1, each variable is grouped into 4 classes ranging from 1 to 4, with rank 1 representing low vulnerability and rank 4 indicating very high vulnerability.

Relative sea-level rise rate is computed by linear interpolation alongshore to correspond to the coastline segments based on long-term tide-gauge data from 52 stations [16]. According to nearest neighbor rule, the geomorphic setting data of each segment is extracted from the national geomorphology map, provided by the Data Sharing Infrastructure of Earth System Science. Extending approximately 15 km landward and seaward of the local shoreline, the coastal slope is derived from SRTM-DEM with about 90m horizontal resolution provided by NASA using ArcGIS. The shoreline erosion rates used in this paper are summarized from [17]. Similar to relative sea-level rise rate, mean tidal range is interpolated alongshore based on 113 tide stations data extracted from literature such as the investigation report on the national ocean hydrologic environment [18, 19]. Mean wave height is achieved from 35 tide stations mentioned in [19, 20] in the same manner as above.

Table 1. Discretization of variables in the BN model.

Variable	Coastal vulnerability			
	Low (1)	Moderate (2)	High (3)	Very high (4)
Relative SLR (mm/a)	<2	2-4	4-6	>6
Geomorphology	Rocky cliff	Headland-bay coast, low cliff, dunes	Firth,delta coast, lagoons, estauries	Coastal plain, beach, mud flat, barrier
Coastal slope (%)	>3	1.5-3	0.5-1.5	<0.5
Coastal erosion rate (m/a)	≤0.5	0.5-2	2-3	≥3
Mean tidal range (m)	>3	2-3	1-2	<1
Mean wave height (m)	0.3-0.6	0.6-0.9	0.9-1.2	1.2-1.5

4. Results

In this section, the BN model associated probability distribution of variables is worked out based on the 4054 data points mentioned above by Equation (1). Erosion rate of each coastline segment is predicted by updating the BN given additional information or constraints of other variables. By comparing the results predicted to existing 4054 data points about erosion rate, the prediction ability of the BN model is evaluated.

4.1. Impact of sea-level rise on Chinese coastal erosion

Based on the 4054 data points, the prior probability of variables are computed, as shown in Figure 3. Results show that the probability of China's shoreline in stability or accretion state denoted by class 1 is highest as 48.2%. In comparison, the probability that shoreline change rates indicate erosion is 51.2%, of which the probability of moderate erosion, high and very high erosion are 23.7%, 13.3% and 14.7%, respectively.

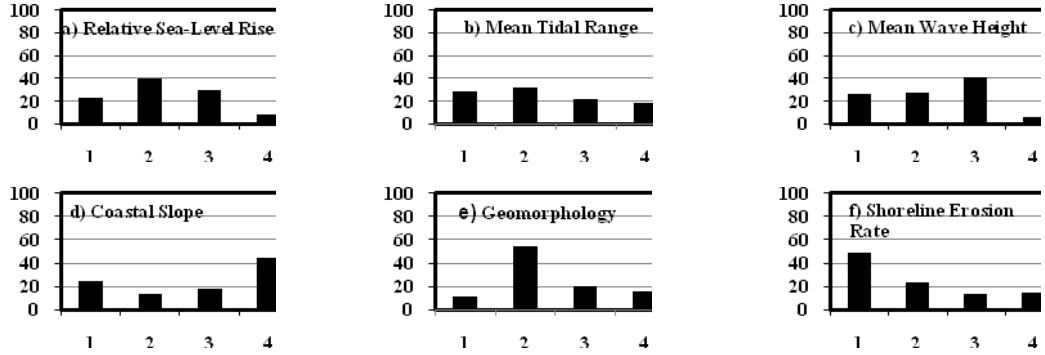
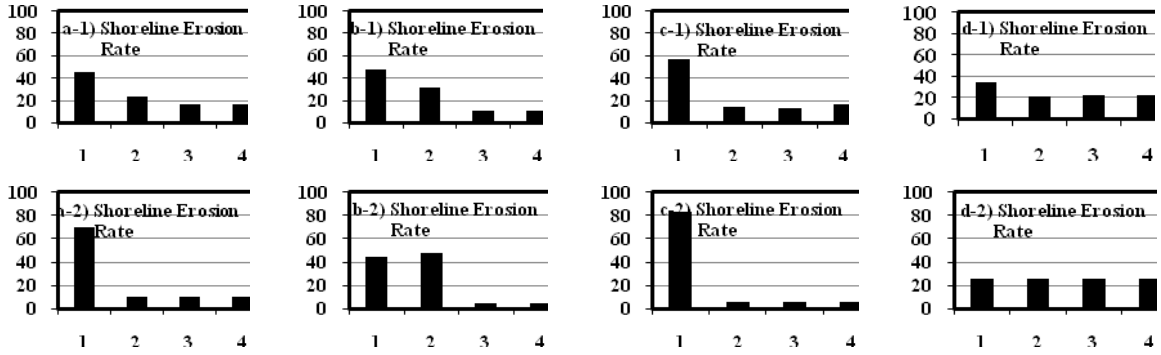


Figure 3. The prior probability of variables in the BN model, in which classes on the horizontal axes from 1 to 4 are confirmed to Table 1 and numbers on the vertical axes are in percent.



a) SLR rate < 2mm/a b) SLR rate = 2-4mm/a c) SLR rate = 4-6mm/a d) SLR rate > 6mm/a

Figure 4. Posterior probability of Chinese shoreline erosion for each relative sea level rise rate category. (a-1, b-1, c-1 and d-1) illustrate the posterior probabilities for cases with only relative sea-level rise rate constrained as Table 1, respectively. (a-2, b-2, c-2 and d-2) show the posterior probabilities when 100% probability is specified for the particular case where mean tidal range, mean wave height, coastal slope and geomorphology are 2-3 m, 0.9-1.2m, less than 0.5% and a geomorphic setting of 2, respectively (see Table 1).

For evaluation Chinese coastal erosion to sea-level rise, several sea-level rise scenarios are used to constraint the BN model in different cases. From these cases, it can be found what the trend of China's shoreline erosion is with sea-level rise by comparing the posterior probability of shoreline erosion to the prior probability. The posterior probability of China's shoreline erosion is illustrated in Figure 4. It can be realized that the probability of Chinese coastal erosion increases as the rate of relative sea-level rise increases. When the rate of relative sea-level rise is more than 6mm/a, the posterior probabilities of China's shoreline in stability or accretion state and moderate erosion state decrease from the prior probabilities of 48.2% and 23.7% to 34% and 21%, respectively. While the

posterior probabilities of high and very high erosion increase from the prior probabilities of 13.3% and 14.7 to 22.5% and 22.4%, respectively.

Given the particular case where mean tidal range, mean wave height, coastal slope and geomorphology are respectively 2-3 m, 0.9-1.2m, less than 0.5% and a geomorphic setting of 2, the posterior probabilities of erosion rates of Chinese coast are demonstrated in Figure 4 (a-2, b-2, c-2 and d-2) as the same sea-level rise scenarios are applied. In the particular case, results show that the posterior probabilities of stability or accretion state decrease from the prior probabilities of 48.2% to 25%. While the posterior probability of erosion is up to 75%, of which the posterior probabilities of high and very high erosion rate are both up to 25%.

4.2. Prediction and model evaluation

Based on the BN model, we predict the rate of Chinese shoreline change by updating the posterior probability of the target variable, namely coastal erosion rate, where the five driving variables are constrained based on the data set mentioned in section 3. The most likely state (i.e. the one with the highest posterior probability) was chosen as its prediction for the case of shoreline segment. In this way, we worked out the spatial distribution of prediction results for Chinese shoreline change, as shown in Figure 5.

Comparing the prediction results to the observed erosion data, the difference between predictions and observations is illustrated in Figure 5. it is evaluated that the BN model correctly reproduces 79.3% of the observations, in detail that correct predictions of stable/accretion and very high erosion are respectively 94.8% and 73.9% in contrast to 36.7% and 43.4% of moderate erosion and high erosion. Results show that the BN model performs well in prediction for stable/accretion and very high erosion, but insufficiently for moderate and high erosion.

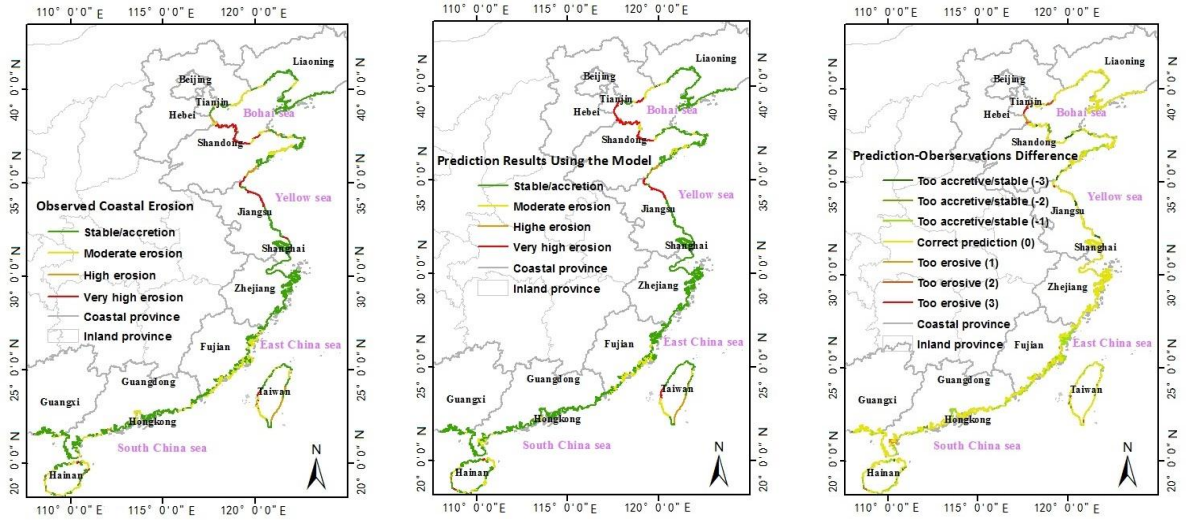


Figure 5. The prediction results of Chinese coastal erosion based on the BN model (middle) and the difference (right) between prediction results and the observations (left).

5. Discussion and conclusion

Using the BN model, this paper makes quantitative assessment of china's shoreline evolution in response to different future sea level rise rates. Results indicate that the probability of coastal erosion with high and very high rates increases from 28% to 32.3% when relative sea-level rise rates is 4~6mm/a, and to 44.9% when relative sea-level rise rates is more than 6mm/a. A hindcast evaluation of the BN model shows that the model correctly predicts 79.3% of the cases. Model test indicates that the BN model shows higher predictive capabilities for stable coasts and very highly eroding coasts than moderately and highly eroding coasts. This study demonstrates that the BN model is adapted to predicting decadal-scale Chinese coastal erosion associated with sea-level rise.

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