Testing the Bayesian network method for exploring the shoreline mobility causes on volcanic islands: The case study of La Réunion (Indian Ocean)

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Abstract

In a previous study, Gutierrez et al. (2011) showed the capability of Bayesian networks (BNs) to predict long-term shoreline changes on U.S. Atlantic coast together with the associated uncertainties. They suggest that a method for analysing shoreline mobility causes in a systematic way could be to (1) build a BN to deal with numerous data and to identify general causes of mobility (2) complete with a more thorough evaluation of specific segments where the predictive capabilities are weak. In this study, a database of recent past shoreline evolution is used for the learning phase of the BN construction. Then we use the BN with 1 to 4 variables to realise a retrospective prediction of the coastline evolution and identify the main mobility drivers. The BN has a good predictive capability using the 4 variables as 80% of past shoreline changes are correctly reproduced, the geomorphic settings being the main factor.

Key words: Bayesian networks, coastline mobility, coastal erosion, geomorphology, modeling, Indian Ocean

1. Introduction

Coastal areas are extremely vulnerable to sea-level rise (Nicholls et al., 2007). Primary impacts include an increased risk of coastal flooding, coastal adjustments to these new conditions and saltwater intrusion into surface and ground water (Mimura, 1999; Nicholls and Cazenave, 2010). In this context, being able to predict shoreline mobility is an important issue for local planning policies. However, the possibility to develop models able to predict future coastal evolution on a multi-decadal time scale depends on our ability to correctly reproduce observed changes in recent past.

This exercise is rather difficult because of the large number of involved processes. Shoreline mobility results from numerous factors acting at different scales (global, regional and local) and from different marine and continental processes such as climate change, geodynamic processes or anthropogenic actions (Garcin et al., 2011). Climate change includes changes in wind and waves patterns and sea level variations. While internal geodynamic processes refer to vertical ground motion, external processes refer to erosion, accretion and sediment transport. Anthropogenic actions may directly affect the coastline, by constructing coastal defence structures, or indirectly, through changes in sediment budget, for example by extracting gravels from the rivers. These different forcing factors interact and influence each other.

In a previous study, Gutierrez et al. (2011) demonstrated the ability of Bayesian networks (BNs) to deal with numerous available data and to predict long-term shoreline changes on U.S. Atlantic coast together with the associated uncertainties; information particularly useful for coastal management decisions. They suggest that BNs can be used in a systematic way on large datasets to identify general causes of shoreline mobility and should be completed with a more thorough evaluation of specific coastal segments where the predictive capabilities of BNs are weak.

In this study, we apply the BN approach and explore its capacity to retrospectively predict the shoreline mobility in La Réunion island. This approach is used here as a mean to better understand the variables that explain shoreline mobility at regional scale.

After a short presentation of the study site, we introduce BNs method and describe the application to the

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test site and the dataset used. This dataset was adapted from a database originally compiled to characterise and map the coastal morphology and morphodynamics of the island (De La Torre, 2004). For each coastal segment, the dataset describes the observed shoreline mobility, the geomorphic settings and the presence of anthropic structures in the vicinity of the segment. Two other variables, namely the exposure to energetic waves and the presence of an estuary, are created to complete the description of the coastal segments. We finally review the results of the model and discuss them.

2. Study site

2.1. Geographical context

La Réunion is an island located in the southern hemisphere in the southwest Indian Ocean at 21° S and 55° E. It is located in the Mascarene Islands at about 700 km east of Madagascar and 170 km southwest of Mauritius. The Piton des Neiges, culminating at a height of 3070 m, was the origin of the formation of this volcanic island 3 million years ago. It occupies the north-western part of the island and has been inactive for 12,000 years. The second volcano, the Piton de la Fournaise, is more recent (500,000 years). It culminates at 2621 m and it is still active. The emerged part of the island (2,512 km ^{2}) represents only 3% of the geological formation which rises from the oceanic floor at 4000 m depth. The contrasted reliefs of the island were shaped by erosion but it is still a young island with a narrow continental shelf and water depth increasing very rapidly from the shore (Bourmaud et al., 2005).

2.2. Geomorphological context

The coastline of La Réunion is 250 km long and is mainly composed of a basaltic rocky coast locally scoriaceous, especially on the eastern part of the Island. Some parts of the coastline are covered with surficial weathering from bedrock and remodeling of slopes (e.g. mudslides, debris flows). The hydrographic network of the island is also very dense and supplies with sediment material the pebble and sand beaches located on both sides of rivers' outlets. In south and west parts of the island biodetritic sandy beaches are protected and nourished by coral reefs.

2.3. Climate and oceanic parameters

La Reunion is characterised by a humid tropical climate influenced by trade winds. The hot and wet season lasts from November to April while the cold and dry season lasts from May to October. The island is exposed to cyclones between November and March. The presence of sharp relief induces highly variable rainfall amount over the island. The eastern coast which is exposed to the wind is rainy with a rainfall rate that may reach 11000mm/y (Violette et al., 1997) while the western coast is protected by the relief and quite dry (average of 900mm/y in Saint-Pierre, Violette et al., 1997).

La Reunion is exposed to three main swell regimes: trade swells, southern swells and cyclonic swells. Trade swells are the most common swell and are responsible for alongshore sediment transport. They come from ESE and are characterised by low significant waves (< 2m) and short periods (5 to 10s). Southern swells from the SW are characterised by moderate amplitudes (generally between 3 and 4m) and longer periods (10 to 20s). They appear far offshore during storms in the southern hemisphere's temperature zone and they get to the coasts during 15 to 25 days per year. Southern swells are very energetic and thus highly erosive (Cazes-Duvat and Paskoff, 2004; Lecacheux et al., 2012). Finally cyclonic swells episodes correspond to high energy events which last a few days (48 to 72 hours). They are dependent on cyclone paths and are mainly observed in the north-east to north-west of the island. The wave amplitude can exceed 10m with periods over 12s. Cyclonic swells can induce intensive coastal erosion events because of their high energy. Moreover, cyclones cause intense rainfalls inland which trigger soil erosion and increase the flow rates and the solid discharges of rivers (Garcin et al., 2005). By initiating flooding events, cyclones and tropical storms largely contribute to the sedimentary supply at the rivers' outlets and to the sedimentary budget of the coast and thus to coastline evolution. In La Réunion, the tidal regime is semi diurnal and unequal. It is microtidal since the tidal range varies between 0.1m (neaps) and 0.9m (springs) (Bourmaud et al., 2005).

Without data attesting of coastal subsidence or uplift, we assume that sea level rise is uniform at the scale of the island.

2.4. Human activities

With an average population of 334 inhabitants per km², la Réunion Island is densely populated. Due to steep topography, dryer climate and the presence of coral reef beaches, 82% of the population is concentrated close to the coast in the north and west parts of the island (Bourmaud et al., 2005).
Because of this concentration of human activities near the ocean, anthropic pressures are particularly strong on the coast, disturbing natural equilibrium. Coastal sand was used for construction, disturbing sedimentary equilibrium of coastal systems. Moreover, from late 70's to the early 90's, mechanical cleaning of coral beaches decreased their sedimentary stocks, leading to increased erosion. Human activities can also impact indirectly coastal evolution; for example, gravel extraction was allowed downstream of the main rivers. This activity leads to a deficit in sediments at the coast. Finally, the increasing artificialisation of the coast (with houses, groynes, harbours, road networks…) contributes to disrupt the sedimentary transfers.

3. Bayesian network methodology

A BN is a tool to graphically represent knowledge about a given system and to compute dependencies between parts of that system in terms of probabilities (Pearl, 1986). Formally, a BN $\mathcal{B} = (\mathcal{G}, \theta)$ is defined by:
- A directed acyclic graph $\mathcal{G} = (X, E)$, E being the set of directed edges representing causal relationships between the nodes of the graph that represent a set of random variables $X = \{X_1, ..., X_n\}$,
- Parameters $\theta = \left\{ P\left(X_i \middle| Pa\left(X_i\right)\right)\right\}_{i=1..n}$ that depict the conditional probability of each node X_i given its parents $Pa(X_i)$ within $\mathcal{G}$.
While $\mathcal{G}$ describes qualitatively the dependence (or independence) between variables, θ provides a more quantitative insight. Because of the conditional independencies represented by $\mathcal{G}$, the joint probability distribution of X can be simplified into a product of local conditional probabilities which depend only on the considered node and its parents (see e.g. Pearl, 1986):

$$P(X_1, ..., X_n) = \prod_{i=1}^{n} P(X_i | Pa(X_i)) = \prod_{i=1}^{n} \theta_i \tag{1}$$

This formula is a fundamental property of BNs. It is used for inference to compute the probability of any random variable from the observation (even incomplete) of the others.
In our study, the network structure $\mathcal{G}$ is part of our prior knowledge of the functioning of the system. Once $\mathcal{G}$ is designed, the use of the BN goes through two phases:
- *Learning phase*, in which the parameters θ are computed from data.
- *Reasoning phase,* which consists in calculating the probability of observing a certain variable given different combinations of the other variables. A specific case is the retrospective predictions which consist in creating a predictive model for a certain variable (in our case the shoreline mobility) by assigning each combination of the others with the response (which could be erosion, stability or accretion) having the maximum conditional probability. Let's O^k represents a realisation of O which is a subset of X. Then the predictive model is:

$$\textit{Predictive Shoreline Mobility for } O^k = \arg\max\left(p\left(ShorelineMobility \middle| O^k\right)\right), \tag{2}$$

where argmax(p(x)) returns the value of x that maximizes p(x).
A method for quantifying the performance of the model is to calculate the model correct predictions percentage by comparing model's outputs with record data. This percentage is obtained by dividing the

sum of the coastal segments lengths for which the predictions are consistent with observations by the sum of all segments lengths.
Calculation of the log-likelihood ratio (LR) for each coastal segment is another way to quantify the performance of the model. It reckons the improvement in the probability of a prediction that matches the observation.

$$LR = \log\left[p\left(Sho.Mob.\middle|O^k\right)\right] - \log\left[p\left(Sho.Mob.\right)\right] \tag{3}$$

The LR is positive when the modeled prediction is better than the prior prediction based only on the frequency of shoreline mobility distribution in the dataset. In this case, the positive LR indicates that the updated distribution is either more accurate (the distribution corresponds to the observations) or more precise (the distribution is narrower) (Yates et Le Cozannet, 2012).

4. Application to La Réunion Island coastline

4.1 Data

The database used for this study was established during field campaigns realised by BRGM (French Geological Survey) in March and June 2004 (De La Torre, 2004). The aim of this study was to characterise and map the morphology and evolution of the island coastline.
First recognised from the land, the entire coastline of the island was then observed from an ULM to understand the different coastal systems. A major aerial photographs campaign was thus conducted and used as a basis for the realisation of a reference state. A final field campaign finally provided detailed information on the areas identified as sensitive.

Table 1. Database parameters

Geomorphic settings	Presence of anthropic structures in the vicinity of segment	Exposure to energetic waves	Presence of estuary in the neighboring of segment
0: Artificial coastline 1: Basalt cliff 2: Basalt cliff behind shingle bar 3: Shingle beach 4: Sand beach 5: Basalt low rocky coast 6: Basalt low rocky coast behind shingle bar 7: Basalt low rocky coast behind sand bar	1: Yes 2: No	1: Mainly exposed to cyclonic waves 2: Mainly exposed to southern waves 3: Protected by coral reef	1: Yes 2: No

Current shoreline evolution indices were searched for. For instance, indicators of erosion might be a steep profile for a beach, a notch at the bottom of the cliff, traces of fallen rocks at the top of the cliff, micro-cliff or apparent tree roots at the upper beach. Indicators of accretion might be a smooth profile of a beach, the presence of an upper beach berm, a small delta, a shingle bar at the foot of the cliff, vegetation of backshore or dunes. The shoreline evolution tendency for some locations was compared using aerial photographs from IGN campaigns of 1966, 1978 and orthophotographs of 1997 which gave an indication of the main trends over about 30 years. Nonetheless this period covers an intense economic and demographic development of the island, several major meteorological events (especially cyclones Hyacinthe (1980), Firinga (1989), Colina (1993) and Hollanda (1994)) as well as volcanic events

(eruptions to the sea of 1977 and 1986).
In addition to the shoreline evolution, the dataset (Table 1) includes for each coastal segment a description of the geomorphic settings (i.e. a geomorphology associated with a lithology, for example sand beach or pebble beach) and the presence of anthropic structures behind or in the vicinity of the segment (e.g. a wall at the upper beach, a wedge for boats on a pebble strike,…). Coastal segments that are completely artificialised are discarded from the dataset as nothing but stability can be expected for the evolution of those segments. Keeping such segments would artificially improve the overall prediction score of the BN.
Two additional variables capable of influencing shoreline mobility are created to complete the description of the coastal segments: the exposure characterization of a coastal segment to energetic waves and a Boolean variable accounting for the sphere of influence of main estuary. The last one is derived from the main rivers of the hydrographical network (extraction from BD TOPO®) (Figure 1) and from the presence of river sediments at the coast in the original database (De La Torre, 2004). We follow here a recommendation of Gutierrez et al. (2011) to include a variable in the BN noting the proximity to a tidal inlet.

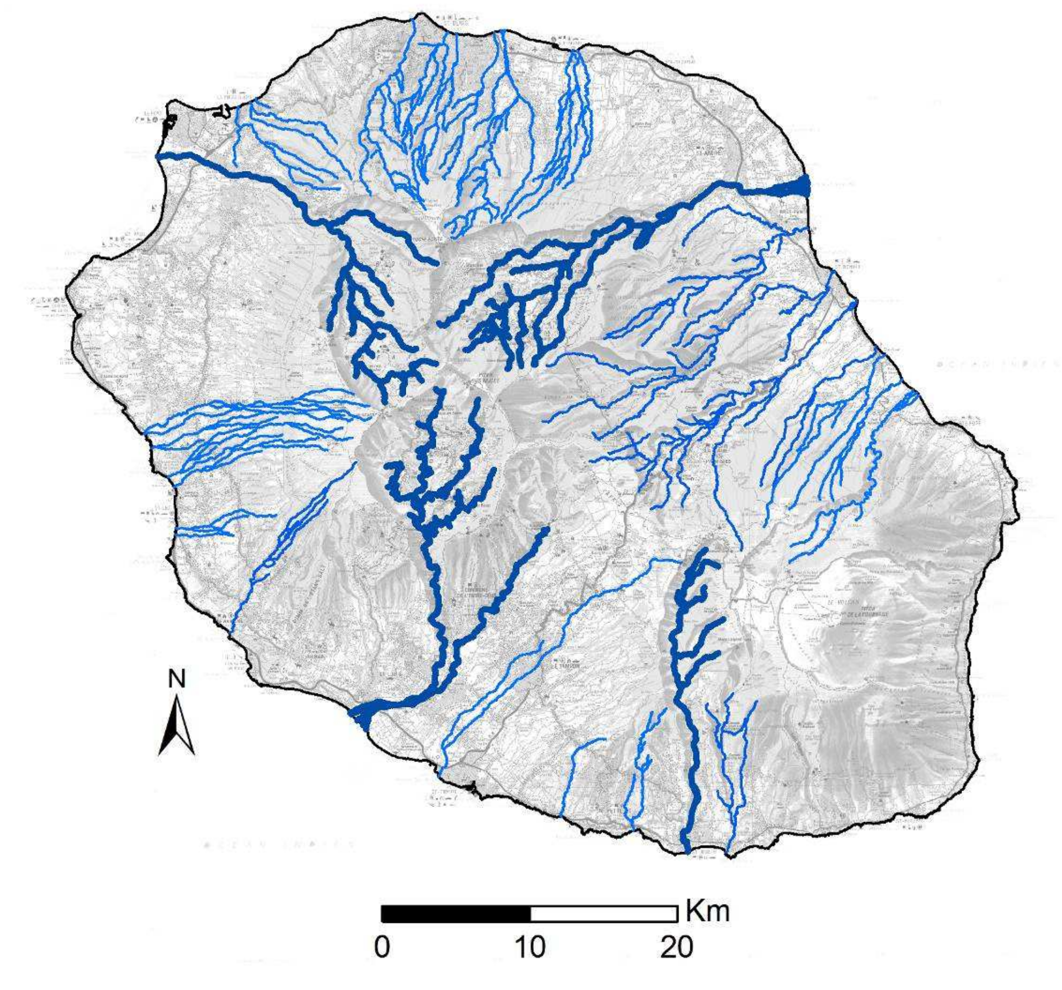

Figure 1. Main hydrological network represented in blue

The exposure characterization to energetic waves is simplified in comparison with reality and based on our knowledge of wave climate in La Réunion (see section 2.3). Cyclonic and Southern swell regimes can trigger erosion, the first being predominant in the eastern part of the island and the second in the western part. The different values of a variable in a BN must be mutually exclusive and collectively exhaustive (Heckerman, 1997). Thus, as a first approximation, we split the island in two categories: "exposed to cyclonic swells” and “exposed to southern swell” (see percentage repartition in Figure 2). In practice, some coastal segments may be equally influenced by both cyclonic and southern swells. Coral reefs lower waves’ energy before they reach coast (Gerritsen, 1981; Gourlay, 1994; Hardy & Young, 1996). To account for this protective role, all coastal segments behind such reefs are categorised in a separate label “protected by reefs” for the exposure-to-energetic-waves variable. This is also a simplification, coral reef hydrodynamics being more complex. The seasonal process of the alongshore sedimentary transport is not taken into account in this study.

The final database divides the island’s coastline into 389 segments with uniform characteristics.

Consequently, all the segments have different lengths. This feature is taken into account in any probability calculation in this study (especially during the learning phase of the BN construction (see section 3)). The prior probability distribution of a given variable in the BN is the probability distribution of that variable calculated from the available information in the dataset, without considering the other variables. It is derived as the cumulative length of coastal segments in which the variable of interest has a given value, divided by the total length of the coastline.

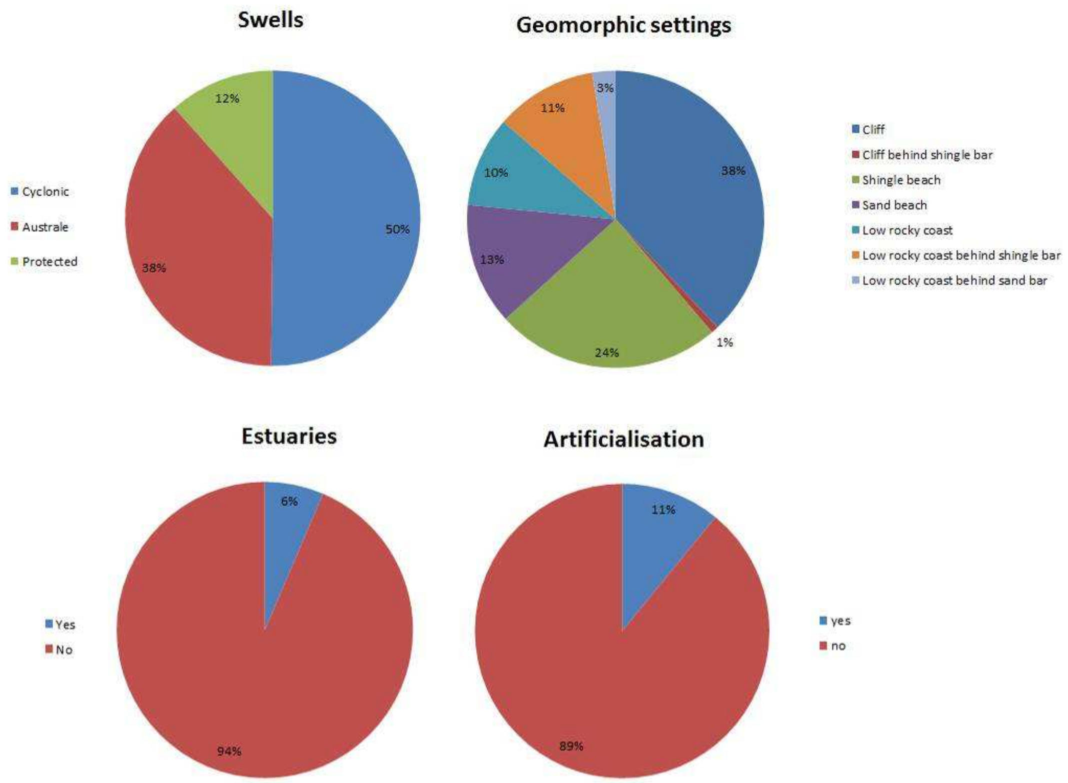

Figure 2. Repartition of the different variables along the coast

It is worth noting that since we assume the relative sea level rise is uniform all around the island, it cannot explain the heterogeneity of the shoreline evolution and neither can the uniform tidal range. Therefore, these two factors are not included in our Bayesian model to understand shoreline mobility.

The analysis of probability distribution of coastal mobility for each variable observed (Figure 3) shows that in general the coast is more in erosion (58%) than stable (35%) or in accretion (7%). Coastal segments listed as in the vicinity of an estuary are mostly in accretion (82%) while the other ones are mostly in erosion (61%) or stable (36%). Exposition to southern swell results in high proportion of coastlines in erosion (73,6%). All categories of geomorphic settings are mainly stable, except for cliffs (93%), low rocky coast behind shingle bar (53,7%) and behind sand bar (100%) which are in erosion.

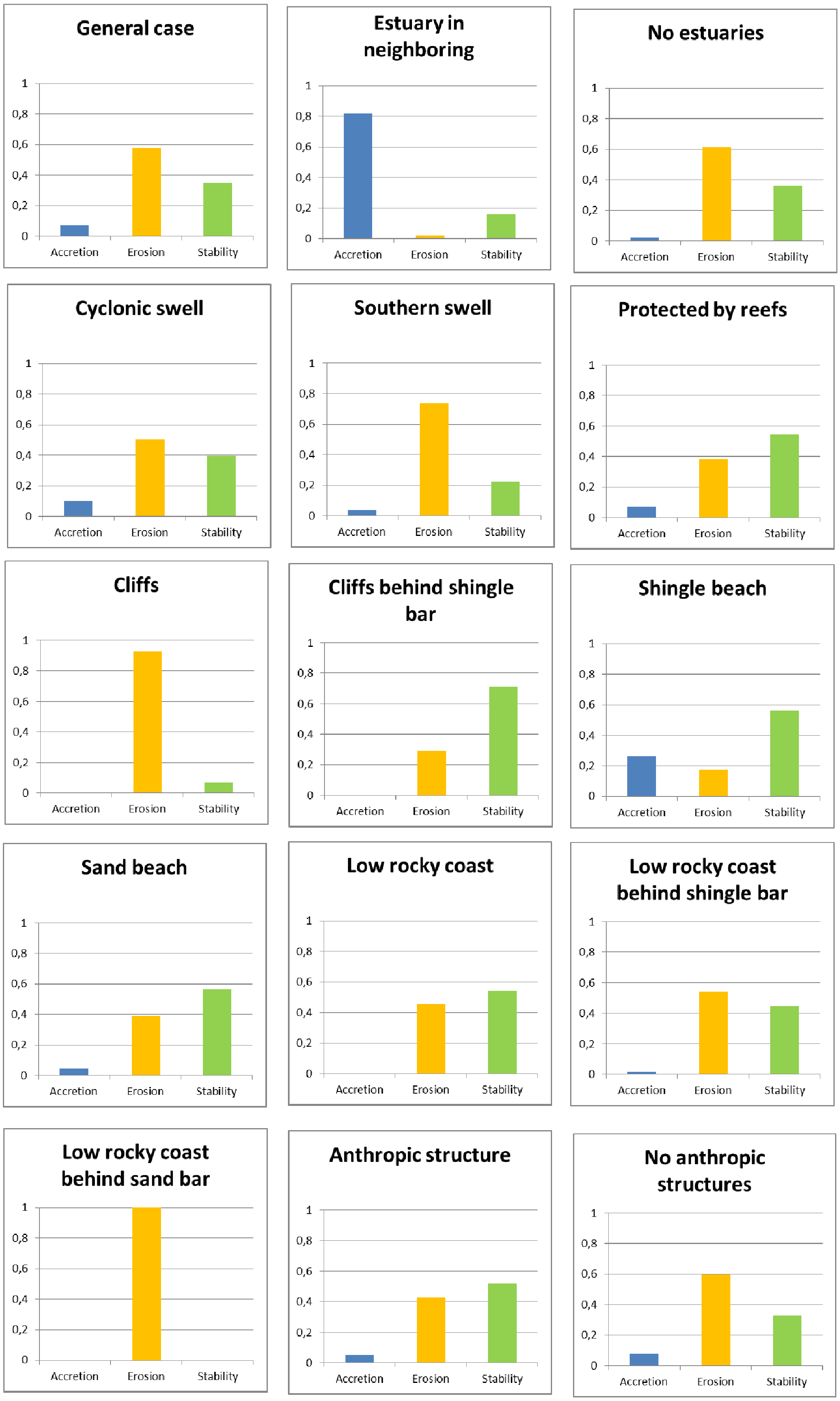

Figure 3. Probability distribution of observed coastline mobility for each class of each variable

4.2 Structure of the Bayesian network for La Réunion Island

In this study, we are interested in shoreline mobility and its conditional probability distribution to some sets of inputs among the explanatory variables. The structure of the BN is represented in Figure 4.The causal relationships reflect our understanding of the functioning of the coastal system. Thus, we consider the geomorphic settings are under direct influence of all the other variables, except for the variable "presence of anthropic structures in the vicinity of the segment". Since coral reefs are usually inexistent in front of estuary mouths, there is a direct influence of the variable "presence of an estuary" on the exposure-to-energetic-waves variable. In the BN, all the variables are discrete and each is resolved in several qualitative categories or bins (Table 1).

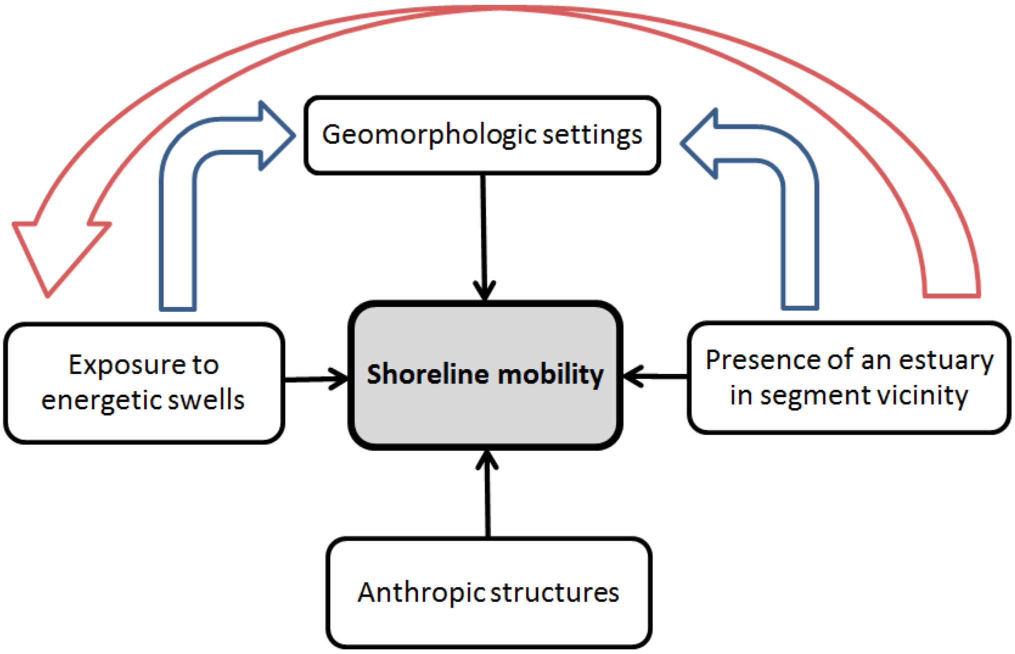

Figure 4. BN structure for La Réunion Island (𝒢)

We use the BNT toolbox for Matlab (http://bnt.sourceforge.net) to construct the BN. Some routines have been modified to account for the lengths of the coastal segments. As we deal with a complete dataset (i.e. no missing data), the learning phase of the BN is straightforward. The parameters are determined using the maximum likelihood approach, which consists in estimating the probability of an event with its frequency of appearance in the dataset (Naïm et al., 2007), weighted by the lengths of the coastal segments.

5. Results

Predictions of the shoreline mobility by the model using all 4 variables are consistent with observations for more than 80% of shoreline length. The percentages of correct predictions are higher for stable areas (85%) than for eroding or accreting areas (79 and 72,5% respectively). The model seems a little less effective in predicting accretion. This may be due to the fact that accreting segments are less represented in the database (7%) which reduces the amount of data available for probabilities.

The sensitivity of the BN to the different variables is tested and a special attention is given to coastal segments that are incorrectly predicted. The segments are analysed in detail using field data (De La Torre, 2004) in order to assess the local causes of observed mobility and to identify the limits of the BN.Figure **5** represents the percentage of correct forecast obtained for BN model simulations using 1 to 4 variables. The red line represents the percentage of correct prediction when the entire dataset is randomised (while respecting the prior probability distributions), which has the effect of removing any dependency among the variables. A blue bar exceeding the red line is therefore an indicator of the significance level of the model.

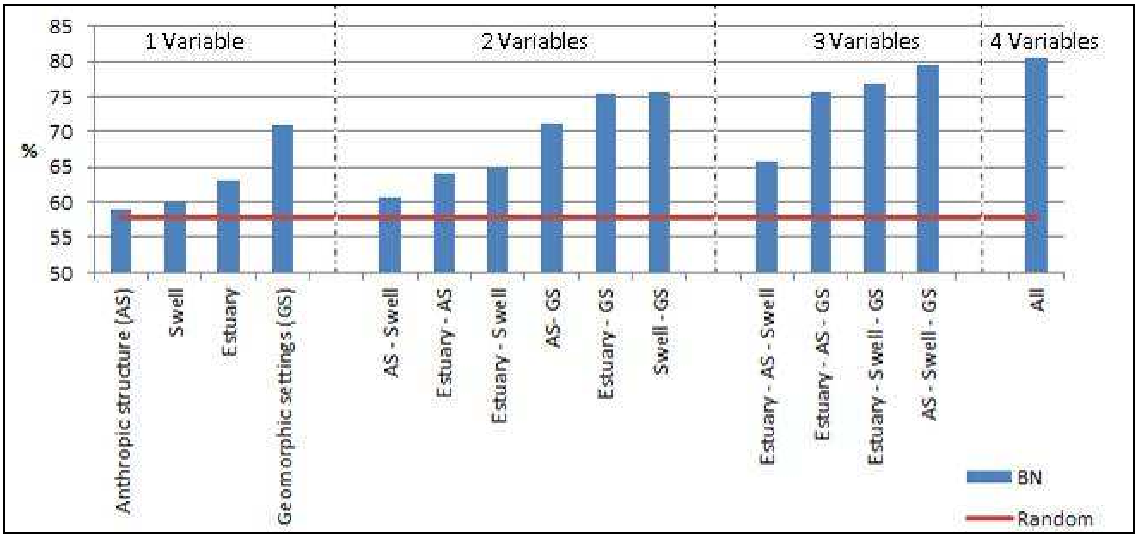

Figure 5. Correct forecast percentage for model runs with 1 to 4 variables

Figure **6** shows the weighted average (the weights are related to segments lengths) of log-likelihood ratios obtained for model simulations for 1 to 4 variables. When considering a 1 variable model, the geomorphic settings parameter is the one that presents the best predictive capacities. For 2 and 3 variable model, the combinations including geomorphic settings also give the best results.

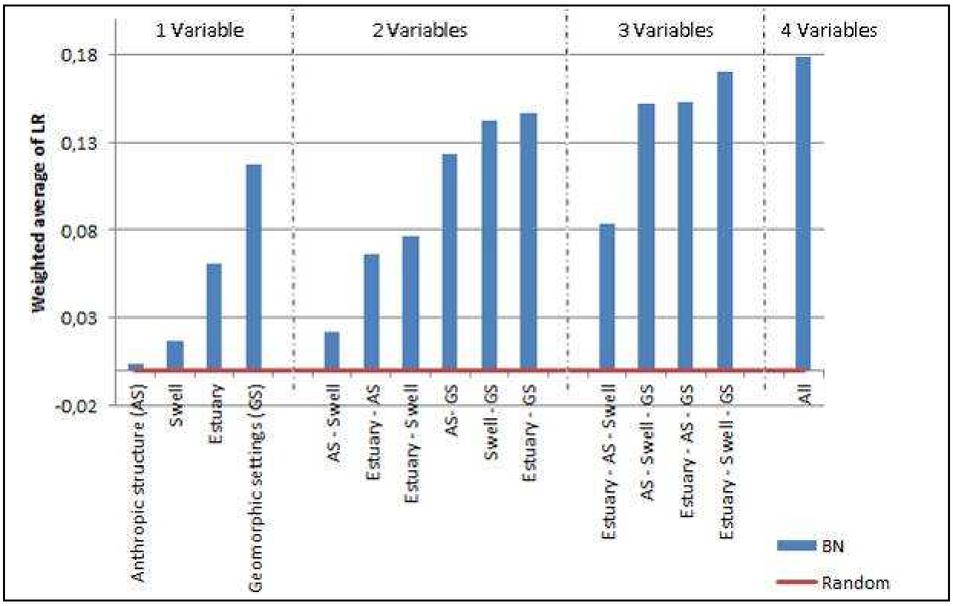

Figure 6. Weighted averages of Log-likelihood ratios for each model run from 1 to 4 variables

Figure **7** gives four types of information: (a) observed mobility of the coastline, (b) mobility of shoreline as predicted by the model, (c) spatial repartition of geomorphic settings categories and (d) areas of correct and incorrect predictions. We can see that the areas of incorrect predictions are distributed all along the coast of La Reunion but are almost inexistent in the southeast part of the island. This area is mainly composed of cliffs or cliff behind shingle bar in erosion without presence of estuary of anthropic structure. So this part of the island presents relatively homogeneous data and even prior probability is very high as more than 91% of the cliffs and cliffs behind shingle bars are in erosion over the island.

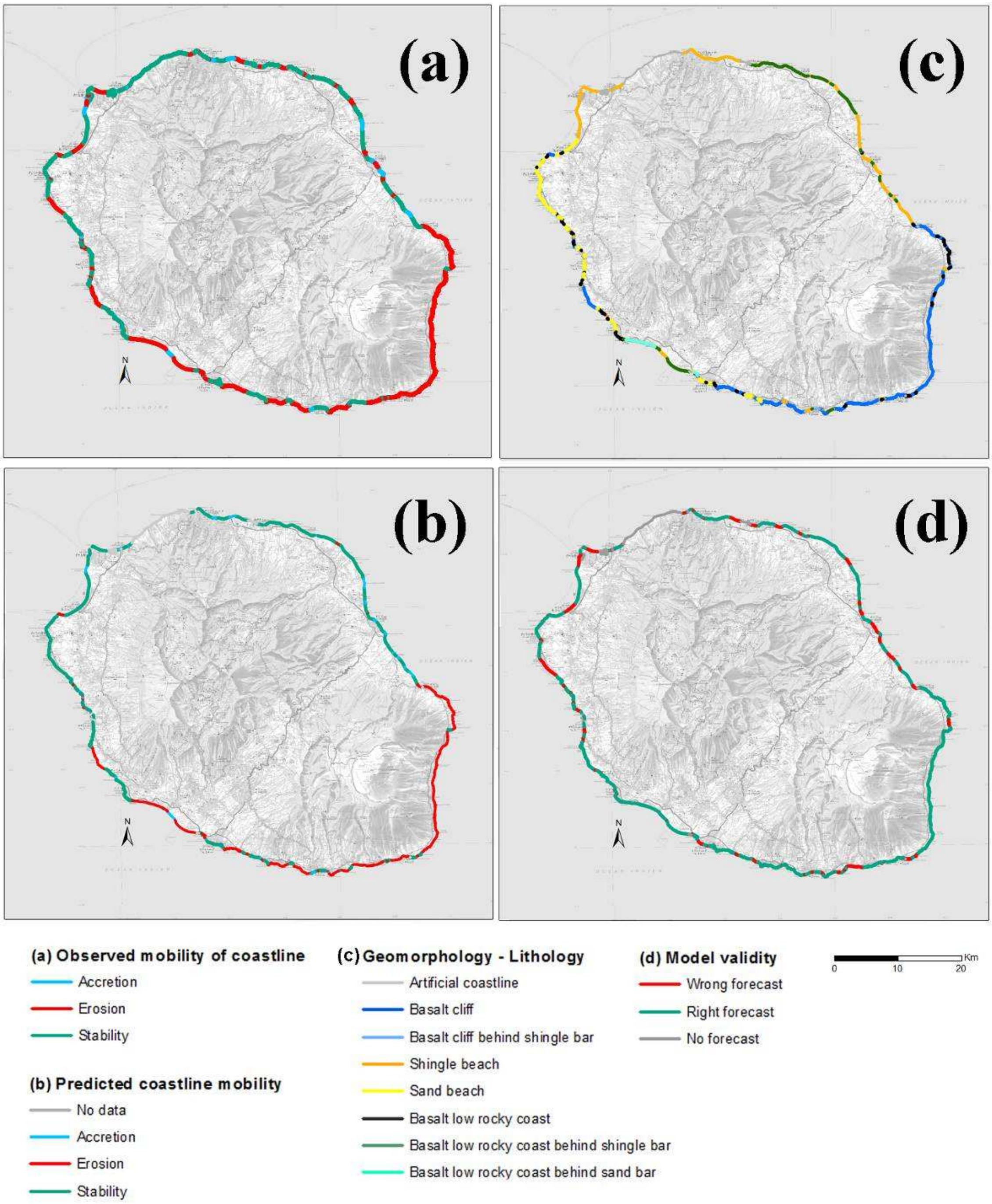

Figure 7. Spatial distribution of (a) observed shoreline mobility, (b) predicted shoreline mobility (no data corresponding to fully artificialised coastal segments), (c) Geomorphology-lithology (no forecast corresponding to fully artificialised coastal segments), (d) difference between BN predictions and observations

Figure **8** maps the probability of the most likely outcome. This map can be used to identify areas where there is a high level of uncertainties or great confidence in the outcome prediction (Gutierrez et al., 2011).

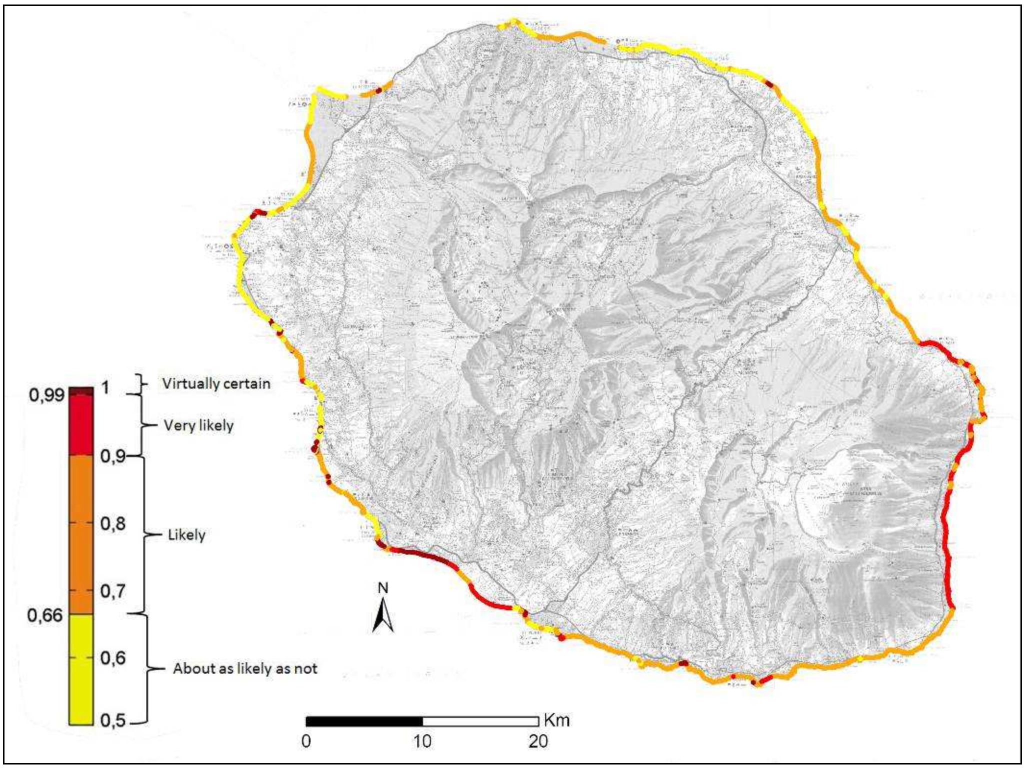

Figure 8. Map of posterior probabilities provided by the model

On the samples analysed, multiple causes of mis-prediction are identified such as the existence of isolated coastal works directly on the coastline, the lack of sediment budget information or even database intrinsic errors. For instance, the presence of one single riprap groyne built in St-Benoit interrupts the alongshore transit and induces a wrong prediction of the model on more than 2 kms. Only four segments are mis-predicted with great confidence; falling into the "Very likely" category on Figure 8. The two longer ones can be explained easily. The first one can be explained by special local conditions: a hollow of the coast and the proximity of a harbour jetty that may protect the shoreline; and the second one appears to be linked to a mis-definition of the sphere of influence of St Etienne river; which thus would need to be refined.

6. Discussion and conclusion

The application of BN on La Réunion shorelines data shows that combined use of BN and of data analysis can be useful for better understanding why shoreline is accreting or eroding. The BN retrospective predictive model reproduces correctly more than 80% of La Réunion shoreline evolution. However, several limitations must be mentioned: first of all our data set could be improved by strengthening observations. The shoreline mobility data used is based on single date observations which could not always be compared with past aerial photographs to confirm tendencies (De La Torre, 2004). Ensuring that the "observed mobility" is typical of mid to long-term (some decades) tendencies would lead to more robust results.

Anthropic structure is the parameter that leads to the smallest improvement (Figure 5 and Figure 6). This may be due to the fact that the corresponding bin describes anthropic structure behind the shore and not directly on the shore. The second one is swell, indicating that the categories in the bin "exposition to energetic swell" were probably too simplified as aforementioned. Refining these categories (for example integrating wave height at the coast as in Gutierrez et al. (2011) might improve the BN performance. Adding other variables may also help refining the predictions. For example, adding data on sedimentary load of the different rivers would refine the information that is already roughly estimated by the "Estuary" variable and adding a variable "alongshore sediment transport" would extend it to the whole coast. Introducing parameters such as "height of cliffs or dunes" or the "width" of sand and shingle bars in front of cliffs or low rocky coast would refine the geomorphic settings categories and thus the results of BNs model. This requires a compromise as too many descriptive variables would lead to little data available for each combination.

In conclusion, this method allows appraising the main variables accounting for shoreline evolution. Those are found to be the geomorphic settings and the presence of an estuary in the vicinity of the segment considered (and thus sediment budget at the estuary). Further work includes the integration of other parameters in the BN like alongshore sediment transport in order to refine the model. Finally, beyond the analysis of retrospective predictions provided in this study, one future perspective could be to test different datasets for the learning phase and the prediction.

Acknowledgements

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