

Combined answer to reviewers with changes in manuscript

Anonymous Referee #1

Received and published: 28 August 2020

I have reviewed the manuscript entitled 'Probabilistic characterisation of coastal storm-induced risks using Bayesian Networks' by Sanuy and Jimenez. Overall the article is of high quality and provides an alternative method for using BN in risk assessment that although it is based on the source-pathway-receptor consequences concept it has some novel methods related with the storm selection.

I believe that the article is of high interest for the journal and well within the journal's scope. However, I believe that in order for the manuscript to be accepted some changes need to be addressed more for clarifying some aspects of the work and for providing further information and limitations of the method.

We thank the reviewer for the detailed review and constructive comments on the manuscript. We have performed a thorough revision to address all the comments, as detailed below.

General comments:

The Abstract of the article although correct is rather general and it is not highlighting the results and the novelty of the work. I believe some addition of more specific results that are present in the discussion will benefit the current version of the abstract.

[R1.1] The Abstract has been modified to incorporate reviewer's suggestions.

The following text has been added:

Abstract (L15) *"As an example, storms with smaller waves and from secondary incoming direction will increase erosion and inundation risks at the study area"*

Abstract (L18) *"Under current conditions, high and moderate inundation risks, and direct exposure to erosion can be reduced with a small coastal setback (~10 m), which needs to be increased up to 20-55 m to be efficient under future scenarios (+20 years)."*

Most of my comments are concentrated in the methodology sections this is partly because the method is rather complex and the proposed novelty although important it is not obvious from the beginning. The results and discussion sections are very well written and explained with high quality figures that although sometime complex they concentrate a large amount of information.

I have made specific comments in the text where I have questions or doubts my main concerns at the moment is that novelty of the method is not properly described in risk terms. I believe that the BN approach proposed is valid for characterizing the risk for the entire storm climate and not for specific storms as proposed by previous works. However, if this is true it needs to be highlighted by the authors in the abstract and in the title is necessary.

[R1.2] We agree with the reviewer and, in fact, this is one of the main novelties of the work. Following reviewer's suggestion, this is highlighted in different parts of the text.

Abstract (L11): *One of the main differences of the developed BN framework is that it includes the entire storm climate (all recorded storm events, 179 in the study case) to retrieve the integrated and conditioned risk-oriented results at individually identified receptors (about 4,000 in the study case).*

Introduction (L54): *The inclusion in the BN of simulation results from a long dataset of storms allows for a fully stochastic assessment in terms of wave climate characterisation. This is a novelty with respect to existing studies (e.g. Van Verseveld et al., 2015; Plomaritis et al., 2018; Ferreira et al. 2019; Sanuy et al., 2018). Although some of these studies introduce copula assessments on source (storm) characteristic variables to generate synthetic events, the training subsets aimed to covering the whole range of possible storm conditions rather than statistically representing the existing storm climate*

Conclusion (L535): *This resulted in a full representation of the storm climate (source) leading to probabilistic characterisation of risks that accounted for climate (storms) and geographic (receptor location) related variabilities, as the BN training followed the response approach (i.e. the simulation of the coastal response for all identified storms).*

My secondly concern is related with the scenarios proposed. Some more explanation is needed on why the shoreline retreat is extended to the entire shoreface.

[R1.3] Future (morphological) scenarios have been defined to consider the background evolution of the area. This is important when assessing risks in dynamic areas because if not, the assessment will strictly be valid just for current conditions (small time scale, few years) and, in consequence, of limited validity for coastal (risk) management. This is the key message, the need of updating beach coastal morphology for an effective risk assessment. We will reinforce this message in the text. With respect to how to do it, it will depend on the specific conditions of the area and on the used tool to mimic/simulate such evolution. Whereas there are many different options, we have chosen a simple one by extending shoreline rates of change to reproduce nearshore bathymetric changes, although as mentioned in the work, it can be substituted by a different choice (e.g. by using a morphodynamic model valid at the appropriate time-scale, e.g. Hanson et al. 2003).

In the study area, observed shoreline retreat is the result of the deltaic front reshaping due to a decrease in river sediment supply whereas the wave-induced littoral dynamics maintained its intensity. Transferring this shoreline retreat to the entire active shoreface implies to apply a hypothesis about the shape of long-term (decadal) profile changes. Thus, the most widely used hypothesis used to convert longshore transport – induced shoreline changes to sediment volume is the one applied in one-line models, where a horizontal displacement of the profile from the emerged beach to the closure depth is assumed (e.g. Hanson, 1989). On the contrary, other works on deltaic reduction processes assume that whereas the shoreline is rapidly eroded, the submerged front retreats at a slower rate (e.g. Refaat and Tsuchiya, 1991). This pattern would be consistent with a wedged-shaped change over the closure depth (instead of a parallel one as before). Other type of approach is the one adopted by Stive and de Vriend (1995) when modelling the long-term shoreface evolution. They proposed a varying type of change through the shoreface, from an upper part experiencing a parallel displacement, to a declining/inclining lower shoreface down to the inner shelf limit. As it can be seen, there are different options to reconstruct beach profiles from a modelled/forecasted shoreline, from which we selected one of the most used (albeit not necessarily the best one).

Regardless of the method used, the most important message is that it is necessary to anticipate future coastal morphology in order to make a reliable risk assessment valid not only for current but also for future conditions. We have highlighted this in the discussion section and also introduced a text discussing how the scenarios were constructed (similar to the previous one, but shorter).

References:

Hanson, H.: GENESIS: a generalized shoreline change numerical model, *J. Coast. Res.*, 1-27, 1989.
Hanson, H., Aarninkhof, S., Capobianco, M., Jiménez, J.A., Larson, M., Nicholls, R.J., Plant, N.G., Southgate, H.N., Steetzel, H.J., Stive, M.J.F, and de Vriend, H.J.: Modelling of coastal evolution on yearly to decadal time scales, *J. Coast. Res.*, 19, 4, 790-811, 2003.
Refaat, H., and Tsuchiya, Y.: Formation and reduction processes of river deltas; theory and experiments, *Bull. Disaster Prevention Res. Inst. Kyoto Univ.*, 41, 177-224, 1991.
Stive, M.J.F., and De Vriend, H. J.: Modelling shoreface profile evolution, *Mar. Geol.*, 126(1-4), 235-248, 1995.

Added text in the manuscript:

Scenario definition (L250): *Here, future morphological scenarios are defined to consider the background erosion in the area*

Scenario definition (L268): *This hypothesis about the shape of long-term (decadal) profile changes follows the hypothesis applied in shoreline evolution models, i.e. a parallel displacement of the active profile from the emerged beach down to the depth of closure (e.g. Hanson, 1989)*

Scenario definition (L274): *When the shoreline reaches a fixed structure limiting the landward translation, it is assumed that, locally, the beach disappears and, in consequence, no further profile retreat will occur.*

Discussion (L511): *It has to be mentioned that to build these morphological scenarios, it is necessary to “forecast” future configurations of the shallow water bathymetry. In this work, this was done by extending shoreline displacements down to the depth of closure by assuming a simple parallel displacement of the active inner profile, which is compatible with the usual hypothesis applied in mid-term shoreline models. However, other profile change modes could also be applied, such as a wedged-shaped change over the closure depth to simulate a slower retreat of the delta front in comparison with faster shoreline changes (e.g. Refaat and Tsuchiya, 1991). In both cases, their morphological consequences are limited to the shallowest and faster part of the shoreface and, in consequence, are strictly applicable to expected mid-term (decadal) changes. Building longer-term morphological scenarios would require to consider other options since the depth limiting significant changes in the beach profile will extend further with time scale (e.g. Cowell et al. 1999). In this line, Stive and de Vriend (1995) proposed a long-term shoreface evolution model that considers a varying type of change through the shoreface, from an upper part experiencing a parallel displacement, to a declining/inclining lower shoreface down to the inner shelf limit.*

In the case of structures/barriers being exposed at the shoreline along the study area due to background erosion, we have assumed that, locally, the active profile will not retreat further once the beach had disappeared. In the event of such situation, the structure would be

subjected to the highest possible risk and as so would be classified in the framework. Further bottom variations in front of the structure which may lead to its collapse due to scouring will not modify this classification.

In any case, it has to be considered that building future morphological scenarios to forecast the evolution of coastal risks at long-term scales will add uncertainty to the analysis, in addition to that associated with expected varying climatic forcing, since long-term morphodynamic modelling integrating all relevant processes is still an unsolved issue (e.g. Ranasinghe, 2020).

Specific comments:

LINE 33: source terms are both the storms and the storm induced hazards.

[R1.4] Adopting the S-P-R-C framework to analyse the risk induced by erosion/inundation (storm-induced hazards), the source (S) term is just defined by the storms. The pathways (P) of flooding/erosion are composed by the beach, defences and even, in some cases, the coastal floodplain. In fact, pathway and receptor (R) can be considered as relative definitions since they may simultaneously function as pathways to “landward” receptors and as receptors in their own right (e.g. Narayan et al. 2012). We slightly rephrased this paragraph in the text for clarification.

Modified paragraph:

Introduction (L35): *When applied to storm-induced coastal risks, it is generally schematised in terms of a source (storms), that propagates and interacts with a pathway (beach or coastal morphology) where hazards (i.e. inundation and erosion) are generated. These affect the receptors (elements of interest), inducing different consequences.*

LINES 53-58: Plomaritis et al 2018 select the events using the same methods as Poehekke et al., 2016. The method is based on a series of copula applications using Hs as a main parameter. I donot think that this method can be consider non-probabilistic but indeed the method can differ. Please explain with more detail the differences in the storm selection. Poehekke et al., 2016 also follows the ideas of response approach with the use of copulas but with triangular storms. I believe that the discussion over the different approaches that the authors provide is very interesting and I would suggest extending it or order for the reader to be better informed on the sometime small but important details.

[R1.5] Following the reviewer’s suggestions, we describe/analyse further the differences between approaches. The reviewer is right in stating that the use of the term “non-probabilistic” to classify the method followed by Poehekke et al’16 and Plomaritis et al’18 is not entirely correct and confusing. We have modified the text to avoid such confusion.

The above methods use copulas to statistically represent storms, which are the events (drivers) that induce the analysed hazards. Adopting a strict response-approach involves calculating the induced hazards for the entire storm climate and performing the statistical analysis on the results obtained in terms of hazards/impacts. This difference is especially relevant when analysed hazards depend on multiple storm variables which are not necessarily correlated and not included in their definition through copulas. Moreover, the mentioned works use a selected group of events, instead of a set representing the storm climate.

Modified paragraph:

Introduction (L56): *Although some of these studies introduce copula assessments on source (storm) characteristic variables to generate synthetic events, the training subsets aimed to*

covering the whole range of possible storm characteristic rather than statistically representing the existing storm climate.

The reference Duo et al., needs updating.

[R1.6] Update in the reference list:

Duo, E., Sanuy, M., Jiménez, JA, Ciavola, P. 2020. How Good Are Symmetric Triangular Synthetic Storms to Represent Real Events for Coastal Hazard Modelling. *Coastal Engineering*, 159, 103728.

Study area: Provide the names of the areas in Figure 1 not only the code. Now they is given in Discussion but the codes are used before. I think some information of the areas and the logic behind the separation could be interesting.

[R1.7] We prefer to do not include names in Figure 1 so as not to “overload” it. However, we have included a text in the “Study area” section in which we provide the full name of each sector and reasons for their selection (this text was included in section 3.4 in the original version of the manuscript).

Modification in the manuscript:

The paragraph describing the sectors that was previously located in the Risks (Methods) section has been moved without changes to the Study Area section.

LINE 95: I think the paper Sanuy et al. (2018) is not in the reference list.

[R1.8] Added to the reference list:

Sanuy, M., Duo, E., Wiebke, Jäger, W, Ciavola, P., Jiménez, JA. (2018) Linking source with consequences of coastal storm impacts for climate change and risk reduction scenarios for Mediterranean sandy beaches. *NHESS*, 18, 1825-1847.

LINE 143: Provide the number or percentage of empty groups

[R1.9] Done, see also [R1.10]

Storm characterisation (L157): Each storm from the dataset falls into one of the resulting $5 \times 4 \times 3 \times 3 = 188$ combinations of bulk characteristics. Some combinations are populated with storms (48), while others are empty groups (140), i.e. storm characteristics that have not been recorded and, therefore, not present in the storm dataset.

LINES 174-175: How many storms per bin you have in the subset group and which are the output paramters you test? My understanding so far is that you have one storm per group in the subset so, I am not sure how you calculate the variance per bin. Are you evaluate the BN output or input with the equations 1 and 2 or the entire BN?

[R1.10] This question is related with the previous comment. The subset method fills with one storm all combinations showed in Table 1 that have at least one historical event. Some combinations remain empty and this will now be introduced following [R1.9]. Then, the subset is used to fill the BN, which, as shown in Figure 6, has a different number of bins per variable than classes depicted in Table 1, leading to more than one event in many variable combinations.

The variance per bin is calculated following Bityukov et al., 2013, where the observed standard deviation per bin is estimated with the observed value per bin (i.e., $n_{ik} = \sigma_{ik}$ in eq. 1).

We evaluate both BN input and output variables with equations 1 and 2 (now they can be interpreted from Table 5 and Results Figures). We perform the evaluation on (i) unconstrained output, (ii) output constrained to given input combinations and (iii) input constrained to a given output. In the modified version of the manuscript, the evaluated variables are detailed, and Table 5 has been adapted to help the correct interpretation of the method.

Modifications in the manuscript

Storm characterisation (L159): This subdivision is only used for the purpose of deriving the subset, allowing finer detail in the source characteristics of the single-peak and multi-peak storms to be selected. Later, the BN will present a coarser binning of such variables, ensuring a better filling of the source variable combinations in the network.

Storm characterisation (L194): The statistics will be calculated for both BN inputs and outputs (see following sections): (i) the distribution of un-constrained output risk variables; (ii) the distribution of H_s , T_p , duration, direction and water level constrained to the different risk levels per sector; and (iii) the risk distributions per area and conditioned to the distance to inner beach limit. This involves the comparison of more than one variable output (e.g. impact results are always three variables), and therefore, results are given as a mean and standard deviation.

Table 5 has been modified naming the variables in it.

Hazard Assessment: Which are the indicator (model output parameter) you use for each hazard
[R1.11] The XBeach model outputs used are *maxzs* for water depth (inundation hazard) and *sedero* for erosion. This is mentioned in the revised version of the manuscript.

Hazards assessment (L209): The XBeach model outputs used for the subsequent risk calculations were *maxzs* for water depth with accompanying *u,v* components of the water velocity (inundation hazard) and *sedero* for bed level change (erosion hazard).

LINES 194-198: The area characteristics can be put in the study area. See my previous comment.
[R1.12] Done. See also [R1.7].

LINES 246-248: Given the steep slopes of the study area I understand the extrapolation of the shoreline retreat values to the upper beach (-2 to -4 m) but continues retreat up to -8 suggest a huge amount of sediment loss and that all sediment from the upper beach is removed by longshore drift. I am not an expert on Catalan coast but some additional justification for the selected scenarios must be provided.

[R1.13] When building the morphological scenarios, we are using recorded decadal-scale shoreline rates of displacement, that for the study area are mostly controlled by longshore sediment transport (e.g. Jiménez et al. 2018). The objective of the extrapolation was to build “possible coastal morphologies” to illustrate future changes in coastal risk associated with morphodynamic changes. We adopted this simple approach in absence of a robust criteria to select a different one. This point has been extensively covered above in [R3] and, as mentioned there, we included this point in the discussion section to let readers to make their own choice when applying the method to a given case.

Modifications in the manuscript: see [R1.3]

LINE 272: Why the storm parameters are linked in Figure 6? How is te term of previous energy is incorporated in the BN?

[R1.14] The storm parameters are linked so that empty combinations of source characteristics do not propagate noise into the outputs.

The term previous energy is now defined in the following added text:

Storm characterization (L147): For each peak, we retain its duration, together with the total accumulated event duration, and the previous energy: e.g. single-peak storms are always characterised as peaks with “peak duration” equal to “event duration” and with “mul”). Although all this information is retained (Figure 2), only event duration together with wave parameters and water level will be used as BN variable here, for the sake of simplicity in a risk-oriented perspective, while more detailed source description may be necessary in morphological analyses.

LINES 274-277: The central variables i and ii are not shown in Figure 6. Please provide more details. Explain where the estimation of the total number of receptors is done, in the BN or before?

[R1.15] In the revised version, Figure 6 will be adapted to show the two variables. The estimation is done before, crossing XBeach output with receptor polygon data, and introduced as an additional variable, at each receptor, that captures the overall number of affected receptors per storm peak. It allows for the assessment, in the same network, of the relation between source characteristics and extension of the impacts, although the presented results put the focus on other variable dependencies found more relevant. A sentence is introduced for further clarification.

Bayesian Network integration (L302): These are counted outside the BN for each simulated storm peak and introduced in the BN as an additional storm characteristic variable

LINES 420-421: What are the advantages of this fully probabilistic BN? I suppose that the previous papers were focused on the individual storm assessment while here is attempted an integrated assessment of the storm conditions. If this is correct it has to be stated and event introduced in the abstract.

[R1.16] This has been raised by the reviewer in previous comments. We have introduced some changes in the text (abstract, introduction, conclusion) to explicitly mention that the representation of the entire wave climate, to obtain integrated or conditioned risk-oriented results, is the advantage of the presented BN.

Modification in the manuscript: See [R1.2]

Anonymous Referee #2

Received and published: 7 October 2020

I have reviewed the manuscript entitled 'Probabilistic characterization of coastal storm induced risks using Bayesian Networks' by Sanuy and Jimenez. Overall the article is very well written and of high quality. It presents a new framework/ approach using the SPRC framework to examine coastal vulnerability to erosion and inundation at an area within the Spanish coastline exposed to Mediterranean storms. The methodology uses Bayesian Networks to take the SPRC inputs/outputs to create a probabilistic outcome of risk assessment. I believe that the article is well within the journals scope and will be of interest to the readers. However, I believe some changes are needed and points clarified as detailed below.

We thank the reviewer for constructive comments. We have performed a thorough revision to address all the comments and incorporated all the suggestions in the manuscript, as detailed below.

General comments:

Unclear to me the reasoning behind running XBeach on the scenario cases for 5, 10, 20 years? As you've just done a linear retreat of the shoreline/ profile and there is no account for changes in storminess or SLR [L482-485], are the results not just XBeach present day + retreat (Where a retreat is limited by hard structures such as seawalls)? I was a bit confused on how you did the retreat as well for the cases where structures were present. My general understanding is that a linear retreat (at all elevations) was done which essentially translated the profile intact. If the profile reached a structure, the landward translation stopped at that elevation, but the rest of the profile was allowed to continue to retreat? Or no? Figure 5 suggests that is not the case but it's not clear what was done? In reality, I think if it ran into a structure (like a seawall) the lower elevations would erode more than the linear trend as there would not be the sand from the land to compensate.

[R2.1] XBeach was run for different scenarios (5, 10, 20 y) to assess how expected changes in geomorphology may affect future risks. This may be relevant for decadal-scale retreating areas where (a given) current morphology is only representative of a relatively short (few years) period. We did not include changes in storminess since for the study area (NW Mediterranean) existing projections do not predict significant changes in storminess. We will include a paragraph where this is explicitly stated. Moreover, we will also recommend to perform the analysis using corresponding future storm climates when existing projections indicate a significant change in storminess.

These simulations are not exactly equal to "present day scenario" + "retreat" since the study site has not a homogeneous alongshore behaviour. Thus, the area has been divided (in terms of its decadal scale behaviour) in three different sectors, each one with its corresponding (and different) retreat rate. As a result of this, the alongshore configuration of the delta is slightly different across scenarios, with differences increasing with time due to the cumulative contribution of the background evolution. This change in morphology may affect alongshore processes and therefore the coastal response to storms (which is resolved with the 2DH - XBeach model).

With respect to the situation when the profile reaches a fixed structure limiting the landward translation, we have assumed that, locally, the beach has disappeared and the profile does not continue to retreat. We recognize that beach behavior in front of seawalls/revetments is more

complicated than this, with different processes taking place at different time scales which may affect beach profiles in front of exposed seawalls (Kraus, 1988). In fact, the observation raised by the reviewer on a larger erosion of the lower elevations due to a lack of compensation of material from the emerged part of the beach is one of the typical ones when cross-shore processes are being considered (e.g. Dean, 1986). In spite of this, existing works have documented different responses under different situations. Thus, whereas variations in hydrodynamics and sediment transport at short-term scale have been reported in front of exposed revetments (e.g. Miles et al. 2001), other authors have found that, in spite of differences in short-term behavior, long-term volume erosion rates are not higher in front of seawalls (e.g. Basco et al. 1997).

In any case it has to be considered that the objective of the framework is not simulate morphodynamic evolution but to assess the expected risk. In the case of structures/barriers being exposed at the shoreline along the study area due to background erosion, the structure would be subjected to the highest possible risk and as so would be classified in the framework. Further bottom variations in front of the structure which may lead to the collapse of the structure due to scouring will not modify this classification, and their prediction is further beyond the objectives of this work.

References:

- Basco, D. R., Bellomo, D. A., Hazelton, J. M., & Jones, B. N. (1997). The influence of seawalls on subaerial beach volumes with receding shorelines. *Coastal Engineering*, 30(3-4), 203-233.
- Dean, R. G. (1986). Coastal armoring: effects, principles and mitigation. In: *Proc 20th ICCE*, ASCE, 1843-1857.
- Kraus, N. C. (1988). The effects of seawalls on the beach: an extended literature review. *Journal of Coastal Research*, S14, 1-28.
- Miles, J. R., Russell, P. E., & Huntley, D. A. (2001). Field measurements of sediment dynamics in front of a seawall. *Journal of Coastal Research*, 195-206.

Thus, the answer given to reviewer 1 on assumptions to simulate the profile retreat **[R1.3]** is also valid for this comment, and we replicate here:

[R1.3] Future (morphological) scenarios have been defined to consider the background evolution of the area. This is important when assessing risks in dynamic areas because if not, the assessment will strictly be valid just for current conditions (small time scale, few years) and, in consequence, of limited validity for coastal (risk) management. This is the key message, the need of updating beach coastal morphology for an effective risk assessment. We will reinforce this message in the text. With respect to how to do it, it will depend on the specific conditions of the area and on the used tool to mimic/simulate such evolution. Whereas there are many different options, we have chosen a simple one by extending shoreline rates of change to reproduce nearshore bathymetric changes, although as mentioned in the work, it can be substituted by a different choice (e.g. by using a morphodynamic model valid at the appropriate time-scale, e.g. Hanson et al. 2003).

In the study area, observed shoreline retreat is the result of the deltaic front reshaping due to a decrease in river sediment supply whereas the wave-induced littoral dynamics maintained its intensity. Transferring this shoreline retreat to the entire active shoreface implies to apply a hypothesis about the shape of long-term (decadal) profile changes. Thus, the most widely used hypothesis used to convert longshore transport – induced shoreline changes to sediment

volume is the one applied in one-line models, where a horizontal displacement of the profile from the emerged beach to the closure depth is assumed (e.g. Hanson, 1989). On the contrary, other works on deltaic reduction processes assume that whereas the shoreline is rapidly eroded, the submerged front retreats at a slower rate (e.g. Refaat and Tsuchiya, 1991). This pattern would be consistent with a wedged-shaped change over the closure depth (instead of a parallel one as before). Other type of approach is the one adopted by Stive and de Vriend (1995) when modelling the long-term shoreface evolution. They proposed a varying type of change through the shoreface, from an upper part experiencing a parallel displacement, to a declining/inclining lower shoreface down to the inner shelf limit. As it can be seen, there are different options to reconstruct beach profiles from a modelled/forecasted shoreline, from which we selected one of the most used (albeit not necessarily the best one).

Regardless of the method used, the most important message is that it is necessary to anticipate future coastal morphology in order to make a reliable risk assessment valid not only for current but also for future conditions. We have highlighted this in the discussion section and also introduced a text discussing how the scenarios were constructed (similar to the previous one, but shorter).

References:

Hanson, H.: GENESIS: a generalized shoreline change numerical model, *J. Coast. Res.*, 1-27, 1989.
Hanson, H., Aarninkhof, S., Capobianco, M., Jiménez, J.A., Larson, M., Nicholls, R.J., Plant, N.G., Southgate, H.N., Steetzel, H.J., Stive, M.J.F, and de Vriend, H.J.: Modelling of coastal evolution on yearly to decadal time scales, *J. Coast. Res.*, 19, 4, 790-811, 2003.
Refaat, H., and Tsuchiya, Y.: Formation and reduction processes of river deltas; theory and experiments, *Bull. Disaster Prevention Res. Inst. Kyoto Univ.*, 41, 177-224, 1991.
Stive, M.J.F., and De Vriend, H. J.: Modelling shoreface profile evolution, *Mar. Geol.*, 126(1-4), 235-248, 1995.

Added text in the manuscript:

Scenario definition (L247): *Here, future morphological scenarios are defined to consider the background erosion in the area*

Scenario definition (L265): *This hypothesis about the shape of long-term (decadal) profile changes follows the hypothesis applied in shoreline evolution models, i.e. a parallel displacement of the active profile from the emerged beach down to the depth of closure (e.g. Hanson, 1989)*

Scenario definition (L270): *When the shoreline reaches a fixed structure limiting the landward translation, it is assumed that, locally, the beach disappears and, in consequence, no further profile retreat will occur.*

Discussion (L509): *It has to be mentioned that to build these morphological scenarios, it is necessary to “forecast” future configurations of the shallow water bathymetry. In this work, this was done by extending shoreline displacements down to the depth of closure by assuming a simple parallel displacement of the active inner profile, which is compatible with the usual hypothesis applied in mid-term shoreline models. However, other profile change modes could also be applied, such as a wedged-shaped change over the closure depth to simulate a slower retreat of the delta front in comparison with faster shoreline changes (e.g. Refaat and Tsuchiya, 1991). In both cases, their morphological consequences are limited to the shallowest and faster part of the shoreface and, in consequence, are strictly applicable to expected mid-*

term (decadal) changes. Building longer-term morphological scenarios would require to consider other options since the depth limiting significant changes in the beach profile will extend further with time scale (e.g. Cowell et al. 1999). In this line, Stive and de Vriend (1995) proposed a long-term shoreface evolution model that considers a varying type of change through the shoreface, from an upper part experiencing a parallel displacement, to a declining/inclining lower shoreface down to the inner shelf limit.

In the case of structures/barriers being exposed at the shoreline along the study area due to background erosion, we have assumed that, locally, the active profile will not retreat further once the beach had disappeared. In the event of such situation, the structure would be subjected to the highest possible risk and as so would be classified in the framework. Further bottom variations in front of the structure which may lead to its collapse due to scouring will not modify this classification.

In any case, it has to be considered that building future morphological scenarios to forecast the evolution of coastal risks at long-term scales will add uncertainty to the analysis, in addition to that associated with expected varying climatic forcings, since long-term morphodynamic modelling integrating all relevant processes is still an unsolved issue (e.g. Ranasinghe, 2020).

Data independence: I have several questions around data independence that I'd like to see addressed.

First, while the data set is 60 years long, there are 179 independent storms (43 of these are multi-peak storms). It's not clear to me (from an erosion sense) why you'd split these 43 up into multiple storms to augment your data set to 237 storms (Which is still quite small in terms of BNs). Similarly, on L 155-160 it's again described about the multi-peak storms where a single multi-peak storm is run and the outputs from the cumulative are saved, but also those of the 'first peak' (but the cumulative output after each peak is saved?). Should (ii) not be the peak of each 'sub-peak' in a multi-peak storm and should the output not be the volume (for example) between the 2 peaks, rather than the cumulative over the full event? As an aside - Your wave height cutoffs (98 and 99.5%) are also quite high, so you could lower these and get more smaller storms (say the 95% level – see Masselink et al).

[R2.2] *With respect to creating a dataset based on storm peaks instead of storms.*

Individual storm events have been identified and isolated by using the P.O.T method that ensures they are independent. Then, from there, any storm consisting in more than one peak is treated by its individual (cumulative) peaks, as the idea was to create a dataset of storm peaks (not to artificially augment the dataset with additional storms). For each peak, we retain its duration, together with the total accumulated event duration, and the previous energy (i.e. single-peak storms are always characterised as peaks with “peak duration” equal to “event duration” and with “zero previous energy”). This was done for a parallel analysis on morphodynamic response where we found that peak sequencing was a key aspect to predict local beach retreats. These variables were included in the network to assess their impact into output risk variables, but for the sake of simplicity only a selection of them, focusing on other variables, is presented here, and due to this they have been shortly described, which could generate some confusion. We have extended the variable description in the revised version.

The reviewer is fully right affirming that each “sub-peak” should be considered (not only the first). In fact, the original dataset contains ALL sub-peaks. Text in L155-160 refers to the fact that

in order to create the subsets for the future scenarios, and with the objective of reducing the number of time-consuming simulations, the first peak of a multipeak storm is also used as a proxy of “single-peak-storms of the same characteristics”. We have rephrased part of the “Storm characterisation” section to clarify this point.

With respect to threshold selection.

The used thresholds when applying the P.O.T method (98% and 99.5% percentiles of the wave height distribution) have been previously used in other works in the study area (Sanuy et al., 2019; Sanuy and Jiménez 2020). Obtained results (identified storms) have been compared with storm conditions associated with representative storm classes (Mendoza et al., 2011) and they fit with values obtained therein for Class 1 and Class 3 storms. Class 1 storms have the minimum H_s historically used in the Mediterranean as threshold for extreme events (2 m), while Class 3 events have the minimum H_s that actually induces hazardous coastal response. This is equivalent to define storms as starting and ending with a Class 1 magnitude, and having at least Class 3 at the peak. This permits to assure that all included events will induce a relevant coastal response from the risk-oriented standpoint.

The obtained event density of 3.5 events/year is appropriate for extreme-climate analysis, and lowering the threshold would increase this frequency by including not too extreme events which would not significantly contribute to overall risk. Due to this, we will maintain the proposed thresholds which have been locally validated for this use. In spite of this, we have stressed the meaning of the thresholds, specifying that the levels are site-dependent both in the Storm Characterization” and “Discussion” sections.

References:

- Mendoza, E. T., Jimenez, J. A. and Mateo, J. 2011. A coastal storms intensity scale for the Catalan sea (NW Mediterranean), *Nat. Hazards Earth Syst. Sci.*, 11, 2453–2462.
- Sanuy, M., Jiménez, J. A., Ortego, M. I. and Toimil, A. 2019: Differences in assigning probabilities to coastal inundation hazard estimators: Event versus response approaches, *J. Flood Risk Manag.*, 13, e12557.
- Sanuy, M., Jiménez, J. A. and Plant, N. 2020. A Bayesian Network methodology for coastal hazard assessments on a regional scale: The BN-CRAF, *Coast. Eng.*, 1572019, 1–10.

Added text in the manuscript:

Storm characterization (L136): *The first threshold, the 0.98 quantile ($H_s = 2$ m, in agreement with Class 1 storms in Mendoza et al. 2011 for NW Mediterranean conditions), is used to identify storm start and end times, and thus, controls the event duration and inter-event fair-weather periods. The second threshold, the 0.995 quantile ($H_s = 2.6$ m), is used to filter events that do not reach this value at the peak and would not be significant in terms of induced impacts. This second threshold retains only storms reaching Class 3 at the peak which is the minimum storm magnitude inducing hazardous coastal response (Mendoza et al., 2011)*

Storm characterization (L147): *For each peak, we retain its duration, together with the total accumulated event duration, and the previous energy (e.g. single-peak storms are always characterised as peaks with “peak duration” equal to “event duration” and with “zero previous energy”). Although all this information is retained (Figure 2), only event duration together with wave parameters and water level will be used as BN variable here, for the sake of simplicity in a risk-oriented perspective, while more detailed source description may be necessary in morphological analyses.*

Storm characterisation (L159): *This subdivision is only used for the purpose of deriving the subset, allowing finer detail in the source characteristics of the single-peak and multi-peak*

storms to be selected. Later, the BN will present a coarser binning of such variables, ensuring a better filling of the source variable combinations in the network.

Storm characterisation (L173): *Thus, to properly account for their potential effects, all existing identified multi-peak storms in the original time-series (43) were included in the subset. Their impact was simulated with the XBeach model saving the cumulative output after each peak. The impact after the first peak of such multi-peak events was used as proxy of equivalent single-peaks already covering 22 source variable combinations. The other 26 combinations were covered by additional single-peak storms.*

Discussion (L453): *The thresholds used to identify independent events in the P.O.T are site dependent. In this work, they agree with the storm classification in Mendoza et al., (2011), and therefore they are valid for the Catalan coast (NW Mediterranean)*

Second, my understanding is that inputs to the BNs are meant to be independent, so closely spaced receptors which are highly correlated shouldn't be included. I couldn't find details on the spacing of the receptors, but they don't look spatially independent to me (Eg. Fig 3). Beuzen et al. (2019 – JGR) I think discussed this and found the alongshore spacing allowed where correlations dropped off (This would be site specific but in his case it was ~500m I think). So I suspect you've padded your BN with a bunch of data that's highly correlated which isn't best practice.

[R2.3] This answer is related with **[R2.5]** (see below). Beuzen et al. (2019-JGR) deals with morphological patterns at regional scale (~400 km). They aim for a predictive BN and therefore they cannot allow for correlations in the input. Indeed, distances would be case specific, and in places as the Tordera Delta (curvilinear shoreline with significant alongshore morphological variability, and beach-structure interactions inducing local processes such as flanking effects) these distances would be much lower, as we found by analysing the morphological response sector by sector (analysed in a companion morphodynamic oriented-paper, currently under review).

However, this is out of the scope of the current paper, which is risk-oriented. Here, the individual receptors must be represented as they indicate the spatial extension and magnitude of the impacts induced by a given coastal response (e.g. its not the same from the risk perspective 100 m of eroded dune in front of 1 receptor than the same 100 m of eroded dune in front of 2 lines of 20 receptors). Thus, we have adopted the Source-Pathway-Receptor-Consequence (SPRC) scheme as in Poelhekke et al (2016), Jäger et al. (2018), Plomaritis et al. (2018) and Sanuy et al. (2018), to account for the actual receptor density and typology at the local scale.

References:

- Jäger, W. S., Christie, E. K., Hanea, A. M., den Heijer, C. and Spencer, T. 2018: A Bayesian network approach for coastal risk analysis and decision making, *Coast. Eng.*, 134, 48-61.
- Plomaritis, T. A., Costas, S. and Ferreira, Ó. 2018: Use of a Bayesian Network for coastal hazards, impact and disaster risk reduction assessment at a coastal barrier (Ria Formosa, Portugal), *Coast. Eng.*, 134, 134-147.
- Poelhekke, L., Jäger, W. S., van Dongeren, A., Plomaritis, T. A., McCall, R. and Ferreira, Ó.: 2016. Predicting coastal hazards for sandy coasts with a Bayesian Network, *Coast. Eng.*, 118, 21–34.
- Sanuy, M., Duo, E., Jäger, W. S., Ciavola, P., and Jiménez, J. A. 2018: Linking source with consequences of coastal storm impacts for climate change and risk reduction scenarios for Mediterranean sandy beaches, *Nat. Hazards Earth Syst. Sci.*, 18, 1825–1847.

Similarly, it's not best practice (And I think even discouraged) to augment your data by multiplying your synthetic cases by the number of storms that were in that bin (L144-146). I know it has been done in the past by others (including myself and I've learned from others this was incorrect) but that doesn't make it correct now. I appreciate you are wanting to keep the original distributions but I'm not sure there is a proper way to do this beyond running each case.

[R2.4] We agree that this is a shortcoming compared to running all cases. However, this method was proposed to reduce computational time when generating future scenarios (which are affected to other additional uncertainties as well). In statistical terms, the method behaves consistently and it is validated by comparing the distributions obtained with the subset with those of the original dataset (for the baseline scenario). This means that for the purposes presented in the current work, i.e. obtaining risk-oriented variable distributions, the obtained subsets can be considered statistically similar to the original dataset (although for more detailed analyses, such as morphological-oriented ones, this may not be enough).

How probabilistic is your output? Your BNs (Fig 6 and 7) are quite complex and in some cases, highly discretised. This immensely increases the number of data points needed to ensure the priors are well represented. As the challenge is with much geophysical data, you look to have a lot of near empty bins in your outputs. How many of the relationships are really deterministic rather than probabilistic?

[R2.5] We understand our BN is probabilistic in the sense that it is used to adopt the SPRC model by using a probabilistic representation of the source (i.e. a probabilistic representation of the storm climate of the study site).

The reviewer is right when pointing out the complexity of the BN, and the data requirements that this involves to properly fill it. In this case, all Source-related parent variables are connected between them (differently e.g. to Beuzen et al., 2019) to ensure that when conditioning is made on these variables all other priors are updated so as not to have noise propagation onto the output variables. In this sense, our BN would fit into the descriptive BN category according to Beuzen et al. (2018). This does not mean that the output is not probabilistic (which is by the schematization of the SPRC and the treatment of the Source) but that the main purpose of the BN is not a predictive one, as e.g. in Beuzen et al. (2019).

The following text has been added:

Bayesian network integration (L327): Notably, both BNs present a certain degree of complexity given the discretization level of some variables and the number of variables used. The BNs are designed to be descriptive BNs (Beuzen et al., 2018b), and thus, source variables are also interconnected to avoid the propagation of noise from empty combinations to the output. This departs from predictive BNs which aim to infer system behaviour and predict combinations beyond those learned from the dataset.

Additionally, the main (and novelty with respect to previous works) purpose of the BN, which is the probabilistic representation of the source, will be also better stressed, as suggested also by reviewer 1 (see answers to reviewer 1 general comments).

References:

Beuzen, T., Splinter, K.D., Marshall, L.A., Turner, I.L., Harley, M.D., Palmsten, M.L. 2018. Bayesian Networks in coastal engineering: Distinguishing descriptive and predictive applications. *Coast. Eng.* 135, 16–30.

Beuzen, T., Harley, M. D., Splinter, K. D., & Turner, I. L. 2019. Controls of variability in berm and dune storm erosion. *Journal of Geophysical Research: Earth Surface*, 124(11), 2647-2665.

What's the difference between distance to public domain (Fig 7) and distance to beach (Fig 10-12)? I feel they must be similar if not the same so why not use the same classification and binning for the 2?

[R2.6] Indeed, they are the same since the line of public domain is running along the inner limit of the beach. The name in figure 7 (and related text) will be changed. The binning is actually the same, but in figures 10-12 the outputs of two lowest bins are summed under the name "Beach to 10m", and the outputs of the four highest bins are summed under the name "> 75 m"

Specific Comments:

[L74]: 'were' should be 'where' in: "study area were"

[R2.7] This has been addressed in the updated version of the manuscript.

[L204]: "Risk to life was also been" should be either 'Risk to live was also' or "Risk to life has also been"

[R2.8] This has been addressed in the updated version of the manuscript.

Fig 5 - can you tell the reader what section these are in and the erosion rate used?

[R2.9] This has been included in the figure caption

[L355] "affecter" should be 'affected'?

[R2.10] This has been addressed in the updated version of the manuscript.

[L341] "front a of a" should be "front of a"

[R2.11] This has been addressed in the updated version of the manuscript.

[L427] "relation" should be "relationship"

[R2.12] This has been addressed in the updated version of the manuscript.

Probabilistic characterisation of coastal storm-induced risks using Bayesian Networks

Marc Sanuy¹, Jose A. Jiménez¹

¹Laboratori d'Enginyeria Marítima, Universitat Politècnica de Catalunya, BarcelonaTech, c/Jordi Girona 1-3, Campus Nord ed D1, 08034 Barcelona, Spain.

Correspondence to: Marc Sanuy (marc.sanuy@upc.edu)

Abstract. ~~Coastal areas are often affected by inundation and erosion storm-induced risks. Detailed local risk assessments usually propagate a source (storm) through a pathway (coastal morphology) to characterise hazards (i.e. erosion and inundation) at the receptors and assess corresponding consequences.~~ A probabilistic estimation of hazards based on the ~~coastal response~~ response approach requires assessing large amounts of source characteristics, representing an entire storm climate. In addition, the coast is a dynamic environment, and factors such as ~~climate change projections or~~ existing background erosion trends require performing risk analyses under different scenarios. This work applies Bayesian Networks (BNs) following the source-pathway-receptor-consequences scheme aiming to perform a probabilistic risk characterisation at the Tordera Delta (NE Spain). One of the main differences of the developed BN framework is that it includes the entire storm climate (all recorded storm events, 179 in the study case) to retrieve the integrated and conditioned risk-oriented results at individually identified receptors (about 4,000 in the study case)~~The BNs allow an efficient assessment of results from a large number of storms (179) and their simulated consequences at the receptor scale (~4000 receptors).~~ Presented Obtained results highlight the storm characteristics with higher probabilities to induce given risk levels for inundation and erosion, and how these are expected to change under given scenarios of shoreline retreat due to background erosion. As an example, storms with smaller waves and from secondary incoming direction will increase erosion and inundation risks at the study area. The BNs also output probabilistic distributions of the different risk levels conditioned to given distances to the beach inner limit, allowing for the definition of probabilistic setbacks. Under current conditions, high and moderate inundation risks, and direct exposure to erosion can be reduced with a small coastal setback (~10 m), which needs to be increased up to 20-55 m to be efficient under future scenarios (+20 years).

25 1. Introduction

The coastal fringe is a highly dynamic zone and one of the most fragile terrestrial areas due to high population, dense infrastructure, intense economic activities, and endangered natural habitats. The progressive occupation of coastal areas increasingly exposes them to storm-induced hazards, such as inundation and erosion (IPCC, 2012, 2013). This, together with future projections of rising sea levels (Vousdoukas et al., 2016; IPCC, 2018), long-term shoreline retreat (Vousdoukas et al. 2020), changes in storminess (Lionello et al. 2008, Conte and Lionello 2013; IPCC, 2014), and/or changes in the directionality of incoming waves (Cases-Prat and Sierra, 2013), highlight the need for local-scale risk assessments considering these current and future scenarios. In the NW Mediterranean basin, storm-induced damages at the Catalan coast have increased during the last decades as a result of increased exposure along the coastal zone and the progressive narrowing of the existing beaches (Jiménez et al., 2012). All these elements have determined that current and future coastal management plans will require a specific chapter on coastal risks as recognised in the Protocol of Integrated Coastal Zone Management in the Mediterranean (UNEP/MAP/PAP, 2008). One of the most used approaches in risk assessment is the Source-Pathway-Receptor-Consequences (SPRC) framework (Sayers et al., 2002; Narayan et al. 2014; Oumeraci et al., 2015). This is a conceptual model describing the propagation of risk across a given domain from the source to the receptors.

When applied to storm-induced coastal risks, it is generally schematised in terms of a source (storms), that propagates and interacts with a pathway (beach or coastal morphology) where hazards (i.e. inundation and erosion) are generated.; These affect the receptors (elements of interest), and inducing different consequences associated with given hazards (i.e. inundation and erosion). When addressing the problem at the local scale (~5–10 km), storm-induced hazards are usually assessed by using detailed process-based models that are fed information on both the source and the pathway. Recent studies use the capabilities of Bayesian Networks (BNs) to assess consequences at the receptor scale, as they can easily handle multidimensional problems while dealing with large amounts of data allowing the assessment of multiple source conditions, hazards, and scenarios (e.g. Van Verseveld et al., 2015; Poelhekke et al., 2016; Plomaritis et al., 2018; Sanuy et al., 2018). BNs allow the analysis of conditional dependencies between variables, and therefore, can be used to reproduce the causal relationships inherent in the SPRC scheme (Jäger et al., 2018).

In this context, this work presents the development of a fully probabilistic BN-based SPRC approach to assess storm-induced risks at a local scale. To illustrate the methodology, the BN approach is applied to characterise coastal risks at the Tordera Delta, a highly dynamic area that is vulnerable to the impact of extreme coastal storms (Jiménez et al., 2018). Risks related to storm-induced erosion and inundation were assessed using current morphology and future configurations considering the existing trends of shoreline retreat due to background erosion (Jiménez et al., 2019). The approach assesses the storm characteristics associated with the spatially variable risks, and characterises the along-shore and cross-shore spatial distribution of given levels of risk under different scenarios. For this purpose, all available storms derived from a long dataset (60 years) of wave time series were simulated by the XBeach model (Roelvink et al., 2009) and the induced hazards analysed. Receptor characterisation was individually performed as described in Sanuy et al. (2018). The inundation risk was assessed in terms of relative damage to structures and risk to life, while the erosion risk was assessed as a function of the loss of protective capacity of the coast in front of the receptors. The inclusion in the BN of simulation results from a long dataset of storms allows for a fully stochastic assessment in terms of wave climate characterisation. This is a novelty with respect to existing studies that only use a non-probabilistic subset of events to describe the source (e.g. Van Verseveld et al., 2015; Plomaritis et al., 2018; Ferreira et al. 2019; Sanuy et al., 2018). Although some of these studies introduce copula assessments on source (storm) characteristic variables to generate synthetic events, the training subsets aimed to covering the whole range of possible storm conditions rather than statistically representing the existing storm climate. In addition, the applied method follows the idea behind the response approach (Garrity et al., 2006, Sanuy et al., 2020a), simulating erosion and inundation hazard for the whole population of events, and while simulatinges the storms using their real shapes (i.e. storm evolution with time), and thus, avoiding the uncertainties introduced by the use of a synthetic representation of the events (Duo et al., ~~n.d.~~2020).

The structure of the paper is as follows: Section 2 presents the study area with the main data sources, Section 3 outlines the methodology and its different steps, and Section 4 presents the obtained risk characterisation at the Tordera Delta; results are discussed in Section 5 and the main conclusions are summarised in Section 6.

2. Study area and data

The Catalan coast is located in the NW Mediterranean Sea (Figure 1). The coastline extends to nearly 600 km with about 280 km of beaches. Storm-induced issues are present along the entire coastline and are especially concentrated in locations with the largest decadal-scale shoreline erosion rates (Jiménez et al., 2011; Jiménez and Valdemoro, 2019). A good example of such an area is the Tordera Delta, located approximately 50 km north of Barcelona (Jiménez et al., 2018) (Figure 1). The deltaic coast is a highly dynamic area composed of coarse sediment and extends to about 5 km, from s'Abanell beach at the northern end to Malgrat de Mar beach in the south (Figure 1). It is currently retreating because of the net longshore sediment transport directed southwest and the decrease in Tordera River sediment supplies. Consequently, the beaches surrounding the

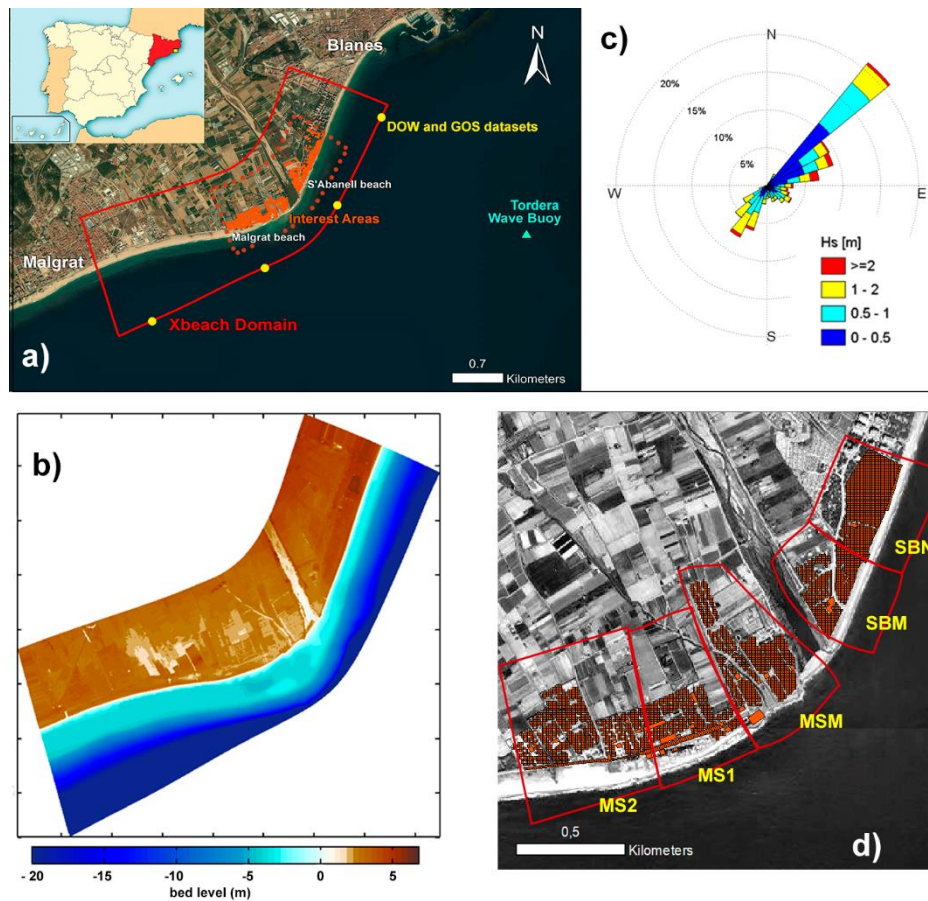
80 river mouth are being significantly eroded (Jiménez et al., 2011; Sardá et al., 2013; Jiménez et al., 2018), and the frequency of inundation episodes and damage to existing infrastructure (beach promenade, campsite installations, roads, etc.) has significantly increased since the beginning of the 90s (Jiménez et al., 2011; Sardá et al., 2013) (Figure 1). The area is composed of multiple campsites that represent the main economical activity of the municipality and was identified as a regional coastal hotspot to erosion and inundation in Jiménez et al., (2018). Therefore, it is the prototype of study area where
85 detailed risk assessments are needed at the local scale to support decision making.

To spatially characterise the risk of the area as a function of the variability of the local geomorphology and coastline orientation at both sides of the river mouth, five different sectors along the coast were defined (Figure 1). Two of them, SBN and SBM, are located northwards of the river mouth (Figure 1), with SBM being limited to the south by the river mouth. The main distinctive feature of SBN is the existence of a promenade limiting the inner part of the beach. Southwards of the river, there are three sectors (Figure 1): MSM being closest to the mouth; MS1, which is located southwards of a coastal revetment; and MS2 located furthest to the south, with wider beaches, and sheltered against Eastern storm waves, which are dominant in the area (Mendoza et al. 2011).

90

The data used to represent the morphology of the study area are comprised of LIDAR-derived topography provided by the
95 Institut Cartogràfic i Geològic de Catalunya, as a high-resolution digital elevation model (DEM) with 1-m × 1-m grid cells and a vertical precision of 5–6 cm (Ruiz et al. 2009). Bathymetry obtained from multi-beam surveys provided by the Ministry of Agriculture, Fish, Food, and Environment was also used.

To characterise the forcing, the present work used hindcast waves from the Downscaled Ocean Waves dataset (Camus et al., 2013) derived from the Global Ocean Waves (Reguero et al., 2012). Hindcast surge from the Global Ocean Surge dataset
100 (Cid et al. 2014), obtained at 4 locations close to the Tordera Delta at ~20 m depth, covering the period from 1954–2014 (Figure 1), was also used. The simultaneous astronomical tide was added to the Global Ocean Sampling (GOS) dataset to obtain the total water level. The astronomical tidal range in the study area was about 0.25 m.



105 **Figure 1: Main locations and characteristics of the study site: a) Location of the Tordera Delta, XBeach model domain (red), location of model boundary conditions (yellow, Downscaled Ocean Waves, and Global Ocean Surge datasets, Camus et al., 2013), receptors of interest (orange) and Tordera wave buoy (light blue); b) Digital Elevation Model (DEM) of the Tordera Delta; c) wave rose at the Tordera delta buoy (Global Ocean Waves; Reguero et al., 2012); d) receptor areas for the local risk assessment. Orthophoto provided by Institut Cartogràfic I Geològic de Catalunya (ICGC).**

110 3 Methodology

3.1 General framework

The methodology used in this work adapts the general approach of Jäger et al. (2018) where BNs were applied to implement the SPRC framework to assess storm-induced coastal risks. This approach has been previously implemented by Sanuy et al. (2018) at the Tordera Delta to compare, in a deterministic manner, different risk reduction measures. In this work, the scheme was upgraded to a fully probabilistic risk characterisation and consisted of the following steps:

- (i) *Storm characterisation.* This step consisted of defining the local storm climate from long-term wave time-series. This stage corresponded to the (probabilistic) characterisation of the source. In practice, the result of this step was a storm dataset containing the hourly evolution of wave parameters during each event for a long period (multiple decades).
- (ii) *Hazard assessment.* Once the forcing was characterised, the next step was the assessment of the storm-induced hazards, i.e. erosion and inundation, which were simulated using a process-based morphodynamic model, XBeach. This stage corresponded to the characterisation of the pathway. To ensure the probabilistic representation of the hazards, this step was performed for all the events of the storm dataset (first step) or for a subset of events that ensures an equivalent representation of the multivariant population representing the source.
- (iii) *Risk characterisation.* In this step, simulated storm-induced hazards across the study area were transformed into risk values at the scale of individual receptors (existing buildings and infrastructure). To this end, vulnerability rules were defined as a function of the receptor typology and analysed hazard. In this stage, the receptor and consequence phases of the SPRC framework were tackled.

(iv) *Scenario definition*. This step consisted of defining the conditions for the assessment in terms of ~~climate and~~ geomorphological scenarios of interest. This might require repeating steps (ii) and (iii), for all identified storms in (i). Here, the entire storm dataset was used to characterise the baseline scenario (current conditions), while the additional scenarios were assessed with a representative subset to reduce the computational effort. The subset was also used to assess the baseline scenario to later verify that it statistically represents the same population as the original dataset from the perspective of the obtained results (for the validation of the method).

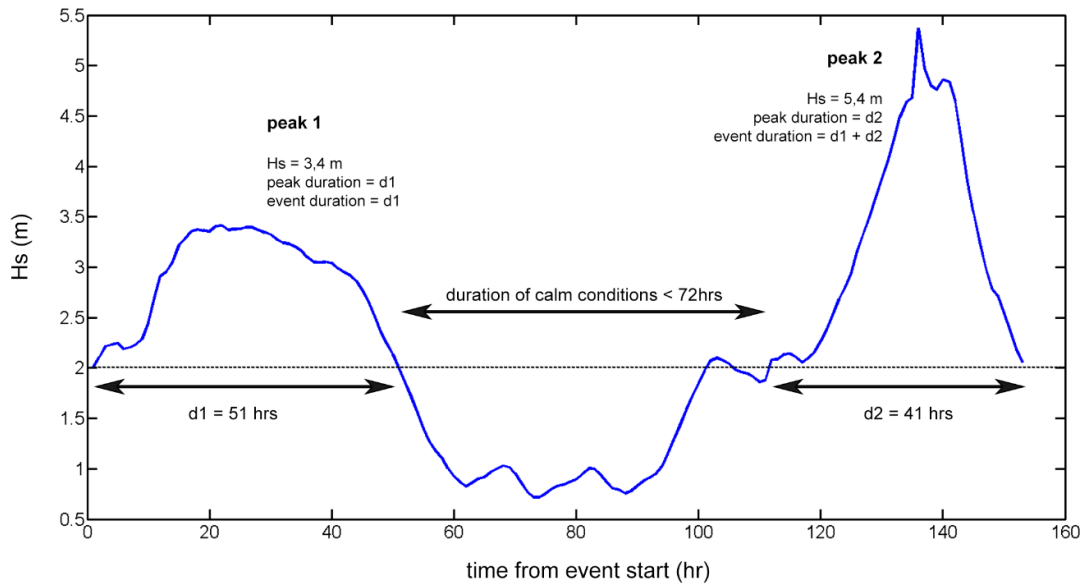
(v) *BN integration*. The obtained results for each event at the receptor scale were related to the variables characterising the storms (e.g. bulk features) and receptor properties (e.g. location) and integrated within the BN. Therefore, the BN outputs risk probability distributions accounted for the variability in the forcing conditions as well as the spatial distribution of receptors.

In the following sections, specific methods used in each step to analyse the Tordera delta case study are presented. Although some specificities are included, adopted methods are general enough to be applicable at nearly any site.

3.2 Storm characterisation

Coastal storms have been identified from wave time-series by employing the peak-over-threshold (POT) method using a double threshold criterion as in Sanuy et al. (2020a). The first threshold, the 0.98 quantile ($H_s = 2$ m, in agreement with Class 1 storms in Mendoza et al. 2011 for NW Mediterranean conditions), is used to identify storm start and end times, and thus, controls the event duration and inter-event fair-weather periods. The second threshold, the 0.995 quantile ($H_s = 2.6$ m), is used to filter events that do not reach this value at the peak and would not be significant in terms of induced impacts. This second threshold retains only storms reaching Class 3 at the peak, which is the minimum storm magnitude inducing hazardous coastal response (Mendoza et al., 2011)

The obtained dataset is composed of 179 storms (~3 storms per year), each being characterised by the hourly evolution of wave conditions (significant wave height, H_s ; peak period, T_p ; storm surge; wave direction; and directional spreading). Of the 179 events, 43 correspond to multi-peak storms. These events occur when fair-weather conditions (H_s below the first threshold) between consecutive peaks last less than 72 hours (Figure 2); they are relatively frequent in this part of the NW Mediterranean (Mendoza et al. 2011). In 12 cases, storms are formed by 3 or more peak sequences, leading to a total number of 237 individual storm peaks. For each peak, we retain its duration, together with the total accumulated event duration, and the previous energy (e.g. single-peak storms are always characterised as peaks with “peak duration” equal to “event duration” and with “zero previous energy”). Although all this information is retained (Figure 2), only event duration together with wave parameters and water level will be used as BN variable here, for the sake of simplicity in a risk-oriented perspective, while more detailed source description may be necessary in morphological analyses.



195 **Figure 2: Scheme of a double peak storm.**

To reduce the computational effort when assessing multiple scenarios, a storm *subset* is built aiming to maintain the statistical representativeness while avoiding the repetition of simulations of strongly similar storm conditions. The procedure consists of grouping the main variables defining the storm (H_s , T_p , duration, and direction) in homogeneous intervals covering the entire range of local conditions (see Table 1). Each storm from the dataset falls into one of the resulting $4-5 \times 4 \times 3 \times 3 = 144-188$ combinations of bulk characteristics. Some combinations are populated with *several* storms (48), while others are empty groups (140), i.e. storm characteristics that have not been recorded and, therefore, not present in the storm dataset. This subdivision is only used for the purpose of deriving the subset, allowing finer detail in the source characteristics of the single-peak and multi-peak storms to be selected. Later, the BN will present a coarser binning of such variables, ensuring a better filling of the source variable combinations in the network.

205 ~~To~~ Therefore, to produce the subset, one storm is selected for ~~all~~ each combinations populated with at least one event. To ensure a probabilistic representation of the source, the number of storms belonging to each combination is counted for later use as a weight (multiplicity factor) when feeding the BN with results from that event.

210 **Table 1: Subset characteristics compared to the original storm dataset. Source variable combinations used to classify storms and select the subset events.**

Original dataset characteristics			
179 storms	136 single-peak	43 multi-peak	237 storm peaks
Subset characteristics			
69 storms	26 single-peak	43 multi-peak	127 storm peaks
Variable combinations to produce subsets			
<u>H_s (m)</u>	<u>T_p (s)</u>	<u>Duration (h)</u>	<u>Direction (°N)</u>
< 3	< 9	< 20	> 110
3 – 3.5	9 – 11	20 – 40	110 – 150
3.5 – 4	> 11	40 – 60	> 155
4 – 4.5		> 60	
> 4.5			

As was previously mentioned, one of the local characteristics of the storm climate in the study area is the presence of multi-peak storms. As the impact of successive storms separated by relatively short fair-weather periods may be different to that of single events depending on storm characteristics and initial beach configuration (e.g. Dissanayake et al. 2015; Eichertopf et al. 2020), we retained these storms in the analysis. Thus, to properly account for their potential effects, all existing identified multi-peak storms in the original time-series (43) were included in the *subset*. ~~To this end, their~~Their impact was simulated with the XBeach model saving the cumulative output after each peak. The impact after the first peak of such multi-peak events was used as proxy of equivalent single-peaks already covering 22 source variable combinations. The other 26 combinations were covered by additional single-peak storms. This allowed treating each simulation of a multi-peak event as a representative of two storms: (i) the multi-peak event itself and (ii) a single-peak storm with properties matching the first recorded peak. Thus, the storm *subset* comprised of 69 storms, including the 43 multi-peak storm events (see Table 1). ~~Note that the intervals used to classify storm variables are more refined than in the BN bins (Section 6), to later ensure intra bin variability during the training.~~

The statistical representativeness of the *subset* with respect to the full storm dataset was tested using the methodology to compare histograms proposed by Bitjukov et al. (2013). This method assumes that values at each bin of the histogram follow a normal distribution with expected value $n_{i,k}$ and variance $\sigma_{i,k}^2$ (with “*i*” representing the bin and “*k*” the histogram). Thus, the significance is defined as:

$$\hat{S}_i = \frac{\hat{n}_{i,1} - \hat{n}_{i,2}}{\sqrt{\hat{\sigma}_{i,1} + \hat{\sigma}_{i,2}}}, \quad (1)$$

where $\hat{n}_{i,k}$ is an observed value at bin “*i*” of histogram “*k*” and $\hat{\sigma}_{i,k} = \hat{n}_{i,k}$. Therefore, we consider the root mean square (RMS) of the distribution of significances as:

$$RMS = \sqrt{\frac{\sum_{i=1}^M (\hat{S}_i - \bar{S})^2}{M}}, \quad (2)$$

where \bar{S} is the mean value of \hat{S}_i and *M* is the number of bins of the histogram. The RMS represents a distance measure with the following interpretation: If $RMS = 0$, both histograms are identical; if $RMS = 0 \sim 1$ both histograms are obtained from the same parent population; if $RMS \gg 1$, histograms are obtained from different parent distributions. The method is applied to compare the output distributions resulting from training the BN with the whole dataset vs. training it with the subset.

The statistics will be calculated for both BN inputs and outputs (see following sections): (i) the distribution of un-constrained output risk variables; (ii) the distribution of Hs, Tp, duration, direction and water level constrained to the different risk levels per sector; and (iii) the risk distributions per area and conditioned to the distance to inner beach limit. This involves the comparison of more than one variable output (e.g. impact results are always three variables), and therefore, results are given as a mean and standard deviation.

3.3 Hazards assessment

Storm-induced hazards (erosion and flooding) have been modelled using the XBeach model (Roelvink et al. 2009), which has been previously calibrated for the Tordera Delta (see Sanuy et al. 2019b). The calibration of the model achieved a Brier Skill Score (BSS) (Sutherland et al. 2014) of 0.68. The model was implemented using a curvilinear grid with a variable cell size around the Tordera River mouth (Figure 1). The extension of the mesh is approximately 1.5 km in the cross-shore direction, with a cell size ranging from 5–6 m at the offshore boundary (20 m depth) to 0.7–0.8 m at the swash zone. In the alongshore direction, the model has an extension of 4.5 km with cell size ranging from 25 m at the lateral boundaries 2–3 m around the river mouth. Storm input consists of time-series of wave conditions characterising each storm obtained from the

290 DOW dataset at the 4 nodes at the offshore boundary (Figure 1), with a time-step of 1 hour, which is the time resolution of
 the original data. The model was used to simulate storm-induced hazards under 455 different events, which correspond to
 179 original storms, plus a *subset* composed of 69 storms under 4 different scenarios. The XBeach model outputs used for
 the subsequent risk calculations were *maxzs* for water depth with accompanying μ, v components of the water velocity
 (inundation hazard) and *sedero* for bed level change (erosion hazard).

3.4 Risks

295 To assess the induced risk, first, receptors in the study area are individually considered by their footprint polygons (~4000)
 and delineated using a Geographic Information Systems (GIS)-based tool to account for their exact position and dimension.
 Once they are defined, a direct correspondence between each receptor with the underlying XBeach model mesh is available
 in such a way that each receptor is associated with the model nodes directly affecting it (see Figures 3 and 4). ~~To spatially
 characterise the risk of the area as a function of the variability of the local geomorphology and coastline orientation at both
 sides of the river mouth, five different sectors along the coast were defined (Figure 1). Two of them, SBN and SBM, are
 located northwards of the river mouth (Figure 1), with SBM being limited to the south by the river mouth. The main
 distinctive feature of SBN is the existence of a promenade limiting the inner part of the beach. Southwards of the river, there
 are three sectors (Figure 1): MSM being closest to the mouth; MS1, which is located southwards of a coastal revetment; and
 MS2 located furthest to the south, with wider beaches, and sheltered against Eastern storm waves, which are dominant in the
 area (Mendoza et al. 2011).~~

305 The vulnerability of each receptor is individually characterised as a function of their structural properties. Receptors in the
 study area comprise hard constructions, such as houses and infrastructures, and softer elements such as campsite elements
 (e.g. bungalows) (Sanuy et al., 2018). To assess the flooding-induced risk, the relative damage to receptors is calculated
 using flood-damage curves (Table 2) using the maximum-modelled water depth within the receptor polygon. No specific
 310 damage curves are available for the Catalan coast, and due to this, we used the curves recommended and used by the Catalan
 Water Agency (ACA, 2014) for the development of inundation management plans. Risk to life ~~was-has~~ also been included in
 the assessment by using the water-depth-velocity product as input (Table 3, Priest et al., 2007) within the receptor's
 boundaries. For the erosion hazard, the magnitude of the associated risk is based on the distance from the significantly
 eroded XBeach nodes to the receptors. Significant erosion was set to 0.25 m of the vertical bed level change and assumed as
 315 the common minimum depth for light structure foundations. The closest distance from the receptor corners to that erosion
 level was compared with the erosion risk thresholds indicated by Jiménez et al. (2018) (Table 4).

Therefore, the result of each simulation (hazard maps) was transformed into a risk value at the individual receptor. Figure 3
 shows an example of simulated inundation water depth for a long return period event and its transformation into relative
 inundation damages to receptors: None (0%), Low (0–30%), Moderate (30–60%), High (60–90%), and Extreme (>90%).
 320 Figure 4 shows, for the same event, results corresponding to the erosion hazard. Individual results were stored at each of the
 ~4000 receptors for each of the simulated events, leading to a total number of 716,000 and 276,000 cases to feed the BN
 with the entire dataset and with the *subset*, respectively.

325 **Table 2: Flood damage curves to obtain relative damage to structures using simulated inundation depth as input (Catalan Water Agency, ACA, 2014).**

INUNDATION DEPTH (M)	RELATIVE DAMAGE (%)	
	Hard structures (Road, promenade, houses)	Soft structures (Campsite elements)
0	0	0

0 – 0.3	18.3	50
0.3 – 0.6	26.5	71
0.6 – 0.9	33.2	82
0.9 – 1.5	44.7	89
1.5 – 2.1	54.9	91
> 2.1	64.5	100

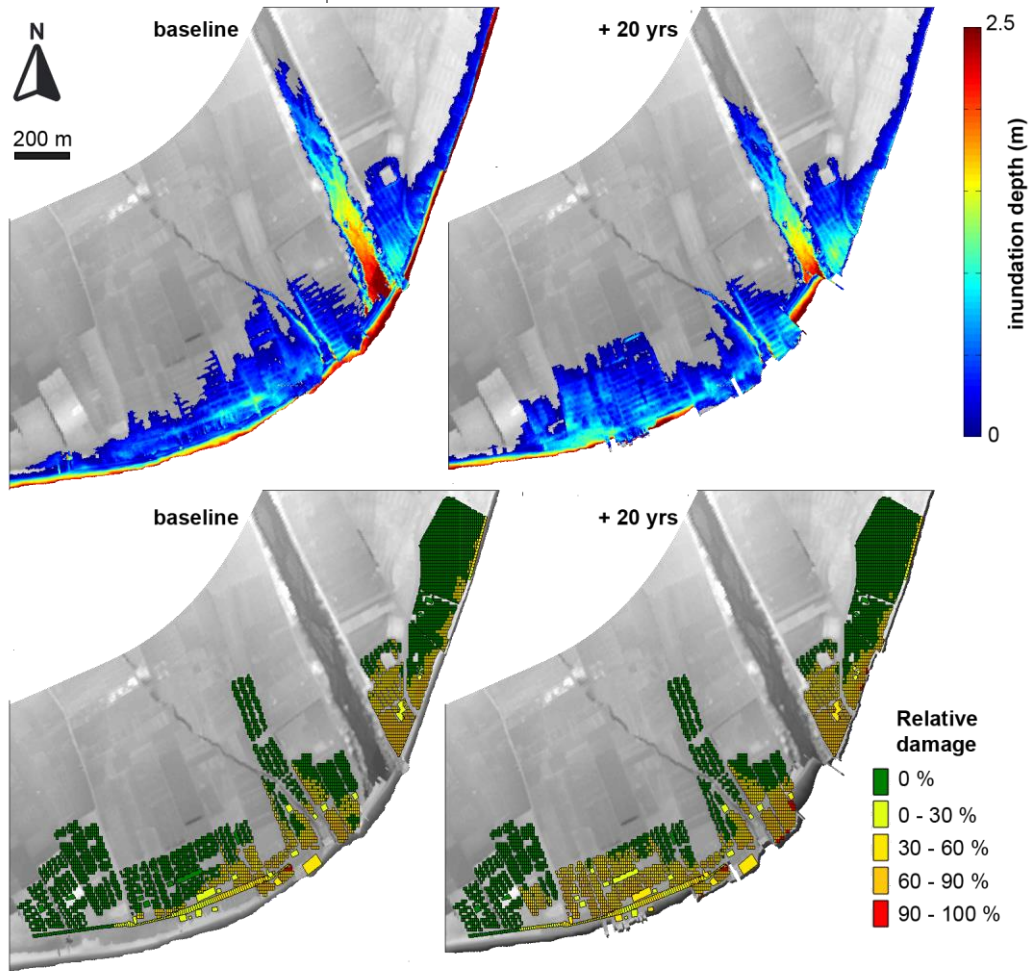


Figure 3: Example of transformation from inundation hazard to risk. Storm event of November 2001, $H_s = 5.4$ m, $T_p = 13$ s, eastern direction, and 96 h of event duration. LIDAR provided by Institut Cartogràfic i Geològic de Catalunya (ICGC).

Table 3: Risk to life calculated as a function of the product between water depth and flow velocity (Priest et al. 2007).

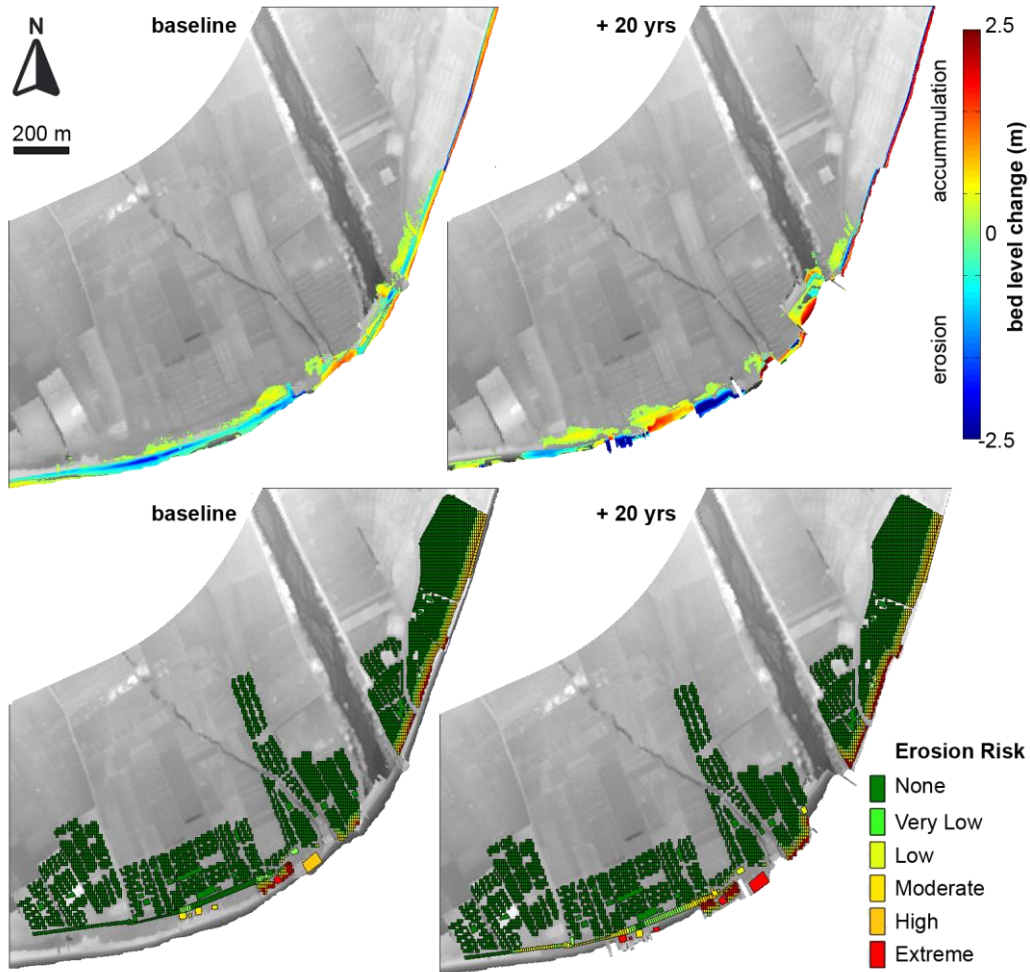
Flood depth-velocity (m^2/s)	Risk to Life
0 – 0.25	None
0.25 – 0.5	Low
0.5 – 1.1	Moderate
> 1.1	High

330

Table 4: Erosion risk as a function of the distance from the receptors to erosion magnitudes greater than 0.25 m of bed level change. A distance of 7.5 m corresponds to the expected retreat for the 10-year return period (Jiménez et al., 2018).

Erosion risk level	Distance to receptor (m)
None	> 30
Very Low	22.5 – 30

Low	15 – 22.5
Moderate	7.5 – 15
High	3 – 7.5
Extreme	0 – 3



335 **Figure 4: Example of transformation from erosion hazard to risk. Storm event of November 2001, $H_s = 5.4$ m, $T_p = 13$ s, eastern direction, and 96 h of event duration. Orthophoto provided by Institut Cartogràfic I Geològic de Catalunya (ICGC).**

3.5 Scenario definition

When assessing risks in coastal areas under changing conditions, it is necessary to consider these potential variations in the assessment, otherwise, its utility for medium-long term risk management will be limited. [Here, future morphological scenarios are defined to consider the background erosion in the area.](#) As previously mentioned, the study area is a highly dynamic sedimentary environment subjected to a background coastal retreat (Jiménez et al. 2018). Thus, in this step, different scenarios characterising future configurations were built based on the expected future coastal changes. This was accomplished by using decadal-scale background erosion rates estimated for the different beach sectors by Jiménez and Valdemoro (2019) by analysing shoreline changes from aerial photographs. The estimated average shoreline retreat at each sector is 1.1, 4.0, and 1.9 m/y at SBN and SBM, MSM and MS1, and MS2, respectively (see Figure 1 for locations). It is assumed that current evolution trends remain constant during the timeframe of the analysis, which is limited to 20 years. However, this could be substituted by time-varying evolution rates provided this should be the case.

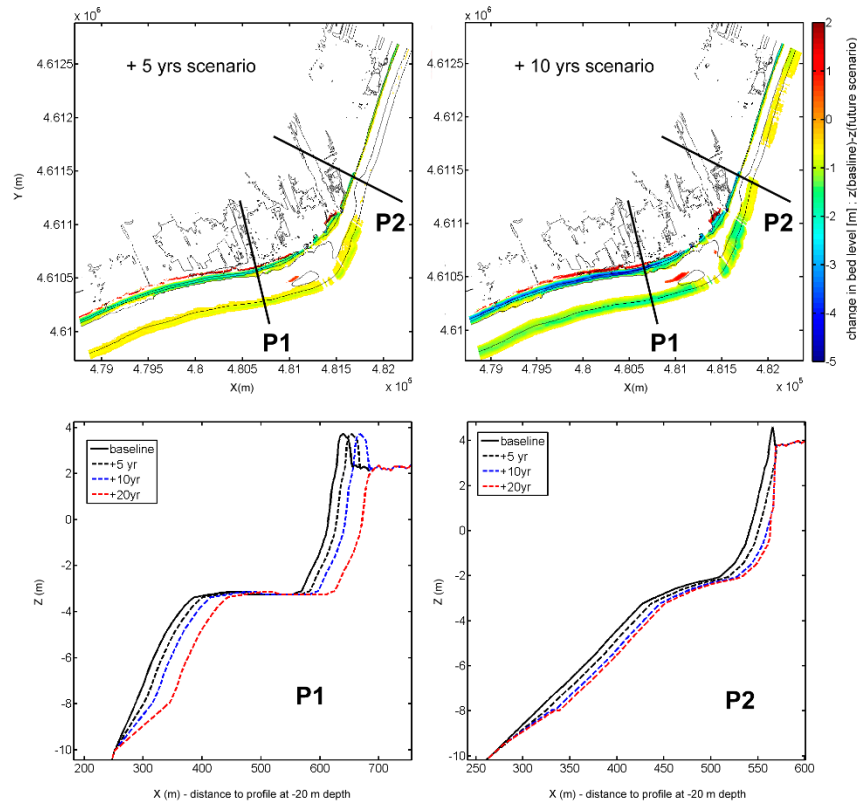


Figure 5: Changes in the bed level grid for the future scenarios. Difference between baseline bed level and scenario bed level (upper). Profile retreat at both sides of the river mouth at the different time horizons (lower). P1 belongs to MS1 (retreat of 4 m/yr) and P2 belongs to SBM (retreat of 1.1 m/yr).

350

355

360

365

Thus, to account for this background response, each scenario was defined based on a given coastal morphology at a given time horizon. The baseline morphology, which corresponds to the current scenario, is the one described in Section 2 (Figure 1) that was directly measured. Future coastal morphology for each scenario corresponding to different time horizons (+5 years; +10 years; and +20 years) were built by retreating the active part of the shoreface, from a -10 m-depth to the subaerial beach, according to erosion rates at the different areas. This hypothesis about the shape of long-term (decadal) profile changes follows the hypothesis applied in shoreline evolution models, i.e. a parallel displacement of the active profile from the emerged beach down to the depth of closure (e.g. Hanson, 1989). To ensure alongshore smoothness after retreating, linear transitions between sectors affected by different retreat rates were applied. Resulting configurations for two scenarios are shown in Figure 5, along with example profiles at locations under different levels of background retreat. Local constraints due to the lack of accommodation space due to the existence of hard structures at the hinterland were also considered. When the shoreline reaches a fixed structure limiting the landward translation, it is assumed that, locally, the beach disappears and, in consequence, no further profile retreat will occur. As an example, Figure 5 shows the beach profile retreat at two locations with different hinterland characteristics: P1 has no hard limit, whereas P2 is limited at the back by a promenade. This results in a continuous retreat of P1 for all scenarios, whereas the retreat of P2 is limited at the beach after 10 years.

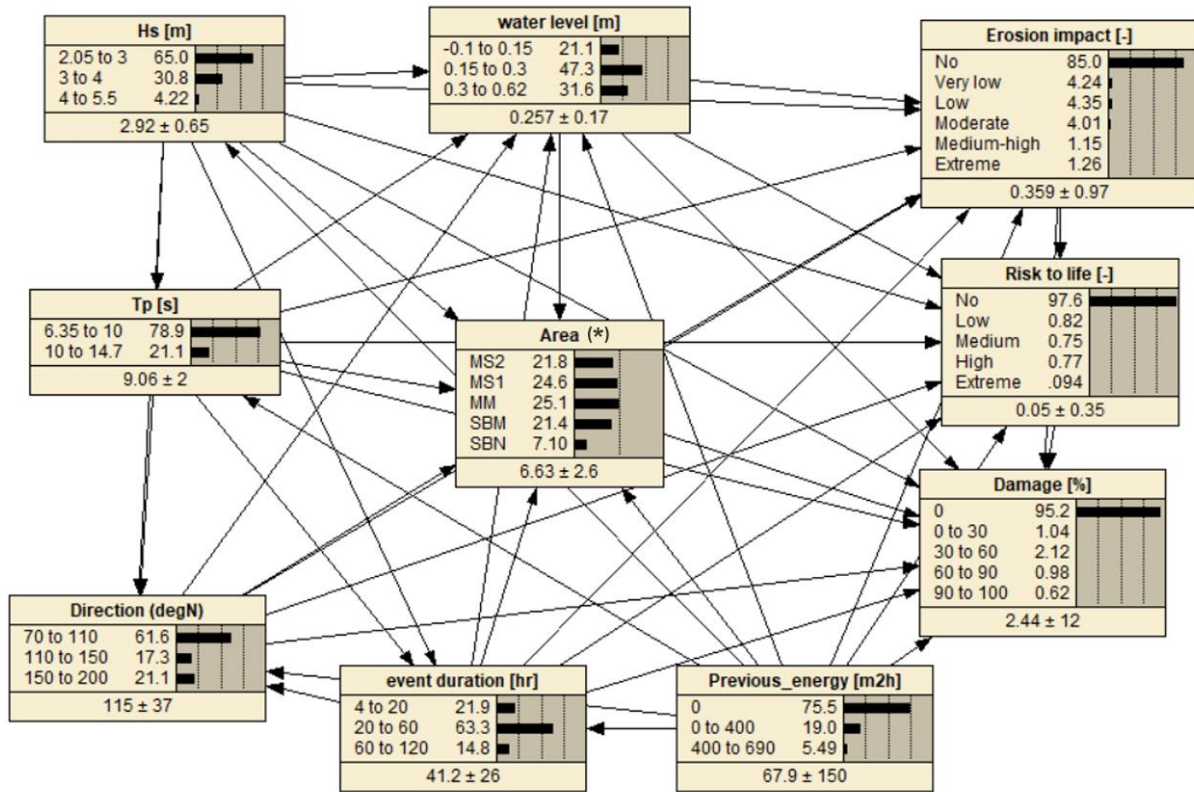
3.6 Bayesian Network integration

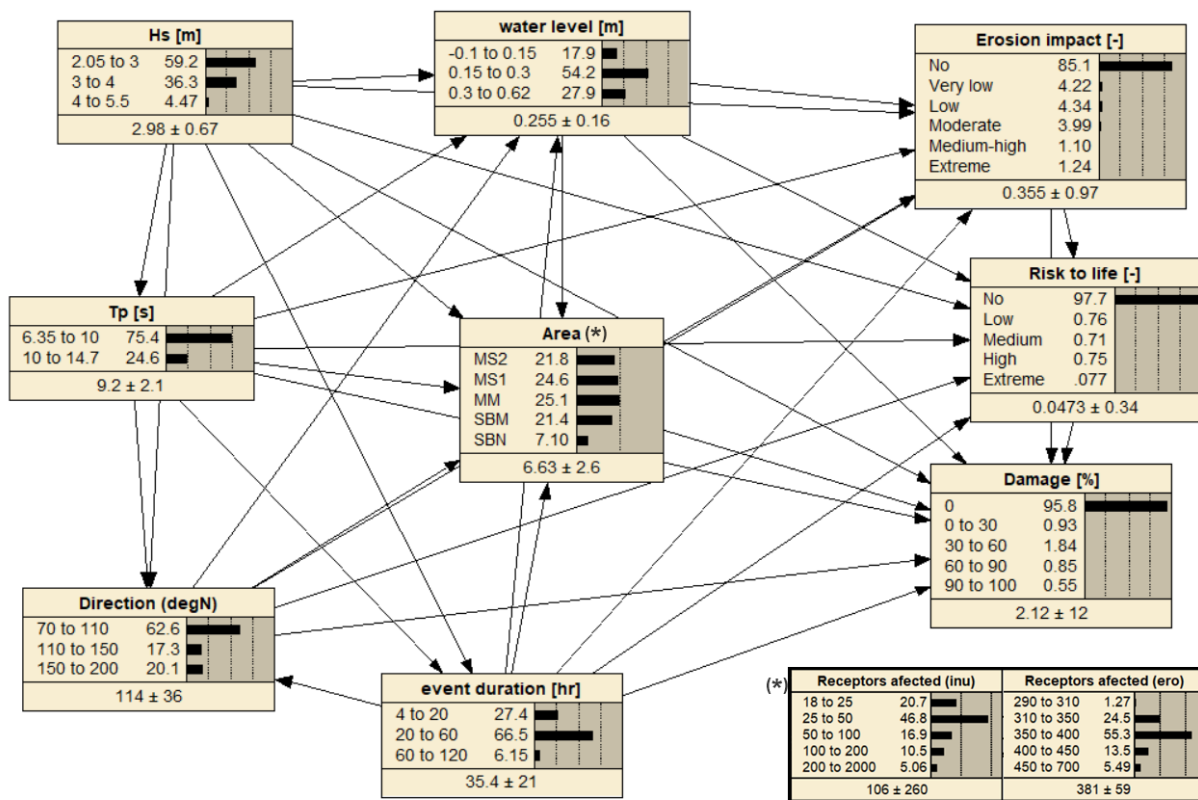
370

The BNs are probabilistic models based on acyclic graph theory and Bayes theorem (Pearl, 1988; Jensen, 1996). They have demonstrated their versatility and utility in efficiently combining multiple variables to predict system behaviour. Within the context of this work, they can be used to represent the SPRC scheme through the dependency relations between the different steps (see e.g. Straub 2005; Jäger et al. 2018). In this sense, they can easily be adapted to assess different natural hazards and

their impacts on many kinds of receptors, for both descriptive as well as predictive applications (see e.g. Beuzen et al. 2018b).

375 In this work, two BN configurations were used to characterise the system response to the impact of coastal storm events. This was done to optimise the BN structure by limiting the number of variables per network while solving the different parts of the SPRC framework. In practice, one BN solved the source-consequences relationships (BN-A), while the other characterised the receptor-consequence spatial distribution (BN-B), providing complementary information on the local risk profile.





385 **Figure 6: BN-A, linking source variables to consequences. Central variable (*) is used for conditioned assessments and is one of three: (i) Total number of affected receptors by inundation within a storm event; (ii) total number of affected receptors by erosion within a storm event, and (iii) receptor area (i.e, SBN, SBM, MSM, MS1, and MS2). Distributions correspond to the baseline scenario.**

BN-A (Figure 6) links storm-defining variables (Hs, Tp, duration, direction, and water level) and impacts to the receptors (erosion impact, risk to life, and structural relative damage). The central variable of the network (indicated by * in Figure 6) was used to perform conditioned assessments. Depending on the objective of the analysis, it can be (i) the total number of affected receptors by inundation within a storm event; (ii) total number of affected receptors by erosion within a storm event, or (iii) receptor area (SBN, SBM, MSM, MS1, and MS2), as shown in Figure 6. To account for the spatial extension of the impacts, we included the total number of affected receptors as an output variable. These are counted outside the BN for each simulated storm peak and introduced in the BN as an additional storm characteristic variable. To characterise the impact extension of inundation, ~~for each storm~~, all receptors presenting a relative damage other than 0%, or a risk to life other than “None” were counted. Similarly, to characterise the impact extension of erosion, all receptors presenting an impact level different than “None” were counted. In practical terms, this means that, in general, the number of affected receptors by erosion was larger than by inundation. This is because, with the used criteria, it is quite probable to have receptors affected by “Very Low” to “Moderate” erosion risks representing the loss of protection provided by the beach, although this does not imply that they will be directly exposed to wave impact. However, inundation-related impacts are always associated with the presence of water at the receptors. This has to be taken into consideration when interpreting the obtained results.

390

395

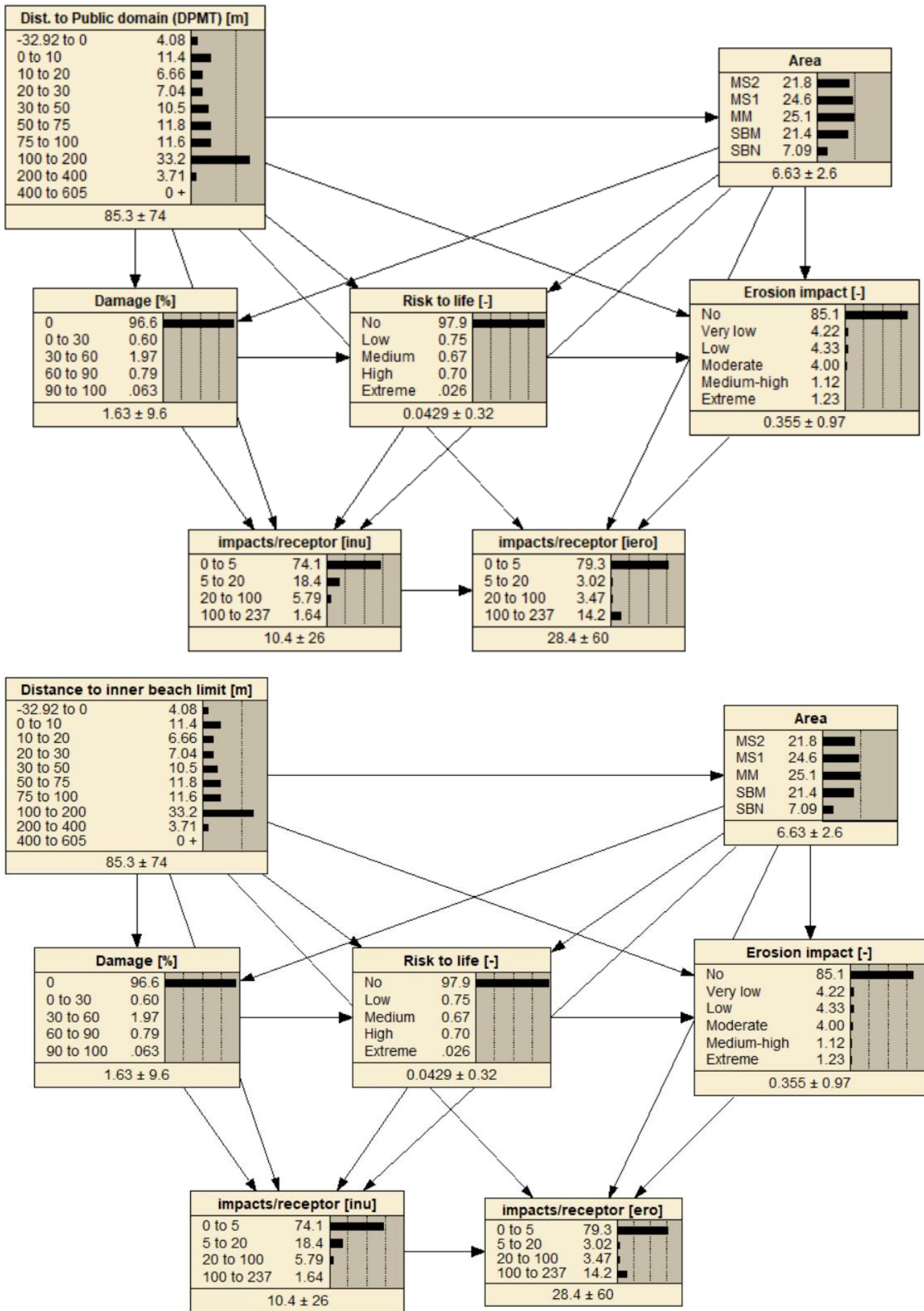


Figure 7: BN-B, linking consequences to receptors spatial locations. Distributions correspond to the baseline scenario.

BN-B (Figure 7) links the simulated impacts on the receptors to their position, characterised by their location along the coast (area) and the distance to the ~~public domain (DPMT) inner beach limit, which is the limit between the beach and the hinterland. Additionally, two variables accounting for the number of impacts per receptor were included.~~ These variables provided additional insight into the system response, as the obtained distributions with the BN merge storm-climate variability and the spatial distribution of receptors. For the inundation risk, the number of impacts with damage different from 0%, and/or with risk to life different from “None” was counted at each receptor. For the erosion risk, the number of impacts different from “None” was counted per receptor. This has the same consequence as that described in the previous case (BN-A) for interpreting the obtained results. It must be noted that from all receptors displayed in Figures 1d, 3, and 4, only those presenting at least one impact for the entire storm dataset, by either inundation or erosion, were used for the BN training. Otherwise, the choice of receptor population to include in the assessment would be arbitrary, affecting the obtained distributions.

The presented BN-model was designed to assess storm-induced risks in a coastal hotspot where the storm climate and coastal response are well known (e.g. Jiménez et al. 2018; Sanuy et al. 2020). Due to this, the discretisation of variables (Figures 6 and 7) was done manually, enabling better accuracy than automatic unsupervised methods and closer accuracy to supervised discretisation with less associated variability on model performance (Beuzen et al. 2018a). Notably, both BNs present a certain degree of complexity given the discretization level of some variables and the number of variables used. The BNs are designed to be descriptive BNs (Beuzen et al., 2018b), and thus, source variables are also interconnected to avoid the propagation of noise from empty combinations to the output. This departs from predictive BNs which aim to infer system behaviour and predict combinations beyond those learned from the dataset.

4. Results

Figures 3 and 4 show the results of a single simulation exercise for 1 of the 455 possible events. Each simulation results in the collection of the BN variables characterising the storm characteristics together with the location and the risk values for each receptor (~4000). The following subsections present the results of the integration of multiple simulations (i.e. 179 in baseline morphology and 69 for each additional scenario). First, the 69-storm *subset* is validated against the 179-storm original dataset using the baseline morphology to ensure that it properly represents the local storm climate. This is followed by the presentation of the risk characterisation of the Tordera Delta, starting with risk probabilities integrating all storms and receptors (global risk probabilities), and then, with conditioned probabilities between forcing-area risk (BN-A, Figure 6) and area-distance risk (BN-B, Figure 7).

4.1 Subset validation

Table 5 shows the obtained statistics using Eq. 1 and 2 to compare the discrete probability distributions obtained with the BN using the 179-storm dataset against those from the 69-storm *subset*. ~~This is done for the different BN outputs, i.e. global risk probabilities, which are the impact distributions in Figures 6 and 7; probabilities of storm characteristics (distributions of Hs, duration, direction, and water level) conditioned to different risk levels and areas; and risk probabilities conditioned to receptors locations (area and distance to the beach limit). This involves the comparison of more than one variable output (e.g. impact results are always three variables), and therefore, results are given as a mean and standard deviation.~~

All obtained values of the mean significance \bar{S} and its root mean square (*RMS*) are close to 0; therefore, from the perspective of obtained results, it can be assumed that the obtained distributions by feeding the BNs with the subset almost identically represent the same source population as that of the complete dataset. This is true both for global distributions and for conditioned discrete probability density functions (PDFs).

Table 5: Results of the histogram comparison between the original storm dataset and the *subset* for the baseline scenario.

Verification case	\bar{S}	RMS
Global risk probabilities		
Histograms of <i>impact-Damage, Risk to life and erosion impact</i> variables without conditioning (Fig. 6 and 7)	-0.009±0.006	0.04±0.05
Storm characteristics conditioned to risk levels Risk probabilities conditioned to source characteristics		
<i>Hs, duration, water level, and direction conditioned to Damage, Risk to life and erosion impact</i> Impact-levels probabilities at different <i>areas, and conditioned to Hs, duration, water level, and direction (e.g. Fig 8 and 9)</i>	0.0006±0.02	0.05±0.03
Risk probabilities conditioned to receptors locations		
<i>Damage, Risk to life and erosion impact</i> Impact -probabilities at the different <i>areas and distance to the beach</i> (Figures 10 to 12)	0.0041±0.02	0.04±0.08

4.2 Risk characterisation

Table 6 shows the obtained probability levels for different tested scenarios in the study area. These so-called prior (unconstrained) probabilities represent the expected frequency of the different risk levels in the study area and account for the variability of the source (storm climate), spatial distribution, and extent of the impacts on the receptors. In general, under current conditions, the probability of receptors being affected by significant (high and extreme) risks is low (1–2%). However, the existence of background erosion in the study area results in a significant increase in future risks. Under the baseline scenario, the computed probability of moderate-high risks associated with erosion is larger than the ones for inundation. However, when we only consider those cases where erosion results in exposing receptors to direct impact (high and extreme risk), the obtained probability values are of the same order of magnitude as those obtained for moderate damages and risks associated with inundation. Additionally, results of number of ~~affected~~ receptors from BN-A (not shown in the table) show an increase in the % of storm conditions affecting a large number of receptors along the study area. As an example, storm conditions with the potential to affect more than 200 receptors with any level of inundation risk increases from 4% under current conditions to 20% and 40% after 10 and 20 years, respectively. Simultaneously, storm conditions affecting more than 450 receptors with any level of erosion risk will rocket from the current 4% to 100% in 10 years. Here, it is important to remember that erosion risk is not only related to direct impact but also the loss of protection function (decrease of beach width in front of a given receptor), while inundation risk implies the direct effect of water on the receptor. In general, estimated probabilities associated with erosion-induced risks are larger than those due to inundation when comparing similar risk levels.

Figure 8 shows the alongshore-spatial distribution of the BN-computed percentages of receptors affected by any level of risk induced by both hazards under all scenarios. Obtained results show a different spatial behaviour according to the considered hazard. Thus, the most erosion-affected areas (those showing a larger percentage of receptors with damage different to zero) are located northwards of the river mouth, whereas areas southwards of the river mouth are more affected by inundation (higher probability values). The time evolution of the affected receptors is also different, reflecting existing spatial variations in shoreline retreat rates. Thus, the largest relative increase in the number of impacted receptors under future scenarios occurs southwards of the river mouth. Notably, the MS2 sector is the most sensitive to future risks, as currently, although it is well protected by a relatively wide beach, this protection will fade after 10 to 20 years.

BN-A was also used to characterise the conditioned probabilities of storm characteristics associated with the highest risks and assess whether these probabilities vary along the study area. As seen in Figure 9, under current conditions, the main storms driving the highest inundation-induced risks are characterised by Hs higher than 4 m and from the E direction. This is valid for the entire area, although their relevance slightly varies along the coast. Thus, the only exception is found in the SBN sector, where the promenade is so close to the shoreline that lower Hs can induce inundation damages. For future conditions (20 years scenario), the relative importance of storms with smaller Hs increases, and the relative importance of present secondary wave directions, S and SE, also increases in relative terms.

515 **Table 6: Global risk probabilities for different risk levels under the different scenarios. Note that global risk probabilities account for the variability in the source (storm climate) and the spatial distribution of impacts on the receptors.**

Global risk probabilities	Baseline	+ 5 yrs	+10 yrs	+ 20 yrs
Inundation				
Moderate risk or higher (damages \geq 30%)	3%	5%	5%	7%
Moderate risk to life or higher	2%	3%	3%	5%
High and extreme risk to life	1%	2%	2%	3%
Erosion				
Moderate risk or higher	6%	9%	13%	13%
High and extreme risks	2%	4%	8%	8%

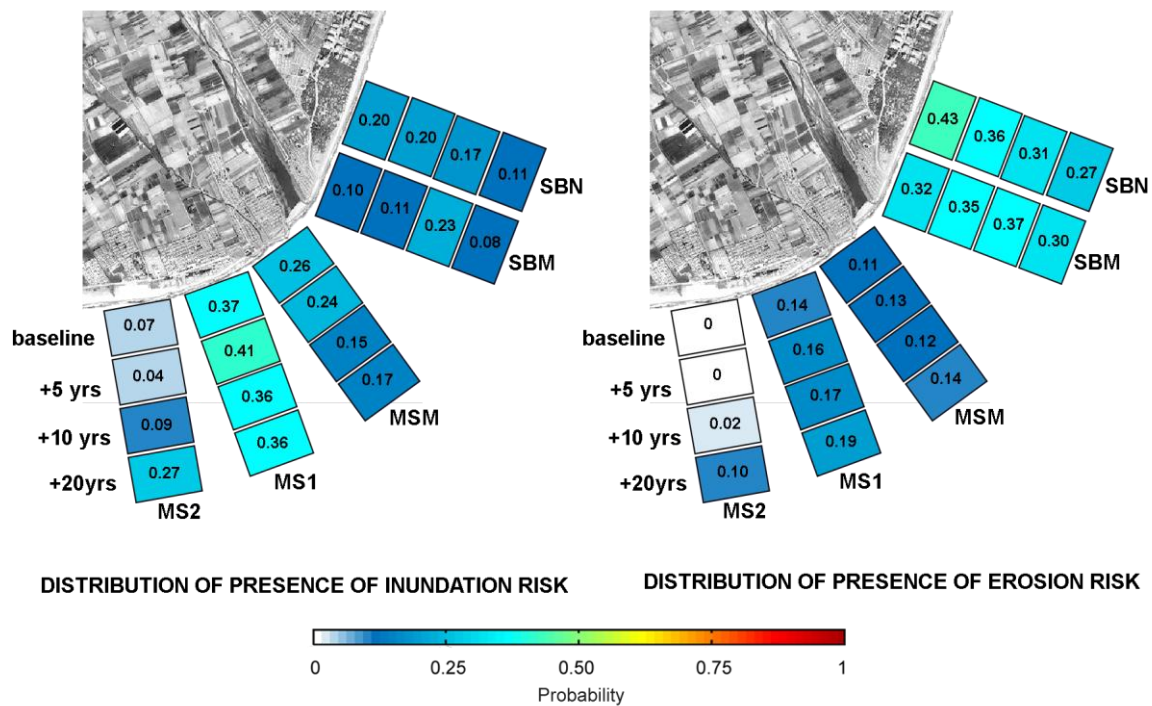
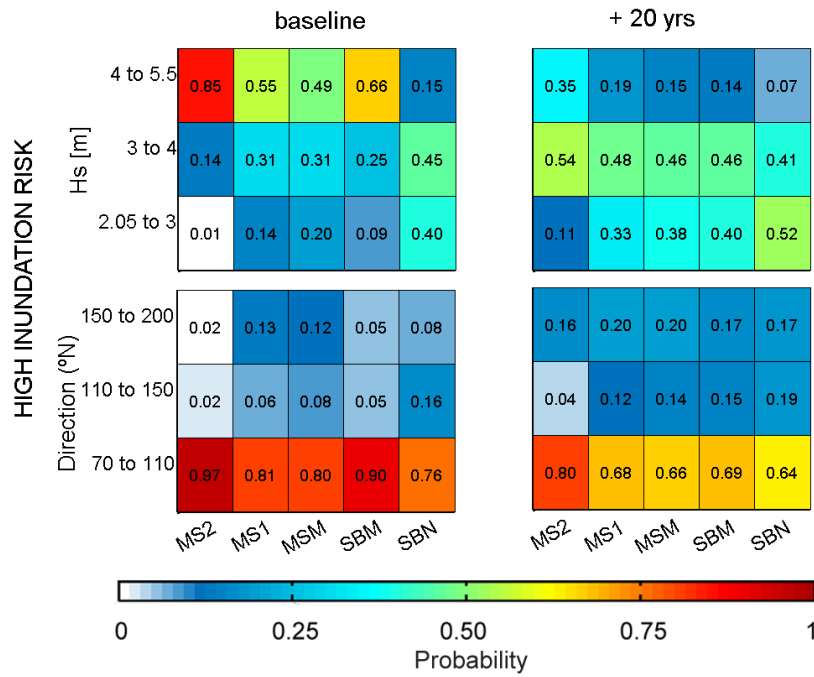
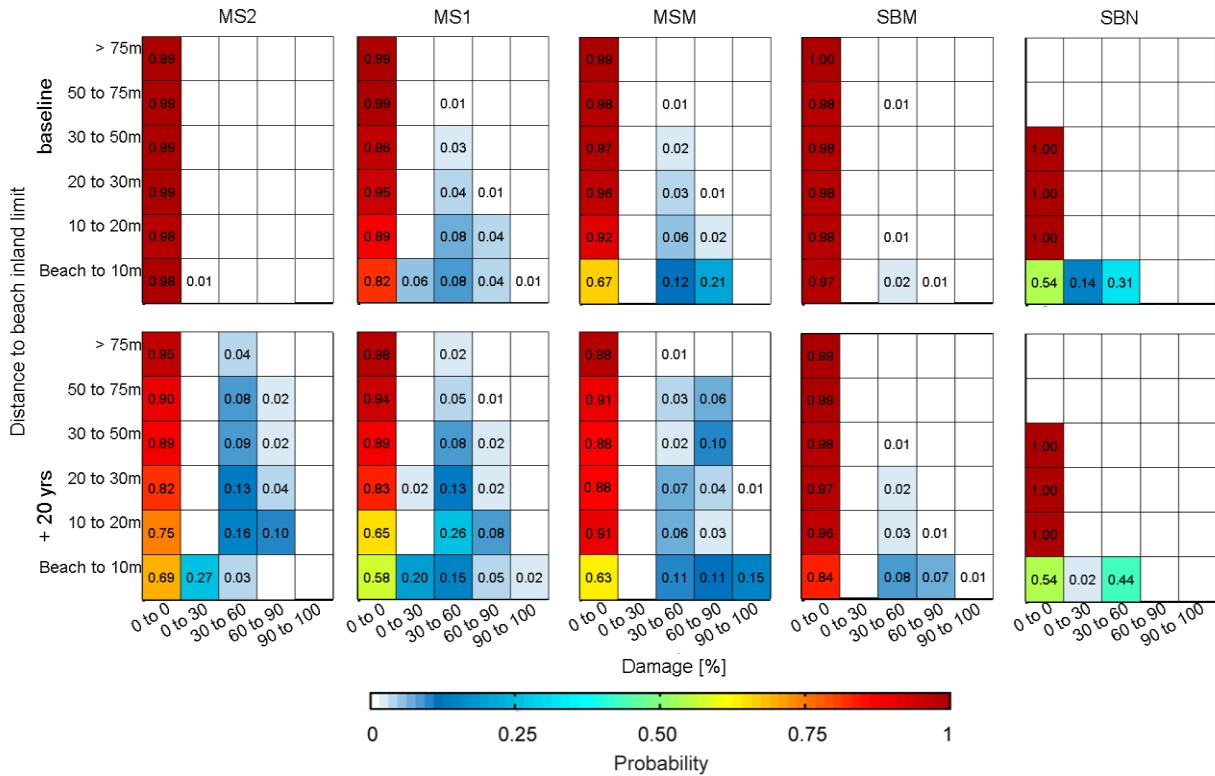


Figure 8: Distribution of risks (at any level) across the different sectors (see specific locations in Figure 1). This shows the relative proportion of impacted receptors in the different areas, under the baseline morphology and the future +5, +10, and +20 yr scenarios. Orthophoto provided by Institut Cartogràfic I Geològic de Catalunya (ICGC).



520

Figure 9: Probability of storm Hs and direction conditioned to the area and to highest intensity inundation risk, i.e. moderate to high risk to life together with high structural damages ($\geq 60\%$). Note that extreme risk to life and damages over 90% are not present for the study site. Results must be read as individual vertical histograms (1 histogram per area).



525

Figure 10: Probability distributions of the relative damage by inundation conditioned to the different subareas (see Figure 1 for locations) and the distance to the inner limit of the beach. Baseline and +20-year time horizon of background shoreline retreat. Results must be read horizontally as individual histograms for each combination of area, distance, and scenario.

530

The spatial distribution of the expected impacts across the study area was analysed using the BN-B. The objective of the analysis was to assess the probability damage occurring at the receptors located at a given distance from the beach (i.e. limit between beach and hinterland). Figures 10 and 11 show obtained results in terms of % of inundation-induced damage and risk to life, respectively, for different time horizons. Consistent with the results shown in Table 6, under current conditions (baseline), storms cannot induce extreme structural damage ($>90\%$) (Figure 10) nor extreme risk to life (Figure 11). High

535 damages (> 60%) are mainly concentrated at the outer fringe of the hinterland of the two locations (MSM and MS1) with associated conditioned probabilities of 21% and 5%, respectively. These two areas also show the highest probabilities of risk penetration into the hinterland. Northwards of the river mouth, the SBN sector presents a large probability of moderate damages, but it is limited to the external fringe. Regarding risk to life, a similar spatial pattern is observed, with MSM showing the largest probability of high risk (20%) at the external fringe, SBN at the north with 12%, and MS1 only showing a residual 3%. The obtained results reflect the role played by the current coastal morphology, where the southern area is

540 characterised by narrow and low elevation beaches (MSM and MS1), whereas the SBN sector in the north is composed of a narrow beach backed by a promenade. Notably, SBM with a narrow beach but higher topography without a promenade and MS2 with low topography but wider beaches are the areas presenting the lowest risks.

Under future conditions (+20-year scenario), significant changes are observed in the intensity of risks and extension across the territory (Figures 10 and 11). The spatial modulation on induced risks as a consequence of the beach narrowing due to background erosion is especially evident in the southernmost area, MS2. Whereas this sector does not experience any risk under current conditions, significant probabilities of moderate and high damage and risk to life is expected to occur in 20 years, not only at the outer fringe but also in inner positions of the hinterland. The other sectors along the coast also show significant increases in the probability of occurrence of any type of risk and extension of the impacts landward (Figures 10

550 and 11).

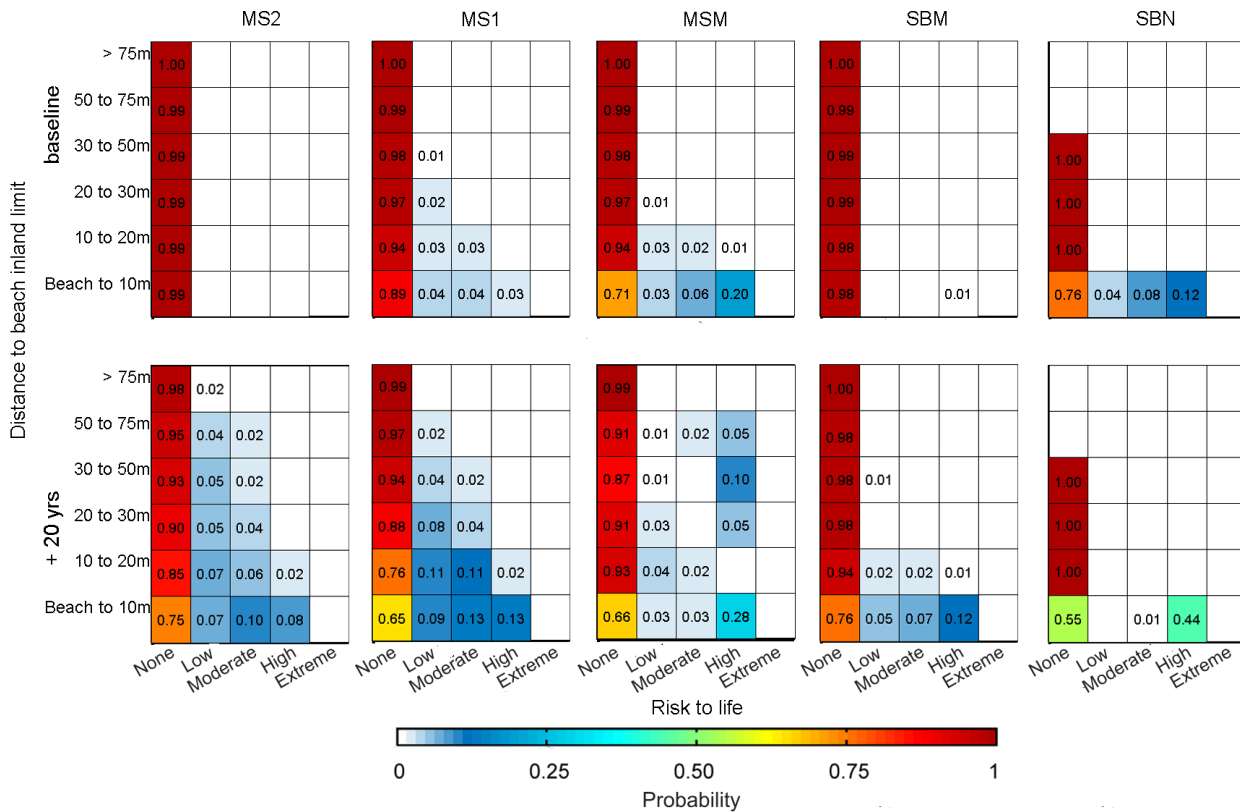
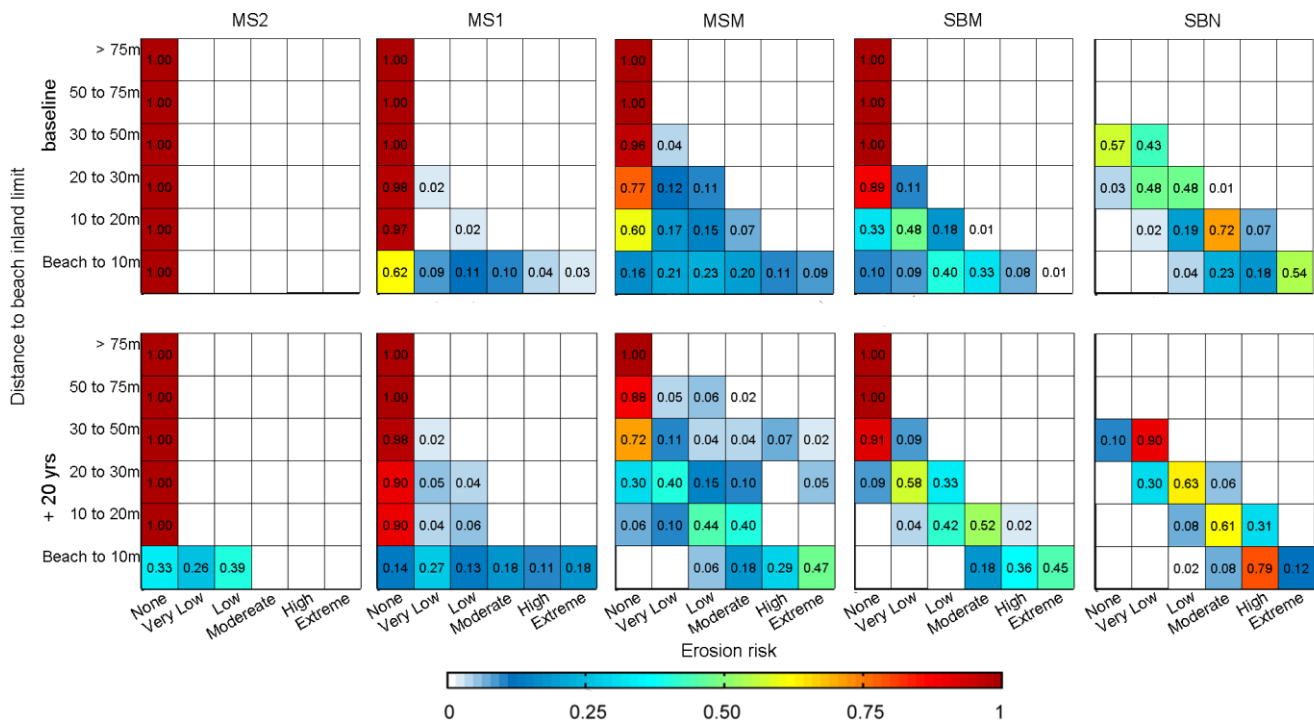


Figure 11: Probability distributions of the risk to life by inundation conditioned to different subareas (see Figure 1 or 8 for locations) and the distance to the inner limit of the beach. Baseline and +20-year time horizon of background shoreline retreat. Results must be read horizontally as individual histograms for each combination of area, distance, and scenario.



555

Figure 12. Probability distributions of the erosion risk conditioned to the different subareas (see Figure 7.1 for locations) and the distance to the inner limit of the beach. Baseline and +20-year time horizon of background shoreline retreat. Results must be read horizontally as individual histograms for each combination of area, distance, and scenario.

560 The spatial distribution of erosion-induced risk under current conditions (Figure 12) reflects the existence of hard elements and varying beach widths along the study area. Thus, SBN presents the largest probability of extreme risks at the promenade (54%), followed by MSM (9%), and MS1 (3%). In SBN, the promenade acts as a physical boundary for erosion; the distribution of risk levels into the hinterland shows a linear pattern reflecting its position. At the southernmost end, MS2 is currently well protected by a wide beach and no risk is predicted under the current conditions. Under the +20-year scenario, the effect of the promenade in SBN is reflected through the unaltered spatial pattern of affected locations and computed probabilities. MSM and SBM show the largest relative increase of extreme risks (probabilities of 45% and 47%, respectively) at receptors located closest to the beach, along with the largest spatial propagation of risks into the hinterland, as no hard elements are present to limit the retreat of the shoreline. At MS1, the probability of extreme risks increases to 18% at the beach limit with small changes at larger distances, while MS2 starts presenting significant probabilities of low risks indicating that the beach will begin to decrease its protective function against storm impacts after 20 years.

565

570

5. Discussion

In contrast to previous applications of the BN-SPRC concept presented in Jagër et al. 2018 (e.g. Van Verseveld et al., 2015; Plomaritis et al., 2018; Ferreira et al. 2019; Sanuy et al., 2018), this paper presents a fully probabilistic characterisation of the source using all available storms in a 60-year long wave time-series hindcast, following the response approach, and

575 modelling their induced erosion and inundation risks over all the identified receptors at the study site.

The methodology was successful in identifying storm characteristics with higher probabilities to induce given risk levels for different coastal hazards (inundation and erosion). It was efficient in assessing the expected changes in storm characteristics and probabilities under different scenarios, which were developed based on the background mid-term coastal evolution. In this sense, the obtained relation-relationship under current conditions of erosion and inundation risks with storm direction and Hs depicts the general characteristics of storm-induced hazards in the study area (Mendoza et al. 2011). The thresholds used to identify independent events in the P.O.T are site dependent. In this work, they agree with the storm classification in

580

[Mendoza et al., \(2011\)](#), and therefore they are valid for the Catalan coast (NW Mediterranean). The BN output showed a lack of correlation between high risks and water levels, consistent with the previous findings of Mendoza and Jiménez (2008) on the non-relevance of storm surges. Under future conditions, the background shoreline erosion changes the sensitivity of the area to storms. Thus, for the tested scenarios, the population of storms with potential to significantly impact the area increases and higher risks will be associated with storms characterised by lower Hs with currently secondary wave directions (Figure 8). If we combine this larger exposure to southern storms with the large sensitivity of the area to the impact of such S storms (Sanuy and Jimenez, 2019), this may have serious implications for the future risk management of the area.

The method has been designed to provide a detailed spatial assessment to assess the sensitivity of the area, which permits the association of the local risk profile with different morphological characteristics such as beach orientations, height, and the presence of hard structures. In this sense, the local response affected by the presence of the promenade at S'Abanell (SBN), and revetment in Malgrat North (MS1) were adequately characterised by the BN. This spatial analysis also permitted the assessment of a differentiated variation in future risks along the study area. Thus, whereas some areas being currently exposed linearly increased the probabilities of higher risks, other areas currently well protected will be subjected to higher future risks without any variation in storminess.

The method can also be used for testing risk management measures such as the performance assessment of different setbacks. While this measure is effective in reducing coastal damages in eroding coastlines, especially in the context of climate change (Sanó et al. 2011), it has to be defined for given time horizons and driving conditions (e.g. Wainwright et al. 2014). To this end, the framework presented herein permits the definition of probabilistic setbacks at the study site. Moreover, as this definition is based on the probabilistic distributions of the different risk levels and impacts per receptor at different locations across the coastal domain, it differs from existing approaches that are essentially based on the probabilistic definition of the shoreline position (e.g. Jongejan et al. 2016). As an example, Table 7 shows the calculated minimum distances landward of the inner limit of the beach according to different risk levels for different time horizons (scenarios). As the BN output combines the natural variability of the storm climate with the spatial variability of the impacted receptors, setbacks can be defined from these (total probability, as in Figures 10 to 12) or by assuming that the presence of a given risk level must be completely tackled, focusing then only on the spatial distribution of receptors under such levels. The second approach will result in more conservative (wider) buffers. Table 7 shows the calculated buffer distances using both perspectives. The obtained setbacks ~~obtained that account for~~accounting for the total probabilities can be used as proposals for managed retreats, as they reflect the areas with a high number of impacts per receptor; the setbacks defined by the presence of a given risk level can be used to inform self-preparedness against risk, as they highlight zones where the existence of risk is possible but highly infrequent. It must be noted that all scenarios have been simulated without any assumption of receptor re-allocation, and therefore, hard limits for erosion remain homogeneous across scenarios. Therefore, the distances presented in Table 7 must be interpreted as the evolution of the baseline setbacks at different horizons in a business-as-usual situation.

Table 7: Characterisation of setbacks for different hazards and risk levels in the Tordera Delta. Baseline scenario and +20-year time horizon using two approaches: (i) Total probability, i.e. natural variability of the storm climate with the spatial variability of the impacts on receptors and (ii) risk presence, i.e. focusing only on the spatial distribution of receptors under that level.

Area	Setbacks (m)				
	Moderate inundation damage (>30%)	Moderate Risk to Life	High Risk to Life	Low Erosion Risk	High and Extreme Erosion Risks
Baseline - based on total probability					
MS1	10	10	0	10	5
MSM	10	10	10	30	10
SBM	0	0	0	25	8

SBN	10	10	10	50	15
Baseline - based on risk presence					
MS1	98	43	9	8	7
MSM	196	110	19	38	9
SBM	150	71	41	23	9
SBN	10	10	10	44	16
+ 20 years - based on total probability					
MS1	50	20	10	25	10
MSM	55	50	10	75	50
SBM	10	10	10	40	10
SBN	10	10	10	50	20
+ 20 years - based only risk presence					
MS1	137	49	10	24	5
MSM	130	98	71	69	44
SBM	111	109	29	38	10
SBN	10	10	10	47	18

620 The presented method is based on the response approach (Garrity et al., 2006; Sanuy et al., 2020a) as it produces probabilities based on how hazards (erosion and inundation) affect the receptors in each of the storm events derived from a long dataset of 60 years; it does not allow the extrapolation of the storm conditions out of the range of the ones registered in such datasets. This has relatively less impacts on the results when compared to the impacts from other sources of uncertainty, such as morphological variability or model error (Sanuy et al., 2020b). Nonetheless, it allows the simulation of all storm events with their real shapes (time evolution of storm characteristics) without introducing large uncertainty in hazard estimation associated with the use of synthetic storms that are commonly used to define the shape of statistically extrapolated storm events (see e.g. Duo et al., n.d.).

630 In this study, hazards were computed using a robust model to simulate the storm-induced coastal response, XBeach, calibrated for an event representative of extreme conditions (see Sanuy and Jiménez, 2019). They were converted to risk by using damage curves recommended for use in the study area. However, the BN methodology is flexible for any kind of model, as well as to include model uncertainties (using different models or setups) and measurements (e.g. Sanuy et al., 2020b for cross-shore parametric models) to extend the data training and improve the results while testing its predictive capacity.

635 With regard to building future scenarios to assess future risks, we have limited the present study to mid-term scenarios, i.e. at the decadal scale (20 years). They were built based on decadal-scale shoreline rates of displacement retreat measured by Jiménez and Valdemoro (2019), which were used to build future coastal configuration assuming that no changes in evolutive conditions will occur. Even in this case where no changes in forcing conditions were applied (no changes in storm conditions nor sea level rise), this approach permitted the identification of significant changes in the storm-induced risk profile.

640 It has to be mentioned that to build these morphological scenarios, it is necessary to “forecast” future configurations of the shallow water bathymetry. In this work, this was done by extending shoreline displacements down to the depth of closure by assuming a simple parallel displacement of the active inner profile, which is compatible with the usual hypothesis applied in mid-term shoreline models. However, other profile change modes could also be applied, such as a wedged-shaped change over the closure depth to simulate a slower retreat of the delta front in comparison with faster shoreline changes (e.g. Refaat and Tsuchiya, 1991). In both cases, their morphological consequences are limited to the shallowest and faster part of the shoreface and, in consequence, are strictly applicable to expected mid-term (decadal) changes. Building longer-term morphological scenarios would require to consider other options since the depth limiting significant changes in the beach profile will extend further with time scale (e.g. Cowell et al. 1999). In this line, Stive and de Vriend (1995) proposed a long-term shoreface evolution model that considers a varying type of change through the shoreface, from an upper part experiencing a parallel displacement, to a declining/inclining lower shoreface down to the inner shelf limit.

650 In the case of structures/barriers being exposed at the shoreline along the study area due to background erosion, we have assumed that, locally, the active profile will not retreat further once the beach had disappeared. In the event of such situation, the structure would be subjected to the highest possible risk and as so would be classified in the framework. Further bottom variations in front of the structure which may lead to its collapse due to scouring will not modify this classification. In any case, it has to be considered that building future morphological scenarios to forecast the evolution of coastal risks at
655 long-term scales will add uncertainty to the analysis, in addition to that associated with expected varying climatic forcing, since long-term morphodynamic modelling integrating all relevant processes is still an unsolved issue (e.g. Ranasinghe, 2020). This could be extended or adapted to changing future conditions using midterm morphological simulations with varying climatic forcing or under different adaptation scenarios, and then, used as an efficient way to test risk management strategies.

660 **6 Summary and Conclusions**

Bayesian networks have proven to be an efficient tool to develop an SPRC-based framework for probabilistic storm-induced risk assessment and risk mapping at a local scale (few kilometres). In this work, BN training has been carried out using storm events identified in a 60-year long wave time-series, and simulated hazards and corresponding risks were evaluated at the receptor scale (few metres). This resulted in a ~~fully~~ full representation of the storm climate (source) leading to
665 probabilistic characterisation of risks that accounted for climate (storms) and geographic (receptor location) related variabilities, as the BN training followed the response approach (i.e. the simulation of the coastal response for all identified storms). The framework is also able to predict how risks will evolve in the near future, both in intensity and spatial distribution, provided that climate and/or geomorphology scenarios are built. One of the advantages of the framework is that it permits the identification of conditional probabilities, and thus, the identification of which are the storm characteristics that
670 induce risks of a given magnitude. This is a very useful property in designing disaster risk reduction (DRR) strategies and measures including the design of early warning systems.

Concerning the analysed case study, the Tordera Delta (NW Mediterranean coast) presents, under current conditions, a larger susceptibility to storm-induced erosion than to inundation, which was identified through computed probabilities of high-risk levels associated to both hazards along the coast. Storms inducing the largest impacts are characterised by high H_s (>4 m)
675 for inundation and long duration (>60 hours) for erosion. In both cases, these correspond to Eastern events, which are the most energetic in the area.

The application of the framework for future scenarios predicted an increase in the local risk as a larger number of storms will be able to induce higher risk levels. As these scenarios were built by projecting the coastal configuration up to two decades from now (based on background erosion), the framework reflected the morphodynamic feedback resulting from the loss of
680 protection provided by progressively narrowing beaches. In addition to the increase in risk levels, it also identified a change in storm threshold conditions affecting the area in a significant manner, characterised by lower H_s values and with an increasing importance of southern events.

Finally, the obtained spatial distribution of risks permitted the identification of the most sensitive areas and their evolution over time. This can be used to make decisions on the required DRR measures both along the coast and across the hinterland.
685 The use of the BN to obtain probability distributions of the different risk levels across the hinterland allowed for a probabilistic definition of setbacks.

Competing interests. The authors declare that they have no conflict of interest.

690 **Author contribution.** **M. Sanuy:** Conceptualization, Methodology, Software, Formal analysis, Writing - original draft, Writing - review & editing. **JA Jiménez:** Conceptualization, Resources, Writing - original draft, Writing - review & editing, Supervision, Project administration, Funding acquisition.

Acknowledgements. This study was conducted in the framework of the RISC-KIT (Grant No 603458) and the *M-CostAdapt* (CTM2017-83655-C2-1-R) research projects, funded by the EU and the Spanish Ministry of Economy and Competitiveness (MINECO/AEI/FEDER, UE) respectively. The first author was supported by a PhD grant from the Spanish Ministry of Education, Culture and Sport. The authors express their gratitude to IH-Cantabria for supplying wave and water level data, to the Spanish Ministry for Ecological Transition for the bathymetric data, and to the Institut Cartogràfic i Geològic de Catalunya by for the LIDAR data used in this study.

700

References

- ACA: Pla especial d'emergències per inundacions (INUNCAT). Agència Catalana de l'Aigua, 2014
- Beuzen, T., Marshall, L., Splinter, K.D., 2018. A comparison of methods for discretizing continuous variables in Bayesian Networks. *Environ. Model. Softw.* 108, 61–66. doi.org/10.1016/j.envsoft.2018.07.007. 2018a
- 705 Beuzen, T., Splinter, K.D., Marshall, L.A., Turner, I.L., Harley, M.D., Palmsten, M.L.. Bayesian Networks in coastal engineering: Distinguishing descriptive and predictive applications. *Coast. Eng.* 135, 16–30. doi.org/10.1016/j.coastaleng.2018.01.005., 2018b
- Bityukov, S., Krasnikov, N., Nikitenko, A., Smirnova, V.V. On the distinguishability of histograms. *Eur. Phys. J. Plus*, 128(11), 143. doi.org/10.1140/epjp/i2013-13143-8, 2013.
- 710 Camus, P., Mendez, F. J., Medina, R., Tomas, A. and Izaguirre, C.: High resolution downscaled ocean waves (DOW) reanalysis in coastal areas, *Coast. Eng.*, 72, 56–68, doi:10.1016/j.coastaleng.2012.09.002, 2013.
- Casas-Prat, M., Sierra, J.P. Projected future wave climate in the NW Mediterranean Sea. *J. Geophys. Res. Ocean.* 118, 3548–3568. <https://doi.org/10.1002/jgrc.20233>, 2013
- Cid, A., Castanedo, S., Abascal, A. J., Menéndez, M., Medina, R. A high resolution hindcast of the meteorological sea level component for Southern Europe: the GOS dataset, *Clim Dyn*, 43:2167-2184., 2014
- 715 Conte, D. and Lionello, P.: Characteristics of large positive and negative surges in the Mediterranean Sea and their attenuation in future climate scenarios, *Glob. Planet. Change*, 111, 159–173, doi:10.1016/j.gloplacha.2013.09.006, 2013.
- [Cowell, P. J., Hanslow, D.J., Meleo, J.F. The shoreface. In: Handbook of beach and shoreface morphodynamics \(ed. Short, A. D.\). Wiley, New York, 39–71, 1999.](#)
- 720 Dissanayake, P., Brown, J., Wisse, P., & Karunarathna, H. Effects of storm clustering on beach/dune evolution. *Marine Geology*, 370, 63-75, 2015.
- [Duo, E., Sanuy, M., Jiménez, JA, Ciavola, P. 2020. How Good Are Symmetric Triangular Synthetic Storms to Represent Real Events for Coastal Hazard Modelling. Coastal Engineering, 159, 103728.](#)
~~[Duo, E., Sanuy, M., Jiménez J.A., Ciavola, P. On the Ability of Symmetric Triangular Synthetic Storms to Represent Real Events for Coastal Hazard Modelling. Coastal Engineering, in review \(n.d.\).](#)~~
- 725 ~~[Duo, E., Sanuy, M., Jiménez J.A., Ciavola, P. On the Ability of Symmetric Triangular Synthetic Storms to Represent Real Events for Coastal Hazard Modelling. Coastal Engineering, in review \(n.d.\).](#)~~
- Eichentopf, S., Alsina, J. M., Christou, M., Kuriyama, Y., & Karunarathna, H. Storm sequencing and beach profile variability at Hasaki, Japan. *Marine Geology*, 106153, 2020.
- Ferreira, Ó., Plomaritis, T. A. and Costas, S.: Effectiveness assessment of risk reduction measures at coastal areas using a decision support system: Findings from Emma storm, *Sci. Total Environ.*, 657, 124–135, doi:10.1016/j.scitotenv.2018.11.478, 2019.
- 730

- Garrity, N.J., Battalio, R., Hawkes, P.J., Roupe, D. Evaluation of the event and response approaches to estimate the 100-year coastal flood for Pacific coast sheltered waters. Proc. 30th Int. Conf. on Coastal Engineering, ASCE, 1651-1663, 2006
- [Hanson, H.: GENESIS: a generalized shoreline change numerical model, J. Coast. Res., 1-27, 1989.](#)
- 735 IPCC, 2014: Climate Change 2014. Synthesis Report. Contribution of Working Groups I, II and III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Core Writing Team, R.K. Pachauri and L.A. Meyer (eds.)]. IPCC, Geneva, Switzerland, 151 pp., 2014
- 740 IPCC: Climate Change 2013: Managing the risks of extreme events and disasters to advance climate change adaptation. A Special Report of Working Groups I and II of the Intergovernmental Panel on Climate Change, edited by C. B. Field, V. Barros, T. F. Stocker, D. Qin, D. J. Dokken, K. L. Ebi, M. D. Mastrandrea, K. J. Mach, G.-K. Plattner, S. K. Allen, M. Tignor, and P. M. Midgley, Cambridge University Press, Cambridge, UK and New York, NY, USA., 2012.
- IPCC: Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change, edited by T. F. Stocker, D. Qin, G.-K. Plattner, M. Tignor, S. K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex, and P. M. Midgley, Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA., 2013.
- 745 IPCC: Climate Change 2018: Global Warming of 1.5°C. An IPCC Special Report on the impacts of global warming of 1.5°C above pre-industrial levels and related global greenhouse gas emission pathways, in the context of strengthening the global response to the threat of climate change, sustainable development, and efforts to eradicate poverty [Masson-Delmotte, V., P. Zhai, H.-O. Pörtner, D. Roberts, J. Skea, P.R. Shukla, A. Pirani, W. Moufouma-Okia, C. Péan, R. Pidcock, S. Connors, J.B.R. Matthews, Y. Chen, X. Zhou, M.I. Gomis, E. Lonnoy, T. Maycock, M. Tignor, and T. Waterfield (eds.)]. In Press.
- 750 Jäger, W. S., Christie, E. K., Hanea, A. M., den Heijer, C. and Spencer, T.: A Bayesian network approach for coastal risk analysis and decision making, *Coast. Eng.*, 134, 48-61, doi:10.1016/j.coastaleng.2017.05.004, 2018.
- Jensen, F. V.: An introduction to Bayesian networks, UCL Press, London, UK., 1996.
- Jiménez, J. A., Gracia, V., Valdemoro, H. I., Mendoza, E. T. and Sánchez-Arcilla, A.: Managing erosion-induced problems in NW Mediterranean urban beaches, *Ocean Coast. Manag.*, 54(12), 907–918, doi:10.1016/j.ocecoaman.2011.05.003, 2011.
- 755 Jiménez, J. A., Sancho-García, A., Bosom, E., Valdemoro, H. I. and Guillén, J.: Storm-induced damages along the Catalan coast (NW Mediterranean) during the period 1958-2008, *Geomorphology*, 143–144, 24–33, doi:10.1016/j.geomorph.2011.07.034, 2012.
- Jiménez, J. A., Sanuy, M., Ballesteros, C. and Valdemoro, H. I.: The Tordera Delta, a hotspot to storm impacts in the coast northwards of Barcelona (NW Mediterranean), *Coast. Eng.*, 134, 148-158, doi:10.1016/j.coastaleng.2017.08.012, 2018.
- 760 Jiménez, J.A., Valdemoro, H.I. Shoreline evolution and its management implications in beaches along the Catalan coast. In: Morales, J.A. (ed), *The Spanish Coastal Systems Dynamic Processes, Sediments and Management*, Springer, 745-764, 2019
- Jongejan, R., Ranasinghe, R., Wainwright, D, Callaghan, DP, Reynolds, J. Drawing the line on coastline recession risk, *Ocean & Coastal Management*, 122, 87-94, doi: 10.1016/j.ocecoaman.2016.01.00, 2016.
- Lionello, P., Boldrin, U. and Giorgi, F.: Future changes in cyclone climatology over Europe as inferred from a regional climate simulation, *Clim. Dyn.*, 30(6), 657–671, doi:10.1007/s00382-007-0315-0, 2008.
- 765 Mendoza, E. and Jiménez, J.: Clasificación de tormentas costeras para el litoral catalán (Mediterráneo NO), *Ing. Hidr. en México*, (2), 23–34, 2008.
- Mendoza, E. T., Jimenez, J. A. and Mateo, J.: A coastal storms intensity scale for the Catalan sea (NW Mediterranean), *Nat. Hazards Earth Syst. Sci.*, 11, 2453–2462, doi:10.5194/nhess-11-2453-2011, 2011.
- 770 Hanson, S., Reeve, D., Horrillo-Caraballo, J., le Cozannet, G., Hissel, F., Kowalska, B., Parda, R., Willems, P., Ohle, N., Zanuttigh, B., Losada, I., Ge, J., Trifonova, E., Penning-Rowsell, E. and Vanderlinden, J. P.: The SPR systems model as a conceptual foundation for rapid integrated risk appraisals: Lessons from Europe, *Coast. Eng.*, 87, 15–31, doi:10.1016/j.coastaleng.2013.10.021, 2014.

- Oumeraci, H., Kortenhaus, A., Burzel, A., Naulin, M., Dassanayake, D. R., Jensen, J., Wahl, T., Mudersbach, C., Gönnert, G., Gerkenmeier, B., Fröhle, P. and Ujeyl, G.: XtremRisK — Integrated Flood Risk Analysis for Extreme Storm Surges at Open Coasts and in Estuaries: Methodology, Key Results and Lessons Learned, *Coast. Eng. J.*, 57(1), 1540001, doi:10.1142/S057856341540001X, 2015.
- Pearl, J.: Probabilistic reasoning in intelligent systems: networks of plausible inference, Morgan Kaufmann, San Francisco, California, USA., 1988.
- Plomaritis, T. A., Costas, S. and Ferreira, Ó.: Use of a Bayesian Network for coastal hazards, impact and disaster risk reduction assessment at a coastal barrier (Ria Formosa, Portugal), *Coast. Eng.*, 134, 134-147, doi:10.1016/j.coastaleng.2017.07.003, 2018.
- Poelhekke, L., Jäger, W. S., van Dongeren, A., Plomaritis, T. A., McCall, R. and Ferreira, Ó.: Predicting coastal hazards for sandy coasts with a Bayesian Network, *Coast. Eng.*, 118, 21–34, doi:10.1016/j.coastaleng.2016.08.011, 2016.
- Priest, S., Wilson, T., Tapsell, S., Penning-Rowsell, E., Viavattene, C., Fernandez-Bilbao, A. Building a Model to Estimate Risk to Life for European Flood Events – Final Report, FLOODsite project report T10-07-10, HR Wallingford, UK., 2007
- [Ranasinghe, R. On the need for a new generation of coastal change models for the 21st century. *Sci Rep* 10, 2010. Doi: 10.1038/s41598-020-58376-x, 2020.](https://doi.org/10.1038/s41598-020-58376-x)
- [Refaat, H., and Tsuchiya, Y.: Formation and reduction processes of river deltas: theory and experiments, *Bull. Disaster Prevention Res. Inst. Kyoto Univ.*, 41, 177-224, 1991.](https://doi.org/10.1007/BF02523911)
- Reguero, B. G., Menéndez, M., Méndez, F. J., Mínguez, R., Losada, I. J. A Global Ocean wave (GOW) calibrated reanalysis from 1948 onwards, *Coast Eng* 65:38-55. <https://doi.org/10.1016/j.coastaleng.2012.03.003>, 2012
- Roelvink, D., Reniers, A., van Dongeren, A., van Thiel de Vries, J., McCall, R. and Lescinski, J.: Modelling storm impacts on beaches, dunes and barrier islands, *Coast. Eng.*, 56(11–12), 1133–1152, doi:10.1016/j.coastaleng.2009.08.006, 2009.
- Ruiz, A., Kornus, W. and Talaya, J.: Coastal Applications of Lidar in Catalonia, 14–16, 2008.
- Sanò, M., Jiménez, J.A., Medina, R., Stanica, A., Sanchez-Arcilla, A., Trumbic, I.: The role of coastal setbacks in the context of coastal erosion and climate change, 2011. *Ocean & Coastal Management*, 54, 943-950, doi: 10.1016/j.ocecoaman.2011.06.008.
- [Sanuy, M., Duo, E., Wiebke, Jäger, W, Ciavola, P., Jiménez, JA. Linking source with consequences of coastal storm impacts for climate change and risk reduction scenarios for Mediterranean sandy beaches. *NHESS*, 18, 1825-1847, 2018](https://doi.org/10.1016/j.nhess.2018.08.011)
- Sanuy, M. and Jiménez, J. A.: Sensitivity of storm-induced hazards in a highly curvilinear coastline to changing storm directions. The Tordera Delta Case (NW Mediterranean), *Water (Switzerland)*, 11(4), doi:10.3390/w11040747, 2019.
- Sanuy, M., Jiménez, J. A. and Plant, N.: A Bayesian Network methodology for coastal hazard assessments on a regional scale: The BN-CRAF, *Coast. Eng.*, 157(April 2019), 1–10, doi:10.1016/j.coastaleng.2019.103627, 2020.
- Sanuy, M., Jiménez, J. A., Ortego, M. I. and Toimil, A.: Differences in assigning probabilities to coastal inundation hazard estimators: Event versus response approaches, *J. Flood Risk Manag.*, 13(July 2019), 1–17, doi:10.1111/jfr3.12557, [20192020](https://doi.org/10.1111/jfr3.12557).
- Sardá, R., Conde, R., Casadesús, M., Sánchez, A. and Pablo, J.: Erosión en las playas y gestión desintegrada: la problemática actual de la playa de S’Abanell, in *Hacia un nuevo modelo integral de gestión de playas*, pp. 51–71, Documenta Universitaria, Girona., 2013.
- [Stive, M.J.F., and De Vriend, H. J.: Modelling shoreface profile evolution, *Mar. Geol.*, 126\(1-4\), 235-248, 1995.](https://doi.org/10.1016/j.mar.1995.01.001)
- Straub, D. Natural hazards risk assessment using Bayesian networks. 9th Int. Conf. Struct. Saf. Reliab. ICOSSAR 05 Rome Italy 2509–2516, 2005.
- Sutherland, J., Peet, A., Soulsby, R. Evaluating the performance of morphological models. *Coastal Engineering* 51(8), 917-939, 2004

Trigo, I. F., Bigg, G. R. and Davies, T. D.: Climatology of Cyclogenesis Mechanisms in the Mediterranean, *Mon. Weather Rev.*, 130(3), 549–569, doi:10.1175/1520-0493(2002)130<0549:COCMIT>2.0.CO;2, 2002.

UNEP/MAP/PAP. Protocol on Integrated Coastal Zone Management in the Mediterranean. Priority Actions Programme, Split. 2008

820 Van Verseveld, H. C. W., Van Dongeren, A. R., Plant, N. G., Jäger, W. S. and den Heijer, C.: Modelling multi-hazard hurricane damages on an urbanized coast with a Bayesian Network approach, *Coast. Eng.*, 103, 1–14, doi:10.1016/j.coastaleng.2015.05.006, 2015.

Vousdoukas, M. I., Ranasinghe, R., Mentaschi, L., Plomaritis, T. A., Athanasiou, P., Luijendijk, A., & Feyen, L.. Sandy coastlines under threat of erosion. *Nature Climate Change*, 10(3), 260-263, 2020

825 Vousdoukas, M. I., Voukouvalas, E., Annunziato, A., Giardino, A. and Feyen, L.: Projections of extreme storm surge levels along Europe, *Clim. Dyn.*, 1–20, doi:10.1007/s00382-016-3019-5, 2016.

Wainwright, D.J., Ranasinghe, R., Callaghan, D.P., Woodroffe, C.D., Cowell, P.J., Rogers, K. An argument for probabilistic coastal hazard assessment: retrospective examination of practice in New South Wales, Australia. *Ocean. Coast Manag.*, 95 pp. 147-155, 10.1016/j.ocecoaman.2014.04.009, 2014.

830