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A multivariate extreme wave and storm surge climate emulator based on weather patterns

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ABSTRACT

Coastal floods often coincide with large waves, storm surge and tides. Thus, joint probability methods are needed to properly characterize extreme sea levels. This work introduces a statistical downscaling framework for multivariate extremes that relates the non-stationary behavior of coastal flooding events to the occurrence probability of daily weather patterns. The proposed method is based on recently-developed weather-type methods to predict extreme events (e.g., significant wave height, mean wave period, surge level) from large-scale sea-level pressure fields. For each weather type, variables of interest are modeled using Generalized Extreme Value (GEV) distributions and a Gaussian copula for modelling the interdependence between variables. The statistical dependence between consecutive days is addressed by defining a climate-based extremal index for each weather type. This work allows attribution of extreme events to specific weather conditions, enhancing the knowledge of climate-driven coastal flooding.

1. Introduction

Coastal flooding results from non-linear interactions of multiple oceanographic, hydrological, geological and meteorological processes (e.g., astronomical tide, monthly sea-level anomalies, storm surge, wave set-up, wind set-up, fluvial discharges, precipitation and land subsidence). Coastal flooding can result from an exceptional intensity of a single process (e.g. storm surge), but more often results from the combination of elevated values of more than one of the aforementioned processes, namely a compound event. As defined by the IPCC SREX report (Seneviratne et al., 2012) and Leonard et al. (2014), the main characteristics of a compound event are: (1) the extremeness of the impact rather than the individual components, (2) the multivariate nature of the impact and (3) the components statistical dependence. In this paper, we examine extreme non-tidal total water level (TWL) defined as the linear summation of storm surge (SS) and wave run-up, which is functionally related to significant wave height, Hs, and mean period, Tm (Stockdon et al., 2006). Because synoptic atmospheric circulation patterns control the magnitude of SS, Hs and Tm, all three variables show strong statistical dependence.

The processes responsible for extreme waves and storm surge are non-stationary. They vary seasonally, interannually and on longer time scales, possibly due to climate change (Milly et al., 2008). Recently, many extreme value models were developed to deal with non-stationarity and multivariate extremes, including conditional approaches (Heffernan and Tawn, 2004; Gouldby et al., 2014), stationary and non-stationary bivariate copula methods (Bender et al., 2014; Wahl et al., 2012, Masina et al., 2015) and higher-dimensional copulas (Corbella and Stretch, 2013; Ben Alaya et al., 2014; Wahl et al., 2016). Despite its predictability, the astronomical tide is also a component that adds non-stationarity to the estimation of TWL (Dixon and Tawn, 1999; Coles and Tawn, 2005), and often requires dependency correction between consecutive events using an extremal index (Leadbetter, 1983; Tawn 1992; Coles, 2001; Batstone et al., 2013).

Statistical models of extreme coastal flooding have been developed by combining highly energetic wave conditions (defined by large values of Hs and Tm) and high water levels (high tides and storm surge), with a time-dependent peak over threshold extreme value model (Serafin and Ruggiero, 2014) that accounts for seasonal and interannual variability based on sea-level pressure (SLP) and sea-surface temperature (SST) indices.

Recently, Camus et al. (2014a) developed a method to obtain daily SLP-based predictors that explain the inter-daily variability

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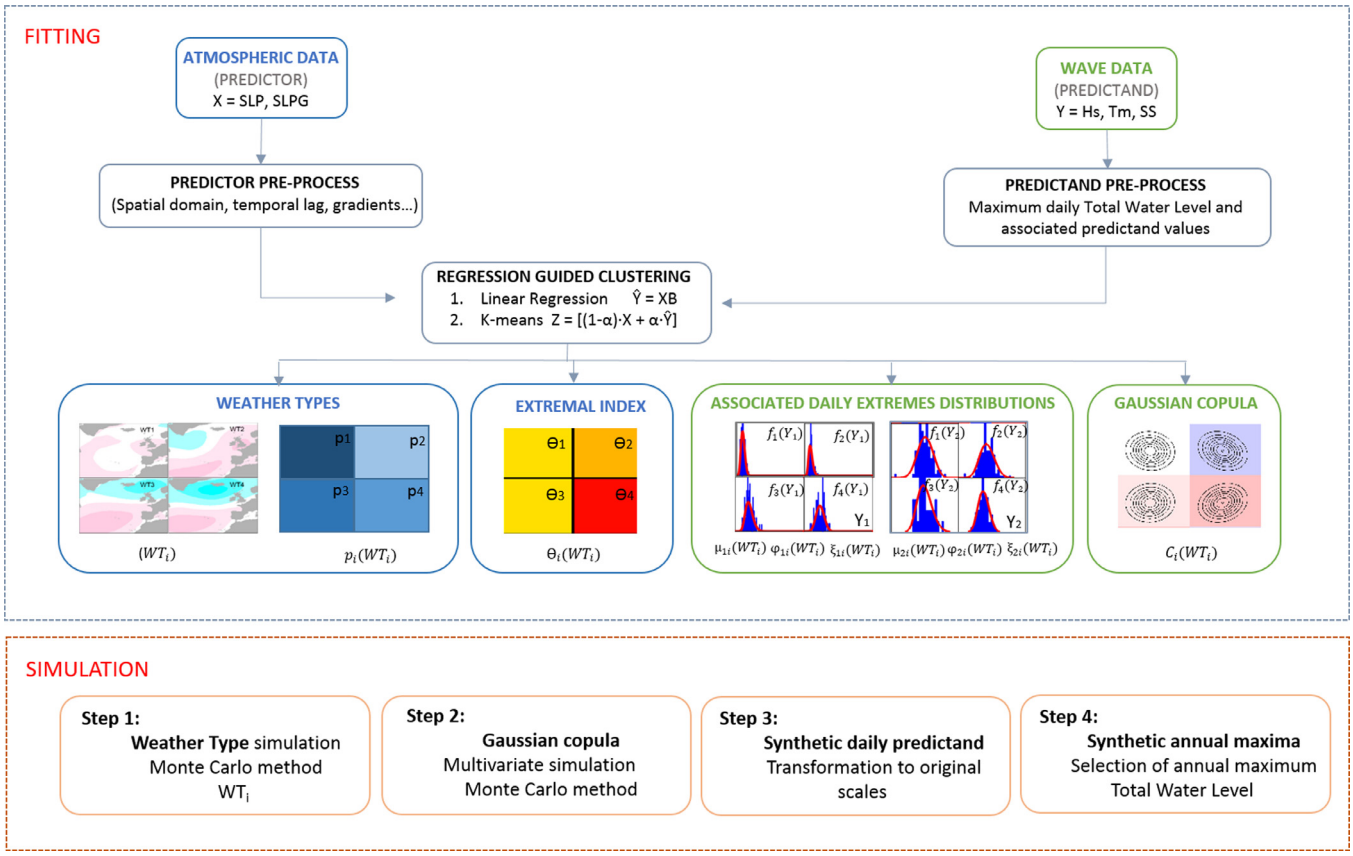

Fig. 1. Proposed methodology to obtain a multivariate climate-dependent extreme model.

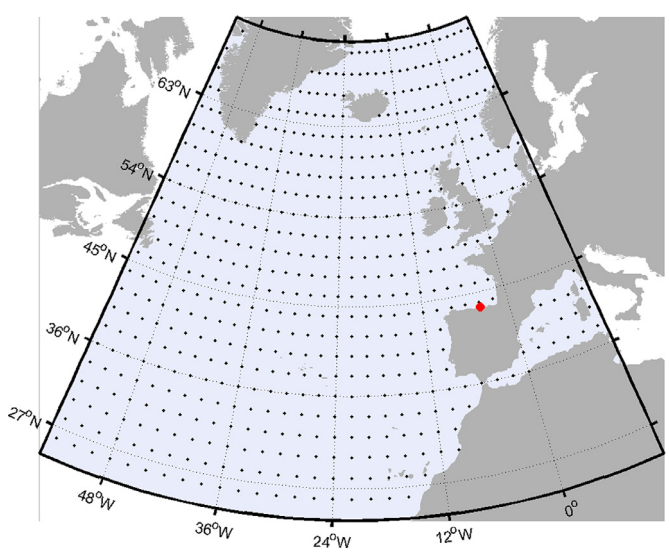

Fig. 2. Selected spatial domain of SLP predictor (black points). The red point shows the study site at Santander (Spain). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of wave climate. Based on these daily predictors, Camus et al. (2014b) presented a weather-type statistical downscaling framework for wave climate at daily scale. Statistical-downscaling methods based on weather types typically apply regional-scale predictors such as a collection of SLP patterns to estimate the local predictand, e.g. wave height, mean period and/or wave direction. Other applications of weather-types methods allow downscaling of multivariate directional spectra (Espejo et al., 2014) and precipitation extremes (Garavaglia et al., 2010).

In this paper, we propose a weather-types framework (Camus et al., 2014b) to model daily multivariate events using Generalized Extreme Value (GEV) marginal distributions for each predictand variable and Gaussian copulas for the correlation between variables. The statistical dependence between consecutive days is addressed by defining a climate-based extremal index for each weather type. We use the coastal flooding index, TWL, to characterize the extremeness of the compound events.

A benefit of the weather-type framework is the ability to trace back weather patterns responsible for large local flooding events. The water level contribution from the astronomical tide is deterministic, and the surge-tide interaction practically negligible in the area of study, therefore it is not considered in this paper. However, the framework could be easily extended to consider time scales of variability of the astronomical tide (e.g. seasonal, spring-neap, 4.4-yr, 8.85-yr and 18.6-yr cycles) and its inclusion in the Monte Carlo simulation of the hydraulic boundary conditions.

The paper is organized as follows: Section 2 describes the methodology, Section 3 presents the application of the method, and finally, Section 4 contains the summary and the conclusions.

2. Methodology

The proposed methodology is an extension of Rueda et al. (2016) to multivariate analysis. The methodology is composed of several steps:

1. Collect and pre-process historical data of predictor (SLP) and predictands (Hs, Tm, and SS).
2. Define weather types from synoptic SLP patterns.

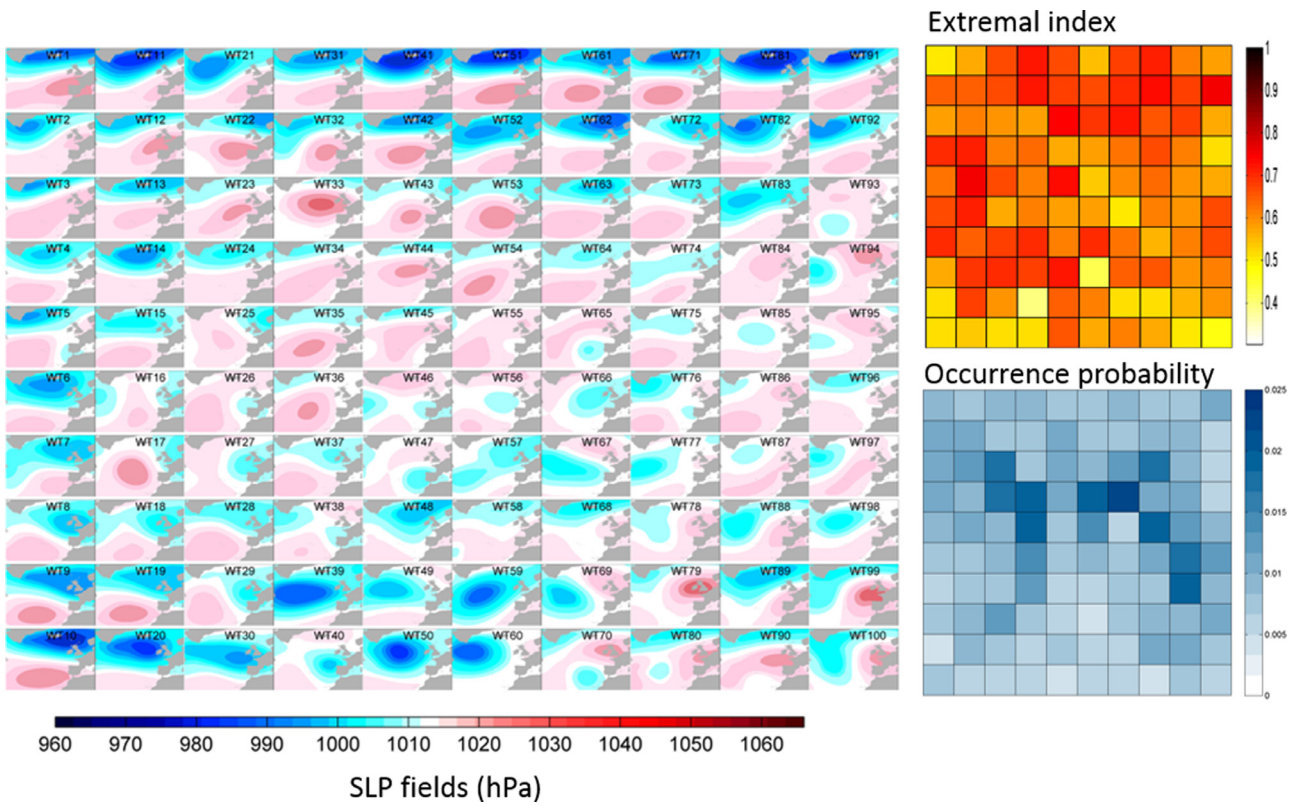

Fig. 3. The regression-guided weather-types (WT) classification represented by SLP fields (hPa) corresponding to the predictor-to-predictand classification obtained for a factor α=0.6. The associated extremal index (θ_i, in red scale) and occurrence probability (p_i, in blue scale) are also represented (right side panels). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3. Fit a stationary extreme value models (e.g. GEV) to the multivariate predictand (Hs, Tm, SS) associated with each weather type.
4. Obtain an extremal index to account for the mean duration of each weather type.
5. Model the dependence between predictand variables for each weather type using a Gaussian copula function.
6. Generate synthetic multivariate extremes taking into consideration the occurrence probability and dependence structure associated with each weather type.

A summary of the methodology is illustrated in Fig. 1. Each step is described in detail below.

2.1. Predictor and predictand definition

The first step is to obtain historical data of both the atmospheric predictor and predictand and construct the statistical model that relates them. In this work, the predictand is defined as the climate-related drivers (significant wave height (Hs), mean period (Tm) and storm surge (SS)) of elevated TWL during storm events. Based on previous works (Camus et al., 2014a; Perez et al., 2014), the daily predictor is defined as the sea-level pressure (SLP) and squared SLP gradients (SLPG), representing the geostrophic wind conditions, in a spatial domain that covers the corresponding wave-generation area. The daily SLP and SLPG fields are averaged over the n previous days in order to account for the recent atmospheric conditions over time scales of the wave generation and propagation.

The daily predictands (Hs, Tm, and SS) are selected based on a coastal flooding response function, in this case defined as the daily maximum TWL, which is the summation of surge level and an empirical estimate of wave run-up on dissipative beaches (Stockdon et al., 2006). The hourly values of Hs, Tm, and SS are used to compute the daily maximum TWL according to the formula (Eq. 1).

$$\mathrm{TWL} = \mathrm{SS} + 0.043 \cdot \sqrt{\mathrm{Hs} \cdot L_0}, \tag{1}$$

where $L_0 = \frac{g}{2\pi} {T_m}^2$.

2.2. Weather types

A regression-guided clustering improves the wave and storm surge downscaling based on weather types (WTs) (Cannon, 2012, Camus et al., submitted). The regression-guided clustering is performed on an augmented dataset (Z) which appends the weighted predictor (X) and predictand estimations ($\hat{Y}$) from a linear regression model () between predictand (Y) and predictor (X):

$$\mathrm{Z} = \left[(1-\alpha)\cdot \mathrm{X};\ \alpha \cdot \hat{Y}\right], \tag{2}$$

where α is a weighting factor which varies from 0 (unsupervised classification) to 1 (fully supervised classification).

In this work, a multivariate regression between the predictand Y (defined by the sea-state parameters: daily Hs, Tm and SS) and the predictor X (defined by the number of principal components (PCs) that explain 95% of the variance of daily SLP and SLPG fields) is fitted. The K-means algorithm (Hastie et al., 2001) is applied to the combined dataset Z, which includes the regression-guided predictions, to obtain N_{WT} clusters. The optimal α is obtained by minimizing the intra-cluster dispersion following the method of Camus et al. (submitted). Increasing cluster homogeneity improves the fit of the extreme value models for annual maxima univariate predictands (Hs, Tm, and SS) and therefore provides a better extrapolation of their joint density function.

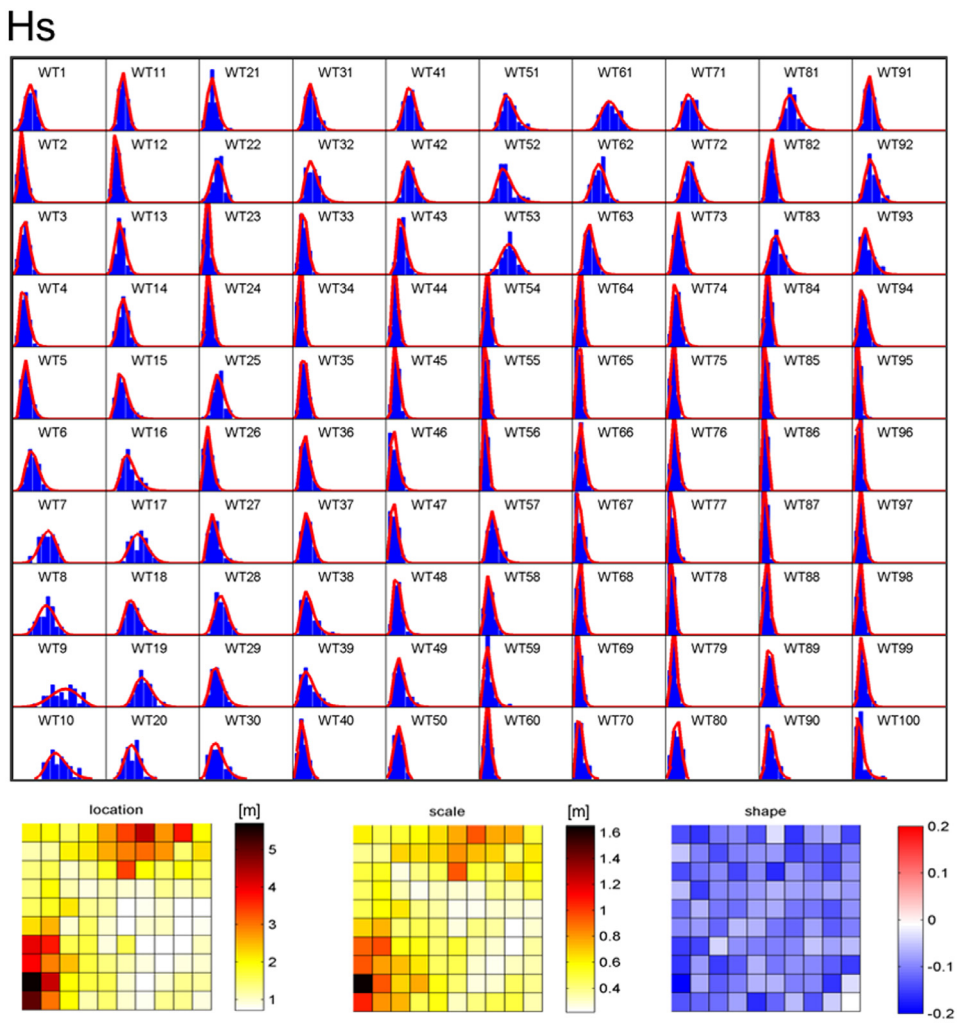

Fig. 4. The associated histogram and GEV probability density function for daily significant wave height (in meters) associated to the maximum TWL at each WT. X-axis [0 11], Y-axis [0 0.95] The corresponding parameter estimates of each distribution are illustrated in the lower panels. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Finally, each weather type (WT_i) is calculated as the mean of the synoptic circulation patterns included in each cluster of the regression-guided classification, and the probability of each cluster (p_i) is calculated from the number of SLP fields belonging to it.

2.3. Fitting the marginal extreme distribution

The marginal distributions of the predictands (Hs, Tm, and SS) for each weather type are fit to a generalized extreme value (GEV) distribution. The GEV distribution describes the probability distribution of block maxima of a sample (Fisher and Tippett, 1928). In this case, the daily block maxima is selected from the hourly predictand data and each sample is defined by those days belonging to a particular WT. The GEV cumulative distribution function (CDF) is given by:

$$F(y) = \exp\left\{-\left[1+\ \xi\left(\frac{y-\ \mu}{\psi}\right)\right]^{\frac{-1}{\xi}}\right\}, \tag{3}$$

where μ is the location parameter, ψ is the scale parameter and ξ is the shape parameter (Coles, 2001). The parameter estimates are calculated using a chi-square test and a weighted average of the shape parameter (with the four immediate neighbors in the PCs space) is performed in order to avoid anomalous values.

2.4. Climate-based extremal index

The statistical dependence between daily data belonging to the same WT is modeled using an extremal index Θ (Coles, 2001). Without applying the extremal index, the frequency of extreme values of the predictand is overestimated. In this work, the extremal index is defined as the inverse of the mean persistence on each weather type. Therefore, increasing the duration of a specific WT, increases the dependence between the associated data of the predictand. For those WTs associated with extreme conditions the value of the extremal index is expected to be close to 1. The dependence estimated using the extremal index influences the GEV parameter estimates. Following Leadbetter (1983), the distribution of the maximum considering the dependence of a stationary process satisfies:

$$H(y) = \{F(y)\}^{\theta}, \tag{4}$$

where $\theta(0 \le \theta \le 1)$ is the extremal index and F(y) is the GEV(μ, ψ, ξ) given by Eq. 3 and H(y) is a GEV(μ_θ, ψ_θ, ξ_θ) distribution with

$$\mu_\theta = \ \mu + \frac{\psi\left(\theta^{\xi}-1\right)}{\xi},\ \ \psi_\theta = \ \psi\theta^{\xi}\ \textit{and}\ \xi_\theta = \ \xi \tag{5}$$

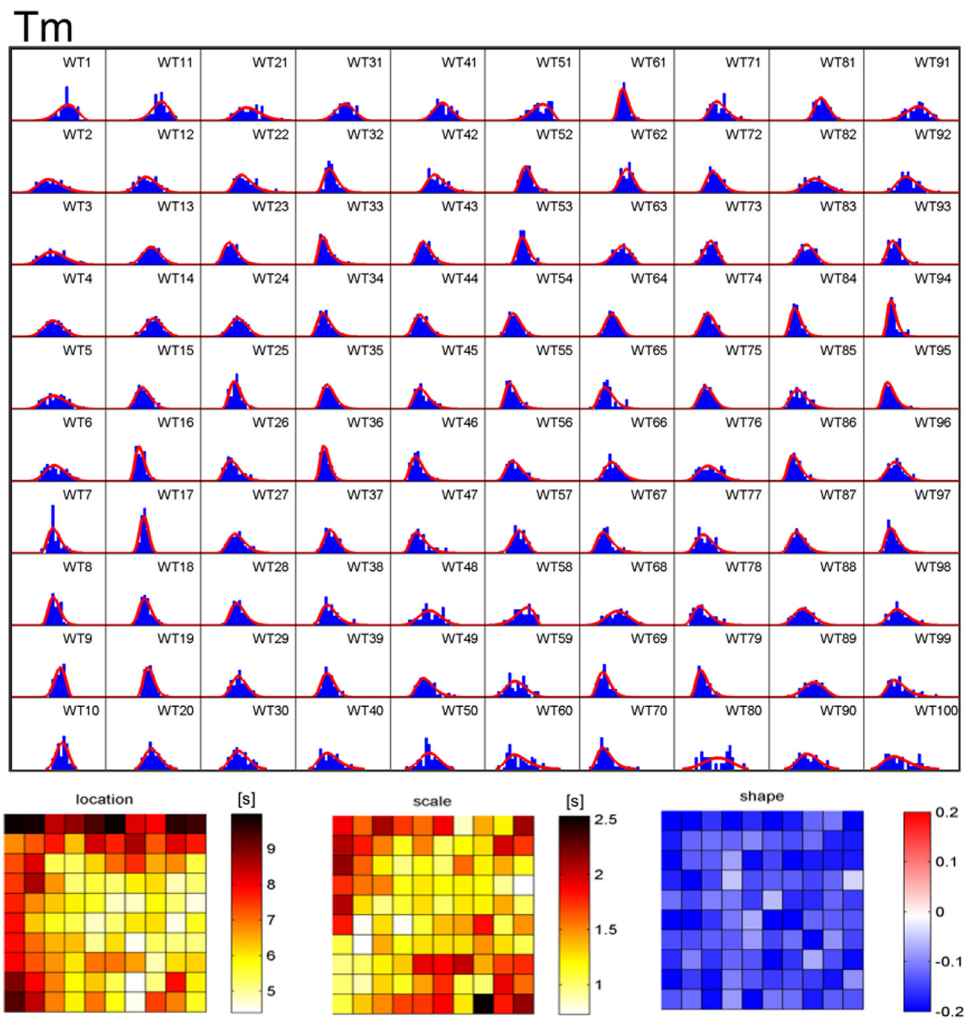

Fig. 5. The associated histogram and GEV probability density function for daily mean period (in seconds) associated to the maximum TWL at each WT. X-axis [0 18], Y-axis [0 0.95] The corresponding parameter estimates of each distribution are illustrated in the lower panels. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

thus, the statistical dependence influences only the location and scale parameters via the extremal index θ. The parameter estimates obtained via Eq. (5) are used during the simulation procedure (Section 2.6).

2.5. Statistical dependence structure

The statistical correlation between environmental variables is a non-stationary process (Wahl et al., 2015). However, few statistical methods resolve the non-stationarity related with the dependence structure. An example can be found in Bender et al. (2014), who introduced a non-stationary copula model to extrapolate joint density functions. However, variables describing coastal hazards such as Hs, Tm, and SS are often strongly correlated to each other and to the weather pattern leading to their generation. We propose the use of a weather-type classification that leverages the statistical dependence of weather and storm-related events (e.g. coastal flooding), since each WT has associated a particular dependence structure. The non-stationarity is introduced in the model by means of the time-dependent behavior of the occurrence probabilities of the daily weather types at seasonal and interannual time scales.

Copula functions are useful tools to model the dependence between variables with different marginal distributions. The use of copulas in multivariate problems, mainly in hydrology, has become popular in recent years (see for example, Nelsen (2006) and Salvadori et al. (2007)). Many different families of copulas are available and we have selected a Gaussian copula approach due to its flexibility to model several variables (Ben Alaya et al., 2014). A copula is a multivariate distribution whose marginals are uniformly distributed in the interval [0, 1]. The marginal functions of each variable are transformed to a normal distribution N(0,1). The dependence between variables is modeled by their correlation in the Gaussian space, defined by a symmetric, positive-definite matrix whose elements represent Spearman´s correlation coefficients. Vogl et al. (2012) and Laux et al. (2011) demonstrate that the marginals of a Gaussian copula must be independent and identically distributed. In this case, grouping predictand variables according to weather types (WTs) satisfies this requirement. The adequacy of the Gaussian copulas to model the dependence structure of the analyzed variables associated to each WT has been tested by a standard model diagnosis following Renard and Lang (2007) (not shown).

2.6. Monte carlo climate-based simulation

Once the marginal distributions and the dependence structure between variables are fit for each weather type, it is possible to generate a synthetic extreme wave climate based on the weather type occurrence probabilities.

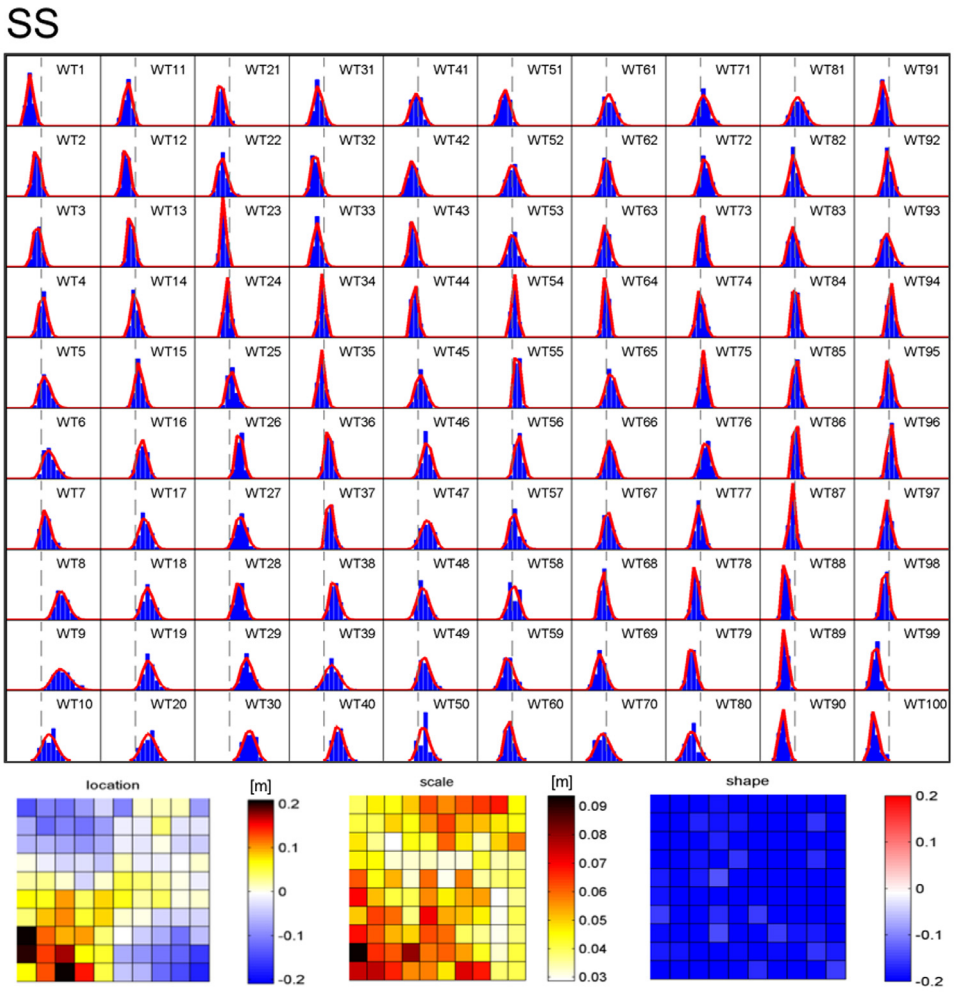

Fig. 6. The associated histogram and GEV probability density function for daily storm surge (in meters) associated to the maximum TWL at each WT. X-axis [-0.4 0.6], Y-axis [0 0.7]. The corresponding parameter estimates of each distribution are illustrated in the lower panels. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The simulation procedure establishes a daily-scale model of extreme wave climate based on the annual occurrence $\{p_i, i=1, \ldots, N_{WT}\}$ of the weather types. In order to construct a synthetic wave climate, the first step is to obtain a random weather type for each day of simulation, which is modeled assuming a Generalized Bernoulli distribution due to the categorical choice of one of the N_{WT}. Then, based on the marginal fits and Gaussian copula associated to the daily simulated WT, random daily synthetic Hs, Tm, and SS are obtained. Finally, the process is repeated thousands of times to obtain a large synthetically-generated sample of daily multivariate extreme events, where the annual TWL maxima are identified and associated values of Hs, Tm, and SS are recorded.

3. Application

3.1. Study location and data

The proposed methodology is applied to Santander bay in northern Spain [4°W, 43.5°N] (see Fig. 2). The data used to establish the statistical downscaling (SD) model is described below.

3.1.1. Predictor

The global SLP fields of the Climate Forecast System Reanalysis (CFSR) (Saha, 2010) are used to define the predictor of the SD model. The temporal coverage of CFSR spans 1979 to 2013 with hourly time resolution and 0.5° spatial resolution.

3.1.2. Predictand

Long-term records of historical data are needed to construct SD models. Reanalysis models often represent the preferred data source due to their spatial and temporal coverage. In this work, we utilize the wave hindcast (of Hs and Tm) from 1979 to 2013 developed by Perez et al. (2015) with hourly temporal resolution and 0.125° spatial resolution. Storm surge data comes from the Global Ocean Surge (GOS) reanalysis (Cid et al., 2014) with hourly temporal resolution and 0.125° spatial resolution.

3.2. Method implementation

The wave climate in Santander is mainly influenced by extratropical storms generated in the north and northwest Atlantic. Fig. 2, shows the spatial domain of the predictor from 24°N to 70°N and 54°W to 10°E. The predictor is defined as the three-day mean SLP and mean SLPG, calculated for each day of the study period. Principal component analysis (PCA) is applied to reduce the data dimensionality. In this particular case, the first 95 PCs were used in the classification algorithm, keeping 95% of the data variance.

A regression-guided classification on 100 WTs is implemented based on the daily PCs of the predictor and the daily multivariate predictand. An optimal factor (α) of 0.6 is used in this study case. Fig. 3 shows the WTs classification, as well as the associated extremal index and average annual occurrence probability. In Fig. 3,

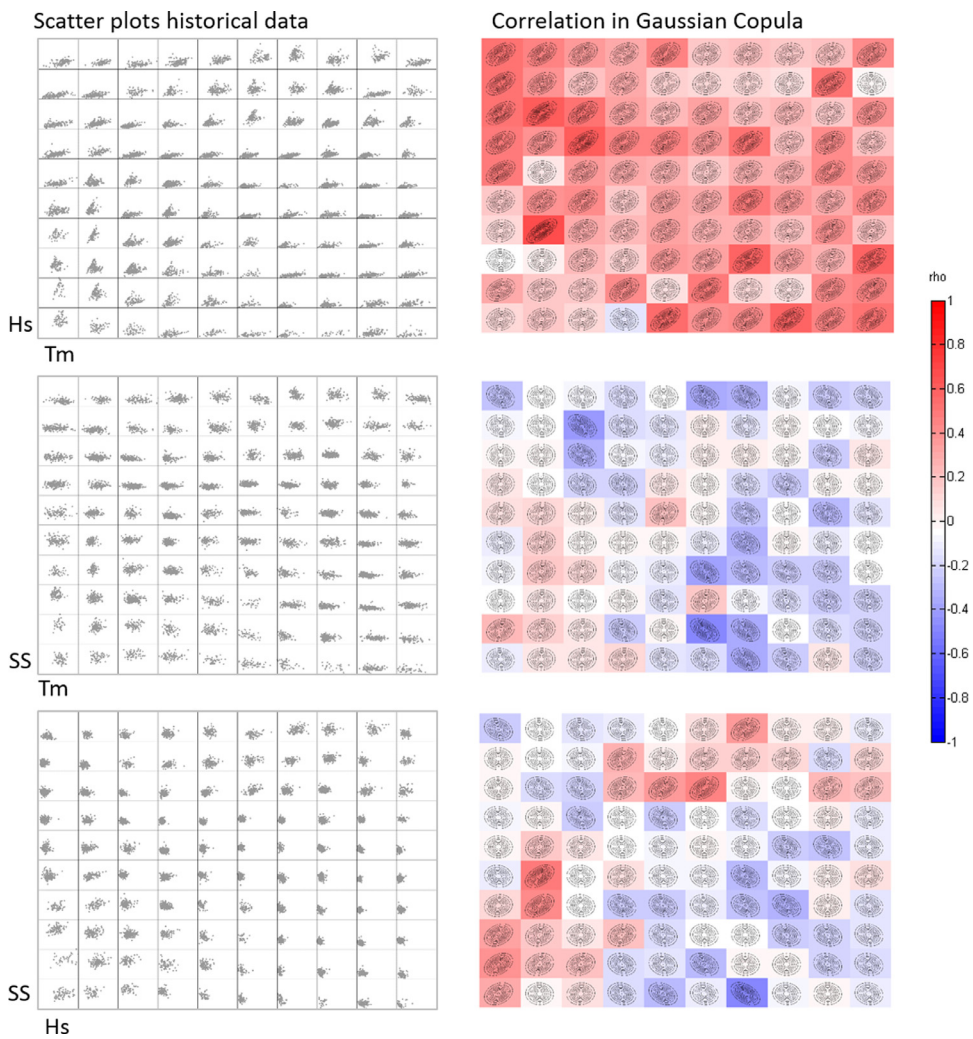

Fig. 7. The left panels represent the scatter plots for each WT of the historical data represented in groups of pairs (from top to down: Hs-Tm; SS-Tm; and SS-Hs). The right panels represent the associated Gaussian copulas, where the background color shows the corresponding correlation coefficient. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the WTs are organized in a bidimensional lattice, where similar weather patterns are located together.

The daily multivariate predictand (Hs, Tm, and SS) is associated to each particular WT, obtaining stationary, identically-distributed samples of each variable. Any remaining time-dependence between samples is overcomed by introducing the extremal index associated to each WT.

Figs. 4–6 show Hs, Tm, and SS distributions, respectively, for each weather type and the best fit GEV distribution and parameter estimates. Low pressure systems centered over the British Isles (WT8, WT9) produce large combined significant wave heights, wave periods, and storm surge in the study location. However, the largest storm surges, accompanied with low wave energy, occur when low pressure systems are located over the study site (WT29, WT30, WT40). On the other hand, the largest wave periods occur when low pressure systems are located in the northern Atlantic Ocean over Iceland (WT1, WT11). The variation in the intensity of each variable according to weather types reflects the importance of modeling wave climate according to large-scale atmospheric predictors.

The dependence structure associated to each weather type is modeled using a multivariate Gaussian copula as described in Section 2.5. The correlation between variables (Hs, Tm, and SS) is illustrated by a 2D comparison in Fig. 7. As expected, the significant wave height and mean period are positively correlated for most weather types. Only one WT (WT40) has a negative correlation between Hs and Tm which corresponds to a low-pressure system close to the study site. Correlations between SS-Tm, and SS-Hs vary significantly between WTs. Generally, positive correlations correspond to low pressure systems and negative correlations to high pressure systems, although each pattern presents particularities. Note that large correlations are found for many WTs, reinforcing the advantage of splitting up the multivariate analysis in independent distributions based on coherent weather types.

Once the marginal distributions and dependence structure between variables are fit and verified (not shown) for each WT, it is possible to generate synthetic time series of extreme events responsible for coastal flooding. To this end, a Monte Carlo simulation is performed where 300 realizations of 1500 years are simulated, obtaining 164,250,000 daily events. The daily realizations of Hs, Tm, and SS that produce the TWL annual maxima from the Monte Carlo simulation are illustrated in the upper panel of Fig. 8 (colored dots). The color represents the WT of origin, which are illustrated in the lower panel of the same figure. Different families of multivariate events can be found on the simulated sam-

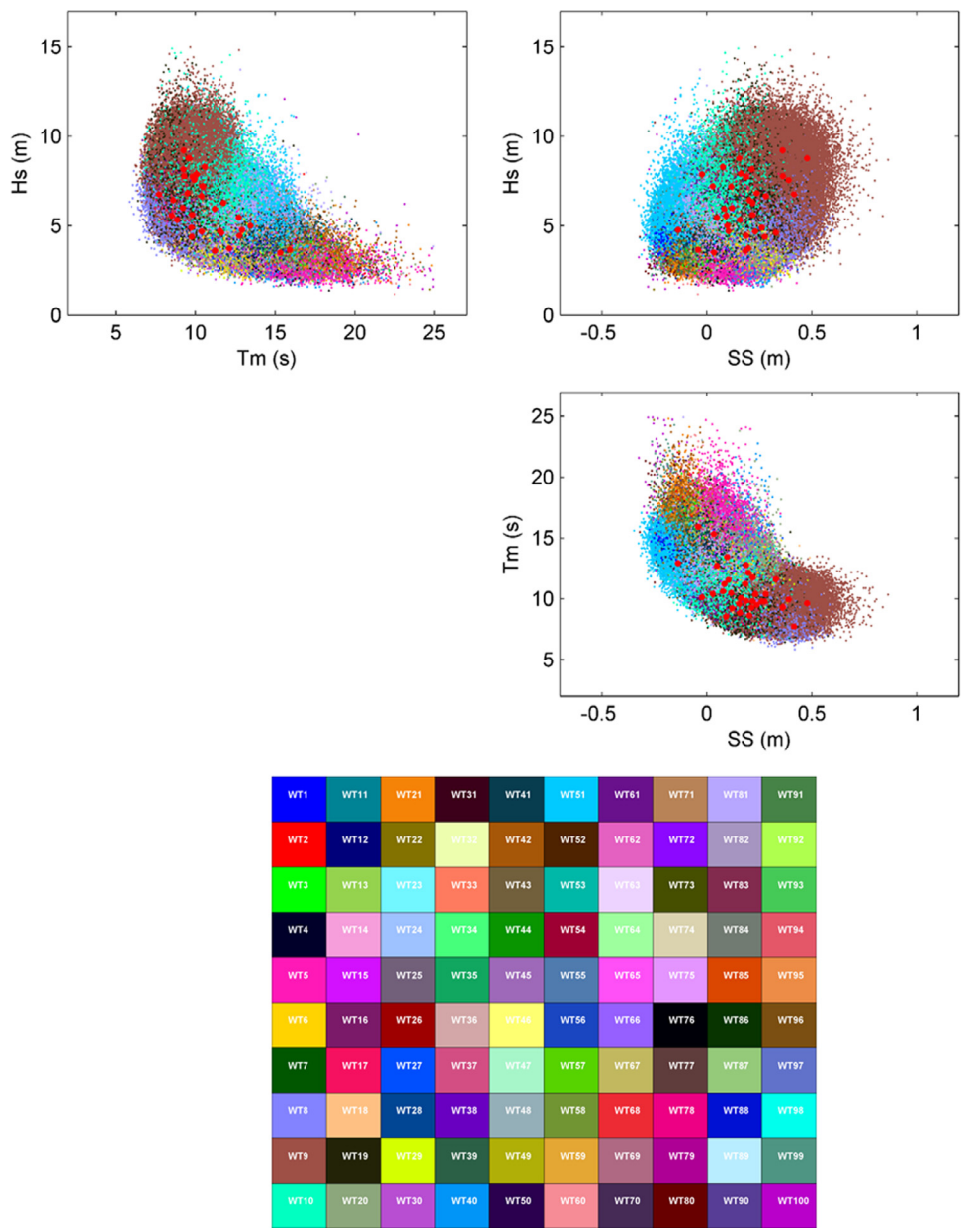

Fig. 8. Historical annual maxima (red dots) and annual maxima of Monte Carlo simulated events based on weather type probabilities and TWL definition. The colors of the simulated events correspond with the WT of origin (represente d in the lower panel). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

ple. For example, WT9 (clear green) and WT10 (brown), on Fig. 9, share large probabilities of producing an annual maximum of TWL. Although WT9 and WT10 have similar synoptic weather patterns (Fig. 3), and therefore exhibit similar ranges of Hs and Tm, anticyclonic circulation over the study area (WT10) reduces the values of the associated SS of the simulated events.

The ultimate goal of the proposed methodology is to estimate the exceedance probability of a response function, in this case TWL. In the upper panel of Fig. 9, the return period of annual maxima TWL obtained using the proposed methodology is compared to historical data. The red line is the mean of the Monte Carlo simulations and grey shaded areas represent the 95% confidence intervals. This result is compared to a standard univariate extreme value method, in this case a stationary GEV of the annual maxima of the historical TWL (blue line). The multivariate approach provides a better fit to the historical data. The differences between the two methods in the upper tail of the distribution are consistent with the findings of Bruun and Tawn (1998) and Gouldby et al. (2014) who proposed that potential erroneous extrapolation can arise in multivariate problems when not using a joint probability method.

The proposed method captures the non-stationary behaviour of climate by accounting for the variability of weather patterns over time. In the current Monte Carlo method, the occurrence probability of each weather type is fixed. However, the change in occurrence probability of weather types, as suggested by GCMs may be easily integrated into the proposed method. In the lower panel of Fig. 9, the WTs responsible for the annual maxima TWL are illustrated. Generally, only 10 individual WTs are responsible for the highest annual TWL and the highest probabilities of producing an annual maximum are shared between WT9, WT10, WT20 and WT1. Thus, the proposed method allows the trace back from

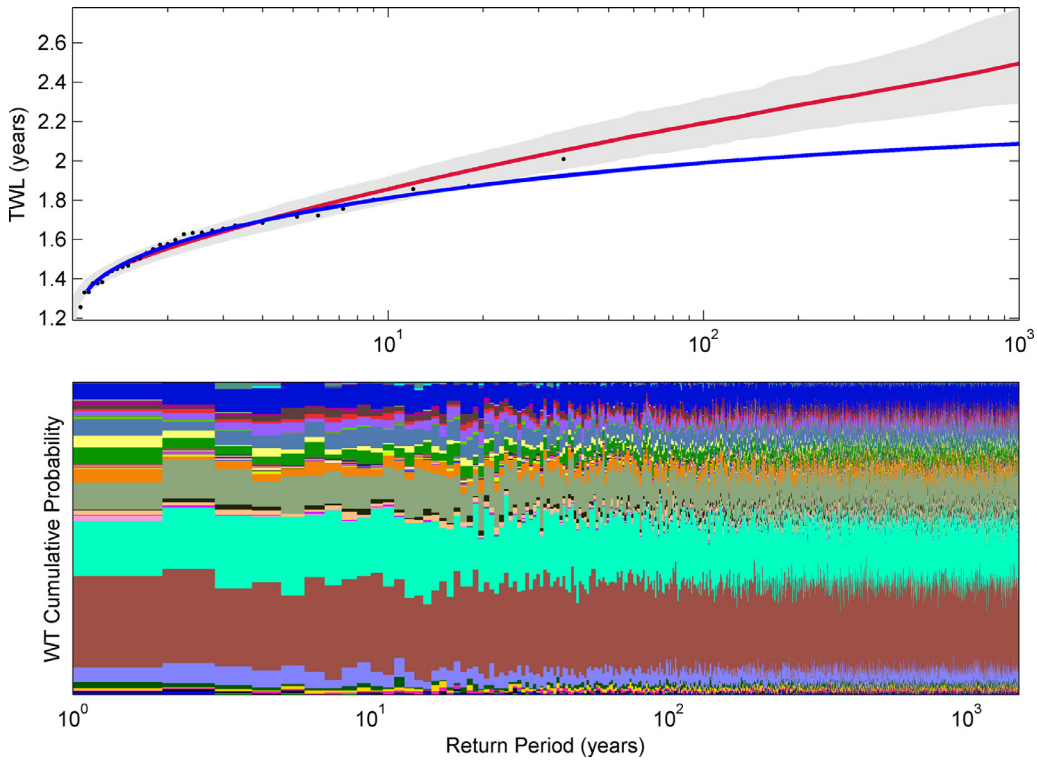

Fig. 9. Upper panel: extreme TWL vs. return period plot. Red line represents the mean of the climate-based simulations and grey shaded area are the 95% confidence intervals. Blue line shows the stationary GEV fit for the historical annual maxima (black dots). Lower panel: WT of origin of the simulated TWL annual maxima. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

extreme flooding events to the weather conditions responsible for their genesis.

4. Summary and conclusions

In this paper, a new climate-based approach to analyze and reconstruct extreme waves and storm surges is presented. The model is based on a predictor-to-predictand synoptic regression-guided classification model that groups extreme events according to similar generating meteorological processes, namely, weather types. Stationary extreme value models for the marginals, significant wave height, mean period, and storm surge are fit to each weather type and a Gaussian copula is used to account for the statistical dependence between the variables. The inter-daily data dependence is modeled with a climate-based extremal index. In this paper, we have focused on a trivariate problem (significant wave height, mean period, storm surge level) but the method is scalable to more variables due to the flexibility of the multivariate Gaussian copula. Non-stationarity (seasonality, interannual variability, and climate change) can be introduced in the model through the occurrence probability of each weather type as a function of time as predicted by global climate models.

The model is applied to the northern coast of Spain and the analysis of the results allows the identification of the weather types responsible for extreme coastal flooding events. In our particular application, the tide-surge interaction is practically negligible. If included, the tidal elevation could be added linearly in a Monte Carlo simulation.

In summary, the proposed multivariate extreme value model is able to extrapolate the joint density function of the variables that influence coastal flooding, providing insight into the connection between weather patterns and multivariate extreme wave climate.

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