

## Reviewer 2 :

### General Suggestions

The manuscript by Turki and co-authors addresses an important issue for the modeling of exceedance probability of extreme surges namely accounting for the dependence with climate patterns. The authors present an approach relying on wavelet analysis to investigate the correlation between the extreme surges and four climate oscillations (North Atlantic Oscillation, and Atlantic Multidecadal Oscillation, and the ones related to Sea-Level Pressure and Zonal Wind) at multiple time scales, \_1.5-years, \_2-4-years, and \_5-8-years and 12-16-years. On this basis, they perform nonstationary extreme value analysis using the English Channel coasts as application cases and show the added-value for accounting for these multiscale processes when deriving the return periods.

#### Main comment

The manuscript is well organized and the presentation is clear. Yet, several aspects should be clarified and further elaborated before publication (state of the art, details of the implementation, discussion regarding the assumptions). Therefore, I recommend additional corrections by incorporating, if possible, the following recommendations.

## Answer to Reviewer 2 :

### Specific comments

#### 1. State of the art.

Some key references about the link between extreme surges and climate variables should be added to the bibliography, namely:

\*\* Marcos, M., Calafat, F.M., Berihuete, Á., Dangendorf, S., 2015. Long term variations in global sea level extremes. *J. Geophys. Res.* 120(12), 8115-8134.

\*\* Marcos, M.; Woodworth, P.L., 2017. Spatiotemporal changes in extreme sea levels along the coasts of the North Atlantic and the Gulf of Mexico. *J. Geophys. Res.*, 122(9), 7031-7048.

\*\* Wahl, T., Chambers, D.P., 2015. Evidence for multidecadal variability in US extreme sea level records. *J. Geophys. Res.* 120, 1527–1544.

**\*\* Wahl, T.; Chambers, D.P., 2016. Climate controls multidecadal variability in US extreme sea level records. J. Geophys. Res. 121(2), 1274-1290.**

My second concern relates to the differences of the present work with the recently published one, namely Turki et al. (2020). As far as I understood, the time scale 12- 16-years and the British part of the Channel coasts were not tackled in this published work, but it would be useful to situate in more details the present study with respect to Turki et al. (2020), for instance in the introduction.

*Thank you for the comments.*

*The proposed references have been revised and added to the state of the art.*

*The new funding proposed in this research, compared to the last work of Turki et al., 2020, has been better explained in the state of the art as suggested in line .....*

### **References Proposed:**

#### *1. Introduction (lines 75 -90)*

Then, Marcos et al. (2015) have investigated the decadal and multidecadal changes in sea level extremes using long tide gauge records distributed worldwide. They have demonstrated that the intensity and the occurrence of the extreme sea levels vary on decadal scales in the most of the sites in relation with a common large-scale forcing. In the same way, the study of extreme sea levels along the coastal zones of the North Atlantic Ocean and the Gulf of Mexico has shown that the mean sea level should be considered as the major driver of extremes (Marcos and Woodworth 2017) since the intensity of extreme episodes increases at centennial time scales, together with multidecadal variability. The extreme sea levels along the United States coastline between 1929 and 2013 have been investigated by

Wahls and Chambers (2015; 2016). Wahls and Chambers (2015) have identified the relation between the multidecadal variations in extreme sea and the changes in mean sea level. Such relation has been mainly pointed toward some regions where storm surges are primarily driven by extratropical cyclones and should contribute in the variation of relevant return water levels required for coastal design. Such extremes have been then investigated in Wahls and Chambers (2016) works aiming to define their relationship with the large-scale climate variability by the use of simple and multiple linear regression models.

## 2. Discussion (lines 624 – 639)

Similar works have been carried out by Wahls and Chambers (2016) to investigate the multidecadal variations in extreme sea levels with the large-scale climate variability. By the use of climate indices on nearby atmospheric/oceanic variables (winds, pressure, sea surface temperature) as covariates in a quasi-nonstationary extreme value analysis, the range of change in the 100-year return water levels has been significantly reduced over time, turning a nonstationary process into a stationary one.

As suggested by Wong (2018), including a wider range of physical process information and considering nonstationary behavior can better enable modeling efforts to inform coastal risk management. In his work, he has developed a new approach to integrate stationary and nonstationary statistical models and demonstrated that the choice of covariate timeseries should affect the projected flood hazards. By developing a nonstationary storm surge statistical model with the use of multiple covariate timeseries (global mean temperature, sea level, the North Atlantic Oscillation index and time) in Norfolk and Virginia, he has shown that a storm surge

model raises the projected 100-year storm surge return level by up to 23 cm relative to a stationary model or one that employs a single covariate timeseries.

## *Clarifications related to Turki et al. (2020) works and the present research*

### *1. Introduction (lines 109 -125)*

Then, similar approaches have been used by Turki et al. (2020) to quantify the nonstationary behaviour of extreme surges and their relationship with the global atmospheric circulation at different timescales along the English Channel coasts (NW France) between 1964 and 2012. They have reported that the intermonthly and the interannual variability of monthly extrema are statistically modelled by nonstationary GEV distribution using the full information related to the climate teleconnections.

In the same context, the present contribution aims to investigate the interannual and the interdecadal dynamics of extreme surges along the English Channel coasts (NW France and SW England) by the use of combining techniques of spectral analyses and probabilistic models. We hypothesize that different large-scale climate variables may be involved in explaining the occurrence of extreme surges, and that this dependence can be a function of each timescale. The rationale behind this hypothesis is based on the following: (1) each timeseries of extreme surges should depend on different timescales; (2) each timescale should be related to a specific large-scale oscillation. Using this hypothesis, the linkages between the local extreme surges and the large-scale climate oscillations are deciphered with the aim to improve the extreme models using the most consistent large-scale oscillations as covariates

## 2. 4. Multi-scale variability of extreme surges

Similar interannual timescales have been observed along the French coasts of Dunkirk, Le Havre and Cherbourg in Turki et al., (2020) works where the intermonthly and the interannual variability of 48-year hourly surges has been investigated. They have demonstrated that the timescales smaller than  $\sim 1.5$ -yr are differently manifested between the different sites. These differences have been associated to the local variability of surges induced by combining the effects of meteorological and oceanographic forces including changes in atmospheric pressures and wind velocities in shallow water areas. As demonstrated in Turki et al. (2020) works, the mean explained variance of the interannual fluctuations ( $\sim 1.5$ -yr,  $\sim 2$ -4-yr, and  $\sim 5$ -8-yr) is around 25% of the total surges along the French coasts (Table 1). This value is higher than 32% in Weymouth and Dover while the explained variance of the interdecadal scales ( $\sim 12$ -16-yr) is also more important with 3.5% (compared to 2% for the French coasts).

## 3. 5. Large-scale climate oscillations

As proposed by Turki et al. (2019; 2020), the hypothesis used in the present work is that the multi-timescale variability of the local extreme surges should be strongly related to different climate teleconnections induced by a complex contribution of many physical mechanisms.

This non-linear relationship varies according to each timescale which depends on a specific large-scale oscillation of atmospheric circulation.

## 2. Details on the implementation.

The authors focus on extreme surges. To do so, the raw data of tide gauges should be pre-processed by accounting for the tide. Could the authors provide more details on how they proceeded? What type of tide data did they use?

Similarly, the authors used climate indices provided by the NCEP-NCAR Reanalysis.

Could the authors provide the web link where they downloaded the data for the climate indices? Besides, the authors mentioned climate oscillations using SLP and Zonal Wind. Are they directly available from NCEP-NCAR Reanalysis or are they derived from a pre-processing using EOF analysis for instance?

3. Model selection in the non-stationary Extreme Value Analysis (EVA). Integrating the climate drivers as covariates in EVA is a good idea, but the selection of the 'most appropriate' model deserves more discussion.

*Regarding the extraction of extreme surges, more details related to the classical model used for calculating tides are provided in the new version.*

*Also, the different climate indices have been better explained.*

*The selection of the most appropriate GEV model has been achieved for each frequency component. The use of the climate information has been differently explained for the different spectral component.*

*More explanations related to this part has been added in the new version (a new section in the methodological approach has been added)*

### **Extraction of surges:**

*A new part has been added in the manuscript (lines 191-213)*

#### ***3. 1 Extraction of residual sea level: 'surges'***

*The total sea-level height, resulting from the astronomical and the meteorological processes, exhibits a temporal non-stationarity which is explained by a combination of the effects of the long-term trends in the mean sea level, the modulation by the deterministic tidal component and the stochastic signal of surges, and the interactions between tides and surges. The occurrence of extreme sea levels is controlled by periods of high astronomically generated tides, in particular at inter-annual scales when two phenomena of precession cause systematic*

variation of high tides. The modulation of the tides contributes to the enhanced risk of coastal flooding. Therefore, the separation between tidal and non-tidal signals is an important task in any analysis of sea-level time-series.

By the hypothesis of independence between the astronomical tides and the stochastic residual of surges, the nonlinear relationship between the tidal modulation and surges is not considered in the present analysis. Using the classical harmonic analysis, the tidal component has been modelled as the sum of a finite set of sinusoids at specific frequencies to determine the determinist phase/ amplitude of each sinusoid and predict the astronomical component of tides. In order to obtain a quantitative assessment of the non-tidal contribution in storminess changes, technical methods based on MATLAB t-tide package have been applied to the seal level measurements, demodulated from long-term components (e.g. mean sea level, vertical local movement ), for estimating year-by-year tidal constituents. A year-by-year tidal simulation (Shaw and Tsimplis, 2010) has been applied to the sea-level time-series to determine the amplitude and the phase of tidal modulations using harmonic analysis fitted to 18.61-, 9.305-, 8.85-, and 4.425-year sinusoidal signals (Pugh, 1987). The radiational components have been also considered for the extraction of the stochastic component of surges (Williams et al., 2018).

### **Detailed information related to Climate Oscillations**

*A new part has been added in the manuscript (lines 183-189)*

Monthly time-series of climate indices have been provided by the NCEP-NCAR Reanalysis fields (<http://www.esrl.noaa.gov/psd/data/gridded/data.ncep.reanalysis.derived.html>) until

2017. The different indices have been extracted during the same period of the sea-level observations at the four stations Cherbourg, Dunkirk, Dover and Weymouth. For the longest timeseries of Brest (1850 - 2018), the use of climate indices has been limited according to their

initial date availability (AMO: 1880 – 2017; NAO: 1865-2017; SLP: 1948-2017; ZW: 1865-2017)

### *Selection of the most appropriate climate oscillation (lines 264-283)*

#### *2. 3. 4 Determination of the most appropriate climate oscillation*

##### *connected to each timescale extreme surges for GEV models*

As suggested previously, the main hypothesis presented in this research is that effects of the physical mechanisms on the extreme surges varies according to the timescale and each scale should be related to a given climate oscillation.

This hypothesis has been supported by two approaches: (1) a spectral approach based on the use of wavelet techniques (wavelet multiresolution and wavelet coherence as detailed in section 3.2) for optimizing the physical relationship between climate index and the extreme surges at each timescale; (2) a Bayesian approach has been used also for assessing extremes in a changing climate oscillation (NAO, SLP, ZW and AMO) at each timescale by making inferences from the Likelihood function. In our case where many parameters of GEV distribution should be optimized by including the most appropriate climate oscillation, Markov Chain Monte Carlo (MCMC) techniques have been implemented based on multiple simulations (the number of simulations varying as a function of the length of the timeseries; it is around 100.000 simulations). For generating the sequences of simulated values, we have applied the evbayes package within R software. By the use of this algorithm, a sequence of parameters with a normal distribution (a mean value equal to the previous value in the chain and a given variance). The



most suitable climate oscillation maximizing the fitting between the observed and the simulated data is identified when a burn-in-period is reached.

### 3.1. Adequacy of GEV.

It is not clear to me whether extreme value distributions are applied to each spectral component. If so, I wonder whether these variables are 'extreme', and whether GEV distribution is appropriate. Could the authors comment on that?

*The monthly extreme surges have been calculated from hourly residual sea level. This signal has been decomposed by the MODWT to study separately the different components. Our hypothesis in the present research is the following: The variability of the local extreme surges should be explained by the global climate patterns described by a series of physical mechanisms associated to the climate indices.*

*We have used the hypothesis that each spectral should be explained by a climate mechanism. Such hypothesis has been justified and validated by (1) the coherence diagrams (see also Table 2) where we have demonstrated that the effect of each climate index on the variability of extreme surges varies as a function of the spectral component and (2) Bayesian approaches applied to each spectral component to select the most appropriate climate index. This analysis has shown a strong coherence with the first validation (1).*

*This suggestion has been considered in the new version by incorporating a new section 3.4/*

*Also more clarifications in the section 5.2 Nonstationary modelling of extreme surges (lines 538-548)*

The connections between the climate oscillations and the monthly maxima at the different timescales (Figure 9), presented previously (section 5.1), have been explored as a first hypothesis for the implementation of the nonstationary GEV models. Indeed, multiple simulations of Markov Chain Monte Carlo (MCMC) techniques based on Bayesian approaches have been employed for extreme surge components (i.e. ~ 1.5-yr, ~ 2-4-yr, ~ 5-8-yr and ~ 12-16-yr provided by the multiresolution wavelet decomposition) to identify the best covariates of

climate oscillation to be used for parametrizing the nonstationary GEV models. The most of simulations has mainly supported the results outlined in the previous section: the  $\sim 1.5$ -yr of SLP,  $\sim 2$ -4-yr of ZW,  $\sim 5$ -8-yr of NAO and  $\sim 12$ -16-yr of AMO oscillations are considered as the best covariates for modelling respectively the  $\sim 1.5$ -yr,  $\sim 2$ -4-yr,  $\sim 5$ -8-yr and  $\sim 12$ -16-yr of monthly extreme surges

### **3.2. Variable selection.**

Table 2 is used to select the most appropriate climate variables to be integrated in the EVA. Though informative and useful to support discussion, my concern is that this selection is mainly based on a correlation analysis (Figure 7 and following ones), and I wonder why the authors did not perform a variable selection for the GEV model directly; for instance using AIC or selection criteria. See a discussion by Wong (2018)

*Thank you for this comment.*

*Indeed and as suggested in the part 3.1 of the present document, the use of the climate index as a covariable in the GEV model has been well justified by (1) the wavelet coherence (Table 2) and (2) a Bayesian approach has been used also for assessing extremes in a changing climate oscillation (NAO, SLP, ZW and AMO) at each timescale by making inferences from the Likelihood function (validation of the first hypothesis).*

*Once the climate covariate has been selected, the AIC criteria have been used for the implementation of the best use of climate index onto the GEV parameters.*

*This part needs to be more explained in the new version. More clarifications related to this point have been added (lines 541-560 in the new version of the manuscript).*

The connections between the climate oscillations and the monthly maxima at the different timescales (Figure 9)., presented previously (section 5.1), have been explored as a first hypothesis for the implementation of the nonstationary GEV models Indeed, multiple

simulations of Markov Chain Monte Carlo (MCMC) techniques based on Bayesian approaches have been employed for extreme surge components (i.e.  $\sim 1.5$ -yr,  $\sim 2$ -4-yr,  $\sim 5$ -8-yr and  $\sim 12$ -16-yr provided by the multiresolution wavelet decomposition) to identify the best covariates of climate oscillation to be used for parametrizing the nonstationary GEV models. The most of simulations has mainly supported the results outlined in the previous section: the  $\sim 1.5$ -yr of SLP,  $\sim 2$ -4-yr of ZW,  $\sim 5$ -8-yr of NAO and  $\sim 12$ -16-yr of AMO oscillations are considered as the best covariates for modelling respectively the  $\sim 1.5$ -yr,  $\sim 2$ -4-yr,  $\sim 5$ -8-yr and  $\sim 12$ -16-yr of monthly extreme surges.

Once the climate covariate has been selected for each timescale, three nonstationary models have been used by introducing the climate information as a covariate into: (1) the location parameter (GEV1); (2) both location and scale parameters (GEV2); (3) all location, scale and shape parameters (GEV3). The structure of the most appropriate nonstationary GEV distribution has been selected by choosing the most adequate parametrization that minimizes the Akaike information criterion (Akaike, 1974). The goodness of fit for each model has been checked through the visual inspection of the quantile-quantile (Q-Q) plots (Figure 10); these plots compare the empirical quantiles against the quantiles of the fitted model. Any substantial departure from the diagonal indicates inadequacy of the GEV model.

### 3.3 Model selection.

Furthermore, the results for Brest in Table 3 may raise some questions:

- For scale  $\sim$ 12-16 years, GEV0 does not seem to be the model that leads to the minimum AIC value (-1258 to be compared to -1980 for GEV1);

- For scale  $\sim$  2-4-yr, the AIC values

for GEV1-3 are very close, which make very hard to identify with high confidence the most appropriate model. The authors should comment on that.

See also Burnham and Anderson (2004) for further details.

Reference:

Wong, T. E. (2018). An integration and assessment of multiple covariates of nonstationary storm surge statistical behavior by Bayesian model averaging. *Advances in Statistical Climatology, Meteorology and Oceanography*, 4(1/2), 53-63.

Burnham, K. P. and Anderson, D. R.: Multimodel inference: understanding AIC and BIC in model selection, *Sociolog. Meth. Res.*, 60, 261–304, 2004.

*It's a very interesting comment which needs more clarifications from the authors.*

*More discussion related to this part has been added basing on the references provided.*

*Also, the different results presented here still preliminary and represent a first step for investigating the nonstationary behavior of the different frequencies. In the light of the present results, the nonstationary behavior is mainly controlled by the high frequencies.*

*More discussion related to the stationarity of the low frequencies ( $\sim$  12-16 years) ; lines 610 -617.*

*Here, the effects of AMO on  $\sim$ 12-16-yr of extreme surges have been largely observed in Figure 9 for the longer timeseries Brest where the lower frequencies could be easily identified.*

*At this timescale, the AIC values given by the different GEV models are pretty close and the difference between the distributions are not statistically significant. The stationary behavior of*

~12-16-yr surges should be more investigated from additional applications in light of the available sea level measurements covering a long period of time, a relevant parameter to characterize the uncertainties in extreme value statistical modeling of flood hazards.

*More discussion using the references proposed by the reviewer has been added (lines 624 – 666)*

Similar works have been carried out by Wahls and Chambers (2016) to investigate the multidecadal variations in extreme sea levels with the large-scale climate variability. By the use of climate indices on nearby atmospheric/oceanic variables (winds, pressure, sea surface temperature) as covariates in a quasi-nonstationary extreme value analysis, the range of change in the 100-year return water levels has been significantly reduced over time, turning a nonstationary process into a stationary one.

As suggested by Wong (2018), including a wider range of physical process information and considering nonstationary behavior can better enable modeling efforts to inform coastal risk management. In his work, he has developed a new approach to integrate stationary and nonstationary statistical models and demonstrated that the choice of covariate timeseries should affect the projected flood hazards. By developing a nonstationary storm surge statistical model with the use of multiple covariate timeseries (global mean temperature, sea level, the North Atlantic Oscillation index and time) in Norfolk and Virginia, he has shown that a storm surge model raises the projected 100-year storm surge return level by up to 23 cm relative to a stationary model or one that employs a single covariate timeseries.

This study has expanded the previous works of Turki et al. (2019; 2020) upon a new approach combining spectral and probabilistic methods to integrate multiple streams of information related to climate teleconnections. Indeed, each timescale has been simulated separately with the nonstationary GEV models and expressed as a function of the most suitable climate index

improving its fitting. The estimation of the total signal of surges should be determined by combining the developed nonstationary GEV models used for the different timescales.

These results should support the hypothesis introduced at the beginning of the present work suggesting that: (i) the extreme surges should depend on different timescales; (ii) each timescale should be related to a specific large-scale oscillation.

The finding is in agreement with the previous works of Lee et al. (2017) and Wang et al. (2018) highlighting the importance of a careful consideration when complex physical mechanisms of different climate indices are included into model structures for estimating extreme surges. Indeed, this work provides a guidance on incorporating nonstationary processes of large-scale oscillations to different spectral components informed by the wavelet techniques, the Bayesian approaches and the GEV model probabilities.

The primary contribution of the present research is to present a new approach for: (1) investigating the multi-timescale variability of the nonstationary extreme surges; (2) identifying their multi-connection with climate oscillations according to the timescale and (3) resolve in part the problems of uncertainty of most appropriate climate to use as covariate for GEV models at each timescale. However, additional models (e.g. significance tests and sensitivity analyses and modelling uncertainties) and application sites (e.g. Mediterranean and pacific ones controlled by other climate oscillations) are required to expand the developed approach.

Also, generating a final robust stochastic model useful for projecting storm surge return levels and assessing the flood risk management requires further efforts to build on the potentially advantageous approach presented here by integrating the GEV models associated with the different timescales through the use of mathematical methods.

#### **4. Correlation.**

The authors analyze the significance of the correlation through a visual inspection of the results provided by wavelet spectral analysis. In lines 339-341, the authors mentioned that they are using a Monte-Carlo-based approach

to identify the most statistically significant correlation: could the authors provide more details on the implementation.

Is it a bootstrap-based approach? How do they analyse the changes of the correlation at the Monte-Carlo iterations? Could the authors provide additional results about this significance assessment?

*Indeed, a bootstrap approach has been applied to assess the statistical significance of the correlation between the spectral component of the extreme surges and the climate oscillation at each timescale. By resampling the timeseries 10.000 times, 95% confidence intervals have been considered to extract the best climate information fitting the extreme surges (Villarini et al., 2009).*

*Villarini, G., F. Serinaldi, J. A. Smith, and W. F. Krajewski (2009), On the stationarity of annual flood peaks in the continental United States during the 20th century, Water Resour. Res., 45, W08417, doi:10.1029/2008WR007645.*

*This part has been added in the manuscript (lines 415 -420).*

For each timescale, a bootstrap approach has been applied to assess the statistical significance of the correlation between the spectral component of the extreme surges and the climate oscillation. By resampling the timeseries 10.000 times, 95% confidence intervals have been considered to extract the best climate information fitting the extreme surges (Villarini et al., 2009).

## **5. Typo.**

Line 70: “investigates” should be “investigate” Line 467: “covariable” should be covariate

*All typos have been checked and corrected.*