Comment on nhess-2021-329

Anonymous Referee #3

Referee comment on "Storm surge hazard over Bengal delta: A probabilistic-deterministic modelling approach" by Md Jamal Uddin Khan et al., Nat. Hazards Earth Syst. Sci. Discuss., https://doi.org/10.5194/nhess-2021-329-RC3, 2021

The manuscript by Khan and co-authors addresses the problem of storm surge hazard assessment over Bengal delta. They propose a hybrid procedure that combines high resolution numerical simulations, ensemble modelling, and probabilistic analysis. Their results are of high interest for coastal risk planning in this region both for present-day and future climate conditions.

Main comment

The manuscript is well organized and the presentation of the methods and results are very clear. The conclusions are sound. I very much appreciate the efforts made by the authors to discuss their results with respect to existing studies and to the limitations of their work (Sect. 5). My background is mainly focused on statistics. Therefore I won't comment on the modelling part (Sect. 2). Regarding the statistical aspects, a few aspects should be clarified and further elaborated before publication. Therefore, I recommend additional corrections by incorporating, if possible, the following recommendations.

Reply: We thank the Reviewer for his/her commendation and useful advice to improve the statistical analysis presented in the manuscript.

1) Return level estimates

1.1. The authors stress several times in the manuscript that the estimate of the return period of the water level is 'robust'. I agree with them that with a dataset representing more than 5000 years of cyclone activity, robustness should be achieved for estimating 100-year return levels. However, for a 500-year return level, some statistical uncertainty could still affect the result. This should be analyzed more carefully. As far as I understand the procedure, the authors calculate the empirical percentile using the results of the ensemble ('ranking-based statistical analysis' as indicated in line 321). I would expect the authors to calculate some confidence intervals, for example using bootstrap approaches; in particular, the results in Figure 8 should be further discussed in relation to this additional uncertainty estimate. An additional interest is to support the discussion in Sect. 5.3, in particular for the comparison with the study of Leijnse et al. who provides such uncertainty estimates.

Reply:

Confidence interval computation

We agree with the Reviewer regarding our unbacked claim about robustness. Following the suggestion, we have computed the 95% confidence interval for the return level estimate using bootstrap method. The bootstrap computation is applied over the full domain, node-by-node. For each node, 10000 instances of sampling were drawn to compute the bootstrap and derive the confidence interval.

We have revised the Statistical analysis section as following -

“...5120 years (for the largest return period). We have used bootstrap technique to compute the confidence interval for the return level estimates (Hesterberg, 2011). Unless otherwise stated, we have pooled 10000 bootstrap samples of the same size as our ensemble (3600 cyclones) with replacements and applied the above mentioned ranking method without considering ties. ¶Estimated quantities at return periods...”

(Note: ¶ means a new paragraph.)

We choose to show the robustness of the storm surge estimate at a few relevant stations. A new figure is now added, Figure 6 in the revised manuscript, as shown in Figure C1 below. The confidence interval remains moderate for the features that have been discussed throughout the manuscript, and none of our conclusions in the original manuscript were altered.

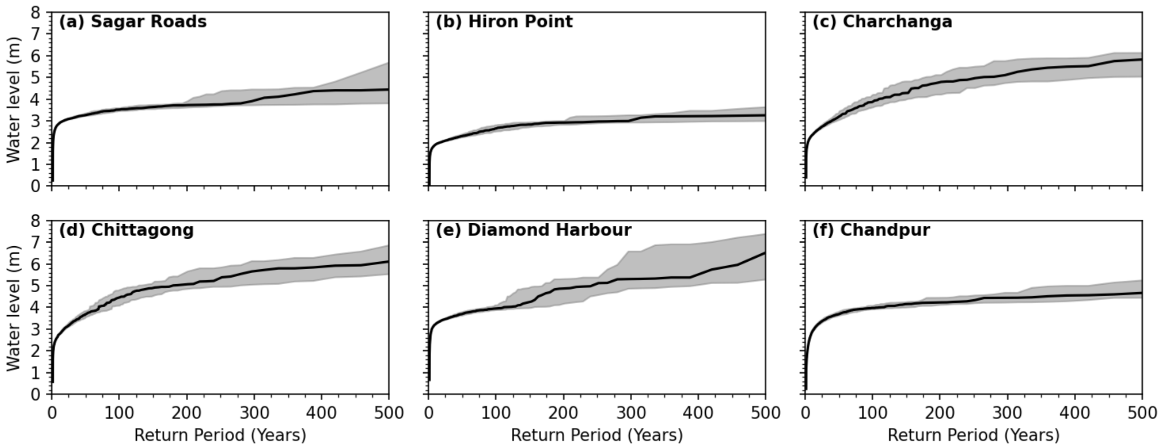

Figure C1. Extreme water level evolution with return period at (a) Sagar Roads, (b) Hiron Point, (c) Charchanga, (d) Chittagong, (e) Diamond Harbour, (f) Chandpur. These station locations are shown in Figure 5. The shaded grey area indicates the 95% confidence interval.

The addition of Figure C1 is reflected in the manuscript as following -

“...above topography. This water level at the 50-year return period is computed from the full ensemble of cyclone simulations using the empirical statistical method described in Section 3.3, pixel-by-pixel. As such, the total water level at the 50-year return period has contributions from hundreds of different cyclones of our ensemble. In our estimate, about 600 individual cyclones contribute to the 50-year return period water level over the illustrated region. To supplement subsequent discussions, in Figure 6 we also present the water level estimates and corresponding 95% confidence intervals at few station locations for a range of return periods (upto 500 years). These station locations are shown in black stars in Figure 5.”

“...delta (barely 3m). At 50-year return level, these estimates of water levels are objectively robust along the open coastlines, as well as inside the estuaries, with a couple of cm range in the computed 95% confidence interval (Figure 6).”

The station locations in Figure C1 are indicated in Figure 5. Revised Figure 5 is as shown in Figure C2 below -

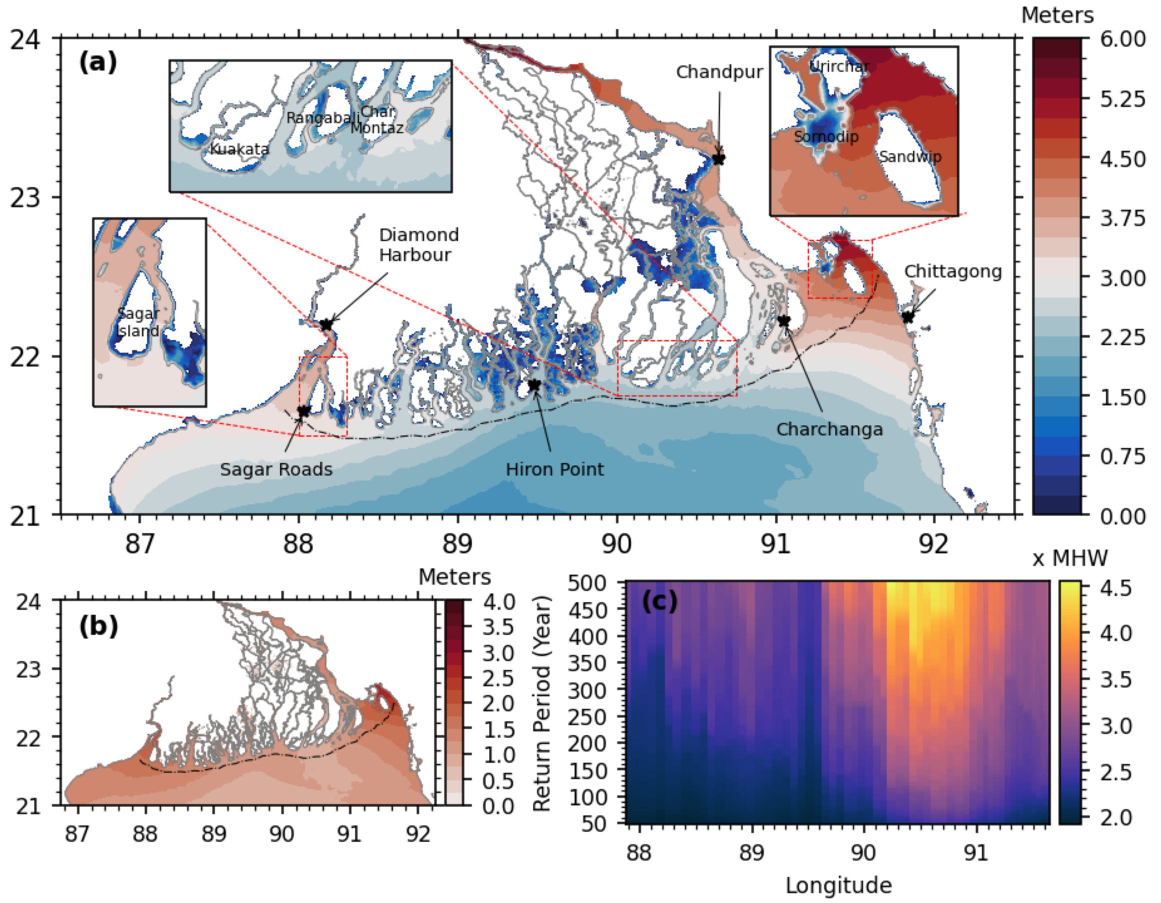

Figure C2. (a) Inundation extent and corresponding water level at 50-year return period. Black star shows the tide gauge location where the confidence interval is reported in Figure 6. (b) Mean High Water (MHW) derived from a year-long tidal simulation. (c) Water level for the 50-500 years return period expressed as a multiple of the MHW level along the nearshore dash-dotted line shown in (a) and (b).

Update to Population Exposure Computation

We have also updated Figure 8 (current Figure 9) with the confidence interval. The updated figure is shown in the reply to the next comment (Comment 2: Population exposure).

Update to Comparison with Previous studies in the Discussion

We have updated the text regarding the comparison with Leijnse et al. The current text reads as following -

"Leijnse et al. (2021) used a somewhat similar approach to ours. They used an extreme value analysis on the surge estimate of 1000 year simulated cyclonic activity using Peak-over-Threshold method and an exponential fit. In their estimate, the surge level (from tide free simulations) at Charchanga and Chittagong at 100-year return period is about 2.8m [2.5-3.1] and 3.3m [3.1-3.6] , respectively. The range in the parenthesis is the 95% confidence interval. To better compare with the estimate of Leijnse et al. (2021) we have re-simulated the ensemble of our 5000 year cyclonic activity (3600 cyclones) again, but without incorporating the tide. In our estimate, the 100-year return period surge level is 3.6m [3.4-4.0] and 4.1m [3.8-4.3] for Charchanga and Chittagong respectively. In other words, in these two locations, the estimate of Leijnse et al. (2021) is more than 60cm lower than ours, while the confidence interval range between there and this study are essentially the same."

We have also updated the comparison with Lee (2013), who provided a 90% confidence interval. The corresponding texts now reads as follows -

"Using a yearly-maximum method, in his extreme value analysis, he obtained a 1.66m [1.50-1.95] surge level at 50-year return period, and 1.75m [1.57-2.14] at 100-year return period. The range in the parenthesis is the 90% confidence interval.

In the previous section, our analysis was focused on the water level rather than surge level. To compare with the estimate of Lee (2013), we reprocessed the whole ensemble of storm event simulation results. We have first extracted the tidal water level from the 3600 cyclones that we simulated. Then, for each cyclone, we extracted the maximum surge level. Finally, on this maximum surge estimate, we applied the same ranking based return period estimate. At Hiron point, our estimation of surge amounts to 1.77m [1.68-1.85] at 50-year, and 2.31m [2.12-2.47] at 100-year return period. The range in the parenthesis is the 90% confidence interval computed from 10000 bootstrap samples. At a 50-year return period, with a difference of only 14cm (inferior in Lee (2013)), our estimated value is comparable to the estimated value by Lee (2013) from the observation time series. The confidence interval was about 2 times tighter compared to Lee (2013). To be noted that the estimated 50-year return period water level from our ensemble is about 3m at Hiron point. At the 100-year return period, the estimate of Lee (2013) was underestimated compared to ours by 56cm. See supplementary for further details."

1.2. A second aspect is the comparison of return levels to observed surge levels during cyclones. Could the authors consider the relevancy of using the surgedat dataset to this aim? http://surge.climate.lsu.edu/data.html

Reply:

We have checked out the dataset, and it was interesting. Figure C3a shows the data points that were reported to the same map extent as Figure 4 of the manuscript.

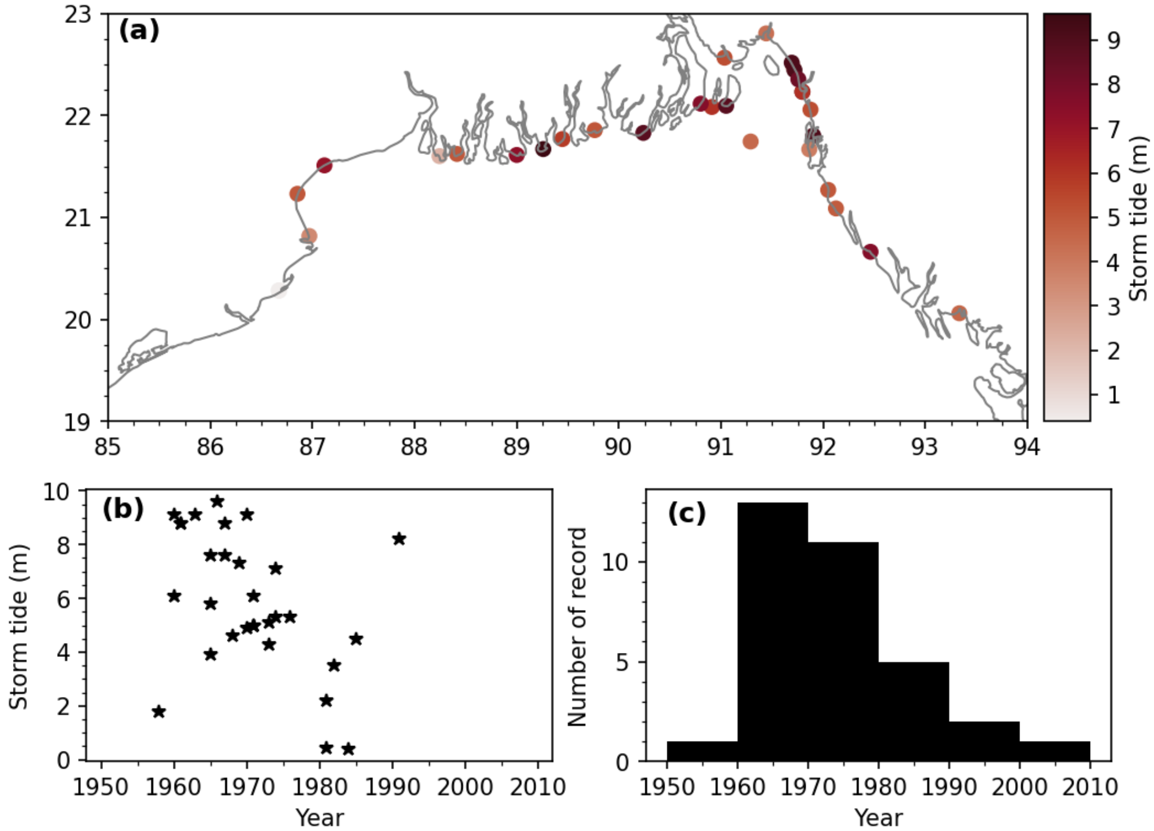

Figure C3. (a) Spatial distribution of the Storm tide in surgedat dataset. Colorbar represents the Storm tide value in the dataset. (b) Time series of the Storm tide. Missing values are not shown (e.g., 2007). (c) Year distribution of the record in surgedat dataset.

From the initial check, it seems that some values are suspiciously high. These values are mostly recorded during the 1950s-1970s. Through personal communication, we got confirmation from the curator of the dataset, Dr. Barry Keim, that the datums of these values are not uniform, often unknown. It is not an easy task to make them uniform, as many records are quite old, concentrated during 1960-1980, and will require an extensive archeology effort. The contrast in the number of records in the surgedat dataset between 1960-1980, and 1980-2000 perhaps also deserves further dedicated research.

By comparing with our modelling results, we suspect that some of the values, particularly those located in the central delta, are probably wrong. For example, the 9m water level around Sunderban is extremely unlikely due to widespread mangrove areas there, which attenuate the surges. The tidal range is also lower there compared to both east and west corners. However, it is still interesting to note that the spatial density pattern of the storm tide record location has a high similarity with the landfall location distribution of our storm dataset.

Finally, due to the uncertainty with the datum, we refrained from reporting further results in our manuscript regarding this dataset.

2) Population exposure

I appreciate the efforts made by the authors to discuss the limitations of their approach. In addition to the limitations raised in Sect. 5.6, could the authors also consider / discuss the use of alternatives population dataset. For instance, the Global Human Settlement Layer - Population Grid r2019a has a spatial resolution of 9 arc sec, and the WorldPop Global High Resolution Population Denominators has a spatial resolution of 3 arc sec. See references below.

Florczyk, A. J., Corbane, C., Ehrlich, D., Freire, S., Kemper, T., Maffenini, L., Melchiorri, M., Pesaresi, M., Politis, 1715 P., Schiavina, M., and others: GHSL data package 2019, 29788, 290498, 2019

Lloyd, C. T., Chamberlain, H., Kerr, D., Yetman, G., Pistolesi, L., Stevens, F. R., Gaughan, A. E., Nieves, J. J., Hornby, G., MacManus, K., Sinha, P., Bondarenko, M., Sorichetta, A., and Tatem, A. J.: Global spatio-temporally harmonised datasets for producing high- resolution gridded population distribution datasets, Big Earth Data, 3, 108– 1780 139, https://doi.org/10.1080/20964471.2019.1625151, 2019.

Reply:

We thank the reviewer for suggesting these datasets. We have now adopted the GHSL dataset for our analyses, which has a resolution equivalent to the resolution of our model in the coastal regions (250m).

Adopting this new dataset reduced the population estimate under exposure to 5-year flood, as well as the increase of population count from 5-year to 50-year flood. But The overall 'percentage' of population under exposure to a 50-year flood remains the same as before, i.e., 10%.

Section 5.6 has been fully revised as following -

“...with a grey colour bar based on GHS Population dataset of 2015 (Schiavina et al., 2019). This dataset is based on GPWv4 dataset (Center For International Earth Science Information Network (CIESIN), Columbia University, 2016) illustrated in Figure 1, but disaggregated from the original administrative/census level data to grid cells based distribution of the built-up areas (Freire et al., 2016). The contours of the flooding extent at return period ranging from 5-year to 500-year are shown in colour.

As the population data is provided at a regular longitude-latitude grid, and the model grid is unstructured, it is first necessary…”

“... the same regular longitude-latitude grid as the population dataset (250m resolution). As the model grid …”

“The estimated population living in our model domain over the Bengal delta extent shown in Figure 9a amounts to 32 million. This count amounts to the fraction of Bangladesh population living at an elevation 5m or less. The estimated size of the exposed population at various return periods of inundation is shown in Figure 9b. The shaded region in Figure 9b is the 95% confidence interval of the exposed population estimate. These estimates correspond to the population exposed to the 95% confidence interval of the water level estimates. Our estimate shows that about 1 million people currently live within the 5-year return period flood level area. Even if the embankments were to work without failure during a cyclone, about 2.5 million more people [95% confidence interval: 2.3, 2.9] would get exposed to the flooding of 50-year return period. This additional count of the population represents about 8% of the total population living inside the study area. At a 100-year return level, the fraction of exposed people increases to about 16% of the total population inside the modelled domain.

In this assessment, we did not consider the probable (although not publicly documented) existence of city protection embankments at local scale, which may distort the patterns of Figure 7a locally. We did not consider either the potential degradation of the earthen dikes, and possible dike breaching during an intense cyclonic event. Knowledge of these factors will surely impact the anticipated exposure of the population to flooding suggested by our analysis. Instead, our focus was mainly on the physical mechanism of the flooding from storm surges. Despite these limitations, our exposed population map provides useful and spatially continuous information at relevant spatial scales to document the exposure to storm surge flooding and to better understand the environmental risks to the vast, densely populated Bengal delta continuum.”

3) Use of JTWC dataset

3.1. As far as I understand the use of JTWC dataset for Fig. 4 is not a validation per se but the objective is to show the consistency of the ensemble results. However we note some discrepancies in Fig. 4(b) and (c) that deserve some additional comments or clarifications.

In particular, the frequency for April drastically differs between JTWC and the ensemble approach. Adding some errorbars to these histograms may here also help nuancing these differences.

Reply: We have revised the figure with errorbars (Standard Error) for JTWC dataset. Before going into further discussion, we recall here that the number of JTWC events is 42 only. The revised figure is shown in Figure C4-

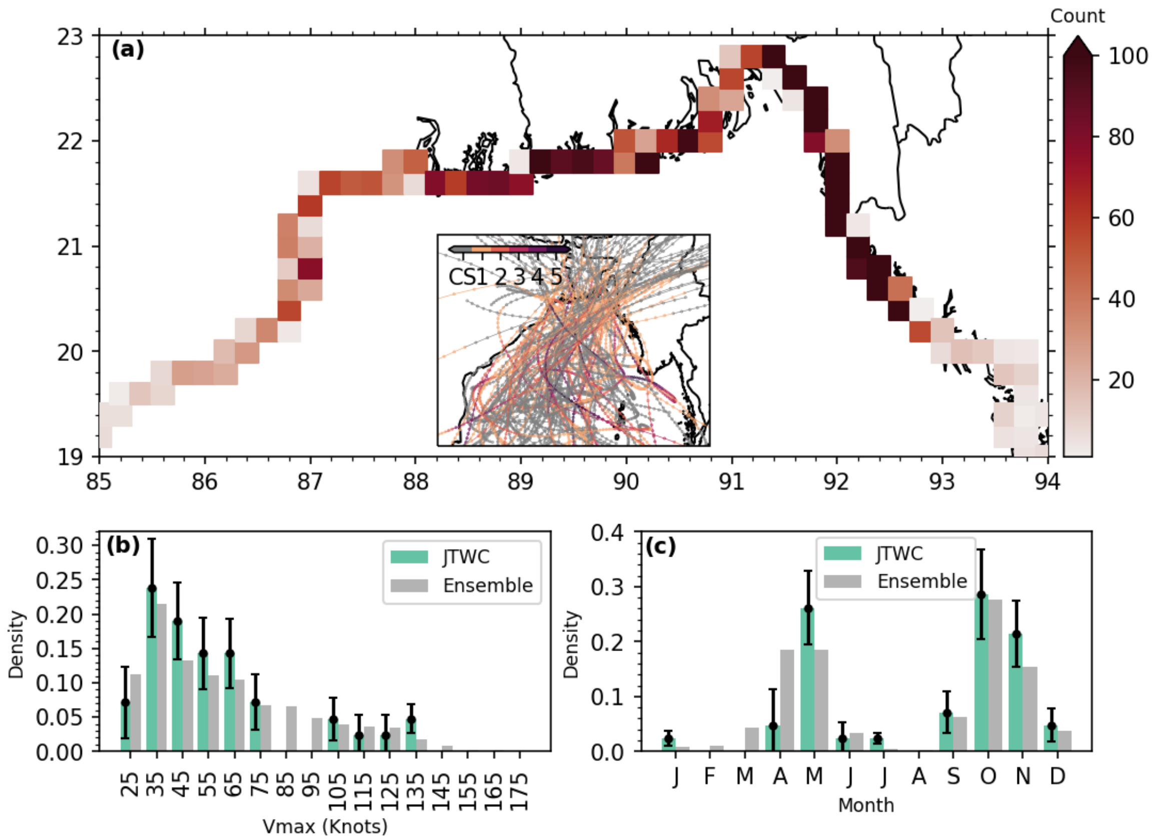

Figure C4. a) Spatial distribution of the paths of the cyclones that make landfall along the coast of Bengal delta. Each square bin is 20 km wide. A small subset of cyclones trajectories is shown in the inset. (b) Distribution of maximum wind speed of the synthetic cyclones compared to the JTWC dataset, (c) Annual distribution of the occurrence of the synthetic cyclones compared to JTWC dataset. In (b) and (c), errorbar indicates the standard error associated to the small sample size in JTWC dataset.

The errorbars in the JTWC values are computed based on the assumption that the number of events occurring in a month is a Poisson process. The location parameter in Poisson distribution (lambda, here the number of events) for each month is computed by multiplying the probability density and number of JTWC events. Then from 10000 values generated from this distribution, the standard deviation is computed - which is the standard error reported here.

A second approach is also tested, using a bootstrap method, where a large set of samples (10000) of the same size as the JTWC dataset (42) is pulled from our ensemble. Then the monthly distribution is computed for the 10000 set, and the standard error is computed as the standard deviation of the 10000 instances for each month. Both the assumption of Poisson distribution and bootstrap method gives essentially similar results (Figure C).

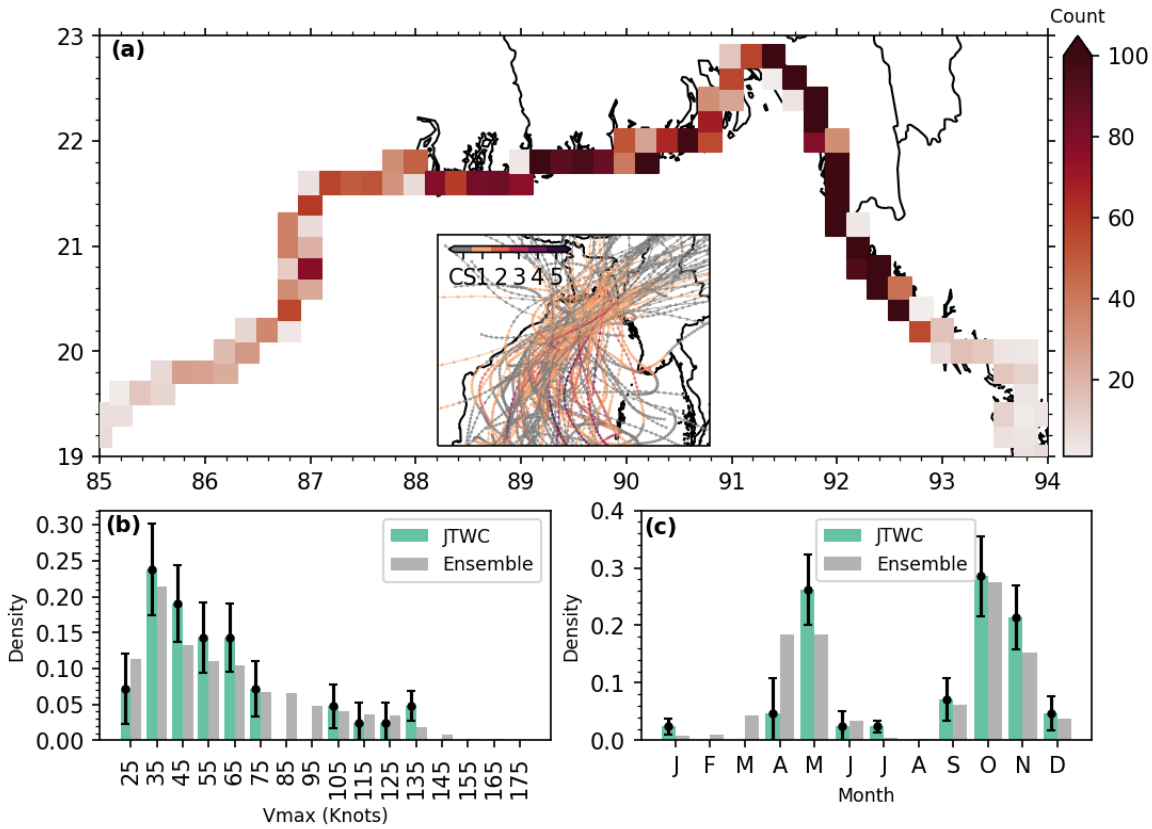

Figure C5. Same as C4 but the uncertainty range is computed using bootstrap method.

We propose to provide a description of these computations in the Supplementary materials.

From both of these figures, what we see is that the small sample size of the JTWC dataset largely explains the variation.

The text was also updated accordingly to incorporate these changes -

“...The consistency of the cyclone ensemble is illustrated through a comparison with the observed JTWC statistics for maximum wind speed (Vmax) (Figure 4b) and seasonal distribution (Figure 4c). Errorbars in both cases indicate the standard error of the observation (i.e., short-length of dataset) given the probability distribution in the ensemble computed assuming a Poisson process. A similar standard error estimate was obtained using bootstrap method (See Supplementary materials).

The distribution of the simulated maximum wind speed (Vmax) shows a good agreement with the observations from JTWC (Figure 4b). The standard errors for the JTWC dataset indicate that the ensemble distribution of Vmax is within the range of observational uncertainty.

Similarly, the seasonal distribution of the cyclone ensemble and that observed from JTWC both show a well matching pattern with a bimodal seasonality (Figure 4c) (Alam and Dominey-Howes, 2014). In the Bay of Bengal, low-pressure systems typically cannot intensify into a storm due to strong vertical wind shear present during monsoon (June-August). During the pre-monsoon (March-May) and post-monsoon (September-November), low vertical wind shear, and high sea surface temperature provide a suitable condition for low-pressure systems to intensify. For all months, except April, the ensemble cyclone density is typically within the range of observational uncertainty indicated by the errorbar (Figure 4c). However, for our storm surge hazard analysis, no measurable impact is expected from such intra-seasonal differences in cyclone distribution. The overall simulated bimodal temporal evolution of the synthetic cyclone indicates that the temporal statistics captured by our statistical-deterministic method correspond well with the seasonal climatic characteristics.”

3.2. Is JTWC dataset used to estimate the average annual frequency of 0.70314 (indicated in line 285)? If so, please specify.

Reply: The model tuning is largely based on the JTWC dataset. The track generation method used in this study (Emanuel 2006) is adjusted by a calibration factor. This calibration constant is the rate at which a random cyclone is generated from a distribution of historical genesis points. In our case, the calibration factor was set to 1.2, and subsequently the average annual frequency of the cyclone was found to be 0.7.

We propose to revise L285 as following to incorporate this information -

“The cyclone generation model was adjusted using a calibration factor based on the observed cyclone genesis and displacement characteristics in the JTWC dataset. The calibration factor was set to 1.2, which indicates the rate of seeding for cyclone genesis in the probabilistic cyclone generation model. With an average annual frequency of 0.7 cyclones, the ensemble of 3600 cyclones considered here represents more than 5000 years of cyclonic activity over the northern Bay of Bengal under present climate conditions.”

3.3. On page 19, in line 400, the authors state that ‘This landfall pattern corresponds to previous observations that the landfalling cyclones in the Bangladesh coastline tend to move north-eastward’. Is this result also confirm by the analysis of the JTWC dataset?

Reply: This statement is supported by the JTWC dataset and discussed in further detail supplemented with numerical modelling in a recent article by Akter and Tsuboki (2021), for the storms recorded during the 1990-2019 period. The same conclusion is also drawn by Mondal et al. (2021). We updated our manuscript to add these references as following -

“This landfall pattern corresponds to previous observations that the landfalling cyclones in the Bangladesh coastline tend to move north-eastward (Ali 1996, Akter and Tsuboki 2021, Mondal et al. 2021).”

References

Akter, N. and Tsuboki, K., 2021. Recurvature and movement processes of tropical cyclones over the Bay of Bengal. Quarterly Journal of the Royal Meteorological Society, 147(740), pp.3681-3702.

Mondal, M., Biswas, A., Haldar, S., Mandal, S., Bhattacharya, S. and Paul, S., 2021. Spatio-temporal Behaviours of Tropical Cyclones over the Bay of Bengal Basin in last Five Decades. Tropical Cyclone Research and Review. doi: 10.1016/j.tcrr.2021.11.004