

Supplementary Information for article "Intercomparison of regional loss estimates from global synthetic tropical cyclone models"

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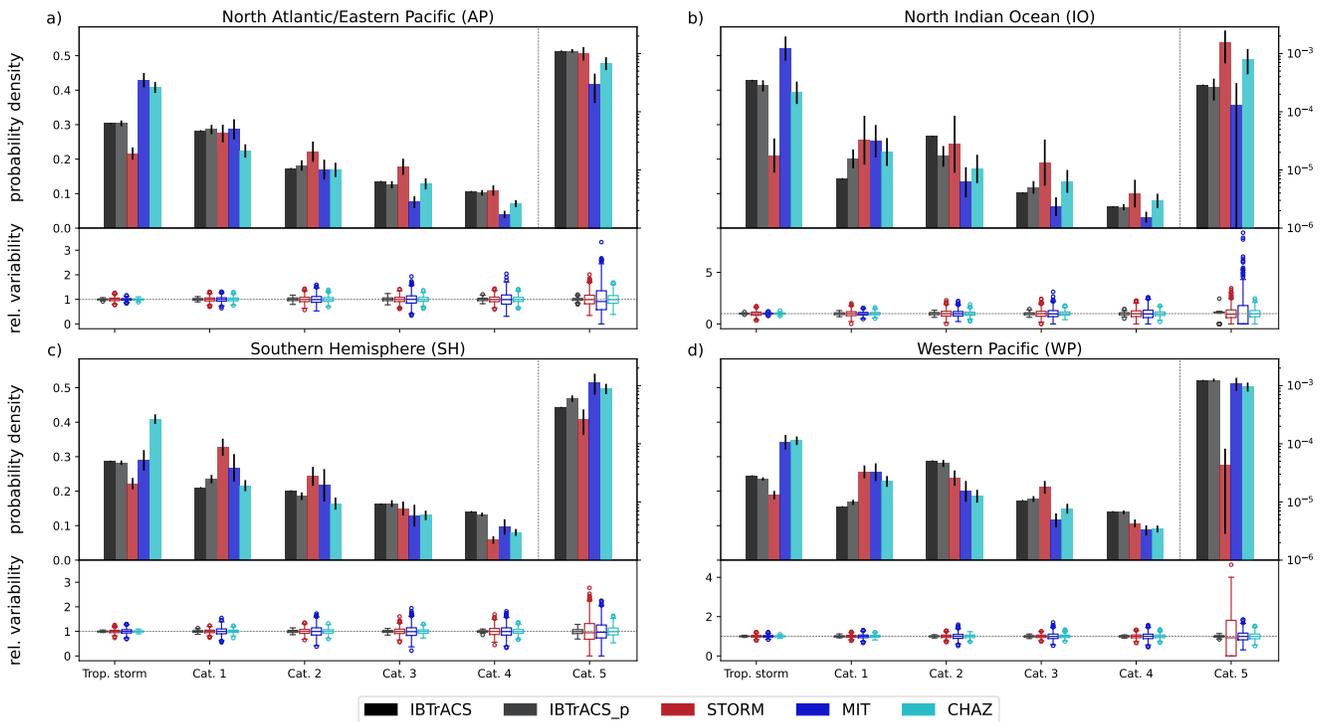
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Supplementary Figure 1. Regional distribution of track intensities for the five datasets. Panels a)-d) compare the relative frequency of tropical cyclones belonging to each category of the Saffir-Simpson Hurricane Wind Scale across the five track sets (IBTrACS, IBTrACS_p, STORM, MIT, CHAZ), separately for the four regions a) North Atlantic/Eastern Pacific, b) North Indian Ocean, c) Southern Hemisphere, and d) Western Pacific. The mean and standard deviation (black error bars) of the frequencies are shown in the upper part of the plots while the lower part displays the relative variability in each intensity bin. Note that the frequencies of Cat. 5 TCs are shown on a secondary y-axis in log scale. For this figure, the maximum wind speed included in the track data at positions that are within 300 km from land are considered. The same plot with wind speeds taken directly from the wind fields over land is provided in Fig. 1.

Supplementary Table 1. Calculated direct economic damages in billion USD for the Expected Annual Damage (EAD). Mean and standard deviation (absolute, relative) for all synthetic tropical cyclone track sets (IBTrACS_p, STORM, MIT, CHAZ) and the EAD for the historical IBTrACS in the four regions are shown.

	North Atlantic/Eastern Pacific			North Indian Ocean			Southern Hemisphere			Western Pacific		
IBTrACS	50.86			2.32			5.41			43.05		
IBTrACS_p	31.50	±1.07	(3.4%)	2.08	±0.16	(3.4%)	6.61	±0.33	(5.0%)	36.68	±1.01	(2.8%)
STORM	55.61	±2.46	(4.4%)	13.25	±1.38	(4.4%)	14.17	±1.23	(8.7%)	169.43	±5.30	(3.1%)
MIT	25.65	±1.34	(5.2%)	8.32	±0.66	(5.2%)	9.36	±0.99	(10.6%)	49.70	±2.89	(5.8%)
CHAZ	82.47	±2.86	(3.5%)	11.51	±0.82	(3.5%)	31.32	±1.72	(5.5%)	115.49	±3.25	(2.8%)

Supplementary Table 2. Calculated direct economic damages in billion USD for the 100-yr and 1000-yr events.

Results are shown for all synthetic tropical cyclone track sets (IBTrACS_p, STORM, MIT, CHAZ) in the four regions. The values in brackets indicate the 90% confidence interval expressed as percent of the median 100-yr and 1000-yr damage values.

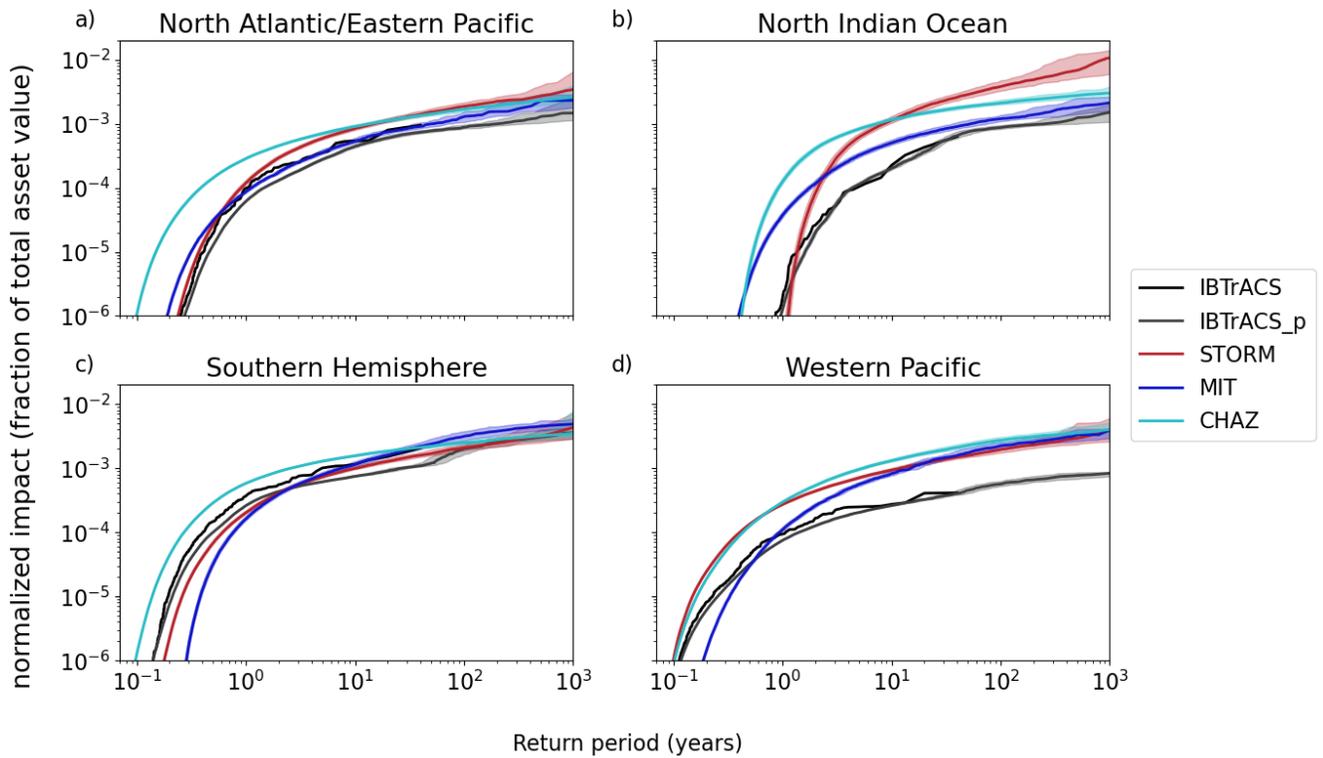
	North Atlantic/Eastern Pacific				North Indian Ocean				Southern Hemisphere				Western Pacific			
	100-yr		1000-yr		100-yr		1000-yr		100-yr		1000-yr		100-yr		1000-yr	
IBTrACS_p	231	(39%)	589	(68%)	40	(39%)	86	(94%)	60	(33%)	111	(37%)	165	(55%)	439	(37%)
STORM	344	(31%)	603	(51%)	246	(54%)	517	(78%)	193	(60%)	529	(143%)	664	(33%)	1213	(66%)
MIT	169	(58%)	379	(185%)	106	(46%)	251	(48%)	109	(54%)	400	(231%)	430	(60%)	1191	(38%)
CHAZ	359	(43%)	813	(98%)	109	(31%)	227	(60%)	295	(52%)	678	(87%)	445	(29%)	814	(70%)

Supplementary Table 3. Calculated normalized impact given as fraction of the area affected for the Expected Annual Damage (EAD). Mean and standard deviation (absolute, relative) for all synthetic tropical cyclone track sets (IBTrACS_p, STORM, MIT, CHAZ) and the EAD for the historical IBTrACS in the four regions are shown.

	North Atlantic/Eastern Pacific			North Indian Ocean			Southern Hemisphere			Western Pacific		
IBTrACS	3.2E-04			7.4E-05			1.1E-03			3.2E-04		
IBTrACS_p	2.4E-04	±4.2E-06	(1.8%)	8.1E-05	±2.5E-06	(3.0%)	7.9E-04	±9.7E-06	(1.2%)	2.6E-04	±2.9E-06	(1.1%)
STORM	4.9E-04	±1.6E-05	(3.3%)	4.0E-04	±2.7E-05	(6.6%)	7.2E-04	±2.0E-05	(2.8%)	9.7E-04	±1.9E-05	(2.0%)
MIT	3.5E-04	±1.1E-05	(3.3%)	2.3E-04	±9.9E-06	(4.3%)	6.8E-04	±2.6E-05	(3.8%)	4.9E-04	±1.8E-05	(3.6%)
CHAZ	9.9E-04	±1.9E-05	(1.9%)	5.9E-04	±2.1E-05	(3.5%)	1.9E-03	±3.0E-05	(1.6%)	1.1E-03	±2.3E-05	(2.1%)

Supplementary Table 4. Calculated normalized impact given as percentage of the area affected for the 100-yr and 1000-yr events. Results are shown for all synthetic tropical cyclone track sets (IBTrACS_p, STORM, MIT, CHAZ) in the four regions. The values in brackets indicate the 90% confidence interval expressed as percent of the median 100-yr and 1000-yr damage values.

	North Atlantic/Eastern Pacific				North Indian Ocean				Southern Hemisphere				Western Pacific			
	100-yr		1000-yr		100-yr		1000-yr		100-yr		1000-yr		100-yr		1000-yr	
IBTrACS_p	0.088%	(14%)	0.146%	(101%)	0.087%	(14%)	0.150%	(60%)	0.202%	(29%)	0.355%	(42%)	0.056%	(18%)	0.083%	(16%)
STORM	0.185%	(25%)	0.340%	(117%)	0.380%	(37%)	1.062%	(75%)	0.209%	(24%)	0.433%	(98%)	0.196%	(26%)	0.386%	(87%)
MIT	0.129%	(37%)	0.231%	(46%)	0.119%	(22%)	0.212%	(49%)	0.315%	(33%)	0.488%	(33%)	0.224%	(25%)	0.397%	(28%)
CHAZ	0.169%	(21%)	0.262%	(66%)	0.210%	(17%)	0.300%	(39%)	0.251%	(13%)	0.349%	(135%)	0.272%	(19%)	0.400%	(43%)



Supplementary Figure 2. Impact return period curves for return periods up to 1000 years for the synthetic track sets (IBTrACS_p, STORM, MIT, CHAZ) and 39 years for the IBTrACS record (black solid curve) in the four regions (a) North Atlantic/Eastern Pacific, b) North Indian Ocean, c) Southern Hemisphere, d) Western Pacific). We use a sub-sampling approach on the synthetic track sets to calculate the mean (colored solid curves), the 90% CIs of the impact distribution over 1000 years. Note, impacts are given as normalized results as fraction of the area affected.

12 **Supplementary Methods**

13 When analyzing the synthetic datasets, we apply a bootstrapping method in which we draw 100 to 1000 subsamples of the
14 synthetic datasets at a chosen length. This allows us to calculate statistics over the subsamples like the mean and standard
15 deviation for the TC track (Section 2.1) and hazard intensities (Fig. 1), EAD estimates (Supplementary Table 1) and the median
16 and 5th and 95th percentile of each subsample to obtain the 90 % confidence interval (CI) of impacts (Fig. 2).

17 Depending on the synthetic track set, varying approaches in the subsampling routine are taken to account for the different
18 ways in which each synthetic dataset integrates probabilistic variability. The only dataset that does not associate a specific year
19 in the historic period to each synthetic track is STORM. In STORM, each of the 10000 years is a representation of the whole
20 observational 1980 to 2018 climatology. Accordingly, we randomly subsampled N=1000 year sets, each at the length of the
21 years covered by IBTrACS (Section 2.1) or 1014 years for the impact analyses (Sections 2.2). For the remaining track sets,
22 we draw subsamples in a way that retains the intrinsic association with historic years. The probabilistic IBTrACS is a dataset
23 that consists of the original historical IBTrACS record plus 99 probabilistic tracks for each observed TC (see Section 5.2); we
24 thus evaluate the desired statistics over the total of 100 probabilistic IBTrACS ensembles. The CHAZ hazard set comes as an
25 ensemble of 10 full model runs, each containing 40 intensity ensembles per track; hence a total of 400 ensembles of 39 years of
26 TC activity. We take these 400 ensembles to generate the CIs and the median value. For each year, the MIT dataset contains a
27 fixed number of 500 synthetic tracks that, together with an information of average number of events to occur, represent the
28 probabilistic variability of that year's TC climatology. For our analysis, we draw N=1000 random subsamples from each year
29 set in such a way that the size of the subsamples is distributed according to a Poisson distribution with mean given by the
30 provided expected number of events for that year.

31 **Supplementary Discussion**

32 First, in STORM the regression coefficients for TC intensity are generally derived in $5^\circ \times 5^\circ$ -boxes¹. However, in the North
33 Indian Ocean, the sample size is too small to adequately fit STORM's regression formulas, and as such these formulas were
34 derived over larger areas (N. Bloemendaal, personal communication, October 2021), thereby omitting spatial heterogeneity
35 within the basin. Furthermore, and perhaps most importantly, TC intensity in STORM is modelled through a strong dependency
36 on the Maximum Potential Intensity (MPI), which, in turn, depends on sea-surface temperatures (SST). In the North Indian
37 Ocean and particularly the Bay of Bengal, there is little variation in SST, which means that obtaining spatially varying MPI
38 values becomes challenging². Without varying MPI values, initiating TC decay is virtually impossible. As a consequence, the
39 entire region is supportive of very intense TCs (<900 hPa). This combined with the regression formula problem allows for
40 TCs to intensify all the way up to category 4 and 5 events in the Bay of Bengal as simulated by STORM. According to Fig. 1
41 in our study, STORM largely underestimates the lowest category events in the North Indian Ocean and overestimates higher
42 category events. However, Bloemendaal et al. (2020)¹ report that the high intensities in the North Indian Ocean are well in
43 line with IBTrACS observations. In contrast to our analysis, Bloemendaal et al. (2020)¹ only analyzed the average max. wind
44 speeds over all events in a basin (not differentiating between TC categories). Presumably, this the reason that Bloemendaal et al.
45 (2020)¹ concluded that STORM is well in line with IBTrACS observations in the North Indian Ocean while our study indicates
46 that STORM overestimates intensities in this basin.

47 **References**

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