# Long-term trends in storm surge climate derived from an ensemble of global surge reconstructions

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#### Abstract

We investigate trends in the magnitude and frequency of extreme storm surge events at 320 tide gauges across the globe from 1930, 1950, and 1980 to present. We use two centennial and three satellite-era daily storm surge time series from the Global Storm Surge Reconstructions (GSSR) database. Before calculating trends, we perform change point analysis to identify and remove data where inhomogeneities in atmospheric reanalysis products could lead to spurious trends in the storm surge data. Even after removing unreliable data, the database still extends existing storm surge records by several decades for most of the tide gauges. Storm surges derived from the centennial 20CR and ERA-20C atmospheric reanalyses show consistently significant positive trends along the southern North Sea and the Kattegat Bay regions during the periods from 1930 and 1950 onwards and negative trends since 1980 period. When comparing all five storm surge reconstructions and observations for the overlapping 1980-2010 period we find overall good agreement, but distinct differences along some coastlines, such as the Bay of Biscay and Australia. We also assess changes in the frequency of extreme surges and find that the number of annual exceedances above the 95th percentile has increased since 1930 and 1950 in several regions such as Western Europe, Kattegat Bay, and the US East Coast.

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14

## 15 Abstract

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#### 30 Introduction

Extreme sea-levels resulting in coastal flooding are mainly driven by waves, storm surges, and tides, and 31 32 are influenced by changes and variability in relative mean sea-level. Understanding the trends in 33 magnitude and frequency of these drivers is crucial for an accurate assessment of present and future 34 coastal flood risk. Surge and tide information are commonly obtained from tide gauge records. Even 35 though tide gauges provide very valuable in-situ sea level observations, short record lengths in many locations (only 15% of tide gauges from the GESLA-2<sup>1</sup> database have observations longer than 50 years) 36 37 often limit robust statistical analysis and the estimation of secular trends in extreme sea-levels. Moreover, 38 the spatial distribution of available tide gauge records in South America, Africa, southeast Asia, and the 39 Southern Hemisphere in general is sparse and they typically only cover short time periods. Existing tide gauge records can be extended through archival measurements<sup>2,3,4,5</sup> or by reconstructing data using 40 different modeling techniques (requiring atmospheric and/or oceanic reanalysis data as forcing)<sup>6,7,8</sup>. Using 41 42 longer records not only allows for a more robust assessment of possible trends in extreme water levels, 43 but also leads to a more accurate representation of return levels, which are important for coastal risk 44 assessments, design, and adaptation<sup>2,9</sup>.

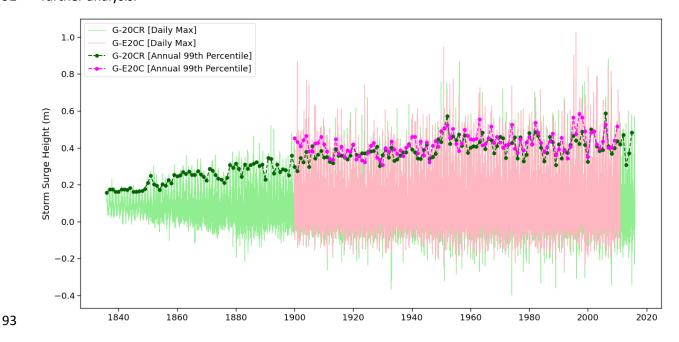
Atmospheric reanalysis datasets result from the combination of models and observations with the 45 46 implementation of data assimilation schemes to generate the state of a system as accurately as possible. 47 Reanalysis data sets provide globally gridded atmospheric variables (e.g., sea-level pressure, winds etc.) 48 over multiple decades or even centuries. Such information can be used for reconstructing continuous 49 historical storm surge time series temporally and spatially where little or no observations exist<sup>10</sup>. For example, Cid et al. (2018)<sup>11</sup> developed a 147-yearlong storm surge reconstruction from a data-driven 50 model for Southeast Asia based on the 20<sup>th</sup> Century Reanalysis version 2c<sup>12</sup> (20CRv2C). Similarly, Cid et al. 51 (2017)<sup>13</sup> reconstructed storm surges globally from 1871-2010 using the 20CRV2 reanalysis. Ji et al. (2020)<sup>14</sup> 52 developed a high spatial resolution storm surge reconstruction for southeast China using the ERA40<sup>15</sup> and 53 ERA-Interim<sup>16</sup> reanalysis datasets, and Tadesse et al. (2021)<sup>17</sup> presented a global reconstruction of storm 54 55 surges (1836-2019) using five different atmospheric reanalyses (the centennial 20CRV3 and ERA-20C<sup>18</sup>, and satellite era ERA-Interim<sup>16</sup>, MERAA V2<sup>19</sup>, and ERA5<sup>20</sup>). Using a physics-based modelling approach, Muis 56 et al. (2016)<sup>21</sup> used data from the ERA-Interim reanalysis as forcing for a hydrodynamic model to derive a 57 global reanalysis of storm surges and extreme sea levels for the 1979-2014 period. Employing an advanced 58 version of the same hydrodynamic model, Muis et al. (2020)<sup>22</sup> used data from the ERA5 climate reanalysis 59 60 to derive a global dataset of extreme sea levels for 1979-2017. Many other studies have been conducted at the local or regional scale using different modelling techniques (data-driven or physics based) to 61

62 develop storm surge hindcasts<sup>23,24</sup>.

63 Reconstructed storm surge data extending the observational records can be used to investigate trends in 64 the storm surge climate at local, regional, and global scales. There is, however, an ongoing discussion about the merits of centennial reanalyses to study long-term climate trends. Donat et. al<sup>25</sup> detected 65 significant positive trends in storminess in western, central, and northern Europe when using the 20CR 66 reanalysis. Wang et al.<sup>26</sup> showed that for the North Atlantic European region and southeast Australia, 67 trends in 20CR extra-tropical cyclone activity are in agreement with trends in geostrophic wind extremes 68 from in-situ surface pressure observations. By contrast, Krueger et al. (2013)<sup>27</sup> argued that the trends 69 reported by Donat et al. (2011)<sup>25</sup> are due to inconsistencies in the 20CR reanalysis related to a rapidly 70 71 decreasing number of assimilated observations in the early 20<sup>th</sup> century. In response to assertions made by Wang et al.<sup>26</sup> that 20CR cyclone trends are in agreement with geostrophic wind extremes trends in the 72

North Atlantic-European region, Krueger et al.<sup>28</sup> showed that 20CR geostrophic storminess deviates 73 strongly from the observation-based storminess before the 1940s. As a result, there is a spurious long-74 75 term trend in the 20CR geostrophic wind extremes which is not reflected in observed geostrophic wind 76 extremes. The authors attribute the spurious trends to the inhomogeneities in the 20CR datasets prior to 77 the 1950s. Inhomogeneities can be caused by inconsistencies in the amount and quality of data that are 78 assimilated into the reanalysis products, including changes in the number of stations from where data is 79 available and used, changes in measurement frequencies, relocation of stations, or instrumental changes 80 <sup>29</sup>. These factors make the assessment of long-term climate trends using reanalysis data challenging.

81 In this study, we quantify trends in the reconstructed daily maximum storm surges obtained from the 82 GSSR<sup>17</sup> database along the global coastlines for the periods from 1930, 1950, and 1980 onwards. The centennial storm surge reconstructions are hereinafter referred to as G-20CR (GSSR surge reconstruction 83 84 forced with the 20CRV3 reanalysis, 1836-2015) and G-E20C (GSSR surge reconstruction forced with the 85 ERA-20C reanalysis, 1900-2010) whereas the satellite era reconstructions are G-EInt (GSSR surge reconstruction forced with ERA Interim reanalysis, 1979-2019), G-Merra (GSSR surge reconstruction 86 87 forced with MERRA-2 reanalysis, 1980-2019), G-E5 (GSSR surge reconstruction forced with ERA-5 88 reanalysis, 1979-2019); we also create an ensemble mean of all reconstructions for the overlapping period 89 1980-2010 (G-EnsMean). Given the known limitations of reanalysis products which could lead to spurious 90 trends, we first implement a Bayesian change point detection technique to identify time periods where 91 reconstructed storm surge data shows suspicious behavior, and those time periods are excluded from 92 further analysis.



94Figure 1. Reconstructed daily maximum surges from G-20CR (green) and G-E20C (pink) and their respective annual9599th percentiles (dashed lines with markers) for the Astoria tide gauge.

96 In order to identify time periods where modelled storm surge data is unreliable, it is preferable to validate 97 against in-situ measurements using metrics such as the Root Mean Squared Error (RMSE) or coefficient of 98 determination (R<sup>2</sup>), as shown for example in Fig. 6 of Dangendorf et al.<sup>30</sup> for the Cuxhaven tide gauge.

corresponding reconstructions. This is not the case for the vast majority of tide gauges; for example, only 100 10 tide gauges in GESLA-2 cover the entire 20<sup>th</sup> century and none goes back to 1836, as G-20CR does. An 101 102 alternative way to identify spurious trends, in the absence of long observational records, is to investigate 103 only the reconstructed surge time series and the corresponding predictors used for the reconstruction. 104 For instance, Fig. 1 shows the daily maximum surge time series and annual 99<sup>th</sup> percentile values for G-105 20CR and G-E20C. While there is no obvious trend in the mean of the daily maximum surge time series, 106 both reconstructions show a persistent decrease in the variability which translates to (spurious) trends in 107 the annual 99<sup>th</sup> percentile values. This is especially obvious for G-20CR where the variability declines before the 1940s and is only a fraction in the mid-19<sup>th</sup> century compared to the last 80 or 90 years. Hence, 108 the resulting increase in the 99<sup>th</sup> percentile values over time should not be interpreted as a significant 109 trend in storm surges, but rather as an artifact stemming from inhomogeneities in the 20CR reanalysis. 110 111 This motivates us to consider the annual variability of the reconstructed surges and their predictors as a 112 proxy for determining time periods where quality of the surge reconstruction is poor and leads to spurious 113 trends. A probabilistic change point detection method paired with visual inspection is employed to pre-

114 process the reconstructed surges before trends are computed (see Methods for details).

#### 115 **Results**

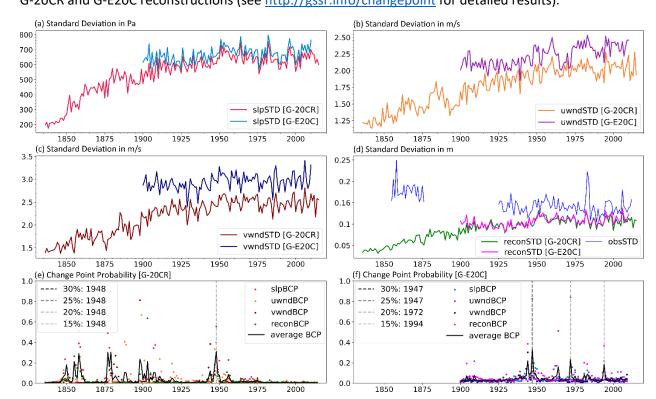
#### 116 Change point detection

117 Based on the model validation results from Tadesse and Wahl<sup>31</sup> and after applying a set of selection

- criteria in terms of model performance (see Methods), 310 and 320 tide gauges are selected with G-20CR and G-E20C surge reconstructions, respectively. These tide gauges adequately cover the Northern
- 120 Hemisphere coastlines and also include several locations in the Southern Hemisphere, while the Tropics
- 121 are under-sampled due to model inaccuracies<sup>32</sup>.

122 We apply the Bayesian change point analysis for all 310 (G-20CR) and 320 (G-E20C) tide gauges on their 123 annual variability (measured in standard deviation) time series in order to identify time periods where the 124 data is less likely influenced by shortcomings in the reanalyses, and we only consider those time periods 125 for the subsequent trend analysis. Figure 2 exemplarily shows the results from the Bayesian change point analysis for Astoria (US) [Figure 2e- f], along with the annual variability of the three predictors used in 126 127 Tadesse and Wahl<sup>31</sup> (Figure 2a-c), as well as the annual variability in the surge reconstructions and the 128 observed surge (Figure 2d). The average of the four change point probabilities corresponding to the zonal 129 wind speed, meridional wind speed, mean seal-level pressure, and reconstructed surge are computed and 130 presented in Fig. 2e-f. The change point detection algorithm computes the probability of each year that it 131 constitutes a change point in the time series (see Methods for more details). We show here four different 132 cut-off probabilities (probability values above which a given year is considered to be a change point) to 133 identify likely change point years: 15%, 20%, 25%, and 30%. In the case of Astoria and for G-20CR, all cutoff 134 probabilities indicate that the year 1948 is the most recent change point in the time series. This is also 135 apparent from the time series shown in Fig. 2a-d. There is a rapid decrease in the annual variability of the 136 predictors before 1948. On the other hand, for G-E20C, three probable change points (1947, 1972, and 137 1994) are identified for the 30%, 20%, and 15% cutoff probabilities, respectively. Visual inspection of the 138 changes in the variability of the reanalysis predictors and reconstructed storm surge time series (Figure 139 2a-d) shows a decrease in the variability of all four variables before 1947. Hence, we choose 1947 as the 140 change point year and assume that data for the time periods 1949 to 2015 (G-20CR) and 1948 to 2010 (G-

E20C) are reliable in Astoria. The same change point detection procedure has been applied for all selected
 G-20CR and G-E20C reconstructions (see http://gssr.info/changepoint for detailed results).



144Figure 2. Results of change point analysis for G-20CR and G-E20C for the Astoria tide gauge. Annual variability145(expressed as standard deviation) time series are shown for (a) sea-level pressure (slpSTD), (b) zonal wind speed146(uwndSTD), (c) meridional wind speed (vwndSTD), and (d) reconstructed surge (reconSTD). (e,f) Bayesian change147point probability (BCP) for the surge reconstruction and predictors (colored dots) and the average of them (black148solid line) for G-20CR (e) and G-E20C (f); vertical dashed gray lines indicate the most recent change point year for a149given cutoff probability for the average BCP.

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150 After removing suspicious data from G-20CR surge reconstructions for tide gauges in southern Australia, 151 New Zealand, Japan, and the northwest coast of the US vary in length from 50 to 75 years, and along the 152 US Gulf coast, US East coast, and across Europe between 125 to 150 years (Figure 3, Table 1). For several 153 tide gauges (16 in total) along the US Gulf and East coast, Spain, Portugal, and France, G-20CR provides 154 150-180 years of surge reconstructions after removing suspicious data. Some tide gauges (red triangles in 155 Fig. 3), mainly in Antarctica, southern Africa, and parts of Australia were discarded after the change point analysis due to significant (and recent) changes in the annual variabilities of predictors (see Discussion). 156 157 For G-E20C, the lengths of the reconstructed surge time series, after removing suspicious data, for tide 158 gauges along the US northwest coast, most of New Zealand, and Japan is 50-75 years. However, data 159 lengths for tide gauges in southern Australia are between 100-110 years, which is in some cases twice as long compared to G-20CR in the same locations, pointing to distinct differences in the quality of the 160 reanalysis data. G-E20C provides 50-75 years of data along the US Gulf and East coast, which is shorter 161 162 than G-20CR. In Europe, most of the tide gauges have 100-110 years of reconstructed surge data. Similar to G-20CR, there are several tide gauges discarded in the southern polar region due to quality issues. 163

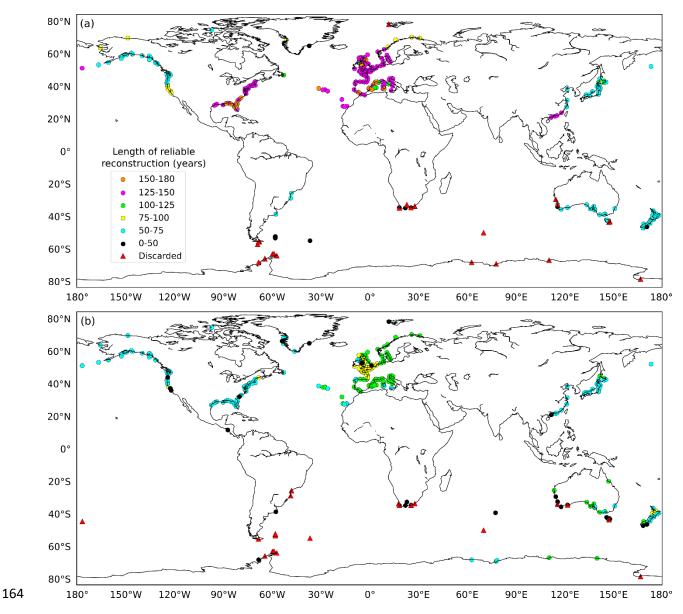


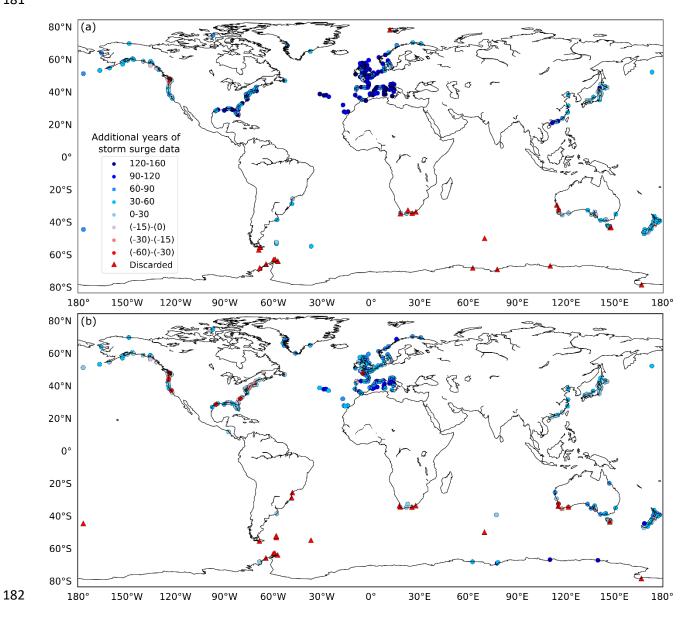
Figure 3. Length of G-20CR (a) and G-E20C (b) reconstructed storm surge time series in years after applying change
 point analysis and removing suspicious data. Red triangles represent tide gauges where surge reconstructions are
 rejected.

On average, and after removing suspicious data, GSSR<sup>31</sup> has extended the average storm surge data 168 169 lengths at the 310 (G-20CR) and 320 (G-E20C) sites from 30 to 111 years (G-20CR) and 16 to 69 years (G-170 E20C), with significant spatial variability. We find that G-20CR provides at least 100 years of additional 171 surge data (on top of available observed surge information) for 40% of the tide gauges and at least 50 172 additional years for 68% of the tide gauges; G-E20C provides at least 100 additional years of surge data 173 for 4% of the tide gauges and at least 50 additional years for 46% of the tide gauges (Figure 4). According 174 to the aggregated results in Table 1, G-20CR leads to the shortest extension of existing data along the US 175 West coast, adding on average 30 years of data. In Europe, on the other hand, an average of 111 additional 176 years of surge data is made available. For instance, at Delfzjil (The Netherlands), G-20CR provides a total

- 177 of 149 years of reconstructed surge data which is 104 more years in addition to the 45 years of existing
- 178 observational data (available in the GESLA-2<sup>1</sup> database).
- 179

Table 1. Number of years provided/extended by each reconstruction after change point analysis

Region	G-E20C		G-20CR	
	Total length	Observation extension [avg]	Total length	Observation extension [avg]
Europe	100-110	69	125-150	111
US East Coast + Gulf Coast	50-75	22	125-150	96
US West Coast	50-75	16	50-75	30
Japan + South East China	50-75	32	50-75	46
Australia + New Zealand	50-75	46	50-75	38



- 183 Figure 4. Additional years of reliable storm surge data after change point analysis obtained from G-20CR (a) and G-
- 184 E20C (b) compared to the existing observed records. Negative numbers indicate that reliable surge reconstructions
- are shorter than observations. Red triangles represent tide gauges where surge reconstructions are rejected.
- G-E20C also provides the shortest extension for tide gauges along the US West coast, with an average of
   additional years of data, and a maximum extension in Europe, with 69 additional years on average
- 188 (Table 1). There are 9 tide gauges along the US East and Gulf coast, where the observational data is longer
- than the reconstruction when using G-E20C (Figure 4b). These are tide gauges with particularly long
- observational records such as Galveston (102 years) and Atlantic City (94 years), where change points are
- 191 detected in the reconstructions leading to shorter records compared to observations.

#### 192 Trend Analysis

#### 193 Long-term trends in storm surge magnitude

194 After removing suspicious data based on the change point detection, we calculate and compare trends of 195 the observed and reconstructed surges (see Methods for details) to assess their similarities. We use annual values of high percentiles (95<sup>th</sup> and 99<sup>th</sup>). For this comparison, we select 122 tide gauges with at 196 least 30 years of overlapping data between observations, G-20CR, and G-E20C and a minimum of 75% 197 198 completeness in the observations. For the majority of the 122 tide gauges, no statistically significant 199 differences (5% level) exist between observed trends and reconstruction trends (Figure 5). Differences between observed surge and G-20CR are found at 25% (95<sup>th</sup> percentile surges) and 19% (99<sup>th</sup> percentile 200 surges) of the tide gauges. When comparing observations and G-E20C, significant differences are found 201 202 at 30% (95<sup>th</sup> percentile surges) and 18% (99<sup>th</sup> percentile surges) of the tide gauges. These differences with 203 observations mainly exist along the Salish Sea (US West coast), New England (northeast US coast), and the Atlantic coast of France. For 64% (95<sup>th</sup> percentile surges) and 78% (99<sup>th</sup> percentile surges) of the tide 204 205 gauges, both reconstructions agree with the observed trends, in particular along the US southeast coast, 206 Japan, and the German Bight.

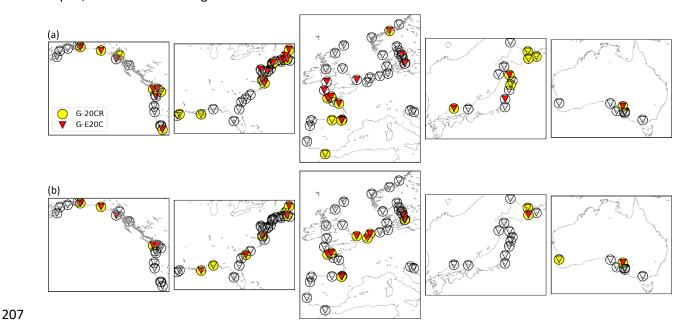


Figure 5. Tide gauges with significant differences in trends between observed surge and reconstructed surge from
 G-20CR (yellow circles) and G-E20C (red triangles) using the annual 95<sup>th</sup> (a) and 99<sup>th</sup> (b) percentiles. Tide gauges
 with insignificant differences in trends are shown as transparent circles and triangles. Trends are computed when

- 211 at least 30 years of overlapping data are available for the 1930-2010 period.
- 212 Next, we investigate G-20CR and G-E20C trends for the 1950-2010(2015) and 1930-2010(2015) periods.
- Figure 6 shows the long-term trends of the annual 99<sup>th</sup> percentile surges from G-20CR (a-e) and G-E20C
- 214 (f-j) for the 1950-2015 and 1950-2010 periods respectively (Supplementary Figure S1 and Supplementary
- Figure S2 show trends for the annual 95<sup>th</sup> percentile surges). Trends are shown for regions with at least
- 10 tide gauges. Note that the number of tide gauges can be different in the same region for the two
- reconstructions, because the change point analysis may have identified suspicious data post-1950 in one
- 218 reconstruction but not the other.

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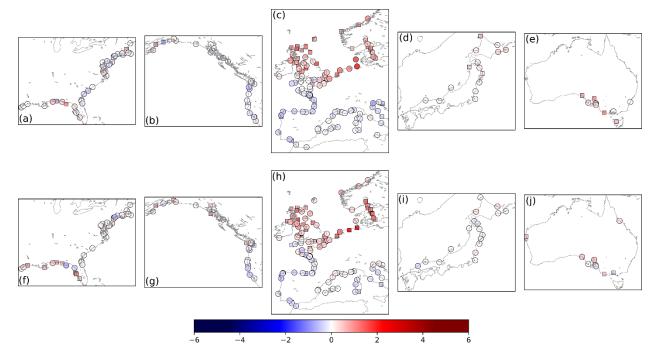


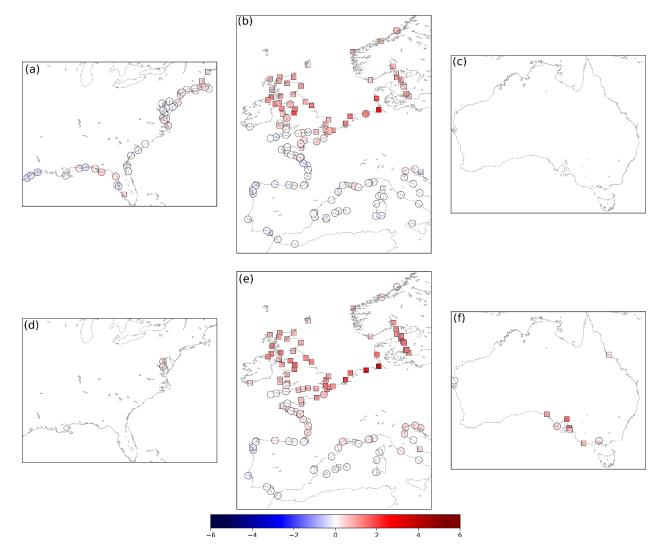
Figure 6. Trends (mm/year) for the annual 99th percentile surge values for G-20CR (a-e) and G-E20C (f-j)
 corresponding to 1950-2015 and 1950-2010 respectively. Rectangle markers indicate significant trends at the 5% significance level.

223 For G-20CR, significant trends at the 5% significance level are found at 26% of the tide gauges (which were 224 considered originally for change point analysis), notably in the northern UK, Kattegat Bay, southeast 225 Australia, and New Zealand. The largest statistically significant positive trends are derived for the northern 226 UK and New Zealand with magnitudes of 1.9 mm/year and 1.6 mm/year, respectively. Although 227 statistically insignificant, Cuxhaven (Germany) and Esbjerg (Denmark) have the largest trends with 228 magnitudes of 2.48 mm/year and 1.89 mm/year respectively. Small but significant negative trends with 229 an average magnitude of -0.6mm/year are derived at 13 tide gauges and those are mostly located along 230 the Atlantic coasts of France and Spain and in the Adriatic Sea.

Similarly, for G-E20C significant trends for the 1950-2010 period are found at 26% of the tide gauges.
Positive trends are derived for the US Gulf coast, UK, Kattegat Bay, and the German Bight. The largest
statistically significant positive trend of 2.9 mm/year is derived in the southeastern North Sea (for both

Cuxhaven in Germany and Delfzjil in the Netherlands), followed by 2.5 mm/year at Nome (Alaska), and
2.1 mm/year at Millport (UK). Very few tide gauges (4%) show negative trends and those are located in
the same regions that had negative trends in the G-20CR reconstruction. The largest negative trend is 1.0 mm/year at Villagarcia (Spain).

238 Over the 1930-2015 (G-20CR) and 1930-2010 (G-E20C) periods, 67% and 85% of the 192(142) tide gauges analyzed show positive trends in the 99<sup>th</sup> percentile surges (Figure 8) (see Methods on how tide gauges 239 240 are selected for trend analysis). This is a higher percentage of tide gauges with positive trends compared 241 to the 56% (G-20CR) and 63% (G-E20C) during the 1950-2015 and 1950-2010 periods respectively. 242 Furthermore, many of the same regions—such as the southeastern North Sea and the Kattegat Bay— 243 show persistent positive trends. Tide gauges along the US West coast, Australia (G-20CR), and New 244 Zealand are not included in the analysis for this period since the change point analysis indicated suspicious 245 data before the 1940s (Figure 2a). Significant positive trends are derived for tide gauges along the US 246 northeast coast (G-20CR), UK, German Bight, Kattegat Bay, and southeast China (G-20CR; results for China 247 are not shown in Fig. 8 because of the small number of tide gauges). The largest statistically significant 248 trends are again derived in the southeastern North Sea with magnitudes of 4.5 mm/year (G-E20C) and 3.0 249 mm/year (G-20CR) at Cuxhaven (Germany), followed by 3.6 mm/year (G-E20C) at Delfzjil (The 250 Netherlands), 2.3 mm/year (G-20CR) at Gladstone (UK), and 2.0 mm/year (G-20CR) at Esbjerg (Denmark).



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Figure 7. Trends (mm/year) for the 99th percentile surges for G-20CR (a-c) and G-E20C (d-f) corresponding to 1930-2015 and 1930-2010 respectively. Rectangle markers indicate significant trends at the 5% significance level.

#### 255 Trend Sensitivity Analysis

256 As discussed in the Introduction, observed surges are usually short and not as continuous as G-20CR and 257 G-E20C. There exist, however, tide gauges with relatively long surge records that can be used to compare against the reconstructed surges. Here we compare 99<sup>th</sup> percentile observed and reconstructed surges by 258 259 computing their corresponding trends for various overlapping time windows. We start with a window 260 length of 30 years which is moved by one year each time step and repeat the same analysis for longer 261 time windows (adding one year each step) [Figure 8]. This allows us to not only compare the reconstructed 262 and observed trends for many more time periods than were used in the previous section, but also shows 263 how multidecadal variability affects observed and reconstructed trends. In Cuxhaven (Figure 9b), for example, negative trends are found in observations early in the record when using shorter window 264 265 lengths; and while G-20CR also shows some negative trends early in the record and for short window 266 lengths, the overall patterns in both reconstructions are different, with more persistent positive trends compared to observations. At Port Pire (Figure 9c), also both G-20CR and G-E20C show positive trends 267 268 for most time periods and window lengths, while observed trends are mostly negative. In Boston (Figure 269 9a), G-E20C agrees well with observations in terms of the sign of the trends, while G-20CR shows very

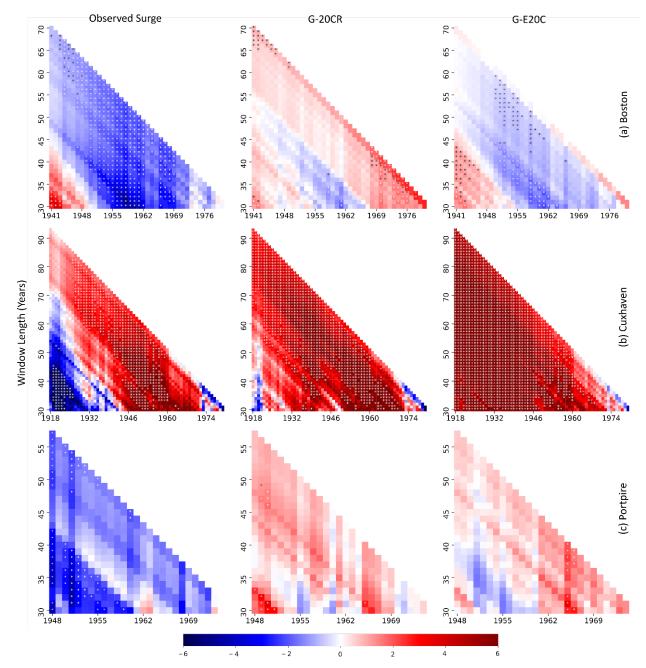
270 different patterns. More examples are provided in Supplementary Figure S5 with similar conclusions, i.e.

- agreement between reconstructions but not with observations in Astoria, relatively good agreement
- 272 between G-E20C and observations in Brest, and general agreement between all three in Fremantle for
- 273 most time periods and window lengths. Overall, there is more agreement when trends are derived for
- 274 longer time windows.

#### 275 Comparison of trends for the satellite era from all GSSR reconstructions

276 Finally, we compare trends in storm surge magnitudes of all five reconstructions available in GSSR with 277 each other and with observations for the overlapping period from 1980 to 2010, for which many more 278 tide gauges provide (near-)continuous records. We also include an ensemble mean (G-EnsMean) based 279 on all GSSR reconstructions. Satellite data is assimilated into all reanalysis products over that time period, 280 and spurious long-term trends due to incosnistancies in the assimilated data are less likely to occur. 281 However, over a 30-year period decadal variability can have significant effects on trends and those long-282 term variations may be represented differently in the reanalysis products and associated GSSR 283 reconstructions (as demonstrated for G-20CR and G-E20C in the previous section for selected locations).

284 Trend analysis for the satelite era shows generally good agreement for Europe in terms of the spatial 285 distribution of observed trends and GSSR trends as well as amongst the different GSSR trends themselves 286 (Figure 9). All seven datasets (including G-EnsMean) show strong negative trends along the southeastern 287 North Sea and the Kattegat Bay, the largest negative trend being -6.9 mm/year at Cuxhaven (G-20CR). The 288 actual magnitude of GSSR trends, however, is smaller than that of observed trends (Figure 10) for most of 289 the tide gauges in Europe. Tide gauges along the Atlantic Coast of France, Spain and North Adriatic Sea 290 have larger negative observed trends which is not reflected in most GSSR reconstructions. Moreover, tide 291 gauges along the Bay of Brest (Brest, Le Conquet) and Loire Estuary (Saint Gildas) show stark differences 292 between observed and GSSR trends. Observed trends at all three tide gauges are negative (-2.58 mm/year 293 at Brest, statistically significant), whereas GSSR trends are mostly positive, except for G-EInt and G-Merra. 294 Along the US East coast, in the New England area all seven datasets indicate a positive trend for the 295 majority of tide gauges. In the Chesapeake Bay region, there are differences between GSSR trends and 296 observed trends. All GSSR reconstructions (except G-E20C) show negative trends in this region, whereas 297 observed trends are all positive. The largest observed trend has a magnitude of 3.4 mm/year (statistically 298 significant) at Chesapeake Bay Bridge Tunnel.



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Figure 8. Trend (mm/year) comparison for 99<sup>th</sup> percentile observed surge (left), G-20CR (middle), and G-E20C
 (right) for Boston (a), Cuxhaven (b), and Portpire (c). Trends are computed for moving time windows (x-axis)
 starting with a window length of 30 years, which increases one year each step (y-axis) up to the length of available
 data. Significant trends at 5% significance level are marked with an asterisk.

Along the US Gulf coast there is a positive trend in most datasets (except G-20CR and G-EInt). The observed trend at Pensacola is 5.2 mm/year (statistically significant), which is the largest positive trend observed in all tide gauges considered in this study during the 1980-2010 period. In general, observed trends are positive and larger in magnitude than GSSR trends in this region which leads to the largest differences between GSSR and observed trends as shown in Figure 10. On the US west coast, differences exist in trends between observed surges and GSSR reconstructions mostly for tide gauges on the Columbia River and Salish Sea. While observed trends are negative at Astoria, (-4.1 mm/year, statistically insignificant) some GSSR trends are positive (G-20CR, G-E20C, and G-EInt) and others negative but very small in magnitude (G-Merra, G-E5, and G-EnsMean). In the southwest (Alameda, Monterey, and Sanfransico), there is a general agreement (statistically insignificant but negative trends) among most datasets (except G-E20C).

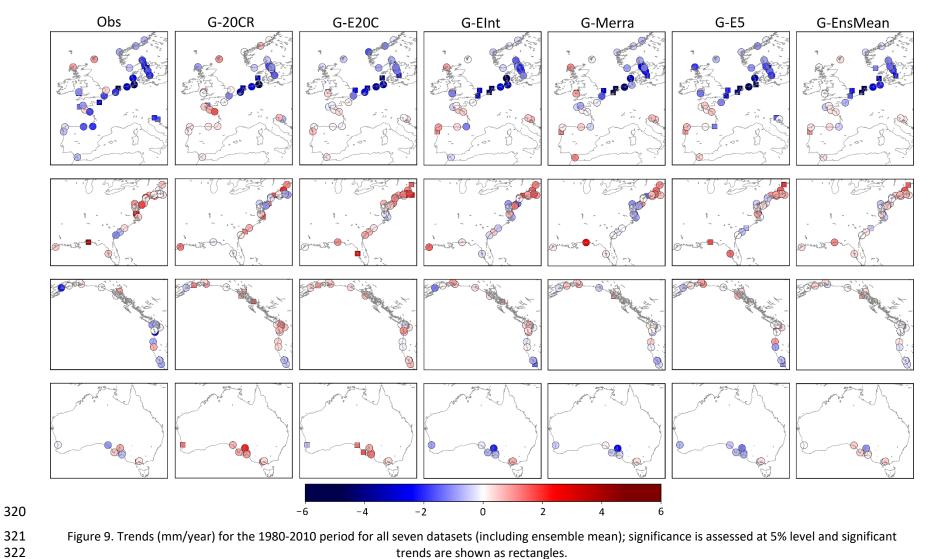
In Australia, G-20CR and G-E20C generally show positive trends (see also Figure 10) which is not the case

316 for the satellite era reconstrutions (G-EInt, G-Merra, and G-E5). Differences are most pronounced at

317 Portpire where observed surge, G-20CR, and G-E20C show statistically insignificant but positive trends

and the other three GSSR reconstructions show negative trends. The ensemble mean reconstruction (G-

319 EnsMean) gives the smallest difference compared to observed trends (Figure 10).



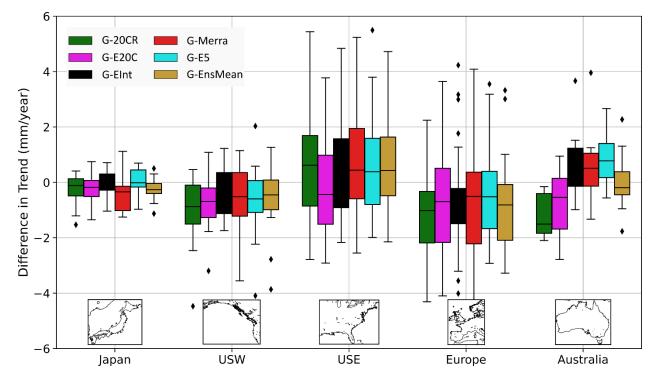


Figure 10. Comparison of GSSR trends with observed trends for six reconstructions (including ensemble mean) and
 five regions. GSSR trends are subtracted from observed trends, including their signs. Boxes indicate the
 interquartile range (IQR) (difference between 75<sup>th</sup> and 25<sup>th</sup> percentiles), upper and lower marks represent 75<sup>th</sup>
 percentile + 1.5\*IQR and 25<sup>th</sup> percentile – 1.5\*IQR respectively, and diamonds are considered outliers.

#### 328 Trends in Storm Surge Frequency

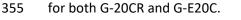
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329 To study the spatial patterns in frequency trends of extreme surges, we cluster tide gauges into eight 330 regions: US east coast, US west coast, US Gulf coast, east Asia (tide gauges from Japan and China), Oceania 331 (tide gauges from Australia and New Zealand), Mediterranean, western Europe, and the Kattegat Bay (tide 332 gauges from Sweden and Norway). Here we investigate the trends in storm surge frequency for both 333 centennial reconstructions (G-20CR and G-E20C) for the 1930-2010(2015) and 1950-2010(2015) periods, after suspicious data identified from the change point analysis is removed. To quantify storm surge 334 335 frequency at individual locations, the 95<sup>th</sup> percentile of the entire reconstructed surge time series is 336 considered as a threshold. The number of annual storm surge events exceeding this threshold is derived 337 at each tide gauge and the resulting time series are averaged per region and a linear trend is estimated 338 for the regional average annual storm surge frequency.

Differences between trends in annual exceedances (after declustering, see Methods) above the 95<sup>th</sup> percentile surges for observed surges and reconstructed surges (G-20CR and G-E20C) are computed for 133 tide gauges that have storm surge data available during the 1930-2010(2015) period (detailed results not shown). Results show that the trends for the number of annual exceedances above the 95<sup>th</sup> percentile of the observed and reconstructed surges for the overlapping periods are not statistically different (at 5% significance level) for 73% and 81% at the tide gauges for G-20CR and G-E20C respectively.

Figure 11 shows the trends for six regions, as the other two regions (Mediterranean and US west coast),
 do not show significant trends at the 5% significance level for either of the reconstructions. East Asia does
 not show significant trends in G-E20C, whereas no significant trends exist for the US Gulf and east coasts

in G-20R (and hence panels are not shown in Fig. 12). Similar to the trend analysis for the surge magnitudes, the frequency trends are computed for two time periods, 1950-2010(2015) and 1930-2010(2015). The gray lines in Fig. 11 represent the number of storm surge events exceeding the 95<sup>th</sup> percentile threshold for individual tide gauges in the given region, whereas the bold black line represents the average number of exceedances from which the two trends are derived. Results show positive trends for all six regions and the two selected time periods (shown by different colors; trend lines are only shown for significant trends). Overall, the largest trends are found across the Kattegat Bay and western Europe



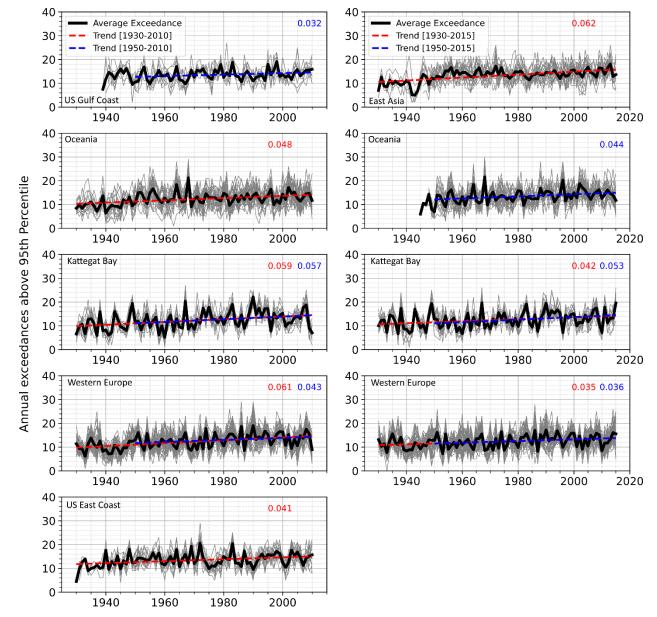


Figure 11. Regional storm frequency trends. Linear trends are fitted to the average number of annual exceedances
 above the 95<sup>th</sup> percentile (bold black line) for G-E20C reconstructions (left) and G-20CR reconstructions (right).
 Gray lines indicate the number of surge events exceeding the 95<sup>th</sup> percentile threshold for individual tide gauges in
 the given region. Only regions with at least one significant trend (dashed lines) are shown.

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### 362 **Discussion**

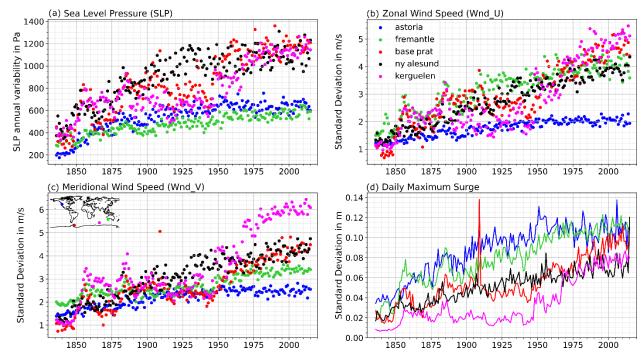
#### 363 Change point analysis

We apply a Bayesian change point analysis on G-20CR and G-E20C storm surge reconstructions as well as 364 365 the predictors that were used to derive them. The goal is to identify and remove suspicious data, related to inconsistencies in the reanalysis products, from the surge reconstructions. Figure 12 shows the annual 366 367 variability time series for 20CR predictors and the associated reconstruction G-20CR for five tide gauges 368 in the Arctic, Antarctica, Australia, New Zealand, and the US northwest coast. In all cases, sharp decreases 369 in the variability of the reanalysis predictors and reconstructed surges exist when going back in time. G-370 E20C (not shown here) also shows such a decrease in annual variability in several but not all of these tide 371 gauges. Some of the tide gauges like Base Prat and Kerguelen show a very rapid decline in the variability 372 leading to a change point year in the 2000s. Therefore, surge reconstructions for these tide gauges and 373 others with similar suspicious behavior are not considered for trend analysis. They are marked as red 374 triangles in Fig. 3 and Fig. 4. For most of the other tide gauges in these regions, our change point analysis 375 shows that G-20CR should be considered only from the mid-20th century onward since change points are 376 detected in the 1940s and 1950s (see Supplementary Figure S3 and Supplementary Figure S4). This aligns with the findings from Brönniman et al. (2013)<sup>33</sup> who showed the strong downward trend in 20CR wind 377 speeds in the Arctic, northeastern Canada, and the northern North Pacific before 1940. This is due to the 378 379 scarcity of observations in these regions used in the data assimilation for the 20CR reanalysis. ERA-20C 380 predictors and G-20C, on the other hand, do not show such rapid decline in variability (see Supplementary 381 Figure S3 and Supplementary Figure S4 for examples). A possible explanation for this might be the assimilation of surface marine wind observations into ERA-20C which is not the case for 20CR<sup>18,26,27</sup>. 382

The comparison presented in this section is not indicative of the superiority of one surge reconstruction (or reanalysis) over the other and should not be interpreted as such. For the majority of the tide gauges used in this study, the record lengths of the observed surges are too short to robustly compare trends in the annual variability with that of the reconstructed surges. However, the two centennial reconstructions, together with the other GSSR reconstructions (depending on the time period of interest) can be considered as an ensemble (Figure 10) when used, for example, in coastal flood risk assessments to better understand the inherent uncertainties.

#### 390 Trend analysis

391 Using the long storm surge reconstructions from GSSR, we investigate how the magnitude and frequency 392 of extreme surges changed over the last ~90 years. One of our key findings is that both storm surge 393 reconstructions, G-20CR and G-E20C, indicate a consistent positive trend for the 1930-2010(15) and 1950-2010(15) periods for extreme surges (annual 99<sup>th</sup> and 95<sup>th</sup> percentiles) in northern UK, the southern North 394 Sea, and the Kattegat Bay. Similar positive trends were reported by Donat et al. (2011)<sup>25</sup> from analyzing 395 396 storminess from the 20CR reanalysis in the North Sea and Baltic Sea regions. Over the 1950-2008 period, 397 Brönniman et al. (2012)<sup>34</sup> also found positive trends in strong and extreme wind speeds in northwestern 398 Europe when using 20CR. Dangendorf et al. (2014)<sup>30</sup> concluded that 20CRv2 provides a useful database 399 for the same region for the time period after 1910 because reconstructed storm surges for the tide gauge 400 Cuxhaven showed similar variability and trends compared to observed storm surges over that period. In 401 our analysis G-20CR and G-E20C show positive trends at Cuxhaven since 1910 (2.6 mm/year and 4.8 402 mm/year for G-20CR and G-E20C, respectively).



404Figure 12. Decreasing variability (expressed as annual standard deviation) for 20CR predictors mean sea-level405pressure (a), zonal wind speed (b), meridional wind speed (c), and G-20CR (d) for selected tide gauges

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407 The positive trends we find in GSSR reconstructions for northern UK, the southern North Sea, and the 408 Kattegat Bay during the 1950-2015 period can be explained, in parts, with long-term variability in the 409 North Atlantic Oscillation (NAO) during the 1950-1990 period<sup>35</sup>. They are also consistent with an eastward 410 shift of the NAO's centers of action that occurred over the same period. NAO is one of the large-scale 411 circulations that determine the storminess in the North Sea region. However, the 1930-2010(2015) trends 412 derived from the surge reconstructions are in contrast to the insignificant trends reported for observed surges in northwestern Europe<sup>30,36,37</sup>, albeit with considerable interannual and multidecadal variability. 413 Focusing on the period from 1970 onwards, Menéndez et al. (2010)<sup>38</sup> found no significant trends in storm 414 surge magnitude in the European Atlantic coast. For the same period, we also find insignificant trends in 415 416 G-20CR and G-E20C (except for a few tide gauges in the northern UK).

Next, we showed that during the common period 1980-2010, where all GSSR reconstructions overlap and 417 418 many more tide gauge provide (near-)complete data, spatial distribution of trends is similar across all data 419 sets (including an ensemble mean of the GSSR reconstructions) in many regions. This is particularly 420 pertinent to tide gauges in northern Europe and northeast coast of the US. There are, however, regions 421 where trends differ (in magnitude and sometimes also in sign), particularly in estuaries and bays. For example, at tide gauges along the Chesapeake Bay, Columbia River, Salish Sea, Bay of Brest, and Loire 422 423 Estuary, observed and GSSR trends (for the majority of reconstructions) have opposite signs. This could 424 be due to the modulating effect of river discharge on water levels in bays and estuaries<sup>39,40</sup> not captured 425 by GSSR.

We also show that GSSR centennial reconstructions exhibit statistically significant positive trends in storm surge frequency during the 1930-2010(2015) and 1950-2010(2015) periods. The tide gauges with the largest positive trends in surge magnitude (95<sup>th</sup> and 99<sup>th</sup> percentile) also often have the highest positive trends in the storm frequency (e.g., northwestern Europe and the Kattegat Bay). This aligns with previous studies that report an increase in the storm frequency for the high-latitude North Atlantic and northern Europe<sup>26</sup>, including the North Sea<sup>25</sup>. On the other hand, Krueger et al. (2013)<sup>27</sup> argued that the long-term positive trend of the storm index, estimated from the 20CR reanalysis in northern Europe and northeast Atlantic, is implausible as the same storm index for the upper percentiles of the observed geostrophic wind speeds doesn't show a similar long-term trend. However, the storm indices from the 20CR reanalysis and the observed geostrophic winds behave similarly in the second half of the twentieth century.

436 As noted above, a limiting factor in our analysis is the potential impact of reanalysis inconsistencies on the 437 reconstructed surges that might introduce spurious long-term trends in some regions. The Bayesian 438 change point detection method successfully identified suspicious changes in the variability of surges and 439 predictors at tide gauges along the northwestern coast of the US, northern Australia and some high-440 latitude regions. These changes in the variability, if not accounted for, would lead to significant and implausible trends in high-percentile surge time series (such as the annual 95<sup>th</sup> and 99<sup>th</sup> percentiles used 441 here). While the change point analysis identified instances where that was the case, the methodology 442 443 might still miss small and subtle trends that can be attributed to inconsistencies arising from the 444 atmospheric reanalyses.

445 The case of Astoria (Figure 2) for instance, shows some of the challenges related to the change point 446 analysis and comparison to in-situ observations. The year 1948(47) is identified as a change point for G-447 20CR(G-E20C), based on the change point probabilities as well as the visually obvious shift in the four variables during the 1940s. This could be associated with the sparse amount of observations assimilated 448 into the reanalysis products during and shortly after World War II<sup>41</sup>. On the other hand, the specific years 449 (1947 and 1948) where the change points are detected, may also be associated with a shift from the warm 450 to the cold phase of the Pacific Decadal Oscillation<sup>42</sup>. In the Pacific Northwest, the cold phase of the PDO 451 452 is associated with cooler water temperatures and changes in streamflow patterns (due to the change in 453 temperature differences between cold and warm PDO phases)<sup>43</sup>, both of which can influence water levels<sup>44,45</sup>. Moreover, the year 1948 was particularly stormy, leading to a large snowpack and the second 454 largest flood on the Columbia River since records began<sup>46</sup>. Hence, the particular attribution of a change 455 456 point to the year 1947-1948 may be related in part to natural variability. We note, however, that the shift 457 to warm PDO phases in ~1925 and ~1977 are not picked up by the change point analysis. Hence, we 458 conclude that inconsistencies in the reanalysis lead to a drop in the variability in the 1940s, with the exact 459 year(s) possibly conflated by background atmospheric/oceanic variability.

460 Overall, the long-term trends found in the extreme surges (obtained from the GSSR centennial surge 461 reconstructions) need to be interpreted with caution. However, the underlying data is also useful for other 462 applications, such as studying intra-annual to multi-decadal variability. In the future we plan to apply bias 463 correction to the GSSR reconstructions and use those for extreme value analysis and to study spatial storm 464 surge footprints<sup>47</sup>, among others.

#### 466 Methods

#### 467 Data

468 We use daily maximum surge reconstructions obtained from the Global Storm Surge Reconstructions database (GSSR, http://gssr.info) developed in Tadesse and Wahl<sup>31</sup>. GSSR comprises two centennial and 469 470 three satellite-era storm surge reconstructions, all of which have been obtained with data-driven models 471 from Tadesse et al.<sup>32</sup> using wind speed and mean sea-level pressure forcing from five different atmospheric 472 reanalysis products. GSSR reconstructions are available for 882 globally distributed tide gauges, and they have been validated against in-situ daily maximum surge observations from tide gauges<sup>32</sup>. Observed 473 storm surges are extracted from sea-level measurements from the GESLA-2 database<sup>1</sup>as the difference 474 475 between the measured water level and the tidal prediction, after removing the annual mean sea-level. 476 We only select GSSR reconstructions corresponding to tide gauges that show correlations with observed 477 daily maximum surges of 0.7 or greater. This results in 310 and 320 tide gauges with G-20CR and G-E20C 478 reconstructions, respectively.

#### 479 Change point Analysis

480 Reanalysis products are sensitive to the assimilated meteorological and/or oceanic observations (changing over time), which may result in spurious trends in key outputs variables<sup>27,48,49</sup>. Furthermore, due 481 to sparsity in assimilated observations, atmospheric events, particularly small-scale events (hurricanes, 482 483 atmospheric rivers), may be poorly represented, which may result in an underestimation of modelled variables such as peak wind speeds or minimum pressure<sup>50,51</sup>. Systematic underestimations would 484 therefore become visible in the variability of output variables from the atmospheric reanalysis products 485 486 and therefore also translate into underestimated variability in the GSSR reconstructions (see Figure 1). 487 We therefore hypothesize that time-periods with a persistent decrease in the variance (or standard 488 deviation) of surges in GSSR and/or its forcing variables likely indicate systematic model drifts rather than 489 real trends.

490 In order to identify suspicious data in GSSR we apply a Bayesian change point analysis to annual standard 491 deviation time series of GSSR surges and the atmospheric forcing datasets from 20CR and ERA-20C. The 492 Bayesian change point analysis is carried out using the R package "bcp" version 4.0.3<sup>52</sup> in RStudio version 493 1.1.453. The package implements a Markov Chain Monte Carlo (MCMC) approximation of the Bayesian 494 change point analysis methodology presented in Wang et al.<sup>52</sup>. It is based on the product partition model<sup>53,54</sup> that separates a time series into several partitions based on different parameters (for instance, 495 496 the mean and variability of the time series). The product partition model considers the number of change 497 points and their positions as random variables and assumes that there exists an unknown partition p of 498 the set {1, 2,..., n} that divides the time series into b contiguous blocks (random variable ranging from 1 to 499 n, where n is the length of the time series). We used 500 MCMC iterations for our analysis. At the end of 500 each iteration, the posterior distribution for the random partition, the number of change points, and 501 change point probability of a given year are updated. For each year, we average change point probabilities 502 corresponding to the four variables (the reconstructed surge and the three predictors). This is done to 503 find the years in the time series where all (or most) of the variables show unusual changes in the 504 variability. Sometimes, one or more variables show a deviation from the "typical" values, but this could 505 be an artifact and may not be reflected in other variables. From the estimated average change point 506 probabilities, we identify years in the time series where change point probabilities are equal or greater

than a set of cutoff probabilities. In our analysis, cutoff probabilities of 15%, 20%, 25%, and 30%, are used
to find change point years. Usually there are multiple years in the annual variability time series where a
given cutoff probability is exceeded. In that case, we select the most recent year as the change point for
the given cutoff probability. Only surge data from change point years onward are considered to quantify
the trends in magnitude and frequency of daily maximum surges.

512 As mentioned in the introduction, using the RMSE time series between observed and reconstructed surges 513 would be the preferred approach to identify spurious trends in reconstructions. Although this is not 514 feasible globally due to lack of data, there are a few tide gauges (Supplementary Figure S6) with long 515 records for which the annual RMSE between daily maximum observed and reconstructed surges time 516 series was used to implement change point analysis (in addition to the annual standard deviation time 517 series). There are noticeable differences in change point analysis results when using annual RMSE vs 518 annual standard deviation time series of the reconstruction alone Supplementary Figure S6. This could 519 be due to unrealistic surge values in observations (e.g., due to time shifts in the tidal analysis or other data 520 issues) or in the GSSR reconstructions that can lead to very high RMSE values for individual years which in 521 turn would be wrongly flagged as change points. For instance, in Brest (France) there is a change point 522 identified in 1975 with high probability (97%) when the annual RMSE time series is used. However, there 523 is no persistent deviation of the annual RMSE time series before or after this period. The change point 524 analysis doesn't detect any change point for the same period when the annual standard deviation time 525 series is used. Similar issues are found in Seattle Supplementary Figure S6d) when using the annual RMSE 526 time series for change point detection (particularly 1960 onward).

As an alternative to the annual standard deviation time series, we tested using the annual interquartile range. This is a measure of variability that is more suitable for skewed distributions and is robust against outliers. The interquartile range is computed by taking the difference of the 75<sup>th</sup> percentile and 25<sup>th</sup> percentile values of the system variable (daily maximum observed and reconstructed surges) for a given year. Using the annual interquartile range time series for change point analysis showed very similar results to that of annual standard deviation. Hence, in this study we focus on the annual standard deviation time series of predictors and surge reconstructions to detect change points.

534 In addition to identifying the change point years corresponding to the different cutoff probabilities, a 535 visual inspection of the individual annual variability time series is carried out. This is done to avoid 536 instances where extreme events (such as surges caused by hurricanes) not adequately represented in 537 either the observations or the reconstructions are identified as change points, or when subtle but 538 consistent changes in the variability time series are not picked up by the change point algorithm (i.e., 539 change point probabilities are below the cutoff values we considered). Furthermore, we assess if similar 540 shifts occur in the different predictors and the surge reconstruction. In other words, if a change point year 541 indicates only a change in one variable but no significant change is reflected in other variables, this change 542 point year is disregarded. Hence, while the automated change point analysis provides initial indication of 543 when change points occurred, the results are manually corrected in some instances for the various 544 reasons outlined here.

#### 545 Trend Analysis

546 First, trends in extreme storm surges are calculated for the two centennial GSSR reconstructions, after 547 suspicious data was removed, and we focus on the periods 1930 to 2010(2015) and 1950 to 2010(2015).

Trends are computed by fitting a linear regression model to the annual 95<sup>th</sup> and 99<sup>th</sup> percentile surges 548 549 from G-20CR, G-E20C, and observations where available. The standard errors of the linear regression coefficients representing the trends are adjusted for heteroscedasticity and autocorrelation using the 550 Newey-West estimator<sup>55</sup>. Before fitting trends to extreme surges from the reconstructions, we compare 551 552 the trends in extreme surges from observations to trends in extreme surges from G-20CR and G-E20C. We 553 limit our analysis to tide gauges with >30 years of data and >75% completeness between the years 1930 554 and 2010. Trends are computed using the common period between observations and reconstructions at 555 each tide gauge. We check if the trends from observations are significantly different from the 556 reconstruction trends at the 5% significance level. Our null hypothesis is that there is no significant difference between the trends obtained from observations and reconstructions for their period of 557 overlap. For the annual 95<sup>th</sup> and 99<sup>th</sup> surge time series, a categorical variable is added to differentiate the 558 559 time series as observation, G-20CR, or G-E20C. An interaction term (product of the categorical variable and the years) is then added as an additional predictor to fit linear trends to the annual 95<sup>th</sup> and 99<sup>th</sup> 560 surges. We calculate the p-values for the coefficient of the interaction term and determine its significance 561 562 at the 5% significance level. If the p-value for the coefficient of the interaction term is higher than 0.05 563 then the null hypothesis cannot be rejected. In other words, there is no significant difference between 564 the trends in observed surges and reconstructed surges.

Following this test, we estimate trends in G-20CR and G-E20C (above 95<sup>th</sup> and 99<sup>th</sup> percentiles) for the 1950-2010 (G-E20C)/1950-2015 (G-20CR) and 1930-2010 (G-E20C)/1930-2015 (G-20CR) periods. As start years for the reconstructions vary among tide gauges due to the change point analysis, we constrain G-20CR and G-E20C strictly to the chosen time period before computing trends. For instance, when computing trends for the 1950-2015 period, we select only tide gauges that have data covering the entirety of this period.

571 To investigate the sensitivity of trends to start dates and periods covered and to compare and contrast 572 trends from observation, G-20CR, and G-E20C (where long enough observations exist), a trend sensitivity 573 analysis is carried out (Figure 8 and Supplementary Figure S5). A window of 30 years is selected as the 574 starting window length where trends are computed, and the window is shifted one year each time step. 575 Trends are then computed for each (moving) window length (by increasing the window length by one year 576 until record length is reached). Availability of 75% of the data is required for each window. For windows 577 where this is not met, trends are not computed (see for example Supplementary Figure S5b). When gaps 578 exist in observations they are also introduced to G-20CR and G-E20C, so that the trend comparison 579 considers exactly the same period. We also compare observed trends with trends from all five GSSR 580 reconstructions, including an ensemble mean (G-20CR, G-E20C, G-EInt, G-Merra, and G-E5, and G-581 EnsMean) for the 1980-2010 period where all datasets overlap (Figure 9, Figure 10) and (near-)complete 582 observations are available for many tide gauges. Results are aggregated for five regions (Europe, US east 583 Coast, US west Coast, Japan, and Australia) (Figure 11).

584 Finally, we compute trends in annual storm surge frequency for G-20CR and G-E20C during the 1930-585 2010(2015) and 1950-2010(2015) periods. Trends are derived for the number of annual exceedances over 586 the 95<sup>th</sup> percentile threshold (calculated from the reconstructions over the 1930-2010(2015) period(s)). 587 We use a 3-day window to decluster daily maximum surges that are above the 95<sup>th</sup> percentile threshold. 588 We group tide gauges into eight different regions across the globe and derive the regional time series of 589 annual number of extreme surges (>95<sup>th</sup> percentile) by averaging them over the tide gauges within each 590 region before fitting a linear regression model and adjusting for heteroscedasticity and autocorrelation. 591 We also compare frequency trends from reconstructions and observations and test whether they are 592 significantly (5% level) different from each other using the same approach as outlined above for 593 comparing observed and reconstructed trend magnitudes.

594

## 595 **Data Availability**

596 The Global Storm Surge Reconstructions (GSSR)<sup>31</sup> (<u>http://gssr.info</u>) is a publicly available database that 597 contains five daily maximum storm surge reconstruction datasets derived by forcing five climate 598 reanalyses into a data-driven storm surge model<sup>32</sup>. The surge reconstructions obtained after incorporating 599 the change point analysis as well as all change point analysis plots can be accessed at 600 (<u>http://gssr.info/changepoint</u>). Trend analysis results for all tide gauges are available at 601 (<u>http://gssr.info/trends</u>).

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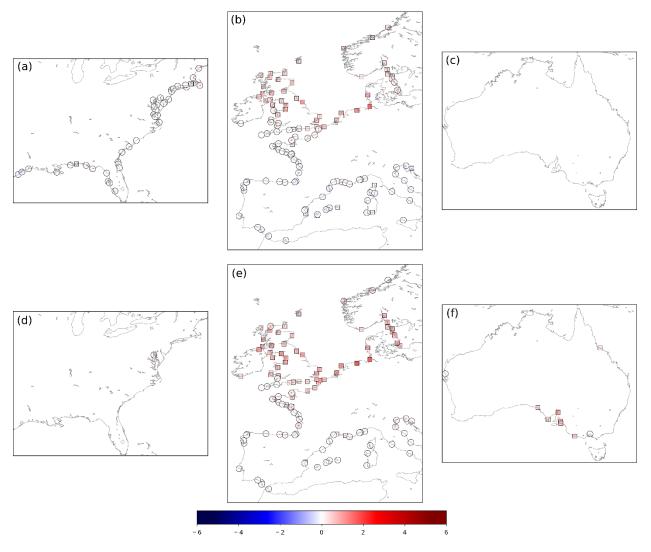
## 728 Author Contributions

M.G.T and T.W. conceived the study and M.G.T. carried out the analysis and interpretation of the data and wrote the first draft of the manuscript. T.W. provided continuous supervision and revisited the work critically for intellectual content. S.A.T., S.D., M.M.R., and A.R.E. participated in regular technical discussions and provided critical input to the analysis design and result interpretation. All authors cowrote the final version of the paper.

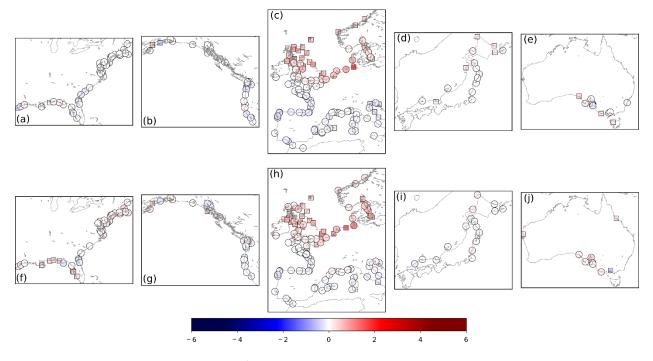
# 735 Competing Interests

736 The authors declare no competing interests.

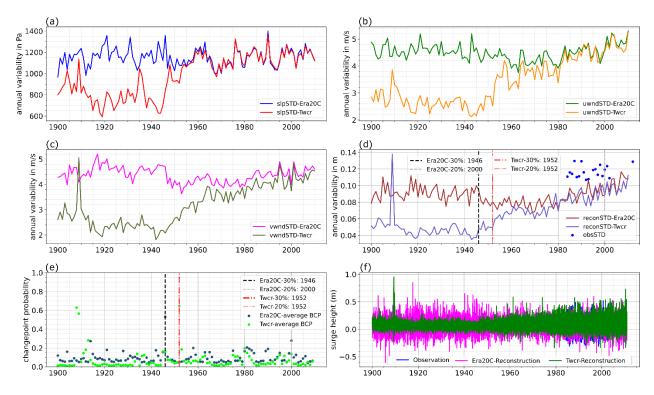
# **Supplementary Figures**



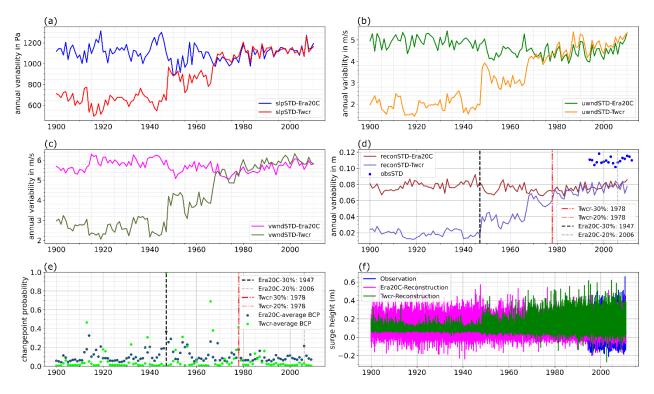
Supplementary Figure S1. Trends (mm/year) for the 95th percentile surges for G-20CR (a-c) and G-E20C (d-f) corresponding to the 1930-2015 and 1930-2010 respectively. Rectangle markers indicate significant trends at the 5% significance level.



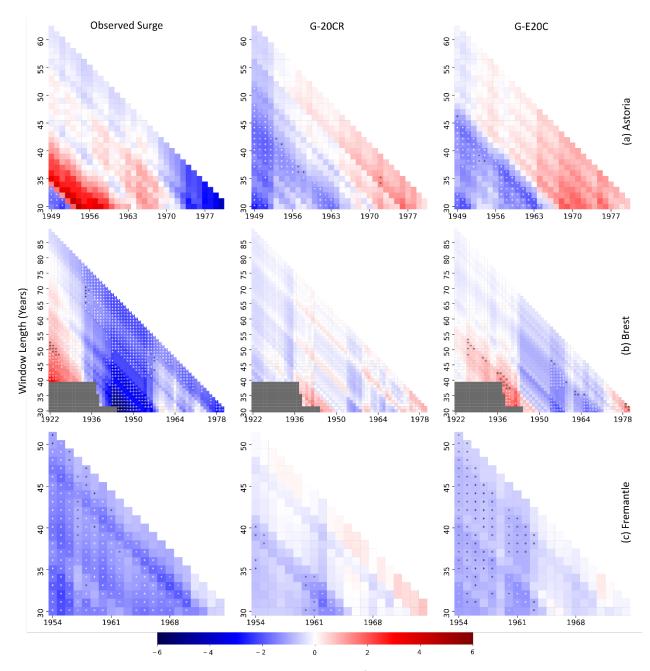
Supplementary Figure S2. Trends (mm/year) for the 95th percentile surges for G-20CR (a-e) and G-E20C (f-j) corresponding to 1950-2015 and 1950-2010 respectively. Rectangle markers indicate significant trends at the 5% significance level.



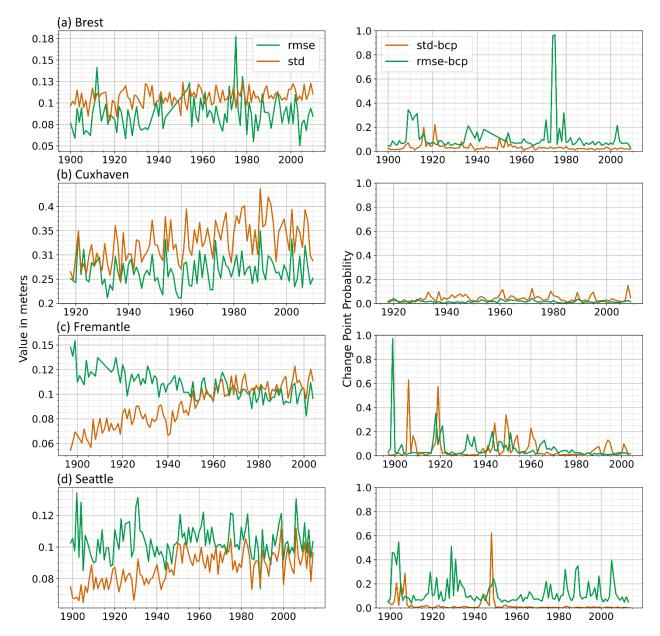
Supplementary Figure S3. Comparison of change point analysis for G-20CR and G-E20C for the 1900-2010 period for Antarctica Base Prat



Supplementary Figure S4. Comparison of change point analysis for G-20CR and G-E20C for the 1900-2010 period for Kerguelen Island



Supplementary Figure S5. Trends (mm/year) comparison for 99<sup>th</sup> percentile observed surge (left), G-20CR (middle), and G-E20C (right) for Astoria (a), Brest (b), and Fremantle (c). Trends are computed starting with a minimum window length of 30 years up to the length of available data. Significant trends at 5% significance level are marked with an asterisk. Grey rectangles indicate time period where data is not at least 75% complete.



Supplementary Figure S6. Annual RMSE (green) and Standard Deviation (std; orange) time series (left) and the corresponding change point probabilities (right) for selected tide gauges with long observational records.