3 Global reanalysis of storm surges
and extreme sea levels

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**Abstract**

Extreme sea levels, caused by storm surges and high tides, can have devastating societal impacts. To effectively protect our coasts, global information on coastal flooding is needed. Here we present the first global reanalysis of storm surges and extreme sea levels (GTSR dataset) based on dynamical modelling. GTSR covers the entire world's coastline and consists of time series of tides and surges and estimates of extreme values for various return periods. Validation showed that there is very good agreement between modelled and observed sea levels, and that the performance of GTSRS is similar to that of regional hydrodynamic models. Due to the limited resolution of the meteorological forcing, the extremes are slightly underestimated, especially for tropical storms. We foresee applications in assessing impacts of climate change and risk management. As a first application of GSTR, we estimate that 76 million people are exposed to a 1 in 100-year flood.

**3.1 Introduction**

Storm surges, a rise in water level due to low atmospheric pressure and strong winds, are the main cause of coastal floods (Resio and Westerink, 2008). The most extreme surges are caused by tropical cyclones, but also extra-tropical storms can produce high surge levels, especially when coinciding with high tide (Pugh, 1988). With over 600 million people living in low-lying coastal areas (McGranahan et al., 2007), coastal floods can have devastating societal impacts. It is estimated that on average 0.8-1.1 million people per year are flooded globally (Hinkel et al., 2014). This is reflected by disasters like the flooding of the Netherlands and the United Kingdom in 1953, which resulted in over 2,000 casualties (Spencer et al., 2013), and led to the construction of extensive flood protection works along the Dutch coast and the Thames Barrier in London. Another more recent catastrophe was the flooding of New Orleans in 2005 due to tropical cyclone Katrina, which resulted in around 1,100 casualties (Rappaport, 2014).

In recent years, coastal flood risk has been increasing due to population and economic growth (Jongman et al., 2012b) and land subsidence (Nicholls and Cazenave, 2010; Syvitski et al., 2009). So far, it has been difficult to attribute the risk increase to climate change (Bouwer, 2011), but sea level rise will lead to increased coastal flooding in the future (Hallegatte et al., 2013; Hinkel et al., 2014). To analyse the trends in coastal flood risk, several continental to global-scale studies have been
carried out (Brown et al., 2013; Hallegatte et al., 2013; Hinkel et al., 2014, 2011, 2010; Jongman et al., 2012b) based on the extreme sea levels in the Dynamic Interactive Vulnerability Assessment (DIVA) database (Hinkel and Klein, 2009; Vafeidis et al., 2008). These studies have provided important insights in the global coastal flood risk, including the impact of sea level rise and adaptation, and have helped to identify which areas face the highest (increases in) risk. Yet, the validation of the extreme sea levels in DIVA has received little attention. In addition, some applications, such as assessing inter-annual variability, the impact of changes in storm regimes, or the modelling of past events, require time series of sea levels (instead of extreme values) and attribution of tides and surge to the total water level. Time series observations can be obtained from tide gauges, but many regions at risk have insufficient sea level tide gauges or record lengths to give a reliable estimate of extreme water levels. Extreme sea levels vary significantly along the coast due to variability in storminess, coastline shape, and bathymetry, and therefore interpolation between different stations will not accurately capture the spatial variation. Recently, more advanced techniques based on altimetry data have been developed (Merrifield et al., 2013), but these are not applicable to low-probability extreme events. Due to these data limitations, there is still limited understanding of the global coastal flood hazard, even under current climate conditions.

To address these issues, we developed the Global Tide and Surge Reanalysis dataset (GTSR). The global dataset consists of time series of tide, surge and total sea levels for 1979-2014, and estimated extreme sea levels for various return periods. GTSR is the first tide and surge dataset based on hydrodynamic model simulations that covers the entire world’s coastline. At the regional scale, hydrodynamic models have become very useful tools to develop consistent and complete sea level reanalyses, also at times and locations where no observations are available. As the modelling of surges in shallow coastal areas requires a high resolution, generally a modelling approach is computationally too costly to apply on the global-scale. We apply the newly developed Global Tide and Surge Model (GTSM) based on the Delft3D Flexible Mesh software (Kernkamp et al., 2011) to obtain the first near-coast global reanalysis of storm surges. The application of unstructured grids (or ‘flexible mesh’) in GTSM allows for sufficient resolution in shallow coastal areas (Haigh et al., 2013b), while maintaining computational efficiency (Kernkamp et al., 2011). By forcing the GTSM model with meteorological fields (i.e. wind speed and atmospheric pressure) derived from the ERA-Interim global atmospheric reanalysis (Dee et al., 2011), we can reconstruct the surge levels for the period 1979-2014. Tides are modelled separately using a recent update of the Finite Element Solution (FES2012) hydrodynamic model (Carrere et al., 2012), a global tide model that
assimilates satellite altimeter data (see Supplementary Note B1: First verification of GSTM over 2007 and Figure B1 in Appendix B). Subsequently, assuming independence of the tide and storm surge processes, tides and storm surges are superimposed to reconstruct the total water levels. Next, we applied extreme values statistics to estimate extreme sea levels (Gumbel, 1941). To validate the GTSR dataset, we compared the results with a global dataset of observed sea levels from University of Hawaii Sea Level Center (UHSLC).

### 3.2 Data and Methods

The method to develop the GTSR time series is based on two global hydrodynamic models: GTSM for storm surges, and FES2012 for tides. Figure 3-1 shows a flowchart of the approach. To simulate water levels in all coastal areas, while not generating huge amounts of data, model output is produced for 16,395 locations along the coastline based on the centroids of the DIVA segments database (Vafeidis et al., 2008) and the locations of observation stations used for validation. Reduced datasets, useful for extreme value analyses were generated by post-processing the results into daily maxima as well as annual maxima, for each of the output locations.

![Figure 3-1](image)

**Figure 3-1** Flowchart of the model approach that was applied to the development and validation of GTSR and the first application for flood risk assessments.

#### 3.2.1 Modelling tides with FES2012

FES2012 is a global tidal model, which assimilates satellite altimeter data. The model is available for download at: [http://www.aviso.altimetry.fr](http://www.aviso.altimetry.fr). Tidal elevations are distributed on a regular grid of 1/16°. Tides are simulated here with a 10-minute
time interval. A review on the performance of global tide models by Stammer (2014) shows that FES2012 performs relatively well in coastal areas compared to other global models.

### 3.2.2 Modelling storm surge with GTSM

GTSM is based on the Delft3D Flexible Mesh software developed by Deltares (Kernkamp et al., 2011). To accurately resolve hydrodynamic equations in topographically complex areas, such as coastal regions, while not decreasing the computational efficiency, it is desirable to locally refine the computational grid (Kernkamp et al., 2011). Delft3D FM enables this by allowing the use of unstructured grids. The cell size of the computational grid is dependent on the bathymetry and increases from $1/2^\circ$ (~50 km) in deeper parts of the ocean towards $1/20^\circ$ (~5 km) in shallow coastal areas (Figure 3-2). The bathymetric data with a resolution of $1/60^\circ$ is collected from the General Bathymetric Chart of Oceans (IOC et al., 2003) and is interpolated onto the computational grid.

To simulate the sea levels resulting from storm surge, the model was forced with 10 m wind speed and atmospheric pressure obtained from the ERA-Interim dataset developed by The European Centre For Medium-Range Weather Forecasts (Dee et al., 2011). The ERA-Interim is a global atmospheric reanalysis from 1979, which is continuously updated in real time. The meteorological fields are available every 6 h and have a spatial resolution of 0.75° x 0.75°. The 10 m wind speed is translated into wind stress using a drag coefficient based on Charnock (Munk, 1955). For consistency with the ECMWF climate model, we applied a Charnock parameter of 0.041. The sensitivity of applying different values for the Charnock parameter are discussed in Supplementary Note B1.

The model simulations were carried out for each year separately, using a spin-up time of 11 days. Using a parallel setup with 16 cores, the simulation of one year takes approximately 30 hours per 1 year run. The different runs were started in parallel, so in theory without other users on the computer cluster, the whole computation can be completed in 30 hours.

### 3.2.3 Data used for validation

A global dataset with observed sea levels is used to validate GTSR. Hourly water levels from 472 stations (Figure B2 in Appendix B) over the period 1980-2011 are obtained from the archives of the UHSLC (dataset is available at http://uhslc.soest.hawaii.edu). Furthermore, all stations are quality-checked by tidal analysis using TideMAT 1.05 (RWS, 2012). Each year is analysed separately and the records of each station are only used when less than 20% of the data are missing.
Using mean annual sea level as reference date, we subtract the tidal component from the total water level in order to obtain the residual water level. This component primarily contains the meteorological contribution to sea level (i.e. surge level), but may also contain harmonic prediction errors or timing errors (Haigh et al., 2010a). However, we consider these errors as negligible as each station has been inspected visually. Decomposing the total water level into a tide and surge component enables the separate validation of the two components. For each station with a record longer than 25 years, we also estimate the extreme sea levels for different return periods and compare those with modelled sea levels (see next paragraph).

![Figure 3-2](image_url) Computational grid of GTSM. Computational grid of GTSM showing: a, the refinement of the grid from the deeper ocean to more shallow areas of the Mediterranean Sea; and b, the thinning of the grid at high latitudes.

### 3.2.4 Extreme value statistics

To estimate the probabilities of extreme sea levels, we apply extreme value statistics using the annual maxima method (Gumbel, 1941; Jenkinson, 1954). For each output location, we extract the annual maximum for the calendar years 1979-2014 and fit a Gumbel distribution. From the parameterised distribution, we can obtain estimates of sea levels corresponding to selected return periods including the fit uncertainty. The Gumbel distribution is often a good approximation of observed extreme sea levels and is frequently applied to estimate return periods (Haigh et al., 2013b; Lowe et al., 2001; Sterl et al., 2009). While more advanced statistical method are available, such as peak-over-threshold or joint probability, the annual maxima method is more robust to temporal and spatial variations, and is thus relatively easy to apply on a global-scale.

### 3.2.5 Modelling inundation and flood exposure

Based on the extreme sea levels, coastal inundation is calculated using a GIS-based planar approach, which uses the tidal water level and a Digital Elevation Model (DEM) as input. Inundated areas are defined as areas that have an elevation lower than the water level, and have a direct connection to the sea, following Hanson et
Global reanalysis of extreme sea levels

The DEM is obtained during NASA’s Shuttle Radar Topography Mission and its original resolution is 1” (approximately 30 meters at the equator). We use a 30” (approximately 1 km at the equator) average to estimate inundation. Impacts of coastal floods are measured in terms of exposed population and exposed urban areas using the GRUMPv1 population counts maps for 2000 (Balk et al., 2011; CIESIN et al., 2011). Flood protection is not included in the analysis and will lead to an overestimation of the flood hazard. Furthermore, the planar approach assumes that a maximum water level during any event will travel infinitely far land inwards and will therefore overestimate the extent of the floodplain, in particular on coast lines with wide flat areas far land inwards. On the other hand, the spatial averaging of the DEM may result in smoothing of local depressions, causing underestimation of the flood extent in coast lines with relatively large upwards gradients land inwards. Also, coastal cities are often in delta areas where the river may propagate the surge into the hinterland. In this sense the approach may underestimate the flood extent.

3.3 Results

3.3.1 Validation of time series

For the total water level, there is generally a good agreement between the modelled and observed sea levels, with 80% of stations having a RMSE (measured from the data at 10 minute temporal resolution) smaller than 0.20 m (Figure 3-3). The average RMSE across all validation sites is 0.17 m (s.d. is 0.15 m). The separate surge levels perform even better, with 95% of the stations having a RMSE smaller than 0.2 m. The average RMSE is 0.11 m (s.d is 0.05 m). For illustration, Figure 3-4 show the modelled and observed surge levels for selected sites around the world. For tidal levels, about 85% of the stations have a RMSE smaller than 0.2 m, but the maximum RMSE value is larger than 1 m. The average RMSE is 0.15 m (s.d. is 0.42 m). Large errors (RMSE > 1m) for gauging stations Windham, Victoria and Puerto Montt (Figure 3-3a) are caused by an over- or underestimation of the tidal amplitude. Figure B3 in Appendix B shows the RMSEs for the surge- and tide levels for all observation stations. To assess whether sea level extremes are also adequately represented in the GTSR time series, we calculate the performance based on daily maxima. Figure 3-5 shows scatter density plots for modelled and observed daily maxima for 12 selected locations. The majority of the daily maxima (orange to red areas in Figure 3-5) are close to the perfect-fit line, indicating a good performance. The performance for the majority of these 12 stations decreases for more extreme sea levels (the least-squares line diverges from the best-fit line). The underestimation of extreme sea levels is related to the resolution of GTSR (see Section 3.4). The average Pearson correlation coefficient is 0.83 (s.d. is 0.14), indicating a good agreement between modelled and
observed maxima. Over 75% of the stations have a correlation coefficient higher than 0.75. In regions prone to tropical cyclones (Figure B4 and Supplementary Note B2 in Appendix B), such as the Caribbean Sea, we obtain correlation coefficients lower than 0.5. The average correlation coefficient in these tropical regions is 0.77, which is significantly lower than the average correlation coefficient of 0.87 in extratropical regions (p< 0.05).

**Figure 3-3** Maps showing the performance of GTSR against observed sea levels. The performance of GTSR showed as a, the RMSE (m) between modelled and observed sea level time series; b, the Pearson correlation coefficient (p) between modelled and observed daily maximum sea levels; and c, the absolute difference (m) between modelled and observed extreme sea levels with a return period of 10 year.
Figure 3-4 Comparison of the modelled and observed surge levels at selected stations. Comparison of the modelled and observed surge levels for 2007 at six selected stations around the world, a, Boston, United States; b, Goteborg-Torshamn, Sweden; c, Mar de la Plata, Argentina; d, Bluff Harbour, New Zealand; e, Kushiro, Japan; and f, Zanzibar, Tanzania. The coloured dots in the world map indicate the location of the observation stations.
3.3.2 Validation of extremes
To obtain extreme sea levels for various return periods, we fit a Gumbel distribution to the annual maxima. The Gumbel plot is shown in Figure 3-6 for five selected stations. For all shown stations, the annual maxima follow a relativity straight line, which indicates there is a good fit with the Gumbel distribution. Average relative errors for return periods from 5 to 100 years are in the range from 11-14%, increasing with higher return periods. As there is a limited number of stations with observation records longer than the 30 years, we focus on 1 in 10 year extreme sea levels and use all stations that have an observation record longer than 10 years. For 75% of these 144 stations, the absolute error is smaller than 0.3 m (Figure 3-3c). On average, the sea level extremes with a return period of 10 years are underestimated with -0.14 m (s.d. is 0.39). The performance of GTSR is best in areas where extremes are dominated by large, extra-tropical storms, like Europe, southeast Australia, eastern South-America, and northwest North-America. In regions where storm surges are largely induced by tropical cyclones, the mean absolute difference between the extreme sea levels with a return period of 10 years is 0.23 m, which is significantly higher than in extra-tropical regions, where the mean absolute difference is 0.08 m (P < 0.05).

3.3.3 Application to assess global flood exposure
To illustrate a first application of the GTSR extremes, we calculate the flood hazard (i.e. inundation extent) and flood exposure (i.e. exposed people) based on 1 in 100 year extreme sea levels. For this first demonstration, the results are shown assuming no protection from coastal flooding. Results show there are large regional variations in the 1 in 100 year extreme sea levels (Figure 3-7a): relatively high extreme sea levels are found in areas with high tidal amplitude, like northwest Europe, south Argentina, China, and Bangladesh. This spatial pattern agrees with other datasets (Merrifield et al., 2013; Vafeidis et al., 2008), and does not change for extreme sea levels with a higher return periods (Figure B5 in Appendix B). Combining the extreme sea levels with elevation shows that major inundation occurs particularly in delta areas in Europe and Asia (Figure B6 in Appendix B). The global population exposed to a 1 in 100 year flood is 76 million, equal to 1.3% of the total world population (Table 3-1). The flood exposure map in Figure 3-7b shows that particularly China has a large exposure, with 37 million people, which is 3% of the country's population and 53% of the global exposure (Figure B7 in Appendix B shows the absolute exposure). Other countries that have a relatively high exposure include the Netherlands (8.4 million people, 53% of total population), Vietnam (4.7 million people, 6% of global exposure), and Egypt (4.3 million people, 6% of global exposure). Relative to the
Figure 3-5 Scatter plot of modelled and observed daily maxima at selected stations. Scatter plots for eight selected stations around the world, a, Abaratsu, Japan; b, Boston, United States; c, Brisbane, Australia; d, Goteborg-Torshamn, Sweden; e, Lerwick, United Kingdom; f, Los Angeles, United States; g, Pohnpei, Micronesia; h, Rio de Janeiro, Brazil; i, Tofino, Canada; j, Valparaiso, Chile; and k, Zanzibar, Tanzania. Colours indicate the data density for bins with a 5 x 5 cm size. The red dots in the world map indicate the location of the observations stations.
Figure 3-6 Gumbel plot for the modelled and observed annual maxima at selected stations. Gumbel plots for five selected stations around the world, a, Aburatsu, Japan; b, Boston, United States; c, Lerwick, United Kingdom; d, Rio de Janeiro, Brazil; and e, Zanzibar, Tanzania. The annual maxima are plotted as against the Gumbel variate, which is equal to $x = -\ln(-\ln(G(y)))$. The red dots in the world map indicate the location of the observation stations.

total national population, the Netherlands and Greenland stand out with respectively 53% and 31% of the population exposed to a 1 in 100 year flood (Figure B7 in Appendix B).

We assess the uncertainty in the extreme value statistics by calculating the 5 and 95% confidence bounds of the Gumbel fit, and express the uncertainty as the percentage difference compared to extreme sea level based on the best-fit. For a return period of 1 in 100 years, the uncertainty of the Gumbel fit is below 10% for half of the world’s coastline (Figure 3-8a). For only 4% of the world’s coastline the uncertainty is larger than 25%. The largest uncertainty is seen in regions where the extreme values are relatively low, like the Mediterranean Sea and Caribbean Sea, where a small change in extreme sea level leads to a large increase in relative terms. To assess how sensitive the exposure estimates are to the uncertainty in extreme values statistics, we use the 5% and 95% as input to the inundation and impact model. Globally, the sensitivity to the uncertainty in extreme values is relatively small, with a range of −8 to +21% around the best-fit for exposed population (i.e. exposure ranges between 70 and 92 million people). The results per country are shown in Figure 3-8b, which shows that particularly the results for the USA, Thailand, Mali and several countries along the Baltic Sea are particularly sensitive, with uncertainty values larger than 50% of the best-fit. Of the top 10 countries listed in Table 3-1, the results for China and Vietnam have the largest uncertainty with exposure estimate ranging from -34% to +39% and -28% to +4% respectively. While the largest uncertainty in extreme sea
levels is found along the north coast of Russia, this does not lead to large uncertainty in exposure, because the area has a very low population density, whereas an uncertainty in extreme sea levels of 10%-50% along the USA east coast and <10% along the USA west coast lead to a uncertainty ranging from -40% to +49% in the country’s exposure estimates.

Figure 3-7 Extreme sea levels with a return period of 100 years and the exposed population. Maps showing a, the height of extreme sea levels with a return period of 100 years (based on the best Gumbel fit) around the entire world’s coastline; and b, the estimated exposed population estimates per country (relative to the global exposure) with return period of 100 years.

3.4 Discussion
The performance of the GTSR time series is similar to that of other hydrodynamic models that have a large domain. For example, Cid et al. (2014) reported a mean RMSE of 0.08-0.10 m for surge levels in the Mediterranean Sea. For a hydrodynamic model covering the entire Australian coastline, Haigh et al. (Haigh et al., 2013a) reported mean RMSEs of 0.14 m and 0.05 m for total sea level and surge respectively. The validation of GTSR shows that extreme sea levels are generally underestimated but that the differences with observed extreme sea levels are rather small (< 1m). For applications to risk assessment, which makes use of data from
global digital elevation models (DEMs), this underestimation is reasonable, since the vertical resolution of such DEMs is much greater. For example, the global SRTM DEM has a vertical resolution of one meter, but its uncertainty amounts up to several meters (Rabus et al., 2003). Hence, whilst acknowledging that the errors can potentially be large in specific locations, we are confident that the GTSR time series (i.e. surge, tide and total sea levels) and extremes are a very valuable addition to the global datasets that are currently available. Further benchmarking may be performed by comparing the GTSR extremes to other modelled datasets, like extreme sea levels in the DIVA database (Vafeidis et al., 2008), and regional hydrodynamic models (Flather et al., 1998; Haigh et al., 2013b). Further research could assess how differences in flood hazard influence the estimated flood exposure and related policy implications.

Table 3-1 Absolute and relative exposed population to a 1 in 100 year flood for the 10 most exposed countries.

<table>
<thead>
<tr>
<th>Country</th>
<th>Absolute exposure (in millions)</th>
<th>Relative exposure (% of population)</th>
</tr>
</thead>
<tbody>
<tr>
<td>China</td>
<td>36</td>
<td>2.9</td>
</tr>
<tr>
<td>Netherlands</td>
<td>8.4</td>
<td>53</td>
</tr>
<tr>
<td>Vietnam</td>
<td>4.7</td>
<td>6.0</td>
</tr>
<tr>
<td>Egypt</td>
<td>4.3</td>
<td>6.4</td>
</tr>
<tr>
<td>Germany</td>
<td>2.9</td>
<td>3.5</td>
</tr>
<tr>
<td>India</td>
<td>2.5</td>
<td>0.3</td>
</tr>
<tr>
<td>United Kingdom</td>
<td>2.4</td>
<td>4.1</td>
</tr>
<tr>
<td>Japan</td>
<td>2.0</td>
<td>1.6</td>
</tr>
<tr>
<td>Bangladesh</td>
<td>1.4</td>
<td>1.1</td>
</tr>
<tr>
<td>Belgium</td>
<td>1.1</td>
<td>11</td>
</tr>
<tr>
<td>World</td>
<td>76</td>
<td>1.3</td>
</tr>
</tbody>
</table>

There are several limitations to the GTSR time series and extremes. We aim to update the dataset in the future, addressing some of the issues described here. First, the validation shows that extreme values are slightly underestimated. This is an inevitable result of the relatively coarse resolution of the model grid, bathymetry and meteorological forcing (compared to point observations). Extremes in wind speed and atmospheric pressure are smoothed in ERA-Interim dataset due to the temporal (6h) and spatial (0.75°) resolution. This is particular problematic for tropical cyclones, which are characterised by strong gradients both in time and in atmospheric pressures and wind fields.
Figure 3-8 Gumbel sensitivity range for extreme sea levels and exposure. Maps showing the uncertainty of the extreme values statistics for the 1 in 100 year return period. The values shown is the range for the 5–95% confidence bounds expressed as a percentage of the value for the best-fit for a, the height of extreme sea around the entire world’s coastline; and b, the estimated exposed population estimates per country.

The validation showed that the underestimation of extreme sea levels is more severe in tropical areas. However, because of the sparseness and shortness of available records the largest tropical cyclone-induced surges are not all included in the available observations (Torres and Tsimilis, 2014). Hence, if we compare the GTSR extremes against reported extreme sea levels induced by tropical cyclones we see larger deviations. For example, the maximum surge levels during tropical cyclone Katrina in New Orleans (2005), and during Typhoon Haiyan (2013), in the Philippines exceeded 8 m (Needham and Keim, 2012) and 4.5 m (Mahar et al., 2014; Mori et al., 2014), respectively, whilst our extreme sea level estimates do not exceed 2–3 m for a return period of 1000 year. This illustrates that accurately modelling these intense storms requires a much higher resolution than atmospheric reanalysis can deliver at present day. This issue could be resolved for updated versions of the GTSR dataset by generating localised wind fields based on storm track data and the parametric model of Holland (Holland, 1980). This is expected to more accurately simulate the surge levels resulting from tropical cyclones. However, even when the
extreme sea level are adequately modelled, time series of 36-years contain insufficient incidences of tropical cyclones needed to obtain reliable statistics of extreme values. Hence, synthetic resampling techniques are needed to extend the tropical cyclone record to a longer record (Emanuel et al., 2006; Haigh et al., 2013a; Lin et al., 2012). Including tropical cyclones will lead to higher coastal flood risk, as in the areas prone to tropical cyclones, the most damaging storm surges are often induced by tropical cyclones (Woodruff et al., 2013).

Second, we apply the annual maxima method to obtain the GTSR extremes. Although the method is widely applied, it neglects the fact that sea levels are composed of two independent processes, being a tide-driven (deterministic) process and a surge-driven (stochastic) process. In addition, data is used inefficiently as extreme values are estimated based on annual maxima only. To address these limitations, more sophisticated statistical methods, like the r largest or joint probability, could be applied (Haigh et al., 2010b). However these methods are also more sensitive to timing errors and/or temporal or spatial variation. Assuming that tides and storm surges behave independently, the estimates of extreme values could also be made more robust by resampling the surge and tide levels in time to obtain longer time series.

Third, the sea level variations in the GTSR time series are strictly due to gravitational tides and barotropic changes (changes in wind and pressure): baroclinic effects (density differences) are not considered. Although in most parts of the world, the generation of extreme sea levels is dominated by tide and surge, in some regions the variations in mean sea level are relatively large (Tsimpis and Woodworth, 1994) and thus have a large effect on the total sea level; this is for example the case in parts of the Australian coastline (Haigh et al., 2013b). Also, non-linear interactions between storm surge and tides, the effect of waves, and precipitation and river flow are not considered. In this version of GTSR, tides and surges are modelled separately and surge-tide interactions are thus not included, although it is known to be important in shallow water areas with a large tidal range (Bernier and Thompson, 2007; Horsburgh and Wilson, 2007). Including the surge-tide interaction has improved the model performance for regional hydrodynamic models (Wolf, 2008). For example, in the case of the North Sea, the RMSE was lowered by ca. 40% (Zijl et al., 2013). However, at this stage this does not apply to GTSM (Supplementary Note B1 in Appendix B), as the current version of GTSM is not capable of adequately reproducing tidal characteristics in all coastal regions. Wave setup may increase total sea levels considerably near the coast, with the largest contribution in regions with steep slopes (Dietrich et al., 2011). In deltas and estuaries, precipitation and river flow may also contribute to coastal flooding (Dietrich et al., 2010). Including all these
processes on a global-scale is not feasible at present day, but it is important to note that these local processes may lead to significantly different extreme sea levels in some parts in the world.

Also, the impact modelling has some limitations. Aside from limitations of the simple inundation model (see Section 3.2), the most important limitation is that flood protection is not included in this analysis, and many exposed countries are protected by dikes and storm surge barriers up to a certain design standard. For example, despite its high exposure rates, the Netherlands has very low flood probabilities as all low lying areas are protected by coastal defences, some with very high protection standards (1 in 10,000 year return period) (Wesselink et al., 2013). However, Hallegatte et al. (2013) estimated protection standards for major cities and found that a city like Jakarta has a protection standard that equals a 10 year return period. Hence, for many countries listed in Table 3-1, the protection standard will be lower than a return period of 100 years. Using a similar methodology (planar inundation and no flood protection), but an alternative population database, Jongman et al. (2012b) estimated that 271 million people are exposed to 1 in 100 year coastal flooding in 2010. Based on the similar elevation and population data, but using a somewhat different methodology that includes flood protection, Hinkel et al. (2014) estimated that between 160 million people are exposed to a 1 in 100 year flood. The differences in methodology and data make a direct comparison difficult. Nevertheless our exposure estimate of 70-92 million seems low compared to previous studies (Hinkel et al., 2014; Jongman et al., 2012b). However, most previous studies of global flood risk, including the studies of Jongman et al. (2012b) and Hinkel et al. (2014), are based on the extreme sea levels in the DIVA database (Vafeidis et al., 2008). This dataset has not been extensively validated. Compared with observed sea levels, Muis et al. (2015) found an overestimation for the DIVA extreme sea levels with a 10 year return period in Indonesia.

In future research the GTSR dataset could be applied to assess global flood risk, both under current- and future climate conditions. Coastal floods may become more severe due to sea level rise and changes in storminess (IPCC, 2012). While sea level rise may be directly added to the return levels (Hinkel et al., 2014), this is not valid for all regions (Zhang et al., 2012), and the advantage of the physical based modelling approach is that changes in storminess can be assessed using a dynamical approach by forcing the model with future global climate model simulations (Brown et al., 2011; Lowe et al., 2001). Furthermore, changes in storm duration can be propagated into the full dynamics of storm surge induced flooding. Such climate change assessments can be used to identify areas that face rapidly increasing risks, which is
important for planning disaster risk reduction efforts and to prioritise adaptation efforts (UNISDR, 2011). Aside from flood risk applications, the GTSR dataset can be used for a variety of other applications. For example, the GTSR time series may be used to assess changes in storminess (Cid et al., 2015), to correct for meteorological effects in mean sea level (Losada et al., 2013), or assess the influence of interannual variability on risk. Because now full time series are available that include the duration of the flood events, another potential research direction may be the improvement of the inundation modelling on a global-scale by including flood duration in the inundation modelling. Recent research demonstrated the importance of assessing compound flooding in major US coastal cities (Wahl et al., 2015). Also in other delta regions including compound flood may be critical for correctly assessing flood risk (Keef et al., 2009; Kew et al., 2013; van den Hurk et al., 2015; Zheng et al., 2014). In combination with time series of precipitation of discharge, the GTSR time series may also be used to assess compound floods on a global-scale. Another application of the GTSM model that is currently being developed is the global operational forecasting system called GLOSSIS (Verlaan et al., 2015), which produces 10 day forecasts of coastal storm surges worldwide. The GTSR extremes may be used to raise warning flags and to identify potential flood hazards. In the future this should not be based only on exceeding a physical threshold, but also include potential impacts of a flood.

3.5 Conclusions

Extreme sea levels, caused by storm surges and high tides, can have devastating societal impacts. To effectively protect our coasts, global information on coastal flooding is needed. Here we present the first global reanalysis of storm surges and extreme sea levels (GTSR dataset) based on dynamical modelling. GTSR covers the entire world's coastline and consists of time series of tides and surges and estimates of extreme values for various return periods. Validation shows that the GTSR dataset has a very good agreement with observed sea levels. The average RMSE is 0.11 m and the average Pearson coefficient for daily maxima is 0.83. Mainly due to the resolution of the meteorological forcing, extreme sea levels are slightly underestimated, especially those induced by tropical cyclones. The average underestimation for a 1 in 10 year extreme sea level is of 0.23 m in tropical regions, compared to 0.08 m in extra-tropical regions. The performance of the GTSR time series is similar to that of regional hydrodynamic models.

We foresee various applications of the GTSR dataset, such as: global flood risk assessment; assessing inter-annual variability of storminess; providing warning thresholds for operational forecasting models; and assessing (the impacts of) climate
change. To illustrate one of the potential applications of the GTSR dataset, we assessed the global flood exposure of coastal inhabitants using a simple inundation model, and found that 76 million people are exposed to a 1 in 100 year flood.

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