**Influence of El Niño Southern Oscillation on global coastal flooding**

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Key Points:

* Significant influence of El Niño Southern Oscillation (ENSO) on mean and extreme sea levels across tropical Pacific
* Simulations show a significant but small influence of ENSO on flood impacts with wide uncertainties prohibiting a robust assessment
* Model-based approach enables the assessments of coastal flood impacts and could be used to assess impacts of future changes in ENSO

# Abstract

Anomalous atmosphere-ocean conditions in the tropical Pacific associated with the El Niño Southern Oscillation (ENSO) drive interannual variations in mean and extreme sea levels. Climate change may lead to more frequent extreme ENSO events in the future. Therefore, it is important to enhance our understanding of ENSO's influence on coastal flood impacts. We assessed ENSO’s influence on extreme sea levels using a global reanalysis of tides and storm surges. This allows for a full coverage of the global coastline from 1979 to 2014. A mean sea level component is added to account for steric effects. This results in a substantial improvement in the representation of the seasonal and interannual variability. Our results show significant correlations across the Pacific between ENSO and extreme sea levels (expressed as 95th annual percentiles), which is consistent with previous studies based on tide gauge observations. Average anomalies in the annual percentiles over El Niño years compared to neutral years show similar patterns. When examining total sea levels, results are largely statistically insignificant. This is because in many regions large tidal variability dominates over the other components. Combining sea levels with an inundation and impact model shows that ENSO has a significant but small effect on the number of people potentially exposed to flooding at the globally aggregated-scale. Our result demonstrate that a model-based approach allows for an assessment of the influence of ENSO on coastal flood impacts, and could be used to assess impacts of future changes in ENSO.

# Introduction

El Niño-Southern Oscillation (ENSO) is the dominant driver of interannual climate variability (McPhaden et al., 2006). ENSO is characterised by a fluctuation between unusually warm (El Niño) and cold (La Niña) oceanic and atmospheric conditions in the tropical Pacific. These temperature anomalies have impacts on global weather and climate system, as well as sea levels. ENSO drives particularly strong anomalies in mean sea level in the tropical Pacific (Barnard et al., 2015; Becker et al., 2012; Merrifield et al., 1999; Miles et al., 2014; Zhang & Church, 2012). For example, in the western tropical Pacific, El Niño and La Niña events result in mean sea level anomalies of ± 20-30 cm (Becker et al., 2012). Along the west coast of North America, winter sea levels were on average 0.11 m higher than normal during the five strongest El Niño events between 1979 and 2012 (Barnard et al., 2015). ENSO also influences interannual variability in extreme sea levels. The generation of extreme sea levels is generally dominated by tides and storm surges. However, in regions with small tidal ranges (Tsimplis & Woodworth, 1994), the relatively large variations in mean sea level can have a significant influence on the generation of extremes (Haigh et al., 2013; Marcos et al., 2009). Furthermore, the anomalous ocean-atmosphere conditions during ENSO can induce changes in the intensity, frequency, and tracks of storms, thereby affecting the generation of extremes. Various studies have shown ENSO’s influence on tropical (Chan, 2000; Feng & Tsimplis, 2014; Kuleshov et al., 2008; Saunders et al., 2000; Torres & Tsimplis, 2014), and extra-tropical cyclone activity (Eichler & Higgins, 2006; Lambert, 1996; Sweet & Zervas, 2011).

As a result of rising sea levels, many densely populated coastal zones are projected to experience increases in coastal flood risk. In addition to sea-level rise, there may be a change in the frequency of storms (e.g. Meza-Padilla et al., 2015; Reed et al., 2015; Vousdoukas et al., 2016). Research also suggests that climate change could lead to an increase in the frequency of extreme ENSO events (Cai et al., 2014; Cai, Santoso, et al., 2015; Cai, Wang, et al., 2015). Climate projections also indicate that the increasing frequency of extreme El Niño events may continue for up to a century after the global mean temperature has stabilized (Wang et al., 2017). This is caused by faster warming in the eastern equatorial Pacific compared to other regions. Similar conclusions have been drawn for sea-level rise, which may continue for several millennia, even if we manage to halt CO2 emissions and stabilize the global mean temperature (Golledge et al., 2015; Levermann et al., 2013). Ultimately, this implies a higher risk of coastal flooding for future generations.

To effectively manage and protect coastal zones, it is essential to not only provide long-term projections of global flood risk, but also to provide projections of short-term climate variability. Most research at the global-scale has been dedicated to assessing scenarios of flood exposure and damages for the 21st century (Hinkel et al., 2014; Jongman et al., 2012; Mendelsohn et al., 2012; Neumann et al., 2015; Peduzzi et al., 2012), rather than assessing variations from year to year. Previous global studies that have assessed ENSO-driven interannual variability in storm surges and/or extreme sea levels have used tide gauge observations (Marcos et al., 2015; Mawdsley & Haigh, 2016; Menéndez & Woodworth, 2010; Woodworth & Blackman, 2004). These studies have shown that ENSO has a strong effect throughout the Pacific Ocean, indicating that there are higher/lower extremes during El Niño/La Niña events in the eastern tropical Pacific along the whole American Pacific coast. Reverse effects are seen in the western equatorial Pacific along the coasts of Indonesia, Malaysia and northern Australia. The main limitation of these studies is that the global tide gauge dataset is geographically biased towards the European and North American coasts. In other regions there is a substantial lack of long records (>20 years), particularly in the Southern Hemisphere and the Indian Ocean. A recent update of the Global Extreme Sea Level Analysis (GESLA) dataset has led to major improvements, but there is still a very limited number of long records available for Africa and South America (Woodworth et al., 2016). Furthermore, tide gauge observations cannot be applied to estimate global coastal flood impacts, as this requires full coverage of the coastline.

As a result, to date there is still a limited understanding of how ENSO-driven variability in extreme sea levels and its individual components (i.e. surges, tides and mean sea levels) may influence the probabilities of extreme events and resulting socio-economic impacts of coastal flooding around the world. As we may expect more frequent extreme ENSO events under future climates, it is even more important to enhance our understanding of potential impacts of ENSO at the global scale. Here we present the first global-scale assessment of the influence of ENSO on extreme sea levels (and its individual components) and population exposed to coastal flooding. To address the limitations of previous studies, and to provide a full global coverage, we use the Global Tide and Surge Reanalysis (GTSR) dataset, described in detail in Muis et al.(2016). In this paper, we improve the GTSR time-series for use in application of interannual variability by including changes in steric mean sea level, which refers to the changes in sea level due to thermal expansion and salinity variations. Subsequently, we assess the correlations between ENSO and extreme sea levels globally and calculate anomalies during ENSO years with respect to neutral years. Using a simple inundation and impact model, we assess the influence of ENSO on exposed population.

# Data and Methods

## Extreme sea levels

We use daily maxima of sea levels and the individual components for the period 1979-2014 extracted from the GTSR dataset (Muis et al., 2016). These daily maxima are calculated based on time-series of astronomical tide and storm surges with a 10-minute resolution. Tides are based on the Finite Element Solution (FES2012; Carrere et al 2012). Storm surges are simulated by forcing the Global Tide and Surge Model (GTSM; Verlaan et al 2015) with wind and pressure fields from the ERA-Interim climate reanalysis (Dee et al., 2011). Total water levels are calculated by superimposing the tides and surge components. GTSR provides time-series for 16,611 output locations along the coast, largely corresponding to the centroids of the coastal segments from the Dynamic Interactive Vulnerability Assessment (DIVA) model (Vafeidis et al., 2008). These coastal segments have varying lengths (average of 70 km), depending on population density of the land adjacent to the segment - the higher the population density, the shorter the coastal segment. Validation of the GTSR time-series shows that generally there is good agreement with observations, although extremes driven by tropical cyclones are underestimated (Muis et al., 2016).

## Mean sea levels

The GTSR time-series only includes variations in mean sea level driven by barotropic effects (i.e. changes in wind and pressure). However, changes in mean sea levels are mostly driven by changes in water mass and water density. For this study, we ignore mass-driven variations in sea level and assume that the majority of the interannual variability is due to variability in water density. This is referred to as the steric component (e.g. Ishii & Kimoto, 2009; Miller & Douglas, 2004). Changes in the global steric component are mainly attributed to thermal expansion/contraction, with the impact of salinity changes being considered smaller and less important (Antonov et al., 2002).

To include steric effects, we add monthly mean steric sea levels to the daily maxima total water levels extracted from GTSR. This is carried out by matching each daily value in GTSR with the corresponding monthly value in the steric sea levels. The combined time-series is referred to as GTSR-ST. The steric sea levels (ηs) are computed from temperature (T) and salinity (S) data profiles by using the following formula (Amiruddin et al., 2015):

( 1 )

where ρs is the reference density; H is the reference depth; ρ' is the density deviation with respect to the time average of the in-situ density; and z is the depth. The reference depth is 800 m. We use monthly means of global gridded temperature and salinity data from Ishii and Kimoto (2009). This dataset ends in 2012, so we use the EN4.1.1 dataset from the UK MET Office for the period 2012-2014 (Good et al., 2013; Gouretski & Reseghetti, 2010). A comparison of the two different datasets for the year 2012 shows good agreement (not shown).

Using this method, we assume that steric sea levels are a function of depth. It is known that in shallow coastal regions, part of the sea level variations are explained by dynamic mass redistribution processes connected to steric processes far away (Dangendorf et al., 2014; Frederikse et al., 2018; Miller & Douglas, 2004). Therefore, the nearest grid point is not necessarily the best representation of the variability at the coast (Cabanes, 2001; Lombard et al., 2006; Miller & Douglas, 2004). The processes that communicate variability to remotely located regions are better resolved in ocean reanalyses such as SODA (Carton & Giese, 2008). However, as SODA includes not only baroclinic but also barotropic processes we cannot simply combine GTSR with SODA. Therefore, for this study we decided to use steric sea levels based on depth.

The approach is validated in Section 3.1. To assess the performance of the modelled monthly mean sea levels, we compare them with tide gauge observations obtained from the Permanent Service for Mean Sea Level (PSMSL) for the period 1979-2014 (Holgate et al., 2013; PSML, 2015). In total we use 1056 tide gauge stations for validation. A simple approach based on Haigh et al. (2013) is used to decompose the monthly mean sea levels into seasonal and interannual components. The monthly sea levels are de-trended using a linear regression analysis. Then, the interannual component is calculated as the 12-month running mean. The seasonal component is obtained by subtracting the interannual component from the de-trended monthly sea levels. The range of the internal variability is defined as the standard deviation of the interannual 12-month running mean, while the range of the seasonal cycle is defined as the difference between the maximum and minimum of the mean seasonal cycle.

## ENSO's influence on extreme sea levels

We assess the correlation between ENSO and extreme sea level time series at each coastal grid point. To do this we calculate the Kendall’s rank correlation coefficient (Kendall, 1938) and test the significance of each correlation by exact permutation distributions using a 95% confidence level (α=0.05). Extreme sea levels are expressed as the 95th annual percentiles from the time-series of total sea levels, as well as the individual components (i.e. surge, tide, and steric levels). We use annual percentiles to characterize extreme sea levels, as this gives a more robust indication of the storminess in a year than the use of methods like block maxima or peak-over-threshold (Woodworth & Blackman, 2004), which are much more variable and biased by very large individual storm events. As ENSO is usually strongest in the boreal winter (Dettinger & Diaz, 2000), we define a year to start in October and end in September of the following year (Ward et al., 2010). To represent the ENSO state, we use the Southern Oscillation Index (SOI), which is the normalized pressure difference between Tahiti and Darwin (Ropelewski & Jones, 1987). The SOI is negative during El Niño events and positive during La Niña events. To ensure sustained ENSO conditions, we use a 3-month mean over the boreal winter (SOIDJF). As the effects of ENSO can be delayed, we apply lag times between 0 and 6 months. To assess the sensitivities of our results with other ENSO indices, we repeat the analysis using: the Oceanic Niño Index (ONI) (Rayner et al., 2003), and the Multivariate ENSO Index (MEI) (Wolter & Wolter, 1987). We use the inverse values of ONI and MEI, as in contrast with the SOI, positive (negative) values of ONI and MEI indicate La Niña (El Niño) conditions.

Correlations ignore asymmetric effects of ENSO, which occur when both El Niño and La Niña induce higher annual percentiles. Therefore, we also calculate the average anomalies of annual percentiles over the 11 El Niño years and 10 La Niña years compared to the 14 neutral years. Years are categorized as El Niño and La Niña based on the Oceanic Niño Index (ONI). Consistent with terminology from the National Oceanic and Atmospheric Administration (NOAA) of the United States, we classify a year as El Niño and La Niña if there are 5 consecutive 3-month periods at or above the ±0.5° anomaly (Table 1). We test the statistical significance at each location by bootstrapping using a 95% confidence level and 1,000 repetitions. First, we draw 1,000 random samples of annual percentiles from the entire series. In the case of El Niño we draw 1,000 samples of 11 values, while in the case of La Niña we draw 1,000 samples of 10 values. Second, we use these 1,000 samples to construct probability density curves. Third, we test whether the empirical anomalies fall outside the 95% confidence bounds.

## ENSO's influence on flood exposure

A similar statistical framework is applied to assess the influence of ENSO on exposed population. We converted the extreme sea levels into high-resolution (30 arc seconds, approximately 1 km x 1 km at the equator) flood maps using a simple, planar inundation model (Muis et al., 2016). To calculate anomalies in flood exposure, inundation maps are simulated for the average 95th annual percentiles over El Niño, La Niña and neutral years. We assess the significance by using the 95% confidence levels of thepercentiles of the neutral years based on bootstrapping.

Inundated areas are defined as areas that have an elevation lower than the extreme sea level and have a direct connection to the sea. As Digital Elevation Model (DEM), we use Shuttle Radar Topographic Mission (SRTM). The original resolution of SRTM is 3 arc-seconds (~90 m x ~90m at the equator), but we use the resampled data at 30 arc-seconds resolution (~1 km x ~1 km at the equator) obtained from CGIAR-CSI (Jarvis et al., 2008). We use the resampled version of SRTM to lower the computational costs, as well as to be consistent with the resolution of the used global population map (see next paragraph). The vertical resolution of SRTM is 1 m, however in many places the vertical accuracy is much lower due to vegetation biases and systemic errors (e.g. Rodríguez et al., 2006; Sampson et al., 2016). Before combining GTSR with SRTM, we convert the vertical datum of the extreme sea levels from mean sea level (MSL) to EGM96 geoid, the reference level of SRTM (Muis et al., 2017). Flood protection is not included in the analysis.

The number of people potentially exposed to flooding is calculated by overlaying the inundation maps with population density. We use the Gridded Population of the World (GPW), adjusted for United Nations total, for the year 2015 (Balk et al., 2011; CIESIN et al., 2011). This map has a resolution of 30 arc-second (approximately 1 km resolution at the equator). Next, we aggregate the number of people potentially exposed to flooding at country and regional level (province, department, states) using the Global Administrative Boundaries (GADM) dataset.

# Results and Discussion

## Validation of seasonal and interannual variability in mean sea levels

To improve the GTSR dataset for use in applications of interannual variability, we add a mean sea level component to account for steric affects (referred to as GTSR-ST). To validate the monthly mean sea levels, we calculate the correlation between the observed and modelled sea levels (Table 2). Across all 1056 tide gauge stations, the average correlation is 0.65 for GTSR-ST, compared to 0.56 for GTSR. There is good performance in regions like northern Europe and eastern Asia (Pearson's *r* >0.8). The performance is poor (Pearson’s *r* < 0.4) in regions where the variability is below 0.1 m. Supplementary Fig. 1 shows the correlations for individual tide gauge stations. The validations of GTSR and GTSR-ST shows that there are major improvements in the performance using the latter, particularly in the tropical Pacific.

To analyze the performance in more detail, we decompose the monthly mean sea levels into a seasonal and interannual component. Figure 1a shows that there is a strong seasonal component with a range in the order of tens of centimetres. Compared to observed sea levels, GTSR severely underestimates the seasonal range in all regions across the globe, except for the coasts along the Arabian Sea, Chinese Sea, and near Cape Agulhas, South Africa (Figure 1c). In the tropical Pacific, there is a severe underestimation of the seasonal range. Adding the steric component leads to a better representation of the seasonal cycle (Figure 1e), particularly along the coasts of Pacific islands, western Australia, and the southwest of the United States. Along the coasts of northern Europe and Russia, as well as several other regions, the seasonal component is still underestimated. Supplementary Fig. 2 shows the performance of GTSR and GTSR-ST for the seasonal variability in more detail for the United States. Averaged across all tide gauge stations, the relative bias of GTSR-ST is -8%, compared to -50% for GTSR. The correlation coefficient between observed and modelled seasonal sea levels is 0.67 for GTSR-ST and 0.58 for GTSR (Table 2). Overall, the inclusion of steric levels leads to a large improvement in the performance of the modelled sea levels.

Figure 1b shows that the interannual component is generally smaller than the seasonal component. Interannual variability is relatively large along the coasts of the Pacific islands, the Baltic, and west Australia. The underestimation of the interannual variability in GTSR is generally more severe than for the seasonal component (Figure 1d). This may be explained by the fact that in some regions the seasonal cycle is partly driven by changes in pressure and wind, while for interannual variability changes in mean sea level are more important. Adding the steric sea level improves the performance, but there is still a considerable underestimation of the interannual variability (Figure 1f). Supplementary Fig. 3 shows the performance of GTSR and GTSR-ST for the interannual variability in more detail for the United States. Averaged across all tide gauge stations, the correlation between observed and modelled interannual sea levels increases from 0.47 to 0.52 (Table 2). The poorer increase in performance between GTSR and GTSR-ST can be partly explained by the smaller range of the interannual variability itself. As a result, for some regions the range of the interannual variability is smaller than 5 cm, which may be within the noise of the dataset. In addition, as our approach is based on steric sea levels, we do not capture the full variability of mean sea levels. This may, for example, explain the poor performance along the Australian coast.

## Sensitivity of extreme sea levels to ENSO

Figure 2a-d shows where the annual 95th percentiles are significantly correlated with SOIDJF for the sea level components we consider (e.g., surge, surge + steric, steric, surge + steric + tide). For all components, there is a clear geographic pattern with increased annual percentiles in the East Pacific Ocean (i.e. east coast Americas and Polynesia) during El Niño and decreased annual percentiles in the West Pacific, Indian, and South Atlantic Ocean (i.e. west coast of South America, East African coast and Southeast Asia). Reverse effects are seen for La Niña. These patterns are consistent with previous studies based on tide gauge stations (Barnard et al., 2015; Feng et al., 2004; Menéndez & Woodworth, 2010; Torres & Tsimplis, 2014; Woodworth & Blackman, 2004). For the surge levels, correlations are significant for 27% of the output locations, with values up to 0.73 (Figure 2a). This suggests that ENSO-induced variability is to some extent driven by variability in storminess, and not just steric effects. For the surge and steric component combined, correlations are significant for 20% of the output locations, with values up to 0.76 (Figure 2c). Adding the steric sea levels to the surge levels results in higher correlations for 79% of the locations. For the total sea levels, which include tides, correlations are significant for 17% of the output locations, with values up to 0.69. Hence, adding the astronomical tides generally lowers the correlations. This is to be expected, as the deterministic variability of astronomical tides is unrelated to climate variability, and tides account for a large part of the variability in extreme sea levels at many locations.

We test the sensitivity of our results by repeating the analysis with the 90th, 99th and 99.9th annual percentiles and using other ENSO indices (SOI, ONI and MEI). Results shown in Supplementary Fig. 4 show the spatial pattern to be robust to the use of different ENSO indices. Supplementary Fig. 5 indicates that the negative ENSO correlations along the west coast of the Americas are very sensitive to the use of different percentiles. For the 90th and 95th percentile, we see significant negative correlations along large parts of the west coast of North America, whereas the significance largely disappears for the 99th and 99.9th levels. Generally, the strength of the correlation weakens when using higher percentiles, which can be explained by the fact that higher percentiles are more influenced by the largest events.

Generally, the spatial pattern is also robust to the use of different lag times. Figure 3 shows that adding lag times increases the number of significant correlations. For the surge component, correlations are significant for 36% with values up to 0.75. For the surge and steric components combined, correlations are significant for 28% of the GTSR locations with values up to 0.79. Hence, there is generally a decrease in the number of significant locations, particularly along the Atlantic coast of South America, but an increase in the strength of the correlation when adding the steric component. Particularly along the Pacific coast of South America and along the coasts in the Indo*-*Pacific, there are lag times of more than 4 months.

## Anomalies in flood hazard

Figure 4a-b shows the significant anomalies in surge and steric level combined during ENSO years compared to neutral years. During La Niña years, there are very few regions with a spatially coherent signal. Generally, the anomalies in annual percentiles are within 10% of the neutral years, except for a small number of isolated locations. During El Niño years, there is a positive anomaly in the South-Atlantic, Indian Ocean and the West Pacific (e.g. southeast Asia, north western Australia, western and southern Africa), whereas there is a negative anomaly in the East Pacific (California, Colombia, Ecuador, Peru). The anomalies have a magnitude of up to several tens of centimetres. The significance of the anomalies largely disappears for the total sea levels (Figure 4c-d), when tides are added to the surge and steric components. This is because in many parts of the world total sea levels are more strongly influenced by the deterministic tidal component than by ENSO. Hence, it is difficult to identify any potential influence of ENSO using these relatively short time-series as the effects are obliterated by the large tidal variability. Our results show that while ENSO has a significant effect on extreme sea level in some regions, the anomalies are rather small compared to the total variability in extreme sea levels, and therefore cannot be detected. This is also because of large statistical uncertainties, which we discuss in Section 4.

## Anomalies in flood exposure

Further, we assess whether the ENSO induced anomalies in extreme sea levels influence changes in the number of people potentially exposed to flooding. As tides greatly distort the ENSO signal in extreme sea levels, we focus on the anomalies in the surge and steric component of the 95th percentiles. Hence, to calculate flood exposure we express extreme sea levels as the 95th percentiles of the surge levels and steric sea levels combined with the average high tide at each location. The results indicate that at the globally aggregated-scale there is little difference in the number of people potentially exposed to flooding, with 76.0 million in El Niño years, 75.2 million in La Niña years, and 75.2 million in neutral years. This is to be expected, as ENSO phases lead to opposite impacts in different regions of the world. Hence, there are larger anomalies at sub-national scale for example in Indonesia and Peru. While the results are consistent with the conclusions for the sea level anomalies, most of the differences in flood exposure at sub-national level are not statistically significant, and there is no coherent spatial pattern. Supplementary Fig. 6 maps the flood exposure at sub-national scale. Overall, the analysis demonstrates the differences in flood exposure under the influence of ENSO are likely to be minor, however because of large uncertainties in global assessments of flood exposure we cannot draw a final conclusion.

# Limitations and directions for future research

Our analysis has a number of limitations. Here we summarize the key limitations of the various parts of our methodology and discuss directions for future research. First, our model framework does not show the full picture of sea level variability. We assess variability in mean sea levels based on steric sea levels, and therefore we exclude mass-contributions as well as remote effects. Our results could possibly be improved by carefully assessing which remote locations give the best performing signal for each location, rather than using the nearest location. However, this will still ignore the mass contribution to the variations in mean sea levels. Another direction for further improvement may be to combine GTSR with ocean reanalysis data such as SODA, but applying a low-pass filter to GTSR to first remove all seasonal and interannual variability. It is also worth investigating whether the framework could be adjusted to fully include the effects of tropical cyclones as it is known that ENSO influences tropical cyclone activity (e.g. Kuleshov et al., 2008; Yonekura & Hall, 2014). Tropical cyclones are underestimated in the GTSR dataset as they are not fully represented by ERA-Interim. The use of tropical cyclone track data or higher resolution climate models may be possible ways to overcome this issue. As it is known that ENSO influences tropical cyclone variability around the world (Chan, 2000; Feng & Tsimplis, 2014; Kuleshov et al., 2008; Saunders et al., 2000; Torres & Tsimplis, 2014), and as tropical cyclones often induce the most extreme surge this may also lead to a larger signal of ENSO in extreme sea levels. Finally, for our analysis we focused on the effect of ENSO on coastal flooding induced by the combination of astronomical tides and storm surges. However, ENSO may also induce changes in wave direction and energy, which can result in large coastal impacts due to beach erosion (Barnard et al., 2015, 2017). Hence, future research should aim to include the wave component, for example by implementing approaches similar to Vitousek et al. (2017) or Vousdoukas (2017).

Second, there are large uncertainties related to the statistical analysis. Using longer simulations, would provide a larger sample and increase the statistical confidence. This could be achieved by forcing GTSM with the 20th Century Reanalysis (20CR), which spans the years 1871 to 2010. Although there are some inconsistencies in this dataset for long-term trends (Krueger et al., 2013), it would provide a larger sample and increase the statistical confidence. The use of very long time-series from climate ensemble simulations also has the potential to reduce the uncertainties (van den Brink et al., 2004; Shimura & Mori, 2017). A larger sample would also allow for the estimation of return periods conditioned on the different ENSO phases (Ward et al., 2014). Such an approach was investigated for this study by fitting a Gumbel distribution to the annual maxima. However, because of the relatively short records, the uncertainties associated with the Gumbel distribution are much larger than the differences in probabilities. We tried reducing the uncertainty by using the peak-over-threshold method. The peak-over-threshold method is however very sensitive to the threshold level and individual extreme events, and as such the methods is not capable of identifying a reliable ENSO signal. Longer simulations may reveal the influence of ENSO, but may also allow the extension of the framework to other ocean-atmosphere oscillations, like the Pacific Decadal Oscillation and the North Atlantic Oscillation. These oscillations act on different time-scales but may also induce interannual variability to coastal flood probabilities (e.g. Marcos et al., 2015; Wahl & Chambers, 2015).

Third, a methodological issue connected to the analysis of flood exposure is the accuracy of available global elevation products. While the vertical errors of SRTM could be reduced by error-removing algorithms like those used by Yamazaki et al. (2017), the vertical resolution of 1m remains a challenge with no ready-made solutions. SRTM elevation data have a vertical resolution of 1m, which is small in comparison to the magnitude of the sea level anomalies. The flood risk community has communicated an urgent need for an improvement of global elevation datasets (Sampson et al., 2016; Schumannm, 2014), and hopefully datasets with higher resolution and accuracy will become publically available in the future (e.g. Schumann et al., 2016; Zink et al., 2014).

# Conclusions and directions for future research

We have presented a first assessment of the influence of ENSO on coastal flood hazard and impacts on a global-scale. Using the GTSR dataset, we assessed ENSO's influence on individual components of extreme sea levels along the entire global coastline, including regions where there is a lack of tide gauge observations. Combining GTSR with steric mean sea levels (named here as GTSR-ST) greatly enhances the model performance in regions where there is a large seasonal and/or interannual signal. Both the 95th annual percentile of the steric sea levels and surge levels are strongly correlated with ENSO. The average anomalies in the 95th annual percentile over the El Niño years compared to neutral years show similar spatial patterns as the correlations. For La Niña, the average anomalies are smaller and do not show a coherent spatial pattern. The significance of the anomalies for El Niño largely disappear when analyzing total sea levels, which include tides. This is to be expected as tides are unrelated to climate variability and account for a large part of the variability in extreme sea levels at many locations.

Our results confirm the influence of ENSO on extreme sea levels, which has been reported in previous studies based on tide gauge stations. Using the GTSR reanalysis of extreme sea levels has the advantage that we have a full global coverage with a consistent time period for all locations, and that we can more easily assess the influence for the individual components of extreme sea levels. An additional advantage of using a model-based approach is that it allows for an estimation of the influence of ENSO on coastal risks. This can be achieved by coupling the sea level extremes with an inundation and impact model. Such a model-based approach also allows for the assessment of impacts of changing ENSO frequencies in future climates, which may become an important topic as recent studies point out the possibility of more frequent extreme ENSO events (e.g. Cai, Santoso, et al., 2015; Wang et al., 2017).

As an illustration of such applications, we assessed ENSO's influence on the number of people potentially exposed to flooding. We conclude that there may be a small influence of ENSO on flood exposure, but results are impacted by the large uncertainties in the elevation datasets used.

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The data used are listed in the references. The Ishii dataset used to calculate the steric sea levels can be downloaded here <http://amaterasu.ees.hokudai.ac.jp/~ism/pub/ProjD/v6.13/>. The EN dataset 4.1.1 can be downloaded here: <http://www.metoffice.gov.uk/hadobs/en4/download-en4-1-1.html>. Daily maxima from the GTSR dataset will be uploaded to a data repository. Data deposition is underway, but incomplete. The authors understand that if the manuscript is accepted data deposition must be completed before publication.

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Table 1 Years categorized as El Niño and La Niña.

|  |  |
| --- | --- |
| ENSO Phase | Years |
| El Niño  | 1979, 1982, 1986,1987, 1991, 1994, 1997, 2002, 2004, 2006, 2009 |
| La Niña  | 1983, 1984, 1988, 1995, 1998, 1999, 2000, 2007, 2010, 2011 |
| Neutral | 1980, 1981, 1985, 1989, 1990, 1992, 1993, 1996, 2001, 2003, 2005, 2008, 2012, 2013 |

Table 2 Performance of the GTSR and GTSR-ST sea levels. We show the mean and standard deviation (S.D.) of the Pearson’s correlation coefficients (r) between observed sea levels from PSMSL and modelled sea levels. We show the correlations for monthly mean sea levels, as well as for the seasonal and interannual monthly mean sea levels. We also show the relative bias for the seasonal range and interannual range.

|  |  |  |
| --- | --- | --- |
|  | Correlation(r) | Relative bias(%) |
|  | GTSR | GTRS-ST | GTSR | GTRS-ST |
| Monthly mean sea levels | 0.56S.D. 0.25 | 0.65S.D. 0.26 | - | - |
| Seasonal sea levels | 0.58S.D. 0.27 | 0.67S.D. 0.28 | -49.3S.D. 31.3 | -8.0S.D. 50.9 |
| Interannual sea levels | 0.47S.D. 0.33 | 0.52S.D. 0.35 | -57.7S.D. 77.4 | -26.5S.D. 84.6 |

Figure 1 The range of the seasonal cycle and interannual variability for monthly mean sea levels over the period 1979-2014. The observed seasonal cycle is shown in panel a, based on tide gauge stations from PSMSL. The observed interannual variability is shown in panel b. Panels c, d, e, and f show the ratio of the observed and modelled range of the seasonal and interannual variability for GTSR and GTSR-ST.

Figure 2 Kendall's rank correlation (*τ*) between SOIDJF and the 95th annual percentile for the various sea level components. We show the results for a) daily maximum surge levels, b) monthly mean steric sea levels, c) daily maximum from the combination of surge and steric sea levels, and d) daily maxima from the combination of surge, tide, and steric sea levels. We only show correlations that are statically significant (α = 0.05). Negative correlations (blue colours) indicate higher annual percentiles under El Niño conditions/lower annual percentiles under La Niña conditions, while positive correlations (red colours) indicate lower annual percentiles under El Niño conditions/higher annual percentiles under La Niña conditions.

**Figure 3** Highest Kendall rank correlation (τ) between 3-month smoothed SOI and the 95th annual percentile using lag times between 0 and 6 months for a) surge levels, and b) surge and steric sea levels. Panel c) and d) show the month that results in the highest τ. Negative correlations (blue colours) indicate higher annual percentiles under El Niño conditions/lower annual percentiles under La Niña conditions, while positive correlations (red colours) indicate lower annual percentiles under El Niño conditions/higher annual percentiles under La Niña conditions.

Figure 4 Anomalies in extreme sea levels, expressed as the 95th percentile, during a and b) La Niña years and c and d) El Niño years (compared with all neutral years). We only show statically significant correlations (α = 0.05).