

Extreme Storm Surge estimates and projection through the Metastatistical Extreme Value Distribution

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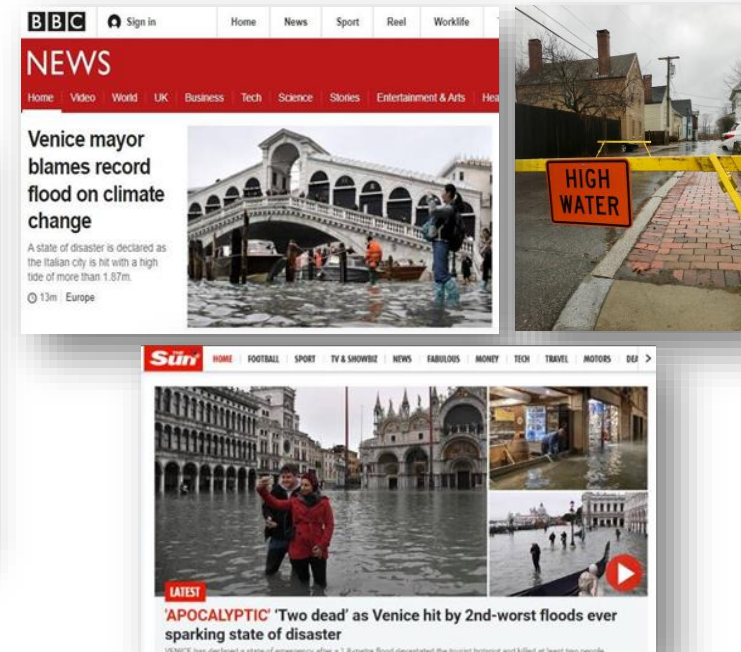
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Coastal flooding hazard has been **increasing** at global scale in recent decades and it is expected to continue as a result of climate change (Meehl et al., 2007; Church et al., 2013).



The **reliable** estimation of the occurrence probability of coastal flooding events of large magnitude is crucial to:

- quantify and reduce risk;
- design adequate coastal defense structures.



Aim of the work:

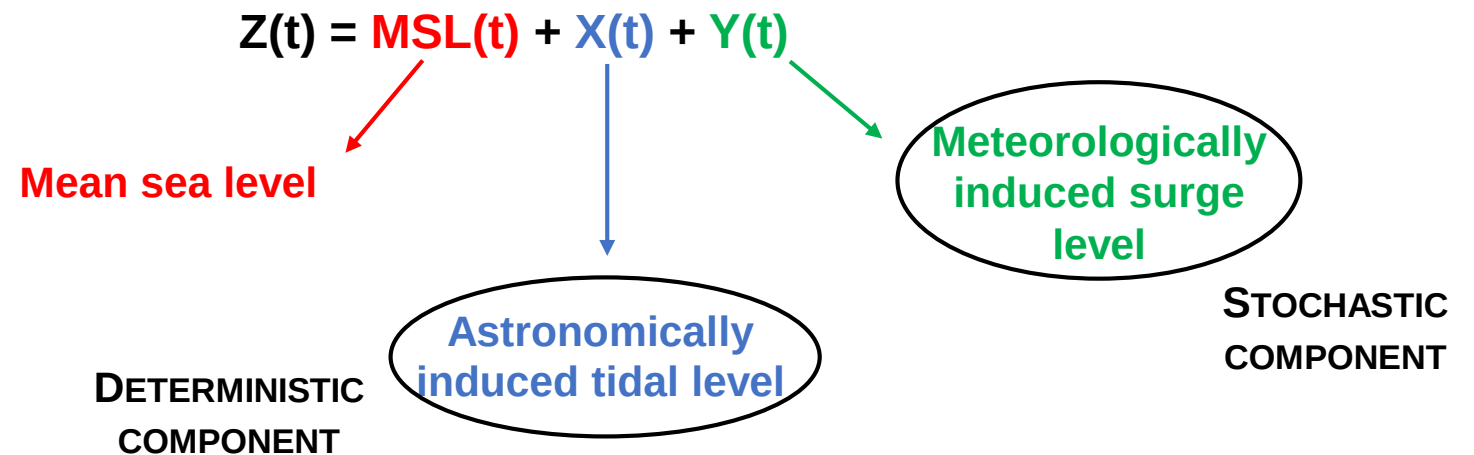
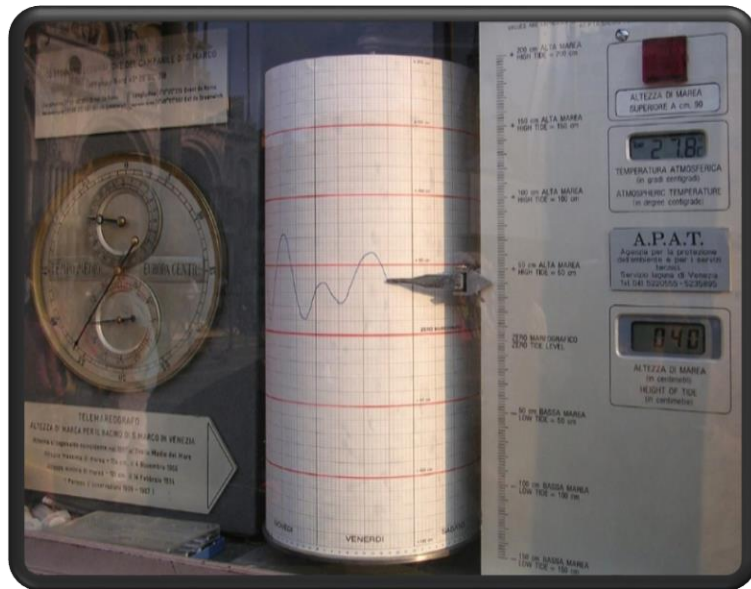
Optimal use of the available information in order to:

- 1) provide a useful and reliable statistical tool to estimate the long-term behaviour of extreme storm surges;
- 2) understand how climate change will affect the extreme sea-level distributions.

How?

- We comparatively analyze the **performance** of the generalized Extreme Value (GEV) distribution, with the block maxima (BM) and peak-over-threshold (POT) framework, and the recently-proposed Metastatistical Extreme Value Distribution (MEVD) in high-quantile estimations.
- We evaluate predictive uncertainty by adopting a cross-validation (CV) approach, in which calibration and test samples are kept separate and independent.
- We investigate the influence of **future sea-level rise** on storm surges frequencies: we consider only the influence of an increased mean sea level (no changes in local “storminess”).

The observed sea level, $Z(t)$, can be considered as the sum of three components (*Pugh and Vassie, 1979*):



HOW TO ANALYZE OBSERVED EXTREME SEA LEVEL?

- ❑ We use direct methods: no separation of the tide (X) and surge (Y).
- ❑ We infer the distribution of their sum: $H(t) = Z(t) - \text{MSL}(t)$.
- ❑ We compute **MSL** on yearly basis.

Marani and Ignaccolo, 2015; Zorretto et al., 2016

MEVD for yearly maxima:

$$\zeta(x) \cong \frac{1}{M} \cdot \sum_{j=1}^M [F(x; \overrightarrow{\theta}_j)]^{n_j}$$

where:

$F(x; \overrightarrow{\theta}_j)^{n_j}$ = c.d.f. of **ordinary events** (i.e. any storm surge water elevation);

θ = parameters vector;

n = number of exceedances/year;

M = number of years on record.

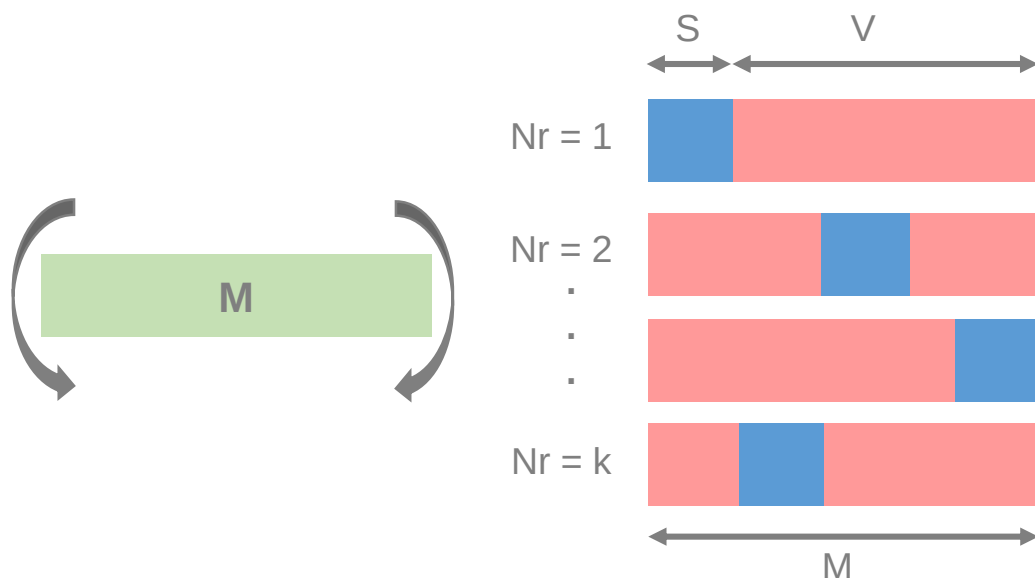
Advantages

- ❖ No asymptotic hypotheses.
- ❖ No hypotheses about distributions.
- ❖ Use of the available sample.
- ❖ Accurate parameters estimation.
- ❖ Inclusion of different storm-surge generating phenomena (i.e. TCs or hurricanes).

MEVD has been shown to **outperform** the traditional GEV distribution in several applications:

- hourly and daily rainfall gauge record (Miniussi and Marani, 2020; Miniussi et al., 2020b; Schellander et al., 2019; Marra et al., 2018; Zorretto et al., 2016; Marani and Ignaccolo, 2015);
- satellite rainfall observations (Zorretto et al., 2019);
- flood peak discharge (Miniussi et al., 2020a);
- extreme hurricane intensity (Hosseini et al., 2020).

Cross-Validation procedure and parameters estimation



M: sample length.

S: calibration sample → parameters estimation.

V = M-S: validation sample → accuracy.

Nr: number of realizations.

PARAMETERS ESTIMATION

BM: Probability weighted moments (PWMs)

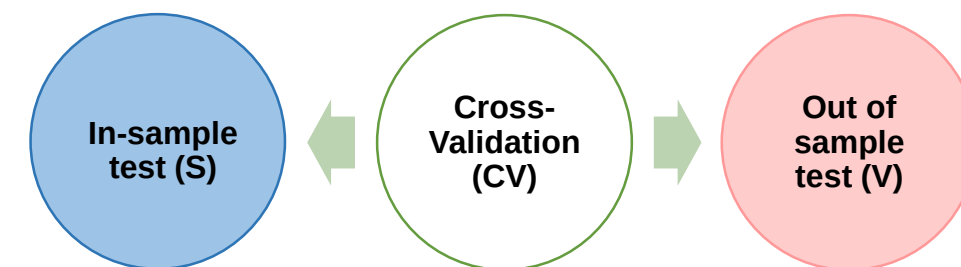
POT: Probability weighted moments (PWMs)

MEVD: Probability weighted moments (PWMs) on non-overlapping estimation windows of 5 years

- Randomly reshuffling the years on record.
- Storm surges occurring in each year are preserved.



This removes possible non-stationarity and correlation in the time series.



S = 5, 10, 20 and 30 years

V = M-S years



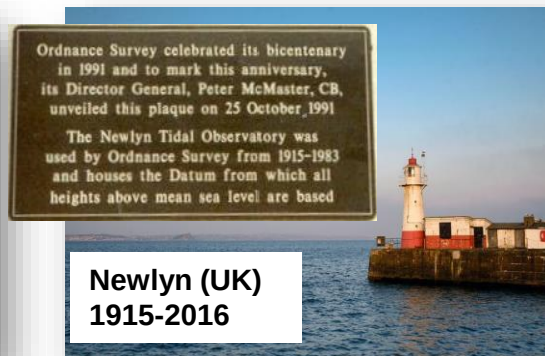
Non dimensional error (NDE)

$$NDE_k(S, Tr) = \frac{x_{est,k}(S, Tr) - x_{obs,k}(S, Tr)}{x_{obs,k}(S, Tr)}$$

We use **long time series** of sea-level observations distributed along European coastlines (4 sites).



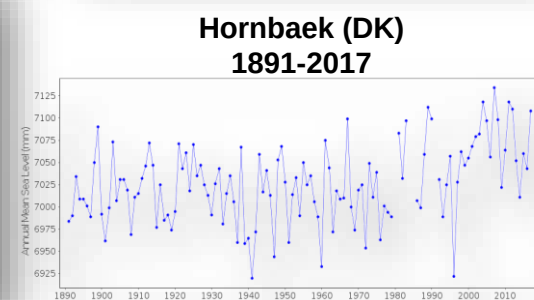
Venice (IT)
1872-2019



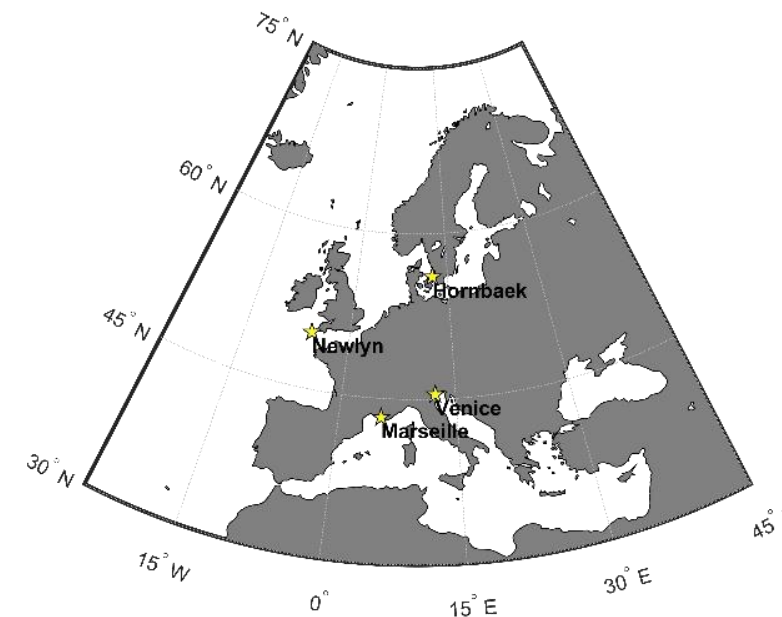
Newlyn (UK)
1915-2016



Marseille (FR)
1885-2018



Hornbaek (DK)
1891-2017



Site name	Country	Location (degree, minutes)		Period	Missing years (%)	Deleted years	Number of years
		Lat.	Lon.				
Venice	Italy	45° 25.0' 50.41" N	12° 20' 10.99" E	1872-2019	-	-	148
Hornbæk	Denmark	56° 06.0' N	12° 28.0' E	1891-2012	-	1985	121
Marseille	France	43° 16.7' N	05° 21.2' E	1885-2018	14.18	1897; 1918; 1919; 1928; 1937; 1940; 1998; 2009; 2010	106
Newlyn	United Kingdom	50° 06.1' N	05° 32.5' W	1915-2016	-	1984; 2010	100

Sea-level records after pre-processing

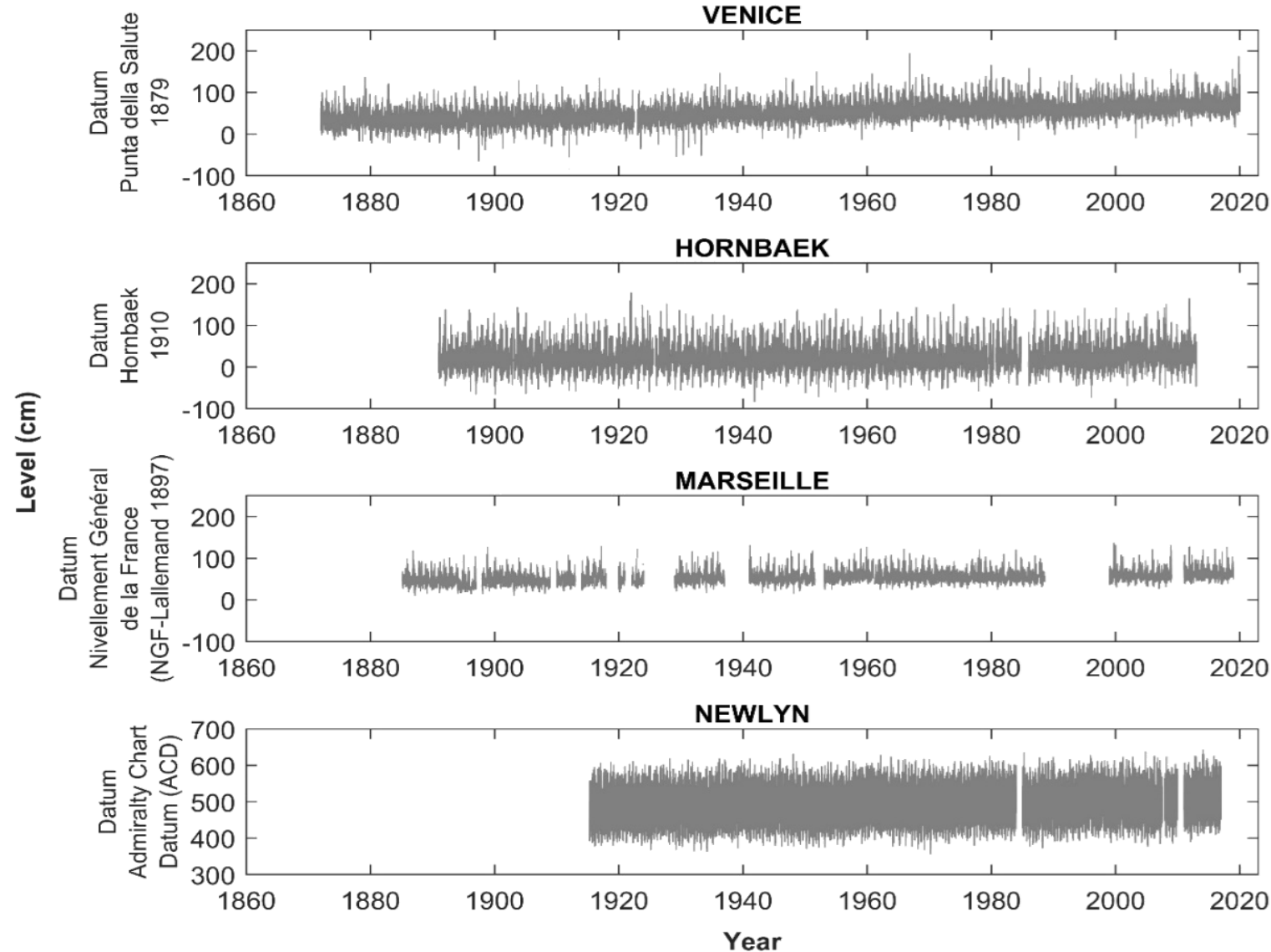
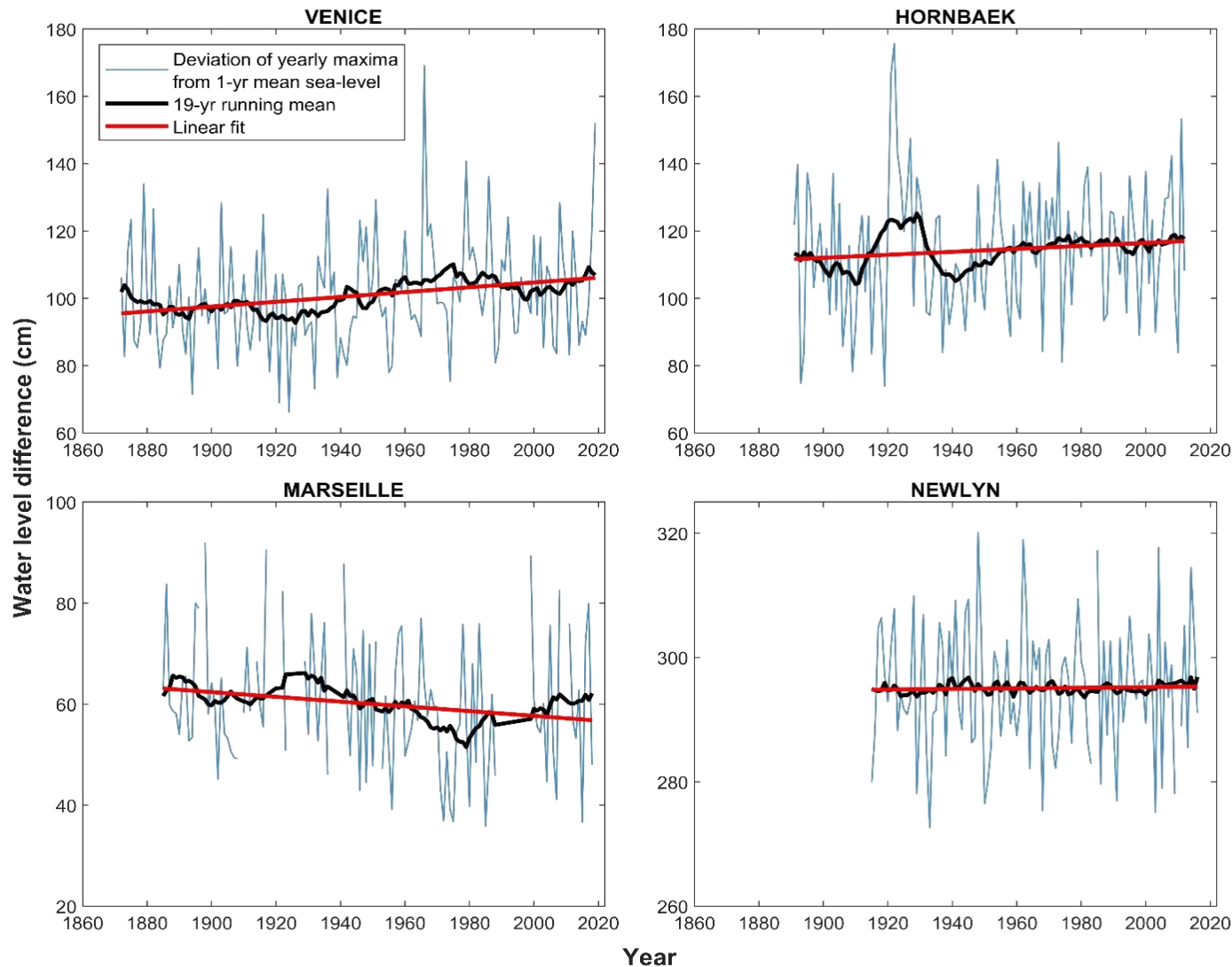


Figure 1. Daily maximum sea levels at different gauge stations explored after pre-processing: Venice (IT), Hornbæk (DK), Marseille (FR) and Newlyn (UK).

Sources: *Centro Maree Comune di Venezia* and *University of Hawaii Sea Level Center*.



Results – Is there any trend?



Is the trend statistically significant?



Mann-Kendall test
(Mann, 1945; Kendall, 1975)

- $\alpha = 5\%$
- $H_0 = \text{no trend}$
- $H_1 = \text{trend}$

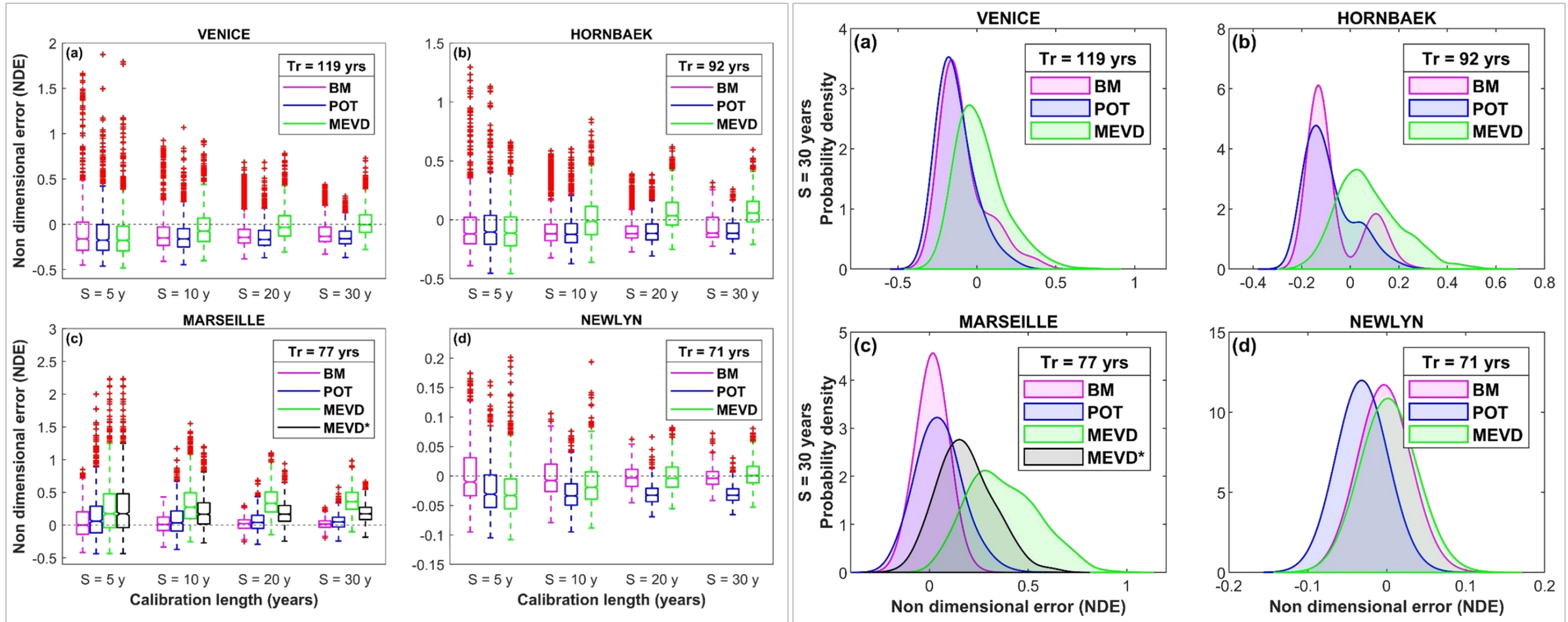
$p\text{-value} < \alpha \rightarrow H_0 \text{ is rejected}$



**There is a trend only for Venice
gauge station!**

Figure 2. Deviation of yearly maxima from yearly mean sea-levels (blue line), 19-yr running mean (black line) and linear fit (red line) at a given site.

Figure 3. Distribution of the Non Dimensional Error (NDE) for maximum sample return period (Tr), represented by box-plots (left panel with different calibration sample size (S)) and probability density (right panel obtained with $S = 30$ years), at given gauge stations explored: (a) Venice (IT); (b) Hornbæk (DK); (c) Marseille (FR); (d) Newlyn (UK). In the case of Marseille (FR), parameter estimation is based: 1) green color: on non-overlapping sub-samples of fixed size (5 years), and 2) black color: on data from the whole calibration sample.



Venice, Hornbæk and Newlyn cases.

When we focus on events with a fixed high return period and short samples (5 years), different sites display variable results. Instead, when we consider **larger calibration sample sizes** (from 10 to 30 years), the MEVD-based estimates outperform the traditional approaches for most gauge stations explored.

Marseille case:

Results display an inferior predictive performance of MEVD with respect to GEV-based approaches.

In order to understand these results, we performed MEVD parameter estimation using two approaches:

- 1) *GREEN COLOR*: estimation based on non-overlapping calibration samples of fixed size (5 years as for the other sites);
- 2) *BLACK COLOR*: parameter estimation on data from the whole calibration sample.

However, in this case GEV-BM is advantageous because the small number of events/year does not provide a more numerous calibration sample with respect to the sample of annual maxima.

Results – Future extreme storm surges

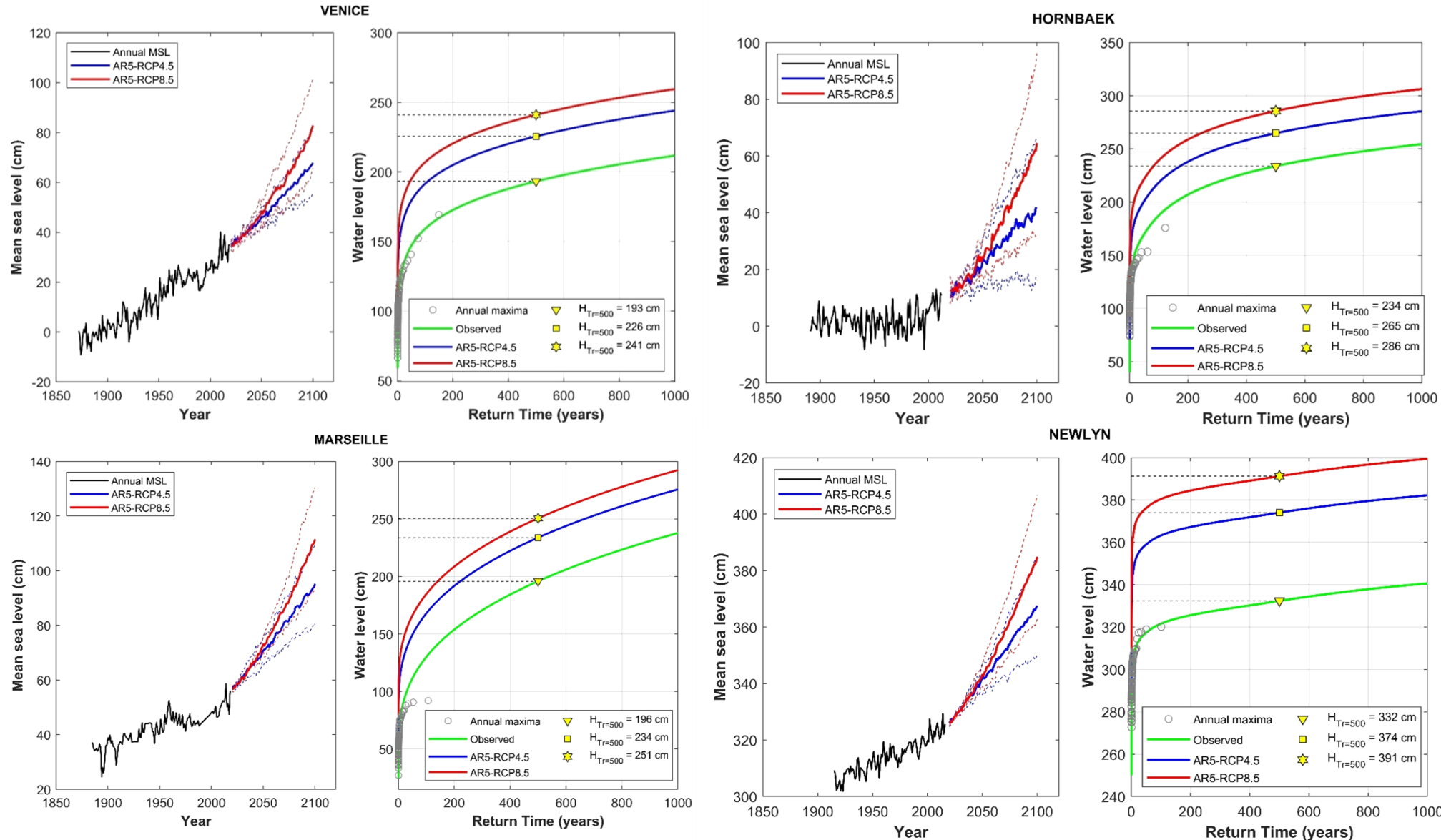


Figure 4. Sea level projections until 2100. For every gauge station explored:

1) Left panel: annual (black line) and future mean sea level until 2100 with RCP4.5 (blue line) and RCP8.5 (red line). Dashed lines represents the 95% confidence intervals.

2) Right panel: return levels curves for extreme water level. Green curve represents the MEVD estimates from observed record; blue and red curves represent the estimates including projected sea-level rise (SLR) until 2100 respectively with RCP4.5 (blue) and RCP8.5 (red); grey dots are yearly sea level observed. Triangle, square and pentagon are the heights of storm surges for a fixed return period equal to 500 years.

Source: IPCC-AR5 Sea Level Rise collected in the “Integrated Climate Data Center (ICDC)” by University of Hamburg.

- ✓ Storm surge data are highly correlated: data must be pre-processed by removing the mean sea-level trend.
- ✓ The use of independent calibration and test sample quantify the "real" uncertainty in the high-return period quantiles estimation.
- ✓ Similarly to other applications (rainfall, flood, hurricane intensity...), MEVD shows practical and conceptual advantages with respect to GEV distribution.
- ✓ MEVD reduces the estimation error in almost all the gauge stations explored especially when longer calibration sample sizes (S) are considered.
- ✓ MEVD can be successfully used to evaluate future storm surges.
- ✓ The projections indicate an increases in the height of storm surges for a fixed return period. These increases are spatially heterogeneous across the coastal locations explored.

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