Environment Systems and Decisions (2024) 44:1019–1028
https://doi.org/10.1007/s10669-024-09974-x

PERSPECTIVE

Estimation of return levels with long return periods for extreme sea levels in a time-varying framework

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Accepted: 27 April 2024 / Published online: 21 May 2024

Abstract

At nuclear power plants, risk analysis concerning environmental extremes is crucial. Based on historical data, estimation of return levels is usually performed. For long return periods, a problem is that the related uncertainties of the return levels often get large. Moreover, models need to take into account possible effects of climate change. In this paper, extreme sea levels close to Swedish nuclear power plants are considered. Non-stationary statistical models and the related results of conditional prediction during a typical time horizon of an infrastructure are studied. The influences of parameters in extreme-value distributions and the lengths of observation records are discussed. The effect of land uplift in parts of the Baltic Sea is seen.

Keywords Risk analysis · Extreme values · GEV distribution · Non-stationary models · Return levels · Climate change

1 Introduction

For risk analysis and assessment, e.g. in the domain of nuclear safety, statistical methodology is of main importance. Statistical analysis of environmental extremes (e.g. temperature or sea level) is a particular field of study. A key issue in extreme-value analysis is that available data series usually are quite limited (typically some decades of data), which implies problems since the probabilities of interest related to the risk scenarios usually are low.

An important measure of risk is the notion of return level, related to a specified return period. For instance, the annual maximum temperature exceeded with a one percent probability in any year is called the 100-year temperature. Several techniques for estimation of return levels from data are well established, e.g. based on the so-called method of block maxima or the POT (Peaks Over Thresholds) method; see, e.g. Coles (2001) for an overview. Facing climate change, statistical frameworks for non-stationary analysis have been introduced. Applications are found for several environmental quantities, and we here give just a few examples: variables like temperature (Rydén 2011, Hamdi et al. 2018), precipitation (Hao et al. 2019; Vu and Mishra 2019), or floods (Delgado et al. 2010, Rydén 2022). A review oriented towards hydroclimatic extremes is given by Slater et al. (2021). However, extension of the notion of return level is not easily made to the non-stationary case. In fact, some definitions have been made in the literature, e.g. by Parey et al. (2010); for a review, see Cooley (2013). Thus, a problem is that there is no unique way of defining the return levels.

Regulations and related safety levels in the field of nuclear engineering are often related to long return periods; for instance, 10^4 years in the U.K. and 10^6 years in Sweden, respectively (Green 2017; SSM 2021). Moreover, it is of interest to consider the actual, or rather intended, lifetime of an infrastructure. This typically is of the order 100 years. Hence, there is a benefit of studying these low risks over a considerably shorter time horizon. A framework for such studies was initiated by Hamdi et al. (2018), where the notion of *conditional prediction* was introduced. Examples were given with 100-year levels of temperatures in France. A software package in the R language, NSGEV, was presented, which also renders uncertainties of the estimated return levels by various methods (R Core Team 2024; Deville 2022). The authors stated about the merits of the methodology that "it provides high return levels for short-term horizons. This attractive feature makes it more interesting from a practical point of view."

In this paper, we extend the analysis by Hamdi et al. (2018). More precisely, we now study considerably longer

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return periods and another environmental variable of interest for nuclear safety, namely sea level. Stations close to Swedish nuclear power plants are considered. Further, related computed uncertainties are presented and the behaviour is also discussed from the perspective of the estimated shape parameter of a so-called GEV distribution at each location. As was claimed by Hamdi et al. (2018): "An in-depth study could help to thoroughly improve the NSGEV package and apply the developed concept at other sites of interest. The concept of conditional predictions and methodology developed here and the integrated return level definition should find additional applications for the assessment of risk associated with other hazards in other climate and geoscience fields (e.g. coastal hazards)". Thus, the present paper is in line with the views of the cited authors and provides a natural continuation of the work (e.g. other environmental variable, various sites, longer return periods).

The paper is organised as follows. In Sect. 2, a description of the datasets is given. A brief review of statistical extreme-value analysis is presented in Sect. 3, where also the aspects on estimation of return levels are discussed in some length, in particular the non-stationary framework. Results after the fitting of several models are given in Sect. 4 and a simulation study, motivated by some results, is presented in Sect. 5. Finally, in Sect. 6, a summary and concluding discussion is provided.

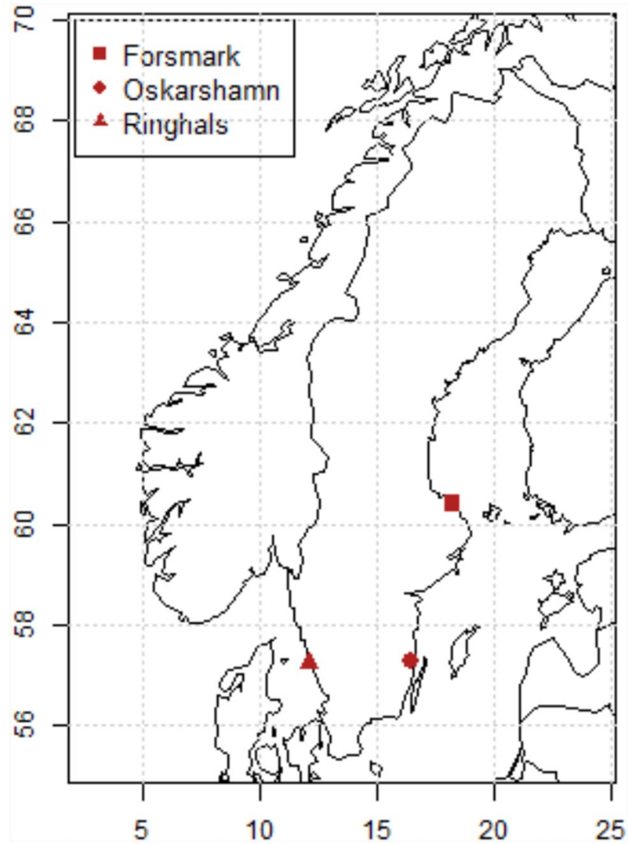

Fig. 1 Map over Scandinavia with the locations of measurement stations indicated

2 Data

Data in this study are hourly measurements of sea level (in cm) from recordings provided by the Swedish Meteorological and Hydrological Institute (SMHI). The sea levels are presented in the vertical reference system RH2000, the national height system in Sweden. In this study, the RH2000 values were kept in the statistical analyses, for the sake of simplicity; the main aim is to illustrate the non-stationary statistical framework presented. Observations can be corrected for relative sea-level change (i.e. isostasy and eustasy). See the document from SMHI (2013), where formulae for such corrections are given, and Posada (2014), Sect. 2.3, for an example.

A recent review on extreme events in the Baltic Sea region, also regarding other quantities than sea level, is given by Rutgersson et al. (2022). In the Baltic Sea, extreme sea levels could be caused by wind, air pressure (inverse barometric effect), and seiches. Concerning internal tides, the amplitude is at most places a few centimetres.

Three stations were considered, all located nearby Swedish nuclear power plants. Table 1 gives a summary including e.g. the lengths of records. Further, the locations are shown on the map of Scandinavia in Fig. 1, and time series of annual maxima are shown in Fig. 2.

Data quality was overall decent, with few major portions missing. Concerning extremes, the winter season yields more extreme observations and needs extra care in examination. Some gaps unfortunately happened during January for Oskarshamn and Ringhals. The treatment is described below.

2.1 Oskarshamn

There is a substantial gap in the time series for 1980: the period January 27 to April 7 is missing (and a few hours in January 26 and April 8). Measurements from a neighbouring site, *Ölands norra udde* (57.37, 17.10) were considered, and a comparison with the original data just before and after the gap period was made. An illustration for the period preceding the gap period is shown in Fig. 3, left panel. The series are quite similar, and as Ölands norra udde in fact had observations for the gap period, hence that period was examined. The maximum of the gap period was 38.8 cm. The tenth largest maximum during 1980 of the Oskarshamn series was 58.5 cm. Thus, the gap in the Oskarshamn series is not that serious with extremes in mind.

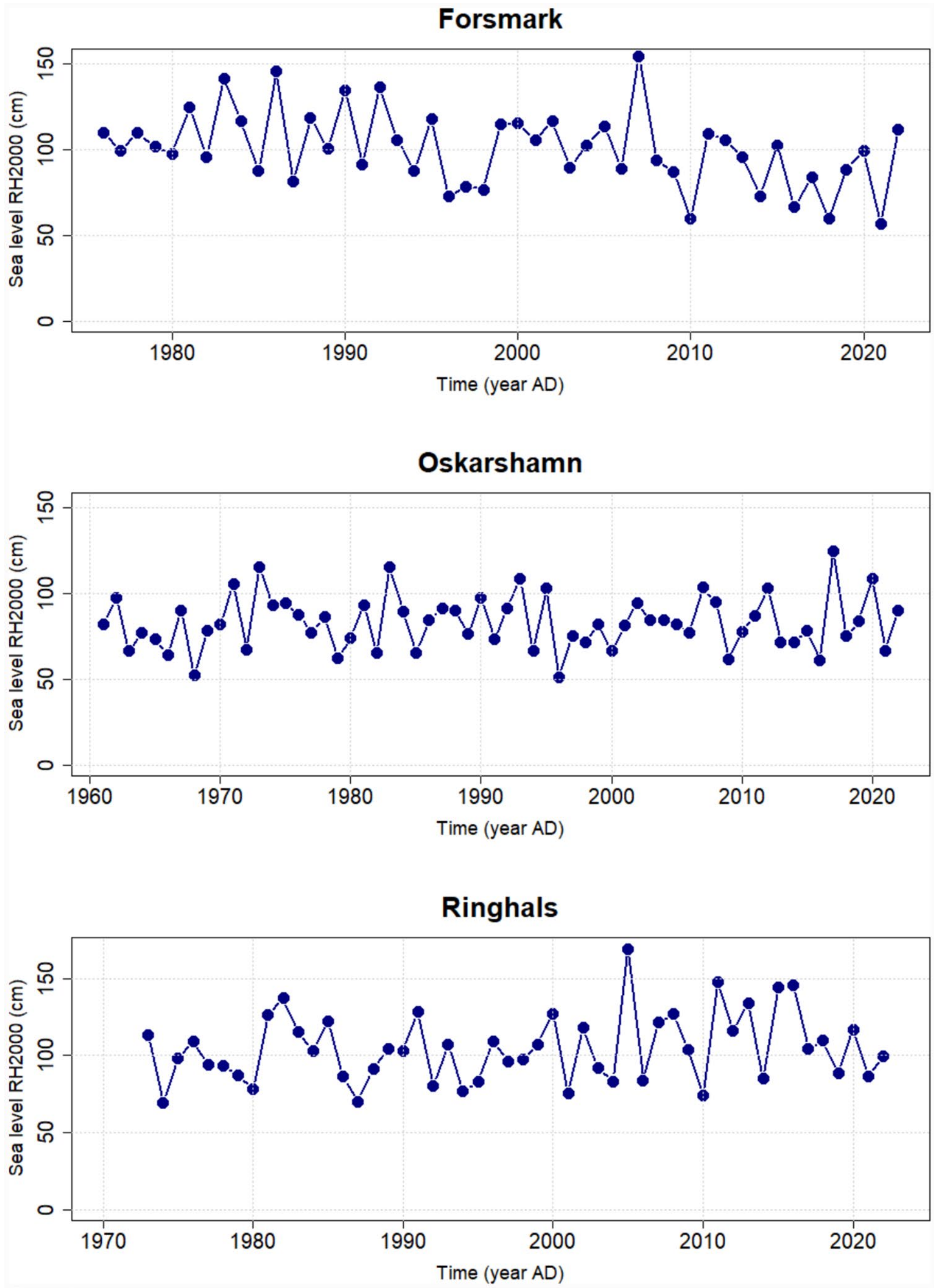

Fig. 2 Time series and annual maxima of sea level at the three locations under study

Table 1 Stations considered in the study

Station	Latitude/Longitude	Period
Forsmark	(60.41, 18.21)	1976-2022
Oskarshamn	(57.28, 16.48)	1961-2022
Ringhals	(57.25, 12.11)	1973-2022

2.2 Ringhals

Observations are missing in 2022, the period January 5 to January 11. This is within the winter season, and hence careful attention needs to be paid. Measurements from neighbouring site *Onsala* were considered for comparison (measurements started there at 2015). An illustration for the period preceding the gap period is shown in Fig. 3, right panel. The time series are close, and Onsala observations for the gap period could be analysed as a proxy. The maximum was found to be 56.9 cm, to be compared with, e.g. the tenth

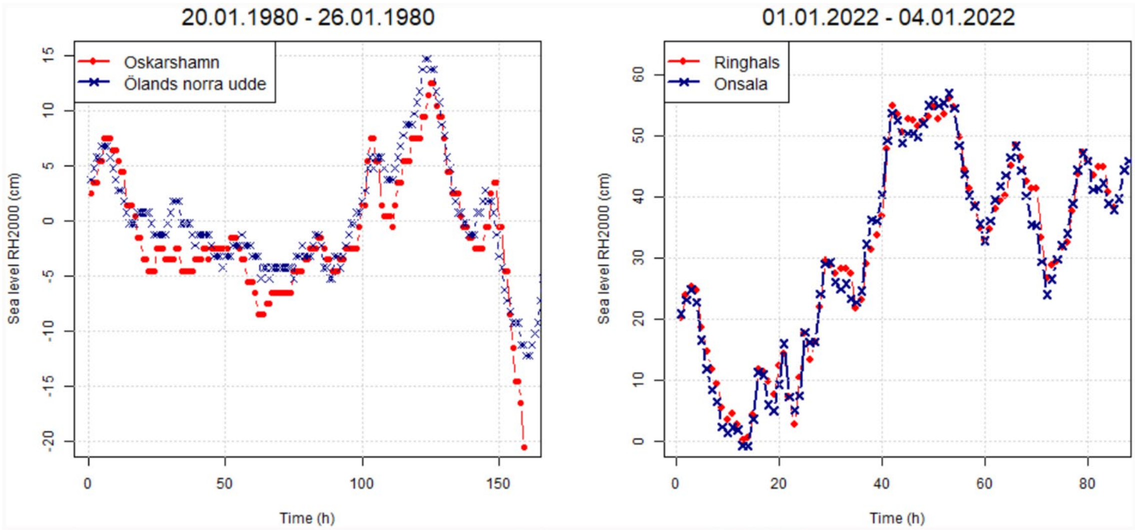

Fig. 3 Comparison of time series from nearby stations and interval preceding period of gap in time series of primary interest. Left panel: Oskarshamn and Ölands norra udde. Right panel: Ringhals and Onsala. In both situations, the neighbouring stations have a similar temporal behaviour

largest maximum during 2022 of the Ringhals series, 70.2 cm. Thus, the gap in the Ringhals is not that severe.

3 Statistical methodology

3.1 Extreme-value analysis

Statistical extreme-value analysis concerns the tails of distributions. The common approach, with roots to Gumbel (1958), is to fit a generalised extreme-value (GEV) distribution to a sample of independent annual maxima ("block maxima"). This then serves as the limiting distribution of independent maxima. The distribution function for the GEV distribution is given as

$$\mathrm{P}(X \leq x) = \exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\}, \quad (1)$$

defined on $\{x : 1+\xi(x-\mu)/\sigma > 0\}$ and where $\mu, \sigma > 0$ and ξ are the location, scale, and shape parameters, respectively (Coles 2001; Dey et al. 2016).

With the GEV distribution, three limiting distributions are unified. These have been studied historically as separate cases, and the shape parameter ξ is related to the nature of the tail. Still, there is interest in discussing these cases. If $\xi < 0$, the upper tail is bounded (reversed Weibull distribution); if $\xi = 0$, the tail decays exponentially (Gumbel distribution); and if $\xi > 0$, the tail decays as a power function (Fréchet distribution). In the case $\xi < 0$, the upper limit is given by $\mu - \sigma/\xi$.

When fitting a conventional GEV distribution to data, estimation is often performed using the maximum likelihood (ML) method. When $-1 < \xi \leq -0.5$, the ML estimate exists, but does not have the standard asymptotic properties. Often in practice, $\xi > -0.5$ (cf. Dey et al. 2016), which is also the case in this study.

3.2 Return levels: conventional analysis

The T-year return level, corresponding to a return period T, is often defined as the high quantile for which the probability that the annual maximum exceeds this quantile is $1/T$. In the stationary case, the return level can be interpreted in two ways: that the expected waiting time until the next exceedance is T years or that the expected number of events in T years is 1. For details and arguments, see Cooley (2013).

For a GEV distribution the return level follows from closed-form expressions as quantiles in the distribution:

$$x_T = \mu - \frac{\sigma}{\xi}\left[1-(-\ln(1-1/T))^{-\xi}\right]. \quad (2)$$

Estimates of return levels are obtained by in Eq. (2) simply plugging in the ML estimates of the parameters μ, σ, and ξ. The uncertainty of the return level is of interest to assess in risk analysis, and statistical procedures are, e.g. the delta method or profile likelihood. Usually the profile likelihood approach is preferred, as the delta method results in symmetric intervals.

3.3 Return levels: non-stationary formulations

Often the scale and location parameters in the GEV distribution are time varying and then assumed to be polynomial functions of time (Coles 2001). A simple example, for the location parameter, is

$$\mu(t) = \mu_0 + \mu_1 t, \tag{3}$$

where μ_0 and μ_1 are parameters, to be estimated. In practice, the shape parameter is kept constant (already in the stationary case, estimation of the shape parameter is more troublesome than for the other parameters). For comparison of time-varying statistical models, computation of the Akaike information criterion (AIC) can be made. This is a comparative measure; the lower, the better, in terms of predictive performance of the model. Another option is to employ likelihood ratio (LR) tests.

Concerning return levels and return periods, several notions have been discussed and suggested in the literature. Following Hamdi et al. (2018) and with predictions in mind, one can speak about two types: *conditional prediction* and *integrated prediction*. In the former case, return period is conditional to a fixed date relative to a future block. In the latter case, return period is integrated over a future period. The calculated return level then corresponds to an expected number of exceedances equal to one over that period.

Hamdi et al. (2018) emphasise advantages of the conditional return period, as there is no need to assume that the current trend will remain unchanged until far time horizons. This is valuable for planning and safety analysis. In this paper, we investigate results by conditional prediction as implemented in the R package NSGEV (Deville 2022). For instance, an algorithm with constrained optimisation is used for the inference based on profile likelihood. Details on the numerical work are found in the vignette related to NSGEV.

3.4 Special case: time-dependent location parameter

We first investigate the simple case of a time-dependent location parameter in a GEV, cf. Equation (3). Estimation is performed by maximum likelihood as implemented in the R package `extRemes`. In Table 2, for each station is presented the p-value of an LR test when comparing the model in Eq. (3) to a stationary model. A low p-value implies rejection of the null hypothesis of stationarity. Moreover, the point estimates of μ_1 are given, along with related standard errors.

We note that for one of the stations, Forsmark, the stationary model is rejected in favour of the model in Eq. (3). The sign of $\hat{\mu}_1$ is negative, implying a decrease in slope.

Table 2 Examination of possible trend in location parameter. LR test: non-stationary against stationary (related p-value) and point estimate of μ_1 with associated standard error

Station	LR test, p-value	$\hat{\mu}_1$ with standard error
Forsmark	0.0019	−0.70 (0.20)
Oskarshamn	0.63	0.050 (0.10)
Ringhals	0.20	0.24 (0.19)

4 Results

We here present the results for the stations: Forsmark, Oskarshamn, and Ringhals. For all locations, the following models were fitted:

m_0:	Stationary model
m_1:	Time-dependent location parameter: $\mu(t) = \mu_0 + \mu_1 t$
m_2:	Time-dependent scale parameter: $\sigma(t) = \sigma_0 + \sigma_1 t$
m_3 :	Time-dependent location and scale parameters (cf. m_1 and m_2)

Return levels were computed for return periods 10^2, 10^3, 10^4, 10^5, and 10^6 (years), following the notion of conditional prediction from Sect. 3.3. The planned time horizon for a power plant is of the order 100 years, so starting from present, say January 2024, we study the behaviour at January 2124.

The results are presented in forms of visualisations, so-called return-level plots. On the abscissa is then showed the return period, and the ordinate shows the related estimated quantile (that is, return level). The plot shows point estimates as well as uncertainties in the form of confidence intervals as implemented in NSGEV: the delta method; profile likelihood; and bootstrap methodology (Hamdi et al. 2018). Confidence intervals are given with the conventional 95% confidence level as well as 70% confidence level, the latter a choice in this context by French nuclear operators. For a given station and type of confidence interval, a pair of return-level plots is shown: to the left, the status of today and to the right, 100 years into the future.

Tables presenting numerical results for all situations (stations, methods for confidence interval, confidence level) would be too spacious. In Table 3 is presented, for reference only, the case for return period $T = 1000$ and significance level 0.95. This might serve as a complement to the figures.

Before proceeding to the results of the model fittings, we present for each station ML estimates of the shape parameter ξ in the GEV distribution. As pointed out in Sect. 3.1, the sign of the shape parameter has implications for the interpretation of e.g. upper bounds of the quantity studied. In Table 4 are given the estimates as well as p-values for Wald tests of the null hypothesis $\xi = 0$. Following common

Table 3 Summary of 1000-year return levels (in cm) as of 2024 and conditional predictions of 1000-year return levels, 100 years ahead (2124). Significance level of confidence intervals: 0.95

Situation	Point estimate	Delta method	Profile likelihood	Bootstrap
Forsmark, 2024	161	(110, 211)	(134, 327)	(122, 218)
Forsmark, 2124	91	(28, 154)	(36, 249)	(15, 183)
Oskarshamn, 2024	136	(112, 160)	(122, 184)	(115, 161)
Oskarshamn, 2124	141	(107, 175)	(111, 192)	(103, 171)
Ringhals, 2024	201	(133, 270)	(167. 407)	(144, 310)
Ringhals, 2124	226	(148, 303)	(166, 431)	(148, 339)

Table 4 Estimates of shape parameter ξ and related p-value for test of the null hypothesis $\xi = 0$

Station	Estimate	p-value
Forsmark	−0.23	$5.2 \cdot 10^{-3}$
Oskarshamn	−0.17	$2.2 \cdot 10^{-2}$
Ringhals	−0.065	0.22

praxis, the null hypothesis is rejected if $p < 0.05$. We find that for the stations Forsmark and Oskarshamn, both situated on the Baltic Sea coast (Fig. 1) evidence of a negative shape parameter, whilst the Gumbel case cannot be rejected at Ringhals station.

4.1 Forsmark station

Comparing the models by AIC, there is a preference for model m_1 (AIC values 429.2, 421.5, 430.3, and 422.5), and LR tests give the same conclusion. In other words, we face a time-dependent location parameter, which follows as $\mu(t) = 112.3 - 0.7t$ (Table 2, with results from the same model being fitted). The negative slope over time can be interpreted as a result of land uplift, present in this part of the Baltic Sea (Fig. 1).

Based on the model m_1, we make predictions following conditional prediction. The results are visualised in Figure 4 in the form of return-level plots. We note the decrease in return level in the future and also the increase in width of confidence interval with increasing return period, in particular, for the case of 95% confidence level. Furthermore, the profile likelihood and bootstrap alternatives yield extraordinarily high upper bounds that seem non-relevant.

4.2 Oskarshamn station

For this station, the stationary model m_0 is the best choice in terms of AIC (520.0, 521.7, 521.9, and 523.7) and LR tests. Although not statistically significant, there is now a positive slope in location parameter (following model m_1) and hence a slight increase in return level over the time horizon to 2124. For an illustration, see Fig. 5. Compared to the previous station, we here note a not that dramatic increase in uncertainty over time, in terms of sea level; about 3 m as upper limit of the 95% confidence interval for $T = 10^6$ years, as compared to over 12 m in the most extreme setting for station Forsmark.

4.3 Ringhals station

Compared to the other two locations, this is situated on the west coast of Sweden (Fig. 1). Again, we compare the three models, and the stationary model m_0 is preferred (lowest AIC: (453.11, 453.45, 454.79, and 454.90)). Return-level plots are shown in Fig. 6, where we chose to present the outcomes of the stationary model m_1 (although not significant). The same features as for Forsmark station can be observed, i.e. unreasonably high upper limits of the 95% confidence intervals with increasing return period.

5 Simulation study: example of Forsmark

We here discuss possible reasons for differences in features, in terms of widths of confidence intervals, at stations Forsmark and Oskarshamn (Figs. 4 and 5). From Table 4, we note that for both sites the shape parameter is significantly negative, which implies from theory an upper limit (case of reversed Weibull distribution). However, there is a slight difference in the length of the original time series, Table 1. The length of the Forsmark series is 15 years shorter, and the station has considerably higher uncertainty for return-level estimates for long return periods.

In this subsection, we simulate a fictive dataset of length 200 years, following a GEV distribution with parameters following the ML estimates of the original time series ($\mu = 92.5$, $\sigma = 21.2$, and $\xi = -0.23$). Since this is a numerical experiment, we for simplicity denote the simulated series of 200 observations as running between 2000 and 2199. Conditional return levels are computed on a 100-year horizon as before, thus ending in 2300, with the resulting return-level plots shown in Fig. 7. Only the profile likelihood intervals are presented here, and we note that the overall uncertainty is now considerably reduced. Even the upper bounds of the 95% confidence intervals have sea levels less than 2 m for this location, for the longest return period

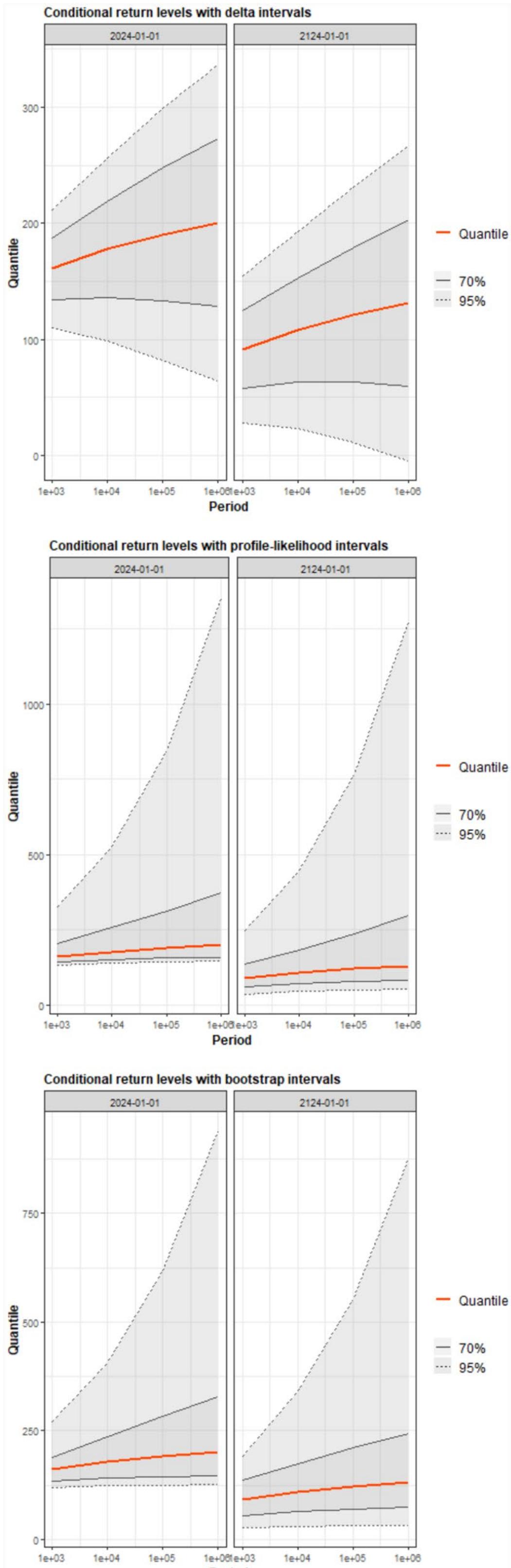

Fig. 4 Return-level plots, Forsmark

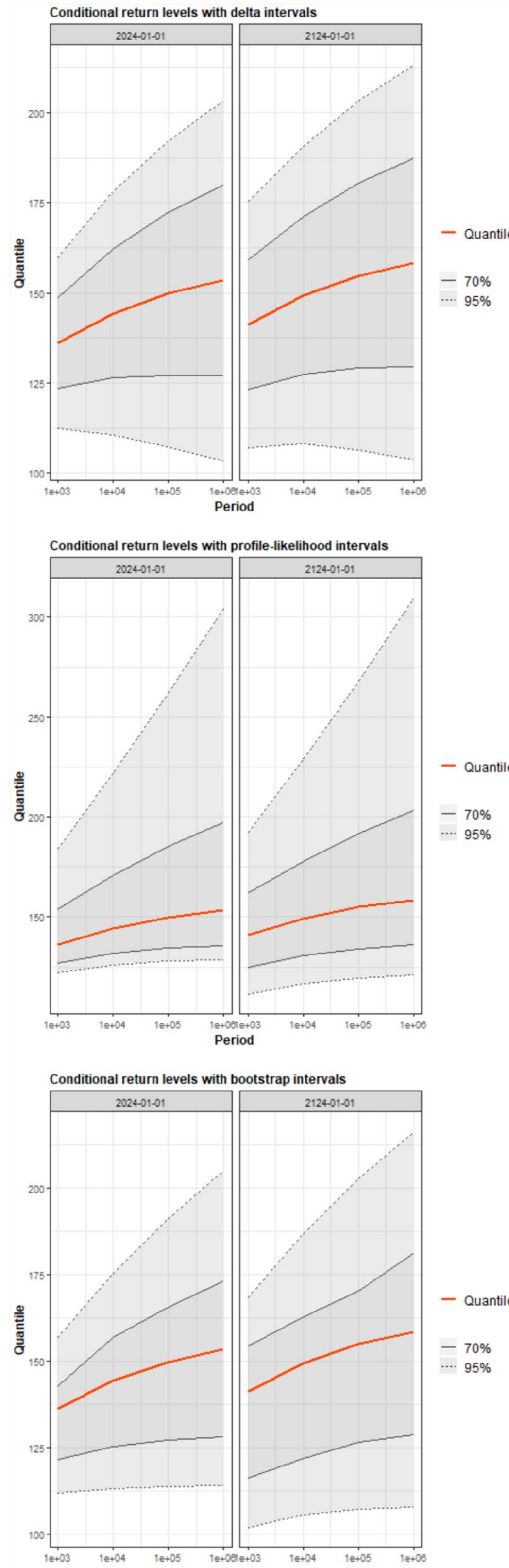

Fig. 5 Return-level plots, Oskarshamn

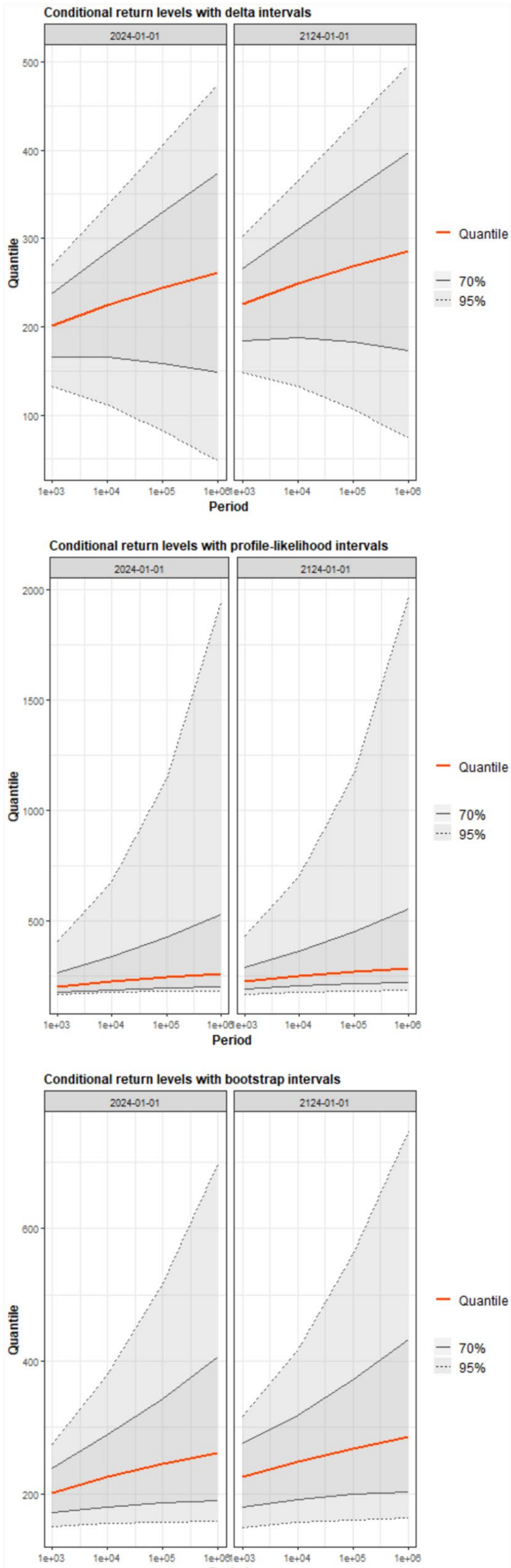

Fig. 6 Return-level plots, Ringhals

of $T = 10^6$ years (Fig. 4). Hence, the length of time series seems highly influential. (Several simulations were performed and typically, the level of 2 m was never exceeded.)

6 Summary and discussion

Estimation of return levels is crucial for risk analysis, for planning and decision-making. Non-stationary models are important in the light of climate change. We found that the notion of conditional prediction is useful for predictions during the time horizon of typical infrastructure. However, in certain cases, the uncertainties may grow very large for the long return periods required in certain applications. In particular, the confidence intervals from profile likelihood and bootstrap methodology, respectively, tend to generate wide intervals with unreasonably high upper limits. One also notes that for two of the stations (Oskarshamn and Ringhals), the non-stationary models were not considered statistically significant. The obtained AIC values are from a practical point of view similar. The figures illustrate the cases when nevertheless applying the non-stationary framework and obtaining conditional predictions. Table 3 shows the slight increase in point estimate of return level (return period 1000 years).

By a simulation study, we observed the impact of length of the original series, Rydén (2023) for similar investigations (then considering rejection of the Gumbel distribution). In addition, the sign of the shape parameter might play a role: a clearly negative shape parameter yields (from theory) an upper bound of the random outcome. For two of the three considered stations, the shape parameter was negative by statistical significance (Table 3).

The sign of the shape parameter, and its implications, has been studied for various meteorological quantities. Concerning for instance wind speed, there was a debate in the literature concerning a possible upper limit (Harris 2005; Simiu 2007). In the study of sea level, Räty et al. (2023) discuss theoretical upper limits on the Finnish coast (see their Table 2). Turning to river floods, Hosking et al. (1985) mention 32 series (of length 30 or more), with estimated shape parameters ranging from −0.32 to 0.48 (hence, varying in sign). Focussing on annual maximum daily rainfall, Papalexiou and Koutsoyiannis (2013) investigated the impressive number of 15,137 records from all over the world, fitting GEV distributions. They found that when the effect of the record length was corrected, the shape parameter ξ varied in a narrow range; moreover, an influence of geographical location on the value of ξ. A variability in sign of ξ was found, but in the majority of cases (about 80%), $\xi > 0$. Finally, the uncertainty of the upper

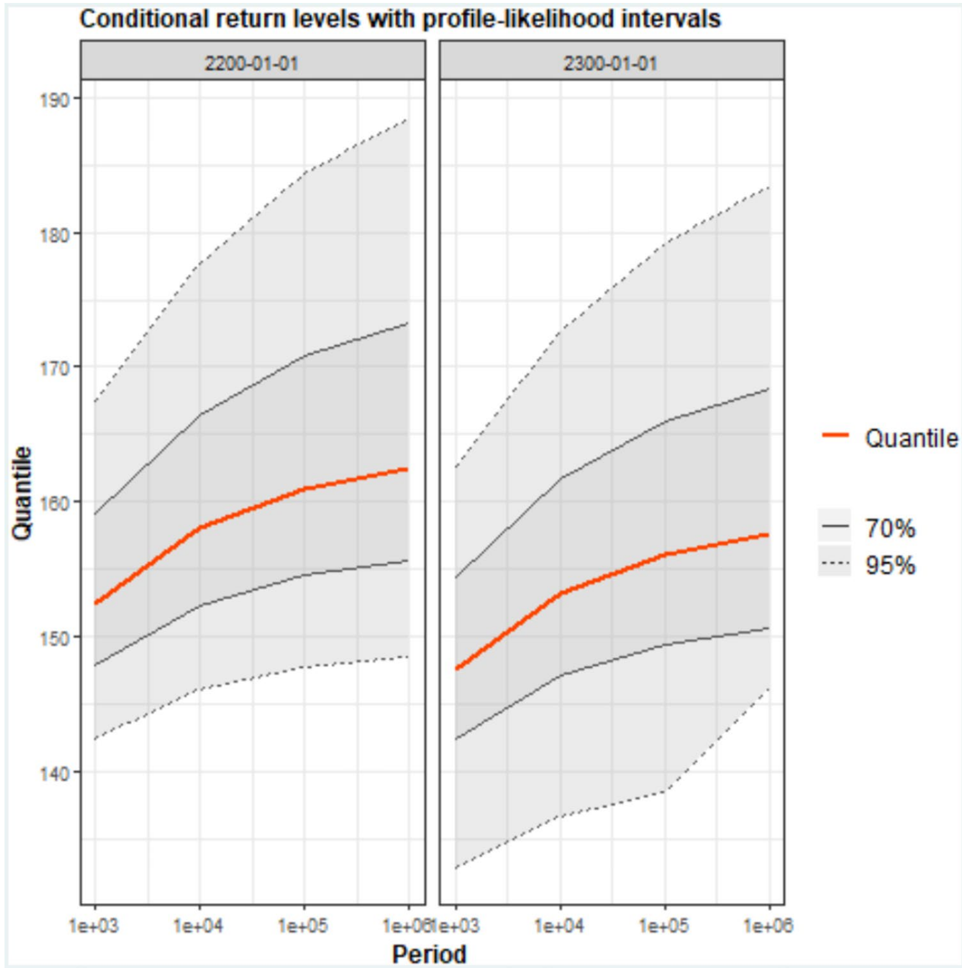

Fig. 7 Return-level plots and simulation study based on power plant Forsmark. Profile likelihood intervals shown

bound is often considerable. This has been for instance been demonstrated through simulation studies based on GEV distributions with parameter values chosen to mimic realistic situations (Rydén, 2024).

Note that this study did not consider potential sea-level rise. Recent research, with focus on Scandinavian coastlines, was reported by Hieronymus and Kalén (2022). Six sites along the Swedish coast were then considered using a so-called flood-risk simulation framework. The general conclusion was that for longer planning periods, the risk of flooding is dominated by high sea-level rise.

Finally, it should be mentioned that the definition of return level is discussed in the literature, see for instance Volpi et al. (2015), where the problem of dependence in time series is in focus. Rootzén and Katz (2013) proposed the notion of design life level. In the future research, it would be of interest to further investigate possible definitions of return levels.

Acknowledgements The author acknowledges the financial support from a grant by the Swedish Radiation Safety Authority. He is grateful for fruitful communication with Yves Deville (Alpestat) and Henrik Hellberg (Swedish Radiation Safety Authority). Thanks also to the reviewers, for insightful comments.

Author contributions One sole author: JR

Funding Open access funding provided by Swedish University of Agricultural Sciences. This research was funded by the Swedish Radiation Safety Authority.

Declarations

Conflict of interest The author declares that there are no competing interests.

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