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# Comparison of non-stationary regional flood frequency analysis techniques based on the index-flood approach

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**Abstract**

Regional flood frequency analysis (RFFA) techniques are used in hydrological applications for estimation of design quantiles at ungauged sites or catchments with sparse observational records. The index-flood method, a popular approach for RFFA, is based on the assumption that the flood records within a homogeneous region are identically distributed, except for a site-specific index-flood. In the light of rapidly changing land-use patterns, human interventions and climate change, recent studies propose extension of the index-flood method to account for non-stationarity in flood records. The aim of this work is to present a comparison of index-flood based non-stationary RFFA techniques, on both synthetically generated and real-world homogeneous regions, with sites marked by significant trends in flood records. From the data used in the analysis, it is evident that the method proposed by O'Brien & Burn (2014) and a non-stationary extension of Basu & Srinivas (2013) are more suitable compared to other methods, and can capture time-varying behavior of floods effectively.

**Key Words:**

Regional flood frequency analysis, non-stationary, index-flood method, annual maximum flood, generalized extreme value distribution, design flood quantiles, uncertainties.

# 1 Introduction

Regional flood frequency analysis (RFFA) techniques (Hosking & Wallis, 1997) are often used to arrive at flood estimates for basins marked with limited or no records. Such techniques involve identifying homogeneous regions and estimation of quantiles from pooled information within that homogeneous region (Burn, 1988; Rao & Srinivas, 2006 etc.). Fitting a regression relationship between the catchment attributes and the design quantiles is one of the pooling approaches (Leclerc & Ouarda, 2007; Ouali et al., 2016; Ouali et al., 2017; Ouarda et al., 2001; Pandey & Nguyen, 1999; Wazneh et al., 2013).

The other approach, the popular index-flood method (Dalrymple, 1960; Hosking & Wallis, 1993) for RFFA, on the other hand, involves normalization of flood records by an at-site scaling factor called the index-flood. Pooled information from the normalized records are used to construct the growth curve in the transformed space. Required flood quantiles at the target site are estimated by multiplying the growth curve with the index-flood. The assumptions of stationarity is inherent in both pooling methods. The stationarity assumption considers flood records to be independent and identically distributed, where the statistical distribution and its parameters do not vary with time. However, such assumption may be questionable (Milly et al., 2015; 2008) due to increasing global average temperatures intensifying the frequency of pluvial flooding through the Clausius-Clapeyron relationship (IPCC, 2012; Kundzewicz et al., 2017), or temperature-induced changes on timing and volume of peak flows through snow-melt and cold-season precipitation changes (Kundzewicz et al., 2010; 2014), or more local, anthropogenic factors such as rapid modifications in land-use/land-cover including urbanization and deforestation, and human interventions interfering floods such as structural flood protection measures (Sivapalan &

Samuel, 2009; Villarini et al., 2009; Kundzewicz et al. 2014). It may be noted, however, that the relative importance of these climatic and non-climatic drivers of non-stationarity in floods may be region-specific (Kundzewicz et al. 2017).

Several recent studies in hydrology have focused on explicitly modeling non-stationarity in extremes (El Adlouni et al., 2007; Katz et al., 2002; Mondal & Mujumdar, 2015; 2016; Salas & Obeysekera, 2014; Vogel et al., 2011; Westra & Sisson, 2011; Westra et al., 2013). However, applications considering non-stationarity in RFFA studies are rather few in number. Some of the approaches to account for non-stationarity in RFFA include the detrending approach to non-stationarity (Cunderlik & Burn, 2003), the trend-based regional flood-duration-frequency model (Cunderlik & Ouarda, 2006) and a regression based approach that uses time-varying flood quantiles (Leclerc & Ouarda, 2007).

More recent studies propose and employ non-stationary index-flood methods. For example, Hanel et al. (2009) (hereinafter referred to as the Hanel Method, HM) and Hanel & Buishand (2010; 2011; 2012) employ a non-stationary index-flood method to compare regional climate model simulations with observations of rainfall extremes. They consider both index-flood and the growth curve to be non-stationary. Renard et al. (2013) use a Bayesian framework for modeling non-stationarity in regional flood frequency analysis. However, their method includes assumption of priors. O'Brien and Burn (2014) (hereinafter referred to as the O'Brien and Burn method, OBM) propose a non-stationary index-flood method and a regional pooling method based on trends, considering the stationary at-site mean as the index-flood, while the growth curve is non-stationary. Nam et al. (2015) (hereinafter referred to as the Nam Method, NM) compare different index-flood approaches under non-stationarity and also propose a third method with non-stationary index-flood and stationary growth curve. Sung et al. (2018) (hereinafter referred to as the Sung Method, SM) address non-stationarity in RFFA by the distribution free approach where the trend is removed from the series before applying the standard index-flood method. Basu & Srinivas (2013) propose a transformation based approach to the index-flood method for stationary flood peak data in a homogeneous region. Here, an extension of that approach is proposed, to account for non-stationarity marked by trends and also compare this new method (hereinafter referred to as the Basu and Srinivas method, BSM*), with the existing non-stationary index-flood approaches. The mathematical transformation in BSM* transposes non-stationary flood records to another dimension where the location, scale and shape parameters are less biased compared to the regional parameters (result not shown). This ensures that the frequency distribution of the flood records both before and after transformation belong to the same family. Further, the transformed records are independent and identically distributed, thereby satisfying the primary assumptions of the index-flood method. This is a particular methodological advantage of BSM*.

The purpose of this paper is to draw a comparison of existing non-stationary index-flood approaches – namely, the OBM, HM, NM, SM. Two new non-stationary index-flood approaches are additionally considered for this comparison – a modified version of HM which is based on the normalization by location parameter (hereinafter referred to as the modified Hanel method, HM*) and the mathematical transformation-based BSM* described above. This study presents the first such comprehensive synthesis of different approaches to non-stationary RFFA with a view to provide a comparative summary of their strengths and weaknesses using synthetic and real-world data.

## 2 Methodology

Let $X_i(t)$ be a random variable that denotes the annual maximum streamflows at the $i$-th site among $N$ sites in a homogeneous region, and at the $t$-th time step. The total number of records at that site is $n_i$. The quantile function of frequency distribution at the $i$-th site is $Q_i$ ($f$) for the stationary case, which is defined as (Dalrymple, 1960)

$$Q_i(f) = \overline{X}_i * q(f), \qquad i = 1, 2, \dots, N; \quad f \in (0,1) \tag{1}$$

where $\overline{X}_i$ is the index-flood at the $i$-th site and $q(f)$ is the dimensionless regional growth curve. Under non-stationarity, since the distribution changes with time, flood quantiles are also time-varying and are given by the function $Q_i$ ($f$, $t$). These flood quantiles are actually 'effective return levels' (Katz et al., 2002) corresponding to a constant probability of exceedance ($f$). Recent studies discuss more precise estimates of non-stationary flood return levels based on different interpretations (Cooley, 2013; Salas & Obeysekera, 2014; Mondal & Daniel, 2019). Some studies (Serinaldi, 2015, Strathie et al., 2017) argue that the concept of the return period can be misinterpreted and propose alternate risk measures based on the risk of failure (for example, Rootzén & Katz, 2013). However, effective return levels are used here, since they are easy to interpret and have been used in earlier studies on non-stationary regional flood frequency analysis (for example Leclerc & Ouarda, 2007; O'Brien & Burn, 2014).

Detailed steps of OBM, HM, NM, SM and BSM* are illustrated in Figure 1, and are also described in Supplementary Information (SI). Additionally, a modified version of HM is used, which is based on the normalization by the location parameter - hereinafter referred to as the modified Hanel method (HM*). HM* is considered to draw comparability with the other existing non-stationary index-flood method, since HM, in the original study, constructs the regional growth curve directly in terms of the dispersion and the shape parameter from pooled data instead of estimation of at-site parameters (See SI). From Figure 1, it is evident that all the methods consider non-stationarity either in the normalization or in the construction of the growth curve.

<Figure 1>

# 3 Results

A synthetic simulation experiment is first executed to compare the performance of the non-stationary index-flood methods. This is followed by a real-world application. All computations are carried out in the statistical R platform, using the package 'extRemes' (Gilleland & Katz, 2011). The synthetic simulation experiment considers a realization of a homogeneous region consisting of *N* sites, each having *n* records, based on a non-stationary Generalized Extreme Value (GEV) distribution having an increasing trend in the location parameter. Since the goal of this paper is a comparison of existing non-stationary index-flood approaches, GEV distribution is chosen for analysis as it used by OBM, HM, NM, SM and BSM. However, it may be noted that the principles elucidated in Figure 1 may be applicable for other distributions as well. This is similar to the synthetic simulation experiments of Sung et al. (2018) and Nam et al. (2015). Following other studies (Katz et al., 2002; Mondal & Mujumdar, 2016; O'Brien & Burn, 2014), the scale and the shape parameters are kept constant. Further, a high-positive value in $\xi$ is chosen to exhibit heavy-tailed behavior found to exist in hydrological extremes (Cavanaugh et al., 2015; Papalexiou & Koutsoyiannis, 2013). The location ($\mu_0$), trend in location ($\mu_1$), scale($\sigma$) and shape($\xi$) parameters of the GEV distribution are assumed to be constant over the homogeneous region. The chosen values of the variables are

$$N = 7, n_1 = n_2 = \cdots = n_7 = 50, \mu_0 = 1, \mu_1 = 0.02, \sigma = 1 \text{ and } \xi = 0.25. \qquad (2)$$

Figure 2 shows the simulated flood records. All the seven sites show significant non-stationarity, as established by the likelihood ratio test (Coles, 2001), as well as the non-parametric Mann-Kendall trend test (Table S1 in SI). Figure 2 also shows the 50-year effective return levels, corresponding to fixed probability of exceedance $p$ = 1/50 = 0.02, for all the methods, along with the true non-stationary quantiles that were obtained by inversion of the GEV cumulative distribution function (cdf) at each time step, corresponding to the fixed probability of exceedance $p$, using the true parameters that were used to generate the flood records. Although there are biases in the estimated quantiles, possibly because of limited sample size, the BSM* and OBM yield results that are closest to the true quantiles.

<Figure 2>

Further, to evaluate the performance of these methods for prediction in ungauged locations, a cross-validation analysis is performed, wherein one site at a time is considered ungauged and the data records for that site are hidden from the regional flood frequency analysis. Since the site-specific index-flood magnitude is unknown in this case, average value of index-flood of the remaining sites is taken as the index-flood for all the methods (Hosking & Wallis, 1997). To assess the performance of the non-stationary index-flood methods, absolute bias for site $i$ is considered, defined by A-Bias $= \sum_{j=1}^{n_i} \frac{|P_j - Q_j|}{Q_j} \times 100$ %, where $P_j$ and $Q_j$ are the predicted and true quantile, respectively, at the $j$-th time step, with $n_i$ number of records at that site. This is repeated 500 times to generate an ensemble. Figure 3 shows the box plot of A-Bias across the ensemble for Site#1. The other sites reveal similar performance and are therefore not shown.

<Figure 3>

It is observed that BSM*, along with OBM, leads to minimal A-Bias, indicating better performance as compared to HM, HM*, NM and SM. It can be observed that both HM and NM lead to over-estimation of $\mu_1$ resulting in underestimation of the quantiles during the initial years and over-estimation during the later years. In HM, normalization of the non-stationary flood records by the time-varying location parameter might remove non-stationarity, at least partially. The forcible fitting of non-stationary regional growth curves after such removal leads to overestimation of trends, thereby resulting in steep slopes of the non-stationary return levels. In NM, on the other hand, partial presence of non-stationarity might lead to overestimation of the stationary regional growth curve, thereby causing steeper estimated non-stationary flood quantiles. In SM, the detrending of records might remove the actual tail behavior, resulting in poor performance in terms of the simulated transient flood quantiles.

Since BSM* and OBM performed best in the simulated experiment, these two methods were further applied for non-stationary RFFA in four Canadian homogeneous regions previously identified by O'Brien and Burn (2014). Annual maximum daily streamflow data is obtained from the Water Survey of Canada's HYDAT database. Three sites were not considered (Site 02LB020 from Region-2; Site 02AB019 & Site 05UA003 from Region-4) in our analysis since they had record length less than 25 years. All the sites considered in the study show significant trends as established by the non-parametric Mann-Kendall trend test. Although the analysis is performed on all sites in each of the four regions, for illustration of non-stationary RFFA, four representative sites are chosen, one in each region, following O'Brien and Burn (2014). The 100-

year effective return levels for the four representative sites and their 95% confidence intervals estimated by the bootstrap-based vector resampling approach (Obeysekera & Salas, 2014; Oehlert, 1992) are shown in Figure 4, along with the stationary quantiles and their confidence intervals. Details of the bootstrap-based vector resampling approach are provided in SI. While the sites in Region#1, Region#2 and Region#3 show decreasing trends, Region#4 has sites with positive trend in peak flows. It is evident that both BSM* and OBM capture the non-stationarity in flood records. The presence of decreasing (increasing) trends can lead to under (over)-estimation of flood quantiles if such non-stationarity is not taken into consideration in RFFA.

<Figure 4>

## 4 Discussion and conclusions

While individual research efforts on non-stationary index-flood approaches for RFFA are reported in hydrologic literature, this paper presents the first comprehensive summary and comparison between them. For such comparison, along with existing methods - OBM, HM, NM and SM, possible alternative extensions HM* and BSM* are also considered. The strengths and weaknesses of the existing non-stationary index-flood approaches are highlighted, and their performances analyzed for synthetically generated as well as real-world applications of RFFA. While methodologically BSM* satisfies the assumptions of the index-flood method even under non-stationarity, making it theoretically more suitable, a synthetic simulation experiment reveals that OBM and BSM* both outperform the other methods. Also, when applied to real-world data, both BSM* and OBM are found to yield comparable results, capturing the time-varying nature of flood quantiles realistically. Additionally, for the real-world RFFA application, uncertainty ranges of the estimated time-varying quantiles corresponding to the 100-year return period are also computed using the non-parametric bootstrap-based vector resampling approach. Though the uncertainty limits resulting from OBM and BSM* are similar, BSM* yields narrower confidence intervals implying more precise estimates of return levels.

It may be noted that the effect of spatial dependence is not accounted in this RFFA study. While some recent studies (Castellarin et al., 2008; Lilienthal et al., 2018; Wang et al. 2014) attempt to address this issue, it requires further investigation. Further, the homogeneity test adopted by O'Brien and Burn (2014) also needs to be reformulated to account for non-stationary flood records. Despite shortcomings and limitations, this study presents a much-needed summary of non-stationary index-flood approaches and provides a basic synthesis of the existing state-of-art on the important topic of non-stationary RFFA.

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**Data availability statement**

Some or all data, models, or code generated or used during the study are available from the corresponding author by request.

The data is freely available from Water Survey of Canada's HYDAT database and the codes generated to produce the results can be shared on request.

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## Figures

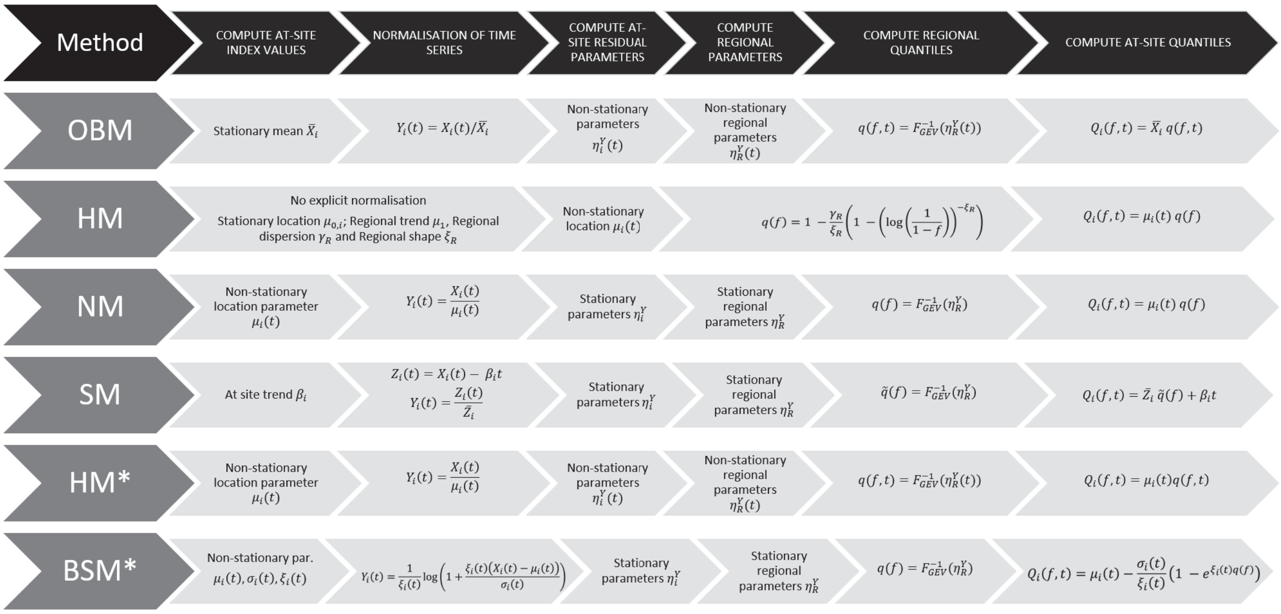


Figure 1. Detailed non-stationary index-flood technique for regional flood frequency analysis in the modified Basu & Srinivas Method (BSM*), vis-à-vis existing methods from literature, namely the O'Brien & Burn Method (OBM), the Hanel Method (HM), the modified Hanel Method (HM*), the Nam Method (NM) and the Sung Method(SM)

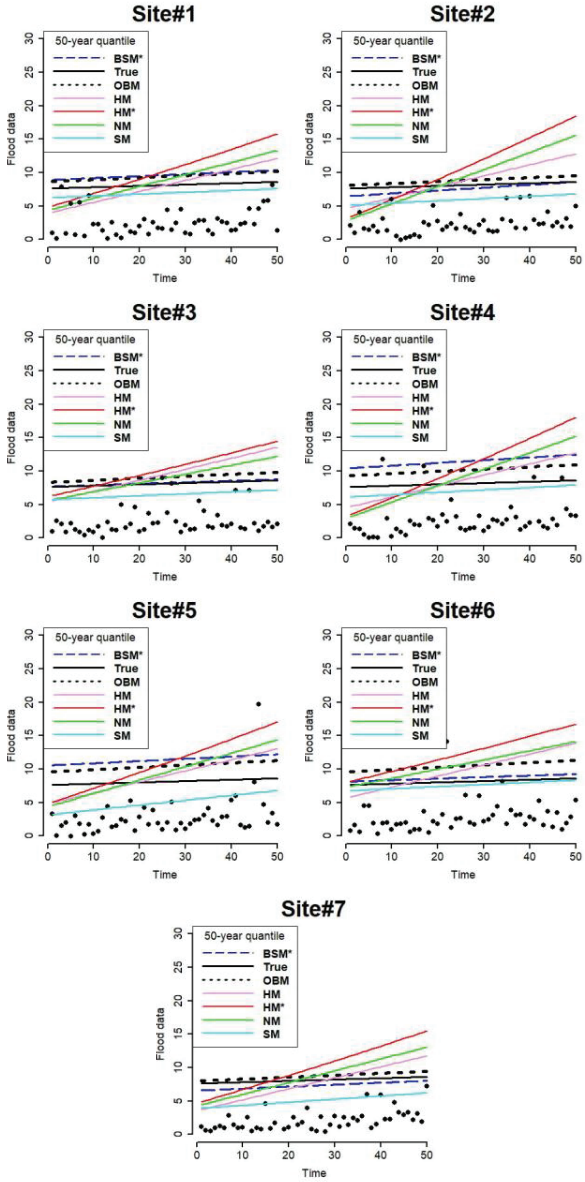


Figure 2. Synthetically generated (unitless) non-stationary flood data (dots) at all the seven sites in the homogeneous region. Time-varying 50-year flood quantile estimates using O'Brien & Burn Method (OBM, black dashed line), Hanel Method (HM, violet line), Modified Hanel Method (HM*, red line), Nam Method (NM, green line), Sung Method (SM, cyan line) and modified Basu & Srinivas Method (BSM*, blue dashed line) along with the true quantile (black line) are shown for each site.

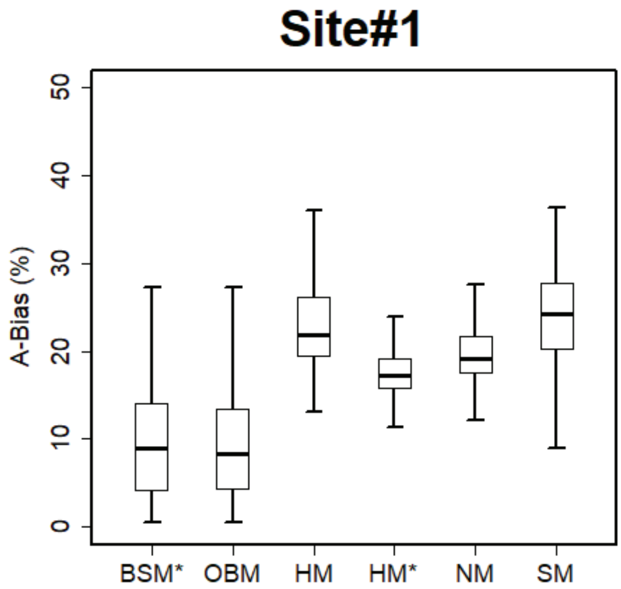


Figure 3. Boxplot of percentage Absolute Bias (A-Bias) of the 50-year effective return levels at Site#1 in the synthetically generated region, obtained by leaving out records of that site in the index-flood framework, over 500 realizations, as computed by the different non-stationary index-flood approaches.

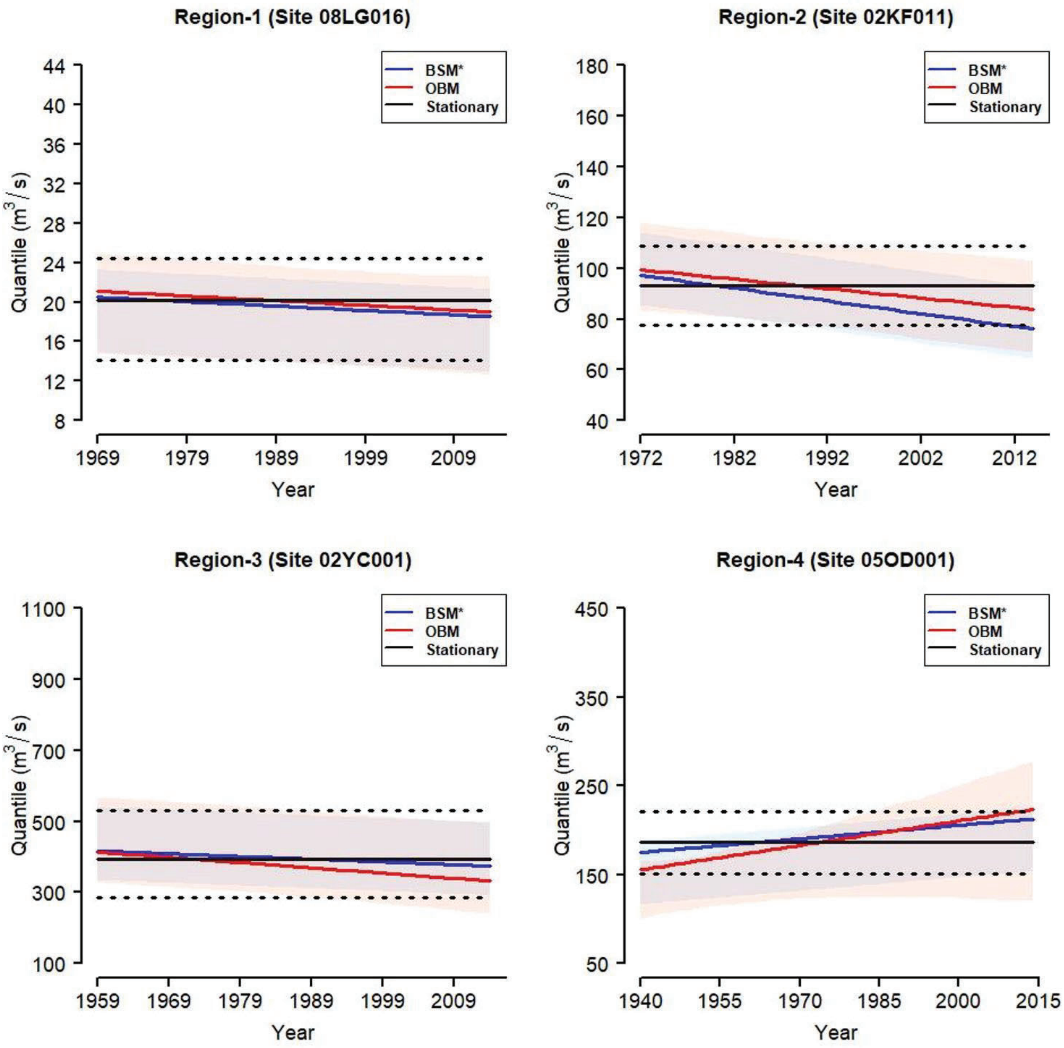


Figure 4. The 100-year flood quantile estimates at a given site and their respective 95% confidence interval considering the stationary index-flood method (black), the O'Brien & Burn method (OBM, red) and the modified Basu & Srinivas Method (BSM*, blue) in (a) Region-1, (b) Region-2, (c) Region-3, (d) Region-4 in Canada.