Nonstationary Flood Frequency Analysis with RMC-BestFit

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The U.S. Army Corps of Engineers (USACE) Risk Management Center (RMC) has developed RMC-BestFit, a Bayesian estimation and fitting software designed to enhance and expedite flood hazard assessments within the Flood Risk Management, Planning, and Dam and Levee Safety communities of practice. RMC-BestFit can incorporate multiple sources of hydrologic information, including historical data, paleoflood indicators, regional rainfall-runoff results, and expert elicitation, into flood frequency analysis. The software now includes the capability to perform nonstationary flood frequency analysis (NSFFA), allowing distribution parameters to vary with time. This feature enables users to identify changing flood risk conditions.

This paper presents a case study demonstrating NSFFA for a high-hazard dam within the USACE portfolio. The study illustrates the assessment of nonstationarity due to factors such as land use changes and climate change. It showcases the selection of appropriate trend models for the distribution parameters and how to incorporate historical, censored data, as well as Global Climate Model (GCM) projections, into the Bayesian NSFFA. The case study reveals that NSFFA can significantly impact the assessment of flood risk and inform potential dam safety and reallocation measures.

Keywords: Bayesian, flood frequency, uncertainty, risk assessment

Introduction

The U.S. Army Corps of Engineers (USACE) Risk Management Center (RMC) has developed RMC-BestFit, a Bayesian estimation and fitting software designed to enhance and expedite flood hazard assessments within the Flood Risk Management, Planning, and Dam and Levee Safety communities of practice (Smith & Doughty, 2020). RMC-BestFit can incorporate multiple sources of hydrologic information, including historical data, paleoflood indicators, regional rainfall-runoff results, and expert elicitation, into flood frequency analysis (Smith & Skahill, 2019). The software now includes the capability to perform nonstationary flood frequency analysis (NSFFA), allowing distribution parameters to vary with time. This feature enables users to identify changing flood risk conditions.

The Centre for Research of Epidemiology of Disasters (CRED) reported that floods were the most common disasters worldwide in 2023, affecting several million people and causing over ten thousand deaths (CRED, 2024). According to CRED, floods and storms accounted for more than 70% of natural disasters on average between 2003 and 2023. Furthermore, flood risk management (FRM) infrastructure in the U.S. and globally is aging, making many existing FRM structures vulnerable to the impacts of climate change. Both natural and anthropogenic influences can alter flood behaviour. Conceptually, a warming climate increases the amount of precipitable water in the atmosphere, which could increase the likelihood of extreme floods over time. Therefore, incorporating climate change into flood hazard and risk analysis is crucial for dam safety professionals.

This paper presents a case study demonstrating NSFFA for a high-hazard dam within the USACE portfolio. The study illustrates the assessment of nonstationarity due to factors such as land use and climate change. It showcases the selection of appropriate trend models for the distribution parameters and how to incorporate historical, censored data, as well as Global Climate Model (GCM) projections, into the Bayesian NSFFA. The case study reveals that NSFFA can significantly impact the assessment of flood risk and inform potential dam safety and reallocation measures.

Nonstationary Flood Frequency Analysis

In recent years, there have been numerous examples of nonstationary flood frequency analysis (NSFFA). Debele *et al.* (2017a, 2017b) demonstrated how to perform NSFFA using generalized additive models for the location, scale, and shape (GAMLSS) parameters. Cheng and AghaKouchak (2014) and Skahill *et al.* (2016) demonstrated how to estimate nonstationary precipitation-frequency curves. Condon *et al.* (2015) and Hesarkazzazi *et al.* (2021) presented general frameworks for performing NSFFA. Renard *et al.* (2006), Luke *et al.* (2017), and Xu *et al.* (2018) offer Bayesian approaches to NSFFA. More recently, Jayaweera *et al.* (2023) demonstrate a nonstationary Generalized Extreme Value distribution for extreme rainfalls across Australia. Additionally, Wasko *et al.* (2024) provide a systematic review of climate change science relevant to Australian design flood estimation, including a review NSFFA approaches.

In the RMC-BestFit software, FFA is performed using a Bayesian analysis framework described by Smith (2020). This approach leverages the power of Bayesian statistics to incorporate various source of uncertainty and prior information into the analysis.

In the Bayesian approach to FFA, the model parameters $\boldsymbol{\theta} = \{\mu, \sigma, \xi\}$, which represents the location (μ), scale (σ), and shape (ξ) of the flood frequency distribution, are treated as random variables with their own probability distributions. Rather than converging to fixed point estimates, these parameters are characterized by their posterior distributions. This allows for a more comprehensive representation of the uncertainty inherent in flood frequency analysis.

Bayes' theorem is used to calculate the posterior density of the model parameters given the observed data. The posterior density $p(\boldsymbol{\theta}|\mathbf{x})$ is derived from the likelihood function $L(\boldsymbol{x}|\boldsymbol{\theta})$, which represents the probability of the observed data $\boldsymbol{x} = \{x_1, x_2, \dots, x_n\}$ given the parameters $\boldsymbol{\theta}$, and the prior density $p(\boldsymbol{\theta})$, which encapsulates any prior knowledge or assumptions about the parameters. The theorem is mathematically expressed as:

$$p(\boldsymbol{\theta}|\mathbf{x}) = \frac{L(\boldsymbol{x}|\boldsymbol{\theta}) \cdot p(\boldsymbol{\theta})}{\int L(\boldsymbol{x}|\boldsymbol{\theta}) \cdot p(\boldsymbol{\theta}) \cdot d\boldsymbol{\theta}}$$ ***Equation 1***

where $p(\boldsymbol{\theta}|\mathbf{x})$ is the posterior density of the parameter set $\boldsymbol{\theta}$ given the observed flow data $\boldsymbol{x} = \{x_1, x_2, \dots, x_n\}$; $L(\boldsymbol{x}|\boldsymbol{\theta})$ is the likelihood function, which measures how well the parameters $\boldsymbol{\theta}$ explain the observed data $\boldsymbol{x}$; $p(\boldsymbol{\theta})$ is the prior density, reflecting any prior information or beliefs about the parameters before observing the data; and $\int L(\boldsymbol{x}|\boldsymbol{\theta}) \cdot p(\boldsymbol{\theta}) \cdot d\boldsymbol{\theta}$ is a normalizing constant ensuring that the posterior density integrates to one.

For stationary FFA, where the assumption is that the data $\boldsymbol{x} = \{x_1, x_2, \dots, x_n\}$ are independent and identically distributed (i.i.d), the likelihood function is computed as the product of probabilities of each individual data point:

$$L(\boldsymbol{x}|\boldsymbol{\theta}) = \prod_{i=1}^{n} f(x_i|\boldsymbol{\theta})$$ ***Equation 2***

Here, $f(x|\boldsymbol{\theta})$ is the probability density function of the flood-frequency distribution given the parameters $\boldsymbol{\theta}$.

However, when dealing with nonstationary data, where changes in climate, land use, or other factors cause the distribution parameters to vary over time, the assumption of identical distribution no longer holds. In this case, the parameters $\boldsymbol{\theta}$ are allowed to vary with time, resulting in a time-dependent likelihood function:

$$L(\boldsymbol{x}|\boldsymbol{\theta}) = \prod_{t=1}^{T} f(x_t|\boldsymbol{\theta}_t)$$ ***Equation 3***

The primary difference between a stationary and nonstationary frequency analysis is that, in the latter, each time step has a unique parameter set, resulting in a unique distribution and distribution properties over time. The likelihood function can be easily expanded to include interval- and threshold-censored data as well as measurement error, as demonstrated by Kuczera (1999), and O'Connell *et al.* (2002), and Reis and Stedinger (2005).

This flexibility allows RMC-BestFit to account for nonstationarity in flood risk assessments, enabling more accurate and dynamic modelling of flood frequency under changing environmental conditions. By using the Bayesian framework, RMC-BestFit provides a robust and flexible approach to FFA, incorporating both prior information and observed data to yield comprehensive probabilistic estimates of flood risk.

In RMC-BestFit, the location (μ), scale (σ), and shape (ξ) parameters can vary with time using a trend or step function as shown below in Table 1 below. However, in practice there is rarely enough data to justify a time-dependent model for the shape parameter.

Table 1 - Trend model options for the location parameter (μ) in RMC-BestFit.

Constant: $\mu_t = \alpha$	Power: $\mu_t = \alpha t^{\beta}$
Cubic: $\mu_t = \alpha + \beta t + \gamma t^2 + \delta t^3$	Quadratic: $\mu_t = \alpha + \beta t + \gamma t^2$
Exponential: $\mu_t = \alpha e^{-\beta t}$	Reciprocal: $\mu_t = \frac{1}{\alpha + \beta t}$
Linear: $\mu_t = \alpha + \beta t$	Sinusoidal: $\mu_t = \alpha + \beta \sin(2\pi\gamma t + \delta)$
Logistic: $\mu_t = \frac{\alpha}{1 + e^{-\beta t}}$	Step Function: $\mu_t = \begin{cases} \mu_1, & t \leq t_c \\ \mu_2, & t > t_c \end{cases}$

Case Study

O.C. Fisher Dam is located on the North Concho River in Texas and has a catchment area of approximately 3,885 square kilometres. The city of San Angelo is directly downstream of the dam, as shown in Figure 1. O.C. Fisher dam is a multi-purpose project that provides flood control, water supply, recreation, and environmental benefits.

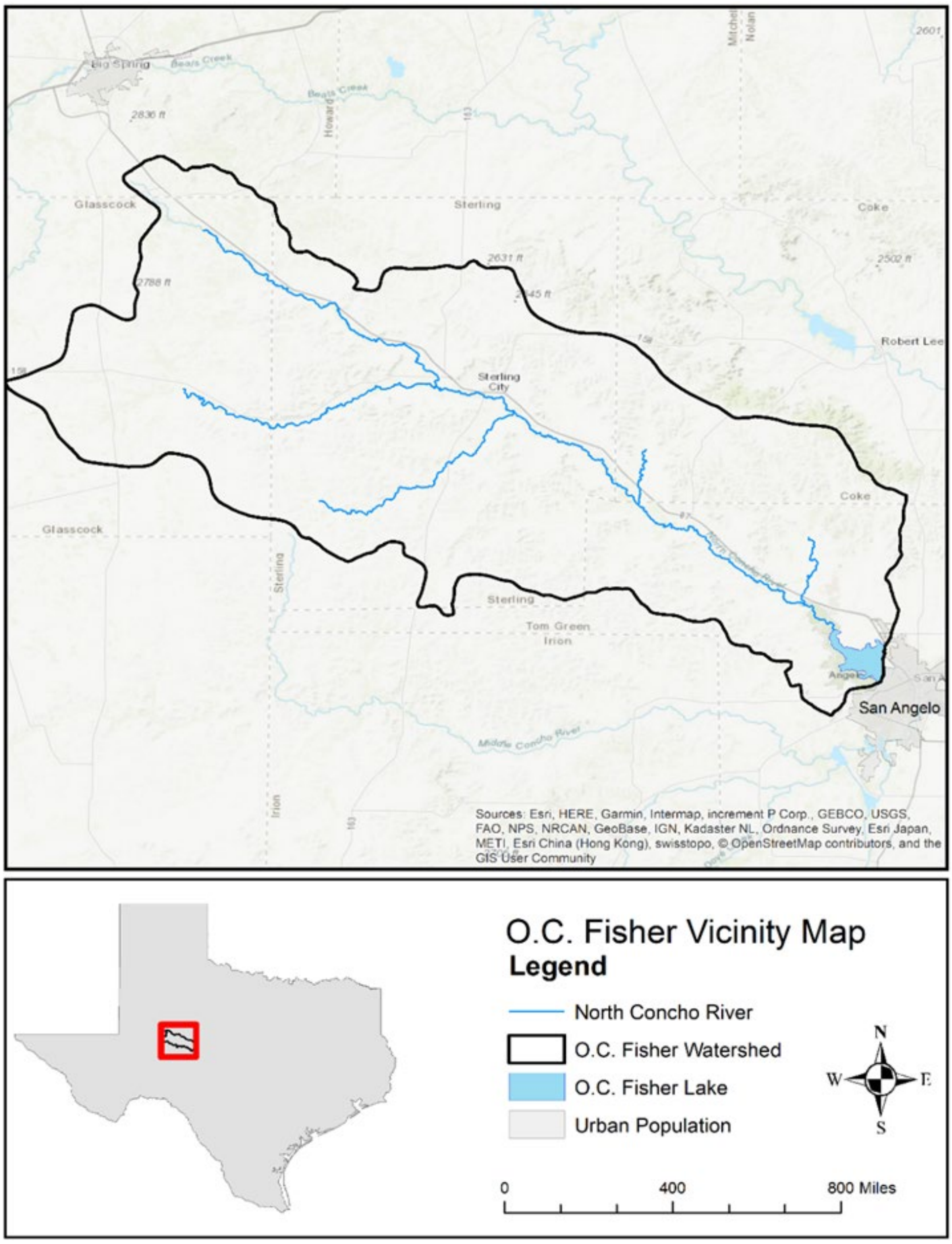


Figure 1 – Vicinity map of O.C. Fisher dam.

Inflow Data

The chronology plot of annual maximum 2-day average inflows to O.C. Fisher Dam is shown in Figure 2 below. Period-of-record inflows to O.C. Fisher were obtained from 1916 to 2021 (labelled as exact data in the figure). The largest flood during this period occurred on September 17, 1936, and was estimated to be about 1,150 cubic meters per second (cms). Based on historical records and reports, the largest flood on the North Concho River occurred in 1853 and was at least as large as the 1936 event. Multiple other large events occurred between 1854 and 1915, but none were larger than the 1936 event.

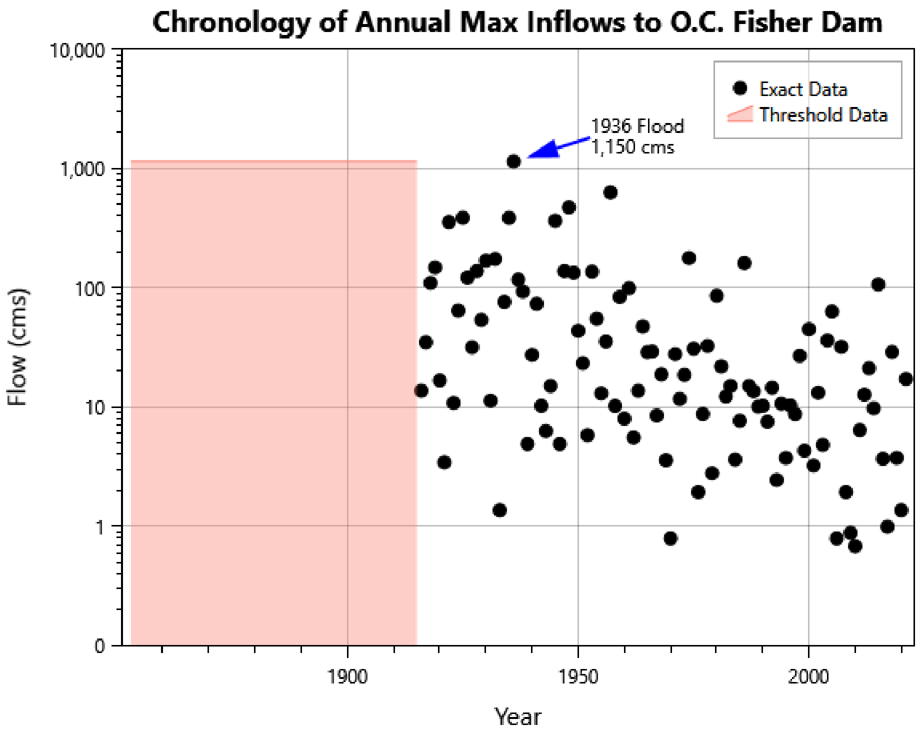


Figure 2 – Chronology plot for the annual max inflows to O.C. Fisher dam.

In RMC-BestFit, the historical period from 1853 to 1915 was treated a binomial-censored (Stedinger & Cohn, 1986), where the data points that occurred during this period have magnitudes that are below (or above) a threshold value, but it is unknown by how much. Figure 3 below shows how the threshold data is entered in the software.

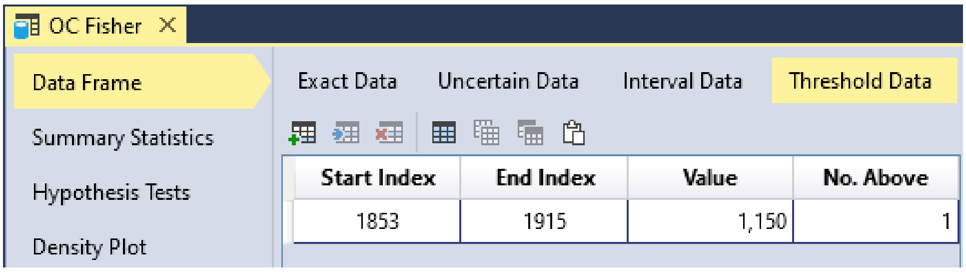


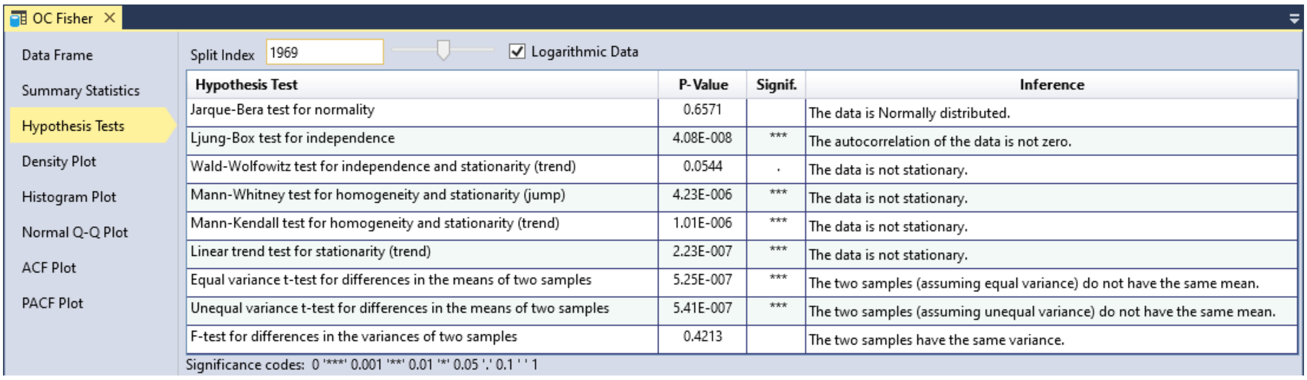
Figure 3 – Threshold data entry in RMC-BestFit.

Hypothesis Testing

From the chronology plot (Figure 2), it is visually apparent that there is a downward trend in annual max inflows. A nonstationary time series will often exhibit a trend or jump that can be increasing or decreasing and may be linear or nonlinear. The cause of the nonstationarity can be a gradual change in hydrological and climatological factors or conditions, or sometimes anthropogenic changes, such as alterations in land use and land cover. Detecting changes in the time series data is the first step in the analysis.

As shown in Figure 4 below, RMC-BestFit provides several widely used hypothesis tests for identifying nonstationarity in the input data. These include the Wald-Wolfowitz, Mann-Whitney, Mann-Kendall, and linear trend tests, all of which indicate that the data is not stationary. The equal and unequal t-tests detect a difference in means in the data, and the Ljung-Box tests indicates that the data has statistically significant autocorrelation.

The autocorrelation function (ACF) plot of the annual max data is shown below in Figure 5. This plot confirms the Ljung-Box test, indicating some persistent autocorrelation at a lag of 10 years. This may suggest that there is some periodicity in the data.



OC Fisher

Data Frame / Summary Statistics / Hypothesis Tests / Density Plot / Histogram Plot / Normal Q-Q Plot / ACF Plot / PACF Plot

Split Index 1969 ☑ Logarithmic Data

Hypothesis Test	P-Value	Signif.	Inference
Jarque-Bera test for normality	0.6571		The data is Normally distributed.
Ljung-Box test for independence	4.08E-008	***	The autocorrelation of the data is not zero.
Wald-Wolfowitz test for independence and stationarity (trend)	0.0544	.	The data is not stationary.
Mann-Whitney test for homogeneity and stationarity (jump)	4.23E-006	***	The data is not stationary.
Mann-Kendall test for homogeneity and stationarity (trend)	1.01E-006	***	The data is not stationary.
Linear trend test for stationarity (trend)	2.23E-007	***	The data is not stationary.
Equal variance t-test for differences in the means of two samples	5.25E-007	***	The two samples (assuming equal variance) do not have the same mean.
Unequal variance t-test for differences in the means of two samples	5.41E-007	***	The two samples (assuming unequal variance) do not have the same mean.
F-test for differences in the variances of two samples	0.4213		The two samples have the same variance.

Significance codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Figure 4 – Hypothesis test results for the annual max inflows to O.C. Fisher dam.

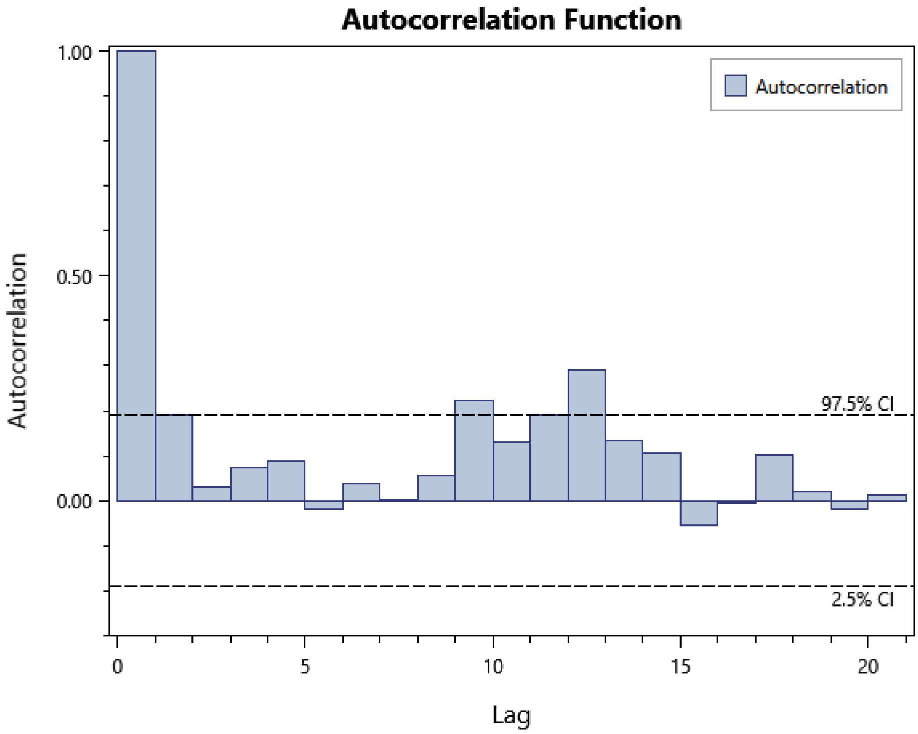


Figure 5 – Autocorrelation function plot for the annual max inflow data.

Bayesian NSFFA

After the user has created the input data, a Bayesian FFA can be setup and performed. The analysis properties and options are shown below in Figure 6. As shown on the left side of the figure, the O.C. Fisher input data is selected, and Log-Pearson Type III (LPIII) distribution is chosen to be consistent with current U.S. flood frequency guidance (U.S. Geological Survey, 2018). A NSFFA can be setup in RMC-BestFit by checking the "Nonstationary" checkbox, as illustrated on the right side of Figure 6. In this study, only the mean of the LPIII distribution was treated as a nonstationary parameter.

Since the distribution parameters vary with time in a NSFFA, the exceedance probability and corresponding return period of a flow value also varies with time. In a stationary frequency analysis, the return period provides a straightforward and consistent measure of the likelihood of an event occurring. For example, if a flood has a return period of 100 years, it means there is a 1% chance (1/100) of that flood being exceeded in any given year.

However, in a nonstationary frequency analysis, where the statistical properties change over time, the concept of a return period becomes more complex. In this context, the return period can vary over time, reflecting the changing probabilities of event magnitudes (Read & Vogel, 2015). Consequently, the return period in a nonstationary analysis must be carefully interpreted, often focusing on specific time steps or conditions to provide meaningful insights.

The "Time Index" property, shown on the right side of Figure 6, determines the time step for evaluating the nonstationary frequency distribution. In the USACE dam safety program, risk is evaluated using the current conditions at the site rather than forecasted or hindcasted conditions. Thus, the parameters from the most recent time step, in this case 2021, are used for flood hazard prediction in the risk analysis. However, users can choose any time step within the study period and forecast up to 100 time steps into the future. This "Time Index" approach follows the procedures demonstrated by Cheng *et al.* (2014).

The "Alpha" property represents the exceedance probability used for evaluating the nonstationary chronology plot. The default probability is 0.5 (or the 2-year return period), ensuring that the frequency distribution visually fits the observed data.

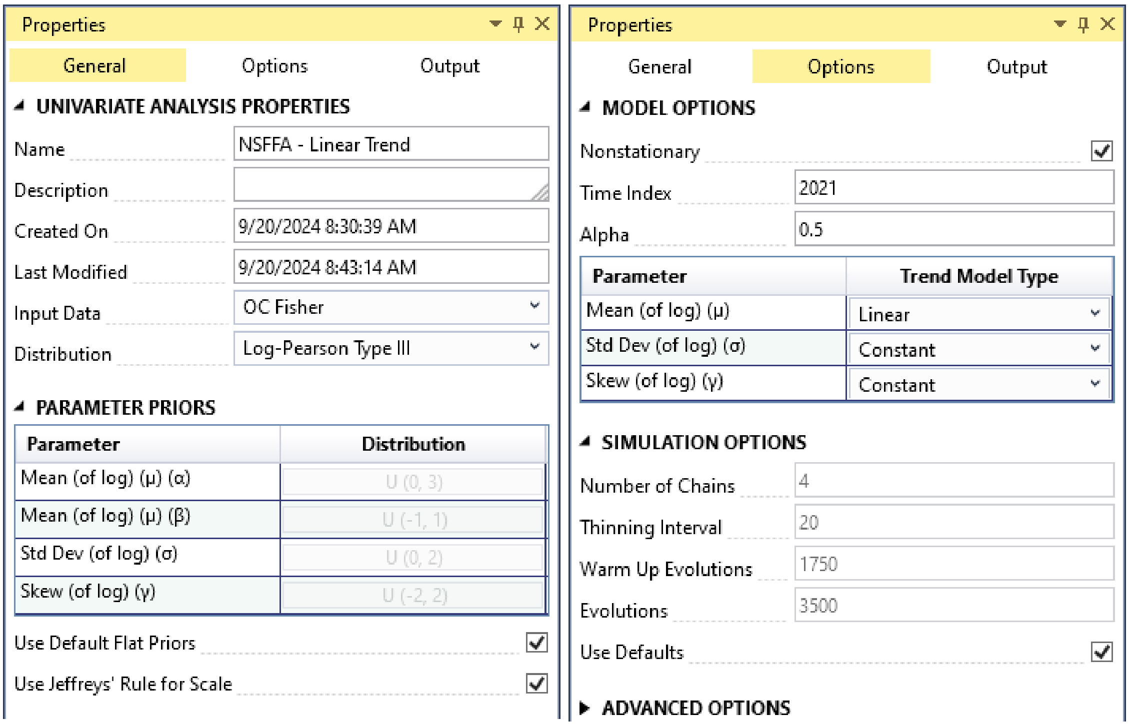


Figure 6 – Model properties and options in RMC-BestFit.

Incorporating GCM Projections

As demonstrated by Coles and Tawn (1996) and Viglione *et al.* (2013), regional precipitation-frequency and modelled rainfall-runoff results can be incorporated in the Bayesian analysis through a prior distribution of flows for a specified exceedance probability, referred to as a quantile prior in the software.

For this analysis, the Rainfall-Runoff Frequency tool (RRFT), a cloud-based system for stochastically sampling HEC-HMS models, was used to estimate quantile priors for the 0.1, 0.01, and 0.001 annual exceedance probabilities (AEPs), as shown in Figure 7 below. For more details on the RRFT, see Avance *et al.* (2021) and Quebbeman *et al.* (2023).

Global Climate Model (GCM) projections can also be incorporated into the NSFFA with quantile priors in RMC-BestFit. For this case study, downscaled hydrology projections from a multi-model ensemble (Maurer, Brekke, Pruitt, & Duffy, 2007) were downloaded and processed for the watershed. From the projections, it was estimated that runoff would continue to decrease by about 5% on average over the next 30 years. Therefore, the mean flows of the quantile priors were reduced accordingly.

Model Selection

As shown in Table 1, there are several trend model options for the location (μ), scale (σ), and shape (ξ) parameters available in RMC-BestFit. Model selection under nonstationarity is a crucial issue, as complex trend options may fit the data well but might not be parsimonious. The modeler should select a simple model that can explain much of the variance of the data.

It is recommended to always start with a stationary model as a baseline, which has the lowest number of parameters, and then test incrementally more complex models. This involves progressively adding parameters and checking whether each alternative model significantly improves over the previous one. The Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) were used to compare the fitness of the models. The model with the lowest AIC or BIC is preferred. When comparing multiple models, additional parameters often yield larger, optimized log-likelihood values. AIC and BIC penalize for more complex models with additional parameters. However, for BIC, the penalty is a function of the sample size, and so it is typically more severe than that of AIC. For details on the measures, see the user guide (Smith & Doughty, 2020).

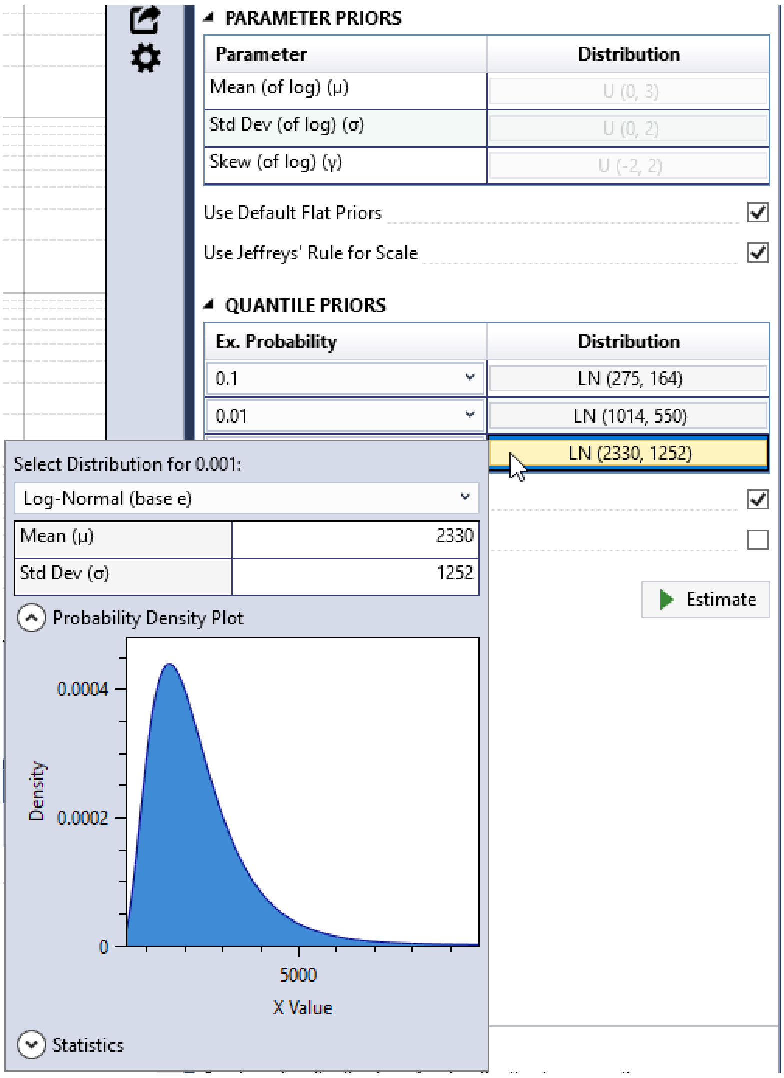


Figure 7 – Parameter and Quantile Prior Options in RMC-BestFit.

In this study, only the mean of the LPIII distribution was treated as a nonstationary parameter, and four model configurations were evaluated: stationary (constant), linear trend, step function, and sinusoidal trend. The linear trend was tested because hypothesis tests results indicate a trend, making it a good default choice for modelling changes in the mean flow. The step function was tested because historical reports suggest a sudden decrease in inflows around 1960, corresponding to increased land use changes and agricultural demands on the groundwater aquifer. The sinusoidal trend was tested because the autocorrelation function of the data exhibited some periodicity.

Table 2 below shows a comparison of the model performance in terms of AIC and BIC. The sinusoidal model has the smallest AIC and BIC. However, there is no hydrological or climatological explanation for why the data should follow a sinusoidal trend. The linear trend model has the second smallest AIC and BIC, is parsimonious, and can be explained based on hydrologic principles. Specifically, there have been persistent changes in the land use in the region, and climate models show a continued decrease in runoff going forward.

Figure 8 below shows a comparison of the chronology plots for all four model configurations. These plots show the distribution of the 0.5 (or 2-year) inflow over time. The plot suggests that the linear trend model provides the best fit to the observations. Consequently, this model was carried forward into the risk analysis.

Table 2 – Selected model options for the location parameter (μ) in RMC-BestFit.

Model Type	AIC	BIC
Constant: $\mu_t = \alpha$	1061.42	1069.41
Linear: $\mu_t = \alpha + \beta t$	1049.23	1059.89
Step Function: $\mu_t = \begin{cases} \mu_1, & t \le t_c \\ \mu_2, & t > t_c \end{cases}$	1054.22	1067.54
Sinusoidal: $\mu_t = \alpha + \beta \sin(2\pi\gamma t + \delta)$	1040.22	1056.20

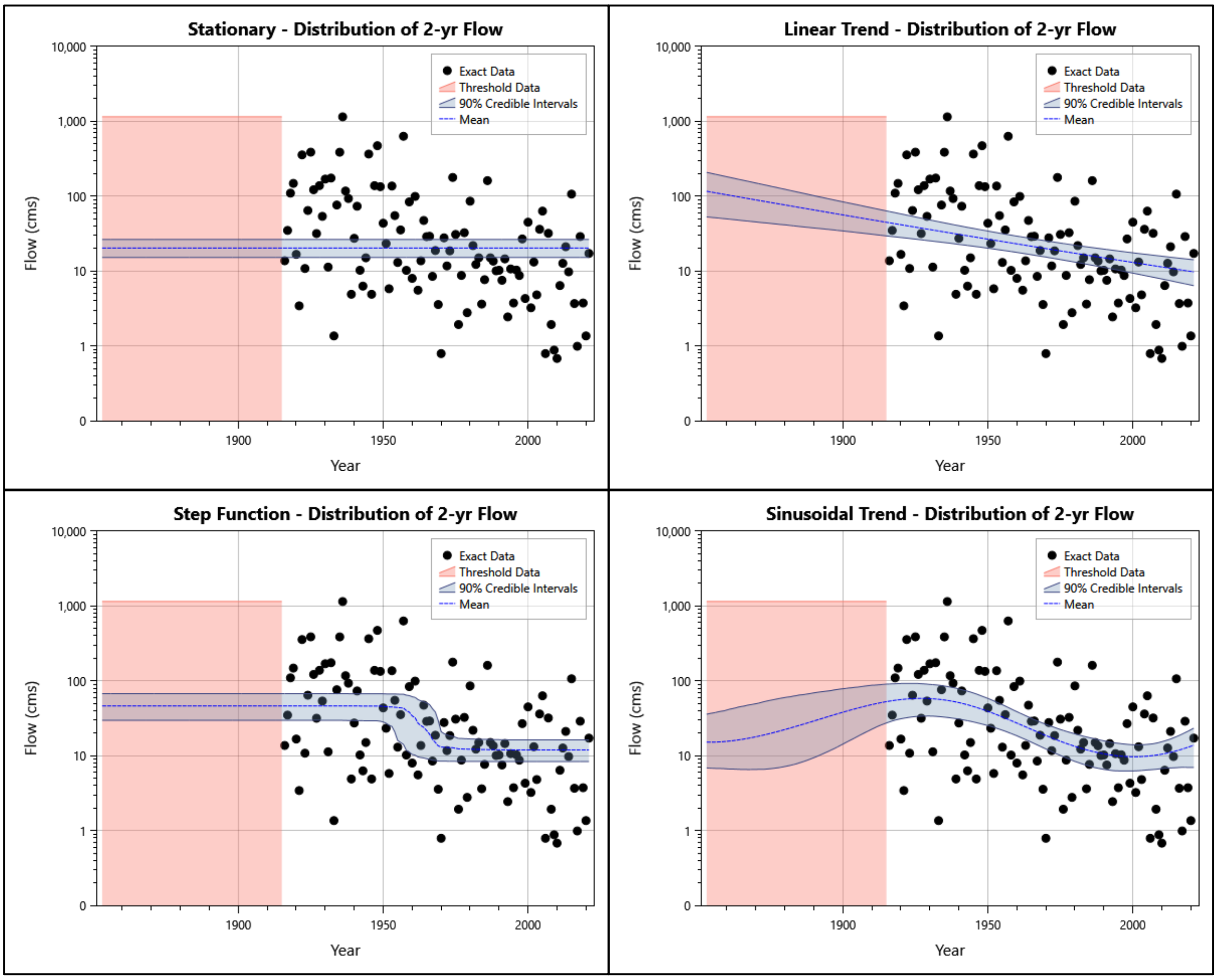


Figure 8 – Comparison of trend model results.

Frequency Analysis Results

After estimating and selecting the best model, flood hazard predictions and risk analyses can be performed. In this study, the parameters from the most recent time step, 2021, were used for prediction. The stationary and nonstationary frequency results are shown below in Figure 9. The probable maximum flood (PMF) is plotted for reference as a horizontal dashed red line.

The stationary posterior predictive curve suggests that the PMF has an AEP of approximately 2E-4 (or a 5,000-year return period). In contrast, the nonstationary posterior predictive curve indicates that the PMF has an AEP slightly less than 1E-4 (or a 10,000-year return period). More significantly, the predicted 0.01 AEP (100-year) flow is much reduced with the nonstationary model, from 950 cms to 425 cms. This reduction in more frequent flows presents an opportunity to potentially decrease flood control storage while increasing water supply storage for climate resiliency.

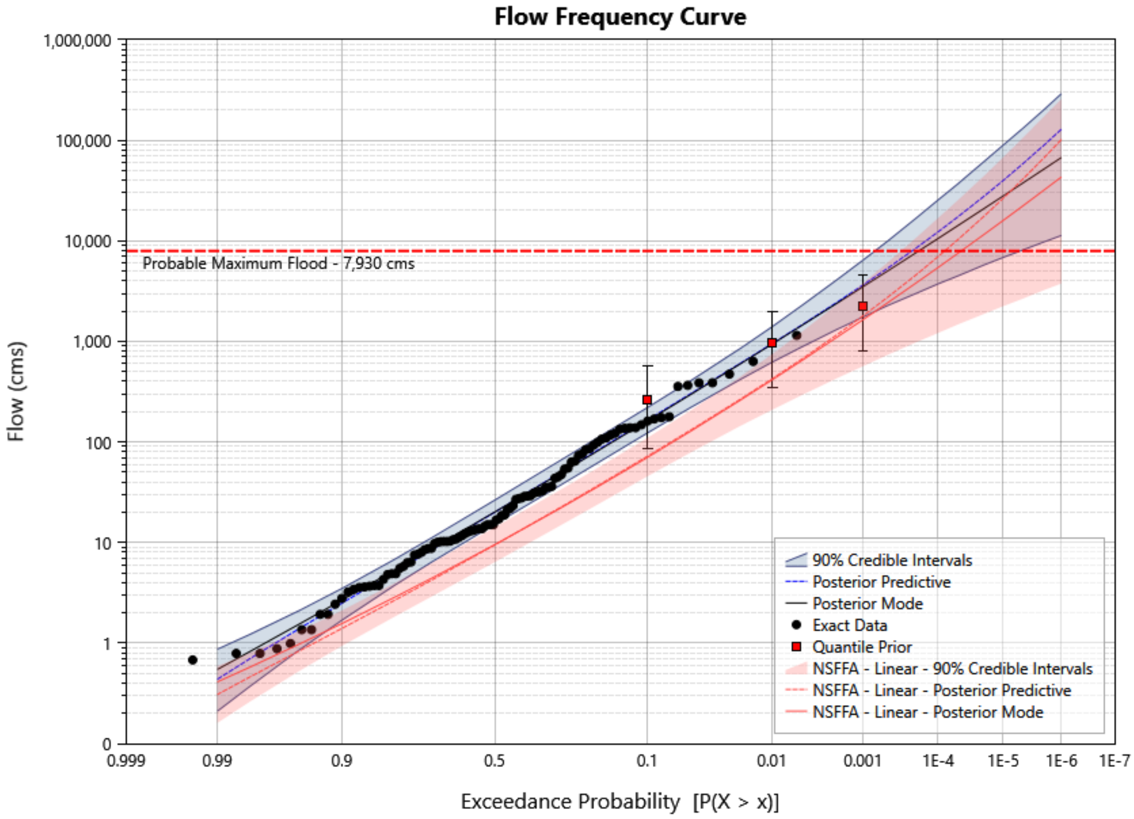


Figure 9 – Comparison of stationary and nonstationary flood frequency results.

Dam safety risk analysis requires that the nonstationary flow-frequency curve be transformed to a reservoir water level, which can be performed using a reservoir routing software, such as the Reservoir Frequency Analysis software, RMC-RFA (Smith, 2018). The results from RMC-BestFit and RMC-RFA can be imported to the quantitative risk analysis software RMC-TotalRisk (Smith & Fields, 2022), where the dam safety risk analysis can be conducted.

In the coming decades, the reallocation of flood storage for water supply, or vice versa, will undoubtedly be necessary to address the impacts of climate change. Increasing water supply will tend to increase the likelihood of spillway discharge at lower water levels, thereby increasing the potential of flood damages during spillway operations. However, if the flood hazard is decreasing over time, the net increase in these damages could be negligible, allowing for positive net benefits and increased water supply.

In general, for sites where the flood hazard is increasing due to climate change, more conservative dam safety modifications that provide higher levels of protection will be preferable. Conversely, for sites where the flood hazard is decreasing, lower levels of flood protection can be justified. Additionally, a decreasing flood hazard would encourage an increase in water supply storage at reservoirs, especially in the semi-arid western United States.

Conclusions

This study demonstrates the importance of incorporating nonstationarity into flood hazard predictions and risk analyses, particularly in the context of changing climatic conditions and land use. By using the Bayesian framework employed in RMC-BestFit, various trend model configurations for the mean of the LPIII distribution were effectively estimated and evaluated. The results indicate that the nonstationary models provide a more accurate and nuanced understanding of flood risks compared to stationary models.

Specifically, the nonstationary posterior predictive curve suggests a lower AEP for the PMF and a significantly reduced flow for the 0.01 AEP, highlighting the dynamic nature of flood hazards in response to ongoing environmental changes. This reduction in predicted flow frequencies offers a valuable opportunity to reallocate flood control storage, thereby enhancing water supply storage and improving climate resiliency.

Furthermore, the case study emphasizes the necessity of selecting parsimonious models that can explain much of the data variance while avoiding overfitting. The linear trend model was identified as the most suitable due to its balance of simplicity and explanatory power, supported by both hydrological principles and climate projections.

As climate change continues to impact hydrological patterns, it is crucial to adopt flexible and forward-looking approaches in dam safety and water resource management. The methodologies and insights from this study provide a foundation for such adaptive strategies, ensuring better preparedness and optimized resource allocation in the face of evolving flood risks.

In conclusion, the RMC-BestFit software offers numerous features to enhance and expedite flood hazard assessments, improving dam and levee safety investment decisions. The RMC-BestFit software is freely available to the public and downloadable from the RMC website (https://www.rmc.usace.army.mil/Software/RMC-BestFit/).

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