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Statistical Modeling Approaches for Nonstationary Flood Frequency Analysis in the Kosi River Basin

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ABSTRACT

Flood frequency analysis (FFA) is essential for hydrological risk assessment and infrastructure planning. However, traditional methods often assume stationarity, a premise increasingly challenged by climate change and human activities. This study explores nonstationary FFA in the Kosi River Basin using three approaches: Maximum Likelihood estimation, two-stage regression modeling, and Generalized Additive Models for Location, Scale, and Shape (GAMLSS). Daily flow records were used to extract annual maximum discharges, which were fitted to time-varying Generalized Extreme Value (GEV) models. Results show clear nonstationarity, with rising flood quantiles, especially for the 50- and 100-year return periods. While the Maximum Likelihood and Two-Stage approaches captured linear trends, GAMLSS revealed nonlinear dynamics. Model comparisons via Akaike Information Criterion (AIC) indicated no single method was best overall; multimodel averaging weighted by AIC provided more reliable quantile estimates. Bootstrap resampling confirmed increasing uncertainty with longer return periods and consistently highlighted growing flood risks. Stationary models tended to overestimate current design floods by about 35–40%, risking over-design if stationarity is wrongly assumed. This research illustrates that combining multimodal averaging with bootstrap uncertainty offers a robust framework for nonstationary flood frequency analysis, aiding climate-resilient water management and flood risk planning.

1. INTRODUCTION

Extreme flood events threaten human lives, livelihoods, infrastructure, and ecosystems, especially in flood-prone areas (Hoq et al. 2021). The socio-economic impacts of these events are compounded by rapid urbanization, land-use changes, and increased extreme precipitation due to climate variability and change (Dewan 2015, Khayyam 2020). Reliable flood frequency analysis (FFA) is essential for risk assessment and guiding the design of hydraulic structures, flood defenses, and water management policies (Machado et al. 2015). Traditionally, FFA has assumed stationarity, meaning flood probabilities are considered constant over time. However, growing evidence indicates that this assumption is increasingly invalid due to changing climate conditions, catchment modifications, and human interventions (Cui et al. 2023, Hounkpè et al. 2015). As a result, nonstationary approaches have been developed to explicitly incorporate the temporal variability of extreme hydrological events.

Over the last twenty years, hydrologists have increasingly utilized nonstationary extreme value theory (EVT) to more accurately represent the shifting risks associated with floods (Razmi et al. 2017). Katz et al. (2002) and Coles et al. (2001) established the theoretical groundwork by introducing covariate-dependent Generalized Extreme Value (GEV) models. Later research highlighted the significance of incorporating climate indices, such as ENSO and PDO, or time as covariates to identify trends in flood extremes (Cheng et al. 2014, López & Francés 2013). Comparative analyses indicate that various nonstationary modeling approaches can produce notably different estimates of return levels, emphasizing the influence of model assumptions on flood risk assessments (Barbhuiya et al. 2023, Debele et al. 2017, Gül et al. 2014, Strupczewski et al. 2001). More recent work recommends multimodel inference and Bayesian model averaging to address structural uncertainties in hydrological extremes (Bhere & Janga Reddy 2025, Cui et al. 2023, Faulkner et al. 2020). Concurrently, bootstrap and Bayesian resampling methods are extensively employed to generate confidence intervals and evaluate uncertainty in non-stationary return level estimates (Kwon et al. 2011, Kwon et al. 2008).

Among various nonstationary methods, the Maximum Likelihood (ML) approach introduces linear trends in GEV parameters, whereas the two-stage method combines regression-based estimation of mean and variance with stationary residual fitting. More adaptable techniques, such as Generalized Additive Models for Location, Scale, and Shape (GAMLSS), enable nonlinear covariate effects on multiple distribution parameters, providing enhanced flexibility for capturing complex hydrological dynamics. Despite their strengths, each method has specific assumptions and limitations (Zhang et al. 2018). Consequently, relying on a single model may result in biased or unstable quantile estimates, especially for higher return periods (de Bruijn et al. 2020, Montello et al. 2022, Rajeshkannan & Kogilavani 2021, Talchabhadel et al. 2023, Zhang et al. 2024, Zheng et al. 2023).

To tackle this challenge, multimodal averaging based on information-theoretic criteria, such as the Akaike Information Criterion (AIC), offers a robust framework for synthesizing multiple models and reducing structural uncertainty (Chow & Watt 1992, Di Baldassarre et al. 2009, Haddad & Rahman 2011, Okoli et al. 2018). Additionally, bootstrap resampling provides a means to quantify estimation uncertainty and develop confidence intervals for non-stationary return levels.

Existing studies on nonstationary flood frequency in the Kosi River Basin and similar monsoon-driven rivers have primarily concentrated on individual modeling approaches or single best-fit models. They have paid limited attention to how model structure and parameter uncertainties jointly influence estimate outcomes. Notably, systematic comparisons of multiple nonstationary estimation methods within a unified framework, as well as the application of information-theoretic multimodel averaging to inform design decisions, remain rare.

This study presents a comprehensive framework for nonstationary flood frequency analysis by explicitly integrating and comparing various statistical methods within a unified model and uncertainty assessment system. Its objectives include (i) evaluating the performance of Maximum Likelihood (ML), Two-Stage, and GAMLSS techniques in modeling annual maximum discharge data, (ii) estimating nonstationary quantiles for return periods of 10, 25, 50, and 100 years, and (iii) assessing model effectiveness using multimodel averaging based on information-theoretic criteria, while quantifying predictive uncertainty with bootstrap confidence intervals. By combining diverse estimation approaches with rigorous uncertainty evaluation, this research aims to overcome the limitations of single modeling techniques, offering more robust and actionable

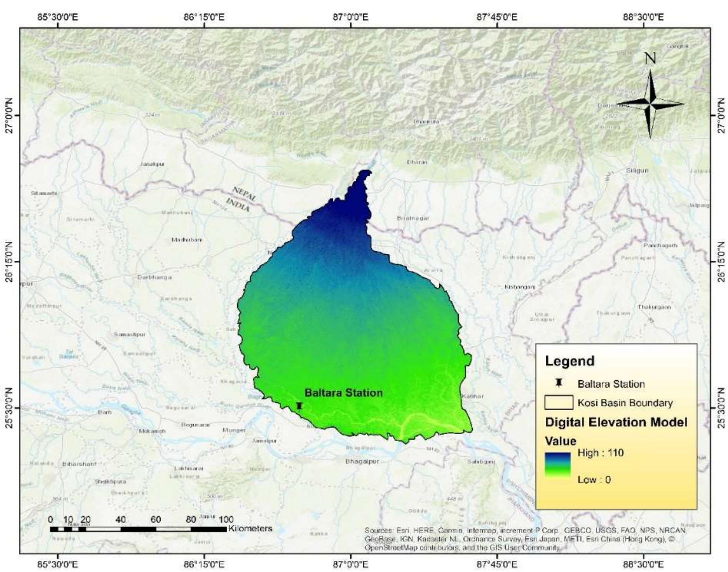

Fig. 1: Study area map showing Baltara station.

insights for flood risk management in dynamic, nonstationary environments.

2. STUDY AREA AND DATA COLLECTION

The Kosi River Basin spans from latitude 25° 21.0' to 26° 21.6' N and longitude 86° 31.8' to 87° 35.4' E. Originating in Tibet, the river flows through Nepal before entering Bihar near Bhimnagar and ultimately merging with the Ganga River near Kurshela (Fig. 1). In Bihar, the river covers a length of 261 km across 10 districts, including Supaul, Saharsa, Madhepura, and Katihar. Located in Bihar's plains, the basin reaches a maximum elevation of 91 meters and features slopes ranging from 0° to 35°. It is vital for agriculture, water supply, and local livelihoods. The climate is tropical monsoon with distinct wet and dry seasons, with most rainfall occurring from June to September.

Daily discharge data were sourced from the Central Water Commission (CWC) for the Baltara gauging station on the Kosi River. Spanning from 1989 to 2022, the dataset encompasses approximately 33 years of continuous observations. The basin exhibits high sensitivity to climate variability, with extreme rainfall events driven by ENSO and other large-scale climate phenomena. Human activities, including land-use changes and agricultural intensification, have also modified catchment responses, highlighting the need for nonstationary flood risk assessment.

3. MATERIALS AND METHODS

Daily discharge records were processed to develop an annual maxima series (AMS), the standard input for extreme value analysis. Initially, the records were examined for completeness and consistency. Years with inadequate daily observations were excluded to avoid bias in estimating the maximum values. Outliers identified through time-series inspection and summary statistics were retained if they represented documented extreme flood events, as removing them would distort the distribution's upper tail, which is essential for flood frequency analysis. Missing values were few and not imputed; instead, years with substantial data gaps were omitted from the AMS. The analysis of the AMS employed nonstationary extreme value frameworks.

3.1. Maximum Likelihood (ML) Estimation

The ML estimation method is widely used for estimating parameters of the Generalized Extreme Value (GEV) distribution under nonstationarity. The GEV distribution is defined as:

$$f(x;\mu,\sigma,\xi) = \frac{1}{\sigma}\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi-1}\exp\left\{-\left[1+\xi\left(\frac{x-\mu}{\sigma}\right)\right]^{-1/\xi}\right\} \quad \ldots(1)$$

where μ is the location parameter, σ > 0 is the scale parameter, and ξ is the shape parameter.

To account for nonstationarity, parameters are modeled as functions of covariates (Z_t). A common formulation is: e.g.:

$$\mu_t = \mu_0 + z_t,\quad \sigma_t = \sigma_0\,\exp(\sigma_1 z_t),\quad \xi_t = \xi(\text{constant}) \quad \ldots(2)$$

Given the relatively short length of the annual maximum series (33 observations), time was selected as the sole covariate in this study to ensure model parsimony and reduce the risk of over-parameterization.

Typically, only μ_t or σ_t are allowed to vary with time (to avoid over-parameterization).In this study, Z_t represents time.

Given a sample $\{x_1, x_2, \ldots, x_n\}$ of annual maximum floods, the likelihood function under nonstationarity is

$$L(\theta) = \prod_{t=1}^{n} f(x_t;\mu_t,\sigma_t,\xi) \quad \ldots(3)$$

Where $\theta = (\mu_0, \mu_t, \sigma_0, \sigma_1, \xi)$ is the parameter vector the log -likelihood is

$$l(\theta) = \sum_{t=1}^{n} \ln f(x_t;\mu_t,\sigma_t,\xi) \quad \ldots(4)$$

The ML estimates are obtained by solving:

$$\hat{\theta} = \arg\max_{\theta}\ l(\theta) \quad \ldots(5)$$

Once the parameters are estimated, the t-year return level is derived from the quantile function.

$$Q_T = \mu_t - \frac{\sigma_t}{\xi}\left[1-\{-\ln(1-1/T\}^{-\xi}\right] \quad \ldots(6)$$

This approach enables the calculation of nonstationary flood quantiles that change with covariates like time. Maximum Likelihood (ML) estimation is highly efficient statistically, as it makes full use of all available data and supports likelihood-based inference with flexible covariate inclusion. Nevertheless, it may encounter numerical instability during optimization, be sensitive to sample size and initial parameter guesses, and become more difficult to interpret when multiple covariates are involved.

3.2. Two-Stage Method

The Two-Stage Method offers an alternative to machine learning for nonstationary frequency analysis by dividing the estimation process into two distinct steps instead of directly fitting the GEV distribution with covariates. Initially, a stationary distribution—typically GEV—is fitted to the data to estimate parameters, which are then used to transform the data into normalized residuals. In the subsequent stage, either the residuals or the distribution parameters are modeled as functions of covariates such as time. This two-step approach reduces computational complexity and facilitates easier interpretation.

Fit the GEV distribution under stationarity:

$$x_t \sim GEV(\mu, \sigma, \xi) \quad \text{....(7)}$$

Where μ, σ, ξ are constant parameters estimated using ML or L-moments. Compute the reduced variate (standardized value):

$$y_t = {x_t - \hat{\mu}} \Big/ {\hat{\sigma}} \quad \text{...(8)}$$

The Two-Stage Method has several advantages over the direct ML approach. It is more computationally efficient because the estimation process is divided into two manageable steps, avoiding complex likelihood optimization with covariates from the start. This division also helps prevent convergence issues that are common in full ML estimation, making the method more stable and easier to implement. Additionally, its interpretability is a key benefit: because regression modeling of parameters occurs separately in the second stage, the effects of covariates on flood frequency can be more clearly understood and communicated. However, this method has some limitations. It is statistically less efficient than ML because it does not utilize all the data in a single, unified estimation, which may reduce precision. If the initial stationary fit is poor, it can introduce bias into the subsequent regression, affecting the accuracy of the nonstationary estimates. Finally, the method does not fully account for parameter uncertainty from the first stage in the second, potentially underestimating variability and leading to overconfident conclusions.

3.3. Generalized Additive Models for Location, Scale, and Shape (GAMLSS)

GAMLSS offers a versatile framework that models all distributional parameters (μ, σ, ξ) as functions of covariates, accommodating both linear and nonlinear (smooth) effects. In this approach, the location parameter was modeled using a quadratic time trend to capture potential nonlinear changes in flood magnitudes, while the scale parameter was modeled with a linear trend. The shape parameter was kept constant to maintain simplicity. The quadratic formulation for the location parameter was chosen to effectively represent nonlinear temporal evolution, balancing model flexibility with parsimony. To ensure numerical stability and parameter identifiability with a limited sample size, the scale parameter was restricted to linear time variation, and the shape parameter was fixed. All parameters were estimated through maximization of the penalized likelihood.

For annual maximum floods:

$$x_t \sim GEV(\mu_t, \sigma_t, \xi_t) \quad \text{...(9)}$$

Nonstationary parameter modeling in GAMLSS, parameters are modeled as:

$$\mu_t = \eta_\mu(z_t) = \beta_o^\mu + \sum_j f_j^\mu(z_{jt}) \quad \text{...(10)}$$

$$\ln(\sigma_t) = \eta_\sigma(z_t) = \beta_o^\sigma + \sum_j f_j^\sigma(z_{jt}) \quad \text{...(11)}$$

$$\xi_t = \eta_\xi(z_t) = \beta_o^\xi + \sum_j f_j^\xi(z_{jt}) \quad \text{...(12)}$$

Where $f_j(\bullet)$ are smooth functions (e.g., splines) or linear terms. Covariates z_{jt} include time. In this study, nonstationarity was introduced using time as the sole covariate.

Likelihood Estimation

The GAMLSS log-likelihood is:

$$l(\theta) = \sum_{t=1}^{n} \ln f(x_t | \mu_t, \sigma_t, \xi_t) \quad \text{...(13)}$$

with optimization performed using penalized maximum likelihood (PML). Smoothness penalties control overfitting.

Return level for return period T:

$$Q_T(t) = \mu_t - \frac{\sigma_t}{\xi_t}\left[1 - \left(-\ln\left(1 - \frac{1}{T}\right)\right)^{-\xi_t}\right] \quad \text{...(14)}$$

This yields time-varying return levels that reflect both linear and nonlinear effects.

The GAMLSS framework offers several key advantages that make it highly effective for nonstationary flood frequency analysis. Its primary strength is its flexibility, enabling it to model nonlinear and non-monotonic trends in the data that simpler models often overlook. Unlike methods that limit covariates to the location parameter alone, GAMLSS allows covariates to influence all three parameters of the GEV distribution, the location (μ), scale (σ), and shape (ξ), providing a more complete picture of non-stationary behavior. Another benefit is the use of penalized likelihood techniques, which regulate the smoothness of the fitted functions and help avoid overfitting, a common issue with flexible models. Additionally, the implementation of smooth functions like splines makes it easier to interpret the effects of covariates visually, helping researchers better understand and communicate how environmental or climate factors impact flood extremes over time.

Although GAMLSS offers several advantages, it also has notable limitations. The method is computationally intensive, often requiring iterative optimization that can be slow and demanding on resources, especially with large datasets or complex models. Interpreting the results becomes more difficult when multiple smooth terms are included, as the combined effects of nonlinear covariates can be hard to disentangle. Additionally, there is a risk of overfitting with small sample sizes, since the model's flexibility may lead to identifying false patterns as true signals. Because GAMLSS estimates multiple parameters simultaneously, it typically needs a relatively large sample to produce stable estimates and reliable inferences. With limited data, parameter estimates may become unstable, reducing the model's predictive performance. Consequently, results from GAMLSS should be interpreted cautiously, particularly when data are scarce.

3.4. Multimodel Averaging

To reduce dependence on a single model, multimodel averaging was employed using Akaike Information Criterion (AIC) weights:

$$w_m = \frac{\exp\left(-0.5\Delta_m\right)}{\sum_{k=1}^{M} \exp\left(-0.5\Delta_k\right)} \quad \ldots(15)$$

Where $\Delta_m = AIC_m - AIC_{min}$, and M is the number of models. The multimodel return level is then:

$$Q_T^{multi}\left(t\right) = \sum_{m=1}^{M} w_m Q_T^{(m)}\left(t\right) \quad \ldots(16)$$

with $Q_T^{(m)}\left(t\right)$ the return level from the model m.

3.5. Bootstrap Uncertainty Analysis

A nonparametric block bootstrap method was used to assess the uncertainty in the return level estimates. This involved repeatedly resampling the AMS with replacement to create synthetic data sets. Each resampled dataset was then used to refit the models, and the multimodel return levels were recalculated. The distribution of these estimates was used to derive the 95% confidence intervals. This method explicitly accounts for sampling variability and provides robust uncertainty bands around time-varying flood quantiles.

4. RESULTS AND DISCUSSION

4.1. Annual Maximum Series (AMS)

The annual maximum discharge series (AMS) for the Kosi River Basin covered 1989 to 2022, totaling 33 years of data. The series shows significant year-to-year variability, with peak discharges ranging from approximately 766 $m^3.s^{-1}$ to 13,500 $m^3.s^{-1}$ (Table 1). Visual analysis indicated no clear increasing or decreasing trend in the annual maxima, although

Table 1: Summary statistics of annual maximum discharge series.

Statistic	Minimum	Maximum	Mean	Standard Deviation	Skewness	Kurtosis
Value [$m^3.s^{-1}$]	766.24	13,500	6,737.12	2,165.92	0.47	5.44

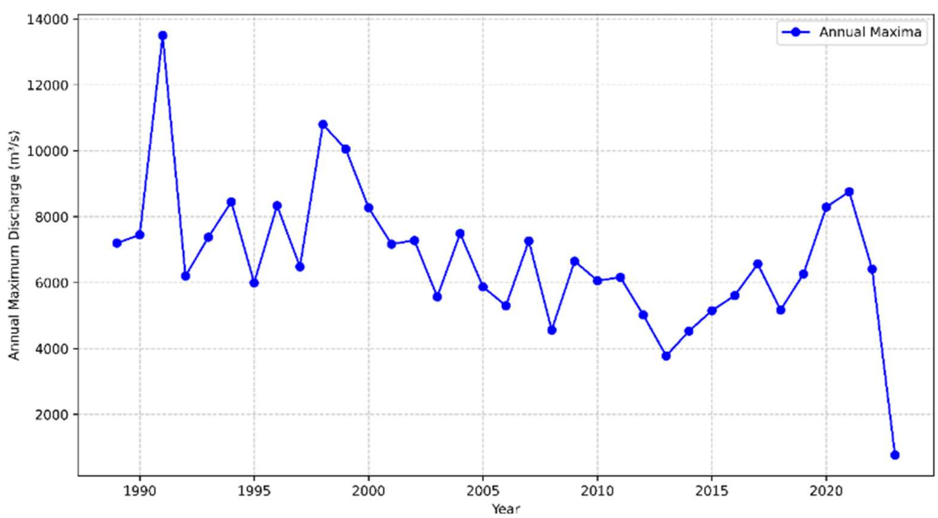

Fig. 2: Time series plot of annual maximum discharge for the Kosi River Basin at the station Baltara.

Table 2: AIC values and normalized weights for ML, Two-Stage, and GAMLSS models.

Model	AIC	Normalized Weight
ML	631.65	0. 70
Two-Stage	1118.09	0.15
GAMLSS	686.81	0.15

notable variability suggested potential nonstationarity (Fig. 2). While the raw AMS data demonstrate considerable interannual fluctuations without a consistent trend, nonstationary analysis indicates rising high-return-period quantiles, reflecting changes in extreme flood events rather than average flow behavior.

4.2. Model Fitting and Information Criteria

Three nonstationary models, Maximum Likelihood (ML), Two-Stage, and GAMLSS, were applied to the AMS using various parameterizations. The model performance was assessed using the Akaike Information Criterion (AIC). The ML-based nonstationary model yielded the lowest AIC, suggesting that it offered the best overall statistical fit among the options (Table 2). Nonetheless, the differences in the AIC weights indicate that no single model clearly outperformed the others, justifying the use of multimodel averaging. Although the ML and Two-Stage models described linear changes in flood behavior, the GAMLSS framework allowed for greater flexibility in capturing nonlinear dynamics, particularly in higher return-period quantiles.

AIC weights showed that no single model dominated across all periods (Table 2), justifying the use of multimodel averaging.

4.3. Time-Varying Flood Quantiles

Nonstationary return levels (T) were estimated for return periods of 10, 25, 50, and 100 years, respectively, as shown in Fig. 3. The maximum likelihood (ML) quantiles showed nearly linear increases over time. The Two-Stage quantiles demonstrated more variability owing to the residual-based variance estimation. The GAMLSS quantiles displayed nonlinear curvature, particularly for higher return periods, indicating increased sensitivity to recent changes in the upper tail of the flood distribution. Multi-model-averaged quantiles provided smoother and more stable estimates by balancing the strengths and weaknesses of the individual models (Fig. 4).

4.4. Bootstrap-Based Uncertainty Bands

A block bootstrap approach was employed to evaluate the predictive uncertainty. For each resampled dataset, the models were refitted, and the multimodel return levels were recalculated. The 95% confidence intervals were obtained from bootstrap distributions. Uncertainty increased with increasing return periods, with the 100-year quantile exhibiting the widest confidence bands. Despite substantial uncertainty at higher return periods, the ensemble of nonstationary models consistently indicates an upward trend in long-period flood quantiles, although the exact extent

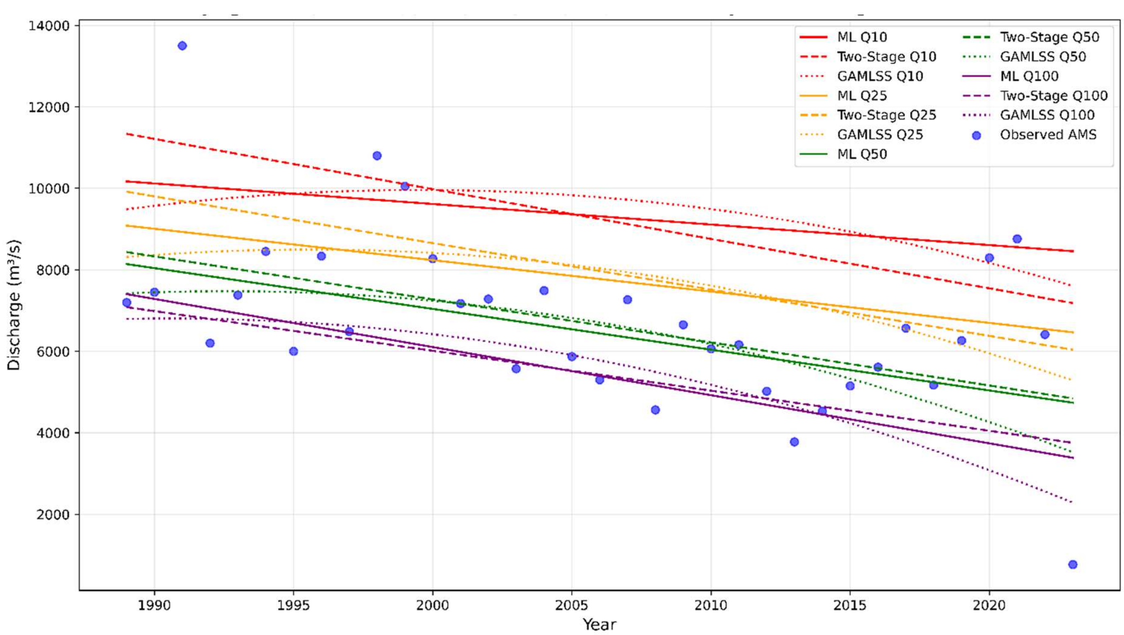

Fig. 3: Time-varying flood quantiles (Q10, Q25, Q50, Q100) estimated by ML, Two-Stage, and GAMLSS models.

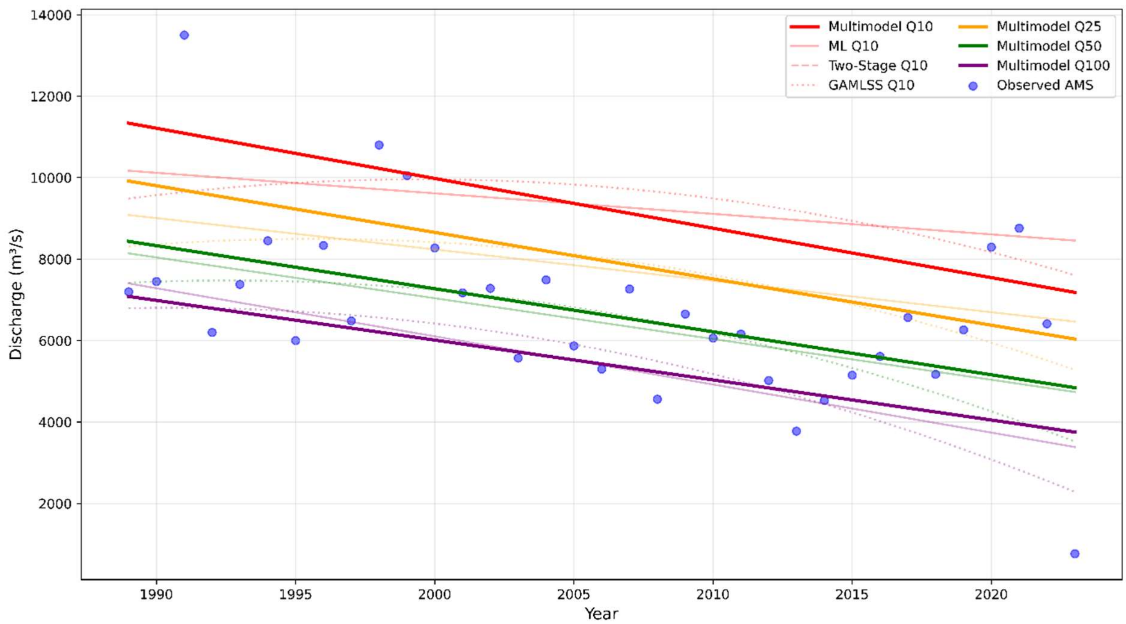

Fig. 4: Multimodel averaged quantiles with individual model contributions highlighted.

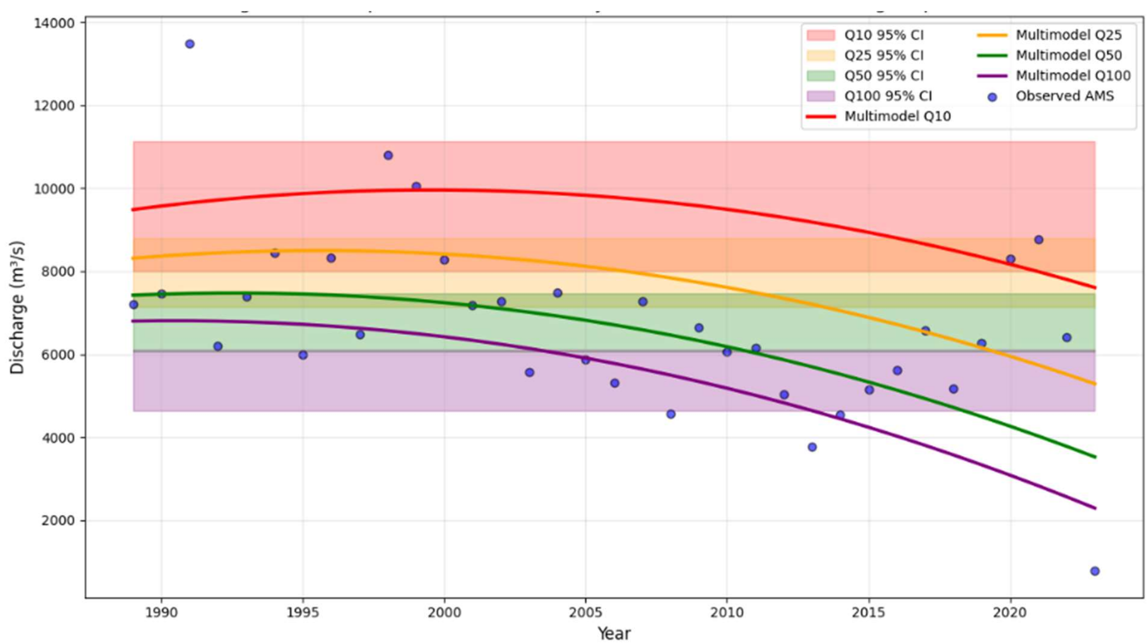

Fig. 5: Bootstrap-based 95% uncertainty bands for multimodel-averaged quantiles.

remains uncertain. The multimodel methodology produced narrower confidence intervals than the single-model estimates, underscoring the benefits of model averaging.

The results highlight the importance of accounting for nonstationarity in flood frequency analysis in the Kosi River Basin. Comparisons with stationary estimates indicated that assuming stationarity led to overestimations of the present-day 50- and 100-year design floods by approximately 40% and 37%, respectively. Although this may result in conservative designs, it also implies potential overdesign and cost inefficiency when nonstationary behavior is ignored.

From a methodological perspective, the integration of multiple nonstationary models, AIC-weighted averaging, and bootstrap uncertainty quantification provides a robust and defensible framework for flood-risk assessment. These insights are particularly relevant for climate-sensitive basins, where both natural variability and anthropogenic changes contribute to the evolution of floods. To illustrate the differences across the models, we examined the estimated design floods for selected return periods in the most recent decade of the record (2013–2023). Table 3 summarizes the estimates from each method and the multi-model average, along with the bootstrap 95% confidence intervals for the multi-model result.

For the 10-year flood, model estimates ranged from 7,725 $m^3.s^{-1}$ (Two-Stage, which coincided closely with the multi-model average) to 8,681 $m^3.s^{-1}$ (ML), with GAMLSS producing an intermediate estimate of 8,385 $m^3.s^{-1}$, the 95% CI for the multi-model estimate spanned approximately 6,630–11,094 $m^3.s^{-1}$. For the 25-year return level, the ML model yielded approximately 10,463 $m^3.s^{-1}$, and the Two-Stage and multi-model both yielded approximately 8,653 $m^3.s^{-1}$ (indicating that ML's trend led to a higher extrapolation), and GAMLSS yielded approximately 10,755 $m^3.s^{-1}$; the CI was 7,546–16,716 $m^3.s^{-1}$, reflecting greater uncertainty. Divergence between models became more pronounced at the higher return periods: the 50-year flood estimates ranged from 9,242 $m^3.s^{-1}$ (Two-Stage, closely followed by the multi-model average) to 12,744 $m^3.s^{-1}$ (GAMLSS), with ML giving 11,794 $m^3.s^{-1}$. The CI of the multi-model 50-year estimate was wide (approximately 8,078–32,827 $m^3.s^{-1}$), indicative of sparse data in the tails. For the 100-year event, estimates varied between 9,755 $m^3.s^{-1}$ (Two-Stage, ~multi-model) and 14,938 $m^3.s^{-1}$ (GAMLSS), with ML yielding 13,124 $m^3.s^{-1}$, correspondingly, the bootstrap CI for the 100-year multi-model estimate extended from approximately 8,519 to 54,223 $m^3.s^{-1}$. These results highlight both the structural differences among nonstationary models and the growing uncertainty at higher return periods, reinforcing the importance of multi-model averaging and rigorous uncertainty quantification in flood-risk assessment. Relying on a single model may lead to the underestimation or overestimation of flood risk, whereas considering outputs from multiple models offers a more comprehensive view of plausible scenarios.

Bootstrap confidence intervals expand significantly with higher return periods, indicating limited data support in the upper tail and structural differences among models. The particularly wide intervals for 50- and 100-year events highlight the substantial uncertainty in estimating rare floods from short records. These findings emphasize the necessity of multimodel averaging and uncertainty assessment, as relying on a single model can result in either underestimation or overestimation of flood risk.

5. CONCLUSIONS

This study employed three nonstationary flood frequency analysis (FFA) methods—the Maximum Likelihood (ML), a two-stage regression-based estimation, and Generalized Additive Models for Location, Scale, and Shape (GAMLSS)—to analyze the annual maximum discharge data from the Kosi River Basin. The findings clearly indicate nonstationarity, with all models showing increasing trends in flood quantiles, especially for long return periods (50- and 100-year events). While GAMLSS captured nonlinear flood behavior patterns, the ML and Two-Stage approaches offered simpler, yet consistent, trend representations. AIC-based information criteria validated that no single model was consistently superior; therefore, AIC-weighted multimodel averaging provided more reliable and stable flood quantile estimates, reducing dependence on any one model. Bootstrap resampling highlighted increasing uncertainty for longer return periods, emphasizing the difficulty of estimating rare flood events.

Nonetheless, the consistent upward trend across models suggests a robust escalation in flood risk. Importantly, assuming stationarity led to overestimates of current 50- and 100-year flood levels by approximately 37–40%, risking overdesign and increased costs in flood infrastructure, potentially resulting in underestimation of risks if nonstationarity is ignored. These results underscore the need to incorporate nonstationary methods into flood frequency analysis for climate-resilient water resource management, flood protection, and policymaking. The framework can be expanded by integrating climate indices and land-use variables into parameter models, exploring Bayesian hierarchical approaches for uncertainty quantification, applying the methodology across multiple basins to identify regional risk patterns, and using the results for flood hazard mapping and early warning systems.

Table 3: Design flood estimates for the most recent decade (2013–2023) from individual nonstationary models and the multimodel average, with 95% bootstrap confidence intervals.

Return Period	ML [$m^3.s^{-1}$]	Two-Stage [$m^3.s^{-1}$]	GAMLSS [$m^3.s^{-}$]	Multi-model Average (95% CI) [$m^3.s^{-}$]
10-year	8,681	7,725	8,385	7,725 (6,630–11,094)
25-year	10,463	8,653	10,755	8,653 (7,546–16,716)
50-year	11,794	9,242	12,744	9,242 (8,078–32,827)
100-year	13,124	9,755	14,938	9,755 (8,519–54,223)

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