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Homogeneity Testing and Quantile Regression for Regional Flood Estimation in the Narayani Basin, Nepal

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Abstract. Regional flood estimation in Nepal is challenged by short, uneven, and spatially sparse hydrometric records, particularly in Himalayan basins where strong physiographic and hydroclimatic contrasts make regional pooling difficult. This study examines the combined use of homogeneity testing and quantile regression for regional flood estimation in the Narayani Basin, Nepal. Annual maximum discharge records from gauged stations, together with selected catchment descriptors, were analyzed within an L-moment framework to evaluate regional homogeneity and identify a pooling group suitable for regional analysis. Quantile regression models were then developed to estimate flood quantiles directly from catchment descriptors and limited annual maximum series. The results show that achieving strict homogeneity in the Narayani Basin is difficult without substantially reducing the available station-year data, reflecting the marked variability of the basin. However, homogeneity screening allowed the identification of a defensible pooling group for regional flood estimation. The quantile regression results indicate that the method makes effective use of limited regional information and provides reasonable flood estimates for low to moderate return periods, with stable performance up to about the 50-year return period. Uncertainty increases for rarer events, and the reliability of regional estimates declines. The study shows that Hosking-Wallis homogeneity assessment combined with quantile regression provides a practical basis for estimating design floods in data-scarce Himalayan basins.

Keywords: Data-scarce Basin, Design Flood, Homogeneity Testing, Narayani Basin, Quantile Regression, QRT, Regional Flood Estimation

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1. INTRODUCTION

Design flood estimation still remains a challenge in Nepal because many river basins are ungauged or poorly gauged. The available hydrometric records are short, uneven and insufficient for reliable at-site design flood estimation [1]. This limitation is more serious in Himalayan basins that produce substantial spatial variability in flood response over short distances due to their characteristic steep topographic gradients, strong monsoon influence and distinct hydroclimatic contrasts. Thus, direct extrapolation of short annual maximum series (AMS) to return periods for design flood has uncertainty, for the design of bridges, culverts, spillways, embankments, and hydropower infrastructure [2, 3, 4].

Regional flood frequency analysis (RFFA) offers a practical alternative where local records are inadequate. Regional methods can improve the stability of flood estimates for ungauged or poorly gauged sites, by pooling information from hydrologically similar catchments [5]. The success of regional methods depends on whether a hydrologically defensible catchment group can be identified. This is especially difficult in Himalayan basins of Nepal, where physiographic diversity is extreme and national scale homogeneity cannot reasonably be assumed. Nepalese basins cannot be treated as a single homogeneous flood region [1, 6]. Regional estimation must be based on careful screening of hydrological similarity and appropriate regional distribution selection [1, 6]. In practice, stricter homogeneity improves regional coherence at the cost of reducing the number of stations and total station-years available for analysis.

Among regional flood estimation methods, regression-based approaches are particularly attractive for data-scarce environments because they relate design floods directly to measurable catchment characteristics [7, 8]. Quantile Regression Technique (QRT) estimates conditional flood quantiles directly and can make efficient use of observed flood information without relying on intermediate at-site quantile estimation only [9]. This framework can exploit available information more effectively than conventional regression approaches in RFFA, even where the record lengths are limited [9]. Subsequent studies have also shown that quantile-regression-based regional models can provide useful predictive relationships in settings where strict regional homogeneity is difficult to achieve, although their performance still depends on descriptor quality, sample support, and model stability [10, 11, 12].

Nepal has remained focused on regionalization using index-flood relationships, simulation-supported analyses and majorly on empirical methods for ungauged basins [1, 13]. QRT for regional flood estimation has not been adequately explored in Nepalese basins. QRT supported within an L-moment-based regional framework that first establishes an acceptable homogeneous pooling group and regional parent distribution.

The present study investigates homogeneity testing and quantile regression for regional flood estimation in the Narayani Basin, Nepal. AMS from gauged stations were analyzed using an L-moment framework to identify an acceptable homogeneous pooling group and to select an appropriate regional parent distribution. QRT models were then developed for selected return periods using catchment descriptors derived from physiographic and climatic data. The regional estimates were finally examined through comparison with at-site flood estimates at a representative station, with the longest available discharge record among the pooled stations. By focusing on a data-scarce Himalayan basin, the study aims: (1) To assess whether a regional framework can be established. (2) To evaluate QRT can provide credible flood estimates for practical design applications.

2. STUDY AREA AND DATA

The study was carried out in the Narayani River system of central Nepal (Fig. 1). The basin extends from the high Himalaya to the middle-mountain valleys and therefore exhibits strong contrasts in elevation, relief and hydroclimatic characteristics. These contrasts are important for regional flood analysis because they influence runoff generation, channel response and the spatial variability of annual flood peaks.

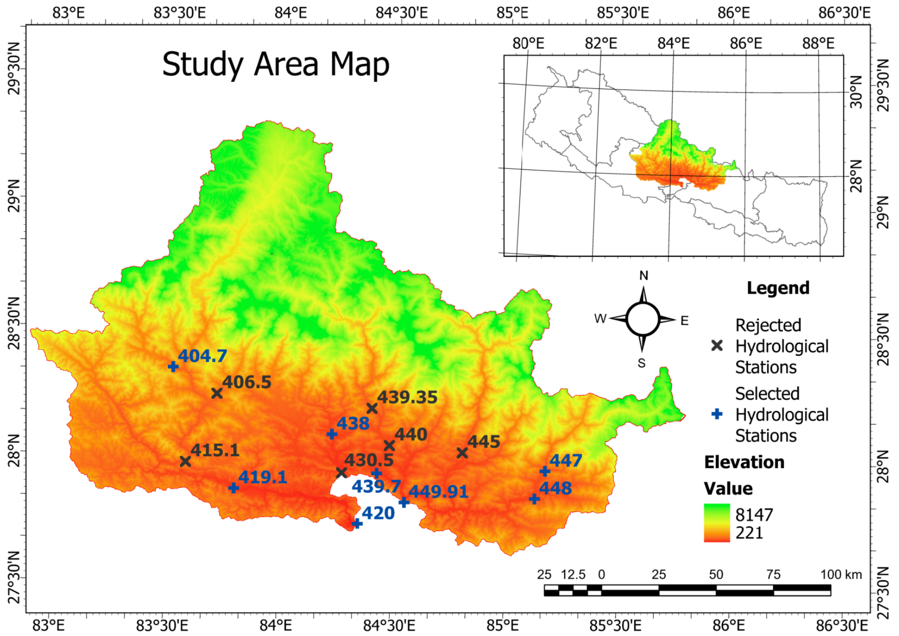

FIGURE 1. Study area map

2.1. **HYDROLOGICAL DATA.** Hydrological data were obtained from the Department of Hydrology and Meteorology (DHM), Government of Nepal. DHM is the national authority responsible for taking hydrological observations and distribution of quality controlled hydrometric records. The dataset comprised maximum monthly and yearly discharge records for the selected gauging stations.

2.2. **CATCHMENT DESCRIPTORS.** The selection of catchment descriptors was based on their hydrological relevance to flood generation and their applicability in regional flood frequency analysis (RFFA). Catchment descriptors should directly influence flood generation processes and be physically meaningful and readily obtainable and provide independent explanatory information.

Seven descriptors were considered in this study: drainage area (AREA), mean basin elevation (ELEV), mean annual rainfall (MAR), basin shape factor (SF), drainage density (SD), main channel slope (S1080) and forest cover (FOREST). Drainage area governs the volume of runoff contributing to flood events, while elevation and mean annual rainfall characterize the topographic and climatic controls on runoff generation respectively. Basin shape, drainage density and channel slope influence flow concentration time and drainage efficiency. Forest cover affects interception, infiltration, and surface runoff generation. These descriptors have been adopted in regional flood frequency studies [11, 12] because they represent the dominant physiographic and climatic controls on catchment flood response.

Catchment descriptors used in the regional analysis were derived from a 30 m digital elevation model (USGS), land-use and land-cover data (ICIMOD) and daily precipitation records from DHM.

3. METHODOLOGY

3.1. **DATA PREPROCESSING.** AMS was constructed using the annual maximum discharge values reported by DHM for each station.

The discharge records were subjected to data screening through visual inspection to identify missing records, inconsistencies and irregular observations. These procedures are consistent with previous regional flood studies conducted in Nepal [1, 6]. Years with incomplete annual records were filled by taking average flood of adjacent months of same year and same month of adjacent year. AMS were extracted from the monthly discharge records for each gauging station.

Hydrological analysis began with 14 gauged stations for which AMS was prepared from the available discharge records. Record lengths ranged from 20 to 60 years providing an initial total of 526 station-years.

The selected catchment descriptors, including drainage area, mean basin elevation, mean annual rainfall, basin shape factor, drainage density, main channel slope and forest cover, were compiled from GIS-based analyses and verified for consistency in units and spatial reference.

Predictor variables were subsequently standardized using log conversion. The standardized catchment descriptors were then used for QRT model and the original hydrological observations were used for L-moment estimation and at-site flood frequency analysis.

3.2. **L-MOMENT FRAMEWORK.** The analysis was based on AMS extracted. AMS was adopted because it provides a consistent representation of annual flood behavior and remains the standard basis for flood frequency analysis [3]. Station wise L-moment ratios were then estimated from the AMS in HEC-SSP v2.3. The regional screening used the dimensionless ratios L-CV (t), L-skewness (t_3), and L-kurtosis (t_4), as they are more stable than conventional product moments for skewed hydrological data [5, 14].

Regional weighted averages of the L-moment ratios were computed using station record length as the weighting factor.

3.3. **HOMOGENEITY ASSESSMENT AND POOL REFINEMENT.** Regional homogeneity was evaluated within the Hosking-Wallis L-moment framework [5, 14]. The procedure began with discordancy screening, in which each station was represented by the vector of its sample L-moment ratios:

$$u_i = [t_i, t_{3,i}, t_{4,i}]^T \tag{1}$$

The discordancy measure D_i was computed as [14]:

$$D_i = \frac{1}{3}(u_i - \bar{u})^T A^{-1}(u_i - \bar{u}) \tag{2}$$

where $\bar{u}$ is the regional mean of the station vectors and A is the pooled sums-of-squares and cross-products matrix. Stations with $D_i > 3$ were treated as discordant [5, 14].

After discordancy screening, heterogeneity was assessed using the Hosking-Wallis H_1 statistic, based on the dispersion of at-site L-CV values about the regional mean:

$$V = \left[\frac{\sum_{i=1}^{k} n_i (t^{(i)} - t^R)^2}{\sum_{i=1}^{k} n_i}\right]^{1/2} \tag{3}$$

$$H_1 = \frac{V - \mu_V}{\sigma_V} \tag{4}$$

where μ_V and σ_V are the mean and standard deviation of V respectively obtained from Monte Carlo simulations of homogeneous regions having the same number of sites and record lengths as the observed candidate pool [5, 14] using R-script libraries. The study used the H_1 measure because the retained pool lies within the low-skewness range [15]. The interpretation followed the standard criteria: $H_1 < 1$, homogeneous; $1 \leq H_1 < 2$, possibly heterogeneous; and $H_1 \geq 2$, definitely heterogeneous [5, 14].

Stations were removed iteratively on the basis of their discordancy and their contribution to regional inconsistency, when the station pool failed the homogeneity test. After each removal, the L-moment ratios, discordancy values and H_1 statistic were recalculated until an acceptably homogeneous pool was obtained. After multiple iterations a defensible homogeneous pool was obtained. The process revealed the trade-off between improved statistical similarity and reduced station-year support.

3.4. **REGIONAL PARENT-DISTRIBUTION SELECTION.** Using the accepted pool stations, candidate three-parameter regional distributions were tested within the Hosking-Wallis goodness-of-fit framework [5]. Candidate models included Pearson Type III (PE3), Generalized Extreme Value (GEV), Generalized Normal (GNO), Generalized Logistic (GLO) and Generalized Pareto (GPA). A distribution was considered acceptable when its absolute goodness-of-fit statistic satisfied:

$$|Z_{DIST}| \leq 1.64 \tag{5}$$

When several candidates were acceptable, the regional parent distribution was taken as the one with the lowest absolute $|Z_{DIST}|$ value [5].

3.5. **DESCRIPTOR SCREENING AND QUANTILE-REGRESSION FORMULATION.** Regional flood quantiles were modeled by quantile regression using the catchment descriptors AREA, ELEV, MAR, SF, SD, S1080, and FOREST. All descriptors were examined in logarithmic form to represent multiplicative scaling behavior and to maintain a linear structure in transformed space. Candidate predictors were screened using pairwise correlation analysis together with hydrologic interpretability. Final predictor combinations for each return period were selected independently using LOOV and MPLF, allowing different descriptor combinations to be retained where they improved predictive performance.

For a selected non-exceedance quantile τ, the general model form was:

$$\log Q_{i,\tau} = \beta_0 + \sum_{j=1}^{p} \beta_j \log X_{ij} \tag{6}$$

where $Q_{i,\tau}$ is the flood quantile τ at station i and the X_{ij} is the jth catchment descriptor for station i and β_0, β_j are regression coefficients. The coefficients were estimated by minimizing the quantile loss function [8]:

$$\min_{\beta} \sum_{i=1}^{n} \rho_\tau(y_i - \widehat{y_i}) \tag{7}$$

with,

$$\rho_\tau(u) = \begin{cases} u(\tau - 1), & u < 0 \\ u\tau, & u \geq 0 \end{cases} \tag{8}$$

where $\rho_\tau(u)$ is the pinball loss function, $y_i = \log(AMS_i)$ and $\widehat{y_i}$ is the fitted value [8]. Separate equations were searched for the return periods $T = 2, 5, 10, 25, 50, 100, 200, 500$ and 1000 years. In the final interpretation, emphasis was placed on the 2-year to 50-year range.

Higher-return period equations were reported only briefly and treated cautiously because they are supported by sparse upper-tail information.

3.6. **LEAVE-ONE-STATION-OUT VALIDATION (LOOV) AND MEAN PIECEWISE LOSS FUNCTION (MPLF) BASED MODEL RANKING.** Candidate equations for each return period were screened by LOOV. In each fold, all observations from one station were withheld, the model was calibrated using the remaining stations and predictive performance was evaluated on the omitted station. LOOV is appropriate for regional modeling because it tests whether a fitted equation can be transferred to an ungauged or withheld basin rather than merely reproducing stations already used for calibration.

Model ranking was based primarily on the MPLF, derived directly from quantile regression loss [9]:

$$MPLF = 1000 \times \frac{1}{N} \sum_{i=1}^{N} \rho_\tau(y_i - \widehat{y_i}) \tag{9}$$

where N is the total number of validation observations across all LOOV folds. Station wise prediction error was also examined as:

$$PE_s = \frac{1}{n_s} \sum_{i=1}^{n_s} \rho_\tau(y_i - \widehat{y_i}) \tag{10}$$

where n_s is the number of AMS observations at station s. Lower MPLF and lower mean station prediction error were interpreted as indicating better transfer performance. Final equations were selected on the basis of both predictive performance and hydrologic defensibility.

4. RESULTS AND DISCUSSION

4.1. **ACCEPTED HOMOGENEOUS POOL.** The initial 14 station candidate pool was clearly heterogeneous, with a starting H_1 value of 6.439 as shown in Figure. 2. Iterative removal of discordant or regionally inconsistent stations was required before pool could be treated as an acceptable regional group. After successive refinement the final pool reached $H_1 = -1.362$, satisfying the criterion for an acceptably homogeneous region. The retained stations were 404.7, 419.1, 420, 438, 439.7, 447, 448 and 449.91, with discordancy values ranging from 0.096 to 1.488, all below the threshold of 3 as observed in Table. 1. The weighted regional L-moment ratios of the accepted pool were $t = 0.197$, $t_3 = 0.140$ and $t_4 = 0.116$, indicating a compact low-skewness regional group.

A key result is that homogeneity was achieved only after a substantial reduction in data support. The original 526 station-years were reduced to 326 station-years, a loss of about 38%. This trade-off is important in the Nepalese context. [1, 6] showed that Nepal cannot be treated as one homogeneous flood region because of strong physiographic and climatic contrasts, and their regionalization study similarly required region revision after L-moment-based homogeneity testing. [1, 6] further showed that some Nepalese hydrologic regions contained too few gauged stations for reliable regional estimation and had to be supplemented with synthetic data. Relative to those studies, the Narayani result confirms the same fundamental difficulty at basin scale: statistical homogeneity is achievable, but only with notable sacrifice of station-year support.

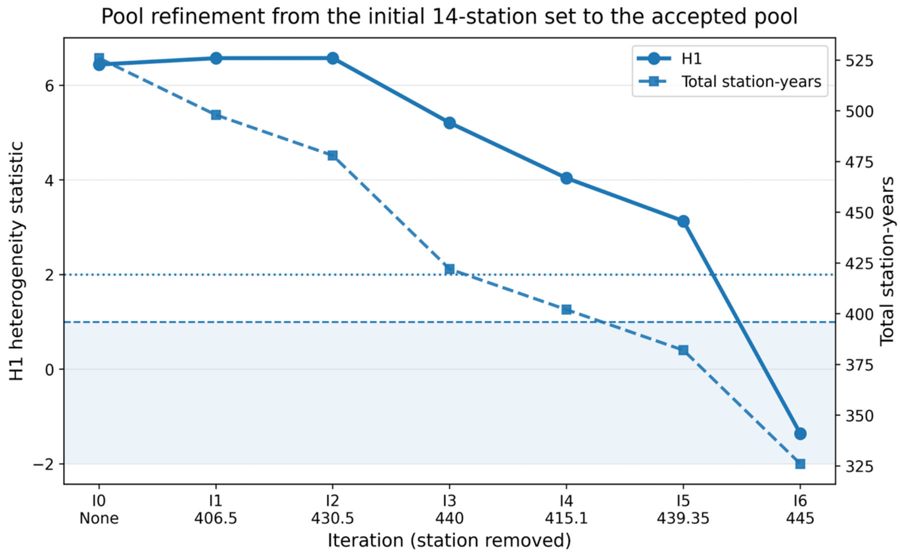

FIGURE 2. Refinement of the candidate pool from the initial 14-station set to the accepted eight-station homogeneous group. The figure combines the decline in H1 with the accompanying loss of station-year support.

TABLE 1. Final accepted homogeneous pool and discordancy values

Station ID	n (years)	Discordancy, D_i
404.7	44	1.328
419.1	24	0.310
420	60	0.686
438	45	0.741
439.7	33	1.026
447	43	1.488
448	51	0.096
449.91	26	1.326

4.2. **REGIONAL PARENT DISTRIBUTION.** After the final pool had been accepted, candidate regional distributions were evaluated using the Hosking-Wallis goodness-of-fit statistic. Three distributions satisfied the acceptability criterion $|Z_{DIST}| \leq 1.64$: PE3, GNO, and GEV as seen in 2. Among these, PE3 gave the lowest absolute goodness-of-fit value ($|Z_{DIST}| = 0.735$) and was therefore selected as the most suitable regional parent distribution. GNO and GEV were also acceptable, but with weaker fit. GLO and GPA were clearly unacceptable.

This result is consistent with the broader pattern that no single parent distribution is universally best. Skewed three-parameter models are often deemed appropriate for flood data in data-scarce basins. Nepal-wide regional scale study [1] also selected regional distributions using the $|Z_{DIST}|$ criterion. It also emphasized that reliable distribution selection depends strongly on the adequacy of regional pooling. In the present study, PE3 was selected only after the candidate pool had first been refined to an acceptable homogeneous group, which strengthens the interpretability of the result.

4.3. **QUANTILE-SPECIFIC QRT EQUATIONS.** No dominant predictor structure was identified for the entire flood return period scale according to the LOOV analysis. Optimal predictor structures for the 2-year and 5-year return periods were equations that contained AREA and SD,

TABLE 2. Goodness-of-Fit of Candidate Regional Distributions for the Accepted Pool

Distribution	**Fitted** t_4	Z_{DIST}	**Assessment**
PE3	0.129	0.735	Selected
GNO	0.138	1.224	Acceptable
GEV	0.139	1.293	Acceptable
GLO	0.183	3.591	Rejected
GPA	0.046	-3.605	Rejected

which implies that floods corresponding to lower return periods are influenced both by basin-scale characteristics and drainage network features. The best performing equation in the case of 10-year return period contains AREA, S1080, and FOREST variables. At the 25-year and 50-year return periods, equations were reduced to AREA variable, while models with higher return periods adopted a completely different set of predictors (ELEV, MAR, and SD). Therefore, it can be said that different predictor structures are supported by the regional sample at different parts of the flood return period distribution.

The appearance of the FOREST variable in the equation for the 10-year return period is explained by return-period-specific variable selection based on the LOOV procedure, rather than being a universal predictor of flood magnitude. In other words, candidate equations for each return period were evaluated separately based on their ability to predict correctly using the MPLF criterion, and only those descriptors that improved the validation performance were selected. While the forest cover contributes to better performance of the 10-year flood model by explaining differences in the basin-scale processes of interception, infiltration, and runoff formation, for lower return periods (2–5 years) drainage characteristics represented by the AREA and SD variables have better explaining power. On the other hand, at larger return periods (starting with 25 years) the magnitude of the flood event depends mainly on basin-scale physiographic and climatic characteristics. Therefore, the FOREST variable adds little to the explanation of the flood magnitude and does not provide additional predictive power to justify its inclusion in the LOOV-selected equations.

From the point of application, the most reliable results of the QRT procedure are those up to 50-year return period. Within this range, the fitted equations remain fairly simple and hydrologically meaningful, and at the same time validation metrics are systematically increasing from $T = 2$ to 50 years. For higher return periods (above 50 years) fitted equations are more affected by upper tail sparsity and therefore should be treated cautiously. This explanation is consistent with the argumentation presented by [9], claiming that one of the main advantages of quantile regression in the regional context is the use of flood observations directly and allowance for sites with short records. However, it suggests, model evaluation should remain grounded in predictive performance rather than apparent fit alone. It also aligns with [10, 11, 12], who found that useful regional prediction equations can still be obtained in difficult settings, even where homogeneity is challenging. Although this study supports the broader view of previous studies, it also suggests that credible practical use should remain focused on low to moderate return periods under the available data support.

4.4. **COMPARISON AT STATION 420.** Station 420 was selected for direct comparison because it has the longest AMS record in the study dataset and therefore provides the strongest at-site reference available. QRT estimates were compared with at-site PE3 quantiles for return periods from 2 to 1000 years. The comparison shows that QRT follows the at-site PE3 estimates reasonably well at low to moderate return periods, but diverges strongly in the upper tail. At the 2-year return period, the QRT estimate (3767.21 m^3/s) was very close to the at-site PE3 value (3714.70 m^3/s), with a relative error of 1.41%. At the 5-year, 10-year, 25-year, and 50-year return periods, QRT overestimated the at-site PE3 quantiles by 12.77%, 1.51%, 15.28%, and 17.08%, respectively. These results suggest that the regional equations provide a mostly credible representation of flood magnitude up to the medium return-period range, with a clear tendency toward positive bias.

TABLE 3. Comparison of QRT and At-Site PE3 at Station 420

T	QRT (m^3/s)	PE3 (m^3/s)	RE (%)
2	3767.21	3714.70	1.4
5	5620.00	4983.50	12.8
10	5810.00	5723.70	1.5
25	7598.86	6591.50	15.3
50	8441.02	7209.80	17.1
100	8517.92	7816.00	9.0
200	17550.35	8421.70	108.4
500	17550.38	9234.80	90.1
1000	17550.38	9867.00	77.9

Beyond 50 years, however, the QRT estimates become much less reliable. At 100 years, the relative error remained moderate at 8.98%. From 200 years onward the QRT estimates increased abruptly to about 17,550 m^3/s and then remained almost unchanged. The at-site PE3 quantiles continued to rise more gradually from 8421.70 to 9867.00 m^3/s for 200 years to 1000 years. This produced very large positive errors of 108.39%, 90.05%, and 77.87% at the 200-year, 500-year and 1000-year return periods respectively.

TABLE 4. Best LOOV-Selected QRT Equations and Validation Metrics

T	Best LOOV Model	MPLF	PEs
2	$\log_{10}(Q_2) = 1.029 + 0.764 \log_{10}(AREA) + 0.947 \log_{10}(SD)$	76.81	8.0%
5	$\log_{10}(Q_5) = 1.131 + 0.791 \log_{10}(AREA) + 1.011 \log_{10}(SD)$	69.34	6.8%
10	$\log_{10}(Q_{10}) = -0.334 + 1.036 \log_{10}(AREA) + 0.536 \log_{10}(S1080) + 1.579 \log_{10}(FOREST)$	38.25	3.7%
25	$\log_{10}(Q_{25}) = 0.553 + 0.817 \log_{10}(AREA)$	19.80	2.0%
50	$\log_{10}(Q_{50}) = 0.599 + 0.817 \log_{10}(AREA)$	11.13	1.1%
100	$\log_{10}(Q_{100}) = 0.758 + 0.779 \log_{10}(AREA)$	5.63	0.6%
200	$\log_{10}(Q_{200}) = 11.248 - 1.788 \log_{10}(ELEV) - 0.674 \log_{10}(MAR) + 1.178 \log_{10}(SD)$	2.36	0.2%
500	$\log_{10}(Q_{500}) = 11.248 - 1.788 \log_{10}(ELEV) - 0.674 \log_{10}(MAR) + 1.178 \log_{10}(SD)$	1.08	0.1%
1000	$\log_{10}(Q_{1000}) = 11.248 - 1.788 \log_{10}(ELEV) - 0.674 \log_{10}(MAR) + 1.178 \log_{10}(SD)$	0.66	0.1%

The comparison therefore indicates that the present QRT framework is defensible mainly for low to moderate return periods and should not be relied upon for higher-return-period design estimation under the available station-year support. This interpretation is consistent with the body of work in regional-flood estimation from the Nepalese region [1, 6, 13] and shows how regional estimation can be significantly constrained by the paucity of gauging information and difficulty in making strong inference given limited sample size. This is consistent with previous study claim that quantile regression-based regional models must be assessed on prediction performance [9].

5. CONCLUSIONS AND RECOMMENDATIONS

This study explores homogeneity testing and quantile regression methods for regional flood frequency analysis using AMS data obtained at 14 gauged stations of the Narayani Basin. The results show that the first group of stations did not exhibit regional homogeneity and needed to be trimmed down to an eight-station final pool, decreasing data support from 526 to 326 station-years. This means that a regionally homogeneous flood frequency analysis is only possible in this area under the condition of considerable data reduction. For the second pool, the most appropriate parent

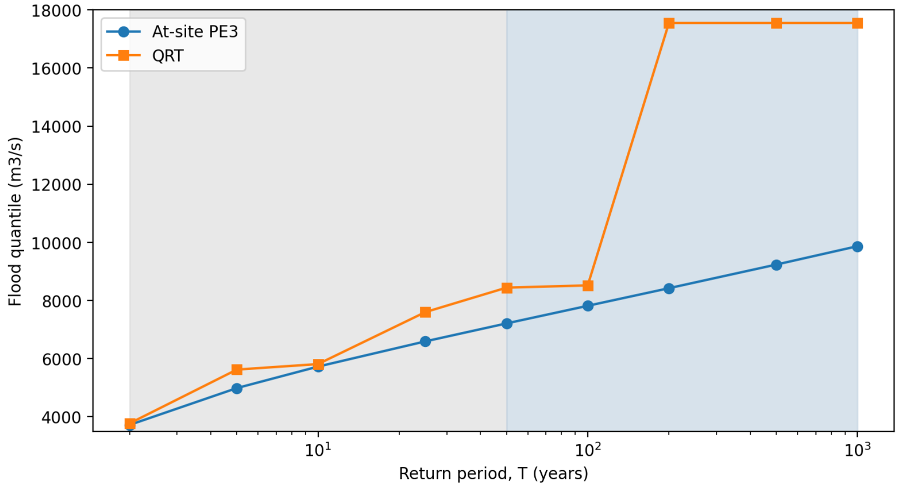

FIGURE 3. QRT versus at-site PE3 at Station with the shaded zone marks the range above 50 years.

distribution is the three-parameter Pareto (PE3).

The results of quantile regression technique (QRT) show that there is no unique predictor set for the entire flood range: equations for lower and moderate return periods can be rather simple and meaningful, while those for higher return periods become different and less defensible. Comparison of the QRT-based estimates and observed values at Station 420 shows that the estimates of QRT can be considered valid for lower return periods up to approximately 50 years, while estimates in the upper tail become increasingly inaccurate starting from this point.

From the practical perspective, this study provides evidence for the applicability of the Hosking-Wallis method and quantile regression technique as a combination for data-scarce Himalayan basin regions but limited to low to moderate return periods. Therefore, when using QRT-based regional estimates in engineering practice, caution is recommended starting from the 50-year return period due to insufficient station-year support. For the future research, extending of hydrometric time series, increasing the density and continuity of the gauging network, as well as testing of other predictors with the physical meaning such as rainfall intensity, snow and glacier impact, and storage effect in the basin can be recommended. This will allow determining if the range of accurate estimates can be extended beyond medium return periods.

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