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RETRACTED: Estimating Non-Stationary Extreme-Value Probability Distribution Shifts and Their Parameters Under Climate Change Using L-Moments and L-Moment Ratio Diagrams: A Case Study of Hydrologic Drought in the Goat River Near Creston, British Columbia

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Abstract: Here, we investigate the use of rolling-windowed L-moments (RWLMs) and L-moment ratio diagrams (LMRDs) combined with a Multiple Linear Regression (MLR) machine learning algorithm to model non-stationary low-flow hydrological extremes with the potential to simultaneously understand time-variant shape, scale, location, and probability distribution (PD) shifts under climate change. By employing LMRDs, we analyse changes in PDs and their parameters over time, identifying key environmental predictors such as lagged precipitation for September 5-day low-flows. Our findings indicate a significant relationship between total August precipitation L-moment ratios (LMRs) and September 5-day low-flow LMRs (τ_2 -Precipitation and τ_2 -Discharge: $R^2 = 0.675$, p -values < 0.001 ; τ_3 -Precipitation and τ_3 -Discharge: $R^2 = 0.925$, p -value for slope < 0.001 , intercept not significant with $p = 0.451$, assuming $\alpha = 0.05$ and a 31-year RWLM), which we later refine and use for prediction within our MLR algorithm. The methodology, applied to the Goat River near Creston, British Columbia, aids in understanding the implications of climate change on water resources, particularly for the yaqan nu?kiy First Nation. We find that future low-flows under climate change will be outside the Natural Range of Variability (NROV) simulated from historical records (assuming a constant PD). This study provides insights that may help in adaptive water management strategies necessary to help preserve Indigenous cultural rights and practices and to help sustain fish and fish habitat into the future.

Keywords: low-flows; hydro-climate extremes; L-moments; non-stationary frameworks; climate change; machine learning; Indigenous

1. Introduction

1.1. Hydrologic Drought and Its Implications

Understanding hydro-climatic extremes, including hydrologic drought, is crucial for managing aquatic habitats and has significant implications for society, ecosystems, and Indigenous people's cultural rights and practices. In particular, adequate September low-flows are necessary for the spawning of Kokanee (*Oncorhynchus nerka*), a culturally important fish species for the yaqan nu?kiy (Lower Kootenay Band) First Nation [1] (a member band of the Ktunaxa Nation). The yaqan nu?kiy reside near the unceded territory of Creston, British Columbia. Fish, particularly Kokanee, have historically been a sustainable food source for the yaqan nu?kiy. Recently, the yaqan nu?kiy have undertaken the Goat River South Channel Restoration Project, reopening a historic channel to support the return of Kokanee populations [1]. This project is vital for the community, aiming

to help restore fish populations and strengthen their cultural ties to the land and water. However, there are concerns that low-flows may inhibit the success of this restoration effort and the health of the Goat River system as a whole [1,2]. Low-flows can impact fish through a myriad of mechanisms, including increased water temperatures, which lead to lower dissolved oxygen (DO) levels [3,4] and reduced availability of critical spawning and rearing habitats [5]. For example, in the Upper Penticton Creek, changes in summer low-flows reduced modelled usable fish habitat by 20–50% [6]. To assess low-flow conditions, representative indices, such as the annual minimum average discharge for set periods, are commonly used (e.g., [7–9]). Similarly, we can define hydrologic droughts as periods when streamflow falls below a designated threshold (e.g., [10]). Thresholds can be defined based on socio-ecological indicators. For example, the Province of British Columbia defines Stage 5 hydrologic drought as “30-day precipitation and 7-day average stream-flows are below the 2nd percentile relative to historic records” [11]. Summer precipitation can control hydrologic drought: for example, ref. [12] found that accumulated rainfall after snow cover disappearance was the primary control on summer low-flows in snow-affected catchments of southern Quebec, while air temperature variability played a lesser role.

Both yaqan nu?kiy and Ktunaxa Nation citizens have observed changes in the Goat River near Creston, British Columbia over time. On 4 October 2023, we used the “One Heart Method” [13], a Ktunaxa framework for sharing information and solving problems with one mind and one heart, to ask citizens and knowledge holders, “how has the Goat River changed in your lifetime?” Participants shared that the Goat River has undergone significant changes over time. It used to be much higher and cleaner, resembling a natural swimming pool where people could jump off bridges and build rafts. There was a marsh rich with wildlife, including songbirds, muskrats, and coyotes, and a greater diversity of bird species, like meadowlarks. The land has since been converted to farmland, and participants cited that this, along with climate change, has significantly impacted the ecosystem and traditional practices, such as Kokanee fishing. Participants noted that in the past, water levels were so high that bridges had to be locked during floods. However, participants also noted that the river’s levels have lowered, and land use practices like logging, coupled with climate change, have accelerated the drying out of the area, affecting creeks in traditional berry-picking spots. Caves in the canyon, once hidden, have become visible, marking the river’s retreat. Participants emphasized that all these waterways are interconnected, with changes in one part impacting the broader region. Additionally, cultural, and ecological shifts have occurred: reduced snow levels and changing access routes mean participants now travel farther for hunting, ceremonial harvesting, and gathering berries. The concerns about the future of the Goat River and its surrounding lands resonate across the entire territory.

1.2. Drivers of Low-Flows

Several processes can alter low-flows. In snow-dominated systems, moderate levels of forest harvesting can influence low-flows via earlier melting of the spring snowpack [14,15], which can result in decreased streamflow during late summer and early fall [6]. Although interception loss and transpiration will increase as the forest regenerates, the immediate reduction in these processes after harvesting can lead to higher summer–autumn baseflow [16,17]. A recent meta-analysis of low-flow impacts in British Columbia found no significant difference in low-flow effects a decade after harvest; however, two studies, including one in a snow-dominated watershed, observed more severe summer low-flows (i.e., lower flows) about two decades after harvest [17]. Other factors influencing streamflow response after harvesting include soil disruption and the watershed’s underlying geology, particularly whether streams have significant baseflow supported by groundwater [18]. Severe topsoil disturbance from harvesting, such as soil compaction or erosion, can reduce soil infiltration capacity, diminishing recharge to surface and deep groundwater pathways, impacting low-flows dependent on groundwater-sustained baseflow [19].

Agricultural withdrawals and practices can also affect low-flows. Increased irrigation demand can lower groundwater levels, reducing baseflow to streams during dry periods [20]. This reduction in baseflow can exacerbate low-flow conditions, particularly in regions where groundwater is a significant source of baseflow [21]. Additionally, land use changes from agriculture can alter stream temperatures via changes to groundwater inputs [22]. Furthermore, climate change is expected to reduce groundwater storage, amplifying mountain streamflow reductions and exacerbating low-flow conditions [23].

In addition to agriculture, groundwater storage, and forestry, hydro-climatic extremes (including low-flows) are influenced by large-scale, low-frequency climate oscillations [24–31] and climate change [31–33]. Collectively, these drivers introduce significant uncertainty into low-flow modelling and prediction: these issues are particularly challenging within a process-based framework, which assumes a comprehensive understanding of the system under investigation a priori.

1.3. Non-Stationary Probabilistic Approaches

Applying a process-based understanding of hydrologic drought can introduce subjective modeller bias into model parameters, assumptions, model type, scope, and spatial scale: “...our [hydrology] community still holds deeply subjective and non-evidence-based preferences for models based on a certain type of ‘process understanding’ that has historically not translated into accurate theory, models, or predictions” [34]. Further, “[m]odels are not ‘value-free’, but uncertain, subjective and a product of the society in which they [are] shaped”, which can lead to uneven power dynamics between disparate stakeholders [35]. Although no panacea, a probabilistic approach may be more appropriate for estimating the likelihood of extreme events for both flooding [36] and droughts [37] when compared with process-based methods.

In extreme-value theory (EVT), theoretical probability distributions (PDs) are usually fit to the extreme variable time series, and quantiles associated with return periods of interest are obtained. The selection of the appropriate PD is a key aspect of frequency analysis [38]. Traditionally, extreme time series are assumed to be independent and identically distributed. However, this assumption is often not valid in real-world contexts. To account for climate variability and change, several stochastic non-stationary models have been developed [30,39–41]. These models typically make PD parameters conditional on covariates representing climate variability or time. In most non-stationary hydro-climate models, the probability function’s location and/or scale parameters are dependent on these covariates. However, the shape parameters and/or the underlying PD are usually assumed to remain constant (e.g., [42,43]). It has been shown that assumptions about the constancy of shape parameters and the underlying PD are often invalid: both can change over time, and L-moment ratio diagrams (LMRDs) can be used to evaluate these changes for several types of hydro-climate extremes [30].

L-moments (LMs) are statistical measures similar to conventional moments (mean, variance, skewness, and kurtosis), but are calculated using linear combinations of ordered data. This makes LMs less sensitive to outliers and more robust for small sample sizes. LMRDs plot the LMRs (e.g., L-Coefficient of Variation (L-CV), L-skewness) for observed data and compare them with theoretical PDs. These diagrams help to select the appropriate PD [44] and evaluate how hydro-climatic extremes’ location, scale, and shape parameters may evolve through time [30]. Failing to understand how both the PDs and parameters may evolve under climate change may dramatically over or underestimate extreme-value risk. By employing time-varying LMs, LMRDs, and LMRs, stationary assumptions can be tested and corrected if they are found to be violated.

Agriculture and forestry have intensified in the Creston Valley, and understanding how extreme low-flows may evolve due to climate impacts is crucial for informing future water allocations and forest management decisions. This is particularly important given the uncertainty in low-flow responses to forestry and the limited data on groundwater usage in the region. In response, we developed a non-stationary methodology based

on the framework in [30] for estimating hydro-climate extremes using rolling-windowed L-moments (RWLMs) and L-moment ratio diagrams (LMRDs). This approach employs statistical analysis and predictive modelling to evaluate extreme low-flow hydrologic data, using forward chaining for model fitting and incorporating LMs and LMRDs for PD characterization and parameters estimation. These metrics then serve as drivers in Multiple Linear Regression (MLR) machine learning models/algorithms. We aim to uncover the relationships between environmental variables, such as lagged precipitation LMs and extreme 5-day September low-flows. By refining these relationships with MLR models, we can predict future 5-day low-flow LMs, and subsequently fit them to appropriate PDs for flow projections over time. Using the estimated PDs and parameters, we simulate flows for each rolling-window stochastically under two Representative Concentration Pathways (RCPs), 4.5 and 8.5. By employing time-varying PDs and parameters, we reduce reliance on subjective assumptions about stationarity, offering a more empirical approach to extreme-value projection. The results provide valuable insights for water resource management, particularly in sustaining fish and fish habitats that are crucial to the yaqan nu?kiy and Ktunaxa people in the face of changing climatic conditions.

2. Materials and Methods

2.1. Data Collection

To assess changes in September 5-day low-flow over time, we examine three primary data sources: air temperature ($^{\circ}\text{C}$), precipitation (mm), and river discharge (m^3/s). These datasets are first assessed to determine if significant relationships exist within L-moment Ratio (LMR) space, and later used to develop predictive models using L-moments (LMs) and Multiple Linear Regression (MLR).

2.1.1. Historical Climate Data Online (HCDO)

Data regarding daily, monthly, and historical climate records were obtained from the Historical Climate Data Online (HCDO) repository, managed by Environment and Climate Change Canada (ECCC). This database provides detailed observations, including air temperature and precipitation. We focus on data from the Creston station in British Columbia, which offers records spanning over a century (1912–2017), allowing for the analysis of long-term climatic trends and variabilities. However, there are missing years in the dataset. The Climate ID for this station is [1142160](#) (Latitude: $49^{\circ}05'49''$ N, Longitude: $116^{\circ}31'04''$ W).

2.1.2. Pacific Climate Impacts Consortium (PCIC)

We use downscaled climate models available through the Pacific Climate Impacts Consortium (PCIC) data portal to gather future climate projections under two emission scenarios, Representative Concentration Pathways (RCP) 4.5 and RCP 8.5. The median of six models in the Coupled Model Intercomparison Project Phase 5 (CMIP5) series is considered: "ACCESS1-0", "CanESM2", "CCSM4", "CNRM-CM5", "HadGEM2-ES", and "MPI-ESM-LR". These six models are the same as those used to generate PCIC's Gridded Hydrologic Model Output. PCIC's single-cell extraction tool extends the record of the HCDO climate station by selecting the nearest grid cell to the HCDO climate station; these data are available from 1950 to 2099, although they are only used for the future projections (2018–2099).

2.1.3. Water Survey of Canada (WSC)

River discharge data are sourced from the Water Survey of Canada (WSC), specifically from the monitoring station [08NH004](#) (also known as the Goat River Near Erikson Hydro-metric Gauge (Latitude: $49^{\circ}05'21''$ N, Longitude: $116^{\circ}27'20''$ W)). This station is part of a national network that records daily mean water flow data. These data are available from 1914 to 1995; however, there are missing years in the dataset.

2.1.4. Methodology of Data Collection

Our data collection process involves accessing databases to download the necessary datasets for the study period. For both the HCDO and WSC databases, data are filtered by date range, ensuring comparability, and specific variables of interest—such as total monthly precipitation, average monthly air temperature, and September 5-day low-flow—are selected. Lagged values for precipitation and air temperature (up to and including September) are also extracted for later analysis. Both the discharge and climatology datasets contain missing years, and since the missing years do not overlap, the total length of the matched dataset is reduced from 82 years to 69 years.

2.2. Rolling-Window Approach

We use a rolling-window approach to estimate the L-moments (LMs) from time-series data, allowing for dynamic analysis of changing trends over time. In this method, a fixed-size window moves across the data points, and calculations are performed for the subset of data within each window position, continuously assessing the probability distribution (PD) characteristics as they evolve. Given a time series $\{x_t\}$ of length N , a window of size n is defined, such that $n < N$. For each window position i , we calculate the LMs using the data subset $\{x_i, x_{i+1}, \dots, x_{i+n-1}\}$. This process is repeated by sliding the window one step forward until it reaches the end of the series. The key LMs calculated within each window are

$$L_1^{(i)} = \frac{1}{n} \sum_{j=i}^{i+n-1} x_j, \quad (1)$$

$$L_2^{(i)} = 2b_1^{(i)} - b_0^{(i)}, \quad (2)$$

$$L_3^{(i)} = 6(b_2^{(i)} - b_1^{(i)}) + b_0^{(i)}, \quad (3)$$

$$L_4^{(i)} = 20b_3^{(i)} - 30b_2^{(i)} + 12b_1^{(i)} - b_0^{(i)}, \quad (4)$$

where the $b_k^{(i)}$ coefficients are given by

$$b_0 = \frac{1}{n} \sum_{i=1}^n x_i, \quad (5)$$

$$b_1 = \frac{1}{n(n-1)} \sum_{i=1}^n (n-i)x_{(i)}, \quad (6)$$

$$b_2 = \frac{1}{n(n-1)(n-2)} \sum_{i=1}^{n-1} (n-i)(n-i-1)x_{(i)}, \quad (7)$$

$$b_3 = \frac{1}{n(n-1)(n-2)(n-3)} \sum_{i=1}^{n-2} (n-i)(n-i-1)(n-i-2)x_{(i)}. \quad (8)$$

Here, $x_{(i)}$ denotes the i -th smallest value in the sample, and n is the sample size.

L-moment ratios (LMRs) provide a standardized way to describe the form of a PD, and are particularly useful for hydrological analysis. LMRs, including L-Coefficient of Variation (L-CV), L-skewness, and L-kurtosis, are defined as follows:

$$\tau_2 = \frac{L_2}{L_1}, \quad (9)$$

$$\tau_3 = \frac{L_3}{L_2}, \quad (10)$$

$$\tau_4 = \frac{L_4}{L_2}. \quad (11)$$

Because L-moment ratio diagrams (LMRDs) can be used to assess changes in hydro-climate extremes over time [30], we plot lagged precipitation and air temperature LMRDs to visually compare them to September 5-day low-flow LMRs. A 31-year window size is selected to balance sample size and fidelity needed for prediction. Air temperature and precipitation LMRDs are generated from preceding months up to and including September, and compared alongside September 5-day low-flow LMRDs. Visual analysis reveals a pronounced trend in total August precipitation compared to discharge, meriting further investigation (Figure 1).

To test our hypothesis, we conduct an Ordinary Least Squares (OLS) regression between September 5-day low-flow and total August precipitation LMRs (Figure 2). For τ_2 , the analysis indicates a significant relationship between τ_2 -Precipitation and τ_2 -Discharge, with an R^2 value of 0.675. Assuming an α of 0.05, the coefficients for both the intercept and slope are significant (p -values < 0.001). For τ_3 , the OLS regression reveals a significant relationship between τ_3 -Precipitation and τ_3 -Discharge, with an R^2 value of 0.925. Assuming an α of 0.05, the coefficients for the slope are significant (p -values < 0.001), although the intercept was not (p -value = 0.451). No such relationships are found with respect to air temperature; therefore, we focus our analysis on total August precipitation and September 5-day low flow LMRs and LMs.

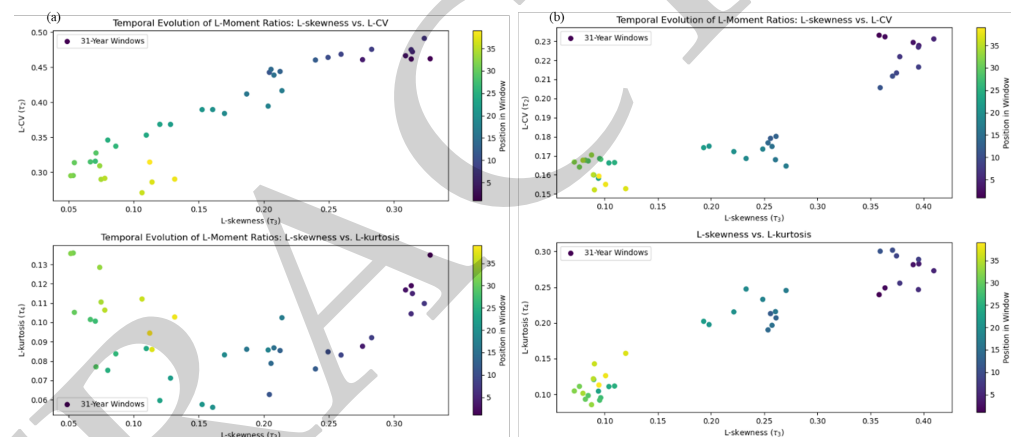


Figure 1. L-moment ratio diagrams (LMRDs) for: (a) August total precipitation (mm) and (b) September 5-day low-flow (m^3/s). Each panel includes the L-Coefficient of Variation ($\text{L-CV}; \tau_2$) versus L-skewness (τ_3) and L-kurtosis versus L-skewness ratios.

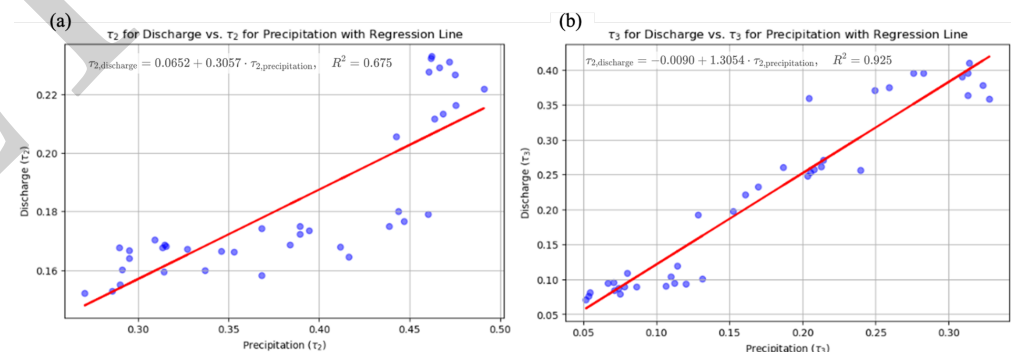


Figure 2. Relationship between L-moment ratios (LMRs) of August total precipitation (mm) and September 5-day low-flow (m^3/s): (a) τ_2 and (b) τ_3 . τ_2 -Precipitation and τ_2 -Discharge: p -values < 0.001 ; τ_3 -Precipitation and τ_3 -Discharge: p -value for slope < 0.001 , intercept not significant with $p = 0.451$, assuming $\alpha = 0.05$ and a 31-year rolling-windowed L-moments (RDLMs).

3. Multiple Linear Regression (MLR) and Forward Chaining

To generalize our methodology beyond LMRs and to allow for later parameter estimation for common extreme value PDs via the method of LMs [45], we use MLR to predict

the September 5-day low-flow LMs from total August precipitation LMs, using a forward chaining approach to maintain the temporal order of the dataset.

3.1. Target and Predictor Variables

Our target variables are S_1, S_2, S_3, S_4 , which represent the 5-day September low-flow LMs. The predictors are the LMs of August total precipitation, denoted by

$$P = \{(i, L_j) \mid i \neq 0, L_j \in L\} \quad (12)$$

where i indexes different time points or features, and L_j represents the specific precipitation-related LMs. We generate all possible combinations of these predictors for the analysis.

3.2. Model Training and Evaluation

For each LM L_j of S_i :

1. Initialize the lowest Squared Error (SE) to a very large value

$$SE_{\min} = \text{Large_Number} \quad (13)$$

where Large_Number is a sufficiently large value to ensure that any computed SE will be smaller.

2. Use forward chaining for training and evaluation:

- (a) Define the training set T_t and test set τ_t

$$T_t = \{D_0(k) \mid k < t\}, \quad \tau_t = \{D_0(t)\} \quad (14)$$

where k indexes time points prior to t in the dataset.

- (b) Define the response variable y_t for the current training period

$$y_t = T_t[L_j] \quad (15)$$

- (c) For each combination $c \in C$ of predictors, extract the predictors for the training set:

$$X_t = [T_t[L_m] \mid (i, L_m) \in c] \quad (16)$$

- (d) Fit the model using Ordinary Least Squares (OLS):

$$\hat{y}_t = \beta_0 + \sum_{(i, L_m) \in c} \beta_{i, L_m} X_t[L_m] \quad (17)$$

- (e) Evaluate the model on the test set and calculate the SE:

$$\hat{y}_{\tau_t} = \beta_0 + \sum_{(i, L_m) \in c} \beta_{i, L_m} \tau_t[L_m], \quad SE_c = (\hat{y}_{\tau_t} - y_{\tau_t})^2 \quad (18)$$

- (f) Update the best model if the current model has a lower SE:

$$\begin{aligned} &\text{if } SE_c < SE_{\min}, \\ &\text{then set } SE_{\min} = SE_c, \\ &\text{Best model} = \{\beta_0, \{\beta_{i, L_m} \mid (i, L_m) \in c\}\} \end{aligned} \quad (19)$$

- (g) Expand the training set for the next iteration by one time-step:

$$T_{t+1} = T_t \cup \tau_t \quad (20)$$

- Record the best-fit model and its equation for each LM (in this case, index (time-step) 38 yields the best-fit model; it is also the final iteration in the time series to undergo training and testing within the forward chaining process):

$$S_i = \beta_0 + \sum_{(i, L_m) \in c} \beta_{i, L_m}(S_i, L_m) \quad (21)$$

The best-fit first four terms of the MLR equations for each LM S_i derived from index 38 are as follows:

$$S_1(L_1) = 4.617 + 0.003 \cdot P_1(L_1) - 0.003 \cdot P_2(L_2) + 0.006 \cdot P_3(L_3) - 0.006 \cdot P_4(L_4) + \dots \quad (22)$$

$$S_2(L_2) = 1.520 - 0.001 \cdot P_1(L_1) - 0.004 \cdot P_2(L_2) + 0.001 \cdot P_3(L_3) + 0.009 \cdot P_4(L_4) + \dots \quad (23)$$

$$S_3(L_3) = 0.727 - 0.001 \cdot P_1(L_1) - 0.004 \cdot P_2(L_2) + 0.007 \cdot P_3(L_3) - 0.000 \cdot P_4(L_4) + \dots \quad (24)$$

$$S_4(L_4) = 0.496 - 0.000 \cdot P_1(L_1) - 0.003 \cdot P_2(L_2) + 0.005 \cdot P_3(L_3) - 0.005 \cdot P_4(L_4) + \dots \quad (25)$$

- Additionally, the algorithm computes the overall Mean Squared Error (MSE) for later sensitivity analysis of window size as follows:

$$\text{Overall MSE} = \frac{1}{T-1} \sum_{t=1}^{T-1} (\hat{y}_{\tau(t)} - y_{\tau(t)})^2 \quad (26)$$

3.3. Estimation PD Parameters from MLR L-Moments

After obtaining the LMs from the MLR algorithm (Figure 3), we use these LMs to estimate the parameters of the Generalized Extreme Value (GEV) PD following [45]'s method (Figure 4). The GEV distribution is selected after comparing common PDs on the LMRD using Euclidean distance to theoretical distributions, as plotted by [45]. The majority of the simulated LMRs are best approximated by the GEV distribution, with 55% of the windows best fitting the GEV line under the RCP 4.5 emissions scenario (Figure 5a). Time-varying PDs are also estimated for each window, showing how the distribution type evolves and becomes more volatile, particularly under the RCP 8.5 emissions scenario (Figure 5b).

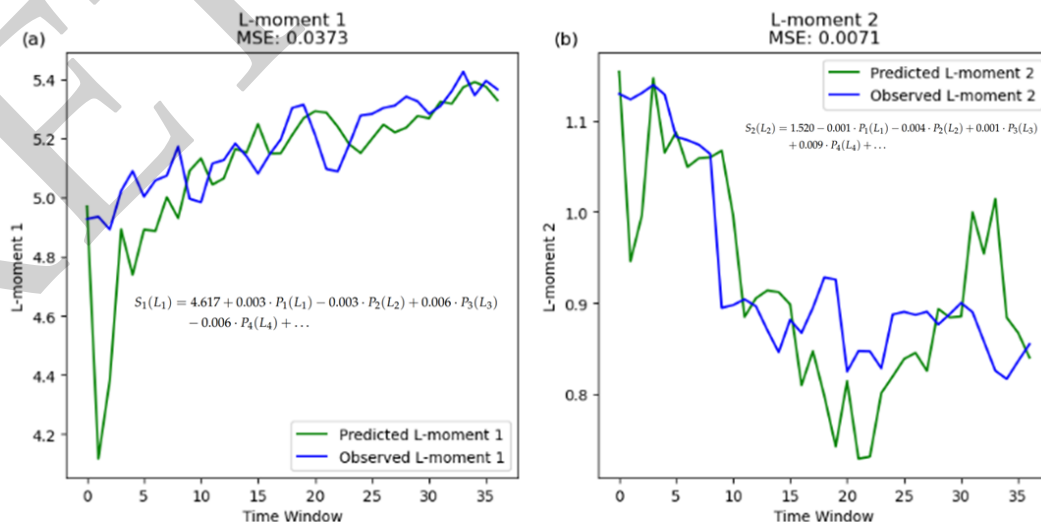


Figure 3. Cont.

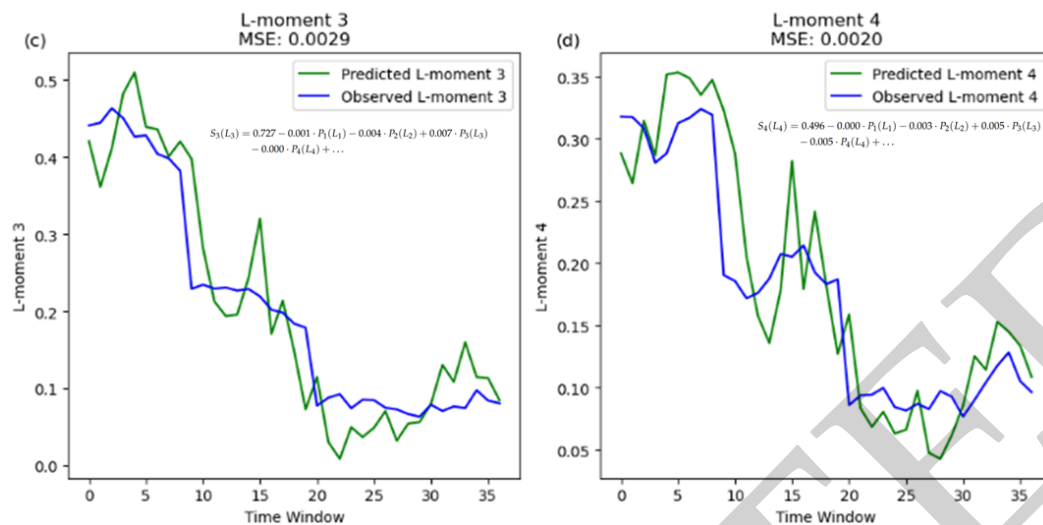


Figure 3. Comparison of predicted and observed L-moments (LMs; testing during training) using a 31-year rolling-window. The plots display the predicted (green) and observed (blue) values for the first (a), second (b), third (c), and fourth (d) LMs. Each subplot includes the Overall Mean Squared Error (MSE) between the predicted and observed values computed by summing and averaging the best-fit model Squared Error (SE) for each step in the forward chaining process. The equations plotted alongside the model are derived from the final (best-fit) iteration (index 38), which demonstrated the lowest SE.

The five distributions explored, as described by [45], include the Generalized Logistic (GLO), GEV, Generalized Pareto (GPA), Generalized Normal (GNO), and Pearson Type III (PE3) distributions. Each distribution is characterized by three parameters: location (μ), scale (σ), and shape (ξ).

Using the LMs derived from the regression outputs, we estimate these parameters for each distribution following [45] as implemented in the 'lmom' R package [46].



Figure 4. Location, scale, and shape parameters estimated using [45]'s method of L-moments (LMs) for the Generalized Extreme Value (GEV) probability distribution (PD) for the observed (blue) and predicted (testing during training; dashed red) LMs under a 31-year rolling-window.

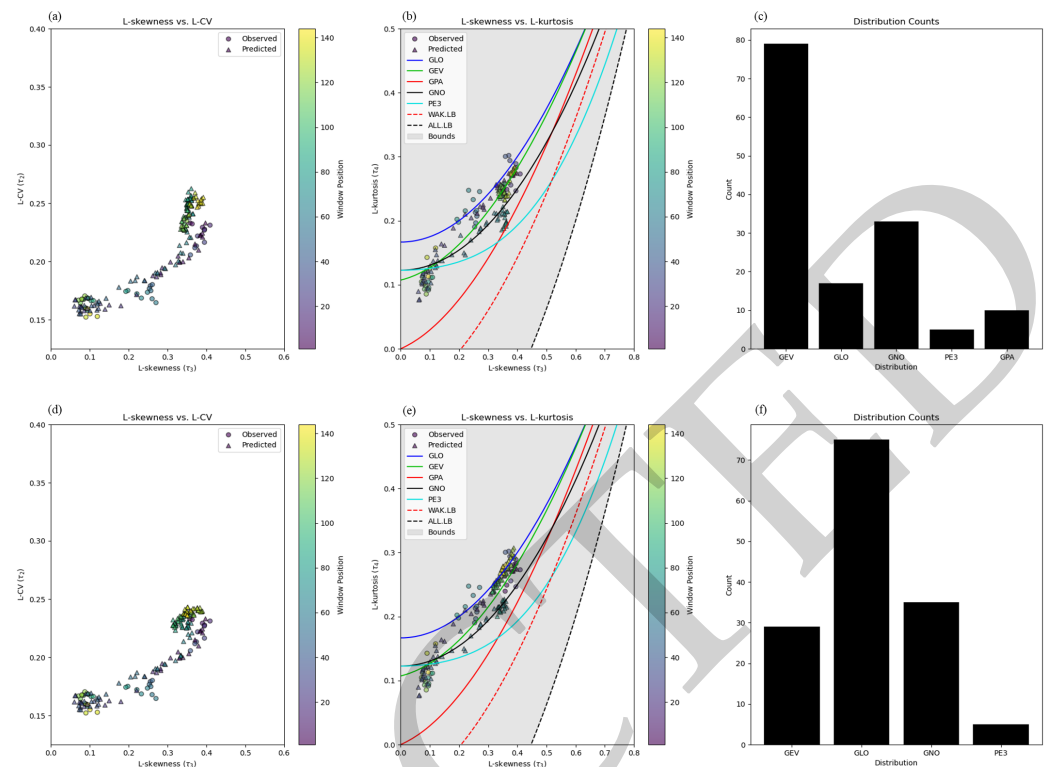


Figure 5. LMRDs using 31-year windows under two Representative Concentration Pathways (RCP) scenarios. Panels (a–c) correspond to the RCP 4.5 scenario, while panels (d–f) correspond to the RCP 8.5 scenario. Diagrams show: (a,d) L-CV/L-skewness, (b,e) L-kurtosis/L-skewness, with theoretical PDs described in [45] (distributions include Generalized Logistic (GLO), Generalized Extreme Value (GEV), Generalized Pareto (GPA), Generalized Normal (GNO), Pearson Type III (PE3), Wakeby Lower Bound (WAK_LB), and All Distribution Lower Bound (ALL_LB)). Plots (c,f) show the distribution count for each window. The observed LMRs for the 5-day September low-flow at the Water Survey of Canada (WSC) Goat River Near Erikson Hydrometric Gauge Station (08NH004) are plotted alongside simulated future data derived from Multiple Linear Regression (MLR) driven with total August precipitation LMs. Future data are generated using a splice of six Coupled Model Intercomparison Project Phase 5 (CMIP5) series downscaled climate models (median of “ACCESS1-0”, “CanESM2”, “CCSM4”, “CNRM-CM5”, “HadGEM2-ES”, and “MPI-ESM-LR” from 2018 to 2100) downloaded using the single cell extraction tool from the Pacific Climate Impacts Consortium (PCIC). Historical climate data are downloaded from Historical Climate Data Online (HCDO) repository for the Creston station (Climate ID 1142160; available from 1996 to 2017).

3.4. Estimating Thresholds for Hydrologic Drought

To estimate the risk of the channel failing, we compute the exceedance and cumulative exceedance probabilities as follows:

1. Generate random data:
for each time window i , generate N data points X_{ij} from the GEV PD with loc_i , scale_i , and shape_i parameters.
2. Count exceedances:
For each simulation, count the number of data points that exceed (fall below) the threshold

$$\text{exceedances}_i = \sum_{j=1}^N I(X_{ij} < \text{threshold}) \quad (27)$$

where $I(\cdot)$ is the indicator function, equal to 1 if the condition is true, and 0 otherwise.

3. Calculate exceedance probability:

The exceedance probability for each window i is calculated as

$$P_{\text{exceed}}(i) = \frac{\text{exceedances}_i}{N} \quad (28)$$

Given the exceedance probabilities $P_{\text{exceed}}(i)$ for each window i :

4. Calculate cumulative exceedance probability:

$$P_{\text{cum_exceed}}(i) = 1 - \prod_{j=1}^i (1 - P_{\text{exceed}}(j)) \quad (29)$$

4. Results and Discussion

4.1. Generalized Extreme Value (GEV) Parameters: Location, Scale, and Shape

Figure 6a,b displays the modelled estimates for the Generalized Extreme Value (GEV) location, scale, and shape parameters over 144, 31-year rolling-windowed time units under Representative Concentration Pathway (RCP) 4.5 and RCP 8.5, respectively. The top plot shows the GEV location parameter, which represents the central tendency of the PD. For both RCPs, the location parameter initially increases, peaking around the 40th time window, and then decreases, stabilizing towards the end of the simulation (Figure 6a,b).

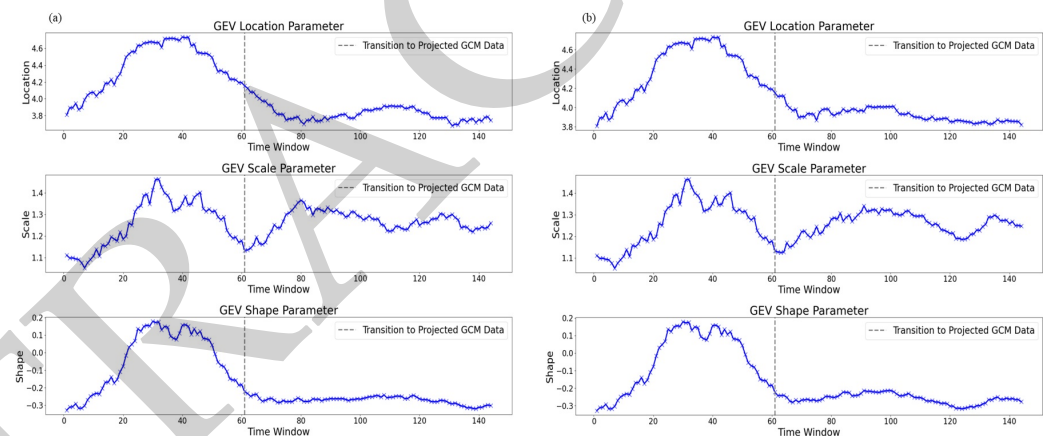


Figure 6. Results of the L-moments (LMs) derived from Multiple Linear Regression (MLR) fit to a Generalized Extreme Value (GEV) probability distribution (PD) to produce shape, scale, and location parameters: (a) GEV parameters (shape, scale, and location) over 144 rolling windowed time units under Representative Concentration Pathway (RCP) 4.5 and (b) RCP 8.5.

The middle plot illustrates the GEV scale parameter, indicating the variability or spread of the PD. For both RCPs, similar to the location parameter, the scale parameter increases, peaks around the 40th time window, and then decreases before increasing again around the 65th time window (Figure 6a,b). This suggests that variability in flow is higher within the middle period (20–80) than in either the earlier (0–20) or later (80–140) periods (these periods are determined based on noteworthy changes in the data, and do not represent even splits).

The bottom plot shows the GEV shape parameter, which describes the tail behaviour of the PD. Again, for both RCPs, the shape parameter follows a similar trend, increasing and peaking around the 40th time window before decreasing and stabilizing and becoming more left-skewed towards the end of the simulation. The left skew of the shape parameter through time indicates changes in the tail of the distribution behaviour towards much lower flow (rather than higher, as observed in the middle period) extreme events.

4.2. GEV Flow Simulation

Figure 7a,b present the results of the GEV model simulations under Representative Concentration Pathway (RCP) 4.5 and RCP 8.5, respectively. Both figures show the median flows with a 99% confidence interval (CI) estimated using the aforementioned parameters, assuming 1000 simulations for each of the 144 rolling-windowed time units. The blue lines represent the median flow values in m^3/s , while the vertical red areas illustrate the 99% confidence intervals, computed numerically from percentiles derived from repeat ($n = 1000$) simulations.

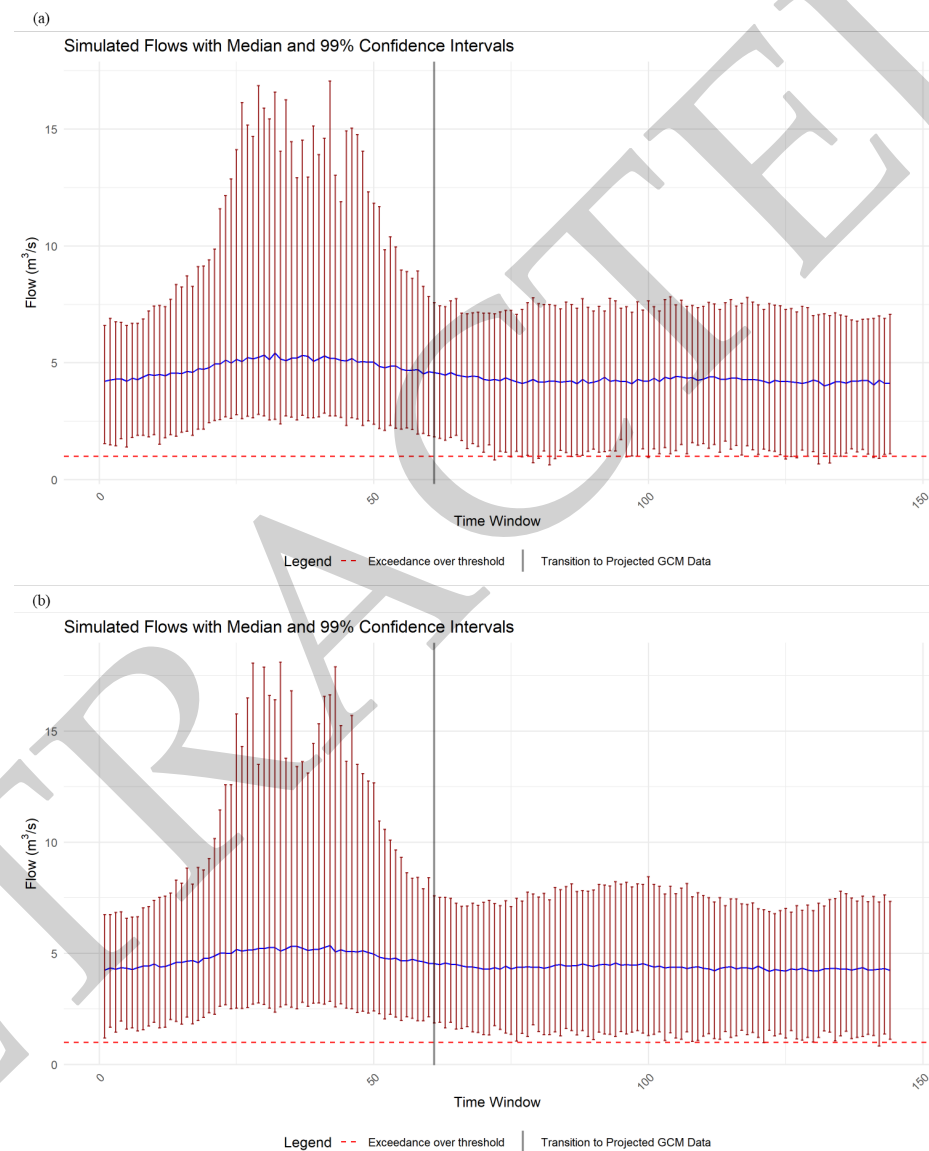


Figure 7. LMs derived from MLR fit to a GEV PD to produce shape, scale, and location parameters to derive median flows (m^3/s) and confidence intervals (CIs) estimated from percentiles: (a) simulated September 5-day low-flows driven by MLR regression using August total precipitation LMs over a 31-year rolling time window under (a) RCP 4.5 and (b) RCP 8.5. The dashed red line denotes a flow of $<1 \text{ m}^3/\text{s}$. Note: each simulation is based on $n = 1000$ iterations for both panels.

GEV Model Simulation (Median Flows with 99% CI)

Within the early period in the RCP 4.5 scenario, the median flow starts around $4 \text{ m}^3/\text{s}$ and gradually increases to about $5 \text{ m}^3/\text{s}$. The CI is relatively narrow, reflecting lower variability in flow during this period. The lower boundary of the 99% CI is slightly above $1 \text{ m}^3/\text{s}$, while the upper boundary is approximately $7 \text{ m}^3/\text{s}$.

Within the middle period in both RCP 4.5 and RCP 8.5 scenarios, the median flow experiences a peak and greater variability. In the RCP 4.5 scenario, the median flow reaches its maximum value of around $5.5 \text{ m}^3/\text{s}$. The CIs are wider during this period, indicating higher variability.

Within the late period in both RCP 4.5 and RCP 8.5 scenarios, the median flow decreases and stabilizes around $4 \text{ m}^3/\text{s}$ towards the end simulation period. The CI narrows again, indicating reduced variability in the flow rates as they stabilize. The lower boundary of the 99% CI during this period drops to less than $1 \text{ m}^3/\text{s}$ (dashed red lines in Figure 7a,b), suggesting that there are periods of extremely low-flows outside of the current Natural Range of Variability (NROV) when compared with simulated flows from the historical record (i.e., compared to the early or middle periods).

4.3. Challenges in Predicting Low-Frequency Oscillations

Predicting the timing of changes in low-frequency oscillations such as the El Niño–Southern Oscillation (ENSO) presents a significant challenge for climate models. This inability may explain why there are large clusters of future L-moment ratios (LMRs) that change relatively little compared to empirical (historical) data (Figure 5). The Pacific Climate Impacts Consortium (PCIC) notes that their statistically downscaled Coupled Model Intercomparison Project Phase 5 (and Phase 6; CMIP6) model simulations are unable to capture the exact day-by-day, month-by-month, and year-by-year sequencing of values concerning low-frequency oscillations, including ENSO. This discrepancy arises because climate models solve a “boundary value problem” and are not constrained to reproduce the timing of natural climate variability seen in observational records.

4.4. Estimating LMs and PD Changes

Our methodology estimates the first four LMs, theoretically allowing for non-stationary PD shifts beyond changes in shape, scale, and location parameters. The majority of the data best fit a GEV PD for the RCP 4.5 emissions scenario; however, we observe that this was not the case for the RCP 8.5 emissions scenario (Figure 5f). We use [45]’s methodology as implemented in [46] to fit different PDs based on Euclidean distance in LMR space for each time window. When we vary PDs for each window, we find distribution changes beyond shape, scale, and location parameters, which modify the modelled flow estimates moderately for RCP 4.5 (Figure 8a) and considerably for RCP 8.5 (Figure 8b). This is interesting, as modelling frameworks that assume a stationary PD may be over- or underestimating future extreme-value risks (for example, compared to the stationary PD approach assuming a GEV PD) when compared to the time-varying PD approach demonstrated and presented in Figure 8. In particular, we find little difference in future modelled flows assuming a GEV PD between RCP 4.5 and 8.5, but substantial differences when the PDs are permitted to vary for each time window, particularly for windows >85 (Figure 8).

4.5. Relationship between LMs and Window Size

In their analysis of another interior British Columbia watershed that flows into Shuswap Lake (the Salmon River), ref. [47] found that July to September precipitation was the strongest correlative predictor of late-summer low-flows: a finding agreeing with the analysis in [12] of low-flows in Quebec. We find that lagged precipitation is the strongest predictor of low flows when compared with other climate indices (e.g., temperature extremes) analysed in rolling-window LMR space. Moreover, we observe that the relationship between the second LMR (τ_2) of lagged precipitation and discharge strengthens with larger rolling-window sizes while the third LMR (τ_3) of lagged precipitation and discharge generally decreases (Table 1). The predictive accuracy of the Multiple Linear Regression (MLR) algorithm generally diminishes, as measured by the Overall Mean Squared Error (MSE), likely due to fewer training data points as window size increases (Table 1, Figure 9) or inaccurate estimation of L-moments when the window size becomes too small (<30). This

reduction in accuracy can lead to numerical instabilities in parameter estimation at later stages of the PD fitting process.

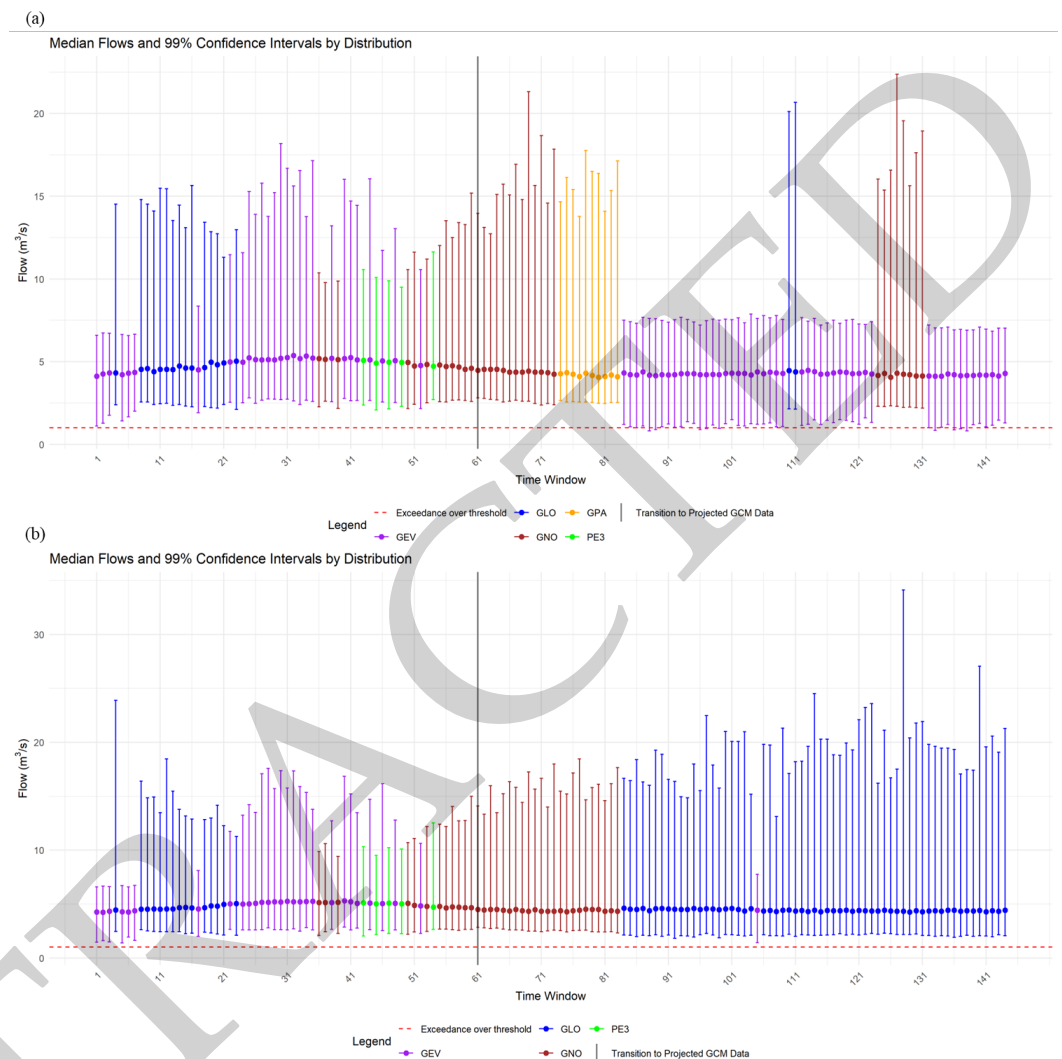


Figure 8. Results of the LMs derived from MLR fit to the best-fit probability distribution (PD) (distributions described in [45]) to produce shape, scale, and location parameters to derive median flows (m³/s) and confidence intervals (CIs) estimated numerically from percentiles: (a) simulated September 5-day low-flows driven by MLR regression using August total precipitation LMs over a 31-year moving window under RCP 4.5 and (b) RCP 8.5. The dashed red line denotes a flow of <1 m³/s. Note: each simulation is based on $n = 1000$ iterations for both panels.

In their assessment of hydro-climate extremes, [30] use a rolling-window size of 40 to evaluate time-varying LMRs and relate these changes to low-frequency oscillations such as the Pacific Decadal Oscillation (PDO). However, we recommend experimenting with window sizes between 25 and 35 for prediction purposes. In our analysis, a 31-year window was selected because it generated stable parameter estimates at later stages, assuming the method from [45] for LMs while providing a sufficiently large sample size to accurately estimate the LMs. Windows > 31 exhibited two problems: (1) unstable parameter estimation at later stages (assuming [45]’s method), and/or (2) unrealistic future clustering of LMRs compared with theoretical distributions (i.e., very large deviations and/or directional changes from historical theoretical distributions). Here, window sizes between 25 and 31 did not exhibit these issues, and displayed relative robustness in PD parameter estimation, regardless of PD selected (Figure 10).

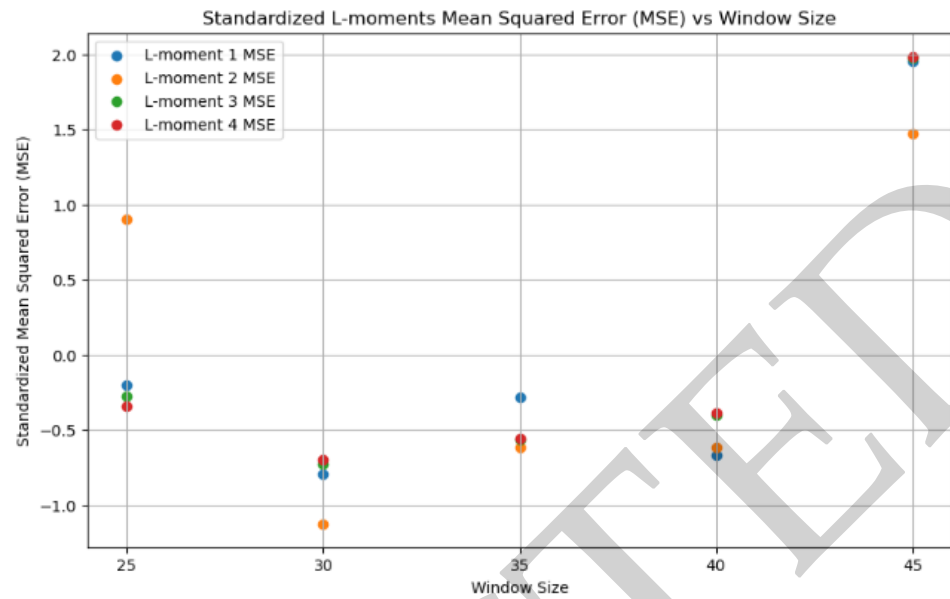


Figure 9. Overall standardized Mean Square Error (MSE) across different window sizes during model training.

Table 1. Correlation and overall Mean Square Error (MSE) analysis for different window sizes during model testing during training.

Window Size	$\tau_2 - R^2$	$\tau_3 - R^2$	L-Moment 1 MSE	L-Moment 2 MSE	L-Moment 3 MSE	L-Moment 4 MSE
25	0.550	0.863	6.64×10^{-2}	2.04×10^{-2}	9.3×10^{-3}	5.4×10^{-3}
30	0.643	0.915	7.3×10^{-3}	4.0×10^{-3}	1.2×10^{-3}	6.0×10^{-4}
35	0.730	0.910	5.88×10^{-2}	8.1×10^{-3}	4.1×10^{-3}	2.5×10^{-3}
40	0.840	0.895	1.96×10^{-2}	8.1×10^{-3}	7.0×10^{-3}	4.8×10^{-3}
45	0.864	0.744	2.837×10^{-1}	2.5×10^{-2}	5.03×10^{-2}	3.68×10^{-2}

4.6. Additional Sensitivities

Different low-flow metrics affect where the windowed data plots in LMR space. For example, for this watershed, the 1-day September low-flow typically plots below the GEV line, while the 7-day low-flow tends to plot above it. These distinctions highlight the sensitivity of LMRs to the chosen extreme-value metric, further emphasizing the need for a methodology that can estimate changes and/or differences in the underlying PD.

However, significant changes were observed when the PDs were allowed to vary over time windows. This suggests that the uncertainties in predicting low-flow conditions are more influenced by the choice and variability of the PDs than by the differences in parameters between emission scenarios, assuming a stationary PD. Consequently, further investigation is warranted to understand the dynamic nature of PDs and their impact on extreme-value projections.

To generalize the findings, we suggest repeating this methodology for other watersheds. Both long-term local climate and discharge data must be available to ensure accurate and reliable predictions. Expanding this analysis to additional watersheds will provide a more comprehensive understanding of hydrological responses to climate change across different regions.

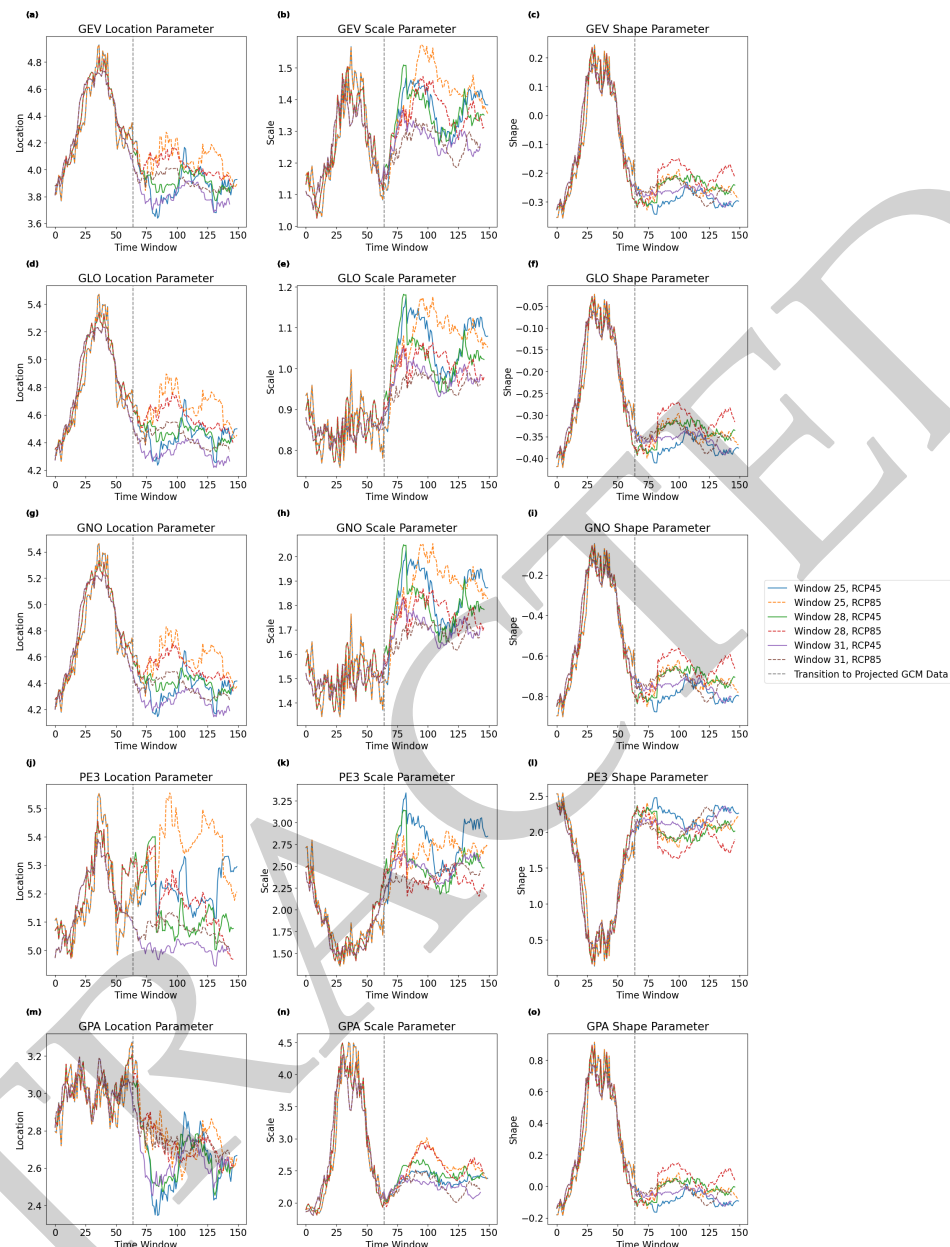


Figure 10. Sensitivity of window size on location, scale, and shape parameters for September 5-day low-flow estimated using the method of LMs described in [45] derived from MLR driven by total August precipitation LMs for six common distributions described in [45] (Generalized Extreme Value (GEV; (a–c)), Generalized Logistic (GLO; (d–f)), Generalized Normal (GNO; (g–i)), Pearson Type III (PE3; (j–l)), and Generalized Pareto (GPA; (m–o)). The solid line displays data under the Representative Concentration Pathway (RCP) 4.5 emission scenario, while the dashed line displays the RCP 8.5 emissions scenario.

4.7. LMs Compared with Other Estimators

In a review of probabilistic approaches to assess hydroclimate extremes, ref. [48] concludes that LMs are generally superior to methods like the Method of Moments (MOM) and Maximum Likelihood (ML) for parameter estimation for extreme-value PDs, particularly for small sample sizes and heavy-tailed distributions. Moreover, ref. [48] note that LMs exhibit lower estimation bias, reduced sensitivity to outliers, and less susceptibility to sampling variability, resulting in more accurate and robust estimates that perform better in goodness-of-fit tests and offer less uncertainty in flood frequency estimates compared to

ML across studies. However, ref. [48] that “[t]here is still no agreement upon a framework for performing extreme frequency analysis under non-stationary conditions”.

In the context of using L-moments for non-stationary hydrological analysis, study [49] on fitting non-stationary GEV parameters to Precipitation Maxima Data (PMD) series, highlights how LMs can be adapted to model changing hydrological extremes under climate change conditions. In their approach, LMs estimate the initial parameters, which are then updated using covariants (such as time) and fitted with ML. Ref. [30] apply a similar approach to estimate the GEV distribution’s shape, scale, and location parameter for flood flows. Our methodology differs from both approaches by introducing time windows rather than time explicitly by estimating the LMs for each window. Our approach thereby allows for distributions to evolve beyond the GEV PD as assessed in LMR space. Because both [30,49] used ML, our methodology, which employs LMs, may provide a better estimate of PD parameters as they evolve.

4.8. Concerns for yaqan nu?kiy

We examine changes in low-flow thresholds to evaluate the concerns related to the yaqan nu?kiy’s recently reopened historical stream, which plays a crucial role in their cultural and ecological rights and practices [1]. This stream channel was designed to accommodate a historical minimum September low-flow of $2.7 \text{ m}^3/\text{s}$. However, there are significant concerns that the channel might receive insufficient flows to help support fish populations if the flow rates fall below this threshold.

Figure 11 presents the low-flow exceedance (Equation (28)) and cumulative exceedance probability (Equation (29)) for the Goat River near Erikson Gauging Station (08NH004), modelled assuming the GEV RCP 4.5 simulation described earlier. The modelled exceedance probability (blue line) shows an increasing trend over time, indicating a higher likelihood of flows falling below $2.7 \text{ m}^3/\text{s}$ moving into the future. The cumulative exceedance probability (dashed purple line) also shows fluctuations, with a noticeable increase after the 60th time window and increasing to 1.0 near the 100th time window.

The potential for reduced flow rates is particularly alarming for the yaqan nu?kiy, as fish populations are integral to their subsistence and cultural heritage. The reopened channel must maintain adequate flow to support fish spawning and other ecological processes. If the flow falls below the designed minimum, it could impact the fish and fish habitats for the yaqan nu?kiy community.

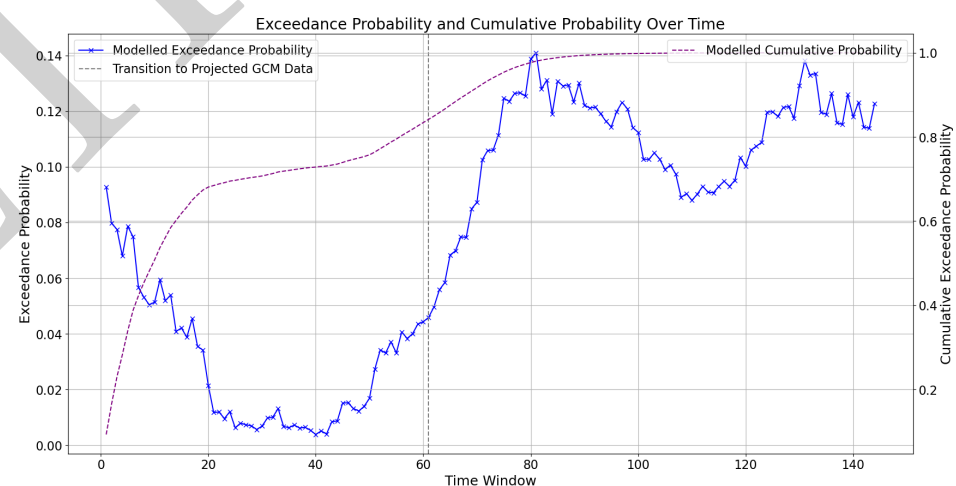


Figure 11. Low-flow exceedance and cumulative exceedance probability for the Goat River near Erikson Gauge Station, showing values less than $2.7 \text{ cubic meters per second (m}^3/\text{s)}$ assuming $n = 1000$ simulations and a Generalized Extreme Value (GEV) probability distribution (PD). Future data assume a Representative Concentration Pathway (RCP) 4.5 emissions scenario.

5. Conclusions

Several findings emerge from this work:

1. We highlight the use of 31-year rolling-windowed L-moments (RWLMs) and Multiple Linear Regression (MLR) within a non-stationary methodology for modelling extreme low-flow hydrologic data, including time-variant shape, scale, and location parameters paired with analysing probability distribution (PD) shifts over time. Our findings indicate a significant relationship between total August precipitation L-moment ratios (LMRs) and September 5-day low-flow LMRs (τ_2 -Precipitation and τ_2 -Discharge: $R^2 = 0.675$, p -values < 0.001 ; τ_3 -Precipitation and τ_3 -Discharge: $R^2 = 0.925$, p -value for slope < 0.001 , intercept not significant with $p = 0.451$, assuming $\alpha = 0.05$ and a 31-year RWLM). We then refine these relationships to develop an MLR machine learning algorithm to predict future September 5-day low-flow L-moments (LMs) using total August precipitation LMs derived from observational records spliced with statistically downscale Coupled Model Intercomparison Project Phase 5 (CMIP5) climate model projections (assuming the median of six downscaled Global Climate Models (GCMs) from the CMIP5 series: “ACCESS1-0”, “CanESM2”, “CCSM4”, “CNRM-CM5”, “HadGEM2-ES”, and “MPI-ESM-LR”). We find that PD shifts do occur, although the majority of the estimated LMs plot closest to the Generalized Extreme Value (GEV) line in L-moment ratio (LMR) space for the Representative Concentration Pathway (RCP) 4.5 emissions scenario, whereas the RCP 8.5 emissions scenario displays wider variability in PD changes over time.
2. We find minimal differences in low-flow projections under Representative Concentration Pathway (RCP) 4.5 and RCP 8.5 scenarios assuming a GEV distribution but substantial differences when PDs are permitted to vary with time window. The 99% confidence intervals for the majority of scenarios assessed (all except the variable PD RCP 8.5 scenario) suggest that flows may be lower than $1 \text{ m}^3/\text{s}$ into the future, which could impact fish populations (e.g., Kokanee) and is outside the Natural Range of Variability (NROV) compared with modelled flows in the observational period. These low-flows threaten fish spawning conditions and, consequently, the fish populations’ sustainability, which are integral to the cultural and subsistence practices of the yaqan nu?kiy First Nation. The results should be considered conservative because future agricultural demand and forestry changes were not assessed explicitly (i.e., a “best-case scenario” for the Creston Valley).
3. To generalize these findings, we suggest that this methodology be applied to other watersheds with long-term local climate and discharge data. This expansion will provide a broader understanding of LM and LMR hydrological responses to climate change across various regions. Future research should focus on applying and refining this approach in different hydrologic and extreme-value contexts to enhance predictive capabilities (e.g., different low-flow metrics, floods, precipitation, etc.).

Author Contributions: Conceptualization, I.D.; methodology, I.D.; software, I.D.; validation, I.D.; formal analysis, I.D.; investigation, I.D.; resources, I.D.; data curation, I.D.; writing—original draft preparation, I.D.; writing—review and editing, I.D., K.L.D., P.J. and R.M.; visualization, I.D.; supervision, K.L.D. and R.M.; project administration, K.L.D.; funding acquisition, I.D. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The study was conducted in accordance with the University of Victoria’s Research Administration Information System (RAIS) and approved by the Institutional Review Board of the University of Victoria (protocol code 21-0305, approval date: 16 December 2021).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: This project follows Ownership, Control, Access and Possession (OCAP™) principles. All scripts and processed data are housed on Lower Kootenay Band repository.

ries and made publicly available, with Band permission, here https://github.com/isaacdekker/L-moment_Low_Flow.git (accessed on 30 July 2024).

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Conflicts of Interest: Dekker is a Status Indian and a member of the Lower Kootenay Band under the Indian Act (R.S.C., 1985, c. I-5). At the time of publication, he was also employed by the Lower Kootenay Band. However, his research work is conducted independently and does not interfere with his other roles within the Band. Dubrawski, MacDonald, and Jones declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

CMIP5	Coupled Model Intercomparison Project Phase 5
CMIP6	Coupled Model Intercomparison Project Phase 6
DO	Dissolved Oxygen
DOAJ	Directory of Open Access Journals
ECCC	Environment and Climate Change Canada
ENSO	El Niño-Southern Oscillation
EVT	Extreme Value Theory
GEV	Generalized Extreme Value
GLO	Generalized Logistic
GNO	Generalized Normal
GPA	Generalized Parento
HDCO	Historical Climate Data Online
KNC	Ktunaxa Nation Council
L-CV	L-Coefficient of Variation
LMR	L-moment ratios
LMRD	L-moment ratio diagrams
LM	L-moments
MDPI	Multidisciplinary Digital Publishing Institute
MSE	Mean Squared Error
ML	Maximum Likelihood
MLR	Multiple Linear Regression
MoH	Ministry of Health
MOM	Method of Moments
NROV	Natural Range of Variability
NSERC	National Science and Engineering Research Council
OCAP	Ownership, Control, Access, and Possession
OLS	Ordinary Least Squares
PCIC	Pacific Climate Impacts Consortium
PDO	Pacific Decadal Oscillation
PD	Probability Distribution
PE3	Pearson Type III
PMD	Precipitation Maxima Data (PMD)
RASI	Research Administration Information System
RCP	Representative Concentration Pathway
RWLM	Rolling-windowed L-moments
SE	Squared Error
WSC	Water Survey of Canada

References

- Goat River South Channel Restoration Project Complete. *My Creston Now*, 4 December 2023. Available online: <https://www.mycrestonnow.com/35551/featured/goat-river-south-channel-restoration-project-complete/> (accessed on 30 July 2024).
- MELTDOWN: As water dries up, Creston Valley's farmers worry for the future *Creston Valley Advance*, 3 May 2024. Available online: <https://www.crestonvalleyadvance.ca/local-news/meltdown-as-water-dries-up-creston-valleys-farmers-worry-for-the-future-7353210> (accessed on 30 July 2024).
- Missaghi, S.; Hondzo, M.; Herb, W. Prediction of lake water temperature, dissolved oxygen, and fish habitat under changing climate. *Clim. Chang.* **2017**, *141*, 747–757. [\[CrossRef\]](#)
- Ali, B.; Mishra, A.; Mishra, A. Effects of dissolved oxygen concentration on freshwater fish: A review. *Int. J. Fish. Aquat. Stud.* **2022**, *10*, 113–127. [\[CrossRef\]](#)
- Lake Sammamish Late Run Kokanee Synthesis Report. 2009. Available online: <https://your.kingcounty.gov/dnrp/library/water-and-land/salmon/kokanee/hdr-lk-sammamish-kokanee-report-012109.pdf> (accessed on 30 July 2024).
- Winkler, R.D.; Allen, D.M.; Giles, T.R.; Brian, A.H.; Moore, D.R.; Redding, T.E.; Spittlehouse, D.L.; Wei, X. Approaching four decades of forest watershed research at Upper Penticton Creek, British Columbia: A synthesis. *Hydrol. Processes* **2021**, *35*, e14123. [\[CrossRef\]](#)
- Gustard, A.; Bullock, A.; Dixon, J.M. Low flow estimation in the United Kingdom. *IJI Rep.* **1992**, *108*, 88. [\[CrossRef\]](#)
- Zelenhasić, E.; Salvai, A. A method of streamflow drought analysis. *Water Resour. Res.* **1987**, *23*, 156–168. [\[CrossRef\]](#)
- Khaliq, M.N.; Quadra, T.B.; Gachon, P.; Sushama, L. Temporal evolution of low-flow regimes in Canadian rivers. *Water Resour. Res.* **2008**, *44*. [\[CrossRef\]](#)
- Tallaksen, L.M.; Madsen, H.; Clausen, B. On the definition and modelling of streamflow drought duration and deficit volume. *Hydrol. Sci. J.* **1997**, *42*, 15–33. [\[CrossRef\]](#)
- British Columbia Government. Provincial Fisheries Management: Drought Response Plan. British Columbia Government. 2023. Available online: https://www2.gov.bc.ca/assets/gov/environment/plants-animals-and-ecosystems/fish-fish-habitat/fishery-resources/provincial_fisheries_management_drought_response_plan-reviewed_oct15_2023.pdf (accessed on 30 July 2024).
- Kinnard, C.; Bzeouich, G.; Assani, A. Impacts of summer and winter conditions on summer river low flows in low elevation, snow-affected catchments. *J. Hydrol.* **2022**, *605*, 127393. [\[CrossRef\]](#)
- Horsethief, C. Three Ktunaxa Research Models. 2021. Available online: <https://vimeo.com/563549077> (accessed on 30 July 2024).
- Macdonald, L.H.; Stednick, J.D.; Forests and Water: A State-of-the-Art Review for Colorado. Colorado State University. 2003, Report No. 196. Available online: https://www.fs.usda.gov/rm/pubs_exp_for/manitou/exp_for_manitou_2003_macdonald.pdf (accessed on 30 July 2024).
- Moore, R.D.; Spittlehouse, D.L.; Story, A. Riparian microclimate and stream temperature response to forest harvesting: A review. *J. Am. Water Resour. Assoc.* **2005**, *41*, 813–834. [\[CrossRef\]](#)
- Goeking, S.A.; Tarboton, D.G. Forests and Water Yield: A Synthesis of Disturbance Effects on Streamflow and Snowpack in Western Coniferous Forests. *J. For.* **2020**, *118*, 172–192. [\[CrossRef\]](#)
- Moore, R.D. Effects of Forest Harvesting on Warm-Season Low Flows in the Pacific Northwest: A Review *Hydrol. Processes* **2020**, *4*, 29. [\[CrossRef\]](#)
- Wei, X.; Lui, W.; Zhou, P. Quantifying the Relative Contributions of Forest Change and Climatic Variability to Hydrology in Large Watersheds: A Critical Review of Research Methods. *Water* **2013**, *5*, 728–746. [\[CrossRef\]](#)
- Zhang, M.; Wei, X.; Sun, P.; Liu, S. The effect of forest harvesting and climatic variability on runoff in a large watershed: The case study in the Upper Minjiang River of Yangtze River basin *J. Hydrol.* **2012**, *464–465*, 1–11. [\[CrossRef\]](#)
- Scanlon, B.R.; Jolly, I.; Sophocleous, M.; Zhang, L. Global impacts of conversions from natural to agricultural ecosystems on water resources: Quantity versus quality. *Water Resour. Res.* **2007**, *43*, W03437. [\[CrossRef\]](#)
- Famiglietti, J.S.; Rodell, M. Water in the balance. *Science* **2014**, *340*, 1300–1301. <https://www.science.org/doi/10.1126/science.1236460>. [\[CrossRef\]](#)
- Essaid, H.I.; Caldwell, R.R. Evaluating the impact of irrigation on surface water – groundwater interaction and stream temperature in an agricultural watershed. *Sci. Total Environ.* **2017**, *599–600*, 581–596. [\[CrossRef\]](#)
- Carroll, R.W.; Castino, F.; Morrison, R.R.; Konrad, C.P.; Danner, E.M. Declining groundwater storage expected to amplify mountain streamflow reductions in a warmer world. *Nat. Water* **2024**, *2*, 419–433. [\[CrossRef\]](#)
- Cayan, D.R.; Redmond, K.T.; Riddle, L.G. ENSO and hydrologic extremes in the western United States. *J. Clim.* **1999**, *12*, 2881–2893. [\[CrossRef\]](#)
- Enfield, D.B.; Mestas-Núñez, A.M.; Trimble, P.J. The Atlantic Multidecadal Oscillation and its relation to rainfall and river flows in the continental U.S. *Geophys. Res. Lett.* **2001**, *28*, 2077–2080. [\[CrossRef\]](#)
- Arblaster, J.M.; Alexander, L.V. The impact of the El Niño-Southern Oscillation on maximum temperature extremes. *Geophys. Res. Lett.* **2012**, *39*, L20702. [\[CrossRef\]](#)
- Ouachani, R.; Bargaoui, Z.; Ouarda, T.B.M.J. Power of teleconnection patterns on precipitation and streamflow variability of upper Medjerda Basin. *Int. J. Climatol.* **2013**, *33*, 58–76. [\[CrossRef\]](#)
- Ouarda, T.B.M.J.; Labadie, J.W.; Zejli, D.; Younes, S.; Leconte, R. Evolution of the rainfall regime in the United Arab Emirates. *J. Hydrol.* **2014**, *514*, 258–270. [\[CrossRef\]](#)

29. Chandran, A.; Basha, G.; Ouarda, T.B.M.J. Influence of climate oscillations on temperature and precipitation over the United Arab Emirates. *Int. J. Climatol.* **2016**, *36*, 225–235. [\[CrossRef\]](#)
30. Ouarda, T.B.; Charron, C. Changes in the distribution of hydro-climatic extremes in a non-stationary framework. *Sci. Rep.* **2019**, *9*, 8104. [\[CrossRef\]](#)
31. Basha, G.; Kurylo, K.; Ouarda, T.B.M.J.; Hossain, F.; Rahman, A.; Boluwade, A. Historical and Projected Surface Temperature over India during the 20th and 21st century. *Sci. Rep.* **2017**, *7*, 2987. [\[CrossRef\]](#)
32. Ouarda, T.B.M.J.; El-Adlouni, S. Bayesian Nonstationary Frequency Analysis of Hydrological Variables. *JAWRA J. Am. Water Resour. Assoc.* **2011**, *47*, 496–505. [\[CrossRef\]](#)
33. Perkins, S.E.; Alexander, L.V.; Nairn, J.R. Increasing frequency, intensity and duration of observed global heatwaves and warm spells. *Geophys. Res. Lett.* **2012**, *39*, L20714. [\[CrossRef\]](#)
34. Nearing, G.S.; Kratzert, F.; Sampson, A.K.; Pelissier, C.S.; Klotz, D.; Frame, J.M.; Prieto, C.; Gupta, H.V. What role does hydrological science play in the age of machine learning? *Water Resour. Res.* **2021**, *57*, 1. [\[CrossRef\]](#)
35. Melsen, L.A.; Vos, J.; Boelens, R. What is the role of the model in socio-hydrology? Discussion of “Prediction in a socio-hydrological world”. *Hydrol. Sci. J.* **2018**, *63*, 1435–1443. [\[CrossRef\]](#)
36. Pham, H.C.; Alila, Y. Science of forests and floods: The quantum leap forward needed, literally and metaphorically. *Sci. Total Environ.* **2024**, *912*, 169646. [\[CrossRef\]](#)
37. Vogel, R.M.; Kroll, C.N. On the need for streamflow drought frequency guidelines in the U.S. *Water Policy* **2021**, *23*, 216–231. [\[CrossRef\]](#)
38. Coles, S. *An Introduction to Statistical Modelling of Extreme Values*; Springer: London, UK, 2001; Volume 208. Available online: <https://api.semanticscholar.org/CorpusID:19678794> (accessed on 30 July 2024).
39. Katz, R.W.; Parlange, M.B.; Naveau, P. Statistics of extremes in hydrology. *Adv. Water Resour.* **2002**, *25*, 1287–1304. [\[CrossRef\]](#)
40. Milly, P.C.D.; Betancourt, J.; Falkenmark, M.; Hirsch, R.M.; Kundzewicz, Z.W.; Lettenmaier, D.P.; Stouffer, R.J. Stationarity is dead: Whither water management? *Science* **2008**, *319*, 573–574. <https://www.science.org/doi/10.1126/science.1151915>. [\[CrossRef\]](#) [\[PubMed\]](#)
41. Cannon, A.J. A flexible framework for non-stationary generalized extreme value modelling with applications to seasonal rainfall extremes. *J. Clim.* **2010**, *26*, 673–685. [\[CrossRef\]](#)
42. Thiombiano, A.N.; St-Hilaire, A.; El Adlouni, S.-E.; Ouarda, T.B.M.J. Nonlinear response of precipitation to climate indices using a non-stationary Poisson-generalized Pareto model: Case study of southeastern Canada. *Int. J. Climatol.* **2018**, *38*, e875–e888. [\[CrossRef\]](#)
43. Nasri, B.; Trambly, Y.; El Adlouni, S.; Hertig, E.; Ouarda, T.B.M.J. Atmospheric Predictors for Annual Maximum Precipitation in North Africa. *J. Appl. Meteorol. Climatol.* **2016**, *55*, 1063–1076. [\[CrossRef\]](#)
44. Hosking, J.R.M.; Wallis, J.R. *Regional Frequency Analysis: An Approach Based on L-Moments*; Cambridge University Press: Cambridge, UK, 1997; Volume 33. [\[CrossRef\]](#)
45. Hosking, J.R.M. L-moments: Analysis and estimation of distributions using linear combinations of order statistics. *J. R. Stat. Soc. Ser. Methodol.* **1990**, *52*, 105–124. [\[CrossRef\]](#)
46. LMOM: L-Moments, L-Moment Ratios, and Probability Distributions. R Package Version 2.8, 2024. Available online: <https://CRAN.R-project.org/package=lmom> (accessed on 30 July 2024).
47. Beebe, C.R.; Goetz, J.; Spittlehouse, D. Updated Water Budget for Salmon River Valley Aquifers Upstream of Falkland. Water Science Series 2024, WSS2024-07, Province of British Columbia, Victoria. Available online: https://a100.gov.bc.ca/pub/acat/documents/r63066/WestwoldWBStudy,June2024_1721325054471_E54B8CD382.pdf (accessed on 30 July 2024).
48. Nerantzaki, S.D.; Papalexiou, S.M. Assessing extremes in hydroclimatology: A review on probabilistic methods. *J. Hydrol.* **2022**, *605*, 127302. [\[CrossRef\]](#)
49. Campos-Aranda, D.F. Fitting with L-Moments of the Non-Stationary Distributions GVE 1 and GVE 2 to PMD Series. Scientific Electronic Library Online. 2019. Available online: https://www.scielo.org.mx/scielo.php?script=sci_abstract&pid=S2007-24222019000500075&lng=en (accessed on 30 July 2024).

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