M.Sc. Dissertation
Master of ENVIRONMENTAL AND LAND ENGINEERING
Department of Environment, Land and Infrastructure Engineering (DIATI)

R-Based Large-Sample Geospatial Analysis of Simulated Flood Extremes in the Greater Alpine Region Using L-Moments and GEV Modelling

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July 2026

Acknowledgements

I would like to express my sincere gratitude to my supervisor, Professor Alberto Viglione, for his guidance and support throughout the development of this thesis. His help and feedback were essential in shaping this work and in helping me complete this important academic step. I would also like to thank my co-supervisors, Luca Lombardo and Anna Basso, for their support and assistance during the research process.

I am deeply grateful to my brother Rahim, without whom this journey would not have been possible. I would also like to thank my parents for everything they have done for me. I am thankful to my siblings and their beloved families for their encouragement and for being a constant source of strength throughout this journey.

A special and heartfelt thanks go to my partner. Her warm presence and endless encouragement have meant more to me than words can fully express.

Finally, I would like to thank everyone who, in different ways, supported me during my studies and contributed to the completion of this thesis.

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Abstract

Floods in mountainous regions are characterized by strong spatial variability due to complex interactions among topography, climate, snowmelt processes, and catchment properties. This thesis investigates the statistical behaviour of simulated annual maximum floods across the Greater Alpine Region using a large-sample hydrological framework. The analysis is based on simulated daily discharge time series for 5,757 catchments over the period 1950–2022. Annual Maximum Series were extracted for each catchment and analysed using descriptive statistics, L-moment-based indicators, and Generalized Extreme Value distribution modelling.

The study focuses on mean annual maximum specific discharge, the coefficient of variation, conventional skewness, L-skewness, and L-kurtosis to evaluate differences in flood magnitude, variability, asymmetry, and upper-tail behaviour. Spatial patterns were assessed across the HISTALP Alpine subregions, while the suitability of the GEV distribution was evaluated using the Anderson–Darling goodness-of-fit test. The results show substantial spatial heterogeneity in simulated flood characteristics across the Alpine domain. Mean annual maximum specific discharge ranges from values close to zero to 0.80 $m^3/s/km^2$, the coefficient of variation ranges from 0.09 to 0.73, and conventional skewness ranges from -0.66 to 3.58. L-moment indicators also vary spatially, with L-skewness ranging from -0.11 to 0.46 and L-kurtosis from -0.01 to 0.39, indicating that differences among catchments concern not only flood magnitude and variability but also distributional asymmetry and upper-tail behaviour. Flood magnitude, variability, and distributional shape are not uniform, and high values of statistical indicators occur in localized clusters rather than forming a single homogeneous regional pattern.

Mean annual maximum specific discharge is spatially fragmented, with high values occurring in several separated zones. In contrast, variability and distributional-shape indicators show more coherent patterns: higher CV, skewness, L-skewness, and L-kurtosis tend to occur in peripheral or transition areas, while lower values are more common along parts of the inner Alpine belt.

These patterns indicate that flood magnitude, interannual variability, asymmetry, and upper-tail behaviour respond differently across the Alpine domain and cannot be summarized by a single regional average. The L-moment analysis confirms that Alpine catchments differ not only in flood magnitude but also in distributional asymmetry and upper-tail behaviour. The GEV distribution provides an acceptable fit for most catchments, rejecting the Anderson–Darling

test at 5% significance in 181 out of 5,576 out of 5,757 catchments, corresponding to a rejection rate of approximately 3.1%. The small proportion of rejected catchments should not be interpreted as evidence that the GEV framework fails regionally. Rather, it indicates that the GEV distribution is generally suitable for the simulated annual maxima.

Overall, the thesis shows that, even under a spatially consistent modelling and statistical framework, simulated Alpine flood extremes retain clear regional and local differences in magnitude, variability, asymmetry, and upper-tail behaviour.

Chapter 1

Introduction

Floods are among the most destructive natural hazards in mountainous environments, where hydrological responses are governed by an intricate interplay of complex topography, steep climatic gradients, and highly heterogeneous catchment properties. In the European Alps, the combination of rugged terrain, diverse geological formations, and mixed rainfall–snowmelt regimes results in a high degree of spatial variability in runoff processes. Consequently, neighboring catchments often exhibit divergent responses to identical meteorological events, complicating the identification of consistent regional flood patterns.

This spatial heterogeneity presents a significant methodological challenge, particularly when the research objective is to compare flood characteristics across a wide range of basins or to derive generalizable insights at a regional scale. Traditional hydrological studies, which often rely on a limited number of gauged basins, frequently fail to capture the full spectrum of variability inherent in these complex mountain systems. There is, therefore, an urgent need for analytical frameworks capable of systematically investigating hydrological behavior across extensive and diverse catchment samples.

1.1 The Role of Large-Sample Hydrology

In response to these challenges, large-sample hydrology has emerged as a robust paradigm for analyzing extensive datasets consistently (Gupta et al., 2014; Addor et al., 2017). By shifting the focus from individual basins to broad spatial domains, this approach facilitates the identification of regional patterns, the quantification of process variability, and a deeper understanding of hydrological drivers. This framework is particularly valuable in mountainous regions where observational data are often sparse, discontinuous, or unevenly distributed across elevations.

Hydrological modeling is a critical enabler of these large sample analyses. Conceptual rainfall–runoff models are frequently utilized for their ability to provide a simplified yet effective representation of dominant hydrological processes. These models are computationally efficient, making them suitable for large-scale applications where they can generate continuous discharge time series across thousands of catchments—including those where direct measurements are unavailable.

1.2 Uncertainty and Statistical Characterization

Despite their utility, model-based discharge data introduce specific layers of uncertainty. The resulting simulated flood characteristics are not only a product of physical processes but are also influenced by the model's internal structure, parameterization, and the quality of meteorological inputs. As a result, simulated extremes require rigorous statistical scrutiny before they can be used for regional inference or comparative analysis.

Flood frequency analysis provides the mathematical structure necessary to define the magnitude and probability of these extreme events. Within this field, L-moments have become a preferred tool for characterizing probability distributions. Unlike conventional moment-based estimators, L-moments are significantly more resilient to sampling variability and the influence of outliers (Hosking, 1990). This robustness makes them uniquely suited for analyzing annual flood maxima across the large, diverse samples required for mountain hydrology.

1.3 Research Objectives and Thesis Structure

The central inquiry of this research concerns whether flood characteristics derived from large-scale simulations exhibit statistical consistency across the Alpine domain, or whether spatial variability remains the dominant feature despite the use of a unified modeling framework. Understanding this balance is essential for assessing the reliability of simulated data and its potential application in regional flood risk assessments.

This thesis analyzes simulated flood characteristics across a large sample of catchments within the Greater Alpine Region. Using annual maximum discharge series extracted from long-term daily simulations, the study focuses on the statistical characterization of flood magnitudes and their spatial distribution.

The specific objectives are:

- To quantify the statistical properties of simulated extremes using L-moment-based indicators.

- To evaluate the spatial variability of these flood characteristics across predefined Alpine subregions.
- To investigate flood frequency behavior through L-moment-based analysis and GEV-based flood frequency modelling.

The analysis utilizes simulated daily discharge data for 5,757 catchments over 73 years (1950–2022), generated via a distributed conceptual rainfall–runoff modeling framework. This extensive, spatially consistent dataset offers a rigorous foundation for identifying regional patterns in flood behavior across the Alps.

1.4 Thesis Organization:

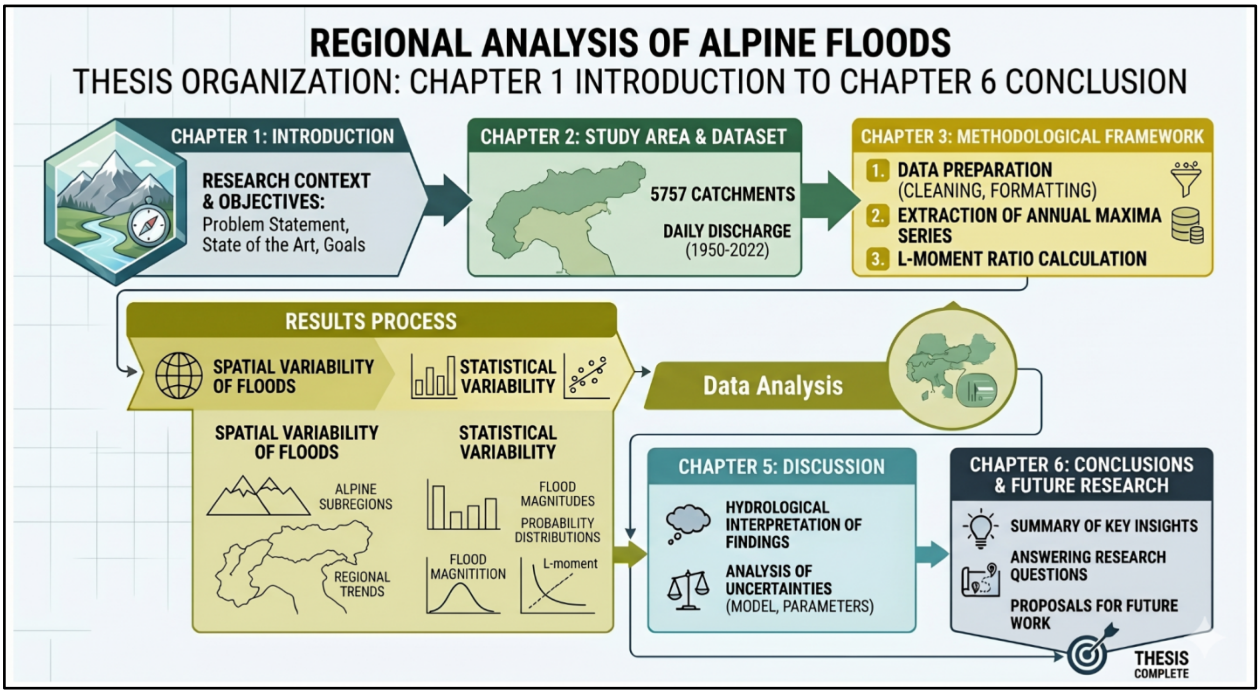

Figure 1- Thesis Organization

Chapter 2

Study Area and Dataset

2.1 Study Area

The geographical scope of this research is the Greater Alpine Region (GAR), a Central European domain defined by its extreme topographical and climatic complexity. Encompassing the main Alpine arc and its immediate forelands, the region is delineated by the HISTALP framework, spanning approximately 4°E to 19°E and 43°N to 49°N. The GAR is a well-established study area in climatological and hydrological literature, valued for its high spatial coherence and the availability of extensive, long-term datasets (Auer et al., 2007).

The climatic profile of the GAR is marked by significant spatial variability, a direct result of the interaction between its rugged terrain and large-scale atmospheric circulation. Positioned as a transition zone where Atlantic, Mediterranean, and continental air masses converge, the region experiences sharp gradients in precipitation volume, intensity, and seasonality (Brunetti et al., 2006). These climatic shifts are further intensified by orographic effects, which are fundamental in governing the distribution of precipitation and the subsequent processes of runoff generation.

Hydrologically, the Alpine environment provides a critical context for the study of extreme events. The combination of steep gradients, shallow soil profiles, and short basin response times facilitates rapid runoff. Furthermore, the interplay between rainfall and snowmelt adds a layer of complexity to flood dynamics that is characteristic of high-altitude environments (Bacchi and Ranzi, 2003). Consequently, flood behavior in the Alps is highly localized, often showing marked differences between adjacent catchments. This inherent variability makes the GAR a highly suitable domain for evaluating regional differences in flood characteristics and testing the statistical consistency of flood properties across a wide range of hydro-climatic conditions.

Figure 2- Location of the Alpine mountain range in Central Europe, showing its extension across France, Switzerland, Austria, Italy, Slovenia, and neighbouring countries. Source: Adapted from Twinkl educational resources (http://www.twinkl.com).

2.2 Regional Subdivision

To facilitate a structured analysis of spatial variability, the study area was partitioned into four distinct subregions based on the HISTALP classification: Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE) (Auer et al., 2007).

This specific subdivision is grounded in the major climatic gradients that characterize the Alpine arc. It accounts for varying precipitation regimes, the influence of different atmospheric circulation patterns, and distinct seasonal shifts (Brunetti et al., 2006; Efthymiadis et al., 2007). Consequently, this framework offers a physically meaningful regionalization that reflects the underlying environmental drivers, rather than relying on arbitrary geographical boundaries.

From a hydrological standpoint, these climatic distinctions are critical as they directly influence flood-generating mechanisms. These include the relative contributions of intense convective rainfall, steady stratiform precipitation, and spring snowmelt. By adopting the HISTALP framework, this study can investigate whether flood characteristics demonstrate consistent statistical behavior within these relatively homogeneous climatic zones, or if significant heterogeneity persists across the broader Alpine domain. To support this comparative analysis, each catchment in the dataset was geographically assigned to one of these four subregions.

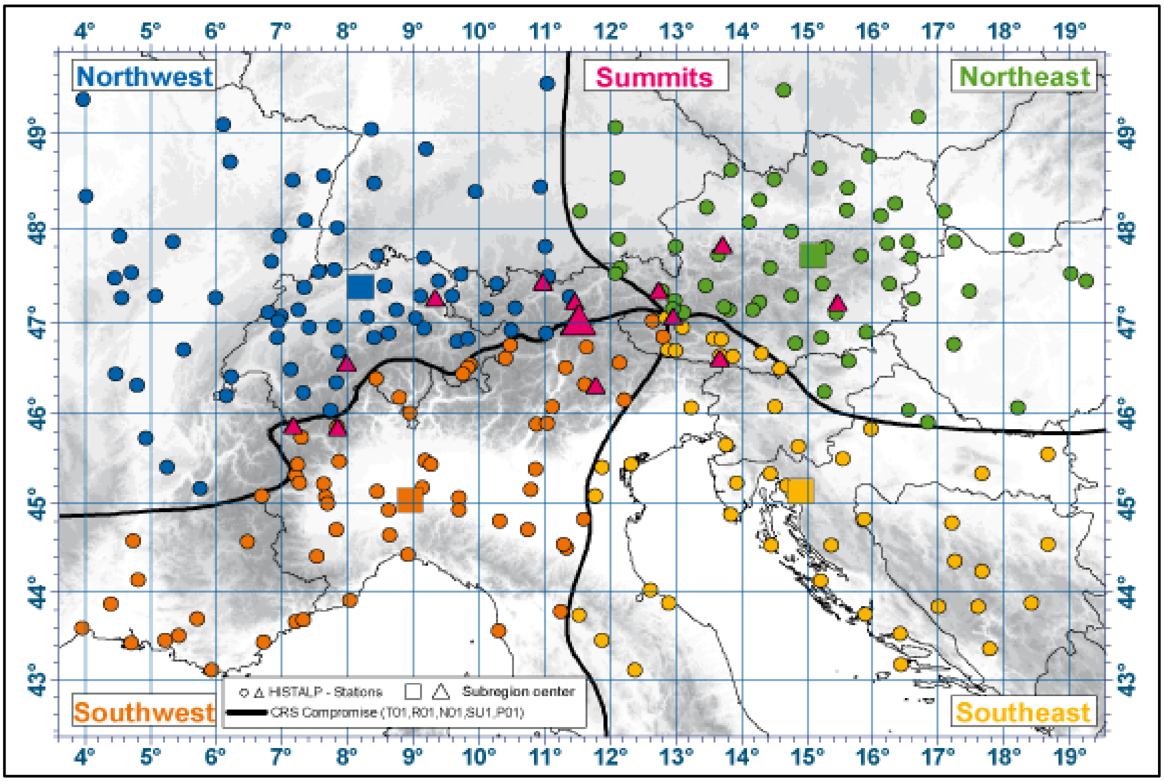

Figure 3 - Greater Alpine Region and its subdivision into the HISTALP subregions: Northwest, Northeast, Southwest, and Southeast. The map shows the regional framework used for the spatial comparison of flood characteristics in this thesis. Source: Adapted from Auer et al. (2007).

2.3 Catchment and Discharge Dataset

The empirical basis of this research is a dataset comprising 5,757 hydrological units, which represent individual sub-catchments across the Greater Alpine Region. These units align with the spatial discretization used in a distributed rainfall–runoff modeling framework, designed to capture the high degree of spatial heterogeneity in hydrological processes across the Alpine domain (Eilander et al., 2021; Merz et al., 2020).

For the purpose of statistical analysis, each hydrological unit is analyzed as an independent catchment. The dataset contains simulated daily discharge time series spanning from 1950 to 2022, yielding a uniform record length of 73 years for every catchment in the sample. This temporal consistency is a significant methodological advantage in regional studies, as it eliminates the statistical biases and uncertainties typically associated with unequal observation periods in gauged data.

Utilizing simulated discharge offers several distinct benefits for large-sample hydrological research. Most notably, it allows for the inclusion of a vast number of catchments, ensures continuous spatial coverage across the study area, and maintains a consistent modeling logic throughout the domain. These factors are essential for identifying robust regional signatures in flood behavior.

However, the use of model-generated data also necessitates a recognition of its inherent limitations. The simulated discharge series are subject to uncertainties stemming from model structure, parameter selection, and the quality of meteorological input data. Specifically, the simplified representation of hydrological processes in models may affect the accuracy of extreme events, potentially influencing the statistical properties of flood magnitudes. These constraints are carefully considered throughout the interpretation of the results.

To facilitate the statistical evaluation, two primary discharge indicators were extracted from the daily time series:

- Annual Maximum Discharge (m^3/s): A measure of the absolute magnitude of flood peaks.
- Annual Maximum Specific Discharge (m^3/s/km^2): Calculated by normalizing peak discharge by the drainage area.

The use of specific discharge is particularly important for regional comparison, as it mitigates the dominant influence of catchment size, allowing for a more direct assessment of flood intensity across the sample. The specific procedures for defining the hydrological year, extracting the Annual Maximum Series (AMS), and calculating the statistical indicators are detailed in Chapter 3.

Chapter 3

Methodology:

3.1 Overview of the Methodological Framework

This study applies a large-sample statistical framework to analyse simulated flood characteristics across the Greater Alpine Region. The methodological workflow consists of the following main steps:

1. Extraction of Annual Maximum Series (AMS) from daily simulated discharge
2. Computation of descriptive statistics and specific discharge
3. Estimation of L-moments and L-moment ratios
4. fitting of extreme value distribution (GEV) using L-moments
5. Evaluation of goodness-of-fit
6. Regional comparison and spatial analysis

All analyses were performed consistently for 5757 catchments over the period 1950–2022.

3.2 Hydrological Data and Preprocessing

The analysis is based on simulated daily discharge time series generated using a distributed rainfall–runoff modelling framework based on a modified version of the TUW model (Parajka et al., 2007). The model provides continuous discharge simulations for all catchments over a common 73-year period.

For each catchment, the available data includes:

- daily discharge time series (m^3/s)
- catchment area (km^2)
- geographical location and regional classification

All time series share consistent temporal coverage, and no additional temporal filtering or gap-filling procedures were required before analysis.

To enable comparison across catchments of different sizes, specific discharge was computed by normalizing discharge by catchment area:

$$\boldsymbol{q} = \frac{\boldsymbol{Q}}{\boldsymbol{A}}$$

where Q is discharge (m^3/s), and A is catchment area (km^2).

3.3 Annual Maximum Series (AMS) Extraction

The statistical characterization of flood frequency in this study follows the Annual Maximum Series (AMS) approach. This method involves extracting the single highest daily discharge value recorded for each catchment during every hydrological year within the 1950–2022 study period.

To ensure the analysis aligns with the physical reality of the region, the hydrological year was defined as the period from 1 October to 30 September of the following year. This temporal window is particularly appropriate for the Alpine domain, as it keeps the cycles of winter snow accumulation and subsequent spring/summer melt within a single analytical unit, preventing the splitting of a single high-flow season across two different years.

The AMS extraction was executed through a systematic three-step process:

1. Temporal Grouping: Organizing the daily discharge records into discrete hydrological years.
2. Peak Identification: Isolating the maximum daily discharge value within each designated year.
3. Temporal Attribution: Recording the specific date of each peak to maintain a record of flood timing.

This procedure yielded a consistent sample of 73 annual maximum values for every catchment. The extraction was performed for both absolute discharge (m^3/s) and specific discharge (m^3/s/km^2) to allow for multi-scale comparisons.

The selection of the AMS framework was based on its established reliability in regional hydrology and its inherent compatibility with standard extreme value distributions, such as the Generalized Extreme Value (GEV) distributions (Brunner et al., 2022). This approach provides a mathematically rigorous foundation for modeling the probability and magnitude of extreme hydrological events across the Greater Alpine Region.

3.4 Statistical Characterization of Flood Magnitudes

To describe flood magnitude and variability, a set of descriptive statistics was computed from the AMS for each catchment.

The mean annual maximum discharge was calculated as:

$$\mu = \frac{1}{n} \sum_{i=1}^{n} x_i$$

where x_i is the annual maximum value in year i, and $n = 73$.

To describe relative variability, the coefficient of variation was also computed as

$$CV = \frac{\sigma}{\mu}$$

Where σ is the sample standard deviation of the AMS.

Since the coefficient of variation is dimensionless, it allows comparison of variability among catchments with different mean flood magnitudes.

The coefficient of skewness was used to describe the asymmetry of the AMS distribution. It was computed as

$$C_s = \frac{1}{n} \sum_{i=1}^{n} \left(\frac{x_i - \mu}{\sigma}\right)^3$$

These statistics were used to describe the magnitude, variability, and asymmetry of flood distributions and to support spatial and regional comparisons.

3.5 L-Moment Estimation and L-Moment Ratios

To provide a robust characterization of flood distributions, L-moments were computed from the AMS of each catchment (Hosking, 1990).

The first two L-moments are defined as:

- L_1, or L-mean (measure of central tendency)
- L_2, or L-scale (measure of dispersion)

From these, the following dimensionless L-moment ratios were derived:

$$\tau = \frac{L_2}{L_1}$$

$$\tau_3 = \frac{L_3}{L_2}$$

$$\tau_4 = \frac{L_4}{L_2}$$

L-moment ratios provide a stable description of distribution shape and are particularly suitable for large-sample hydrological analyses because they are less sensitive to outliers and sampling variability.

In this study, L-moments were used to:

- characterize flood distribution properties
- support L-moment ratio diagrams
- guide the fitting of extreme value distributions

3.6 Extreme Value Distribution Fitting

Flood frequency curves were derived by fitting the Generalized Extreme Value (GEV) distribution to the AMS of each catchment. The Generalized Extreme Value (GEV) distribution was used to model the annual maximum floods.

The cumulative distribution function of the GEV is:

$$F(x) = exp\left\{-\left[1 + \xi\left(\frac{x - \mu}{\sigma}\right)\right]^{\frac{-1}{\xi}}\right\}$$

$$1 + \xi\left(\frac{x - \mu}{\sigma}\right) > 0$$

where μ is the location parameter, $\sigma > 0$ is the scale parameter, and ξ is the shape parameter.

3.6.1 Estimation of GEV Parameters Using L-Moments

The parameters of the GEV distribution were estimated using the L-moment method (Hosking, 1990).

For each catchment, the first three L-moments L_1, $L2$, and $L3$ were computed from the AMS. The L-skewness ratio was defined as:

$$\tau_3 = \frac{L_3}{L_2}$$

The shape parameter ξ was obtained as a function of τ_3 Using standard numerical approximations. Once ξ was determined, the scale parameter σ and location parameter μ were calculated as:

$$\sigma = \frac{L_2 \, . \, \xi}{(1 - 2^{-\xi}) \, \Gamma \, (1 + \xi)}$$

$$\mu = L_1 - \frac{\sigma}{\xi} \, [1 - \Gamma \, (1 + \xi)]$$

where $\Gamma(\cdot)$ is the Gamma function.

3.6.2 Flood Quantile Estimation

Flood quantiles were estimated for selected return periods T using the fitted distributions. The relationship between return period and non-exceedance probability is:

$$F = 1 - \frac{1}{T}$$

GEV-based quantiles were computed for return periods including 2, 5, 10, 20, 50, and 100 years and used to construct flood frequency curves.

3.7 Goodness-of-Fit Assessment

The adequacy of the fitted distributions was evaluated using the Anderson–Darling (AD) test (Laio, 2004).

For an ordered sample $x_1 \leq x_2 \leq \ldots \leq x_n$. The AD statistic is defined as:

$$A^2 = -n - \frac{1}{n}\sum_{i=1}^{n}(2i-1)[lnF(x_i) + ln(1 - F(x_{n+1-i}))]$$

The test emphasizes discrepancies in the distribution tails, which is particularly relevant for extreme value analysis.

The test was applied separately for each catchment to evaluate the fitted GEV distribution. A significance level of $\alpha = 0.05$ was used, and a distribution was considered acceptable when $p \geq \alpha$.

Results were summarized in terms of:

- percentage of catchments where the GEV distribution was not rejected.
- spatial patterns of goodness-of-fit performance.

3.8 Regional Comparison and Spatial Analysis

To investigate spatial variability, all statistical indicators and model results were analyzed across the four HISTALP subregions (NW, NE, SW, SE).

The analysis included:

- spatial mapping of mean discharge, CV, and skewness
- L-moment ratio diagrams

- Evaluation of spatial patterns in GEV goodness-of-fit results

These analyses provide a coherent framework for identifying spatial patterns in flood behavior and assessing regional consistency in statistical properties across the Greater Alpine Region.

Chapter 4

Results

4.1 Overview

This chapter presents the statistical results obtained from the Annual Maximum Series extracted from the simulated daily discharge records across the Greater Alpine Region. The analysis was conducted for 5,757 catchments and focuses on the spatial variability of flood characteristics across the four HISTALP subregions. The results are organized around four main components: the spatial classification of catchments, descriptive flood statistics, L-moment-based indicators, and the goodness-of-fit performance of the fitted Generalized Extreme Value (GEV) distribution.

The descriptive analysis includes the mean annual maximum specific discharge, the coefficient of variation, and the coefficient of skewness. These indicators describe, respectively, the average magnitude of annual flood peaks after normalization by catchment area, the relative variability of annual maxima, and the asymmetry of the annual maximum flood distributions. The L-moment analysis then provides a robust characterization of distributional shape through L-skewness and L-kurtosis. Finally, the fitted GEV distribution is evaluated using the Anderson–Darling goodness-of-fit test at the 5% significance level.

The results presented in this chapter are mainly descriptive. Their objective is to identify spatial patterns and statistical differences across the Alpine domain. Physical interpretation of these patterns is reserved for the discussion chapter.

4.2 Spatial Organization of the Catchments

The study area was divided into four HISTALP subregions: Northwest (NW), Northeast (NE), Southwest (SW), and Southeast (SE). Figure 4 shows the regional classification of the catchments used in the analysis. The classification provides the spatial framework for examining flood characteristics across the Greater Alpine Region.

The regional map shows that the catchments cover the full Alpine domain, including both the western and eastern sectors of the study area. The NW and NE regions represent the northern Alpine sector, while the SW and SE regions represent the southern part of the domain. This classification is used as a spatial reference for interpreting the distribution of the statistical indicators presented in the following sections.

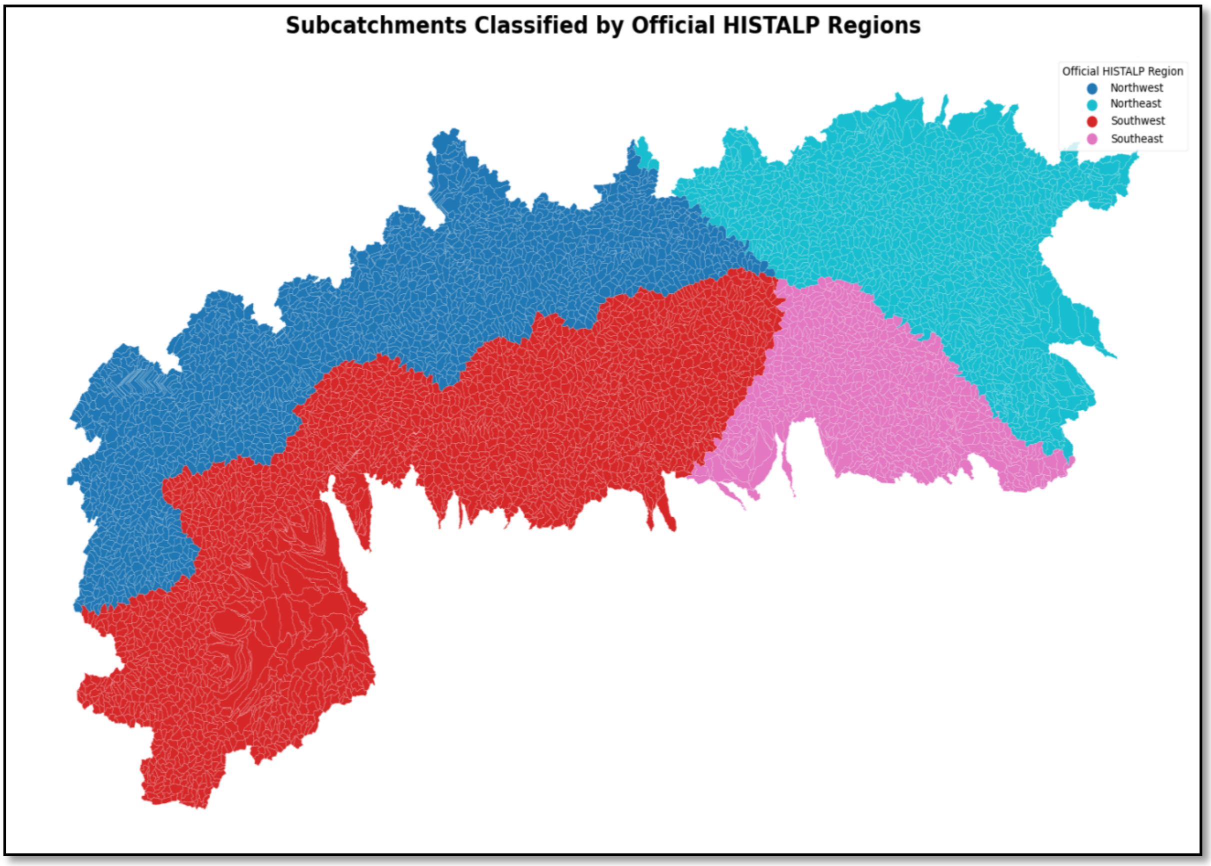

Figure 4 - Regional classification of the 5,757 catchments according to the HISTALP subdivision.

4.3 Spatial Patterns of Descriptive Flood Statistics

4.3.1 Mean Annual Maximum Specific Discharge

Figure 5 presents the thematic map of mean annual maximum specific discharge across the 5,757 catchments of the Greater Alpine Region. This indicator represents the average magnitude of annual flood peaks normalized by catchment area and provides a measure of flood intensity that is comparable among catchments of different sizes. The mapped values range from values close to zero to approximately 0.80 $m^3/s/km^2$.

The thematic map reveals a not uniform spatial distribution of mean annual maximum specific discharge across the study area. Most catchments belong to the lower to intermediate classes, indicating relatively low average flood intensity over large parts of the Alpine domain, whereas a smaller number of catchments are classified within the higher-value categories. These higher values are not evenly distributed throughout the region but occur in distinct spatial clusters, highlighting areas where annual maximum floods are comparatively more intense after normalization by catchment area.

The use of custom classification bins allows the spatial pattern of discharge intensity to be interpreted according to fixed value ranges rather than relative quantile groups. Therefore, the mapped classes represent fixed value intervals of mean annual maximum specific discharge and should be interpreted as classification ranges used for visualization, rather than as formally defined hydrological threshold levels.

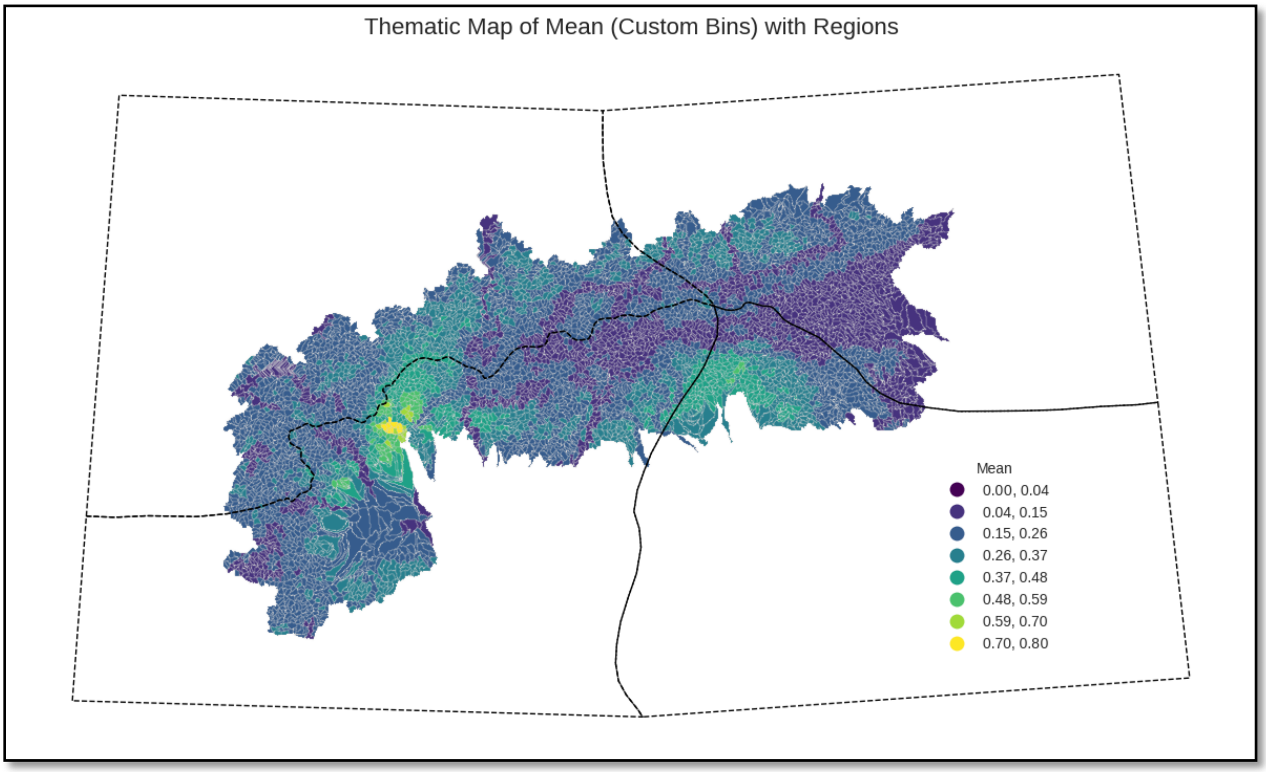

Figure 5 - Thematic map of mean annual maximum specific discharge (m^3/s/km^2)

4.3.2 Coefficient of Variation

The coefficient of variation describes the relative variability of annual maximum floods. Figure 6 presents the thematic map of CV values across the study area using quantile classification. The values range from approximately 0.09 to 0.73.

The map shows considerable spatial variation in flood variability among the catchments. Lower CV values are distributed across parts of the study area, while higher values occur in several distinct clusters. The quantile classification highlights relative differences among catchments by grouping them into classes containing similar numbers of observations.

The spatial distribution indicates that the variability of annual maximum floods is not uniform across the Greater Alpine Region. Catchments with comparable mean flood magnitudes may nevertheless exhibit different levels of year-to-year variability, emphasizing that flood variability represents a distinct characteristic of the Annual Maximum Series.

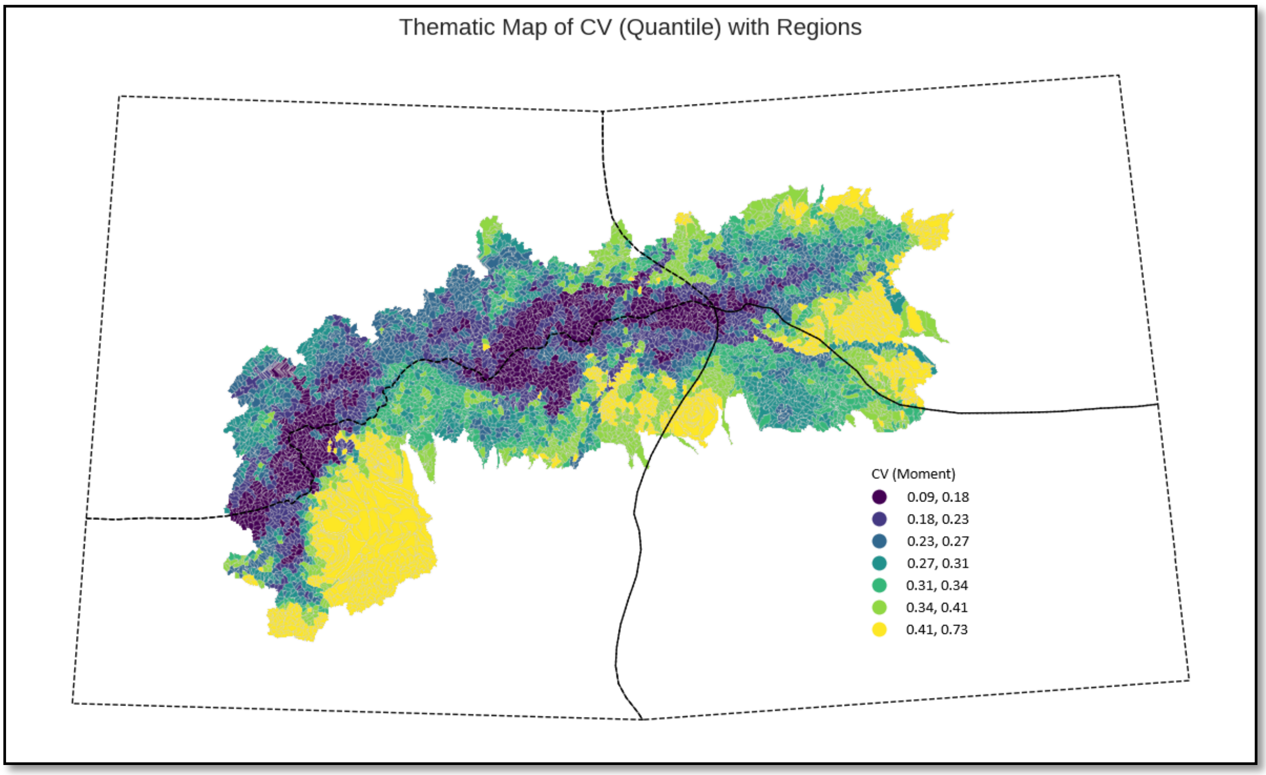

Figure 6 - Thematic map of the coefficient of variation of annual maximum floods using quantile classification

4.3.3 Coefficient of Skewness

Figure 7 presents the spatial distribution of the coefficient of skewness, labelled as CA in the figure. The values range from approximately -0.66 to 3.58. This indicator describes the asymmetry of the Annual Maximum Series for each catchment.

Most catchments show positive skewness, indicating that annual maximum flood distributions are generally characterized by occasional high values relative to their central tendency. The highest skewness classes are spatially clustered in selected parts of the study area, while lower and moderate values are more widely distributed. Negative or near-zero skewness values occur only in a limited part of the dataset.

The spatial pattern of skewness indicates that the shape of flood distributions varies strongly among catchments. Annual maximum floods therefore differ not only in magnitude and variability, but also in the degree of asymmetry.

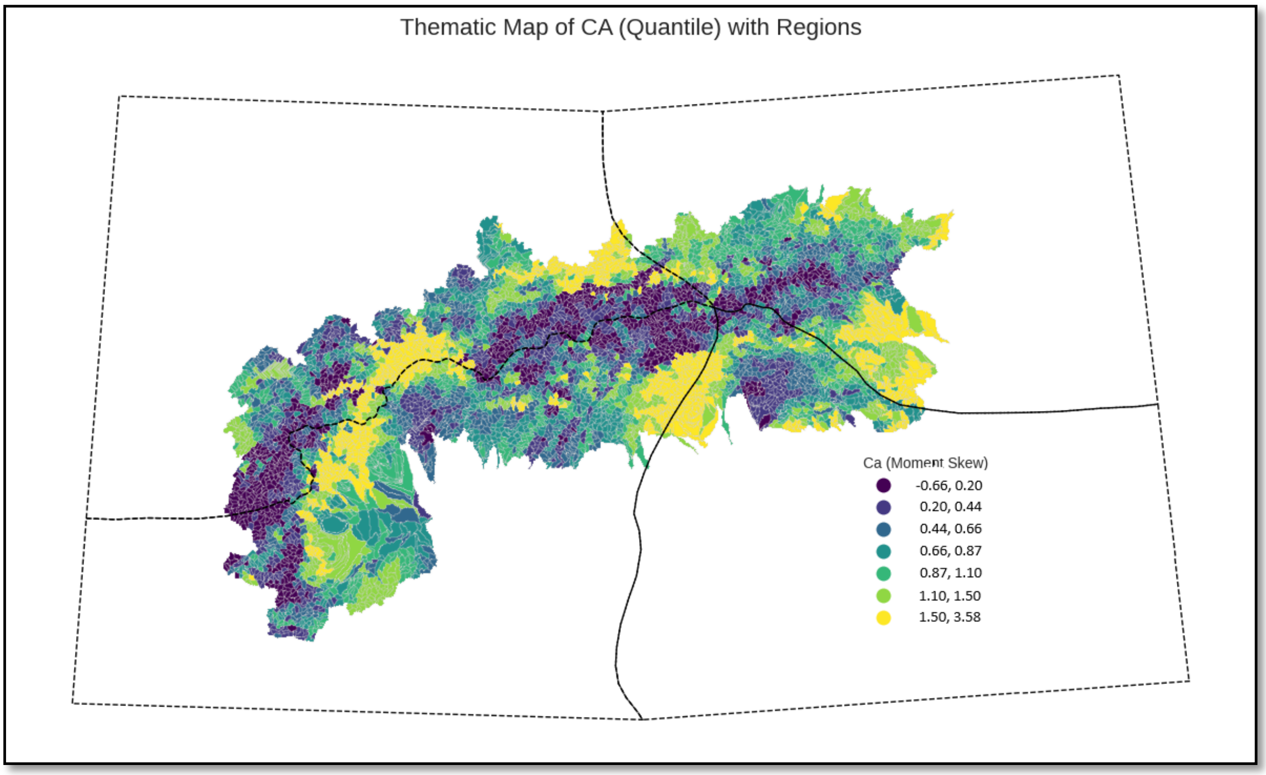

Figure 7- Thematic map of the coefficient of skewness of annual maximum floods using quantile classification

4.3.4 Summary of Descriptive Statistics

The descriptive statistics show substantial spatial variability in the statistical behaviour of annual maximum floods. Mean annual maximum specific discharge highlights differences in normalized flood magnitude. The coefficient of variation shows that the relative variability of floods changes across the domain. The coefficient of skewness further indicates that the asymmetry of flood distributions is not spatially uniform.

Indicator	Approximate range	Interpretation
Mean annual maximum specific discharge	close to 0–0.80 $m^3/s/km^2$	Normalized flood magnitude
Coefficient of variation	0.09–0.73	Relative variability of AMS
Coefficient of skewness / CA	-0.66–3.58	Asymmetry of AMS

Table 1- Summary of mapped descriptive indicators

Overall, these results confirm that the Annual Maximum Series show marked spatial heterogeneity across the Greater Alpine Region.

4.4 Relationship Between Flood Magnitude, Variability, and Skewness

Scatter plots were used to examine the relationship between mean annual maximum specific discharge and two distributional indicators: the coefficient of variation (CV) and the coefficient of skewness. Both linear-scale and logarithmic x-axis versions were produced to improve interpretability across the full range of catchments.

In the linear-scale plots, most catchments are concentrated near the lower end of the mean specific discharge axis. This pattern reflects the strongly right-skewed distribution of mean specific discharge values, with a small number of catchments exhibiting much higher means that compress the bulk of the data near the origin. For this reason, the plots with the mean specific discharge axis shown on a logarithmic scale provide a clearer view of the internal structure of the dataset.

Figure 8 shows the relationship between mean specific discharge and CV. With the mean specific discharge axis shown on a logarithmic scale, CV values are distributed across a broad range for catchments with low to moderate mean specific discharge, while the spread becomes somewhat narrower at higher mean values. Nevertheless, several outliers remain visible. Overall, the scatter pattern does not suggest a strong linear relationship between flood magnitude and CV, indicating that mean flood magnitude alone does not fully explain relative variability.

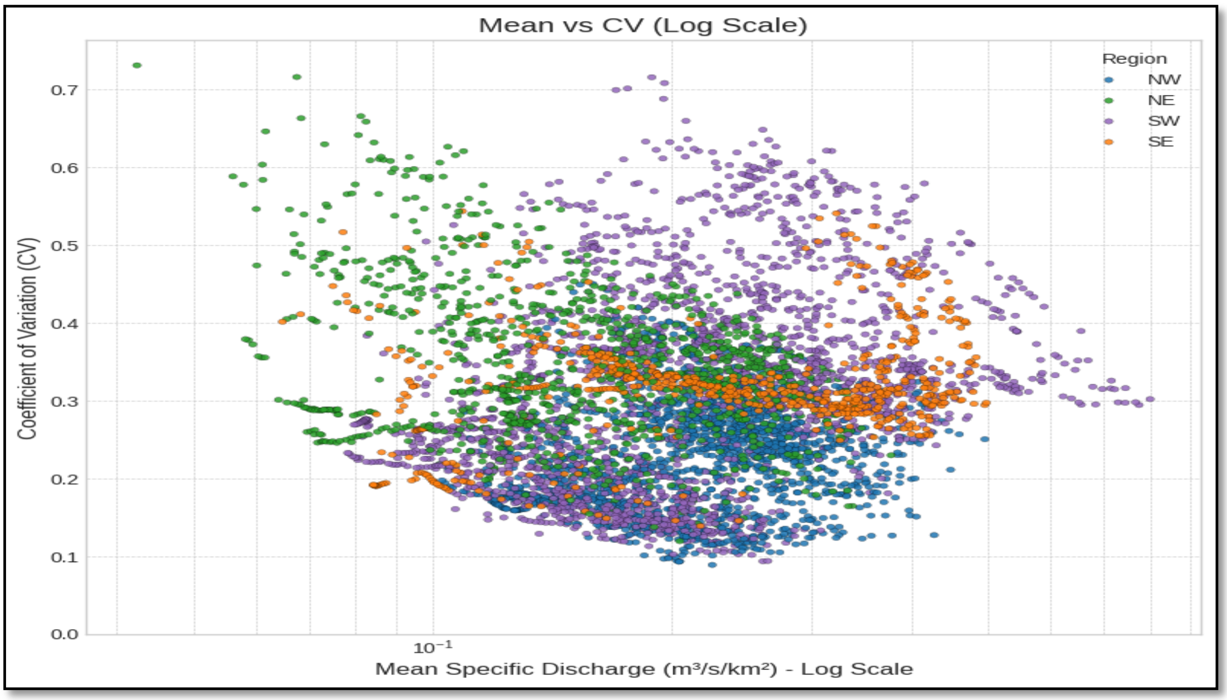

Figure 8 - Relationship between mean annual maximum specific discharge and coefficient of variation (CV) across the four HISTALP subregions, with mean specific discharge shown on log scales.

Figure 9 shows the relationship between mean specific discharge and skewness. As in the CV plot, the linear-scale version is dominated by a small number of high-magnitude catchments, whereas the logarithmic x-axis version reveals a more informative structure. High skewness values occur mainly among catchments with low to moderate mean specific discharge, although the overall relationship remains widely scattered. This suggests that strongly asymmetric flood distributions can occur even where mean flood magnitude is not exceptionally high.

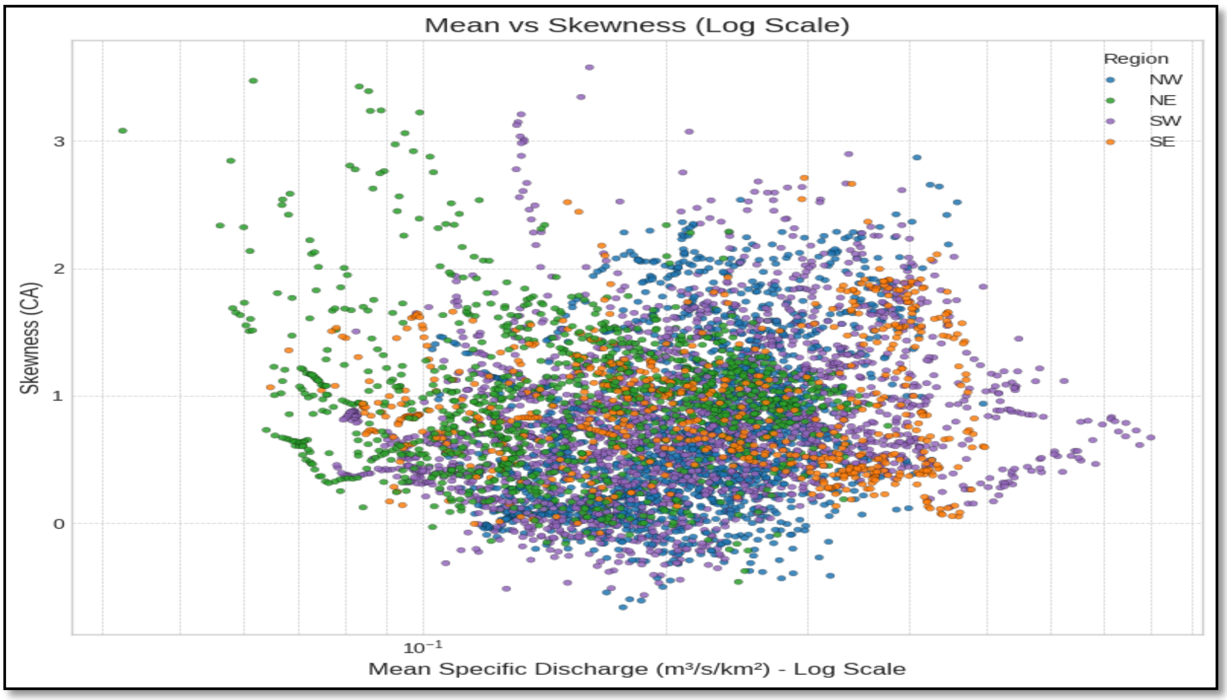

Figure 9 - Relationship between mean annual maximum specific discharge and coefficient of skewness (CA), across the four HISTALP subregions, with mean specific discharge shown on log scales.

Together, these scatter plots support the spatial analysis by showing that mean flood magnitude, relative variability, and asymmetry are not interchangeable. Each indicator captures a different aspect of the Annual Maximum Series, and their relationships are only partially connected.

4.5 L-Moment Characteristics of Annual Maximum Floods

4.5.1 Spatial Distribution of L-Skewness

Figure 10 shows the spatial distribution of L-skewness, expressed as $\tau 3$. The values range from approximately -0.11 to 0.46. The map shows that L-skewness varies across the study area. Lower and moderate classes are widespread, while higher L-skewness values occur in localized clusters. Positive L-skewness dominates the dataset, indicating that many catchments have annual maximum flood distributions with a longer upper tail. However, the degree of asymmetry differs considerably among catchments.

The spatial distribution of L-skewness is broadly consistent with the conventional skewness results, but L-skewness provides a more robust representation of distributional asymmetry. The presence of spatially clustered high values suggests that the asymmetry of flood distributions follows a spatially structured pattern across parts of the Alpine domain.

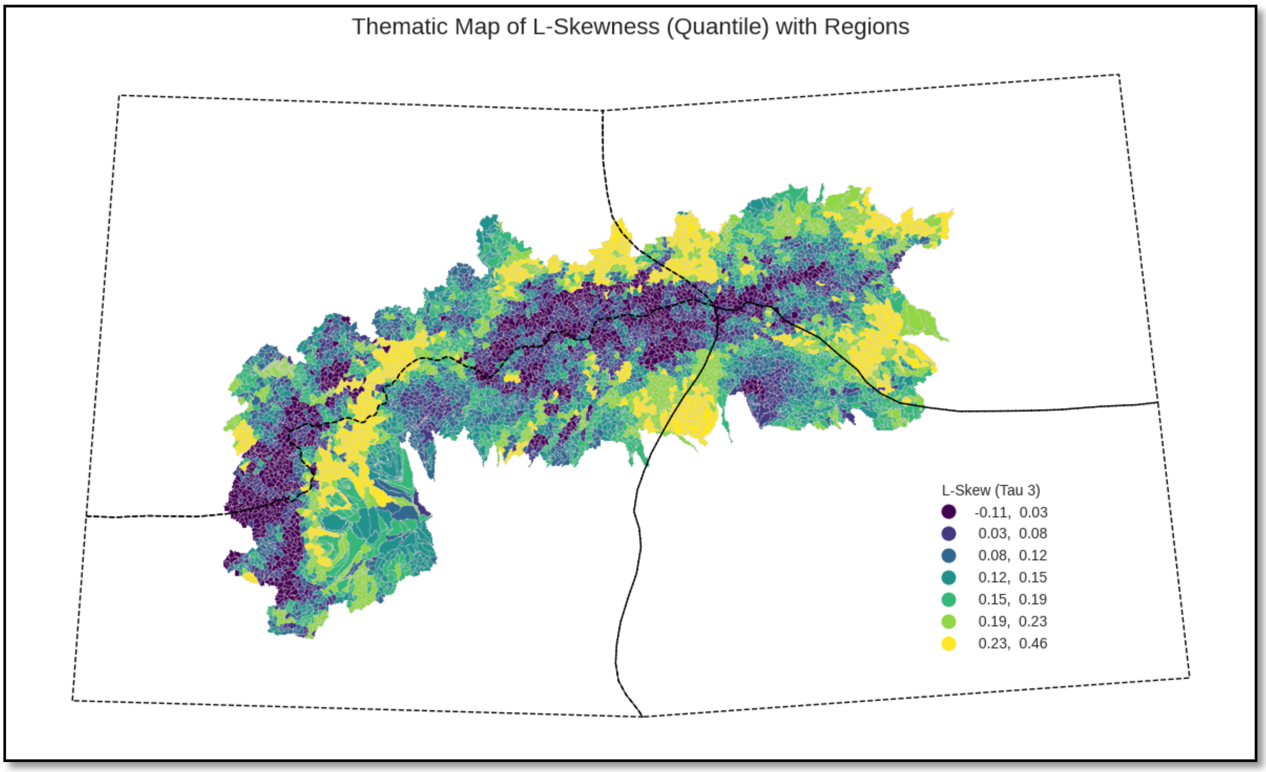

Figure 10 - Spatial distribution of L-skewness, τ3, using quantile classification

4.5.2 Spatial Distribution of L-Kurtosis

Figure 11 presents the spatial distribution of L-kurtosis, expressed as τ4. The mapped values range from approximately -0.01 to 0.39.

L-kurtosis describes the upper-tail behaviour and peakiness of the distribution in an L-moment framework. The map shows that L-kurtosis also varies spatially across the Greater Alpine Region. Higher L-kurtosis values occur in selected areas rather than throughout the whole domain. Lower and intermediate values are more widely distributed.

The spatial pattern of L-kurtosis indicates that differences in flood frequency behaviour are not limited to the mean, variability, or skewness of annual maxima. The upper-tail characteristics of the flood distributions also vary among catchments.

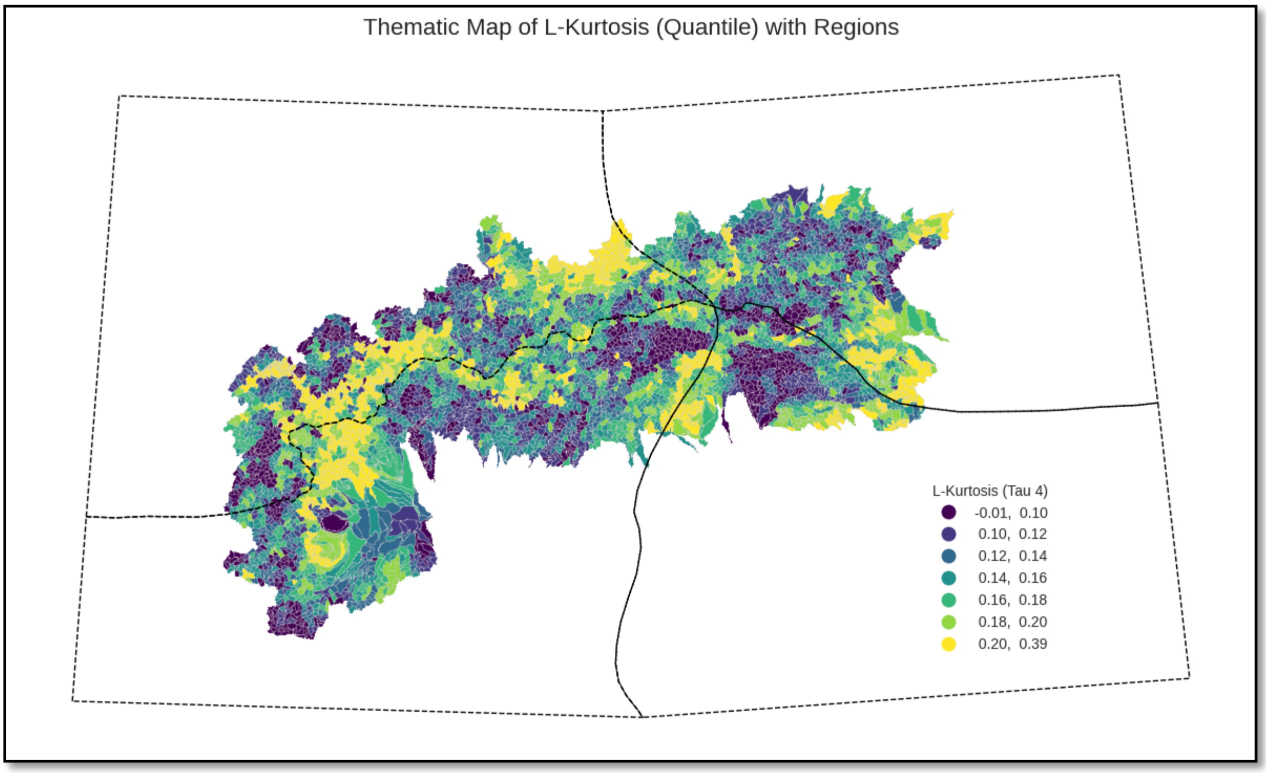

Figure 11 - Spatial distribution of L-kurtosis, using quantile classification

4.5.3 Summary of L-Moment Results

The L-moment results indicate that the distributional properties of annual maximum floods vary across the Greater Alpine Region. L-skewness shows spatial differences in distributional asymmetry, while L-kurtosis indicates that upper-tail behavior also changes across the study area.

Indicator	Approximate range	Interpretation
L-skewness / τ3	-0.11–0.46	Distributional asymmetry
L-kurtosis / τ4	-0.01–0.39	Upper-tail behavior and distributional shape

Table 2 - Summary of mapped L-moment indicators.

These results show that the catchments differ not only in flood magnitude but also in the shape and upper-tail characteristics of their annual maximum flood distributions.

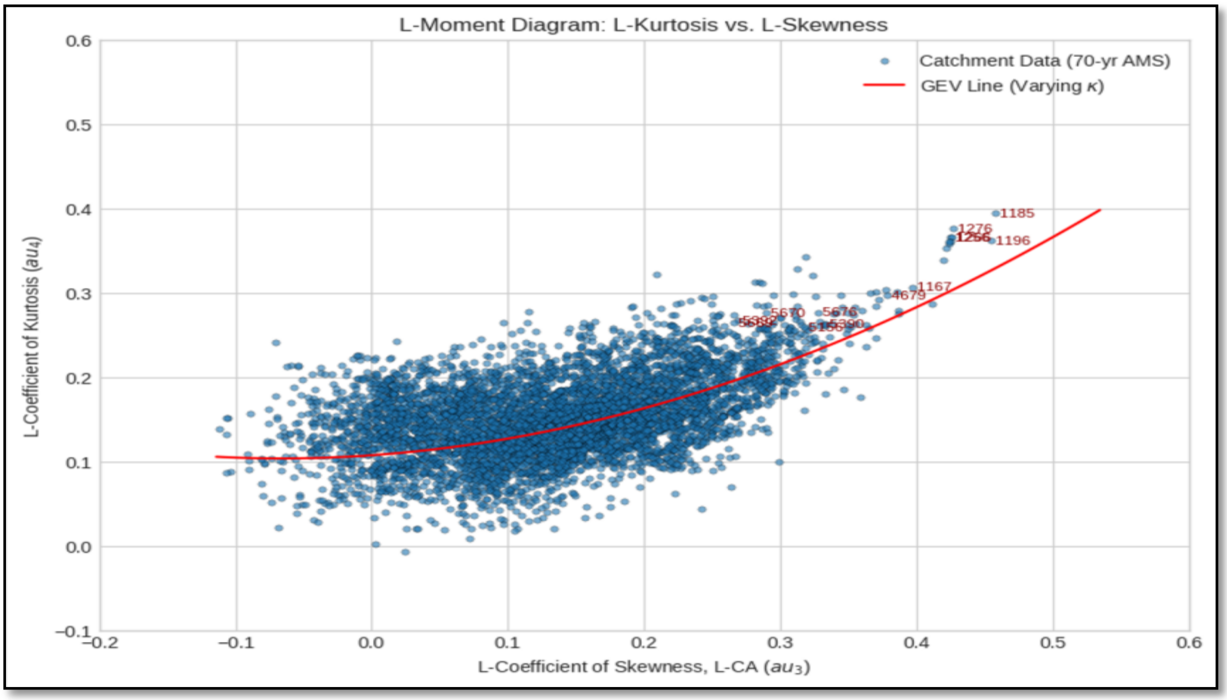

Figure 12 - L-moment ratio diagram of L-kurtosis (τ4) versus L-skewness (τ3) for the catchment Annual Maximum Series, with the theoretical Generalized Extreme Value (GEV) curve shown for comparison.

4.6 Goodness-of-Fit of GEV Distribution

The GEV distribution was fitted to the Annual Maximum Series of each catchment. Its goodness-of-fit was evaluated using the Anderson–Darling test at the 5% significance level. The fitted distribution was considered acceptable when it was not rejected by the test.

Figure 13 shows the spatial distribution of the Anderson–Darling test results for the GEV distribution. The GEV distribution passed the test in 5,576 catchments and failed in 181 catchments. This corresponds to a pass rate of approximately 96.9%. The failed catchments are spatially limited and appear as localized clusters rather than as a dominant pattern across the study area.

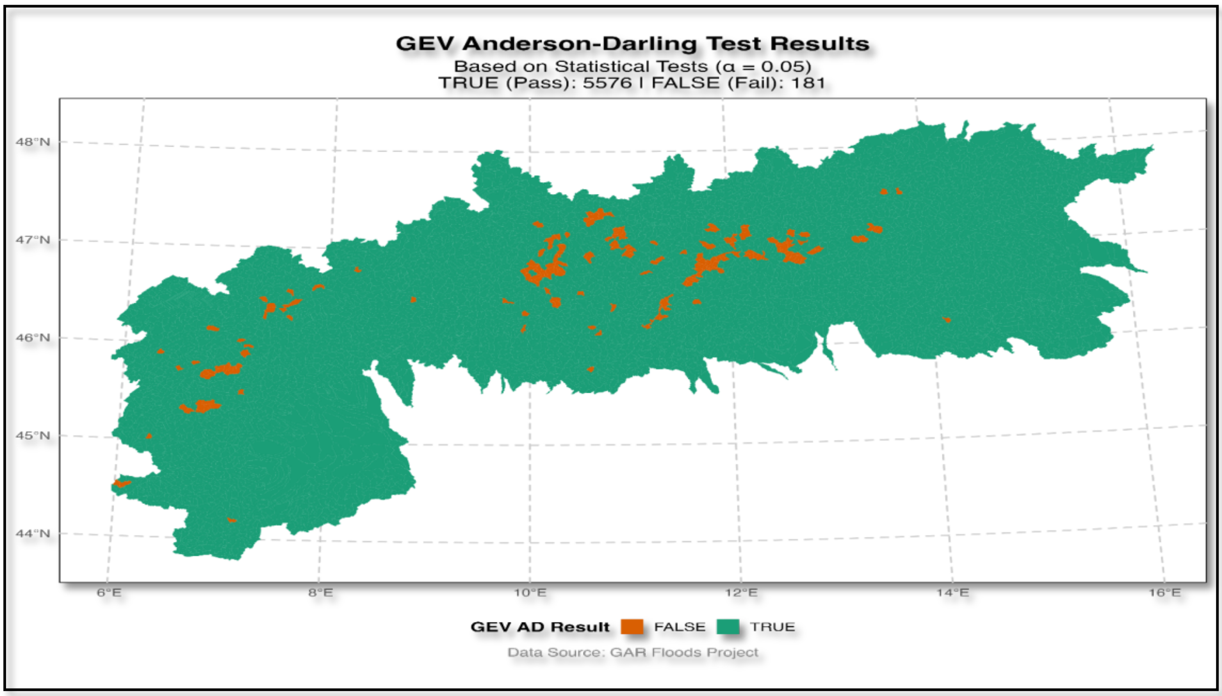

Figure 13 - Anderson–Darling goodness-of-fit results for the GEV distribution.

Distribution	Test type	Passed	Failed	Pass rate
GEV	Anderson–Darling	5,576	181	96.9%

Table 3 - Anderson–Darling goodness-of-fit results for fitted distributions.

The Anderson–Darling results indicate that the GEV distribution provides an acceptable fit for most catchments. The high pass rate suggests that the GEV distribution is generally suitable for representing the simulated Annual Maximum Series across the study area. However, the failed catchments indicate that the fit is not spatially uniform and that local deviations remain present in a small part of the dataset.

Overall, the goodness-of-fit results show that the Annual Maximum Series can generally be represented by the GEV distribution across the Greater Alpine Region, with only a small proportion of catchments rejected by the Anderson–Darling test.

4.7 Summary of Results

The results show that simulated annual maximum flood characteristics vary substantially across the Greater Alpine Region. The spatial distribution of mean annual maximum specific discharge indicates that normalized flood magnitude is not uniform across the catchment sample. Most catchments fall within lower magnitude classes, while high values are concentrated in localized areas. The coefficient of variation and coefficient of skewness reveal additional differences in flood behaviour. CV shows that year-to-year variability in annual maximum floods differs across catchments, while skewness indicates that many catchments have asymmetric flood distributions with occasional high flood values. The scatter plots further show that flood magnitude, variability, and asymmetry are not interchangeable and do not visually follow a simple linear pattern.The L-moment analysis supports these findings using a more robust distributional framework. L-skewness and L-kurtosis vary spatially, showing that flood distributions differ in asymmetry and upper-tail characteristics. These results demonstrate that the flood behaviour of the Alpine catchments cannot be described by mean magnitude alone.

The Anderson–Darling goodness-of-fit results show that the GEV distribution provides an acceptable fit for most catchments. The GEV distribution passed the test in 96.9% of catchments. These results indicate that the GEV distribution is broadly suitable for representing the simulated Annual Maximum Series in the study area.

Together, the results provide a statistical basis for discussing flood behaviour in the Greater Alpine Region. The main finding is that flood characteristics are spatially heterogeneous: catchments differ not only in magnitude but also in variability, asymmetry, and distributional shape.

Chapter 5

Discussion

5.1 Overview of the Main Findings

The results of this thesis show that simulated annual maximum floods across the Greater Alpine Region are spatially heterogeneous. Even though the discharge series were generated using a consistent modelling framework and analysed with the same statistical procedure for all catchments, the resulting flood characteristics were not uniform across the study area. Differences were observed in flood magnitude, relative variability, asymmetry, and distributional shape.

The analysis of mean annual maximum specific discharge showed that flood intensity is not evenly distributed across the catchment sample. The coefficient of variation and coefficient of skewness added further information by showing that catchments also differ in the stability and asymmetry of their Annual Maximum Series. The L-moment results confirmed that the distributional shape of annual maximum floods varies across the Alpine domain. Finally, the Anderson–Darling goodness-of-fit results showed that the GEV distribution provides an acceptable fit for most catchments, although a small number of local deviations remain.

Overall, the main message of the results is that flood behaviour in the Greater Alpine Region cannot be described by a single indicator. Mean flood magnitude, variability, skewness, and upper-tail behaviour each describe a different aspect of the flood regime. This is particularly important in a complex mountain environment, where spatial heterogeneity is expected to remain strong even when the same modelling and statistical framework is applied across the whole domain.

5.2 Spatial Heterogeneity of Flood Magnitude and Variability

The spatial distribution of mean annual maximum specific discharge shows that normalized flood magnitude varies considerably across the Greater Alpine Region. Because specific discharge is normalized by catchment area, the observed differences cannot be interpreted only because of catchment size. Instead, they indicate that some parts of the Alpine domain produce higher annual flood peaks per unit area than others.

This finding is consistent with the general understanding of the Alps as a highly heterogeneous hydro-climatic region. Previous studies have described the Greater Alpine Region as an area characterized by strong spatial gradients in climate, precipitation regime, topography, and runoff generation processes (Auer et al., 2007; Brunetti et al., 2006; Bacchi and Ranzi, 2003). The results of this thesis are in line with this broader context. However, the present analysis does not directly separate the effect of individual physical drivers such as precipitation intensity, snowmelt, elevation, geology, or land cover. For this reason, the spatial patterns observed in the maps should be interpreted as statistical flood signatures rather than direct causal explanations.

The coefficient of variation provides a second important result. It shows that the relative variability of annual maximum floods changes across the study area. This means that two catchments with similar mean flood magnitude may still have different year-to-year variability. In practical terms, mean flood intensity alone is not enough to describe the behaviour of annual maximum floods. Some catchments may have relatively stable annual maxima, while others may experience much larger fluctuations from year to year.

The coefficient of skewness adds another layer of information. Most catchments show positive skewness, which indicates that annual maximum flood distributions are often characterized by occasional high values. This is a typical feature of flood data, where rare events can strongly influence the upper part of the distribution. The spatial clustering of higher skewness values suggests that the asymmetry of the Annual Maximum Series is also spatially structured, rather than randomly distributed across the domain.

Together, these descriptive indicators show that the simulated flood regime is not only spatially variable in terms of magnitude but also in terms of variability and distributional asymmetry. This supports the main objective of the thesis, which was to evaluate whether simulated flood characteristics show statistical consistency across the Alpine domain or whether spatial heterogeneity remains dominant.

5.3 Relationship Between Flood Magnitude, Variability, and Asymmetry

The scatter plots between mean annual maximum specific discharge and the distributional indicators help clarify the relationship between the different flood statistics. The results show that flood magnitude, variability, and asymmetry are related only in a limited sense and cannot be used as substitutes for one another.

The relationship between mean specific discharge and CV does not visually suggest a strong linear pattern. Catchments with low or moderate mean specific discharge can still show a wide range of CV values. This indicates that relative variability is not controlled by flood magnitude alone. A catchment may have moderate average annual maxima but still show strong interannual variability.

A similar point applies to the relationship between mean specific discharge and skewness. High skewness values occur mainly among catchments with low to moderate mean specific discharge, although the general pattern remains scattered. This means that strongly asymmetric flood distributions can occur even where the mean annual maximum specific discharge is not particularly high. Therefore, a catchment with a moderate average flood magnitude may still be affected by occasional extreme annual maxima.

These results are important because they justify the use of multiple statistical indicators. If the analysis had been limited only to mean annual maximum specific discharge, it would have missed important differences in variability and asymmetry. The use of CV, skewness, and L-moment indicators gives a more complete picture of simulated flood behaviour across the Alpine region.

5.4 Distributional Shape Based on L-Moments

5.4.1 Interpretation of L-skewness and L-kurtosis

The L-moment analysis provides a more robust description of the shape of the Annual Maximum Series. L-moments are widely used in flood frequency analysis because they are less sensitive to sampling variability and outliers than conventional moments (Hosking, 1990). This makes them particularly useful in a large-sample study where thousands of catchments are analysed consistently.

The spatial distribution of L-skewness shows that the asymmetry of annual maximum flood distributions varies across the Greater Alpine Region. This result is broadly consistent with the conventional skewness analysis, but the L-moment framework provides a more stable representation of distributional shape. Positive L-skewness dominates the dataset, suggesting that many catchments have annual maximum flood distributions with longer upper tails.

L-kurtosis provides additional information about upper-tail behaviour and distributional shape. The spatial variation of L-kurtosis indicates that catchments differ not only in central tendency and asymmetry, but also in the structure of the upper tail of the distribution. This is relevant for flood frequency analysis because the upper tail controls the estimation of rare and high-magnitude floods.

The combined interpretation of L-skewness and L-kurtosis supports the idea that flood behaviour in the Alpine domain is not statistically uniform. The catchments differ not only in how large annual maximum floods are, but also in how their distributions are shaped.

5.4.2 Interpretation of the L-moment Ratio Diagram

The L-moment ratio diagram provides a useful summary of the relationship between L-skewness and L-kurtosis. In this diagram, each catchment is represented in the τ_3–τ_4 space, and the theoretical GEV curve is shown for comparison. The presence of the GEV curve allows the empirical L-moment ratios to be compared with the expected behaviour of the fitted distribution.

The diagram supports the use of the GEV distribution as a general modelling framework for the Annual Maximum Series. At the same time, the spread of the catchment points around the theoretical curve indicates that the distributional shape is not identical for all catchments. This is consistent with the spatial patterns shown in the L-skewness and L-kurtosis maps.

This result should not be interpreted as proof that the GEV distribution perfectly represents every catchment. Rather, it suggests that GEV is a suitable overall framework, while local differences in distributional behaviour remain present. This interpretation is also consistent with the Anderson–Darling goodness-of-fit results, where most catchments passed the test, but a small number were rejected.

5.5 Suitability of the GEV Distribution

The Anderson–Darling goodness-of-fit test showed that the GEV distribution provides an acceptable fit for the vast majority of catchments. The distribution passed the test in 5,576 catchments and failed in 181 catchments, corresponding to a pass rate of approximately 96.9%. This high pass rate supports the use of the GEV distribution for modelling simulated annual maximum floods in this dataset.

The use of the GEV distribution is also consistent with common practice in flood frequency analysis. Recent studies continue to apply GEV-based approaches for flood frequency estimation and the analysis of hydrological extremes (Brunner and Slater, 2022; Anghel and Ianculescu, 2025). In this thesis, the GEV distribution was fitted using L-moments, which is coherent with the statistical framework adopted for describing distributional shape.

However, the high pass rate should be interpreted carefully. It does not mean that all catchments behave in the same way, and it does not remove the spatial heterogeneity observed in the previous sections. The failed catchments show that the fit is not spatially uniform. These local deviations may reflect local hydrological behaviour, limitations of the simulated discharge data, or the difficulty of representing all annual maximum distributions with the same theoretical model.

It is also important to note that this thesis does not compare GEV with other distributions. Therefore, the results support the suitability of GEV as an acceptable model for most catchments, but they do not demonstrate that GEV is the best possible distribution in all cases. This distinction is important for keeping the interpretation consistent with the methodology.

5.6 Implications for Large-Sample Flood Analysis in the Alpine Region

The results of this thesis show the value of a large-sample approach for analysing flood behaviour in a complex mountain region. Large-sample hydrology emphasizes the importance of analysing many catchments in a consistent way, rather than focusing only on a small number of gauged basins (Gupta et al., 2014; Addor et al., 2017). This approach is particularly useful in the Alpine region, where hydrological behaviour is strongly affected by spatial variability.

The use of a spatially consistent simulated dataset made it possible to apply the same statistical workflow to 5,757 catchments over a common 73-year period. This uniformity is a major advantage because it avoids problems caused by unequal record lengths or missing observations across catchments. It also allows spatial patterns to be interpreted within a common analytical framework.

At the same time, the results show that a consistent modelling framework does not remove regional and local differences in flood behaviour. Even when the same data source, AMS extraction method, L-moment estimation, and GEV fitting procedure are used, the resulting flood characteristics remain spatially heterogeneous. This suggests that the variability of flood behaviour across the Alpine domain is strong enough to remain visible even after applying a unified modelling and statistical approach.

The study is also connected to regionalized hydrological modelling. The simulated discharge series used in this thesis are derived from a modelling framework based on TUWmodel and HydroPASS. Previous work using HydroPASS focused on generating spatially consistent discharge simulations through regionalized model parameters, while this thesis uses those simulations as the basis for statistical flood analysis. This creates a link between distributed hydrological modelling and flood frequency analysis.

Recent work on PASS-based regional calibration has shown that regionalized modelling can provide useful distributed discharge simulations, but that the results remain dependent on the quality of model structure, calibration, catchment descriptors, and input data (Merz et al., 2020; Pesce et al., 2024). Therefore, the flood statistics analysed in this thesis should be interpreted as statistical properties of the simulated discharge archive, not as direct observations of flood risk.

5.7 Limitations of the Study

Several limitations should be considered when interpreting the results.

The first limitation is the use of simulated discharge data. The discharge series analysed in this thesis are not direct observations. They are outputs of a distributed conceptual rainfall–runoff modelling framework. As a result, the statistical flood characteristics are influenced by model structure, parameterization, and meteorological input data. This is especially relevant for extreme events because flood peaks may be more difficult to simulate accurately than average flow conditions.

A second limitation is the daily temporal resolution of the discharge data. The Annual Maximum Series were extracted from daily discharge values. This means that instantaneous flood peaks are not represented directly. Recent research has shown that the use of mean daily flows instead of instantaneous peak flows can affect flood frequency estimates, particularly in small and fast-responding catchments (Bartens et al., 2024). For this reason, the flood magnitudes analysed here should be interpreted as daily annual maxima, not instantaneous peak discharges.

A third limitation is the absence of independent validation against observed flood peaks. The analysis focuses on the statistical behaviour of simulated annual maxima across a large number of catchments. It does not test the simulated AMS against observed annual maximum discharge records for each catchment. Therefore, the results are useful for comparing spatial patterns in simulated flood behaviour, but they should not be interpreted as a direct validation of observed flood hazard.

A fourth limitation is that the analysis is mainly descriptive. Maps, scatter plots, L-moment diagrams, and goodness-of-fit results were used to identify spatial patterns and distributional differences. However, the study does not formally attribute these patterns to individual physical drivers such as precipitation regime, snowmelt, elevation, geology, or land use. Any physical interpretation must therefore remain cautious.

The final limitation concerns the use of quantile classification in the maps. Quantile classes are useful for visualizing relative differences among catchments, but they do not represent fixed hydrological thresholds. A catchment belonging to a high quantile class should therefore be interpreted as high relative to the dataset, not necessarily as exceeding an externally defined flood-risk threshold.

5.8 Synthesis

The discussion confirms that the main outcome of this thesis is the spatial heterogeneity of simulated flood characteristics across the Greater Alpine Region. The results show that annual maximum floods differ in magnitude, variability, asymmetry, and distributional shape. These differences remain visible even though all catchments were analysed using the same modelling and statistical framework.

The L-moment results and the L-moment ratio diagram support the use of the GEV distribution as a general framework for modelling annual maximum floods, while also showing that catchment-level differences remain important. The Anderson–Darling test further indicates that GEV provides an acceptable fit for most catchments, but not uniformly across the whole domain.

Overall, the results support the use of large-sample statistical analysis for investigating flood behaviour in complex mountain regions. At the same time, they highlight the need for careful interpretation when working with simulated discharge data, daily time resolution, and descriptive spatial patterns. The following chapter summarizes the thesis's main conclusions and relates them directly to the research objectives.

Chapter 6

Conclusions

6.1 Summary of the Thesis

This thesis investigated the statistical behaviour of simulated annual maximum floods across the Greater Alpine Region. The analysis was based on daily simulated discharge series for 5,757 catchments over the period 1950–2022. From these time series, Annual Maximum Series were extracted and analysed using descriptive statistics, L-moment-based indicators, and GEV flood frequency modelling.

The main aim was to assess whether simulated flood characteristics show consistent statistical behaviour across the Alpine domain or whether spatial heterogeneity remains the dominant feature. The results clearly show that spatial heterogeneity is a central characteristic of the simulated flood regime. Catchments differ not only in mean annual maximum specific discharge but also in relative variability, skewness, L-skewness, L-kurtosis, and goodness-of-fit behaviour.

The study therefore shows that a large-sample approach is useful for identifying spatial patterns that would be difficult to detect using only a small number of gauged basins. At the same time, it confirms that the interpretation of simulated flood statistics must consider the limitations of model-generated data.

6.2 Conclusions Related to the Research Objectives

The first objective was to quantify the statistical properties of simulated extremes using L-moment-based indicators. This objective was achieved by computing descriptive statistics and L-moment indicators from the Annual Maximum Series of each catchment. The results show that the simulated annual maxima vary substantially in magnitude, variability, asymmetry, and upper-tail behaviour. L-skewness and L-kurtosis provided a robust description of distributional shape and confirmed that the catchments do not share a uniform flood distribution structure.

The second objective was to evaluate the spatial variability of flood characteristics across predefined Alpine subregions. This objective was addressed through spatial mapping of the main statistical indicators within the HISTALP regional framework. The results show that flood characteristics are not spatially uniform across the Greater Alpine Region. High values of mean annual maximum specific discharge, CV, skewness, L-skewness, and L-kurtosis occur in localized areas rather than forming a single homogeneous pattern across the domain. This indicates that spatial variability remains important even when the same modelling and statistical procedure are applied to all catchments.

The third objective was to investigate flood frequency behaviour through L-moment-based analysis and GEV-based flood frequency modelling. This objective was addressed by fitting the GEV distribution to the Annual Maximum Series of each catchment and by evaluating the fit using the Anderson–Darling test. The GEV distribution passed the test in 96.9% of catchments, indicating that it provides an acceptable general representation of the simulated annual maxima. The L-moment ratio diagram also supports the use of the GEV distribution as a general modelling framework, although the spread of catchment points shows that local differences in distributional shape remain present.

6.3 Main Findings

The main findings of the thesis can be summarized as follows.

First, mean annual maximum specific discharge is not spatially uniform across the Greater Alpine Region. This shows that normalized flood magnitude differs among catchments and that flood intensity cannot be explained only by catchment area.

Second, flood variability and asymmetry provide information that is not captured by mean magnitude alone. The coefficient of variation shows differences in year-to-year variability, while skewness indicates that many catchments are affected by occasional high annual maximum values.

Third, L-moment indicators show that differences among catchments also concern distributional shape. L-skewness and L-kurtosis reveal spatial variation in asymmetry and upper-tail behaviour, confirming that the Annual Maximum Series differ not only in magnitude but also in structure.

Fourth, the GEV distribution is generally suitable for representing the simulated Annual Maximum Series. The high Anderson–Darling pass rate indicates that GEV can be used as an acceptable modelling framework for most catchments in this dataset.

Finally, the study confirms the usefulness of large-sample hydrological analysis for complex mountain regions. The consistent analysis of thousands of catchments enabled the identification of spatial patterns and distributional differences across the entire Alpine domain.

6.4 Limitations

The conclusions of this thesis should be interpreted in light of several limitations.

The analysis is based on simulated discharge data rather than direct observations. Therefore, the results depend on the quality of the hydrological model, its parameterization, and the meteorological input data. The statistical indicators describe the behaviour of the simulated discharge archive, not necessarily the exact behaviour of observed floods.

The use of daily discharge data is another important limitation. Daily maxima may not capture instantaneous flood peaks, especially in small and fast-responding catchments. As a result, some flood magnitudes may be lower than the corresponding instantaneous peaks.

The study also did not include an independent validation of the simulated Annual Maximum Series against observed annual maximum flood records. This means that the results should be used mainly for spatial comparison and statistical interpretation of simulated flood behaviour.

Finally, the analysis was mainly descriptive. It identified spatial patterns but did not formally test the physical causes of those patterns. Future work would be needed to link the observed statistical differences to specific drivers such as precipitation regime, snowmelt contribution, elevation, catchment morphology, or land cover.

6.5 Final Remarks

This thesis shows that simulated flood behaviour across the Greater Alpine Region is strongly spatially heterogeneous. A unified modelling framework and a consistent statistical methodology make it possible to compare thousands of catchments, but they do not remove the underlying variability of flood characteristics across the Alpine domain.

The combination of AMS extraction, descriptive statistics, L-moment analysis, and GEV modelling provides a coherent framework for studying simulated flood extremes at large scale. The results support the use of the GEV distribution for most catchments, while also showing that local differences in variability, asymmetry, and upper-tail behaviour remain important.

Overall, the study contributes to the statistical interpretation of large-scale simulated flood data in mountain regions. It highlights both the value and the limitations of model-based flood frequency analysis and provides a basis for future work on observed validation, physical attribution of spatial patterns, and improved representation of flood extremes in complex Alpine catchments.

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