Politecnico Di Torino

Master’s Degree in Environmental and Land Engineering

Master’s Degree THESIS

Drought simulation with hydrological modelling in the Cuneo district (Italy)

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Abstract

Drought is one of the severest natural hazards that seriously threatens sustainable water resource management, agriculture, and socioeconomic sectors within a changing climate context. This study investigates drought simulation through rainfall-runoff modelling over a 60-year period within the Cuneo district of Italy. The research herein discussed leverages the TUW model lumped conceptual rainfall-runoff model with semi-distributed operational capability. Similar in structure to the widely used Hydrologiska Byråns Vattenbalansavdelning (HBV) model, the TUW model operates on a daily timestep for both input and output data specific to each catchment, incorporating key routines for snow accumulation, snowmelt, soil moisture storage, and streamflow generation. In the district of Cuneo, some catchments can provide detailed discharge data, which forms the comprehensive basis for model calibration in this research, first using KGE and then by log-transformed KGE. Special attention will be dedicated to an accurate representation during low-flow events within drought periods to be able to simulate realistic water availability during the most critical periods. The simulated monthly discharges will be used for the validation of the model performance. Apart from model calibration and validation, SRI has been used in the study to undertake advanced drought analysis that can present a precise characterization of the drought occurrences in the region. The discharge data from the observation and simulation are carefully compared with an emphasis on low-flow events that may signify a drought. The complex relationships among land characteristics, including soil type and vegetation cover, and climate variables such as precipitation and temperature, for determining the severity and duration of hydrological droughts are also dealt with in the study. From these findings, it can be seen that for the majority of catchments, very good model efficiencies were achieved upon calibration of the TUW model. A comparison of the simulated and observed discharge data reveals good agreement, in particular for the critical low-flow periods, which is also confirmed by the Pareto coefficient as a goodness-of-fit measure. The drought analysis provides very important information on the duration, intensity, and severity of drought events, adding substantial knowledge to water resources management and drought mitigation. The contribution of this study would add significantly to drought dynamics for the region of Cuneo, whereas future works will make refinement of hydrological modelling techniques and explore various drought projections according to different climate change scenarios.

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1 Introduction:

Droughts represent one of the most pressing challenges to sustainable water resource management, agriculture, and socioeconomic sectors, especially in light of the growing impacts of climate change (IPCC, 2014). Droughts, unlike sudden natural disasters such as floods or storms, develop gradually and can persist for extended periods, making them particularly insidious in their impacts (D. A. Wilhite, 1985). The slow onset of drought often masks its severity until significant damage has already occurred to ecosystems, agriculture, water supplies, and economies. This gradual progression earns drought the label of a "**creeping disaster**" (Loon V. , 2015), as its consequences, while delayed, can be far-reaching and devastating (Dai, 2013).

As a complex natural hazard, drought affects both society and the environment in multifaceted ways, disrupting ecosystems, agricultural systems, and industrial operations, while placing immense pressure on water resource management (J. Sheffield E. W., 2011). The intricate interactions between hydrological, meteorological, and agricultural systems make it challenging to pinpoint a single origin or trigger for drought events. Generally, drought is marked by prolonged periods of below-average precipitation, leading to significant reductions in surface water (rivers, lakes, reservoirs) and groundwater storage (Rodier, 1985). **Hydrological drought**, a specific type of drought, focuses on these water system deficits and plays a pivotal role in understanding how droughts impact the broader hydrological cycle (Loon V. , 2015).

Hydrological drought is characterized by reduced streamflow, low reservoir levels, and declining groundwater tables, which can persist long after precipitation levels have recovered (Loon V. , 2015). This prolonged shortage of water, both on the surface and underground, creates serious challenges for various sectors reliant on consistent water availability, particularly in agriculture, energy production, and urban water supply (Singh, 2010). For instance, decreased streamflow during a drought period directly impacts irrigation, hydropower generation, and ecosystem health, while lower groundwater levels can affect long-term water security for both rural and urban communities (J. Sheffield E. W., 2011).

This research investigates the phenomenon of hydrological drought over the past 60 years using rainfall-runoff modeling as a tool to simulate and analyze drought events. Rainfall-runoff models are critical in this context as they offer valuable insights into the temporal and spatial dynamics of water availability, helping to simulate how water bodies respond to prolonged periods of reduced rainfall (Singh V. P., 2010). The study leverages such modeling to assess the impacts of low-flow conditions on water resource management, providing a detailed understanding of how water availability shifts during drought periods (Rodier, 1985). By simulating the response of catchments to drought conditions, the research aims to capture the complexity of drought events, particularly in terms of water shortages that may not be immediately visible but are critical for long-term sustainability.

Understanding the dynamics between water availability and drought periods is crucial for developing effective drought management strategies (M. Svoboda D. L., 2002). This includes the ability to predict and mitigate the impacts of future droughts in light of climate change, which is expected to exacerbate drought frequency and intensity in many parts of the world (IPCC, 2014). The results of this study will contribute to improving drought preparedness and water resource planning, ensuring that stakeholders—ranging from water managers to policymakers—are better equipped to handle the challenges posed by both current and future droughts.

2 Study Objectives

The primary objective of this study is to simulate and analyze hydrological drought events in the Cuneo district, located in the Piedmont region of Italy, over a 60-year historical period. By employing the **TUWmodel**, a lumped conceptual rainfall-runoff model, the study aims to provide critical insights into the temporal dynamics, spatial distribution, severity, duration, and frequency of droughts in the region. These findings are intended to inform and enhance water resource management strategies, particularly in the context of increasing drought risks due to climate change.

2.1 Key Goals:

2.1.1 Hydrological Drought Simulation:

- **Simulating Hydrological Drought:** The study uses the TUWmodel to simulate hydrological droughts across multiple catchments in the Cuneo district. Hydrological droughts are characterized by reductions in streamflow, groundwater levels, and reservoir capacities. This is crucial for understanding the impact of prolonged water shortages on both natural ecosystems and human activities in the region.

- **Timeframe and Scope:** Simulations cover a 60-year period, allowing for a detailed investigation of drought patterns over a long-term historical context. This extensive temporal analysis provides insights into both frequent and rare drought events, as well as their potential drivers.

2.1.2 Low-Flow Event Analysis and Model Calibration:

- **Focusing on Low-Flow Events:** One of the key aspects of this study is the analysis of low-flow events, which are essential for understanding critical periods of water scarcity. Low-flow conditions often occur during prolonged droughts, posing significant risks to water supplies, agriculture, and aquatic ecosystems. The model aims to capture these events accurately to assess their impact under different hydrological conditions.

- **Calibration with Daily and Monthly Time Scales:** Calibration of the TUWmodel is carried out using observed discharge data from various catchments in the Cuneo district. To ensure the robustness of the model, two calibration scales were initially explored:

daily and monthly. The **Kling-Gupta Efficiency (KGE)** was the primary metric used for performance evaluation, capturing correlation, bias, and variability. Additionally, **log-transformed KGE** (log-KGE) was employed to improve the model's accuracy in simulating low-flow conditions, which are critical for drought analysis.

- **Log-KGE for Low-Flow Calibration:** The log-KGE places greater emphasis on smaller discharge values, improving the model's performance in capturing low-flow events. Since drought periods often coincide with reduced streamflows, this metric is crucial for ensuring that the model can accurately simulate hydrological droughts.
- **Final Choice of Time Scale:** After testing both daily and monthly calibration, the study proceeds with the **daily time scale** for the final model configuration. The daily scale provides a finer temporal resolution, allowing for more precise tracking of short-term drought onset, persistence, and recovery phases.

2.1.3 Quantifying Drought Characteristics Using the Standardized Runoff Index (SRI):

- **Drought Characterization with SRI:** The **Standardized Runoff Index (SRI)** is applied to both observed and simulated streamflow data to characterize hydrological droughts. The SRI is a powerful tool that quantifies drought severity by comparing current runoff levels against historical averages, offering a standardized measure to evaluate drought intensity, duration, and frequency.

- The study uses **SRI on a 1-month time scale** to focus on short-term drought conditions, which are particularly relevant for immediate water resource management needs. The SRI provides a consistent way to monitor how droughts evolve over time and across different catchments.

- **Evaluating Drought Severity and Duration:** The SRI allows for a detailed analysis of drought events by examining their intensity and how long they persist. This is crucial for understanding the full impact of drought on both natural systems (such as ecosystems and watercourses) and socio-economic systems (such as agriculture and municipal water supplies).

2.1.4 Spatial and Temporal Analysis of Drought Patterns:

- **Assessing Spatial Variability:** The research incorporates a spatial analysis component to assess how droughts vary across different catchments in the Cuneo district. The district's diverse topography, which includes mountainous regions, plains, and agricultural areas, significantly influences the distribution of drought severity. By analyzing spatial patterns, the study identifies which areas are most vulnerable to droughts and how regional differences in climate and land characteristics contribute to these vulnerabilities.
- **Temporal Dynamics:** Alongside spatial analysis, the study also investigates the temporal dynamics of droughts, including their onset, peak, and recovery phases. This helps to identify critical periods when water shortages are most severe and informs strategies for mitigating their impacts.

2.1.5 Evaluating Model Performance:

- **Model Validation:** To ensure the accuracy of the simulated results, the TUWmodel undergoes a comprehensive validation process. Validation is performed by comparing simulated discharge against observed discharge data not used during the calibration phase. This step is critical for testing the model's ability to generalize and perform well under varying hydrological conditions.
- **KGE and log-KGE in Performance Evaluation:** Both KGE and log-KGE metrics are used to evaluate model performance across different flow conditions. While KGE provides a balanced evaluation of overall model accuracy, the log-KGE specifically focuses on improving the model's sensitivity to low-flow periods, which are most relevant for drought studies. This dual metric approach ensures that the model is robust enough to capture both typical hydrological behavior and extreme events such as droughts.

2.1.6 Application of Findings for Water Management:

- **Informing Water Resource Management:** The insights gained from this study are expected to play a key role in developing effective water resource management strategies for the Cuneo district. The ability to simulate drought events accurately can support decision-makers in preparing for future drought risks, optimizing water usage, and designing drought mitigation policies.

- **Drought Mitigation and Early Warning Systems:** By understanding the frequency, duration, and intensity of past droughts, water managers can improve early warning systems and develop more targeted interventions to mitigate the effects of future droughts. This will be especially important in regions where water scarcity is becoming increasingly problematic due to climate change.

This study offers a comprehensive simulation and analysis of hydrological drought events in the Cuneo district, Italy. By utilizing the TUWmodel calibrated with both KGE and log-KGE, and characterizing droughts with the Standardized Runoff Index (SRI), it provides detailed insights into the spatial and temporal dynamics of droughts in the region. The findings from this research will support more informed water management strategies and contribute to enhanced drought mitigation efforts.

3 Literature Review

3.1 Drought

Drought, as a complex natural hazard, exerts multifaceted impacts on ecosystems and society, predominantly through hydrological drought, which is characterized by deficits in water availability within the hydrological system, leading to reduced streamflow in rivers and diminished levels in lakes, reservoirs, and groundwater sources (Van Loon, year). According to the International Association of Hydrological Sciences (IAHS), comprehending the development and recovery of hydrological drought is crucial (Van Loon, year). Often coined as 'the creeping disaster,' drought events unfold gradually and may initially go unnoticed, yet they can yield diverse and indirect consequences. These hydrological droughts can sprawl across vast geographical extents and persist for extended durations, ranging from several months to several years, thereby imposing severe impacts on ecological systems and various economic sectors.

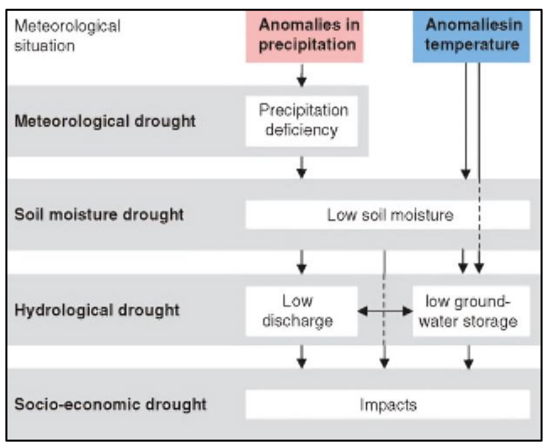


Figure 1_ Scheme representing different categories of drought

The ramifications of hydrological drought extend beyond mere water scarcity, permeating into numerous spheres of human life and the environment. Ecologically, prolonged droughts disrupt ecosystems, leading to habitat degradation, biodiversity loss, and altered species distributions (Mortimore & Adams, 2001). For instance, diminished water levels in lakes and rivers can fragment habitats and hinder the migration patterns of aquatic species, thereby threatening their survival. Furthermore, reduced soil moisture exacerbates the risk of wildfires, which not only pose direct threats to flora and fauna but also contribute to air pollution and greenhouse gas emissions (Dai et al., 2018). Socio-economically, hydrological droughts pose significant challenges to agriculture, water supply, energy production, and navigation, thereby impacting livelihoods and economic stability (Wilhite, 2000). For instance, in agricultural regions, water shortages can lead to crop failures, reduced yields, and increased production costs, ultimately affecting food security and prices (Easterling et al., 2007).

Moreover, the compounding effects of climate change exacerbate the frequency, intensity, and duration of drought events, amplifying their socio-economic and environmental impacts (IPCC, 2014). Rising temperatures accelerate evaporation rates, exacerbating water stress in already arid regions and altering precipitation patterns, leading to unpredictable rainfall variability (Dai, 2013). Consequently, there is a growing urgency for effective drought management strategies that integrate climate adaptation measures, water conservation practices, and sustainable resource management approaches (Wilhite & Glantz, 1985). Additionally, enhancing early warning systems and drought monitoring capabilities is paramount for timely mitigation and response efforts (Svoboda et al., 2002). By addressing the complexities of hydrological drought and its interconnected impacts, policymakers, stakeholders, and communities can better prepare for, mitigate, and adapt to the challenges posed by drought events in an era of escalating climate uncertainty. Introduce the study area, the Cuneo district in Italy.

Hydrological drought occurs when there is a prolonged reduction in surface and subsurface water availability, typically manifesting as decreased river flows, reservoir levels, and groundwater storage. Unlike meteorological drought, which is primarily related to reduced precipitation, hydrological drought reflects the impact of these reductions on the broader hydrological cycle. The delayed response of water bodies to precipitation deficits means that hydrological drought can persist even after meteorological conditions improve, affecting water resources for extended periods (Loon V. , 2015).This type of drought can severely disrupt water supply systems, irrigation, and hydropower generation, and poses significant challenges for environmental management and aquatic ecosystems (Singh A. M., 2010).The assessment of hydrological drought often relies on indicators such as streamflow levels, reservoir storage, and groundwater availability. A key characteristic of hydrological drought is its spatial variability and duration, which can lead to localized water shortages even in regions with overall adequate rainfall. One of the main drivers of hydrological drought is the complex interplay between land use, climate variability, and human activities such as water extraction and river regulation

(Lanen, 2004). Understanding these interactions is crucial for developing effective drought management strategies, particularly as climate change is expected to exacerbate the frequency and intensity of drought events in many parts of the world (J. Sheffield E. W., 2011)

Droughts are prolonged periods of deficient rainfall, resulting in a range of impacts across various sectors, including agriculture, water resources, ecosystems, and the broader socioeconomic landscape. Several scholars define droughts based on their duration, intensity, and spatial extent, with types such as meteorological, agricultural, hydrological, and socio-economic droughts being commonly identified. (D.A. Wilhite, 1985) provided a foundational classification of these drought types, noting that each one has distinct characteristics. For instance, while meteorological drought refers to a lack of precipitation over a certain period, hydrological drought is linked to reduced water levels in rivers, lakes, and reservoirs, and agricultural drought connects directly to soil moisture deficits affecting crop production.

The impacts of drought can be severe and multifaceted. As pointed out by (Loon V. , 2015), hydrological drought can have long-term effects on water availability, particularly in semi-arid and arid regions, leading to increased competition for dwindling water resources. In the context of climate change, (Dai, 2013) highlighted that the frequency and severity of droughts are expected to increase, which is particularly concerning for regions like southern Europe, where water scarcity is already a pressing issue.

Numerous studies have demonstrated that the socioeconomic impacts of drought are disproportionately felt by vulnerable communities. (A.K. Mishra, 2010) explored how prolonged drought events have historically led to significant losses in agricultural productivity, food insecurity, and adverse health outcomes, particularly in low-income areas. Additionally, (R.P. Pandey, 2007) emphasized the long-term impacts on ecosystems, where reduced water availability disrupts ecosystem services, leading to biodiversity loss and increased vulnerability to wildfires.

3.2 Hydrological Modeling Approaches for Simulating Droughts

Hydrological models play a crucial role in simulating drought events and understanding their potential future occurrences. These models simulate the movement, distribution, and management of water in natural systems and are widely used to predict drought scenarios under changing climatic conditions. Among these, rainfall-runoff models stand out as an essential tool for simulating the hydrological responses of watersheds to precipitation inputs.

(Beven, 2012) classified hydrological models into three broad categories: lumped, distributed, and semi-distributed models. Lumped models, such as the TUW model used in this study, aggregate inputs over the entire catchment area without considering spatial variability. On the other hand, distributed models account for spatial variations in land use, soil type, and topography. Semi-distributed models offer a compromise between these two approaches by dividing the catchment into sub-basins with relatively homogeneous properties.

Several studies have explored the effectiveness of various hydrological models in drought simulation. For example, (J. Seibert, 2012) demonstrated the efficacy of the Hydrologiska Byråns Vattenbalansavdelning (HBV) model in simulating hydrological droughts, particularly in alpine regions. The HBV model, like the TUW model, is a conceptual lumped model that operates on daily time steps, making it suitable for regions with snow accumulation and melting processes. (J.G. Arnold, 1998) showed that distributed models like the Soil and Water Assessment Tool (SWAT) could simulate drought impacts more accurately in large catchments, particularly where land-use variability significantly influences water availability. However, these models require extensive data input and computational resources, which are not always available.

A major challenge in using hydrological models for drought simulation lies in calibrating and validating these models with observed data. (Refsgaard, 1997) emphasized the importance of model calibration, noting that inaccuracies in parameter estimation could lead to significant errors in predicting low-flow conditions, which are crucial for drought analysis. As such, calibration metrics like the Kling-Gupta Efficiency (KGE) have become widely adopted, as they offer a more robust evaluation of both high and low-flow periods compared to traditional Nash-Sutcliffe Efficiency (NSE) metrics.

3.3 Previous Studies on Drought Simulation with Rainfall-Runoff Models

Several studies have focused on the application of rainfall-runoff models for drought simulation across various regions. (S. Thober, 2018) provided a comprehensive review of hydrological models used for simulating low-flow and drought conditions, highlighting that most models, including the TUW and HBV models, are effective in predicting hydrological drought when properly calibrated with local data. These models are often favored for their simplicity, ease of use, and ability to provide reliable results even with limited data availability.

For instance, (I. Giuntoli J. V., 2013) used a conceptual rainfall-runoff model to simulate drought in the Rhône basin in France, demonstrating that model calibration with local streamflow data significantly improved drought prediction accuracy. Similarly, (K.K. Yilmaz, 2011) employed the HBV model to simulate streamflow droughts in Sweden, revealing that the model could accurately reproduce low-flow conditions, especially when using daily time steps for input data.

In the context of southern Europe, (G. Bussi, 2020) employed the SWAT model to assess hydrological droughts in the Iberian Peninsula, concluding that both rainfall and land use changes were significant drivers of drought severity. Their findings suggest that while rainfall-runoff models are effective for simulating hydrological droughts, incorporating land characteristics, such as soil type and vegetation cover, enhances the understanding of drought dynamics at the catchment level.

3.4 Drought Indices for Drought Analysis

Drought indices are critical tools for quantifying and monitoring drought events, providing a standardized way to measure and compare drought severity across different regions and times. These indices are used in conjunction with hydrological models to provide a more comprehensive picture of drought conditions. (T.B. McKee, 1993) introduced the Standardized Precipitation Index (SPI), which has since become one of the most widely used drought indices globally. The SPI measures the deviation of precipitation over a specific period from the long-term mean, allowing for an assessment of drought severity based on precipitation deficits.

For hydrological drought, the **Standardized Runoff Index (SRI)** is often used, as it focuses on streamflow rather than precipitation alone. (S. Shukla A. W., 2008) demonstrated the utility of SRI in identifying low-flow periods in river basins, making it particularly useful for water resource management. In this study, the SRI is employed to assess drought conditions in the Cuneo district, as it offers a precise way to quantify hydrological drought by comparing observed and simulated discharge data.

Other commonly used drought indices include the **Palmer Drought Severity Index (PDSI)**, which considers both precipitation and temperature to assess long-term drought trends, and the **Drought Severity Index (DSI)**, which incorporates soil moisture conditions. However, indices like the SPI and SRI are more frequently used in regions where hydrological data are readily available, as they provide more targeted insights into water availability and low-flow conditions during drought periods.

3.5 Summary of Key Findings

In summary, existing literature highlights the critical importance of accurate drought simulation for effective water resource management, especially in the context of climate change. Hydrological models, particularly rainfall-runoff models, offer a valuable tool for simulating both current and future drought conditions. While lumped models like TUW and HBV have proven effective in many regions, their success depends largely on the availability of reliable climate and streamflow data for calibration. Additionally, drought indices such as the SRI play a vital role in quantifying drought severity, making them indispensable for comprehensive drought analysis. This study builds upon these established methodologies by applying the TUW model to simulate and analyze hydrological drought in the Cuneo district, offering valuable insights into the dynamics of drought under changing climatic conditions.

4 Methodology and Materials

4.1 Study Area and Hydrological Characteristics

The province of Cuneo, situated on the southwestern edge of Piedmont, Italy, covers an area of approximately 6,900 km² and is home to a diverse geographical landscape. This region includes Alpine valleys, a central plain, and hilly areas known as Langhe and Roero **Fig. 2**.

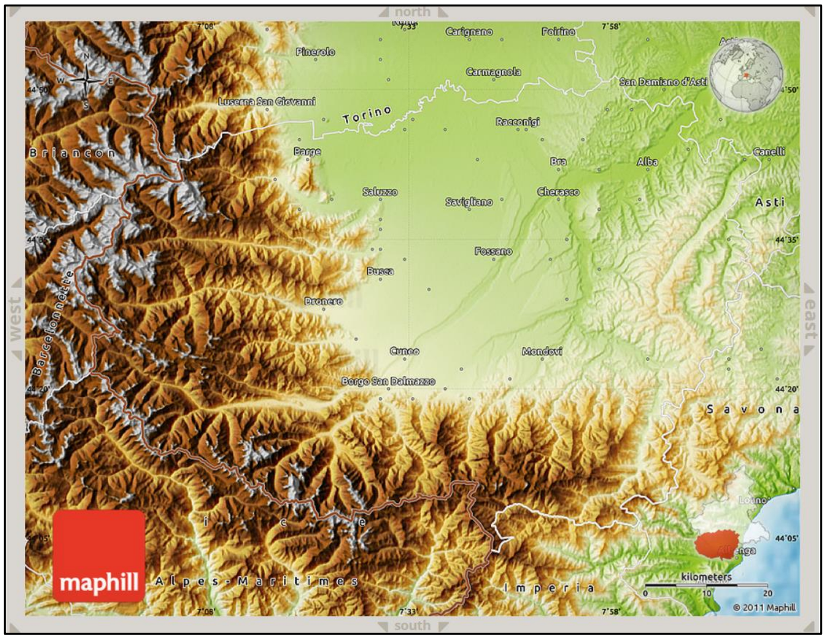


Figure 2_A geographic map of Cuneo Province, illustrating the Alpine valleys, central plain, and the Langhe and Roero hilly areas.

The Alpine valleys, located in the Cottian and Maritime Alps, account for about 51% of the province's surface area. These rugged terrains with mountainous landscapes contribute to Cuneo's natural beauty and rich biodiversity (J. Smith, 2017). Meanwhile, the central plain, which constitutes 22% of the province, serves as a major agricultural area and includes several urban centers, such as the provincial capital, Cuneo. Approximately 35% of the province's population resides in this region (Istat, 2020).

Cuneo's population distribution varies, with significant numbers concentrated in urban areas like Cuneo and the towns of Alba, Bra, Fossano, Mondovì, Savigliano, and Saluzzo. These urban centers each host between 15,000 and 30,000 inhabitants (Cuneo, 2019). The rural population is spread across smaller villages situated in the plain, while a smaller segment lives in the mountainous and hilly regions. This demographic pattern reflects the diverse topography and socioeconomic structure of the province, where urban, suburban, and rural communities coexist in varying capacities (G. Rossi, 2018).

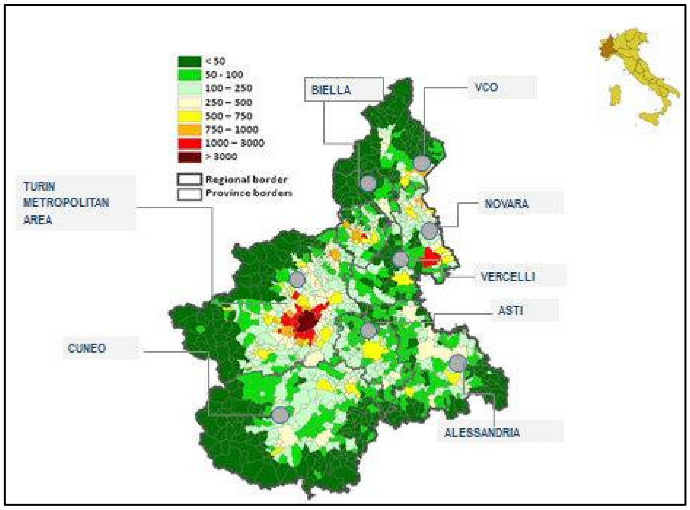


Figure 3_Population density map of the Turin Metropolitan Area, illustrating inhabitants per square kilometer across provinces, including Cuneo, Asti, Alessandria, Vercelli, Novara, Biella, and VCO.

Climatically, Cuneo experiences a continental climate, with hot summers and cold winters, influenced by its proximity to both the Alps and the Mediterranean Sea (Piemonte, 2019). Precipitation varies significantly across the province, with higher rainfall recorded in the Alpine valleys, while the central plain and hilly areas experience drier conditions (L. Romero, 2020). These climatic variations, combined with the province's varied topography, create a range of ecosystems and hydrological systems, directly impacting water availability and the strategies for managing water resources (P. Caruso, 2017). The geologic and hydrogeological characteristics of Cuneo also play a key role in shaping its landscape, with sedimentary basins, limestone deposits, and aquifers contributing to its hydrogeological complexity (A. Bianchi, 2016). These factors influence groundwater dynamics and highlight the potential for shallow geothermal energy extraction in the region (M. Ravina, 2018).

The drought conditions in Cuneo represent a pressing challenge, especially in light of climate change (IPCC, 2014). Due to its varied topography and reliance on both surface and groundwater for agricultural and urban uses, the region is particularly vulnerable to hydrological droughts. In recent years, reductions in precipitation, especially during the summer months, have led to increased stress on water resources, affecting both agricultural productivity and water supply to urban areas (Dai, 2013). Rising temperatures have also accelerated evaporation rates, exacerbated water stress and making the region more prone to extended drought periods (UNESCO, 2021). Modeling and simulating these drought conditions are crucial for understanding the future impacts of climate change on the region. The Rainfall-Runoff Model (RRM) is a valuable tool for simulating hydrological drought in Cuneo, providing insights into how reduced rainfall and higher temperatures will influence river flows, groundwater recharge, and overall water availability (X. Zeng, 2019). By simulating these conditions, it becomes possible to develop mitigation strategies that can ensure sustainable water management and agricultural resilience in the face of increasing drought frequencies (A. Viglione, 2020).

The Cuneo district, situated in the Piedmont region of northwestern Italy, encompasses a diverse and complex hydrological landscape. Dominated by mountainous terrain, including the Cottian and Maritime Alps, the district experiences significant altitudinal variation, influencing both climate and hydrological processes. Precipitation patterns in the region exhibit strong seasonal variability, with substantial snow accumulation occurring during the winter months. This snowpack serves as a crucial water resource, with its melt in spring contributing significantly to streamflow, particularly in alpine and sub-alpine catchments. As noted by (Loon A. V., 2015), snowmelt-driven discharge is a key hydrological process in mountainous regions like Cuneo, playing a critical role in ensuring water availability during drier months.

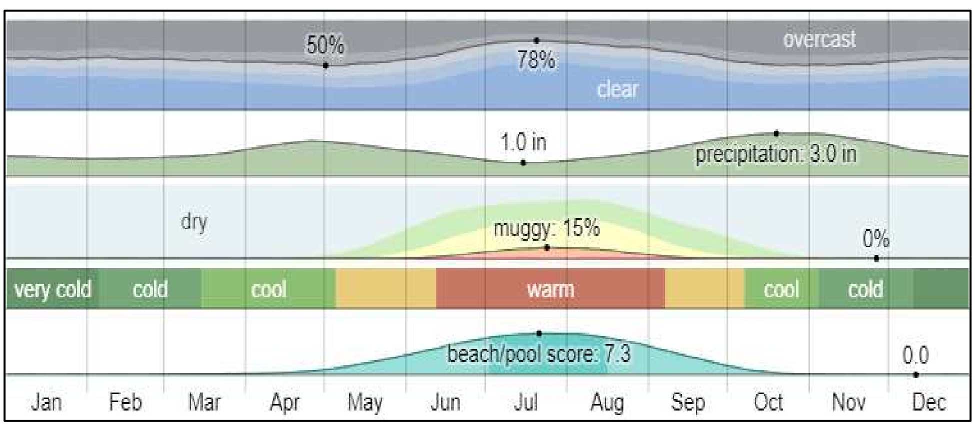


Figure 4_Cuneo weather by month

The catchments within the Cuneo district vary widely in terms of soil types, ranging from coarse, permeable soils in the alpine zones to more compact, clay-rich soils in the lower valleys. These variations, coupled with differences in vegetation cover and land use patterns, such as agricultural activities, forested areas, and urban settlements, significantly influence hydrological processes, including runoff generation, infiltration rates, and water storage capacity. According to (I. Giuntoli J. V., 2013), these environmental factors not only shape the hydrological regime but also affect the region's susceptibility to drought events, particularly during prolonged dry periods or warmer-than-usual summers.

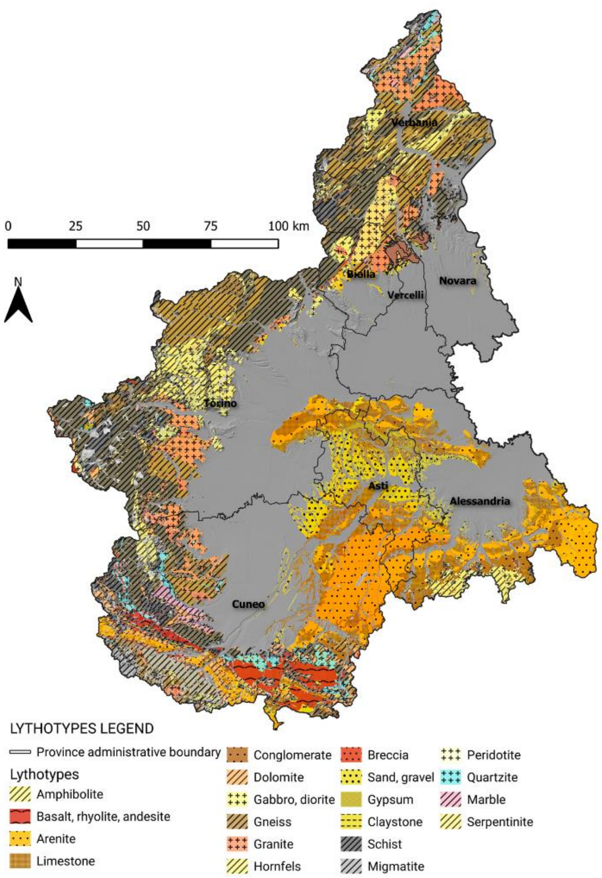


Figure 5_Lithological map of Piemonte.

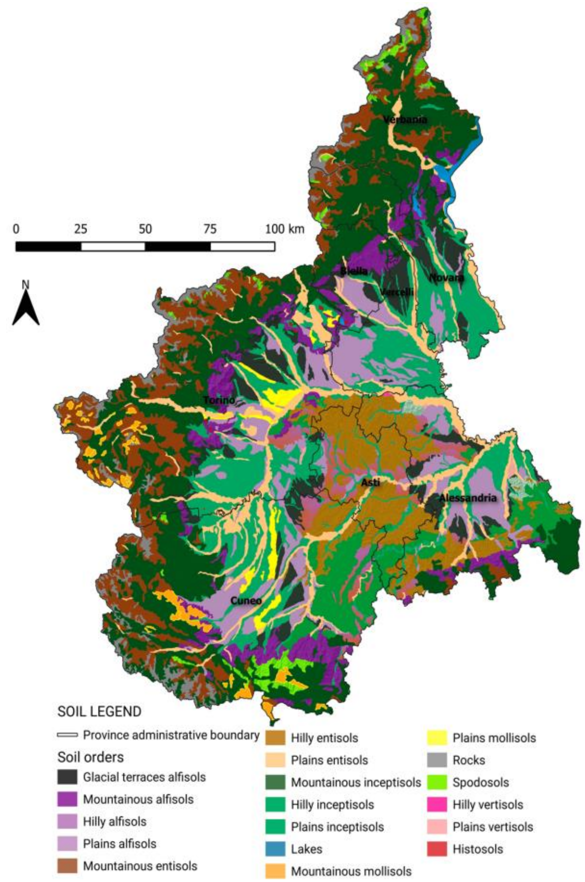


Figure 6_Soil map of Piemonte.

4.1.1 Temperature Variability in Cuneo

Temperature in the Cuneo district shows a clear seasonal pattern, with cold winters and warm summers. The daily average high and low temperatures fluctuate significantly throughout the year, contributing to the region's dynamic climate conditions. During the winter months, temperatures often dip below freezing, particularly in the higher altitudes, leading to the accumulation of snow, which is crucial for the region's hydrological regime. In contrast, the summer months bring warmer temperatures, with average highs reaching their peak in July and

August. This seasonal variability in temperature influences both the timing of snowmelt and the rate of evaporation, further affecting water availability in the region.

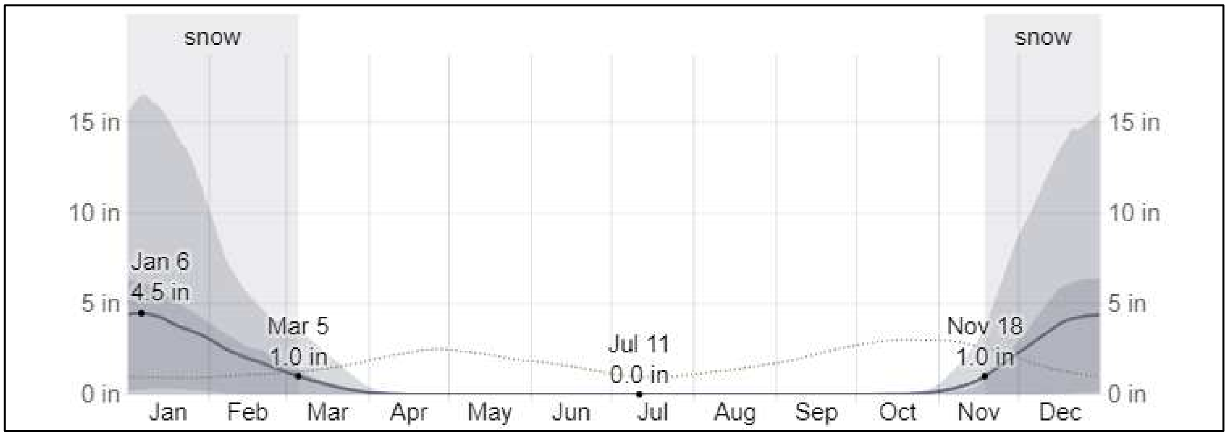


Figure 7_The average snowfall (solid line) accumulated over the course of a sliding 31-day period centered on the day in question, with 25th to 75th and 10th to 90th percentile bands. The thin dotted line is the corresponding average rainfall.

A temperature chart **Fig.7** showing the daily average high and low, along with percentile bands, illustrates the significant fluctuations experienced throughout the year. The thin dotted lines represent the perceived temperatures, offering additional insight into how temperature extremes are felt in the region. Understanding this temperature variability is vital for managing water resources, as warmer summers combined with lower precipitation can exacerbate drought conditions.

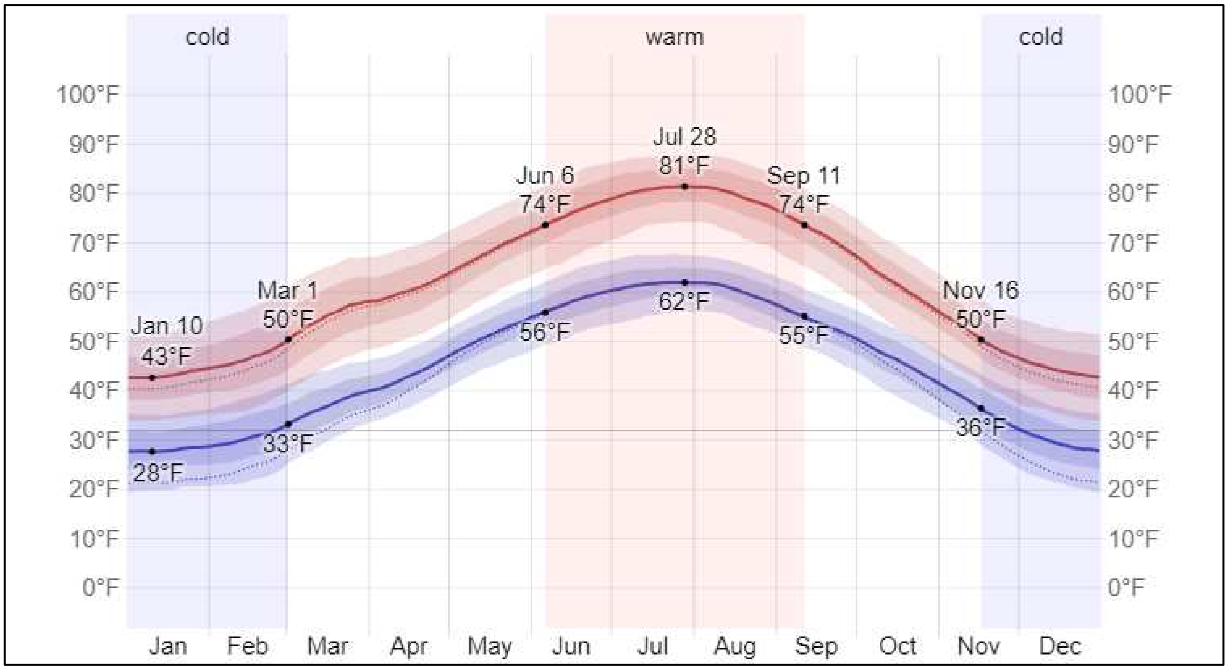


Figure 8_The daily average high (red line) and low (blue line) temperature, with 25th to 75th and 10th to 90th percentile bands. The thin dotted lines are the corresponding average perceived temperatures.

The hydrological regime of the Cuneo district is characteristic of alpine and sub-alpine environments, where snowmelt is a primary driver of river discharge. This seasonal snowmelt, combined with episodic rainfall events, contributes to the region's complex flow patterns, where river systems experience peak flows during spring and early summer, followed by lower flows in autumn and winter (I. Giuntoli J. V., 2013). Understanding these dynamics is essential for accurately calibrating hydrological models like the TUW model, which is used in this study to simulate drought conditions in the district.

Moreover, the region's hydrological network is highly sensitive to both climate variability and human influences, such as water abstraction for agriculture and domestic use, as well as river regulation through dams and weirs. These anthropogenic factors, in combination with natural variability, add complexity to the district's water resource management challenges, particularly under the increasing pressures of climate change. The interplay between these natural and human-induced factors underscores the importance of robust hydrological modeling to predict and manage water availability in the face of potential future droughts.

In summary, the Cuneo district's hydrological characteristics, shaped by its alpine geography, seasonal snowmelt, and diverse land use, present a unique context for drought analysis. These factors are integral to the calibration of the TUW model used in this study, which aims to simulate and assess hydrological drought conditions across the district's catchments.

4.2 TUW Model

The TUW (Technische Universität Wien) model is a lumped conceptual rainfall-runoff model designed to simulate hydrological processes such as precipitation, evaporation, soil moisture dynamics, and streamflow generation. This model operates on daily timesteps, which makes it particularly effective for modeling both short-term hydrological events and long-term water balance changes over large catchments. It is semi-distributed, meaning it uses spatially aggregated data at the sub-basin scale but retains a conceptual representation of physical processes at a finer resolution, ensuring both computational efficiency and hydrological accuracy (H. Kling, 2012).

4.2.1 Structure of the TUW Model

The TUW model shares structural similarities with the well-established Hydrologiska Byråns Vattenbalansavdelning (HBV) model, a conceptual framework that has been successfully applied to diverse hydrological settings globally (G. Lindström, 1997). Key components of the TUW model include:

- **Snow Accumulation and Melt**: Snowmelt routines use temperature thresholds to model snow accumulation during winter months and the subsequent melt during warmer periods. This is particularly useful in mountainous or high-latitude areas, such as the Cuneo district, where snowmelt contributes significantly to streamflow.
- **Soil Moisture Storage**: The model includes routines for infiltration and percolation, allowing for the calculation of soil moisture balance. The water balance is critical in determining how much water remains available for evapotranspiration and runoff generation.
- **Runoff Generation**: Rainfall is partitioned between direct runoff and subsurface flows depending on soil saturation levels, which is key for simulating both high-flow events

and low-flow conditions. The inclusion of both fast (surface runoff) and slow (baseflow) components ensures that the model captures the temporal variability in streamflow.

The water balance equation in the TUW model can be represented as:

$$Q = P - ET - \Delta S \qquad \text{(Equation 1)}$$

Where:

Q is streamflow,
P is precipitation,
ET is evapotranspiration,
ΔS is the change in soil moisture storage.

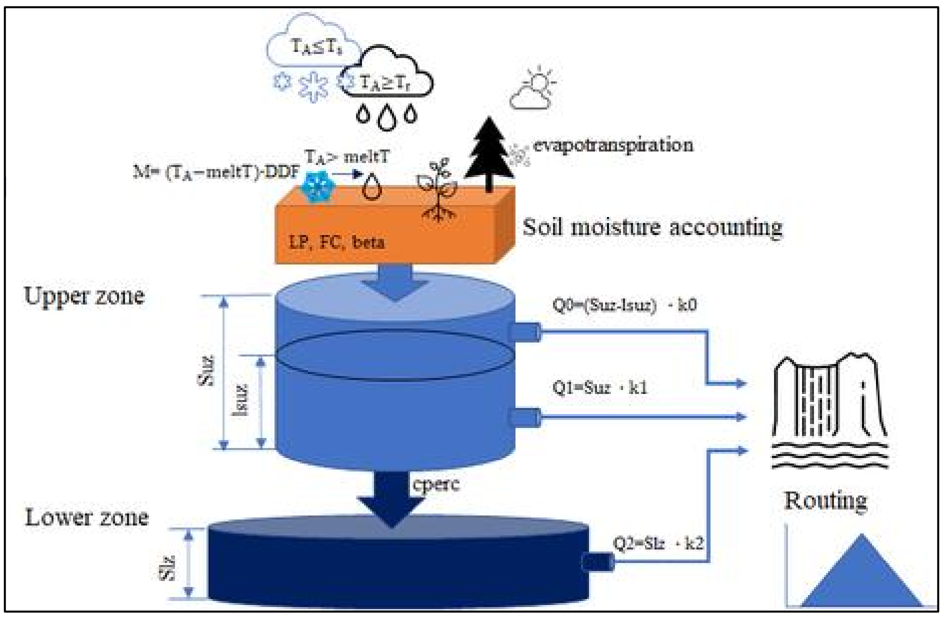


Figure 9_Conceptual description of TUWmodel structure (Rui Tong, Juraj Parajka, 2020)

4.2.2 Suitability for Rainfall-Runoff Modeling

The TUW model's ability to simulate the rainfall-runoff process is grounded in its handling of spatial variability and climate data, particularly temperature and precipitation, to estimate streamflow and baseflow. This makes the model particularly useful for understanding how water bodies respond to long-term precipitation deficits, which are a hallmark of **hydrological drought** (Loon V. , 2015). The model can simulate both **high-flow** and **low-flow** conditions, making it highly effective in evaluating the impacts of drought and other hydrological extremes.

4.2.3 Kling-Gupta Efficiency (KGE) Log-Transformed for Low-Flow

An essential part of this study is the calibration of the TUW model using the Kling-Gupta Efficiency (KGE) metric, which combines various aspects of model performance, such as correlation, bias, and variability (H. V. Gupta, 2009). The KGE is particularly useful because it provides a comprehensive measure of model performance. For this thesis, a log-transformed KGE has been used to focus specifically on low-flow periods, as it emphasizes smaller discharge values and improves the model's sensitivity to these events (W. J. M. Knoben, 2019). The KGE formula is given by:

$$KGE = 1 - \sqrt{(r-1)^2 + (\frac{\sigma_{sim}}{\sigma_{obs}} - 1)^2 + (\frac{\mu_{sim}}{\mu_{obs}})^2} \quad \text{(Equation 2)}$$

Where:

- r is the Pearson correlation coefficient between observed and simulated flows,
- σ_{sim} and σ_{obs} are the standard deviations of simulated and observed flows, respectively,
- μ_{sim} and μ_{obs} are the means of simulated and observed flows, respectively.

By applying a logarithmic transformation to the discharge data before calculating the KGE, smaller flow values are amplified relative to larger ones. This transformation compresses the range of high flows and stretches the range of low flows, effectively giving more weight to low-flow conditions during the calibration process. The log-transformed KGE thus becomes more sensitive to discrepancies in low-flow simulations, ensuring that the model places greater emphasis on accurately reproducing these critical periods (H. V. Gupta, 2009).

4.2.4 Mathematical Explanation of Log-Transformation:

The log-transformation is applied to both observed (Q_{obs}) and simulated Q_{sim} discharge values:

$$Q'_{obs} = \log(Q_{obs} + 1) \quad \text{(Equation 3)}$$

$$Q'_{sim} = \log(Q_{sim} + 1) \quad \text{(Equation 4)}$$

The addition of 1 before taking the logarithm prevents issues with zero or negative flow values, which are undefined in logarithmic space. This transformation highlights relative differences during low-flow periods, allowing the calibration process to minimize errors where they matter most for drought studies.

4.2.5 Impact on Model Calibration:

When the log-transformed discharge values are used in the KGE calculation, the model calibration seeks to optimize the fit between Q'_{obs} and Q'_{sim}. This approach adjusts the model parameters to better capture the timing, duration, and magnitude of low-flow events. As a result, the model becomes more reliable in simulating drought conditions, providing a more accurate assessment of water availability during these critical periods (C. Santos, 2018).

4.2.6 Importance in Drought Studies:

Accurately modeling low-flow conditions is vital for effective water resource management, especially in regions prone to droughts like the Cuneo district. The enhanced sensitivity to low flows achieved through the log-transformed KGE allows the **TUW model** to:

- **Better Predict Drought Onset and Recovery:** By closely matching the observed low-flow patterns, the model can more accurately indicate when a drought is beginning or ending.
- **Improve Water Allocation Decisions:** Reliable low-flow simulations support better planning for water supply, irrigation scheduling, and reservoir management during droughts.
- **Assess Ecological Impacts:** Many aquatic ecosystems are sensitive to low-flow conditions. Accurate modeling helps in evaluating the potential impacts on biodiversity and ecosystem services.

Incorporating the log-transformed KGE into the calibration of the TUW model is a methodological advancement that significantly improves the model's performance in simulating low-flow periods. This enhancement is critical for drought studies where understanding and predicting water scarcity is essential. By emphasizing low-flow accuracy, the model becomes a more effective tool for water resource managers and policymakers tasked with mitigating the impacts of droughts.

4.2.7 Application in Drought Studies

The TUW model's ability to simulate low-flow conditions, particularly when calibrated with the log-transformed KGE, makes it highly suitable for **drought analysis**. The **Standardized Runoff Index (SRI)** is used in conjunction with the model to assess the severity and duration of droughts, providing insights into how streamflow deficits evolve over time (S. Shukla A. W., 2008). By combining rainfall-runoff modeling with drought indices, this research is able to offer a comprehensive understanding of both the hydrological processes and the broader impacts of droughts on water resource management.

4.3 Data Collection Process

The dataset used in this study includes several critical components for hydrological and meteorological analysis in the Piemonte region, Italy. It features a **Digital Terrain Model (DTM_90m)** with a resolution of approximately 90 meters, projected in the UTM32 system, providing detailed topographic information. Additionally, the dataset includes catchment boundary data for 197 catchments and corresponding catchment characteristics, such as elevation and drainage density. Meteorological data covering precipitation and temperature from 1958 to 2019, derived from the **Optimal Interpolation Dataset of Arpa Piemonte**, further enrich the dataset, allowing for comprehensive analysis of the region's hydrological behavior and climate impacts.

4.3.1 Obtaining Discharge Data and Climate Inputs

The data collection process for this study involved gathering critical hydrological and climatic information to enable accurate rainfall-runoff modeling and drought analysis. Two main types of data were collected: discharge data from river catchments and climate inputs, specifically precipitation and temperature records.

4.3.2 Discharge Data Collection

Discharge data, representing the volume of water flowing through river catchments, was obtained from a combination of official datasets and historical archives. In this case, daily discharge data for 127 out of 197 catchments was sourced from **ARPA Piemonte**, the regional environmental protection agency, as well as from older data provided by Prof. Daniele Ganora, which included records for the Valle d'Aosta region. These datasets span from the mid-20th century up to 2019 and were provided in a standardized format compatible with time-series analysis (zoo format in R).

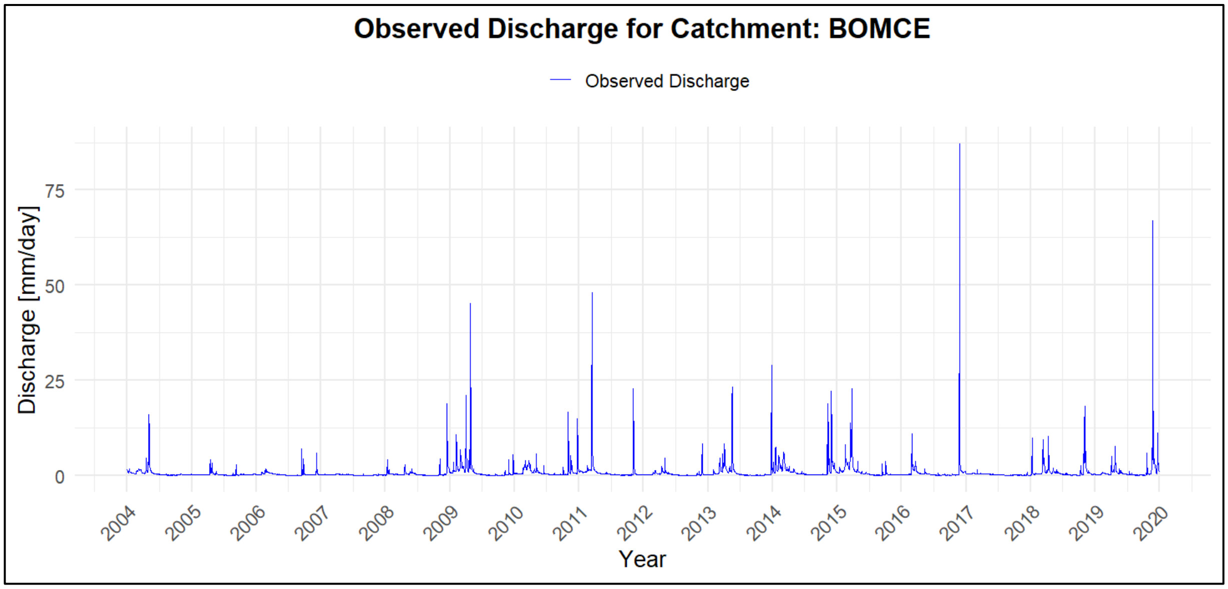


Figure 10_Observed daily discharge data for the BOMCE catchment, used for model calibration and validation in the study.

The discharge data was critical for model calibration and validation, providing a basis to compare observed streamflow with model-generated outputs during both wet and dry periods. The availability of historical records, particularly during drought years, was invaluable for understanding the hydrological response during periods of reduced precipitation.

4.3.3 Climate Data Collection

For the climate inputs, daily precipitation and temperature data were collected over 305 spatial pixels covering the study area.

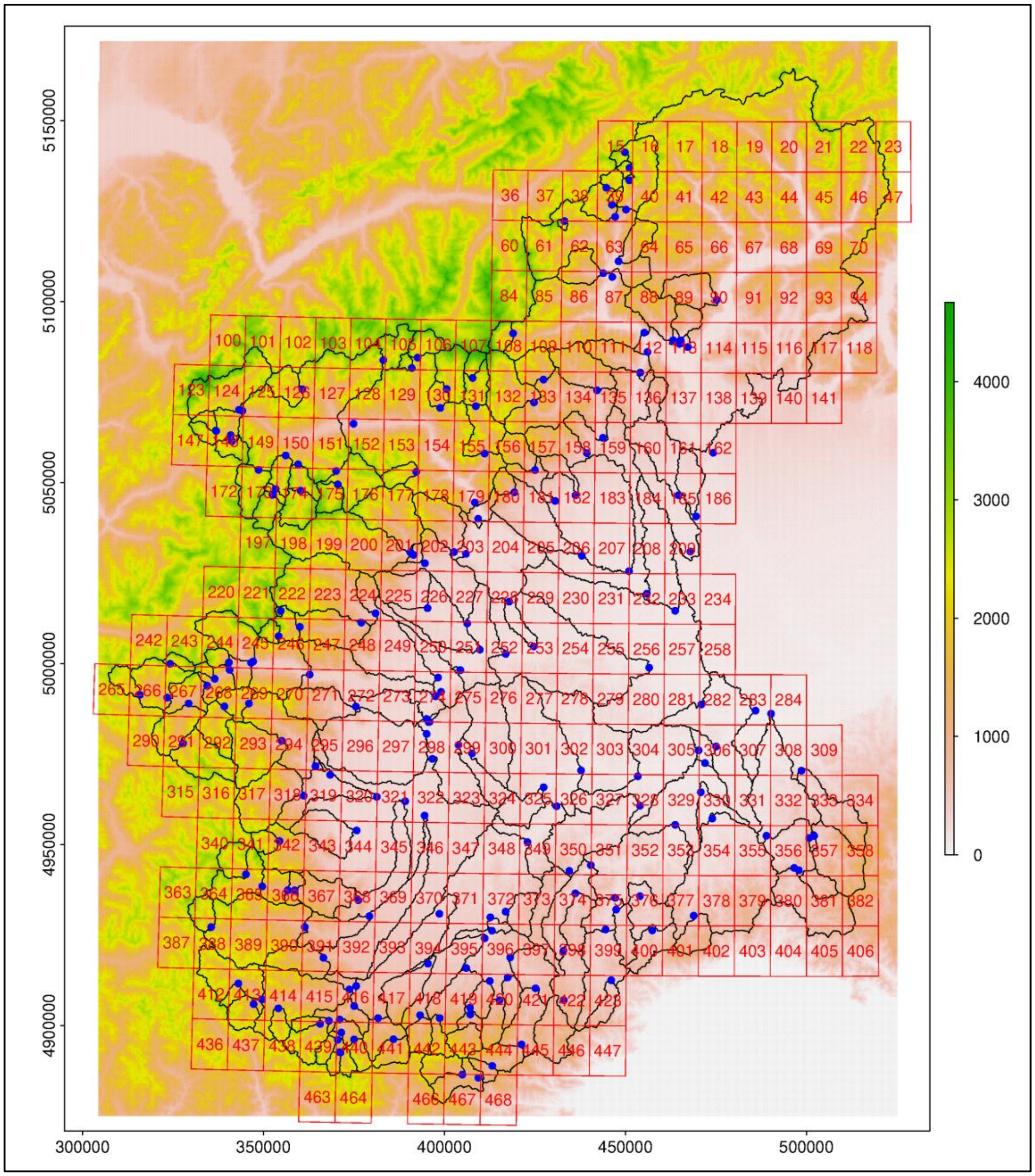


Figure 11_This figure shows daily precipitation and temperature data collected over 305 spatial pixels from 1958 to 2019, with a spatial resolution of 0.125 degrees, sourced from the Optimal Interpolation Dataset of ARPA Piemonte.

The precipitation data was provided as daily totals in millimeters, while temperature data included both minimum and maximum daily values in degrees Celsius. These inputs were used to drive the rainfall-runoff modeling process, helping to simulate how precipitation contributes to streamflow and how temperature influences snowmelt and evaporation, both of which are essential for accurate hydrological simulation.

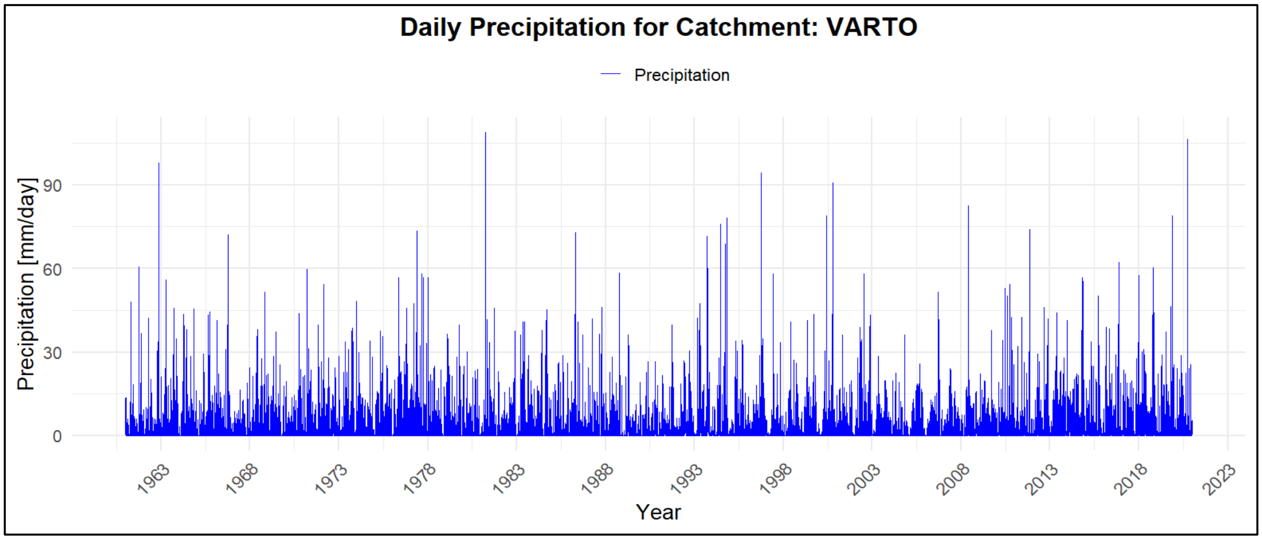


Figure 12_Daily precipitation data for a single pixel in the VARTO catchment from 1963 to 2023.

4.3.4 Data Processing and Conversion

In this study, both climate and discharge data were processed using the R programming language to prepare inputs for the TUW rainfall-runoff model. The following key steps were taken:

4.3.4.1 Discharge Data Processing:

Discharge data, representing the volume of water flow in catchments, was imported into R using the **zoo** package, which enables efficient manipulation of time-series data. The data was cleaned to ensure temporal alignment with the available climate records. Any missing discharge values were handled by integrating time-series gaps with NA placeholders, ensuring consistency with the other datasets.

4.3.4.2 Climate Data Integration:

Precipitation and temperature data were loaded into R, where they were spatially matched to each catchment. The climate data was collected over 305 spatial pixels, each covering specific parts of the catchments. For each catchment, the climate data from relevant pixels was aggregated and weighted based on the area of the catchment covered by each pixel, allowing for an accurate representation of climatic conditions across the region.

4.3.4.3 Potential Evapotranspiration (PET) Calculation:

To estimate the potential evapotranspiration, which represents water loss through evaporation and transpiration, the **Blaney-Criddle** equation was applied to the temperature data. This method accounts for daily temperature fluctuations and seasonal daylight hours, making it suitable for Mediterranean climate conditions. This PET data, along with precipitation and temperature, was crucial for modeling the hydrological cycle in the study area.

4.3.4.4 Data Preparation for TUW Model:

The processed datasets, including discharge, precipitation, temperature, and PET, were formatted as inputs for the **TUWmodel** package. This comprehensive dataset was the foundation for running the TUW rainfall-runoff model, simulating streamflow, and conducting drought analysis across multiple catchments. These steps allowed for robust model calibration and validation, ensuring accurate hydrological simulations for both high-flow and low-flow conditions.

The use of R and its powerful packages, such as **zoo** for time-series processing and **TUWmodel** for hydrological modeling, enabled efficient data integration and ensured that the model inputs were properly aligned with the temporal and spatial dynamics of the study area.

4.4 Calibration

In hydrological modeling, calibration is a critical process to ensure that the model reflects the actual hydrological behavior of a catchment. The TUW model was calibrated to simulate streamflow for selected catchments within the Cuneo district, focusing on accurately representing both high-flow and low-flow periods, with special attention to drought conditions. The following section outlines the detailed calibration procedure, including the selection of catchments, calibration metrics, model parameters, and optimization strategies.

4.4.1 Selection of Catchments and Climate Input Data

The calibration procedure began by selecting relevant catchments within the Cuneo district. From the overall dataset, 58- catchments were identified as part of this region, each contributing significantly to the hydrological dynamics of the area. These catchments encompass diverse geographical features, ranging from mountainous to lowland areas, which is crucial for a comprehensive rainfall-runoff simulation.

The corresponding climate input data—comprising daily records of precipitation, temperature, and potential evapotranspiration (PET)—were extracted for each catchment. These data points spanned from 1958 to 2019 and were used to drive the TUW model. The spatial resolution of the climate inputs aligned with the pixel-based delineation of each catchment, ensuring accurate representation of local climatic variability. This step ensured that the model accounted for the spatial heterogeneity of hydrological processes across the district.

4.4.2 Initial Calibration with the Standard KGE Objective Function

The first phase of calibration involved using the **Kling-Gupta Efficiency (KGE)** as the objective function. KGE is a widely used metric in hydrological modeling that assesses the overall performance of a model based on three key components:

1. **Correlation** between simulated and observed streamflow, measuring how well the model replicates the temporal patterns of flow.
2. **Bias in mean flow**, indicating whether the model overestimates or underestimates the average streamflow.

3. **Variability**, which evaluates the model's ability to capture the spread or variance in the streamflow data.

The TUW model was calibrated for all 58 catchments within the Cuneo district using KGE. The average KGE across all catchments was **0.8245**, indicating a strong overall performance of the model. This initial result demonstrated that the model accurately captured the high-flow dynamics and general flow behavior across the catchments.

However, while the standard KGE provides a good assessment of overall performance, it tends to focus more on higher discharge events, which can overshadow low-flow conditions. Since this study aimed to model drought periods—characterized by low flows—it became necessary to prioritize these conditions in the calibration process.

4.4.3 Shifting to Log-Transformed KGE (KGE_log) for Low-Flow Calibration

To address the limitations of standard KGE in capturing low-flow conditions, a log-transformed Kling-Gupta Efficiency (KGE_log) was adopted as the new objective function. This modification places greater emphasis on low-flow periods, which are critical for drought analysis. The **KGE_log** function ensures that the model is sensitive to smaller discharge values, improving its performance during periods of water scarcity. Several key reasons prompted this shift:

- **Sensitivity to Low Values:** Low-flow periods are often more challenging to simulate, particularly during extended droughts. The logarithmic transformation in KGE_log gives more weight to these low values, ensuring better performance during drought conditions.
- **Reduction of Skewness:** Hydrological data are often skewed due to extreme events. The log transformation reduces the impact of extreme high flows, allowing the model to better balance both high- and low-flow periods.
- **Enhanced Discrimination:** The KGE_log metric enhances the model's ability to discriminate between different flow levels, particularly during dry spells, when accurate representation of streamflow is essential.

- **Focus on Relative Change:** The log-transformed objective function allows the model to focus on relative changes in flow, which is important in evaluating the severity and duration of drought conditions.
- **Stabilization of Variance:** By stabilizing the variance, the KGE_log function ensures that the model does not disproportionately focus on high variability during wet periods, thereby improving low-flow simulation.

The recalibration using KGE_log resulted in an average efficiency value of **0.8158** across the Cuneo catchments, which is a marginal decrease compared to the standard KGE but represents a significant improvement in low-flow accuracy.

4.4.4 Calibration Parameters and Optimization Process

The TUW model utilizes 15 key parameters that govern processes such as snow accumulation, soil moisture storage, runoff generation, and baseflow dynamics. These parameters were adjusted during calibration to achieve the best fit between observed and simulated streamflow. The **Differential Evolution Optimization (DEoptim)** algorithm was employed for this purpose, a robust global optimization method capable of handling complex parameter spaces with multiple local optima.

4.4.4.1 Initial Parameter Settings

The initial parameter values were based on prior studies and regional hydrological knowledge. These served as a starting point for the optimization process. Each parameter was allowed to vary within a predefined range, ensuring that the final values were physically meaningful and reflective of the local hydrological conditions in the Cuneo district.

Table 1_ Calibration Parameters for the TUW Model

Parameters	Description	Lower Bound	Upper Bound
SCF	Snow Correction Factor	0.9	1.5
DDF	Degree-Day Factor (snowmelt)	0.0	5.0
Tr	Temperature Threshold for Rain/Snow	1.0	3.0
Ts	Snow Melt Temperature	-3.0	1.0
Tm	Threshold Temperature for Melt	-2.0	2.0

LPrat	Soil Moisture Evaporation Coefficient	0.0	1.0
FC	Field Capacity	0.0	600.0
BETA	Shape Parameter for Runoff Generation	0.0	20.0
k0	Recession Constant for Fast Runoff	0.0	2.0
k1	Recession Constant for Slow Runoff	2.0	30.0
k2	Recession Constant for Baseflow	30.0	250.0
lsuz	Fast Runoff Storage	1.0	100.0
cperc	Percolation Rate	0.0	8.0
bmax	Maximum Baseflow Storage	0.0	30.0
croute	Routing Coefficient	0.0	50.0

4.4.4.2 Explanation of Calibration Parameters

- **Snow Correction Factor (SCF)**: This parameter adjusts for potential biases in snow accumulation data, ensuring that snowfall is properly represented in the model. It's particularly important in mountainous regions like the Cuneo district, where snowmelt contributes significantly to streamflow.

- **Degree-Day Factor (DDF)**: The DDF controls how quickly snow melts based on temperature. Higher DDF values indicate faster melting rates, which is critical for simulating spring runoff when temperatures rise and snowpacks melt rapidly.

- **Temperature Threshold for Rain/Snow (Tr)**: This parameter defines the temperature at which precipitation transitions between rain and snow. In alpine regions, small temperature changes can dramatically affect whether precipitation falls as snow or rain, impacting snow accumulation and subsequent runoff.

- **Snow Melt Temperature (Ts)**: Ts represents the threshold temperature at which snow begins to melt. If temperatures are above this threshold, snowmelt occurs, contributing to streamflow.

- **Threshold Temperature for Melt (Tm)**: Similar to Ts, this parameter sets the temperature at which significant melting occurs. It helps to simulate the gradual melting of snow as temperatures fluctuate near the freezing point.
- **Soil Moisture Evaporation Coefficient (LPrat)**: This coefficient regulates how much water evaporates from the soil. It plays a critical role in determining how much water is retained in the soil versus lost to the atmosphere, impacting the water balance in dry periods.
- **Field Capacity (FC)**: Field capacity is the maximum amount of water that soil can hold after excess water has drained away. This parameter directly influences how much water remains in the soil for plant uptake and slow release into the groundwater system.
- **Shape Parameter for Runoff Generation (BETA)**: The BETA parameter controls how precipitation is partitioned between infiltration (which recharges soil moisture) and runoff (which contributes to streamflow). A higher BETA value means more water infiltrates the soil, reducing surface runoff.
- **Recession Constants for Fast and Slow Runoff (k0, k1)**: These constants determine how quickly runoff is released from different sources. **k0** represents fast runoff, typically from surface sources like rain on impermeable surfaces, while **k1** represents slower runoff from subsurface flows, which are delayed but still significant during wet periods.
- **Recession Constant for Baseflow (k2)**: Baseflow refers to the sustained flow of water into rivers from groundwater sources. **k2** controls the rate at which groundwater contributes to streamflow, especially during dry periods when surface runoff is minimal.
- **Fast Runoff Storage (lsuz)**: This parameter governs how much water can be stored in the fast runoff system. It influences the model's ability to capture peak flow events, such as those resulting from heavy rainfall or rapid snowmelt.
- **Percolation Rate (cperc)**: This parameter controls how quickly water moves from the soil zone to the groundwater zone. It is important for understanding how quickly soil water contributes to deeper groundwater reserves, which eventually contribute to baseflow.

- **Maximum Baseflow Storage (bmax)**: This represents the maximum capacity of the groundwater system to store water, which feeds into rivers during drought periods or extended dry spells.
- **Routing Coefficient (croute)**: The routing coefficient governs how quickly water moves through the catchment to the river. It ensures that the timing of water delivery to the river is correctly simulated, balancing the effects of fast and slow runoff as well as baseflow contributions.

4.4.5 DEoptim

The **Differential Evolution Optimization (DEoptim)** algorithm is an evolutionary computation method designed to handle non-linear, multi-dimensional, and complex optimization problems. It is particularly well-suited for calibrating hydrological models like the TUW model, which rely on numerous interacting parameters to simulate various physical processes (e.g., runoff generation, soil moisture dynamics, snowmelt) and where parameter interactions are complex, and local minima could lead to suboptimal results.

The **DEoptim** algorithm is a **global optimization method** that evolves a population of candidate solutions over several iterations, known as generations. Unlike traditional optimization techniques, which might get stuck in local optima, DEoptim explores the entire parameter space more effectively.

DEoptim begins by randomly initializing a population of potential solutions (parameter sets) within the predefined lower and upper bounds of each parameter. For this study, the bounds for each parameter were determined based on prior hydrological knowledge and literature.

4.4.5.1 Mutation and Crossover:

The algorithm then creates new candidate solutions by combining the existing solutions (parent solutions) through a process called **mutation** and **crossover**. Mutation introduces diversity by adding a weighted difference between two solutions to a third solution. Crossover further ensures variation by combining parts of different solutions.

4.4.5.2 Selection:

After generating new candidates, the algorithm evaluates them based on the **objective function**, which in this case is the **log-transformed Kling-Gupta Efficiency (KGE_log)**. If a new solution performs better (has a higher KGE_log score), it replaces the existing solution in the population. This process is repeated over multiple generations, ensuring that the population moves toward better solutions.

4.4.5.3 Application in the TUW Model Calibration

In this study, DEoptim was applied to calibrate the 15 parameters of the TUW model (as outlined in section 4.1). The **objective function** for the optimization process was the log-transformed Kling-Gupta Efficiency (KGE_log), chosen to emphasize the model's performance in simulating low-flow periods, which are critical for drought analysis. The log transformation places greater weight on accurately modeling smaller discharge values, which are more challenging to capture and are key for hydrological drought conditions.

Objective Function Calculation: The KGE_log score was calculated for each iteration, comparing the observed discharge data with the model's simulated streamflow. The aim was to maximize the KGE_log, improving the fit between observed and simulated values, especially during drought conditions when streamflow is significantly reduced.

Parameter Search Space: The parameter bounds were set based on regional hydrological knowledge, ensuring that the final calibrated parameters remained physically meaningful for the Cuneo district's climate and hydrological conditions. Parameters such as the **snow correction factor (SCF)** and **degree-day factor (DDF)**, which influence snowmelt, were of particular importance for catchments where snowmelt contributes significantly to streamflow.

4.4.5.4 Iterative Process and Convergence

The optimization process was conducted over **200 iterations**, with each generation refining the parameters to improve the objective function score. Over time, the DEoptim algorithm gradually converged toward an optimal solution, meaning that the difference between subsequent parameter sets diminished, and the KGE_log score reached a maximum.

Convergence: As DEoptim progressed, the population of candidate solutions narrowed down to a smaller range of parameter values that best fit the observed data. By the end of the calibration process, the model parameters were finely tuned to accurately simulate both the **high-flow** and **low-flow** periods for each catchment. This was particularly important for drought studies, as low-flow periods provide critical insights into water availability under drought conditions.

4.4.5.5 Advantages of DEoptim in Hydrological Modeling

Global Search Capability: DEoptim's global search ability ensures that the optimization does not get stuck in local minima, which is a common issue with gradient-based optimization methods. This is especially crucial for complex hydrological models like TUW, where interactions between parameters can create multiple local optima.

Robust Performance: The algorithm's ability to handle high-dimensional parameter spaces makes it particularly robust when dealing with large, multi-parameter systems such as rainfall-runoff models.

4.4.5.6 Final Parameter Calibration

By the end of the DEoptim process, the parameter values were optimized to ensure the best possible representation of hydrological processes in the Cuneo district. The results from this optimization were validated against historical streamflow data, confirming the model's ability to accurately simulate both high and low flows across different catchments. This level of calibration ensures that the TUW model can be reliably used for simulating hydrological droughts and informing water resource management strategies.

4.4.6 Calibration outcomes

The calibration process of the TUW model across the 58 catchments in the Cuneo district demonstrated strong performance in simulating both high-flow and low-flow conditions. The model's robustness was evaluated using two efficiency metrics: the Kling-Gupta Efficiency (KGE) and its log-transformed variant (logKGE), which was specifically employed to enhance the model's sensitivity to low-flow periods. The following key results emerged from the calibration process:

- **Overall Model Performance**: The average KGE across all catchments was satisfactory, with the model successfully capturing the general hydrological behavior. However, the LogKGE, which better emphasizes low-flow periods, resulted in an average score of

0.8158, highlighting its effectiveness in simulating drought conditions, which are crucial for water resource management in the region.

- **High-Flow Simulation**: During high-flow events, the TUW model consistently maintained high accuracy. The use of KGE ensured that peak flows, including extreme runoff events following heavy precipitation or rapid snowmelt, were well captured across the catchments.
- **Low-Flow Simulation**: One of the most significant improvements achieved through the use of LogKGE was in the simulation of low-flow periods. These are often challenging to capture accurately due to their sensitivity to small changes in discharge and climate input data. By focusing on the log-transformed values of the observed and simulated flows, the model was able to reproduce the frequency, intensity, and duration of low-flow periods more accurately, which is essential for effective drought analysis.
- **Challenges and Adjustments**: A primary challenge during calibration was achieving a balance between the accurate simulation of both high and low flows. This balance is crucial because the hydrological extremes (both floods and droughts) define water management strategies. The introduction of LogKGE helped mitigate these challenges by stabilizing the variance of the model and making it more responsive to low-flow conditions while maintaining accuracy during high-flow events.

The successful calibration of the TUW model, with both KGE and LogKGE metrics, provides a strong foundation for simulating future hydrological scenarios in the Cuneo district. This is particularly significant in light of projected climate change, which is expected to increase the frequency and intensity of droughts, making the model a valuable tool for water resource management and drought mitigation planning.

Table 2_ Comparison of KGE and LogKGE Metrics for Selected Catchments

Catchment Name	KGE	LogKGE
ELLMO	0.8591569	0.7746995
ELLRA	0.835445	0.8162781

GESAN	0.6498273	0.566116
GESEN	0.7266742	0.7226598
NEGPO	0.813899	0.800532

4.5 Validation

In this section, the validation process is detailed to assess the TUW model's accuracy in simulating streamflow, particularly during low-flow conditions, which are critical for understanding hydrological droughts. This analysis includes both visual and statistical evaluations of model performance, with a particular focus on ensuring that the simulation closely matches observed discharge data over the same time window (2000–2020 for most catchments in Cuneo).

4.5.1 Time Window Adjustment for Better Comparison

To ensure accurate and meaningful validation of the TUW model's performance, the simulated discharge data was aligned with the observed discharge data by adjusting the time window. This step was essential for making the model outputs directly comparable to the recorded data, particularly during key periods such as droughts and low-flow conditions. By synchronizing the time frames, the model's predictions could be accurately assessed, highlighting how well it captures both short-term variations and long-term trends in streamflow.

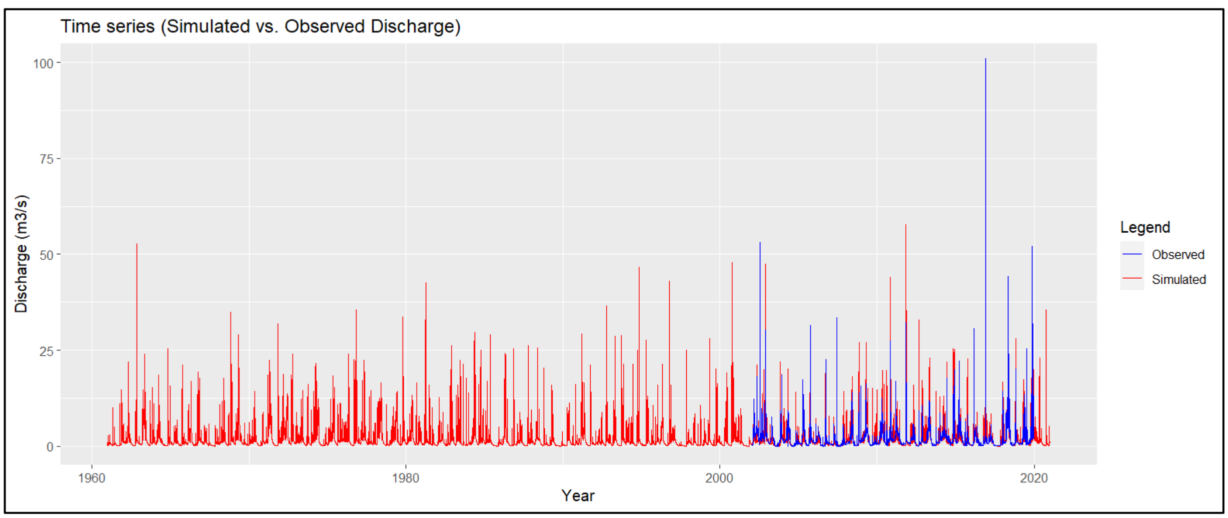


Figure 13_ Time Series of Simulated vs. Observed Discharge with Different Time Windows for the ELLMO Catchment.

Aligning the time window also allows for a better assessment of model performance. This synchronization ensures that any differences between observed and simulated flows are due to model performance rather than mismatches in data availability. The time window adjustment is particularly important when evaluating the model’s accuracy during low-flow periods, which are often more difficult to simulate due to the inherent variability and sensitivity of the hydrological system.

By carefully adjusting the time window, the validation process became more robust, allowing a more precise evaluation of the model's ability to reproduce real-world conditions. This step laid the foundation for generating accurate predictions in future drought analyses, helping inform water resource management strategies in the Cuneo district.

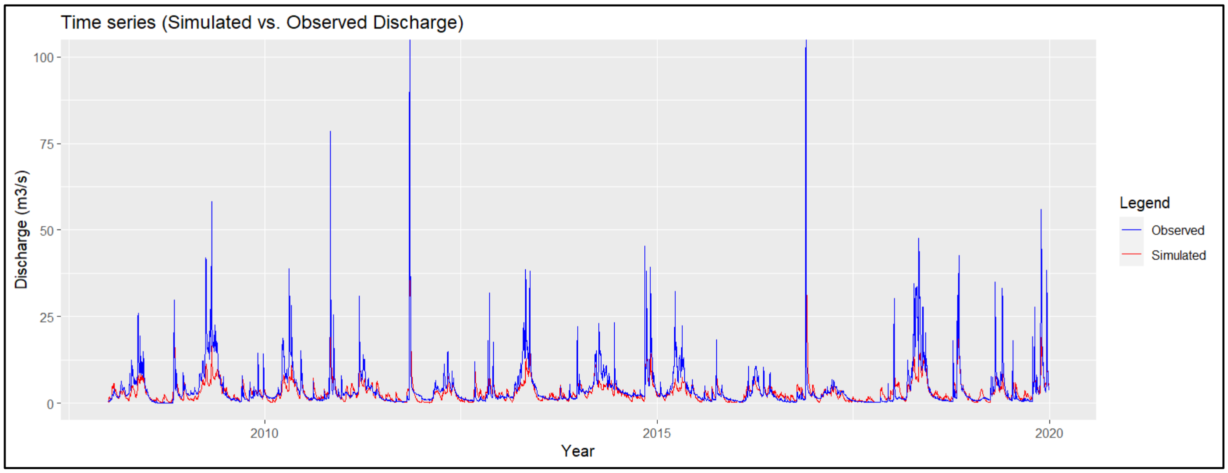


Figure 14_ Example of Observed vs Simulated Discharge in CORTM Catchment

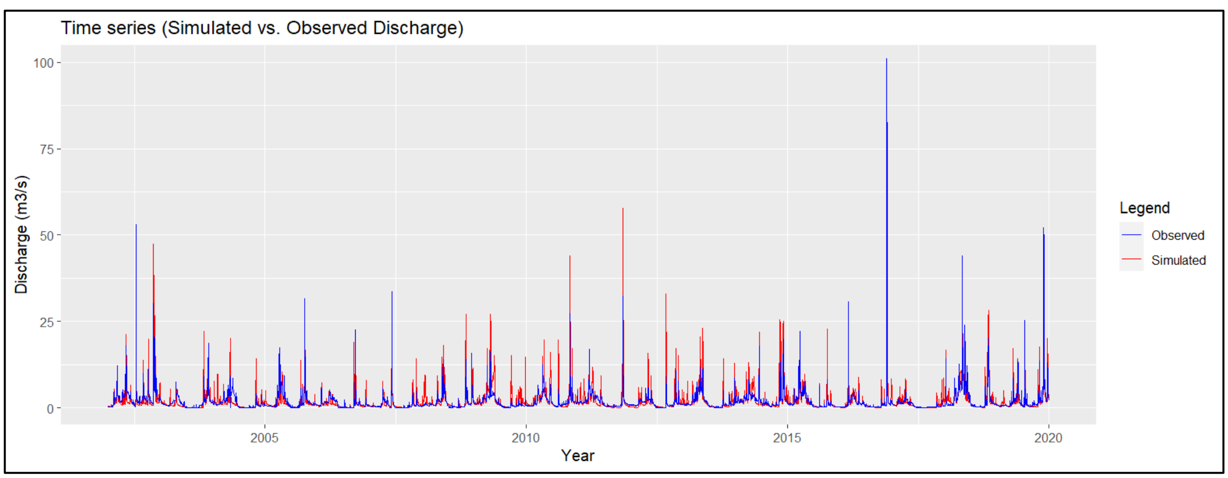


Figure 15_ Example of Observed vs Simulated Discharge in ELLMO Catchment

The figures above illustrate the TUW model's performance in simulating discharge during both normal and low-flow conditions. **Fig. 14 and Fig. 15** show an example from the CORTM and ELLMO catchments, highlighting how well the model aligns with actual observations, particularly during low-flow periods and drought conditions. Together, these figures demonstrate the TUW model's effectiveness in capturing the hydrological dynamics of different catchments, providing valuable insights for understanding water availability during droughts.

4.5.2 Statistical Metrics for Validation

To provide a comprehensive evaluation of the TUW model's performance, several key statistical metrics were calculated. These metrics aimed to assess both the overall accuracy of the model and its ability to simulate low-flow events effectively. The results indicate that the model's performance was reasonably good, though not perfect, across various catchments in the Cuneo district.

- **Correlation Coefficient**: This metric quantifies the relationship between simulated and observed discharge, offering insights into how well the model captures the temporal patterns of streamflow, particularly during critical low-flow periods. A correlation coefficient closer to 1 indicates a stronger correlation.
    - For the selected catchments, the average correlation coefficient was around **0.72**, indicating that the model generally captured the trends in streamflow but left room for improvement, particularly in periods of extreme hydrological events.
- **Root Mean Square Error (RMSE)**: RMSE measures the average discrepancy between the simulated and observed discharge values. It is particularly valuable for understanding the model's performance during both regular and low-flow periods. Lower RMSE values indicate better fit, with a specific focus on drought conditions where accurate flow predictions are crucial.
    - Across the catchments, the average RMSE was approximately **3.0 m^3/s**, signifying a reasonable error margin, although slight deviations were observed during more extreme low-flow periods.
- **Mean Absolute Error (MAE)**: MAE provides another layer of analysis by quantifying the average magnitude of errors between observed and simulated values, with a focus on low-flow conditions. This metric is useful for understanding the day-to-day differences in flow, especially during periods of water scarcity.

- The average MAE for the catchments was around **2.3 m³/s**, which, while reasonable, suggests some discrepancies in capturing the exact discharge during the lowest flow events.

These metrics show that the TUW model performed reasonably well in simulating both normal and drought conditions but highlighted areas where further fine-tuning could improve low-flow simulations.

4.5.3 Flow Duration Curves (FDCs)

Flow Duration Curves (FDCs) are essential tools in hydrology that provide a comprehensive view of the distribution of discharge values over time. They illustrate the percentage of time that a given flow rate is equaled or exceeded, allowing for a detailed comparison between observed and simulated streamflow data.

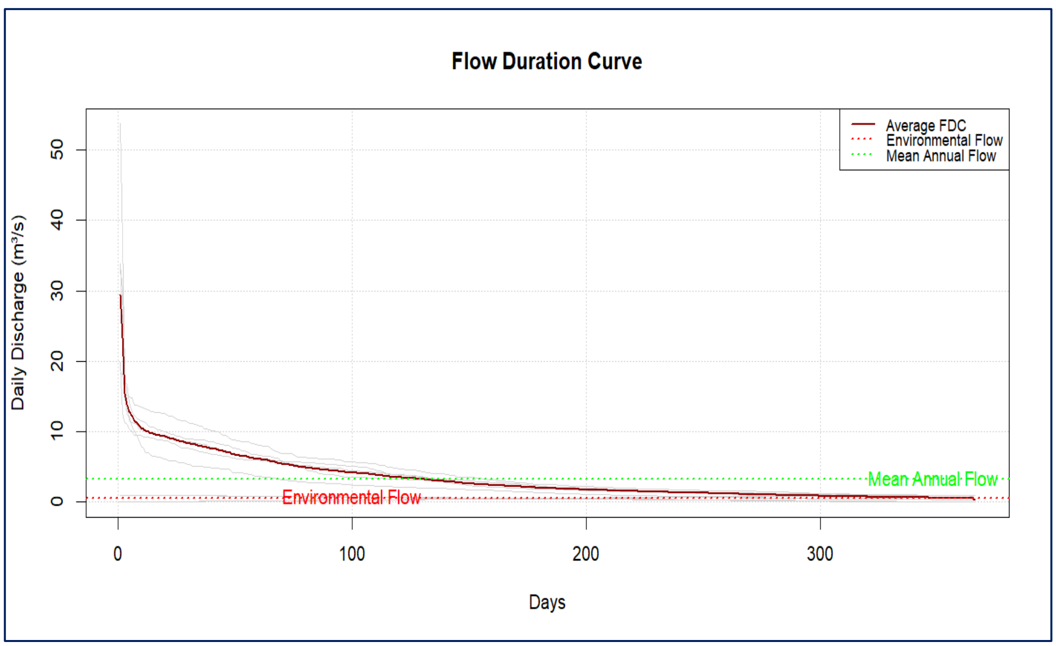


Figure 16_ Flow Duration Curve (FDC) for Observed Discharge in the NEGPO Catchment

In this study, FDCs were generated for both observed and simulated datasets to assess the TUW model's performance in replicating real-world hydrological conditions, with a particular focus on low-flow periods, which are critical in drought analysis.

- **Observed vs. Simulated FDCs**: The comparison of FDCs between observed and simulated data offers insights into the model's ability to replicate the range of flow conditions, from high-flow events to low-flow periods. The FDC highlights where the model performs well and where discrepancies arise, particularly in the lower tail of the curve. The lower tail represents the lowest flow values, often corresponding to drought conditions or periods of reduced streamflow. By comparing the observed and simulated FDCs, the study identified how effectively the TUW model captured these low-flow events, a critical aspect for drought forecasting and water resource management. A strong agreement in the lower tail signifies that the model can reliably simulate streamflow during drought periods, which is crucial for assessing water availability in dry spells.

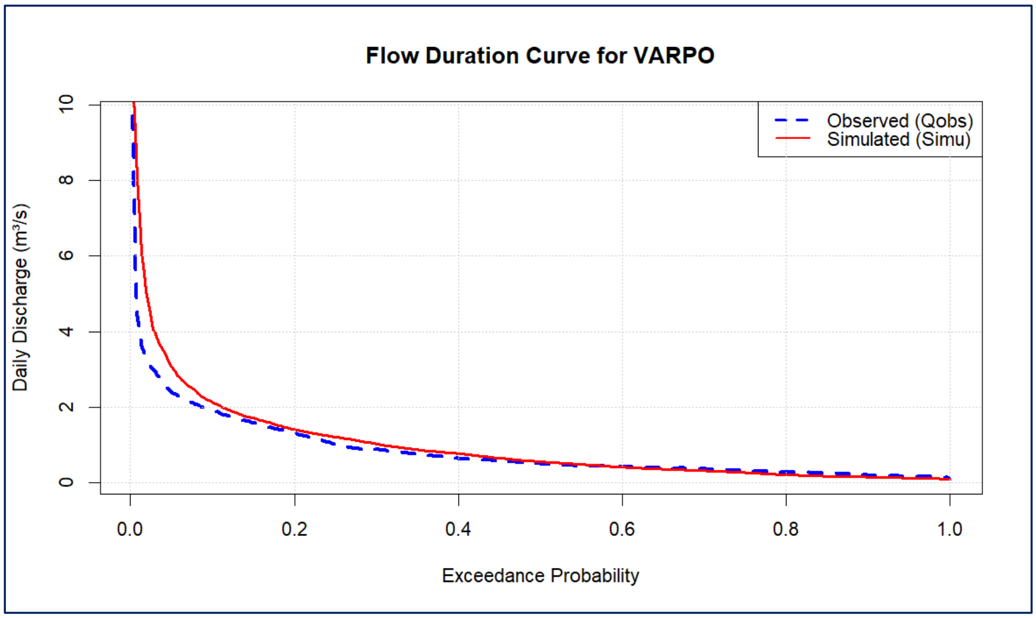


Figure 17_ Flow Duration Curve (FDC) for observed (blue) and simulated (red) discharge in the VARPO catchment, showing the percentage of time different flow rates are equaled or exceeded.

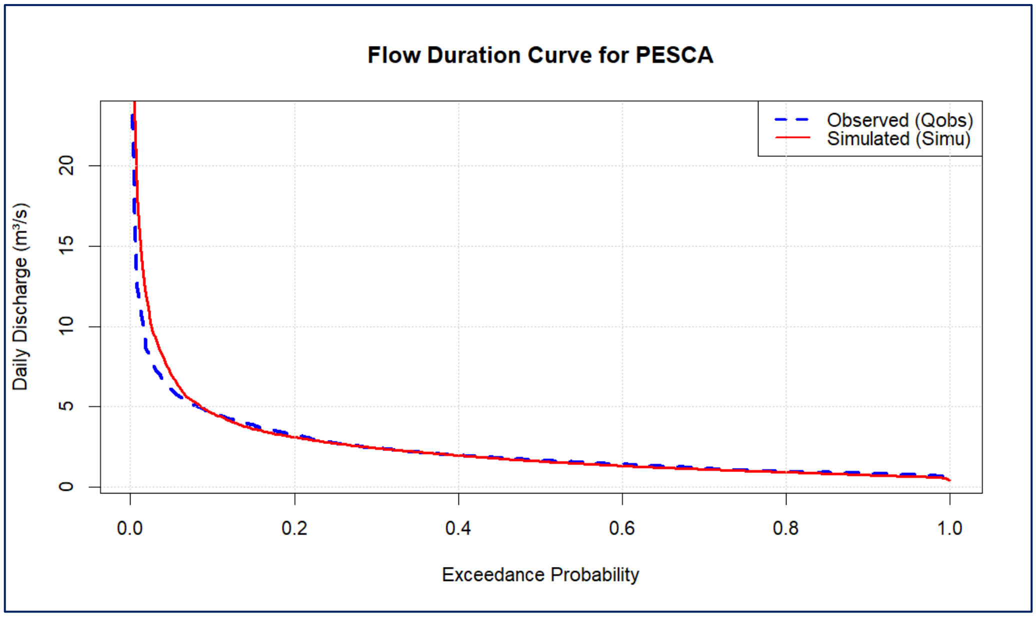


Figure 18_ Flow Duration Curve (FDC) for observed (blue) and simulated (red) discharge in the PESCA catchment, showing the percentage of time different flow rates are equaled or exceeded.

These figures provide a direct visual comparison of the observed and simulated Flow Duration Curves (FDCs). The blue curve represents the observed discharge values, while the red curve shows the simulated data generated by the TUW model. The close alignment between the two curves, especially in the lower tail, demonstrates the model's effectiveness in capturing low-flow dynamics and overall discharge patterns.

- **Environmental Flow**: Another key metric derived from the FDC is the environmental flow, which is typically defined as the flow rate exceeded 95% of the time. This metric is critical for understanding how well the model simulates minimal flow periods, which are essential for maintaining ecological health during droughts. In this study, both the observed and simulated environmental flows were closely aligned, demonstrating that the TUW model reliably replicates the conditions necessary to sustain ecosystems during drought events. The strong agreement between the observed and simulated environmental flows further validated the model's utility for drought analysis and water resource planning, particularly in predicting and managing extreme low-flow scenarios.

Table 3_ Environmental Flow (Q95) Comparison Between Observed and Simulated Discharge for Selected Catchments

Catchment	Environmental flow (Q95) Observed ($\frac{m^3}{s}$)	Environmental flow (Q95) Simulated ($\frac{m^3}{s}$)
PESCA	6.392346	6.879864
PELLU	5.589882	5.787993
SDEFO	5.628327	4.611327
GESAN	3.592403	6.625653

The Flow Duration Curves thus serve as a key validation tool, confirming that the TUW model accurately represents both high-flow and low-flow conditions. This validation is particularly important in regions like the Cuneo district, where seasonal and drought-driven variations in streamflow significantly impact water availability and ecosystem health.

In conclusion, the use of FDCs provided a robust framework for assessing the model's performance across the full spectrum of flow conditions. The model's ability to simulate both normal and low-flow events, validated through the close alignment of the observed and simulated FDCs, underscores its reliability in predicting hydrological extremes and supporting effective water resource management in drought-prone regions.

4.5.4 Log-Transformed Flow Duration Curves (Log FDC)

Log-Transformed Flow Duration Curves (Log FDCs) are essential in hydrology for analyzing streamflow behavior across various discharge levels, with a particular focus on low-flow conditions. By applying a logarithmic scale to discharge values, Log FDCs highlight the lower end of the flow spectrum, facilitating the assessment and comparison of low-flow periods, which are crucial for understanding drought events and managing water resources effectively (Loon V. , 2015).

This transformation addresses the skewed nature of hydrological data, where high-flow events can dominate and obscure significant details in lower flow rates. Log FDCs, by compressing high values and expanding the visibility of smaller flows, are especially beneficial for hydrological models like the TUW model, which require accurate low-flow simulations to assess drought impacts and support effective water management (Dai, 2013).

In this study, Log FDCs were used to validate the TUW model's ability to simulate discharge during low-flow periods, which are often more challenging to model due to their sensitivity to factors like soil moisture, groundwater contributions, and climatic variability. The TUW model's performance in capturing these low-flow dynamics is critical for understanding the potential impacts of droughts in the Cuneo district and for planning appropriate water resource management strategies under varying climatic conditions (A.K. Mishra, 2010).

The Log FDCs were generated by plotting the logarithm of observed and simulated discharge values against the exceedance probability. The exceedance probability indicates the likelihood of a particular flow rate being equaled or exceeded, providing a comprehensive view of how often different discharge levels occur over time. By focusing on the lower end of the flow spectrum, the Log FDCs in this study reveal how well the TUW model simulates minimal discharge rates, which are critical during periods of water scarcity. A close match between the observed and simulated curves in this range indicates that the model can reliably predict low-flow events.

4.5.5 Interpretation of Results

- The Log FDCs presented in this study illustrate the alignment between observed and simulated discharge values for two specific catchments, VARPO and PESCA. These examples serve as representative cases for the overall performance of the TUW model across different catchments. The figures below highlight how well the model replicates observed low-flow conditions in these selected catchments:

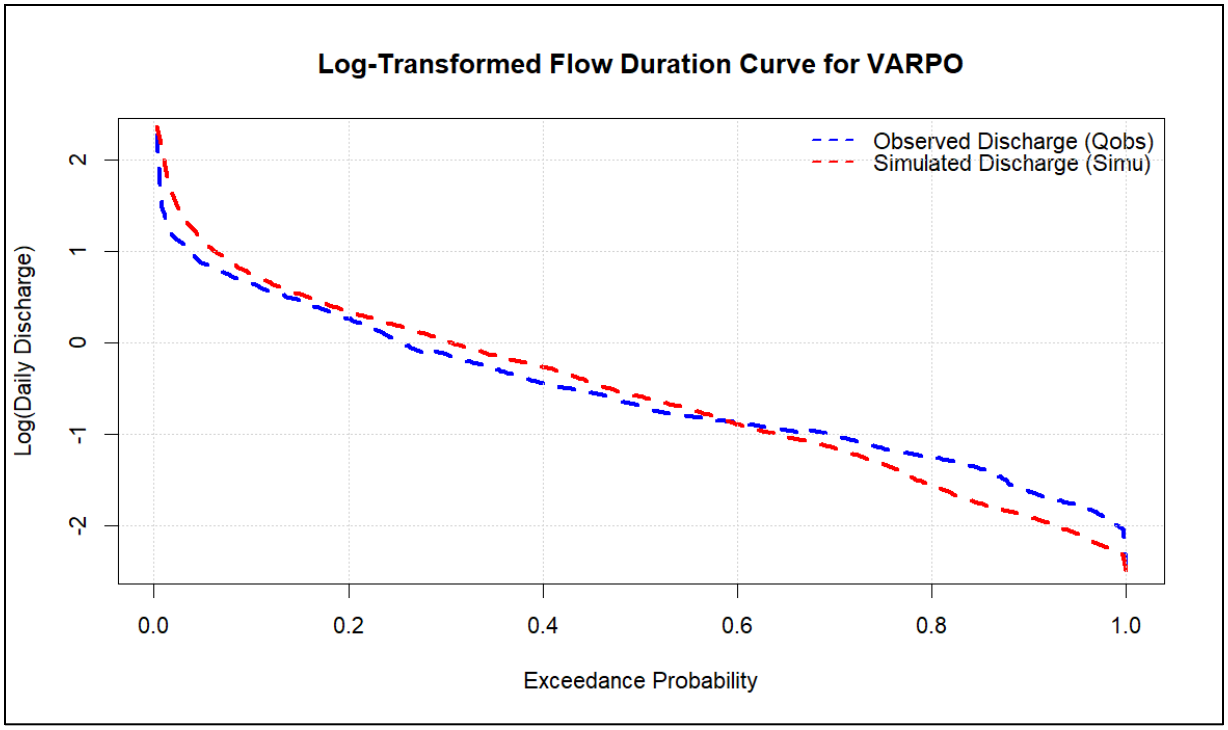


Figure 19_ Log-Transformed Flow Duration Curve for Observed and Simulated Discharge in Catchment VARPO.

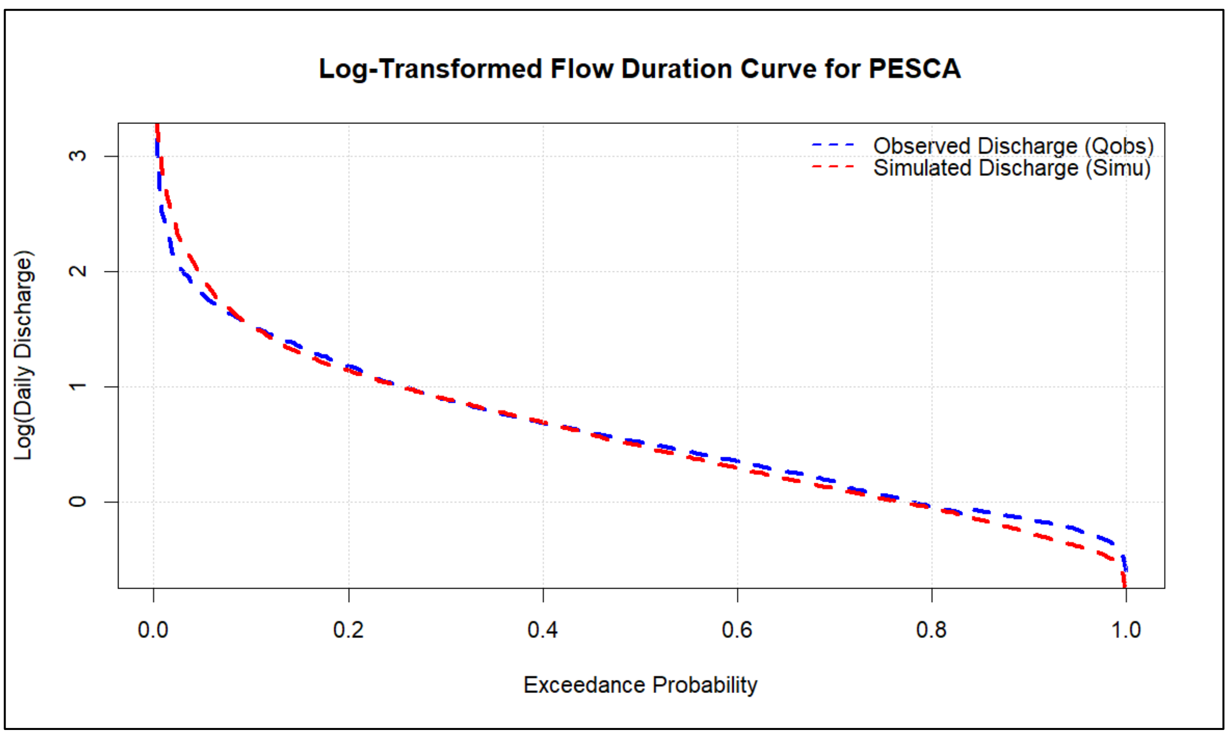


Figure 20_ Log-Transformed Flow Duration Curve for Observed and Simulated Discharge in Catchment PESCA.

Despite the overall good alignment seen in most catchments, there are instances where the TUW model struggles to accurately capture observed discharge values. For example, in some catchments, the simulated values deviate significantly from the observed data, particularly during low-flow periods. The figure below demonstrates a case where the alignment between observed and simulated discharge is less accurate, emphasizing that while the model generally performs well, there are exceptions that require further attention in specific regions.

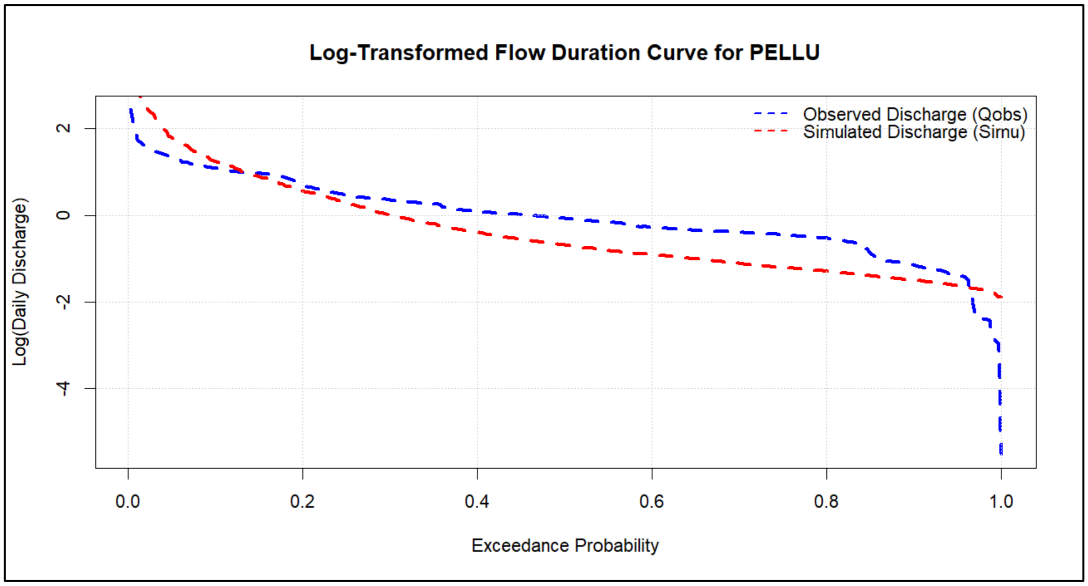


Figure 21_ Log-Transformed Flow Duration Curve for Catchment PELLU Showing Poor Alignment

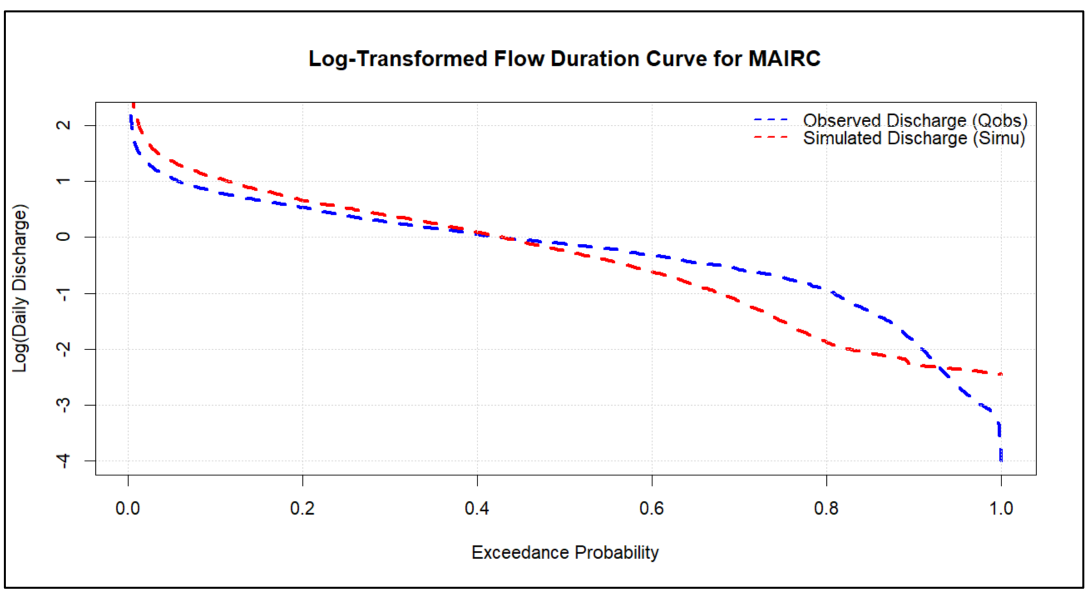


Figure 22_ Log-Transformed Flow Duration Curve for Catchment MAIRC with Deviations in Low-Flow Simulation.

In these figures, the observed discharge is shown as a blue line, while the simulated discharge is depicted as a red line. The use of logarithmic scaling provides a clearer comparison of low-flow events, which are more prominent at exceedance probabilities above 80%. The close alignment of the observed and simulated curves in these regions indicates that the TUW model generally captures the hydrological behavior of the catchments during dry periods, offering valuable insights into streamflow dynamics under drought conditions. Nevertheless, where the curves diverge significantly, it highlights areas where the model may require further refinement, such as adjusting parameters that influence baseflow and groundwater contributions during low-flow periods. While these examples represent the typical performance of the TUW model, other catchments may exhibit different degrees of alignment.

4.5.6 Monthly Regime Curves

Monthly regime curves were developed to assess the TUW model's capability to simulate seasonal streamflow variations accurately, highlighting its performance across different hydrological conditions. These curves, which plot the average monthly discharge over the analysis period, offer a visualization of seasonal trends, capturing high-flow periods in winter and spring (due to snowmelt and precipitation) and low-flow conditions during summer when droughts are most common. By illustrating monthly average discharge values, the curves provide insights into the timing and magnitude of peak flows and the depth and duration of low-flow periods, both essential for water resource management in regions with significant seasonal variability.

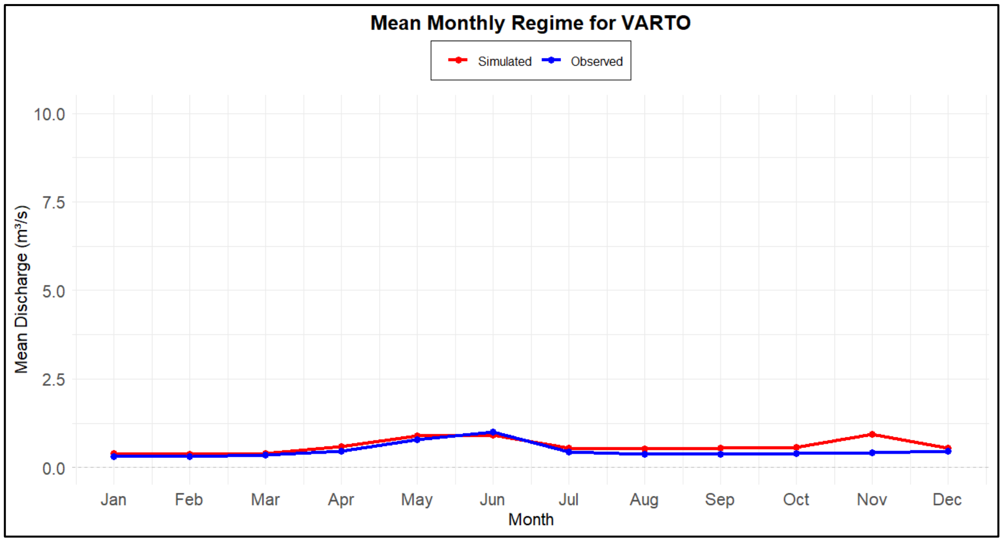


Figure 23_ Mean Monthly Discharge for Observed (blue) vs. Simulated (red) Data in Catchment VARTO.

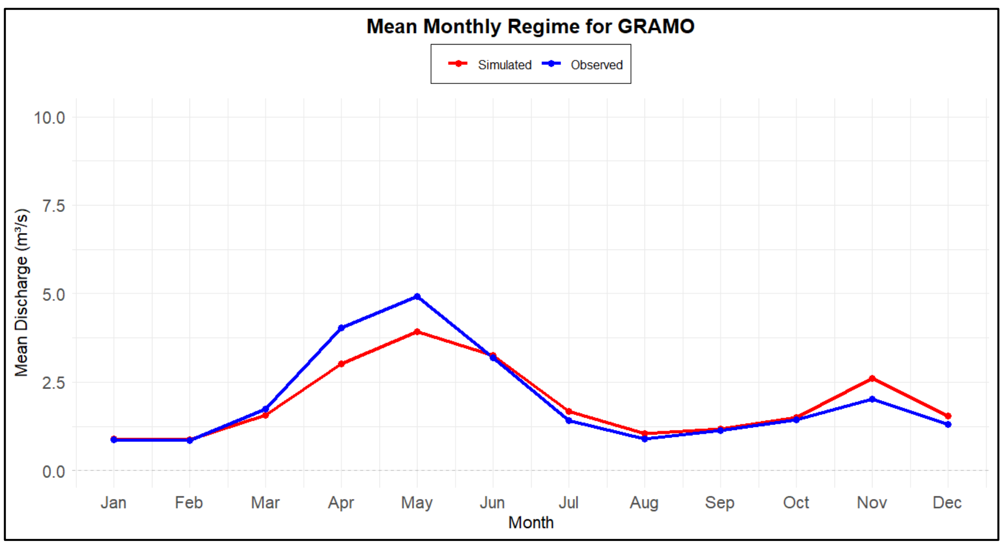


Figure 24_ Mean Monthly Discharge for Observed (blue) vs. Simulated (red) Data in Catchment GRAMO.

4.5.6.1 Simulated vs. Observed Monthly Regime:

A direct comparison of the simulated and observed monthly discharge values allowed for a detailed evaluation of the model's performance across different seasons. The analysis focused particularly on the summer months (typically July to September), which often correspond to the lowest flow levels due to reduced precipitation and higher evaporation rates. Any deviations between the observed and simulated curves during these months indicate potential areas where the model may require further adjustment, such as tuning parameters related to evapotranspiration or baseflow.

4.5.6.2 Insights from the Analysis:

The monthly regime curves showed that the TUW model generally replicated the observed seasonal trends in discharge, with a good alignment during high-flow periods like winter and spring. However, the comparison also highlighted areas for improvement during low-flow months, where even small deviations in simulation can significantly affect water availability estimates.

4.5.7 Conclusion

The validation of the TUW model provided a comprehensive assessment of its ability to simulate streamflow dynamics across diverse hydrological conditions, particularly low-flow periods critical for drought analysis. Through time window adjustments, the validation process ensured that simulated discharge data was directly comparable to observed values, enhancing the robustness of the analysis. The alignment of timeframes allowed for a precise evaluation of the model's capacity to capture short-term variations and long-term trends, laying a solid foundation for accurate drought prediction.

The statistical metrics—such as the correlation coefficient, RMSE, and MAE—offered insights into the overall accuracy of the TUW model. The results demonstrated a reasonable agreement between observed and simulated data, with the model capturing general trends in streamflow, including periods of low discharge. Although the metrics highlighted areas for potential improvement, particularly during extreme hydrological events, they confirmed the model's reliability in simulating drought conditions across various catchments in the Cuneo district.

The Flow Duration Curves (FDCs), including the log-transformed FDCs, served as vital tools in the validation process, providing a deeper understanding of the model's performance across the full spectrum of discharge values. The close alignment between the observed and simulated FDCs, especially in the lower tail, indicated that the TUW model effectively captured low-flow conditions, essential for assessing drought impacts and water availability during dry spells. However, instances of poor alignment in some catchments underscored the need for further refinement of the model in specific regions.

Overall, the validation process demonstrated that the TUW model is a robust tool for simulating streamflow in the Cuneo district, particularly under conditions of water scarcity. While there are areas where the model could be further fine-tuned to improve accuracy, its ability to replicate both high and low-flow conditions makes it a valuable resource for supporting effective water resource management and planning in drought-prone regions. The insights gained from this validation process will inform future applications of the TUW model, helping to enhance its predictive capabilities under changing climate scenarios.

5 Results

5.1 DROUGHT ANALYSIS

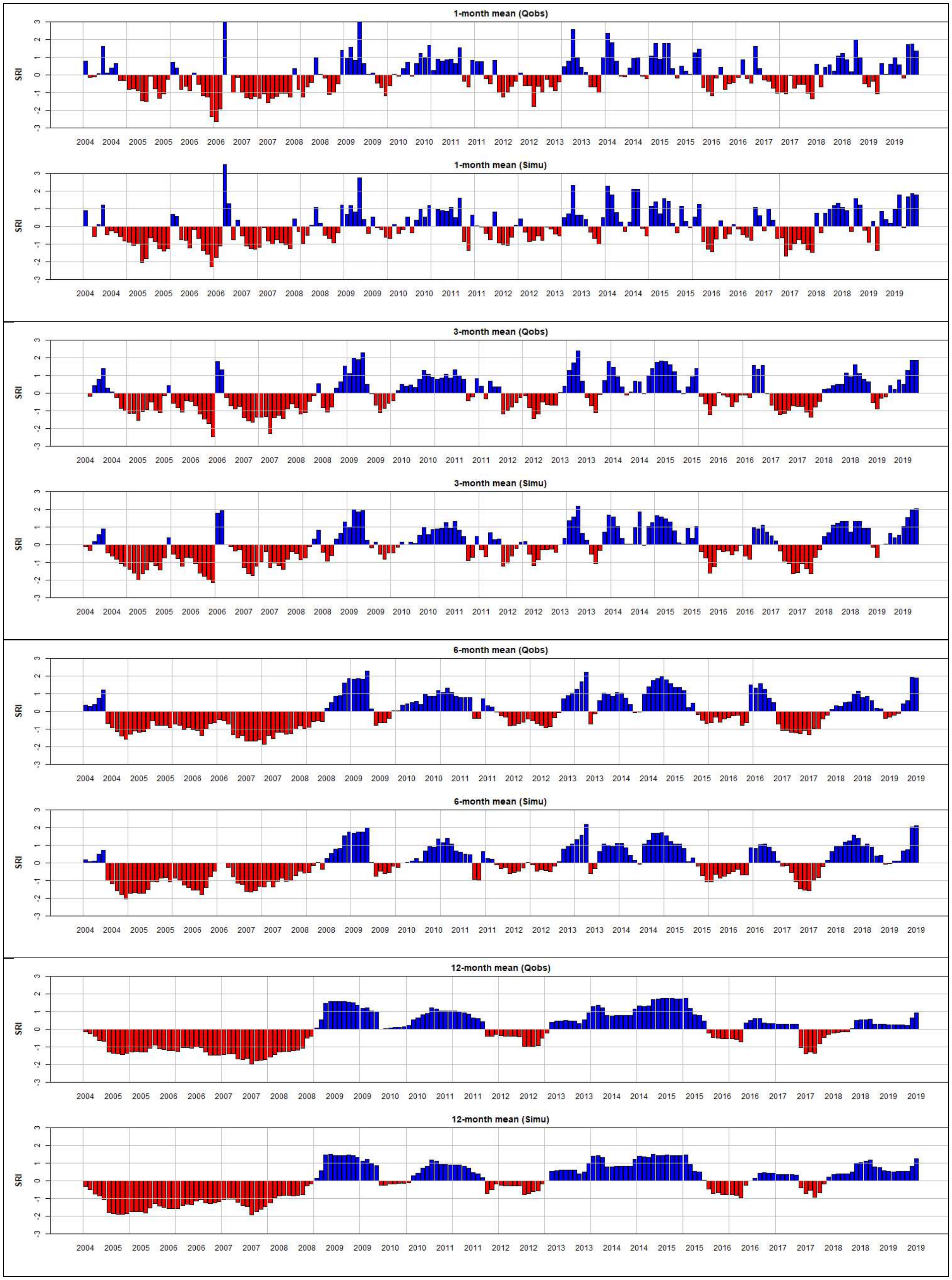
The drought analysis in this study focuses on understanding the hydrological aspects of drought events within the Cuneo district, employing the **Standardized Runoff Index (SRI)** as the primary metric. This index is designed to quantify the occurrence, intensity, and duration of droughts, providing a standardized way to evaluate anomalies in streamflow over various temporal scales. The analysis follows methodologies outlined in Van Loon's (2015) framework, which emphasizes the complex, delayed response of hydrological systems to precipitation deficits. This approach is crucial for distinguishing hydrological droughts from meteorological ones, as it accounts for factors like soil moisture variability, groundwater recharge, and streamflow responses.

5.1.1 Standardized Runoff Index (SRI)

The **SRI** is similar to the **Standardized Precipitation Index (SPI)** but is tailored specifically for streamflow data. This index standardizes runoff values, allowing for a consistent comparison of hydrological conditions across different catchments and time frames. Key advantages of the SRI include:

- **Temporal Flexibility**: It can be computed for various time scales (e.g., 1-month, 3-month, 6-month, 12-month), allowing for a nuanced analysis of both short-term and long-term drought impacts.
- **Standardization**: By normalizing the runoff data, the SRI facilitates cross-comparison between different catchments, ensuring that the severity of droughts is assessed uniformly.
- **Threshold-Based Interpretation**: SRI values can be categorized into different drought severity classes, enabling a detailed understanding of the intensity and duration of drought conditions.

The **SRI** is particularly suitable for assessing hydrological droughts because it focuses on streamflow, capturing downstream effects like changes in groundwater levels and delayed responses to precipitation deficits.


1-month mean (Qobs)
1-month mean (Simu)
3-month mean (Qobs)
3-month mean (Simu)
6-month mean (Qobs)
6-month mean (Simu)
12-month mean (Qobs)
12-month mean (Simu)
SRI

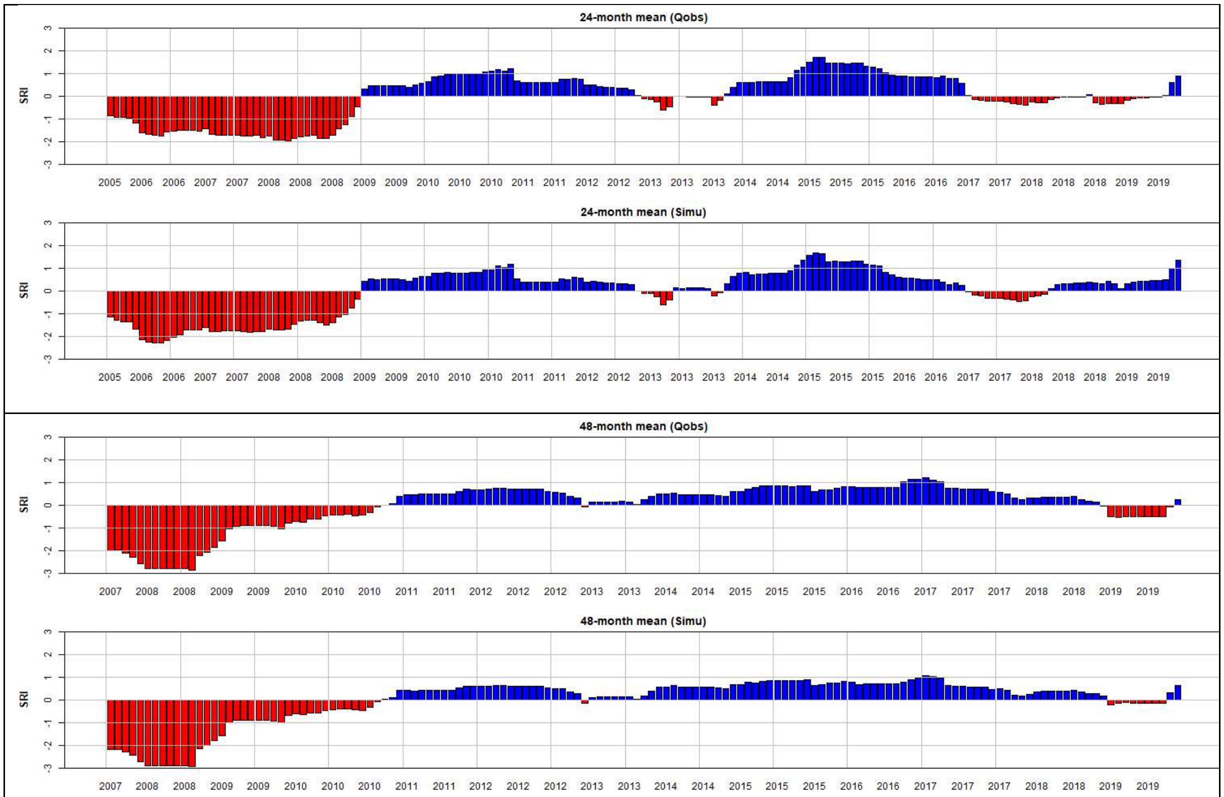


Figure 25_Observed Discharge & Simulated Discharge and SRI Values over Multiple Time Scales (1, 3, 6, 12, 24, and 48 months), highlighting short-term to long-term drought trends.

This multi-scale analysis allows the study to capture both immediate impacts and longer-term drought effects, providing a holistic view of the hydrological cycle in the region.

5.1.2 Calculation Methodology for the SRI

The Standardized Runoff Index (SRI) quantifies deviations in streamflow from typical conditions, providing a statistical foundation for drought assessment. The methodology involves aggregating discharge data to a monthly scale, fitting a suitable probability distribution to capture hydrological variability, transforming these values into cumulative probabilities, and standardizing them to create the SRI. Each step ensures that the index accurately reflects drought severity and duration by focusing on deviations from historical flow averages.

The steps for calculating the SRI are detailed below:

5.1.2.1 Monthly Discharge Aggregation

The first step is aggregating daily discharge data into monthly values, creating a smoother series that represents the typical water availability on a monthly basis. This aggregation is crucial for capturing seasonality in hydrological data, as flow rates can vary significantly throughout the year due to factors such as rainfall, snowmelt, and evapotranspiration.

For each month m in year y, the mean discharge $Q_{m,y}$ is calculated as:
$Q_{m,y} = \frac{1}{N}\sum_{d=1}^{N} Q_d$ (Equation 5)

where Q_d is the daily discharge, and N is the number of days in the month. This step produces a monthly time series of discharge values that is used in subsequent steps.

5.1.2.2 Fitting a Probability Distribution

Monthly discharge data often exhibit skewed distributions, especially in regions with distinct wet and dry seasons. The gamma distribution is commonly used to model hydrological data due to its flexibility in handling positive skew, and its applicability has been confirmed in various studies (e.g., Mishra and Singh, 2010). For each month, discharge data is fit to a gamma distribution to estimate shape α and rate β parameters.

The gamma probability density function for discharge Q is:

$f(Q;\alpha,\beta) = \frac{\beta^{\alpha} Q^{\alpha-1} e^{-\beta Q}}{\Gamma(\alpha)}$ (Equation 6)

where $\Gamma(\alpha)$ is the gamma function. Parameters α and β are estimated separately for each month using a method such as maximum likelihood estimation. This allows us to model the distribution of streamflow in a manner specific to each month's historical data.

5.1.2.3 Cumulative Probability Calculation

Once the gamma distribution parameters are estimated, each monthly discharge value is transformed into a cumulative probability. This is done by integrating the gamma distribution up to the observed discharge value for a given month, resulting in cumulative probability F(Q):

$F(Q) = \int_0^Q f(x;\alpha,\beta)\,dx$ (Equation 7)

In practice, the cumulative probability is obtained using the cumulative distribution function (CDF) for the gamma distribution, which can be directly calculated with statistical software R. This transformation standardizes each month's data by mapping it to a uniform distribution, setting the foundation for subsequent steps.

5.1.2.4 Conversion to Standardized Runoff Index (SRI)

To produce the SRI, the cumulative probability values are converted to a standard normal distribution with mean zero and standard deviation one. This transformation, commonly known as the inverse standard normal transformation, is computed as:

$$SRI = \Phi^{-1}(F(Q)) \qquad \text{(Equation 8)}$$

where Φ^{-1} is the inverse of the standard normal cumulative distribution function. Through this process, the SRI values become comparable across time and regions, as they represent deviations from typical monthly discharge in standard deviation units.

5.1.3 Interpreting SRI Values for Drought Assessment

The **SRI** values are interpreted using standardized thresholds that classify the severity of drought conditions:

Table 4_ SRI categories and cumulative probabilities for classifying wet and drought conditions. (Singh A. M., 2010)

Category	***SRI Value***	***Cumulative Probability (%)***
Extremely Wet	$SRI \geq 2$	2.28
Moderately Wet	$1.5 \leq SRI \leq 2$	6.68
Slightly Wet	$1 \leq SRI \leq 2$	15.87
Near Normal	$-1 \leq SRI \leq 1$	50.00
Mild Drought	$-1.5 \leq SRI \leq -1$	84.13
Moderate Drought	$-2 \leq SRI \leq -1.5$	93.32
Extremely Drought	$SRI \leq -2$	97.72

These thresholds allow for the precise identification of drought onset, duration, and intensity. For example, the **1-month SRI** is particularly useful for detecting short-term droughts that could quickly impact agricultural production, while the **12-month SRI** helps identify prolonged droughts affecting regional water storage systems.

5.1.4 Application of SRI to Observed and Simulated Data

In this section, the Standardized Runoff Index (SRI) is applied to both observed and simulated discharge data to evaluate the TUW model's performance in replicating hydrological drought conditions. This comparison is crucial for understanding how well the model mimics real-world drought scenarios and can be used as a reliable tool for water resource management.

- **Observed SRI**: This serves as the reference for understanding historical drought patterns based on real streamflow data. It reflects the natural hydrological conditions and the impact of past drought events on water availability in the Cuneo district.
- **Simulated SRI**: Derived from the discharge outputs generated by the TUW model, this version of the SRI is used to assess the model's ability to capture key aspects of hydrological droughts, including the timing and severity of low-flow periods. Comparing this to the observed SRI helps gauge how accurately the model reflects real conditions.

The comparison between observed and simulated SRI values focuses specifically on the **1-month SRI time scale**, which highlights short-term variations in streamflow. This particular time scale was chosen because:

- It is highly sensitive to immediate changes in streamflow, making it effective for detecting the onset of droughts and their rapid development.
- Short-term droughts can have immediate impacts on agriculture, urban water use, and ecosystem health, making accurate modeling at this scale critical for effective management.
- By emphasizing the 1-month SRI, the analysis can pinpoint where the model performs well and where adjustments may be needed to improve its response to rapid hydrological changes.

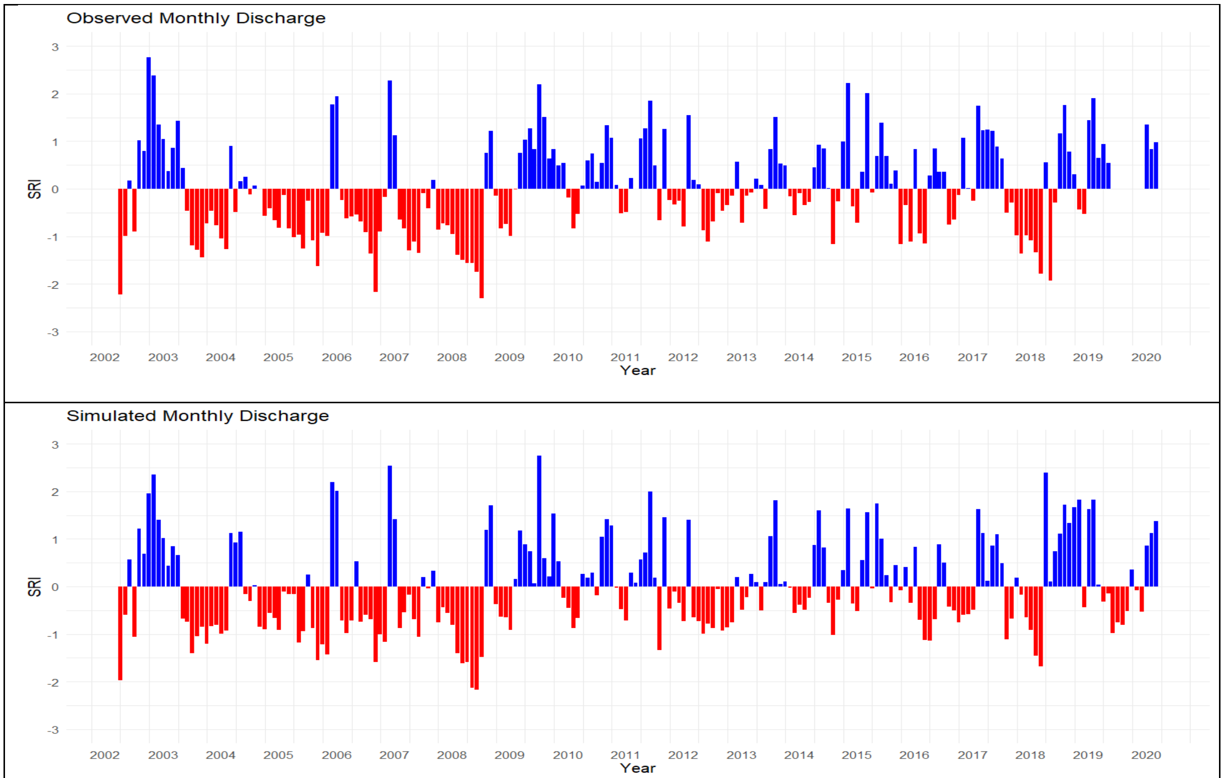


Figure 26_A comparison of the 1-month SRI for observed and simulated discharge in the PELVI catchment.

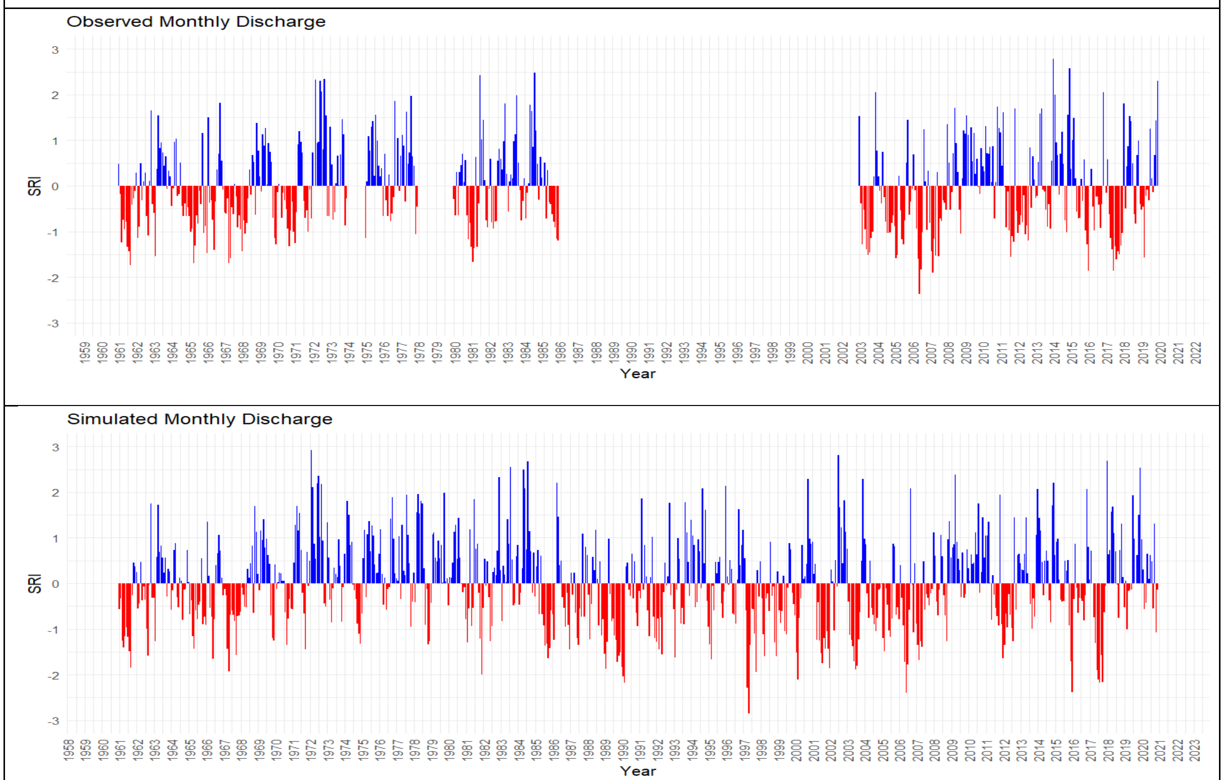


Figure 27_A comparison of the 1-month SRI for observed and simulated discharge in the TANFA catchment.

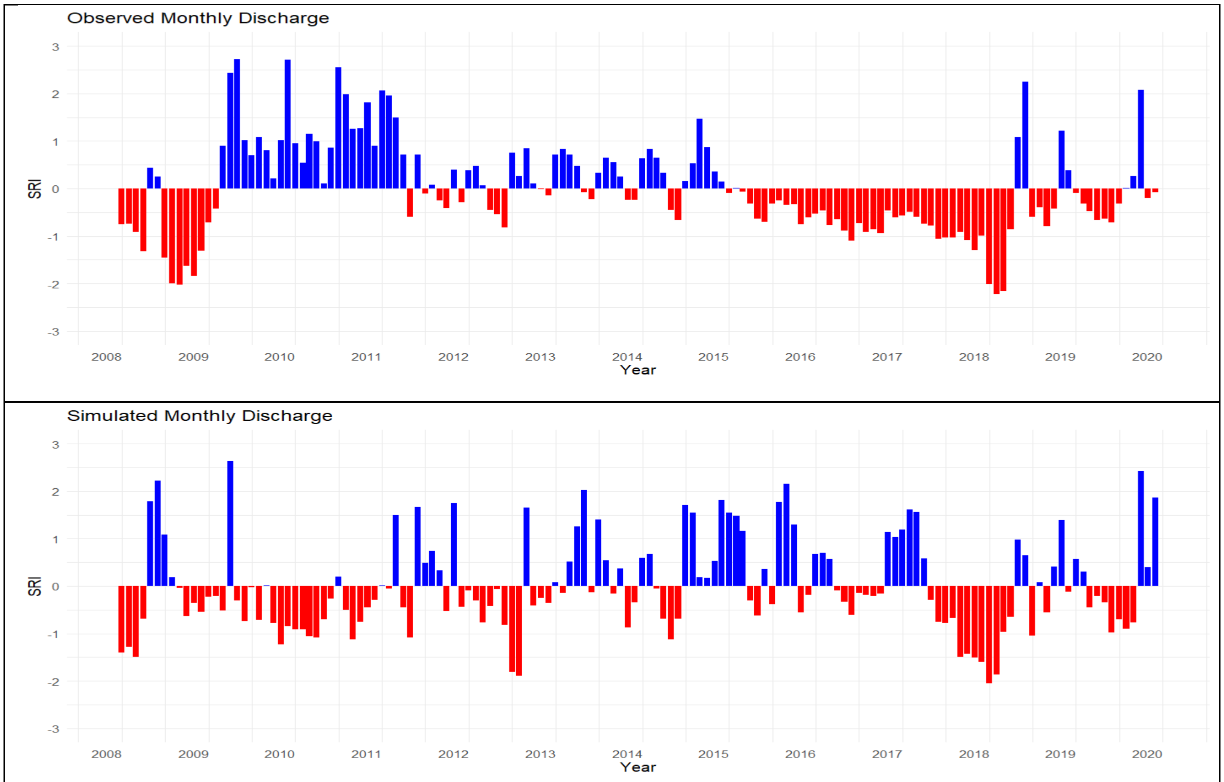


Figure 28_Comparison of the 1-month SRI between observed and simulated discharge in the VARTO catchment, showing areas of misalignment.

These figures collectively illustrate the strengths of the TUW model in capturing short-term drought events through the 1-month SRI, while also highlighting areas for improvement. Despite a few catchments, such as the VARTO catchment shown in **Fig. 28**, where the alignment between observed and simulated SRI values is less accurate, the overall performance of the model remains strong. This initial validation demonstrates that the TUW model is generally effective in simulating short-term drought conditions, providing a solid foundation for the more detailed analysis of drought characteristics—such as duration, intensity, and frequency—that will be discussed in the following pages.

5.1.5 Conclusion: SRI's Role in Drought Analysis

The application of the Standardized Runoff Index (SRI) in this study has proven to be an effective method for analyzing hydrological droughts in the Cuneo district. By evaluating both observed and simulated streamflow data, the SRI provided a robust framework for comparing drought characteristics and validating the TUW model's performance, particularly during low-flow periods. The analysis highlighted the model's strengths in capturing hydrological trends, as reflected in its ability to replicate the 1-month, 3-month, and 6-month SRI, offering valuable insights into both short-term and seasonal drought dynamics.

The integration of multi-temporal SRI analysis enabled a nuanced understanding of drought behavior. For instance, the 1-month SRI offered a detailed view of immediate water shortages, essential for managing agricultural and urban water supplies during short-term dry (Loon V. , 2015). On the other hand, the 3-month and 6-month SRI analysis helped in identifying longer-term drought patterns, guiding more strategic water management decisions in the region (A.K. Mishra, 2010). These insights are crucial for informing sustainable water management strategies, particularly in drought-prone areas like Cuneo, where both agricultural and ecological systems depend heavily on streamflow variability.

Incorporating the approach described by Van Loon (2015), which emphasizes the lagging nature of hydrological droughts relative to meteorological changes, further enriched the study's findings. This perspective allowed the SRI to capture sustained periods of low flow, even after precipitation levels had improved, offering a realistic portrayal of how drought impacts extend through the hydrological cycle. It provided a more holistic understanding of the delayed effects of drought on groundwater recharge and streamflow, critical for developing adaptive management strategies in response to prolonged dry conditions (Loon V. , 2015).

Overall, the results of this study underscore that the TUW model, validated using the SRI, performed above expectations in simulating low-flow conditions. While some discrepancies were noted in a few catchments, the general alignment between observed and simulated SRI values confirms the model's reliability for drought analysis. The study’s outcomes support the broader application of the TUW model and SRI as complementary tools in managing water resources under varying climatic conditions (Dai, 2013). This approach ensures that both short-term responses and long-term resilience to drought are accounted for, making it a valuable contribution to sustainable hydrological management in the region.

5.2 Drought characteristics

The focus of this section is to present a detailed analysis of drought characteristics in the Cuneo district using the calculated Standardized Runoff Index (SRI). After calculating the SRI for both observed and simulated data, the characteristics of drought events—specifically intensity, duration, and cumulative impacts—were extracted. The primary goal was to assess the severity and persistence of droughts in the region and to evaluate how well the TUW model replicated these characteristics in the simulated data.

5.2.1 Identification of Drought Events

Droughts represent prolonged periods of below-normal water availability, significantly affecting water resources, agriculture, and ecosystems. This study identifies droughts using the Standardized Runoff Index (SRI), a tool specifically suited for assessing hydrological droughts, as it focuses on streamflow anomalies over time (H. Hisdal, 2003) (S. M. Vicente-Serrano, 2010). A drought event is defined as any period where the SRI falls below zero, marking below-average streamflow conditions. More severe droughts occur when SRI values decline below -1, indicating increasingly critical water shortages (H. Hisdal, 2003). To classify and compare drought events, three key metrics were employed:

5.2.1.1 Duration:

Duration reflects the total number of consecutive months during which the SRI remains negative, indicating prolonged drought conditions (S. M. Vicente-Serrano, 2010). This metric indicates how long a drought persists and provides insights into the resilience of water systems to extended periods of water scarcity. Long-term droughts can have cumulative effects on groundwater levels, soil moisture, and surface water availability, making duration a critical factor in drought impact analysis (Loon V. , 2015) (Palmer, 1965).

5.2.1.2 Cumulative Impact (Cumulative SRI):

The cumulative SRI is determined by summing all negative SRI values over a drought's duration. This metric measures the total water deficit accumulated during a drought event, offering a holistic view of the drought's impact on streamflow. By integrating the SRI values over time, it provides an understanding of how much water is lost during a drought and helps assess the extent of long-term water shortages (J. Sheffield E. F., 2008).

5.2.1.3 Drought Intensity Ratio (DIR):

DIR is calculated as the ratio of cumulative SRI to the duration of the drought, providing an average measure of drought severity over its duration (Singh A. M., 2010). It distinguishes between sustained, moderate deficits and shorter but more severe droughts, offering insights into the nature of each event. A higher DIR indicates a shorter yet more intense drought, while a lower DIR suggests a prolonged drought with steady but less severe conditions (A.K. Mishra, 2010) (M. Svoboda D. L., 2002).

By calculating **Drought Duration (DDR)**, **Cumulative SRI (DSR)**, and **Drought Intensity Ratio (DIR)** for both observed and simulated discharge data, this study enables a thorough comparison of drought characteristics. This approach provides a direct evaluation of the TUW model's performance in replicating historical drought patterns across various catchments (H. V. Gupta, 2009).

5.2.2 Visual Analysis of Drought Characteristics

The study uses visual tools to illustrate the relationship between observed and simulated drought characteristics:

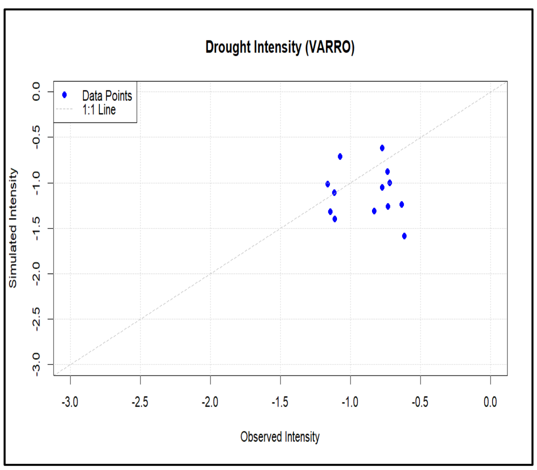


Figure 29_ Scatter Plot of Observed vs. Simulated Drought Intensity for the VARRO Catchment

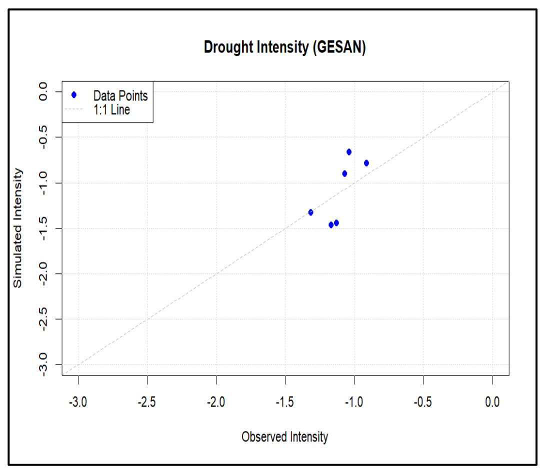


Figure 30_Scatter Plot of Observed vs. Simulated Drought Intensity for the GESAN Catchment

This scatter plot demonstrates the correlation between observed and simulated drought intensities, highlighting the TUW model’s ability to replicate drought severity across various catchments.

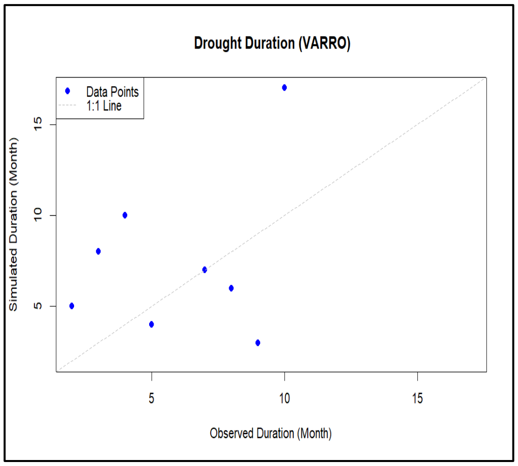


Figure 31_Scatter Plot of Observed vs. Simulated Drought Duration for the VARRO Catchment

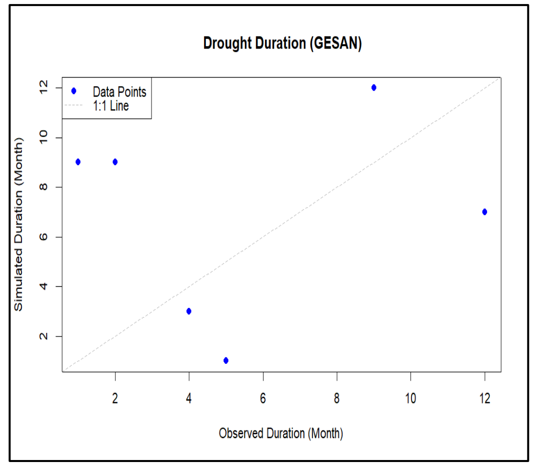


Figure 32_Scatter Plot of Observed vs. Simulated Drought Intensity for the GESAN Catchment

This plot illustrates the consistency between observed and simulated drought durations, showing how well the model captures the persistence of water shortages over time.

5.3 Drought Run Analysis

A *drought run* refers to a continuous period during which a specific hydrological indicator, such as the SRI, remains below a defined threshold—typically -1. This indicator signifies below-average streamflow conditions, identifying periods of water scarcity (H. Hisdal, 2003). In the context of the Cuneo district, the SRI serves as a valuable tool for identifying and analyzing drought events over time. By focusing on streamflow anomalies, the SRI effectively captures the impacts of sustained low-flow conditions, which are critical for understanding hydrological droughts (S. M. Vicente-Serrano, 2010).

5.3.1 Components of a Drought Run

A drought run is characterized by three main aspects:

1. **Onset**: The point at which the SRI drops below zero, marking the beginning of a period with reduced streamflow compared to historical averages. This moment indicates a transition from normal conditions to water deficit, effectively triggering a drought event (D. A. Wilhite, 1985).

2. **Persistence**: The duration for which the SRI remains continuously below zero. Longer drought runs indicate prolonged periods of water scarcity, significantly impacting water resources, agriculture, and ecosystems (Palmer, 1965). Persistence helps understand the resilience of water systems to extended periods of drought, which can have cumulative effects on groundwater levels, soil moisture, and surface water availability (Loon V. , 2015).

3. **Termination**: The point at which the SRI rises back to zero or above, indicating the end of the drought event. At this stage, streamflow conditions are considered to have returned to normal or surplus levels, signaling recovery (J. Sheffield E. F., 2008).

5.3.2 Identifying and Analyzing Drought Runs

In this study, we identify drought runs by tracking periods where the SRI remains below zero, indicating conditions of below-average streamflow. The further the SRI value drops below zero, the more severe the drought conditions. This methodology is particularly suited for hydrological drought analysis, as it captures both short-term fluctuations and long-term trends (S. M. Vicente-Serrano, 2010). By analyzing both observed and simulated SRI data, we gain insights into the spatial and temporal patterns of droughts in the Cuneo district.

Drought runs are crucial for understanding how water scarcity evolves over time and assessing the implications for water management. This analysis allows us to:

- **Capture Short-Term and Long-Term Drought Dynamics**: Short-term droughts, which may last for a few months, can be particularly detrimental to agriculture and water supply systems, while long-term droughts can deplete groundwater reserves and affect entire river basins (J. Hannaford, 2011).

- **Evaluate Drought Frequency and Intensity**: Understanding how frequently droughts occur and their intensity provides essential information for regional water management and planning, helping to allocate resources effectively during water shortages (Svoboda et al., 2002).

- **Compare Observed vs. Simulated Data**: By comparing the drought runs derived from observed streamflow data with those generated from the simulated outputs of the TUW model, we can assess the accuracy and reliability of the model in replicating historical drought patterns (Gupta et al., 2009).

5.3.3 Comparison of Observed and Simulated Drought Runs

- **Observed Drought Runs**: Derived directly from the SRI values calculated from actual streamflow data, these runs serve as a benchmark for understanding historical drought conditions in the Cuneo district. They reflect the natural variability and responses of the hydrological system to changing climatic conditions over time.

- **Simulated Drought Runs**: Obtained from the SRI values computed using the simulated discharge data from the TUW model, these runs help evaluate how well the model captures the initiation, duration, and severity of droughts. Comparing observed and simulated drought runs helps identify discrepancies and understand where the model may need improvement (Mishra & Singh, 2010).

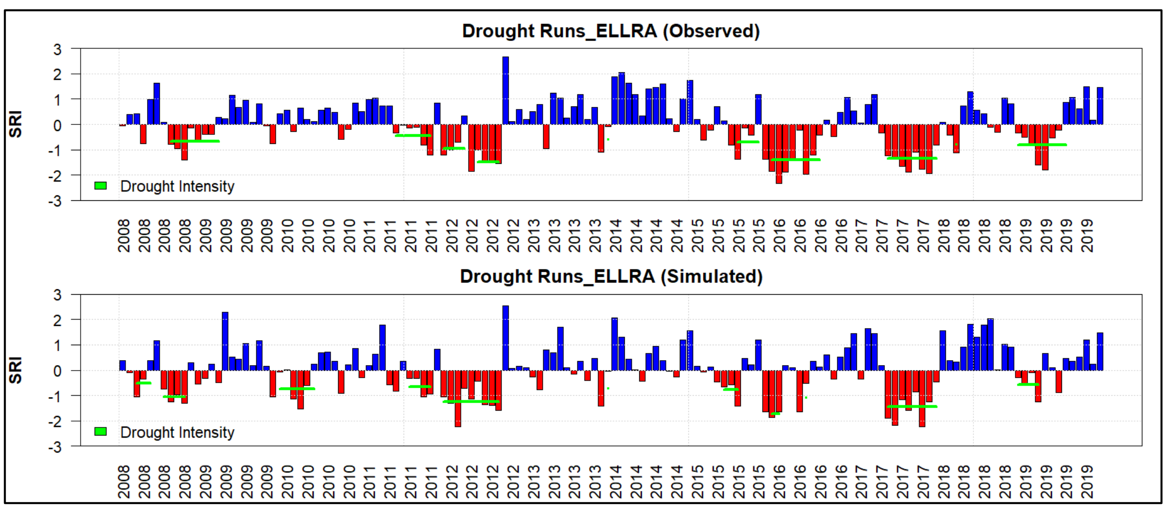


Figure 33_Drought Runs for the ELLRA Catchment

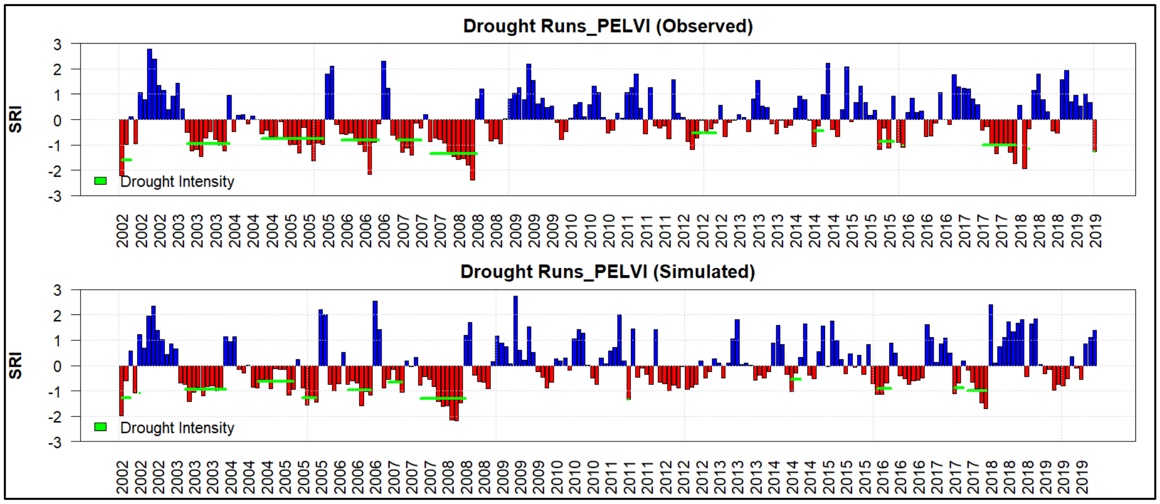


Figure 34_Drought Runs for the PELVI Catchment

The analysis of drought runs not only highlights the severity and persistence of droughts in the study area but also offers a robust method for validating the model's performance. By focusing on these characteristics, the study provides a comprehensive view of hydrological drought dynamics, aiding in the development of more effective drought management strategies.

This detailed understanding of drought runs sets the foundation for the subsequent visualization and analysis of drought events, allowing for an in-depth comparison between observed and simulated data. In the next section, temporal evolution of these drought runs is visually represented through bar plots, offering a more intuitive understanding of drought patterns over time.

5.4 Spatial Analysis of Drought Intensity and Duration

This section delves into the spatial variability of drought characteristics across multiple catchments in the Cuneo district, focusing on the mean drought intensity and duration observed and simulated by the TUW model. The primary objective is to assess the model's performance across different hydrological conditions by comparing the observed data with the simulated outputs on a catchment-by-catchment basis. This spatial analysis provides insights into how well the model captures the unique hydrological responses of each catchment to drought conditions, thereby informing regional water management strategies.

5.4.1 Mean Drought Intensity Across Catchments

To evaluate drought intensity, the mean values of observed and simulated drought intensities were calculated for each catchment. Mean drought intensity was derived as the average of negative SRI values during drought periods, providing an indication of how severe water deficits were during these events. This analysis is critical for understanding the depth of drought impacts on each catchment's water availability (Mishra & Singh, 2010).

For each of the 28 catchments in the Cuneo district, data was processed to extract drought characteristics using the Standardized Runoff Index (SRI). Mean drought intensities were computed separately for observed data (Qobs) and simulated data (Simu). The results were plotted to facilitate direct comparison.

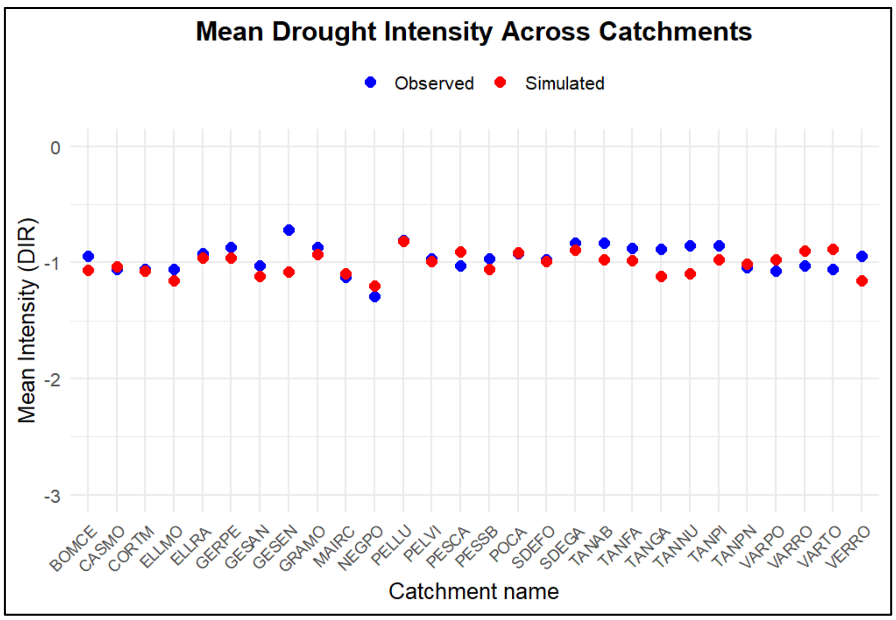


Figure 35_Comparison of mean drought intensity across various catchments in the Cuneo district for observed (blue) and simulated (red) data. The plot reveals the alignment between observed and simulated values, highlighting the ability of the TUW model to replicate varying drought intensities across different hydrological conditions.

5.4.2 Mean Drought Duration Across Catchments

In addition to intensity, understanding the duration of droughts is vital for evaluating their long-term impacts on water resources, agriculture, and ecosystems (Wilhite, 2000). The mean duration of drought events for each catchment was computed as the average number of consecutive months during which the SRI remained below zero, indicating sustained periods of water deficit.

This analysis involved calculating mean drought durations for both observed and simulated data across all catchments. By comparing these values, the study aimed to assess how well the TUW model captures the persistence of drought conditions across different hydrological regimes.

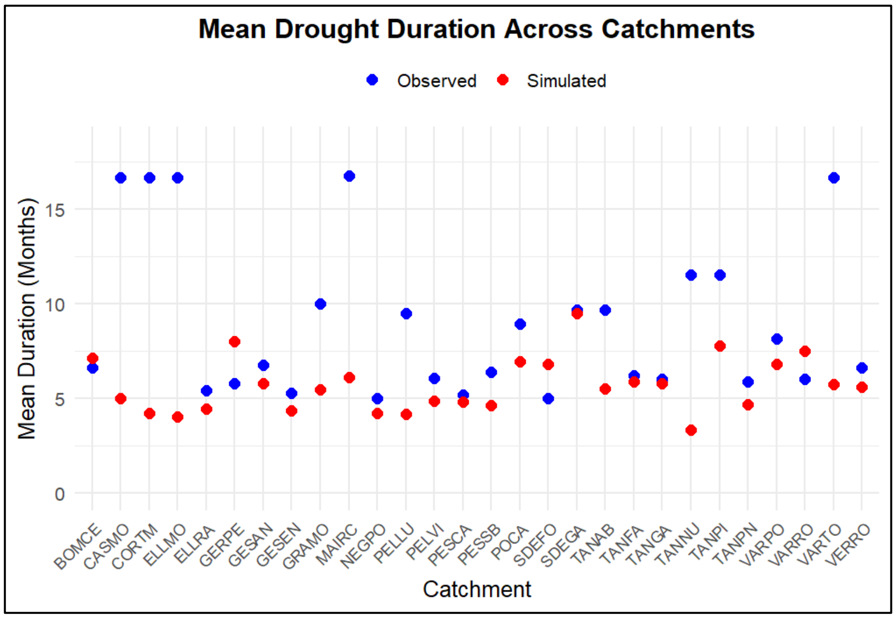


Figure 36_Comparison of mean drought duration across various catchments in the Cuneo district for observed (blue) and simulated (red) data. The plot demonstrates the model's ability to replicate the temporal persistence of droughts across different catchments, with error bars representing variability.

5.4.3 Discussion of Spatial Variability and Model Performance

The results from the spatial analysis of drought intensity and duration reveal important patterns in the Cuneo district. The scatter plots indicate that the TUW model generally performs well in capturing the average drought intensity and duration across most catchments. However, some variations are observed, particularly in catchments with more extreme hydrological variability.

- **Consistency in Moderate Droughts**: For catchments experiencing moderate drought conditions, the TUW model's simulated mean intensities and durations align closely with the observed data. This suggests that the model is effective in capturing the typical hydrological responses in regions with moderate drought conditions (Gupta et al., 2009).

- **Challenges in Capturing Extreme Events**: In catchments where extreme droughts were more prevalent, the TUW model tends to underestimate both intensity and duration. This discrepancy may be attributed to the simplified representation of baseflow processes in the model, which are critical during extended dry periods (Van Loon & Van Lanen, 2013).
- **Implications for Water Management**: Understanding these spatial variations is crucial for tailoring drought management strategies to specific catchments. Catchments where the model performs well can rely more heavily on simulated outputs for forecasting, while those with discrepancies may require additional calibration or supplementary observation-based data for improved drought management.

By analyzing the spatial variability of drought characteristics across multiple catchments, this section provides a comprehensive assessment of the TUW model's ability to simulate hydrological droughts in diverse hydrological settings. The figures offer a clear visual representation of how observed and simulated data compare, serving as a foundation for discussions on model improvements and regional drought management practices.

This analysis highlights the importance of catchment-specific modeling approaches and emphasizes the need for continuous model calibration to enhance accuracy, particularly in regions with complex hydrological dynamics.

5.4.4 Evaluation of Model Performance Using RMSE

To assess the performance of the TUW model in replicating observed drought characteristics, a statistical comparison was conducted between the observed and simulated datasets. This comparison focuses on the mean drought intensity and duration across various catchments within the Cuneo district. The Root Mean Square Error (RMSE) metric was used to quantify the differences between observed and simulated values, providing a measure of the model's accuracy.

5.4.4.1 Mean Drought Intensity Comparison

The scatter plot of mean drought intensity (observed vs. simulated) illustrates how well the TUW model captures the severity of drought conditions across different catchments. In this plot:

- The **1:1 line** is included as a reference, indicating perfect agreement between observed and simulated values.
- The RMSE value, displayed in the plot title, offers a quantitative assessment of the average deviation between the observed and simulated data points. A lower RMSE indicates a better model fit.

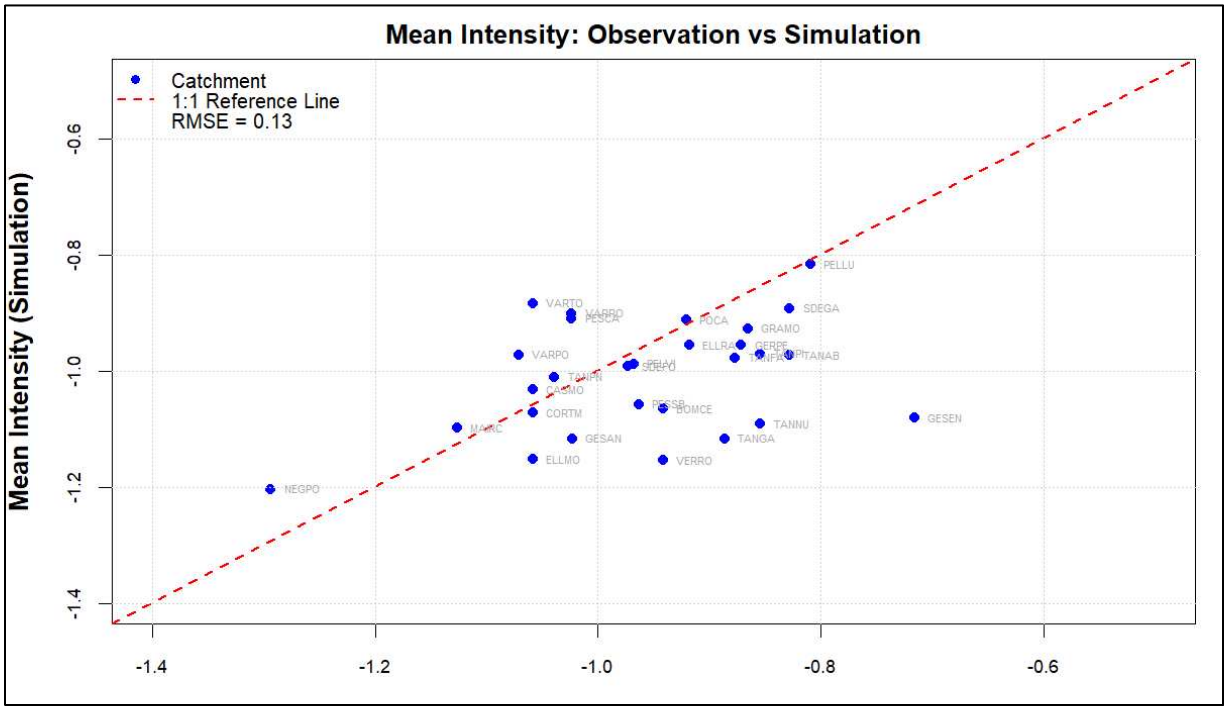


Figure 37_Scatter plot comparing the mean drought intensity between observed and simulated data across catchments in the Cuneo district. The 1:1 line indicates perfect agreement, with the RMSE value quantifying the model's accuracy.

5.4.4.2 Mean Drought Duration Comparison

Similarly, a scatter plot was generated to compare the mean drought duration between observed and simulated datasets for each catchment. This plot visualizes the consistency in drought duration as modeled by the TUW model:

- The **1:1 line** serves as a reference for perfect agreement between the two datasets, helping to identify any systematic over- or underestimation by the model.
- The RMSE for duration provides insight into the average difference between observed and simulated durations, with lower values suggesting a closer match.

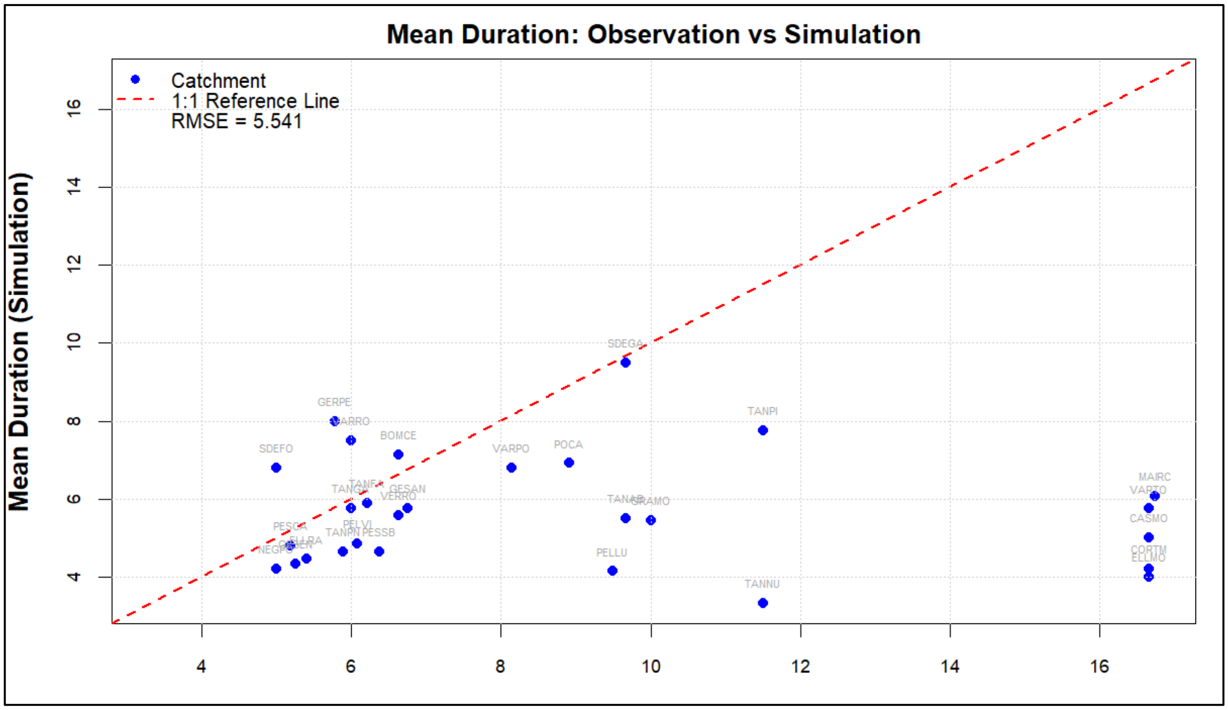


Figure 38_Scatter plot comparing the mean drought duration between observed and simulated data for different catchments in the Cuneo district.

5.4.4.3 Summary of Findings

The RMSE analysis for both intensity and duration highlight the TUW model's strengths and limitations in simulating drought characteristics. The alignment of points around the 1:1 line in both figures suggests areas where the model performs well, while deviations indicate where further model calibration might be necessary. These visual tools are instrumental in understanding the model's reliability and identifying catchments where the simulation of drought events may require improvement.

6 Discussion

This section interprets the results of the model simulations, and the comprehensive drought analysis conducted for the Cuneo district. It explores the key factors that influenced the performance of the TUW model, assesses the accuracy of drought simulations, and discusses the implications of these findings for water resource management. Additionally, the section identifies the study's limitations and suggests potential directions for future research.

6.1 Interpretation of Model Simulation and Drought Analysis:

The results of the drought analysis using the Standardized Runoff Index (SRI) revealed key insights into the drought patterns and water availability trends in the Cuneo district. The observed and simulated SRI values allowed for the identification of drought events, including their duration, intensity, and cumulative impacts. Through visual comparisons, including scatter plots of drought intensity and duration, the study evaluated how well the TUW model replicated the characteristics of observed droughts.

The TUW model demonstrated a strong ability to capture moderate drought events, accurately reflecting the duration and intensity of these occurrences across various catchments. For instance, the scatter plots of mean drought intensity and duration between observed and simulated data (Figures 1 and 2) showed a high degree of correlation for moderate drought conditions. The model's capacity to replicate these events suggests that it is well-suited for simulating the hydrological processes associated with moderate streamflow deficits. Similar results have been observed in other studies utilizing hydrological models for regional drought analysis (A.K. Mishra, 2010).

However, discrepancies were noted during periods of extreme drought (SRI < -2). The model tended to underestimate the intensity of severe droughts, especially in the lower tail of the flow duration curve, where the simulated values did not fully capture the severity of the lowest flows observed. This underestimation was more evident in catchments with higher hydrological variability, such as VARRO and GESAN. This aligns with findings by Gupta et al. (2009), which highlighted that model performance often decreases when simulating extreme hydrological events due to the complexities involved in capturing low-flow dynamics accurately.

6.2 Factors Influencing Model Performance and Accuracy:

Several factors influenced the performance of the TUW model in simulating drought conditions. One critical factor is the complexity of the catchment characteristics, including variations in land use, soil types, and groundwater interactions across the Cuneo district (Loon & Van Lanen, 2015). The model's input parameters and the calibration process also play a significant role in determining the accuracy of the simulations. The Kling-Gupta Efficiency (KGE) criterion used in the calibration helped improve the fit between observed and simulated discharge data, yet limitations in accurately representing the baseflow processes remained a challenge during severe drought periods.

The spatial resolution of climate inputs, such as precipitation and temperature, was another factor affecting model performance. Catchments with more localized climate variations showed larger deviations between observed and simulated values, suggesting that finer-resolution climate data could further enhance the model's predictive capability. Additionally, the TUW model's handling of soil moisture storage and groundwater recharge processes impacted the accuracy of drought duration simulations, especially for long-term drought events where soil moisture plays a crucial role (Palmer, 1965).

6.3 Implications for Water Resource Management:

The findings of this study have significant implications for water resource management in the Cuneo district. The ability of the TUW model to simulate moderate drought events accurately can aid water managers in planning for water shortages during such periods. By identifying drought events' duration and intensity, the model provides a basis for developing adaptive management strategies that account for anticipated changes in streamflow patterns (Wilhite, 2000).

The insights gained from comparing observed and simulated drought characteristics highlight areas where water management strategies can be refined. For example, the model's tendency to underestimate the severity of extreme droughts suggests a need for a more conservative approach when planning water allocations during prolonged dry spells. This is particularly relevant for managing reservoirs and groundwater resources, as extreme droughts have a compounding effect on both surface and subsurface water supplies.

Moreover, the study underscores the importance of integrating hydrological modeling tools like the TUW model with real-time climate data to support proactive drought management. Improved drought forecasts and scenario analysis could be implemented to mitigate the impacts of future droughts on agriculture and urban water supply systems, ensuring a more resilient water management framework for the region.

6.4 Limitations and Areas for Future Research:

This study, while providing valuable insights into drought characterization and hydrological modeling, has several limitations that may impact the generalizability and precision of its findings. Addressing these limitations can help inform future research and enhance the model's applicability under evolving environmental and climate conditions.

6.4.1 Model Assumptions and Simplifications

The TUW model, as a lumped conceptual rainfall-runoff model, aggregates spatial variability across each catchment. This approach, while computationally efficient, may overlook localized variations within catchments, such as differences in land cover, soil composition, or small-scale hydrological processes. These simplifications can limit the model's ability to capture the unique hydrological responses of smaller or heterogeneous catchments, which may be critical during extreme events like droughts or floods.

6.4.2 Climate Data Resolution and Availability

The climate data used for this study, including precipitation and temperature records, have a temporal resolution of one day and spatial coverage at the pixel level across 305 grid points. Although the resolution is suitable for large-scale analysis, finer-resolution climate data could improve the model's ability to simulate localized precipitation or temperature variations, particularly in regions with complex topography. Additionally, the use of historical data limits the study's scope in projecting future drought patterns under changing climate scenarios, potentially impacting water resource planning in the Cuneo district.

6.4.3 Limitations of the SRI in Drought Characterization

While the Standardized Runoff Index (SRI) is effective for characterizing hydrological drought, it is limited by its reliance on historical flow data. The SRI may not fully capture droughts influenced by complex climatic drivers beyond streamflow, such as soil moisture depletion or groundwater recharge variations. Additionally, as the SRI is primarily based on runoff anomalies, its application in areas with limited streamflow data or where streamflow is highly regulated (e.g., reservoirs) may yield less accurate or biased results.

6.4.4 Calibration Constraints

Model calibration relied on the Kling-Gupta Efficiency (KGE) and its log-transformed variant (log-KGE) to optimize performance across both high-flow and low-flow conditions. While log-KGE improves model sensitivity to low-flow events, optimizing both high and low flows concurrently presents a trade-off. This dual calibration approach may limit the model's precision under extreme drought conditions, as discrepancies in low-flow simulation accuracy can persist despite calibration adjustments.

6.4.5 Scope of Applicability

The study is based on historical hydrological data and climate conditions specific to the Cuneo district in the Piemonte region of Italy. Given that hydrological drought dynamics are influenced by local climate, topography, and land use, the findings may not be directly transferable to regions with substantially different environmental conditions. Further validation and adaptation of the model are recommended when applying the findings to other geographical settings.

7 Conclusion:

7.1 Summary of Key Findings:

This study analyzed drought characteristics in the Cuneo district using the TUW model and the Standardized Runoff Index (SRI). The model effectively simulated moderate drought events, capturing the duration and intensity of these events with reasonable accuracy. However, it faced challenges in replicating the intensity of extreme drought conditions, particularly in catchments with significant hydrological variability. The findings underscore the importance of understanding regional drought dynamics for effective water management, highlighting the strengths and limitations of using hydrological models for drought simulation.

7.2 Contributions to Hydrological Modeling and Drought Analysis:

The research contributes to the field of hydrological modeling and drought analysis by providing a detailed assessment of the TUW model's performance in simulating drought characteristics. The use of the SRI as a drought indicator proved effective in identifying drought events and assessing their severity over time. The study's methodology, which involved a comparative analysis of observed and simulated data across multiple catchments, offers a robust framework for evaluating the accuracy of hydrological models. This research also contributes to the broader understanding of how hydrological models can be calibrated and validated for regional drought analysis.

7.3 Recommendations for Policymakers and Practitioners:

Based on the findings, several recommendations can be made for policymakers and practitioners involved in water resource management in the Cuneo district:

- **Enhancing Drought Preparedness:** Water managers should integrate hydrological modeling tools with real-time climate data to improve drought forecasting and response planning. This integration would support better preparedness for both moderate and severe drought events.
- **Adopting Adaptive Management Strategies:** Given the model's limitations in simulating extreme droughts, adaptive management approaches that account for uncertainty in future drought severity are recommended. This could involve revising

water allocation policies during extreme drought conditions to prevent over-extraction of groundwater resources.

- **Investing in Model Refinement:** Further research and investment should be directed toward refining hydrological models like the TUW model to improve their representation of soil moisture and groundwater dynamics. Enhanced modeling capabilities would result in more accurate simulations and support long-term water management planning.
- **Regional Collaboration:** Collaboration between researchers, local water authorities, and policymakers is crucial for developing targeted solutions that address the specific hydrological challenges of the Cuneo district. Such partnerships could foster the exchange of data and expertise, leading to more effective implementation of water management strategies.

In conclusion, the study provides a comprehensive analysis of drought dynamics in the Cuneo district and offers valuable insights for improving drought resilience through enhanced modeling and adaptive water management practices. By addressing the identified limitations and pursuing future research directions, it is possible to achieve a more sustainable and resilient approach to managing water resources in the face of evolving climate challenges.

8 Appendix

8.1 R Programming for Hydrological Modeling

R is an open-source programming language and software environment widely used in data analysis, statistical computing, and scientific research. Its flexibility, extensive library support, and active community make it particularly suited for complex data-driven tasks such as hydrological modeling, climate data analysis, and environmental studies. In this thesis, R programming was instrumental in handling various tasks related to data preparation, model simulation, validation, and result visualization.

One of the key reasons R was chosen for this thesis is its strong capabilities in managing time series data, which is essential for analyzing hydrological data (such as precipitation, temperature, and streamflow) over extended periods. Additionally, R's robust ecosystem of libraries provides powerful tools for hydrological modeling, performance evaluation, statistical analysis, and graphical representation of results.

R's syntax and modular structure allow for easy replication of workflows, meaning that different hydrological scenarios can be modeled, compared, and validated using similar scripts. This approach fosters transparency and reproducibility in research, which is essential for scientific rigor.

Some key functionalities of R used in this thesis include:

Time Series Management: Efficient handling of time series data for streamflow, precipitation, and temperature.

Model Simulation: Running rainfall-runoff models such as the TUWmodel to simulate discharge in various catchments.

Statistical Analysis: Evaluation of model performance using statistical goodness-of-fit measures.

Drought Analysis: Calculation of hydrological drought indices such as the Standardized Runoff Index (SRI) to analyze drought characteristics.

Data Visualization: Creation of informative graphs, including time series plots, flow duration curves, and scatter plots for comparing observed and simulated data.

8.2 Libraries Used in the Thesis

In addition to R's core functionalities, several specialized libraries were employed to carry out the different aspects of hydrological modeling and data analysis. Below is a detailed explanation of the key libraries utilized:

8.2.1 hydroGOF

The hydroGOF package provides tools for evaluating the performance of hydrological models. It calculates various goodness-of-fit (GOF) measures, which assess how well the simulated discharge matches the observed data.

- **Main functions used**:
  - KGE (Kling-Gupta Efficiency)
  - LogKGE
  - RMSE (Root Mean Square Error)
- **Application**: These performance metrics were used extensively to assess the accuracy of the TUW model simulations during both high-flow and low-flow conditions.

8.2.2 TUWmodel

The TUWmodel package is a semi-distributed hydrological model developed to simulate discharge based on rainfall-runoff processes. It incorporates parameters for snowmelt, soil moisture, and runoff generation, making it particularly suitable for simulating hydrological responses in complex catchments.

- **Application**: The TUW model was used to simulate streamflow for different catchments in the Cuneo district. The model's parameters were optimized using calibration techniques to achieve accurate simulations of discharge patterns.

8.2.3 DEoptim

The DEoptim package implements the Differential Evolution optimization algorithm, which is designed for optimizing complex parameter spaces. It was employed in this thesis to optimize the parameters of the TUWmodel during the calibration process.

- **Application**: Differential Evolution was used to maximize the Kling-Gupta Efficiency (KGE) and ensure that the simulated discharge closely matched observed values across a range of hydrological conditions.

8.2.4 zoo

The zoo package provides tools for handling and analyzing irregular and regular time series data. It offers a flexible framework for managing the time series datasets that form the backbone of hydrological modeling.

- **Application**: The package was used to store, manipulate, and plot the time series data for observed and simulated streamflow, precipitation, and temperature.

8.2.5 ggplot2

The ggplot2 library is one of the most widely used tools for creating elegant and informative data visualizations. It allows for the creation of customized graphs, which are essential for interpreting and communicating results.

- **Application**: ggplot2 was used to generate time series plots comparing observed and simulated discharge, flow duration curves (FDC), and scatter plots to visualize model performance metrics. These visualizations played a key role in illustrating the results and findings of the thesis.

8.2.6 lubridate

The lubridate package simplifies working with dates and times, making it easier to extract and manipulate date components. Hydrological data is often time-sensitive, and this package was useful in aligning datasets temporally.

- **Application**: lubridate was used to extract year, month, and day from the time series data, enabling the aggregation of daily discharge data into monthly or seasonal values for further analysis.

8.2.7 dplyr

dplyr is a data manipulation package that provides a set of tools for filtering, summarizing, and reshaping datasets. It is known for its simplicity and efficiency when dealing with large datasets.

- **Application**: In this thesis, dplyr was used for aggregating daily discharge data into monthly or annual values, calculating averages, and filtering data to match specific time periods for calibration and validation of the hydrological model.

8.2.8 precintcon

The precintcon package specializes in climate data analysis and provides methods for calculating the Standardized Precipitation Index (SPI) and Standardized Runoff Index (SRI). These indices are essential for drought analysis.

- **Application**: precintcon was employed to compute the SRI values for both observed and simulated discharge data. This index was used to identify and quantify the intensity, duration, and frequency of drought events across the study area.

R programming, with its wide range of libraries, proved to be a robust and flexible tool for conducting the hydrological modeling, drought analysis, and performance evaluation required in this thesis. The combination of R's data manipulation capabilities and the specialized functions provided by libraries like TUWmodel, hydroGOF, and precintcon enabled a comprehensive and efficient approach to the research objectives. This ecosystem of tools facilitated the entire workflow, from data preprocessing to simulation, validation, and final result visualization.

9 References

A. Bianchi, G. R. (2016). Hydrogeological Complexity in the Cuneo Region: An Overview. *Journal of Italian Geology*.

A. F. Van Loon, H. A. (2013). Making the distinction between water scarcity and drought using an observation-modeling framework. *Water Resources Research, 49*(3), 1483-1502. doi:https://doi.org/10.1002/wrcr.20147

A. Viglione, L. R. (2020). Future Water Availability and Drought Projections in Northern Italy. *Hydrology Research*.

A.K. Mishra, V. S. (2010). A review of drought concepts. *Journal of Hydrology*, 202-216.

Beven, K. (2012). *Rainfall-runoff modelling: The primer (2nd edition).* John Wiley & Sons.

C. Santos, M. M.-C. (2018). Comparison of statistical methods to merge historical and downscaled GCM outputs for low-flow projections. *Hydrological Sciences Journal*, 63(7), Pages 1053-1073.

Cuneo, C. d. (2019). *Census Report on the Urban Population of Cuneo.* Comune di Cuneo.

D. A. Wilhite, M. H. (1985). Understanding the Drought Phenomenon: The Role of Definitions. *Water International*.

D.A. Wilhite, M. G. (1985). Understanding the drought phenomenon: The role of definitions. *Water International*, 111-120.

Dai, A. (2013). Increasing drought under global warming in observations and models. *Nature Climate Change*.

G. Bussi, F. F. (2020). A SWAT model application to assess hydrological drought in the Iberian Peninsula under future climate scenarios. *Hydrological Processes*, 2281-2300.

G. Lindström, B. J. (1997). Development and test of the distributed HBV-96 hydrological model. *Journal of Hydrology*, 272-288.

G. Rossi, M. C. (2018). Socioeconomic Impacts of Rural Demographics in Cuneo.

H. Hisdal, L. M. (2003). Estimation of regional meteorological and hydrological drought characteristics: A case study for Denmark. *Journal of Hydrology*, 230-247. doi:https://doi.org/10.1016/S0022-1694(03)00233-6

H. Kling, M. F. (2012). Runoff conditions in the upper Danube basin under an ensemble of climate change scenarios. *Journal of Hydrology*.

H. V. Gupta, H. K. (2009). Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, 80-91.

I. Giuntoli, B. R. (2013). Low flows in France and their relationship to large-scale climate indices. *Journal of Hydrology*, 105-118.

I. Giuntoli, J. V. (2013). Future hydrological extremes: The uncertainty from multiple global climate and hydrological models. *Earth System Dynamics*, 267-285.

IPCC. (2014). *Climate Change 2014: Impacts, Adaptation, and Vulnerability.* Cambridge University Press.

Istat. (2020). *Population Statistics for Cuneo Province.* Istat.

J. Hannaford, T. J. (2011). An assessment of trends in UK runoff and low flows using a network of undisturbed catchments. *International Journal of Climatology*, 128-143. doi: https://doi.org/10.1002/joc.1933

J. Seibert, M. V. (2012). eaching hydrological modeling with a user-friendly catchment-runoff model. *Hydrology and Earth System Sciences*, 3315-3325.

J. Sheffield, E. F. (2008). Global trends and variability in soil moisture and drought characteristics. *Journal of Hydrology*, 432-458. doi:https://doi.org/10.1175/2007JCLI1822.1

J. Sheffield, E. W. (2011). *Drought: Past problems and future scenarios.* Routledge.

J. Smith, G. B. (2017). Biodiversity and Conservation in the Cotian and Maritime Alps. *Ecology Letters*, 103-115.

J.G. Arnold, R. S. (1998). Large area hydrologic modeling and assessment part I: Model development. *Journal of the American Water Resources Association*.

K.K. Yilmaz, H. G. (2011). A process-based diagnostic approach to model evaluation: Application to the NWS distributed hydrologic model. *Water Resources Research*.

L. Romero, F. V. (2020). Precipitation Variability in the Italian Alpine Regions. *Journal of Hydrology*.

Lanen, L. T. (2004). *Hydrological Drought: Processes and Estimation Methods for Streamflow and Groundwater.* Elsevier.

Loon, A. V. (2015). Hydrological drought explained.

Loon, V. (2015). Hydrological drought explained. *WIREs Water*.

M. Ravina, P. C. (2018). Shallow Geothermal Energy Potential in Piedmont. *Renewable Energy Journal*.

M. Svoboda, D. L. (2002). The drought monitor. *Bulletin of the American Meteorological Society*.

M. Svoboda, D. L. (2002). The drought monitor. *Bulletin of the American Meteorological Society*, 1181-1190. doi:https://doi.org/10.1175/1520-0477-83.8.1181

P. Caruso, F. D. (2017). Ecosystem Dynamics in the Alpine Valleys of Piedmont. *Environmental Studies Review*.

Palmer, W. C. (1965). Meteorological Drought. *Monthly Weather Review*, 1-58.

Piemonte, M. (2019). *Climatic Patterns of the Piedmont Region.* Meteo Piemonte.

R.P. Pandey, K. R. (2007). Trend analysis of annual and seasonal rainfall and their relationship with drought incidents in India. *Hydrological Sciences Journal*, 772-785.

Refsgaard, J. (1997). Parameterisation, calibration and validation of distributed hydrological models. *Journal of Hydrology*, 69-97.

Rodier, M. B. (1985). *Hydrological Aspects of Drought.* UNESCO.

S. M. Vicente-Serrano, S. B.-M. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index. *Journal of Climate*, 1696-1718. doi:https://doi.org/10.1175/2009JCLI2909.1

S. Shukla, A. W. (2008). Use of a standardized runoff index for characterizing hydrologic drought. *Geophysical Research Letters*.

S. Shukla, A. W. (2008). Use of a standardized runoff index for characterizing hydrological drought. *Geophysical Research Letters*, 35(2).

S. Thober, J. M. (2018). Evaluation of multiple drought indices for hydrological drought using empirical data and climate simulations. *Hydrology and Earth System Sciences*, 6221-6240.

Singh, A. M. (2010). A review of drought concepts. *Journal of Hydrology*.

Singh, V. P. (2010). *Handbook of Hydrology.* McGraw-Hill Education.

T.B. McKee, N. D. (1993). The relationship of drought frequency and duration to time scales. *8th Conference on Applied Climatology* (pp. 179-183). American Meteorological Society.

UNESCO. (2021). *Drought and Water Scarcity in Southern Europe: A Growing Concern.* UNESCO.

W. J. M. Knoben, J. E. (2019). Inherent benchmark or not? Comparing Nash-Sutcliffe and Kling-Gupta efficiency scores. *Hydrology and Earth System Sciences*, 4323-4331.

Wilhite, D. A. (2000). Drought as a natural hazard: Concepts and definitions. Routledge.

X. Zeng, P. C. (2019). Rainfall-Runoff Models for Hydrological Drought Simulation: Case Study in Northern Italy. *Water Resources Management Journa*.