SLOVAK UNIVERSITY OF TECHNOLOGY IN BRATISLAVA
FACULTY OF CIVIL ENGINEERING

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Dissertation Thesis Abstract

Integrating Statistical, Machine Learning, and Deep Learning Approaches for Predicting Hydrological Extremes in Slovak River Basins

To obtain the Academic Title of „philosophiae doctor ", abbreviated as„PhD. "

in the doctorate degree study programme: D-VHI4 Water Resources Engineering

in the field of study: Civil Engineering

Form of Study: full-time

Place and Date: Bratislava, 31. May 2025

Dissertation Thesis has been prepared at the Department of Hydraulic Engineering, Faculty of Civil Engineering, Slovak University of Technology in Bratislava

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Dissertation Thesis Abstract was sent:

The dissertation defense will take place on …………………. in the meeting room of the Department of Hydraulic Engineering, Faculty of Civil Engineering, Slovak University of Technology in Bratislava, Radlinského 11, 810 05 Bratislava.

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1. CONTENTS

2. INTRODUCTION

Effective water resource management and safety depend fundamentally on predicting river discharge and hydrological extremes like floods and droughts [1, 2]. While numerous modelling approaches exist, ranging from traditional statistical methods to advanced machine learning (ML) and deep learning (DL) [1-6], the inherent complexity of hydrological systems is intensifying due to climate change impacts on precipitation, temperature, and snowmelt [2, 3]. This evolving complexity demands integrated, region-specific predictive frameworks that combine rigorous statistical analysis with cutting-edge modelling techniques [3, 4]. Addressing these challenges, particularly the persistent gap in synergistically integrating traditional and modern methods for predicting regional extremes [3, 4, 6], is crucial. Current predictive accuracy is often constrained by limitations in data availability, resolution (e.g., reliance on daily data), and variety, hindering the capture of complex streamflow dynamics [2, 3, 4, 6]. This dissertation confronts these issues using Slovakia's Topľa and Gidra rivers as pertinent case studies, selected for their distinct hydrological regimes and susceptibility to climate change [2].

Understanding the context requires reviewing the nature of hydrological extremes and the evolution of forecasting methods. Drought, a complex phenomenon of prolonged water scarcity [3, 7], manifests in meteorological, agricultural, hydrological, and socioeconomic forms [3, 8, 9]. Its assessment relies on indices like SPI, PDSI, SPEI, SDI, and WBC [3, 9-11, 13, 14], with climate change exacerbating drought frequency and severity through mechanisms like increased evapotranspiration [7, 8, 11-13]. Floods, conversely, involve inundation driven by extreme rainfall, snowmelt, or infrastructure failure, modulated by land use and catchment characteristics [14-17]. Climate change is intensifying flood regimes globally by altering precipitation patterns and snowmelt dynamics [15, 16].

Historically, statistical models formed the bedrock of hydrological forecasting. Classical time-series models like ARMA and ARIMA capture temporal dependencies but struggle with non-stationarity and nonlinearity [21, 22]. Regression methods (e.g., MLR) offer interpretability but are limited by linear assumptions [22]. Flood Frequency Analysis (FFA) and its regional counterpart (RFFA) estimate flood probabilities and return periods, essential for design and risk assessment [23-25]. However, these classical methods face challenges: violating stationarity assumptions under climate change [26, 27], sensitivity to data limitations [1, 18, 20, 26, 27], inability to capture complex nonlinear dynamics [21, 26, 27], and difficulties in quantifying uncertainty [28, 29].

To address these limitations, modern data-driven approaches using ML and DL have gained prominence [1-6]. Techniques like Artificial Neural Networks (ANNs), Multilayer Perceptrons (MLPs), Support Vector Machines (SVMs), Recurrent Neural Networks (RNNs, including LSTMs and GRUs), Convolutional Neural Networks (CNNs), and more recently, Transformers with attention mechanisms, offer powerful capabilities to model complex, non-linear relationships and long-range dependencies directly from data [1-6, See Methods Section for details]. While highly effective, these methods also present challenges regarding data requirements, interpretability ('black box' problem), and computational cost.

Recognizing the strengths and weaknesses of both traditional and modern approaches, the primary objective of this research is to deliver a comprehensive hydrological assessment of the Topľa and Gidra rivers, explicitly examining climate change effects, and crucially, to develop and evaluate an integrated methodological framework combining statistical insights with ML/DL predictive power [3, 5]. The study focuses specifically on the Topľa and Gidra rivers

[3, 5], acknowledging limitations related to data availability (e.g., reliance on daily data for some analyses). Theoretically, this research contributes by demonstrating the value of an integrated statistical-ML/DL approach for understanding climate-induced hydrological shifts [1, 2]. Practically, the developed predictive models offer valuable tools for water managers, enabling early forecasting to inform adaptive strategies, optimize water storage, reduce risks, and support resilient infrastructure and sustainable policies in a changing climate [3, 5]. The subsequent chapters detail the study area, data, methodologies employed (statistical, ML, DL), present the results, and conclude with a synthesis of findings and implications.

3. Goals of the Dissertation

The overarching goal of this dissertation was to enhance the understanding and prediction of hydrological processes, particularly extreme events like droughts and floods, within Slovakia's Topľa and Gidra river basins, especially under the influence of climate change. This involved pursuing several interconnected objectives: (1) To conduct a comprehensive hydrological assessment characterizing the long-term trends and seasonal dynamics of streamflow in both rivers using statistical methods; (2) To develop and evaluate machine learning models capable of providing early forecasts of annual drought conditions based on initial hydrological indicators; (3) To design, implement, and test a novel deep learning framework, Hydro-Informer, leveraging advanced architectures like Transformers for accurate short-term flood forecasting (specifically, water level prediction); and (4) To demonstrate the synergistic value of integrating traditional statistical analysis with modern data-driven computational techniques (ML/DL) for improved hydrological prediction and water resource management in a regional context.

Ultimately, the research aimed to bridge the gap between classical hydrological methods and cutting-edge AI, providing practical tools and insights to support more effective water management strategies, enhance flood and drought preparedness, and contribute to climate resilience in the studied Slovak river systems.

4. Study Area and Hydrological Characteristics

4.1. Hydrological Extremes in Slovakia

Recent hydrological drought patterns in Slovakia reflect changing conditions, with prolonged low flows linked to climate shifts such as reduced snow cover and rising temperatures impacting runoff seasonality [3, 5, 31]. While studies confirm decreasing spring and summer flows in certain periods [3, 5, 14, 31], analysis suggests no significant increase in overall drought frequency compared to the past, indicating instead a recurring vulnerability across different regions [32]. Climate projections present a potential paradox: despite forecasts of stable or moderately increased annual precipitation, runoff may decrease due to higher evapotranspiration driven by rising temperatures, potentially exacerbating hydrological drought [33]. Drought severity shows regional variation and complex drivers, including climate, geology, basin characteristics, and antecedent moisture conditions [31-34].

Flooding remains a significant hazard, encompassing various types like flash floods (anticipated to intensify with climate change), river floods, urban floods, and summer floods [35, 37, 38]. Key drivers include extreme precipitation, rapid snowmelt, influential land use changes (urbanization, deforestation), and sometimes, infrastructure failures [36-38]. Slovakia has experienced major historical floods [38], and recent events underscore ongoing risks and impacts like channel erosion (e.g., Topľa 2010) [39]. The Slovak Hydrometeorological Institute

(SHMI) plays a vital role in flood management through enhanced monitoring networks, advanced modelling, and the development of specialized forecasting systems like those for flash floods [37].

4.2. TOPĽA RIVER CASE STUDY

The Topľa River, situated in eastern Slovakia, originates in the Čergov Mountains, flows 129.8 km to join the Ondava River, and drains a catchment of 1,544 km² [5, 40, 41]. The basin experiences a temperate climate with annual precipitation ranging from 600 to 1000 mm across different zones [5, 40, 41]. Monitored at gauging stations like Bardejov (mean annual discharge 1961-2000: 2.978 m³/s), its hydrological regime is characterized by high flows in spring (dominated by snowmelt) and potential peaks in summer (from intense rainfall), with low flow periods in late summer/autumn and winter [5, 40-42]. River morphology has been altered by human activities such as channelization [5, 41, 42]. The basin has a documented history of significant floods (e.g., 2010) and droughts (e.g., 2003, 2015, 2022), emphasizing the need for robust analysis and forecasting [40, 42]. Data procured from SHMI for the Topľa River analysis includes:

- Daily mean discharge (1988–2020): Used for comprehensive hydrological assessment employing the Water-Bearing Coefficient (WBC) and Streamflow Drought Index (SDI), and for classifying hydrological years (dry, normal, wet).
- Hourly water level, discharge, and precipitation (2008–2020): This dataset required substantial preprocessing to address anomalies and missing data (notably 2016-2017), resulting in a cleaned dataset covering 2008–2015 and 2018–2020. This curated hourly data formed the basis for developing the Hydro-Informer deep learning model aimed at forecasting water levels at the Bardejov station, particularly during extreme events.

4.3. GIDRA RIVER CASE STUDY

The Gidra River is a smaller foothill stream located on the southeastern slopes of the Little Carpathians in western Slovakia. It flows 38.5 km to the Dudváh River, draining a predominantly forested catchment of 32.95 km² [3, 43]. Its hydrological regime is primarily influenced by winter and spring precipitation and snowmelt dynamics, monitored via a single gauging station (Píla) with a long-term mean annual discharge (1961-2000) of 0.298 m³/s [3, 5, 43]. Peak discharge typically occurs in March or April, while the lowest flows are observed from August to October [3, 5, 43]. Water management in the basin is complicated by numerous water abstraction points, which significantly affect flow, contributing to instances where the lower reaches of the river have reportedly dried out completely in recent dry years (e.g., 2018) [5, 43]. Statistical analysis indicates a decreasing trend in mean discharges, aligning with its classification as a hydrologically vulnerable region, further corroborated by local reports [44, 45].

Data utilized for the Gidra River study consists of Daily mean discharge (1961–2020): Obtained from SHMI for the Píla gauging station [3]. This extensive dataset, combined with information on water abstractions [3], facilitated the hydrological assessment, classification of hydrological years, and the development of machine learning models for drought forecasting based on early hydrological year discharge data [3, 33].

5. METHODS

5.1. STATISTICAL METHODS

5.1.1. Water-Bearing Coefficient (WBC)

The WBC quantifies a year's hydrological status by comparing its annual mean discharge (Q_m) to the long-term average discharge (Q_a) over a reference period [3, 15, 47]. It is calculated as:

$$WBC = \frac{Q_m}{Q_a} \times 100\% \quad (4.1)$$

The resulting percentage classifies the year based on standard intervals, indicating conditions from extreme drought to extreme wetness (Table 4.1).

Table 4.1. Hydrological Status Classes According to WBC [Adapted from 3, 15, 47]

Standard Intervals (%)	Hydrological Situation
10 – 29	Extreme Drought
30 – 49	Severe Drought
50 – 69	Moderate Drought
70 – 89	Mild Drought
90 – 110	Normal
111 – 130	Mild Wet
131 – 150	Moderate Wet
151 – 170	Severe Wet
171 – 180	Extreme Wet

5.1.2. Streamflow Drought Index (SDI)

The Streamflow Drought Index (SDI) is utilized to assess the severity of hydrological drought by normalizing streamflow data relative to their long-term statistical properties [14, 47, 48]. The process involves calculating cumulative monthly streamflow volumes $V_{i,k}$ for defined reference periods (k, such as 3, 6, or 12 months) within each hydrological year (i). The SDI value is then derived by standardizing these cumulative volumes against their long-term mean $\overline{V_k}$ and standard deviation Sk, as shown in Equation 4.2:

$$\mathrm{SDI}_{i,k} = \left(V_{i,k} - \overline{V_k}\right)/S_k. \quad (4.2)$$

Negative SDI values signify drier-than-average conditions, while positive values indicate wetter conditions. Drought severity is classified based on the SDI value using standardized ranges, presented in Table 4.2.

Table 4.2. Hydrological Drought Classification based on SDI [14]

State	Drought Level	SDI Range
0	Non-Drought	SDI ≥ 0.0
1	Mild Drought	–1.0 ≤ SDI < 0.0
2	Moderate Drought	–1.5 ≤ SDI < –1.0
3	Severe Drought	–2.0 ≤ SDI < –1.5
4	Extreme Drought	SDI < –2.0

5.1.3. Seasonal Decomposition Method

Time series decomposition is applied to partition hydrological data (y_t) into its underlying components: Trend (T_t) Seasonality (S_t), and Residual (R_t) This is often expressed using an additive model [50, 51], as shown in Equation 4.3:

$$y_t = T_t + S_t + R_t \quad (4.3)$$

While classical methods exist, this study utilizes modern techniques like STL (Seasonal and Trend decomposition using Loess). STL employs iterative local polynomial regression (Loess smoothing), offering enhanced flexibility and robustness, particularly for capturing non-linear trends or time-varying seasonality [49, 50, 51]. The decomposition aids interpretation (Figure 4.1). The Trend component highlights long-term shifts (e.g., climate change influence), the Seasonal component reveals regular intra-annual patterns (e.g., spring melt, dry seasons), and the Residual component isolates short-term irregularities, noise, or extreme events like flash floods [49, 50-52]. Standard statistical software packages facilitate this analysis [52].

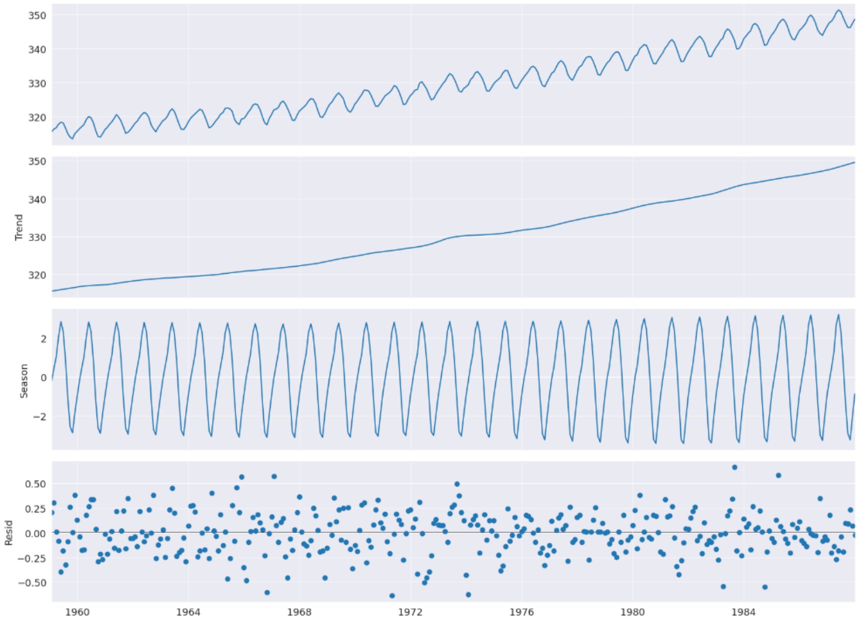

Figure 4.1 Example of Seasonal Decomposition using STL

5.2. Machine Learning Methods

Machine learning (ML) provides powerful techniques for hydrological assessment and prediction, excelling at identifying complex, nonlinear patterns within hydrological data, often surpassing traditional statistical models in forecasting accuracy [1, 2].

5.2.1. Artificial Neural Networks (ANNs) / Multilayer Perceptrons (MLPs)

ANNs are computational systems inspired by biological neural networks, adept at learning intricate relationships directly from observational data like precipitation, streamflow, and climate variables [1-5, 54, 57, 62]. The Multilayer Perceptron (MLP), a common type of feed-forward ANN, features an architecture comprising an input layer, one or more hidden layers, and an output layer (Figure 4.2). Neurons within the hidden and output layers process information by computing a weighted sum of their inputs, adding a bias, and applying a nonlinear activation function (such as sigmoid, ReLU, or tanh) [53]. This layered, nonlinear processing enables ANNs/MLPs to approximate complex functions effectively, making them suitable for diverse hydrological tasks including rainfall-runoff modelling and flow forecasting [1-5, 54, 58, 62].

Training is typically performed using supervised learning, most commonly with the backpropagation algorithm. This iterative process involves propagating input data forward through the network to generate predictions, calculating the error between predictions and actual observations (e.g., using Mean Squared Error), and then propagating this error backward to compute gradients. Network weights and biases are adjusted based on these gradients, often using optimization algorithms like gradient descent or more advanced methods such as Adam, to progressively minimize the prediction error [53, 54, 55, 56].

Key challenges associated with ANNs/MLPs include the empirical nature of selecting an optimal architecture (number of layers and neurons), their characteristic 'black box' behavior which can hinder interpretability (although methods like SHAP or LIME aim to mitigate this), and the potential for significant computational demands during training and hyperparameter optimization [1, 4, 57]. Nevertheless, their demonstrated capacity for modelling complex hydrological dynamics renders them indispensable tools in contemporary hydrology [5, 54].

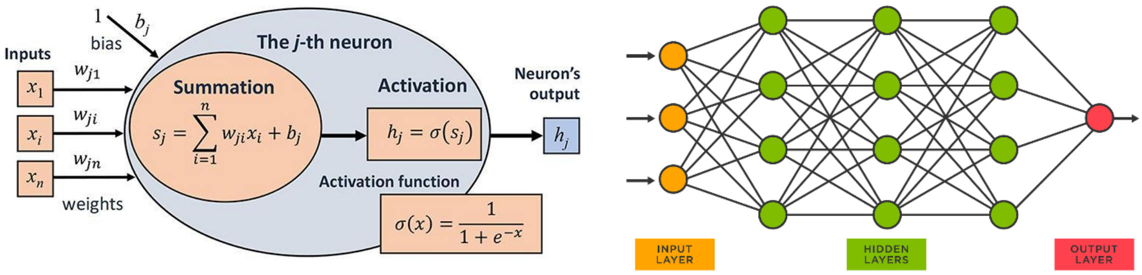

Figure 4.2 Example of the caculations in a single neuron (Left), The architecture of an *MLP model (Right) [19]*

5.2.2. Support Vector Machines (SVM)

Support Vector Machines (SVMs) are supervised learning algorithms effective for both classification and regression tasks, particularly with high-dimensional data, finding use in applications like flood risk assessment and drought classification [59, 60]. In binary classification (e.g., distinguishing between "flood" and "no-flood" conditions), the fundamental idea is to identify an optimal hyperplane that separates the data points of the two classes with the largest possible margin [59]. The data points lying closest to this hyperplane, on the edge of the margin, are termed "support vectors" as they critically define the boundary's position (Figure 4.3).

To accommodate data that cannot be perfectly separated by a linear boundary, SVMs employ two key strategies. First, the 'soft margin' formulation introduces slack variables and a regularization parameter (C) that permits some data points to be misclassified or fall within the margin, providing robustness to noise and outliers [59, 60]. Second, for intrinsically nonlinear relationships, the 'kernel trick' is used. This technique implicitly maps the original input data into a higher-dimensional feature space using a kernel function (common examples include Polynomial or Radial Basis Function (RBF)/Gaussian kernels), where a linear separation might be feasible. This allows SVMs to model complex, nonlinear decision boundaries without the computational burden of explicit high-dimensional mapping [59, 60].

The Support Vector Regression (SVR) adaptation extends SVM principles to predict continuous variables, such as streamflow discharge. SVR aims to find a function such that the majority of data points fall within a predefined margin of tolerance (the 'epsilon-insensitive tube') around the function, balancing model complexity and prediction error [60].

SVMs offer advantages like good generalization performance, effectiveness in high dimensions, and a solid theoretical basis that often guarantees a unique, optimal solution. However, their performance is sensitive to the choice of the regularization parameter (C) and kernel parameters (e.g., gamma in the RBF kernel), necessitating careful tuning, often via cross-validation. Training complexity can be high for very large datasets, and interpreting the learned model in terms of physical processes can be challenging [59-61]. Despite these considerations, SVMs remain valuable for threshold-based hydrological classification and regression problems [1-3].

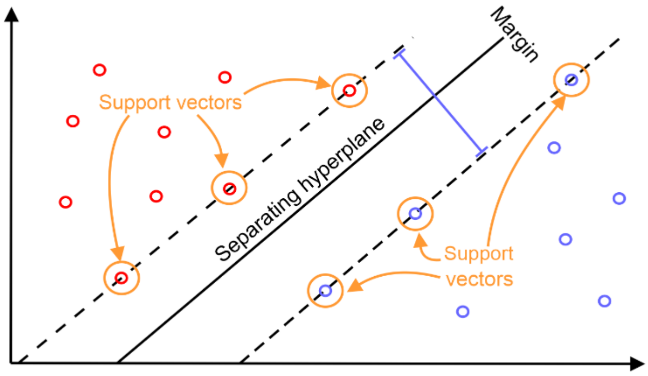

Figure 4.3 Illustration of a 2D Hyperplane and Support Vectors in a Support Vector Machine (SVM)

5.3. Deep Learning Methods

Deep learning (DL) techniques are increasingly prominent in hydrological science, offering sophisticated tools capable of learning hierarchical features and complex temporal or spatial dynamics directly from large datasets. DL models enhance predictive accuracy for challenging tasks such as flood and drought forecasting, extreme event analysis, and interpreting remote sensing data [1-6].

5.3.1. Recurrent Neural Networks (RNNs) and Variants (LSTM, GRU)

RNNs are neural networks specifically architected for processing sequential data, making them inherently suitable for hydrological time series forecasting where the sequence of past events (e.g., rainfall, discharge) influences future outcomes [1, 2, 4, 6, 55, 64]. Standard RNNs utilize recurrent connections that create an internal memory (hidden state) to capture temporal dependencies. However, they often suffer from the vanishing or exploding gradient problem, limiting their ability to learn dependencies over long time intervals [6, 64].

Advanced RNN architectures like Long Short-Term Memory (LSTM) [63] and Gated Recurrent Units (GRUs) [1] were specifically designed to mitigate these issues. They incorporate gating mechanisms within their recurrent cells (an LSTM unit is depicted in Figure 4.4) that regulate the flow of information. These gates enable the network to learn which information to retain over long periods and which to discard, proving effective for modelling processes with extended temporal dependencies, such as drought development or seasonal streamflow patterns [1, 63]. LSTMs employ input, forget, and output gates, while GRUs use a simplified structure with update and reset gates, potentially reducing computational cost [1].

These models have proven highly effective in applications like flood forecasting (leveraging historical discharge and precipitation), drought monitoring and classification (analyzing long-term hydrological indicators), and forecasting reservoir inflows [1, 2, 4, 6]. Their primary strength lies in capturing long-term temporal patterns. Drawbacks include higher computational costs, sensitivity to hyperparameter choices, and inherent challenges in interpretability [1, 4, 6, 64]. Effective application often requires careful data preprocessing (e.g., normalization), appropriate sequence length selection, regularization techniques (like dropout) to avoid overfitting, and the use of explainability tools (e.g., SHAP) to gain insights into model behavior [1, 4, 6, 57, 64].

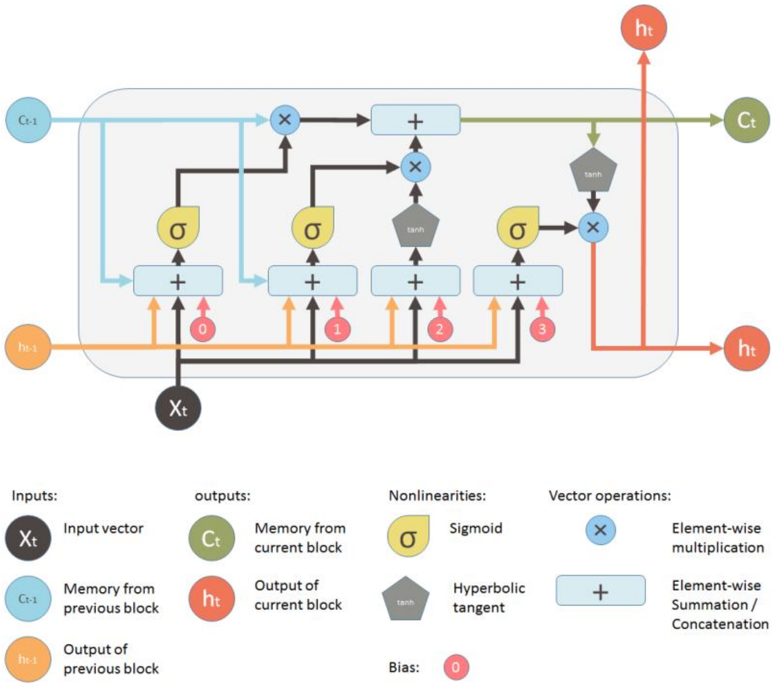

Figure 4.4 Architecture of a Long Short-Term Memory (LSTM) unit

5.3.2. Convolutional Neural Networks (CNNs)

CNNs are deep learning models originally developed for image analysis, excelling at identifying spatial hierarchies and patterns within grid-like data structures. This makes them highly applicable to hydrological problems involving spatial data, such as analyzing precipitation maps derived from radar or satellite, mapping flood extents from imagery, or utilizing digital elevation models [1, 2, 65-69]. A typical CNN architecture (example in Figure 4.5) includes layers specifically designed for spatial processing: convolutional layers apply learnable filters to detect local features; pooling layers reduce spatial dimensions and provide translational invariance; and fully connected layers integrate spatial features for final prediction or classification.

The core components are the convolutional layers, which use filters (kernels) to scan the input and extract relevant spatial features (e.g., patterns indicating high rainfall intensity or specific land cover types). A key advantage is parameter sharing: the same filter is applied across the entire input, drastically reducing the number of parameters compared to fully connected networks and improving efficiency for large spatial inputs [65, 62, 70]. Pooling layers (e.g., max pooling) summarize features in local regions, making the model more robust to variations in feature location [66-67, 62, 70].

CNNs can be adapted for different data structures: 1D CNNs are used for time series analysis (detecting temporal patterns), 2D CNNs are standard for spatial maps (e.g., rainfall images), and 3D CNNs can process spatio-temporal data (e.g., tracking flood evolution over time) [66-67, 62]. Common hydrological applications include flood mapping and prediction using remote sensing data, short-term precipitation forecasting (nowcasting), and regional flood susceptibility mapping based on geographic and climatic data [1, 2, 66-67, 62].

The strengths of CNNs include their powerful spatial feature extraction capabilities, computational efficiency due to parameter sharing, and robustness. However, they typically require large amounts of labeled data for training, can be difficult to interpret directly ('black box' issue), and training deep CNNs remains computationally demanding [1, 57, 65, 62]. Best practices involve careful design of network architecture (e.g., kernel sizes), applying regularization methods, and utilizing interpretability techniques (like saliency maps) to understand model decisions [68].

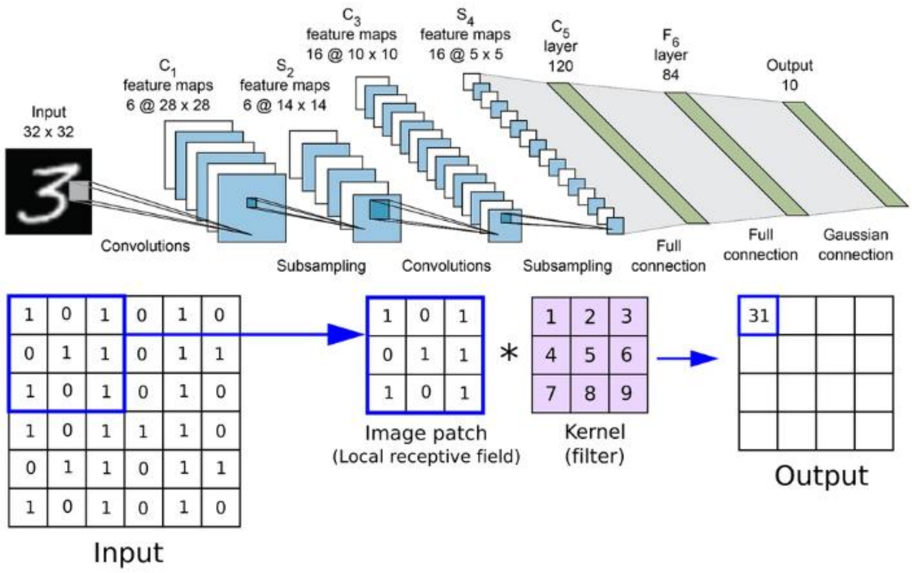

Figure 4.5 Example Architecture of a Convolutional Neural Network

5.4. TRANSFORMERS AND ATTENTION-BASED MODELS

Transformers and attention mechanisms, originally developed for natural language processing and computer vision, have demonstrated considerable potential in hydrological forecasting. Their ability to capture long-range temporal dependencies effectively and utilize parallel computation makes them promising alternatives to traditional sequential models for analyzing time series like streamflow and precipitation [1, 71-77]. Studies applying these techniques to tasks such as rainfall-runoff modelling and streamflow projection often report improved performance compared to conventional methods [1, 72, 76].

5.4.1. ATTENTION MECHANISMS

Attention mechanisms fundamentally allow a model to dynamically weight the importance of different parts of the input data when generating an output. This selective focus helps overcome the limitations of fixed-length context windows or decaying memory in sequential models, particularly for capturing long-range interactions [1, 71]. The mechanism typically operates by computing compatibility scores between a 'query' (representing the current focus) and multiple 'keys' (representing elements in the input sequence). These scores are converted into weights (often via softmax normalization), which are then used to compute a weighted sum of corresponding 'values' (representing the content of input elements) [71, 72].

Self-Attention: In self-attention, the queries, keys, and values are all derived from the same input sequence through learned linear transformations. This allows each element in the sequence to attend to every other element, calculating attention weights based on pairwise similarity (e.g., using scaled dot-products, as illustrated conceptually in Figure 4.6). The output for each element is a context-aware representation formed by the weighted sum of values from the entire sequence, enabling direct modelling of relationships regardless of distance [71-73].

Attention Variants (Figure 4.6): While standard self-attention (Full Attention) considers all pairwise interactions, its quadratic computational complexity ($O(T^2)$) can be prohibitive for long sequences. Variants like Sparse Attention reduce complexity by limiting connections to selected pairs, while LogSparse Attention uses exponentially spaced connections to efficiently capture both local and global dependencies ($O(T \log T)$). Auto-Correlation Attention specifically leverages time series periodicity to focus on relevant lagged correlations [72]. Since attention mechanisms are permutation-invariant, positional encodings are essential to provide the model with information about the sequence order [74]. Attention models offer significant advantages, including improved accuracy through data-driven weighting and the ability to handle complex temporal dependencies effectively [4, 72, 74-77].

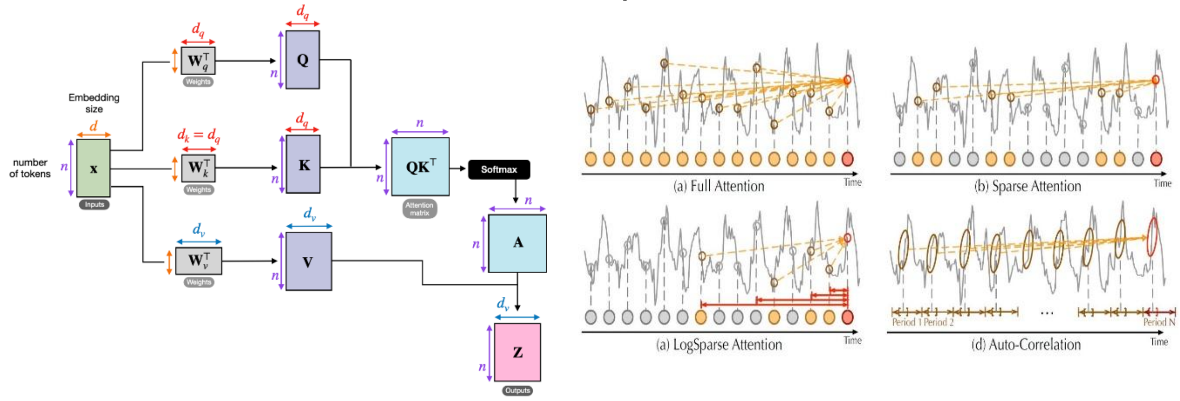

Figure 4.6 Conceptual Illustration of Self-Attention Calculation (Left) and Illustration of Different Attention Patterns (Right)

5.4.2. TRANSFORMERS

The Transformer architecture [71], introduced initially for machine translation, replaces recurrence entirely with attention mechanisms, primarily self-attention. This design facilitates parallel processing across the sequence and enhances the capture of long-range dependencies compared to models like LSTMs [1, 4].

Architecture Overview (Figure 4.7): A standard Transformer comprises an encoder and a decoder. The encoder processes the input sequence using stacked layers, each containing a multi-head self-attention module (allowing attention to different aspects of the sequence simultaneously) and a position-wise feed-forward network. The decoder generates the output sequence autoregressively, employing self-attention on the previously generated outputs (masked to prevent seeing future tokens) and cross-attention to focus on relevant parts of the encoder's output. Positional encodings are added to the input to retain sequence order, and residual connections and layer normalization help stabilize training [71].

Application to Time Series Forecasting: Transformers are adapted for forecasting using sequence-to-sequence frameworks, where the encoder maps historical data to a representation used by the decoder to predict future values step-by-step (using masking) [75]. Encoder-only architectures can also be used for direct multi-step forecasting [76]. Auxiliary variables (e.g., meteorological data) can be integrated alongside the main time series [77]. For very long hydrological time series, efficient attention variants like Sparse, LogSparse, or specialized models like the Autoformer are often employed [72].

Advantages and Challenges: Transformers excel at modelling long-range dependencies and capturing complex patterns through multi-head attention. Their parallel nature allows for faster computation than sequential RNNs. They offer flexibility in incorporating various data inputs [1, 4, 72, 74, 76]. However, the standard self-attention mechanism has quadratic complexity with sequence length, potentially limiting applicability to extremely long series (though variants mitigate this). Transformers typically require substantial data for training and can be prone to overfitting without careful regularization. Interpretability, while aided by visualizing attention weights, remains a challenge compared to simpler models [1, 4, 72, 76].

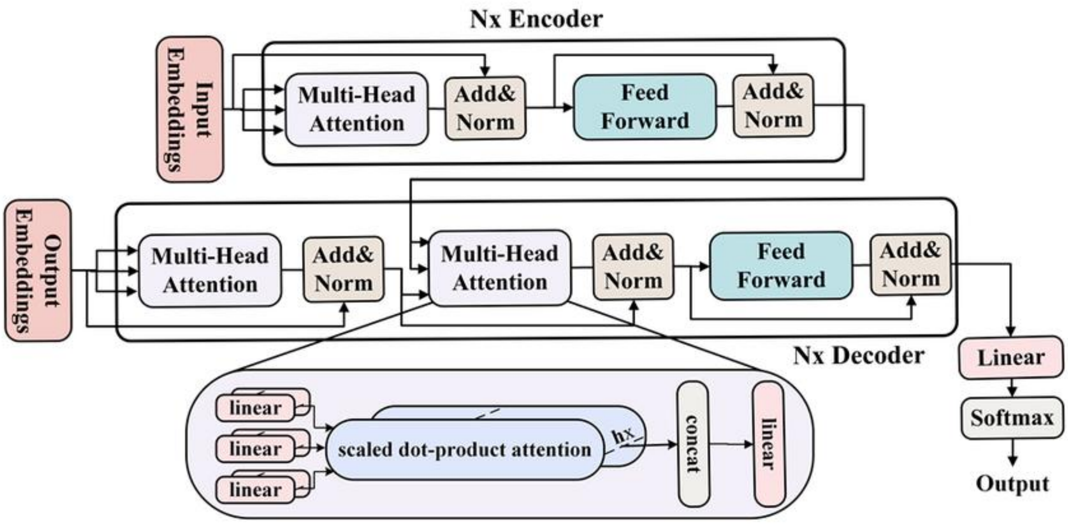

Figure 4.7 Architecture of the Transformer Model

6. RESULTS AND ANALYSIS

6.1. HYDROLOGICAL DROUGHT ASSESSMENT

The WBC, comparing annual mean discharge (Q_m) to the long-term average (Q_a), was used to classify hydrological years [3, 47]. Analysis of the 2010-2020 period (Table 5.1) revealed predominantly dry conditions for both rivers. The Gidra River experienced 7 dry, 3 wet, and 1 normal year, with WBC values ranging from 35% to 186%. This aligns with its documented long-term decreasing discharge trend (Fig. 5.1) and vulnerability. The Topľa River showed 7 dry, 2 wet, and 2 normal years, with a WBC range of 62% to 197%. The Gidra exhibited more severe drought conditions (lower minimum WBC), and both rivers had notably few normal years during this recent decade, consistent with regional observations [5]. A longer analysis of the Topľa River (1988–2020) using WBC identified 18 dry, 7 normal, and 8 wet years (Fig. 5.2). The most severe drought occurred in 2003, matching regional reports [5, 48, 83, 84]. While a relatively wetter period occurred from 2004–2010, the overall pattern indicates vulnerability to prolonged dryness. Comparing drought classifications for the Topľa (1988-2020) using SDI (based on monthly flows) and WBC revealed differences (Table 5.2). SDI classified 59% of years as mild drought and 41% as non-drought, failing to identify more severe conditions. WBC yielded similar overall proportions (57% dry vs 44% normal/wet) but distinguished between mild (41%) and moderate (16%) drought. This highlights the sensitivity of classification to the chosen index, aggregation level (monthly vs. annual), and threshold definitions [48, 83]. The prevalence of dry conditions underscores the need for adaptive water management strategies informed by multiple drought indicators [3, 5, 48, 84].

Table 5.1. Hydrological drought assessment of Topľa and Gidra rivers (2010–2020)

	Gidra River			Topľa River		
year	Qm	Qm/ Qa	Status	Qm	Qm / Qa	Status
2010	0.55	186%	Wet	5.86	197%	Wet
2011	0.38	127%	Wet	2.44	82%	Dry
2012	0.15	51%	Dry	1.84	62%	Dry
2013	0.35	117%	Wet	2.53	85%	Dry
2014	0.24	80%	Dry	2.98	100%	Normal
2015	0.30	102%	Normal	2.27	76%	Dry
2016	0.22	74%	Dry	2.63	88%	Dry
2017	0.11	35%	Dry	3.33	112%	Wet
2018	0.15	50%	Dry	2.11	71%	Dry
2019	0.21	72%	Dry	2.76	93%	Normal
2020	0.25	85%	Dry	2.54	85%	Dry

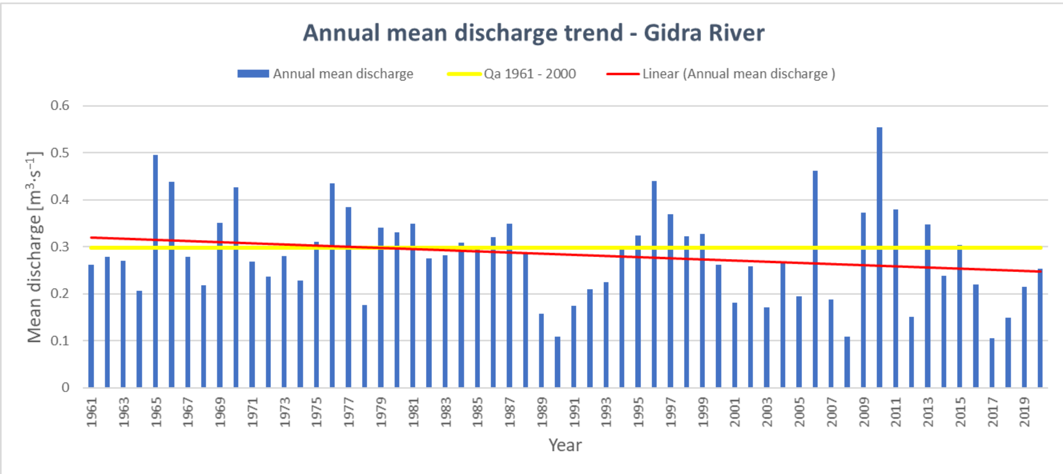

Figure 5.1 Gidra Annual Discharge Trend

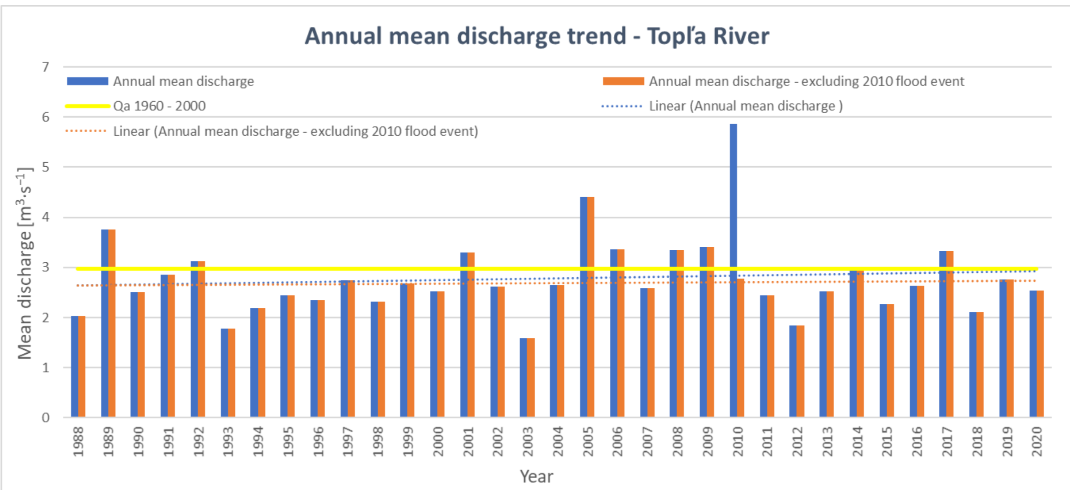

Figure 5.2 Topľa Annual Discharge Variability

Table 5.2. Comparison of Drought Frequency/Severity (SDI vs. WBC) for Topľa River (1988–2020)

Drought Characteristic	Period of Study (years)	SDI Frequency	SDI % Occurrences	WBC Frequency	WBC % Occurrences
Non-Drought	32	13	41%	14	44%
Mild Drought	32*	19	59%	13	41%
Moderate Drought	32*	0	0%	5	16%
Severe Drought	32*	0	0%	0	0%
Extreme Drought	32*	0	0%	0	0%

6.2. Seasonality Analysis using STL Decomposition

Seasonal discharge patterns were investigated using STL decomposition applied to the logarithm of daily discharge data [49, 79]. Comparison between the Gidra and Topľa rivers showed distinct annual cycles (Figure 5.3). The Topľa River exhibits a primary discharge peak in mid-April (associated with spring snowmelt), potential secondary peaks influenced by summer storms, and minimum flows in autumn. The Gidra River, characteristic of a foothill stream, displays an earlier peak (February–early April), a more pronounced decline through summer leading to an August/September minimum, followed by a gradual recovery in late autumn/winter [3, 5, 49].

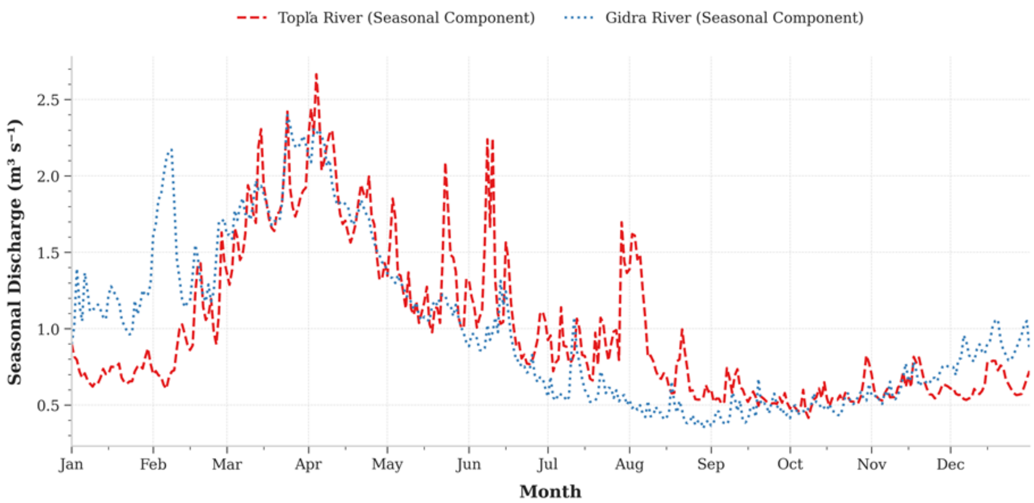

Figure 5.3 Comparison of seasonal discharge components between Gidra and Topľa rivers.

Analysis of the Topľa River's seasonality across different hydrological conditions (dry, normal, wet years from 1988–2020) revealed significant variations (Figure 5.4). While the general pattern is dominated by a spring snowmelt peak, dry years show a sharper decline in summer and autumn. Normal years feature distinct secondary peaks suggesting different precipitation timings. Wet years exhibit notably higher peaks in April and June, reflecting amplified runoff from snowmelt and/or storm events. These findings illustrate that seasonal dynamics are strongly modulated by the overall hydrological state and support the notion of a regional shift towards drier conditions affecting long-term patterns [49, 79, 80].

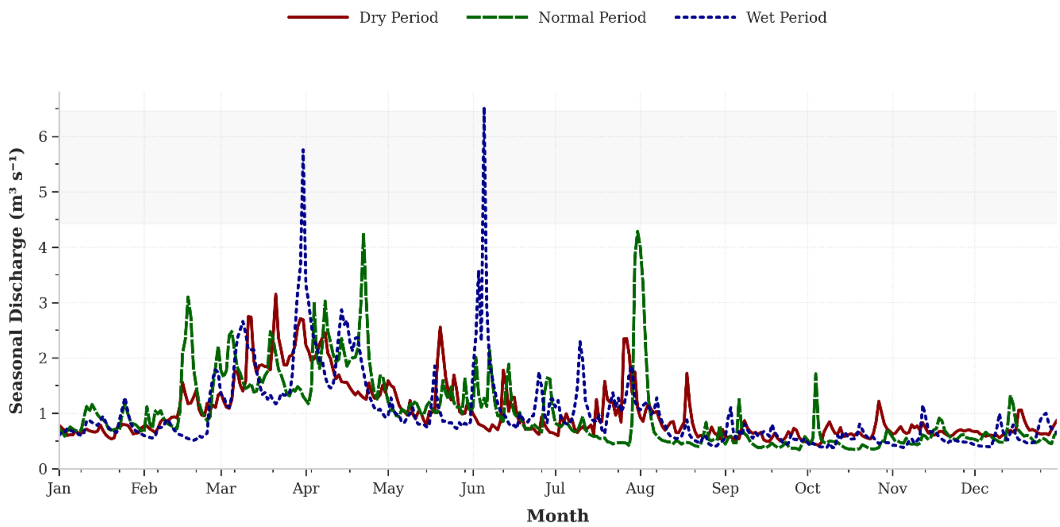

Figure 5.4 Comparison of seasonal discharge components of the Topľa River across different hydrological situations

6.3. DROUGHT FORECASTING USING MACHINE LEARNING

A primary goal of this research component was to develop reliable data-driven models for early-warning prediction of annual hydrological drought conditions in both the Gidra and Topľa rivers. These models utilize hydro-meteorological data from the initial months of the hydrological year to classify the likely overall status (dry vs. normal/wet) for the entire year.

Gidra River (SVM & ANN Models): For the Gidra River, Support Vector Machine (SVM) and Artificial Neural Network (ANN) models were trained to distinguish between 'dry' and 'non-dry' years, where the classification was based on the Water-Bearing Coefficient (WBC) [3]. The models used daily discharge data from the first 120 days (January-April) of each year as predictive inputs. A linear SVM was chosen for its interpretability, while a multi-layer ANN was employed to capture potentially complex nonlinear relationships. Using data from 1961–2018 (trained on 1961–2000, tested on 2001–2018) preprocessed with robust scaling, both models demonstrated perfect classification accuracy on the 18-year test period. This perfect performance, indicating zero false positives or negatives, is visually confirmed by the confusi on matrices (Figure 5.5) and was further corroborated using partial data from 2019 and 2020 [3].

Topľa River (MLP Model with SMOTE): For the Topľa River, a Multi-Layer Perceptron (MLP) model was developed to predict the annual status ('dry' vs. 'normal') based on the full-year Streamflow Drought Index (SDI) classification [78]. This model utilized daily discharge, water level, and temperature data from the first 183 days (October–March) as inputs. The dataset spanned 1989–2020, with training conducted on 1989–2010 data and testing on 2010–2020 data. Recognizing the limited size of the training dataset (21 years), the Synthetic Minority Over-sampling Technique (SMOTE) was applied exclusively to the training set after the train-test split. This balanced the class distribution and increased the effective training data size without introducing data leakage from the test set. Input features were standardized prior to modelling. The multi-input MLP achieved perfect classification accuracy on the 10-year test set, successfully predicting the status for all years, including identifying six drought years and four normal years. This result was also validated using partial 2019/2020 data, and the perfect test accuracy is shown in the confusion matrix (Figure 5.5) [78].

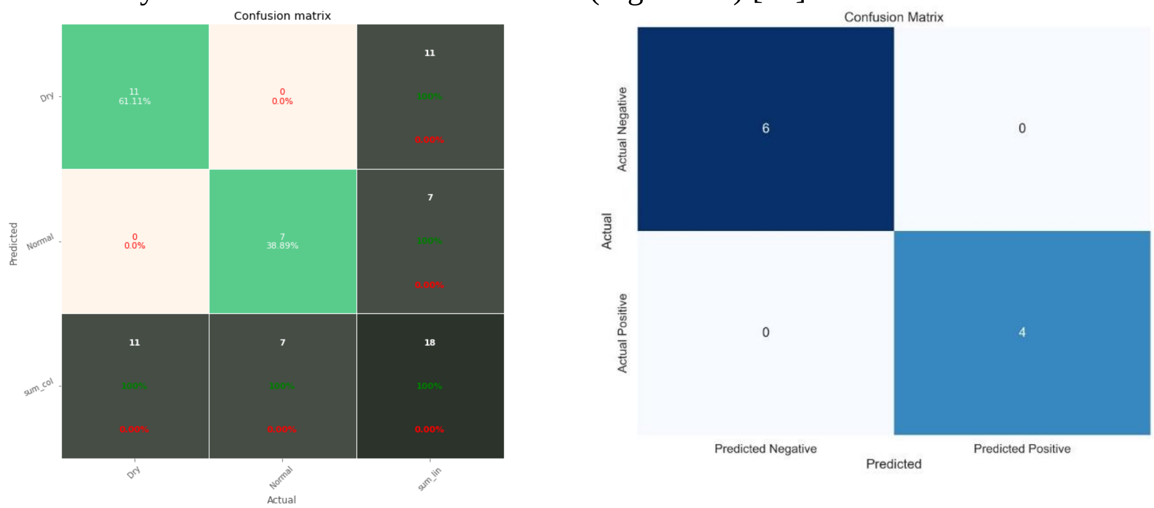

Figure 5.5 Confusion Matrices for SVM and ANN model testing (Gidra River, 2001–2018) (Left) and Confusion Matrix for MLP model testing (Topľa River, 2010–2020) (Right)

Significance and Future Directions: The exceptional predictive performance of these models highlights the feasibility of using machine learning for effective early warning of hydrological drought in these Slovakian river basins. By leveraging data available several months in advance, these tools can provide crucial lead time for proactive water resource management decisions, such as optimizing reservoir releases or planning agricultural water use [3, 78]. Future research could explore the integration of additional meteorological inputs (e.g., precipitation forecasts, snowpack data) to potentially further improve predictive accuracy and extend the forecast horizon. These findings strongly support the integration of advanced computational techniques into operational hydrology for enhanced resilience against drought impacts.

6.4. Flood Forecasting with Hydro-Informer

To address the complexities of accurate flood forecasting, a novel deep learning model, Hydro-Informer, was developed. This model is designed to predict water levels by effectively capturing intricate spatiotemporal dependencies within hydrological data streams (including precipitation, discharge, and historical water levels). A central challenge during development was to create a model that generalizes well across diverse hydrological conditions, accurately predicting both typical fluctuations and extreme flood events, while remaining computationally tractable for potential operational use.

6.4.1. Hydro-Informer Architecture Overview

Hydro-Informer utilizes a sophisticated encoder-decoder framework integrating several deep learning components tailored for hydrological time series [81]:

Input Processing: Input data streams are initially processed through embedding layers to create higher-dimensional representations, facilitating the learning of interactions. These embedded inputs are then concatenated and scaled to ensure numerical stability and balanced feature influence during training.

Hydro Encoder (Feature Extractor): The encoder module processes a window of historical data (e.g., the past 36 hours) to extract and encode relevant patterns. Its key components work synergistically:

- Convolutional 1D (Conv1D) Layers: Detect local temporal features, such as rapid changes or short-term trends.
- Spatial Dropout: Improves model generalization by preventing over-reliance on specific input features.
- Bidirectional GRU/LSTM Layers: Capture short- and long-term temporal dependencies by processing the input sequence in both forward and backward directions.
- Multi-Head Self-Attention: Enables the model to simultaneously weigh the importance of different segments and features within the input sequence.
- Gating Mechanisms: Selectively control information flow, emphasizing critical signals.
- Residual Connections & Layer Normalization: Facilitate stable training of the deep network architecture.

The encoder produces a condensed, context-aware representation of the historical hydrological state.

Hydro Decoder (Prediction Generator): The decoder uses the representation generated by the encoder to produce the future forecast (e.g., water levels for the next 12 hours). Its primary mechanisms include:

- Multi-Head Cross-Attention: Allows the decoder, at each forecast step, to dynamically focus on the most pertinent parts of the encoded historical sequence provided by the encoder.
- Time-Distributed Dense Layers: Generate predictions for each future time step (e.g., hourly forecasts) independently, ensuring that the output structure matches the desired forecast horizon while leveraging the comprehensive context provided by the attention mechanisms.
- The final output layer synthesizes this information into the structured water level forecast.

This integrated architecture enables Hydro-Informer to process multi-variable inputs, model dependencies across various time scales, and generate precise, actionable forecasts for flood management and early warning [81].

6.4.2. HYDRO-INFORMER TRAINING AND OPTIMIZATION

The training methodology for Hydro-Informer was specifically tailored to enhance its reliability for flood forecasting, employing several key strategies [81]:

- Custom Loss Function: A bespoke loss function was developed to prioritize the accurate prediction of extreme water levels. This function imposed substantially higher penalties for underestimating water levels above critical flood thresholds (e.g., 200 cm), compelling the model to be more sensitive to high-risk situations compared to standard loss functions like Mean Squared Error.
- Ladder Training: Training was conducted in four progressive phases, constituting a "ladder" approach. Each phase refined the model's predictions over increasingly higher water level ranges, starting with low flows and systematically improving performance up to extreme flood conditions. This structured approach enabled the model to learn effectively across the full spectrum of hydrological variability.
- Hyperparameter Tuning & Regularization: The Adam optimizer with learning rate decay was utilized for efficient convergence. A batch size of 16 was employed, with 10% of the training data reserved for validation. To mitigate overfitting, essential

given the model's complexity (incorporating LSTM, GRU, Conv1D, and Attention layers), multiple regularization techniques were applied, including spatial dropout, L2 regularization, early stopping based on validation loss, and model checkpointing to retain the best-performing iteration.

6.4.3. HYDRO-INFORMER PERFORMANCE EVALUATION

The predictive capability of the trained Hydro-Informer model was thoroughly evaluated on an independent test dataset using a suite of standard performance metrics (Table 5.3) [81].

Table 5.3 Hydro-Informer Performance Metrics Summary.

Metric	Value
Mean Squared Error (MSE)	18.0704
Root Mean Squared Error (RMSE)	4.2509
Mean Absolute Error (MAE)	1.8226
Mean Absolute Percentage Error (MAPE)	1.11%
Coefficient of Determination (R^2)	0.8785
Mean Squared Logarithmic Error (MSLE)	0.0005
Root Mean Squared Logarithmic Error (RMSLE)	0.0227
Symmetric Mean Absolute Percentage Error (sMAPE)	13.30%

The results demonstrate strong overall performance. Low absolute errors (RMSE ≈ 4.25 cm, MAE ≈ 1.82 cm) and low mean absolute percentage error (MAPE ≈ 1.11%) indicate high accuracy in predicting water levels. A high coefficient of determination ($R^2 \approx 0.88$) confirms that the model captures a significant portion of the observed variance. Low logarithmic error metrics (MSLE, RMSLE) further suggest reliable performance across different water level magnitudes.

However, the relatively higher Symmetric Mean Absolute Percentage Error (sMAPE ≈ 13.30%) points towards areas where relative error could be improved, potentially during low flow periods or rapid transitions. Visual inspection of prediction quality supports these quantitative findings. A scatter plot of predicted versus actual water levels (Figure 5.7) shows a strong correlation but reveals some instances of underestimation, particularly for higher water levels, despite the custom loss function's intent. The time series plot (Figure 5.8) illustrates that the model tracks actual water levels closely under normal conditions, with most observations falling within the confidence interval, but shows larger deviations during extreme peak events. Encouragingly, the model successfully identified nearly all major flood events exceeding 300 cm, with exceptions potentially attributable to data anomalies [81].

In conclusion, the Hydro-Informer model, benefiting from its advanced architecture and specialized training regimen, achieves robust predictive performance for hydrological forecasting. While highly accurate overall, the evaluation identifies the need for continued refinement, particularly concerning the prediction of extreme peaks, to maximize its reliability as an operational flood warning tool [81].

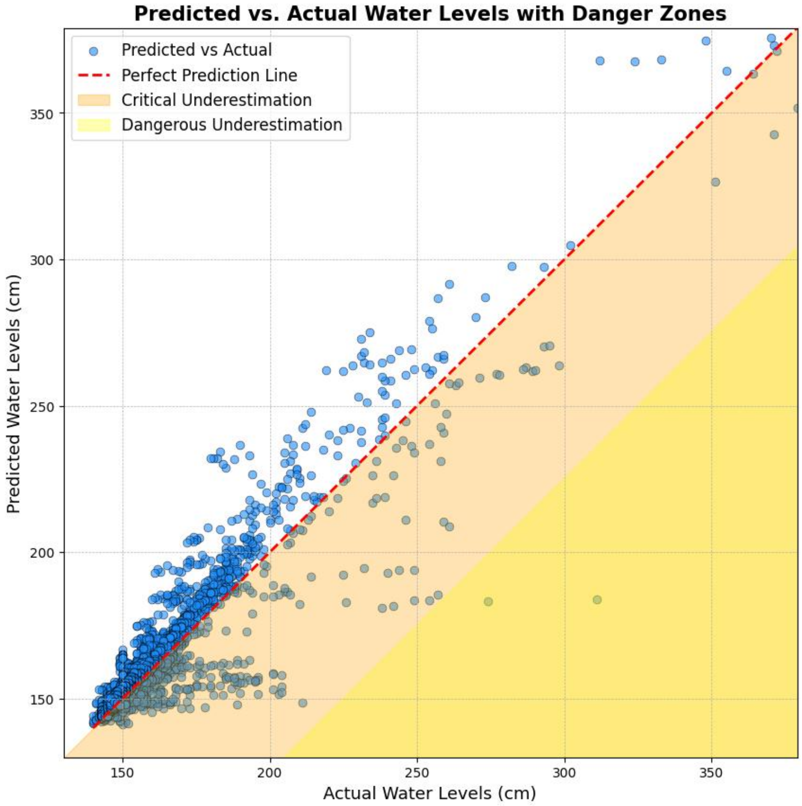

Figure 5.7: Scatter plot of Predicted vs. Actual Water Levels, highlighting danger zones for underestimation

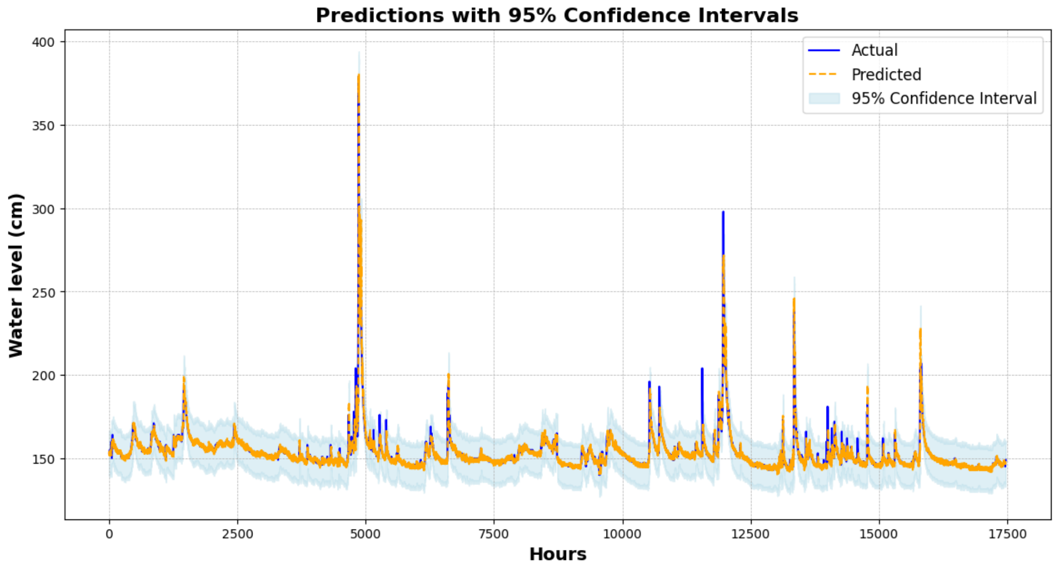

Figure 5.8: Time series comparison of Actual Water Levels (blue) vs. Predicted Water Levels (orange) with confidence intervals

6.4.4. PERFORMANCE ON EXTREME PEAK PREDICTIONS

The ultimate test of a flood forecasting model lies in its performance during extreme events. Hydro-Informer's ability to predict the magnitude and timing of the highest flood peaks was specifically evaluated using the three most significant peaks within the test dataset. Performance was measured by Δ Peak Value (the difference between actual and predicted peak magnitude) and Δ Time (the lead time achieved by the prediction before the actual peak) [81]. The model generates 12-hour forecasts using the preceding 36 hours of input, with forecasts updated every 12 hours.

Analysis of the three major peak events revealed the following key outcomes:

- Peak 1 (Actual Peak ≈ 322 cm): The model prediction was ≈317.21 cm, resulting in a small underestimation (Δ Peak Value = 4.79 cm). Crucially, the prediction provided a lead time of 2 hours (Δ Time = 2 hours) before the actual peak occurred (Figure 5.9).
- Peak 2 (Actual Peak ≈ 280 cm): The prediction was ≈257.92 cm, indicating a significant underestimation (Δ Peak Value = 22.08 cm). However, the model still provided a 1-hour lead time (Δ Time = 1 hour) (Figure 5.9).
- Peak 3 (Actual Peak ≈ 244 cm): The prediction was ≈236.34 cm, a relatively minor underestimation (Δ Peak Value = 7.66 cm). Notably, the model achieved a substantial lead time of 5 hours (Δ Time = 5 hours) for this event (Figure 5.9).

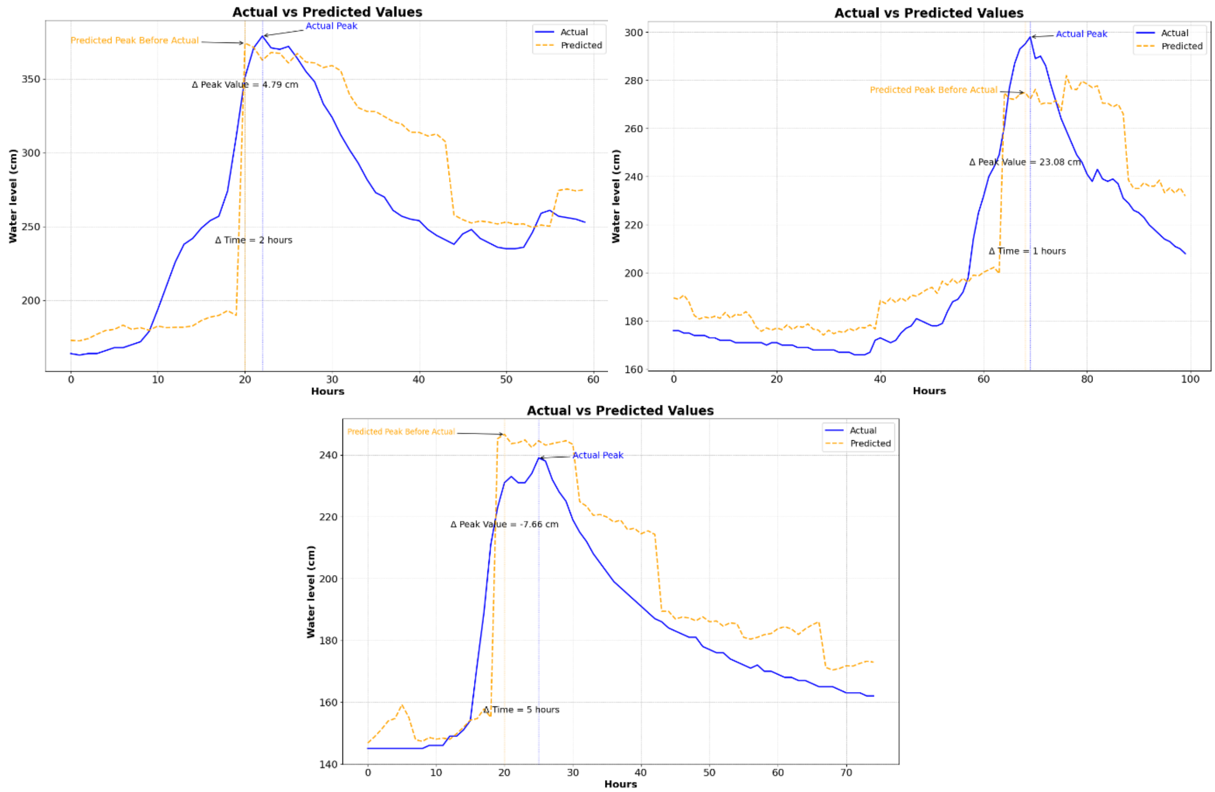

Figure 5.9 Detailed view of Peak Case 1 analysis (Top lift), Detailed view of Peak Case 2 analysis (Top right), Detailed view of Peak Case 3 analysis (Bottom)

These results demonstrate that Hydro-Informer consistently provides valuable early warning lead times (1 to 5 hours) for critical flood peaks. While the accuracy in predicting the exact peak magnitude varied, with one significant underestimation observed, the model's ability to anticipate the timing of these events is a key strength. This analysis suggests that even with advanced architectures and tailored training objectives (like the custom loss function), predicting the precise magnitude of the most extreme, rapidly changing events remains a significant challenge, potentially influenced by factors like input data quality or inherent model limitations. Nonetheless, the consistent positive lead times highlight the model's practical utility for initiating timely flood mitigation and response actions [81].

7. Discussion and Future Work

This dissertation integrates statistical analysis, machine learning (ML), and deep learning (DL) to enhance the understanding and prediction of hydrological processes, specifically drought and flood events, in Slovakia's Gidra and Topľa rivers. The findings contribute valuable insights and tools for water resource management while also illuminating key areas for future research.

7.1. Drought Characterization, Seasonality, and Future Directions

The hydrological assessment using the Water-Bearing Coefficient (WBC) confirmed a concerning prevalence of dry years in both rivers during the 2010-2020 period [5]. This quantitatively supports observations of the Gidra River's vulnerability and decreasing discharge trend (Section 3.4) and suggests a potential shift in the regional hydrological baseline, possibly linked to climate change impacts observed elsewhere in Central Europe [82]. The infrequent occurrence of 'normal' hydrological years presents significant challenges for sustainable water management and ecosystem health [5]. Comparing drought indices (WBC vs. SDI) for the Topľa River highlighted differing sensitivities to drought severity based on temporal aggregation [83], reinforcing the established best practice of using multiple indicators for comprehensive drought assessment [14, 49]. Future work should focus on developing a composite, multi-index drought characterization system specific to Slovakia, incorporating meteorological (SPI, SPEI) and agricultural (soil moisture) indicators. Furthermore, dedicated studies are needed to disentangle the relative contributions of climate drivers versus local anthropogenic factors (land use, abstractions) to observed drought trends [84].

The seasonal decomposition analysis successfully identified the distinct hydrological regimes of the Topľa (lowland response) and Gidra (foothill response), governed by catchment characteristics [85]. Recognizing these unique seasonal patterns is crucial for optimizing water use and managing ecological flows [3, 5, 49, 79]. Importantly, the analysis revealed significant non-stationarity in the Topľa's seasonal patterns across dry, normal, and wet years, with variations in peak timing and magnitude aligning with expected hydrological responses to anomalous conditions [86]. This non-stationarity implies that management strategies based solely on long-term seasonal averages may be insufficient [49, 80]. Future research should aim for a deeper mechanistic understanding of these seasonal variations by integrating high-resolution meteorological data and utilizing advanced time series techniques (e.g., wavelets) to identify specific drivers, including land-use change impacts.

7.2. Drought Forecasting Capabilities and Future Directions

A key practical achievement was the successful development of ML models (SVM, ANN, MLP) providing accurate early classification of annual drought status for both rivers using only early-season data [3, 78]. The high accuracy suggests robust predictive signals within initial hydrological dynamics. The Gidra models' success with both linear and non-linear approaches indicates potentially distinct class separation [2], while the Topľa MLP model highlighted the value of multi-variable inputs and the effectiveness of SMOTE in addressing limited/imbalanced datasets common in environmental ML [88]. These models offer valuable operational lead times (4-6 months) for proactive drought mitigation [3, 78].

While promising, the "perfect" test accuracy warrants caution and requires validation over longer independent periods and potentially with more granular severity classes. A primary limitation is the reliance on hydrological inputs. Future enhancements must involve incorporating a wider array of predictors, such as meteorological variables, snowpack data, climate model projections, detailed land use, and water abstraction data, potentially within more sophisticated ML frameworks [12, 87]. This could improve robustness, enable drought severity prediction, and help forecast compound events. Testing model transferability and exploring ensemble techniques to quantify uncertainty are also essential next steps [12, 87].

7.3. Flood Forecasting with Hydro-Informer and Future Directions

The Hydro-Informer model showcased the capability of advanced hybrid DL architectures for operational flood forecasting. Its strong overall accuracy (e.g., $R^2 \approx 0.88$) is attributed to the synergistic combination of Conv1D layers, LSTM/GRU units, and Multi-Head Attention mechanisms, effectively capturing complex spatio-temporal dependencies [1, 71, 72, 81], aligning with state-of-the-art hydroinformatics [4]. The model's ability to consistently provide valuable warning lead times (1-5 hours) for extreme flood peaks represents its most significant practical contribution [81].

However, accurately predicting the magnitude of the highest peaks remained challenging, with one instance showing significant underestimation despite the use of a custom loss function. This highlights the persistent difficulty in modelling rare, extreme events, potentially due to data limitations or inherent process stochasticity [89]. While lead times are operationally valuable, magnitude errors necessitate careful interpretation for detailed impact assessments. Future work should prioritize refining peak magnitude predictions through methods like ensemble forecasting, improved data assimilation, or exploring architectures specialized for extremes. Integrating real-time meteorological forecasts (NWP, radar) offers potential to extend lead times considerably [81]. Critically, linking accurate water level predictions with detailed geospatial data (DEMs, land cover) is necessary for dynamic flood inundation mapping and comprehensive risk assessment [90]. While Hydro-Informer surpasses traditional methods [81], further validation and testing its transferability to diverse basins are needed [67, 91, 92].

Several broader research directions are essential for advancing hydrological prediction. Exploring cutting-edge AI, especially Transformer models with various attention mechanisms, holds promise for capturing complex dependencies more effectively [71, 72]. Hybrid models combining process-based knowledge with data-driven AI could enhance interpretability. Reinforcement learning presents opportunities for developing adaptive water management strategies. Foundational to all progress is strengthening data infrastructure—improving quality control, expanding monitoring networks (including remote sensing), establishing accessible national datasets, and developing integrated platforms for model deployment and stakeholder communication. Testing methodologies in diverse global contexts is crucial for ensuring broader applicability and scalability.

In conclusion, this dissertation advances the hydrological understanding and predictive capabilities for the Gidra and Topľa rivers by integrating statistical analysis with bespoke ML and DL models. It provides practical tools for drought and flood management and identifies clear pathways for future research. Continued efforts focusing on multi-index approaches, deeper process understanding, enhanced AI techniques, robust data infrastructure, and operational integration are essential for developing sophisticated and reliable systems to support water resource management and climate resilience in Slovakia and globally.

8. Conclusion

This dissertation addressed the critical need for improved hydrological forecasting in Slovakia's Topľa and Gidra river systems, particularly for predicting drought and flood extremes under increasing climate variability. By strategically integrating traditional statistical methods with modern machine learning (ML) and deep learning (DL) techniques, the research aimed to develop a more accurate, reliable, and actionable forecasting framework. The study successfully met its primary objectives. A comprehensive hydrological assessment characterized the baseline seasonal and long-term streamflow regimes of both rivers. Building upon this, advanced predictive models for hydrological extremes were successfully developed and validated. This includes effective ML models (SVM and ANN) for early drought classification in the Gidra River using initial discharge patterns, and a robust MLP model, enhanced by SMOTE to handle data limitations, for drought forecasting in the Topľa River using multi-variable inputs (discharge, water level, temperature).

A standout achievement of this dissertation is the development, implementation, and validation of the novel Hydro-Informer model for flood forecasting. This sophisticated, Transformer-based deep learning architecture demonstrated significantly enhanced predictive accuracy for extreme water levels in the Topľa River compared to conventional approaches, effectively capturing complex temporal dependencies. The research confirmed that integrating statistical and computational methods improves predictive skill and successfully identified critical early-season hydrological indicators reliable for forecasting annual drought status and impending flood events. This work makes several significant contributions. It bridges traditional statistical hydrology with cutting-edge computational methods, showcasing their synergistic benefits for extreme event prediction. The developed models offer tangible potential for enhanced early warning systems for both droughts and floods in the region, providing valuable lead time for proactive management. Pioneering the application of a Transformer-based model (Hydro-Informer) for water level forecasting in this context highlights the value of adapting advanced AI techniques from other fields to hydrology. Consequently, the findings provide actionable insights for Slovak water resource management policy and practice, supporting adaptive strategies and infrastructure resilience.

The innovative Hydro-Informer model and the successful use of early-season indicators for drought prediction are particularly noteworthy achievements. While acknowledging the inherent limitations imposed by historical data availability and quality, which temper claims of "perfect" prediction, this research provides a strong foundation and demonstrates clear advancements. The methodologies and findings possess potential applicability to other river basins facing similar challenges, contributing to broader climate change adaptation efforts in the water sector. Acknowledging data constraints as a primary limitation, future research, as outlined previously, should focus on integrating diverse data sources (remote sensing, climate projections), exploring more advanced AI architectures, and refining extreme event prediction. Expanding monitoring networks and improving data infrastructure remain crucial foundational steps.

In conclusion, this dissertation makes a substantial contribution by successfully developing and applying an integrated methodological framework that leverages statistical analysis, machine learning, and state-of-the-art deep learning (Transformers) to significantly improve the early prediction of hydrological extremes in the Topľa and Gidra river systems. The research provides valuable tools and insights for water management, demonstrates the power of advanced AI in hydrology, and establishes a strong basis for future work aimed at building more resilient water resource systems in Slovakia and beyond.

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