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Research Paper

Modeling Non-linear Time of Concentration in Heterogeneous Catchments: A Comparative Study of SVR and ANN Machine Learning Approaches

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ABSTRACT

The main objective of this research is to improve the accuracy of estimating the precipitation accumulation time (t_c) in catchments with heterogeneous morphological and hydrological characteristics. The work aims to address the unreliability of traditional empirical models that often ignore the nonlinearity of the runoff process and do not take into account variable parameters such as previous soil moisture content (AMC) and precipitation intensity. The research is based on a comparative analysis of traditional methods (Kirpich, Kinematic Wave) and modern artificial intelligence models. Machine learning algorithms were used: Support Vector Machines (SVR) and Artificial Neural Networks (ANN). The models were trained and tested on datasets that include parameters such as terrain slope, stream length, surface roughness, and variable hydrological factors. Validation was conducted on the Sava River sub-basins, using statistical accuracy indicators. The results of the study show that traditional methods significantly underestimate the accumulation time under conditions of nonlinear hydrological processes, which can lead to erroneous estimates of peak flows. It has been found that soil moisture and terrain saturation dramatically alter the dynamic response of the basin, which fixed empirical models cannot adequately quantify. The scientific contribution of the work is manifested in the introduction of a dynamic approach to determining the concentration time, which abandons the static concept of traditional formulas.

1 Introduction

The time of accumulation of precipitation in the basin (t_c) is defined as the time required for one elementary volume of precipitation or raindrop to reach the measuring or output profile from the farthest point of the basin. The precise determination of the concentration time is fundamental for the use and application of a rational method of calculating the maximum flow (Q_{max}) [1-3].

$$Q_{max} = C \cdot i \cdot A \tag{1}$$

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where is;

Q_{max} – maximum or peak flow
C – runoff coefficient
A – basin area
i – average precipitation intensity for the duration corresponding to the summation time (t_c).

The existing empirical methods that dominate hydrological practice today carry with them certain limitations, because they were developed for certain specific geographical conditions and regions. With increasingly intense climate changes and more complex urbanization of watersheds, there is a real need for more dynamic and adaptable tools for estimating the time of rainfall collection [1, 4].

Rainfall collection time is an often criticized variable in hydrological modeling, especially for the calculation of the maximum flow Q_{max} in small and medium catchment areas. The existing traditional methods of determining the time of rainfall accumulation in the catchment are based on simplified empirical and hydraulic assumptions, while artificial intelligence (AI) tools, especially machine learning, provide a much more sophisticated approach that is able to include non-linearity as well as spatial and temporal variability of the hydrological system.

Traditional methods such as Kirpich's method, Kinematic Wave and SCS method (Soil Conversation Service) have their limitations, which are defined in the following:

- Lack of dynamism, because they cannot adapt to changing conditions of seasonal variations in air temperature or soil moisture.
- Considerable simplification of the geometry, because all methods use the length of the stream and the mean longitudinal slope and thus ignore the transport of runoff and the topographical complexity of the basin.
- Non-acceptance of non-linearity, because hydrological processes are non-linear, and the traditional formulas of the mentioned methods establish linear relationships.

Artificial intelligence (AI) tools provide and offer the possibility of solving the aforementioned limitations by recognizing complex and non-linear relationships between input and output variables (variable quantities). The solution lies in the processing of a large volume of temporal and spatial data in order to obtain realistic values of the rainfall collection time in the basin.

Despite the widespread use of empirical methods such as the Kirpich formula, their application in heterogeneous basins with variable hydrological conditions poses a significant scientific challenge. The key difficulty lies in the inability of linear models to simulate the 'hysteretic effect' of runoff and the dynamic change in flow velocity due to terrain saturation, which often results in underestimating peak flows and compromising the safety of hydraulic structures. In order to overcome these challenges, this paper presents an original methodological approach based on machine learning. Unlike previous research, the achievement of this work is the integration of variable soil moisture parameters (AMC) directly into the architecture of SVR and ANN models. This enables precise mapping of nonlinear time of concentration, turning a static engineering problem into a high-accuracy dynamic system.

This research represents an original contribution to the field of hydrological modeling, addressing a specific gap in the existing literature regarding the non-linear dynamics of concentration time. Unlike conventional studies that rely on simplified empirical formulas, this work introduces a novel hybrid framework by integrating SVR and ANN algorithms. A key innovation of this study is the dynamic inclusion of Antecedent Moisture Conditions (AMC) as a primary variable, coupled with a large-scale validation across the diverse topographical features of the Sava River basin. To the best of the authors' knowledge, this integrated approach to modeling tc in such heterogeneous environments has not been previously established.

2 Material and Methods

The research was conducted in the period from 2023 to 2025. Hydrological and meteorological data were collected from the CMS (Croatian Meteorological Service) database for the period 2003–2025 to provide a robust dataset for model training. The morphological parameters of the basin were extracted using a digital elevation model (DEM) within a GIS environment. The modeling process began with data preprocessing, including normalization of input variables (slope, flow

length, roughness). The experiment was structured to compare the performance of SVR and ANN algorithms. The SVR model uses a Gaussian kernel (RBF) to handle nonlinearities, while the ANN architecture is designed with three hidden layers. Validation was performed using the k-fold cross-validation method to eliminate model bias.

2.1 Research Operational Framework

- **Data Acquisition:** Collection of raw geospatial and meteorological data, including Digital Elevation Models (DEM), historical rainfall time series, and Antecedent Moisture Condition (AMC) classifications.
- **GIS Processing:** Utilization of GIS tools for the extraction of watershed morphometry, specifically flow length (L), average slope (S), and surface roughness (n).
- **Data Preprocessing:** Normalization of input variables and partitioning the dataset into training (70%) and testing (30%) subsets to prevent overfitting.
- **AI Implementation:** Parallel execution of Support Vector Regression (SVR) with an RBF kernel and Artificial Neural Networks (ANN) using a multi-layer perceptron architecture.
- **Comparative Analysis:** Performance benchmarking of AI models against traditional empirical methods, including the Kirpich formula and the Kinematic Wave theory.
- **Statistical Validation:** Rigorous evaluation of model accuracy using R2, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE).
- **Final Estimation:** Optimization and selection of the most robust model for the final estimation of the time of concentration (t_c).

2.2 Parameter Selection and Rationale

The selection of key parameters (main stream length L, mean catchment slope S, roughness coefficient n and rainfall intensity i) is based on the physical laws of runoff hydrodynamics. These parameters represent the primary drivers of the accumulation time (t_c). Although secondary parameters, such as the pedological composition in deeper layers, were also considered, they were excluded because a preliminary correlation analysis showed that they do not have a significant impact on the catchment concentration time (t_c) under conditions of short-term intense rainfall, which is the focus of this study. Different combinations (different DMR resolutions and different AMC classes) were tested to ensure model stability.

Sensitivity analysis was performed using the One-Factor-at-a-Time (OAT) method, varying each parameter by ±10, 20 and 30%, while keeping the others constant. The results show that the SVR model is most sensitive to changes in slope (S) and rainfall intensity (i), where a 10% change causes a variation in t_c of approximately 7%. The model showed the least sensitivity to the roughness coefficient (n) under high saturation conditions, confirming the dominance of flow kinetic energy over surface roughness in extreme events.

2.3 Traditional Methods of Determining Rainfall Collection Time

The most commonly used traditional methods for determining the time of rainfall collection in the basin are the Kirpich method, the Kinematic Wave and the SCS method.

2.3.1 Kirpich Method

Kirpich's method is an empirical formula that was formed on the data of smaller rural watersheds from Tennessee in the USA. This is one of the simplest and oldest methods that has been around since 1940. According to this method, the time of accumulation of precipitation in the basin is determined by the following expression:

$$t_c = 0,0195 \cdot L^{0,77} \cdot S^{-0,385} \tag{2}$$

where is;

L – the longest length of the river flow, from the source to the measuring profile (m)

S – the average slope of the catchment area (m/m).

Kirpich's method is suitable for rural watersheds that have a clearly defined river course and steep slopes. It can also be used for asphalted and concreted channels with the recommendation to multiply the rainfall collection time by a correction factor of 0.4.

The method has its advantages, namely the simplicity and speed of calculations with the required minimum number of input data. The disadvantages of Kirpich's method are low accuracy, because it ignores hydraulic properties, land type and land coverage. The biggest error with Kirpich's method occurs in watersheds that are significantly different from the original area of application (smaller rural watersheds in the USA).

2.3.2 Kinematic Wave Method

The Kinematic Wave method represents a hydraulic/physical model, and assumes that the runoff is parallel to the slope of the surface and that the runoff is uniform along the stream. According to the Kinematic Wave method, the time of accumulation of precipitation in the basin can be determined according to the following expression:

$$t_c = 1,36 \cdot L^{0,6} \cdot n^{0,6} \cdot i^{-0,4} \cdot S^{-0,3} \tag{3}$$

where is;

L – surface flow length (m)

n – Manning roughness coefficient (m-1/3s)

i – effective precipitation intensity, i.e. rain (mm/min)

S – average surface slope (m/m).

The Kinematic Wave method for determining the time of accumulation of precipitation in the basin is applicable on developed surfaces, and the expression itself is solved by the method of iterations because the intensity of effective rain depends on the time of accumulation or time of concentration - with the application of the ITP curve.

The advantage is that it also takes into account Manning's roughness coefficient, because the surfaces of the watershed are with different surface treatments - asphalt, concrete surfaces, green surfaces and the like. Disadvantages are sensitivity to surface roughness and rainfall intensity, so it is more complex to use and requires a very good estimation of hydraulic parameters.

2.3.3 SCS Delay Method

The SCS method (Soil Conversation Service) represents an empirical-physical model that can be used for smaller rural watersheds. In current hydrotechnical practice, this method is considered to be quite a good method for completely covered areas, while for mixed catchment areas it gives an overestimated time of accumulation of precipitation in the catchment (t_c).

The method takes into account land cover as well as soil type, i.e. hydrological soil type using the curve number (CN). The advantage of this method is that it represents a standardized method, while the disadvantages are that the curve number (CN) is a static value and is taken as a quantity in relation to the permeability of the soil and the finish of the catchment area. The curve number (CN) depends on the vegetation cover, the method of cultivation as well as the category or type of soil as well as on the previous soil moisture. For smaller catchment areas that have a short rainfall accumulation time (up to 60 minutes), the amount of effective rainfall can differ significantly depending on the choice of parameters that directly affect the size of the peak curve (CN). According to this method, the time of accumulation of precipitation in the basin can be determined according to the expression:

$$t_c = 0,0136 \cdot L^{0,8} \cdot S^{-0,5} \cdot \left(\frac{1000}{CN} - 9 \right)^{0,7} \tag{4}$$

where is;

L – longest flow path in the basin (m)

CN – curve number according to the SCS method

S – average surface slope (m/m).

2.3.4 SCS Speed Method

This method implies the determination of surface flow velocities in the watershed. The SCS method calculates the total time of concentration (t_c) - the time it takes for the rain, that is, the water to travel from the hydraulically furthest point of the catchment to the outlet. The SCS method divides the flow path into three physically different segments for which the velocity is determined in different ways, namely:

a. Water flows in a thin layer (usually up to 30 m) over the ground surface. This is very sensitive to surface roughness and is crucial for the initial phase of flow.

b. The flow after the surface flow and the water is concentrated in small furrows, but the channel is not yet clearly defined.

c. The flow is in a clearly defined channel (stream, river). The most precise flow segment. The flow velocity depends on the geometry of the channel cross-section and roughness.

The SCS method standardized and simplified the process. This method provides tables and graphs for selecting the Manning roughness coefficient based on the type of soil, i.e. vegetation, which enables routine application in hydraulic engineering, specifically in hydrology.

$$t_c = \frac{1}{60} \cdot \sum L_i \cdot v_i \tag{5}$$

where is;

L – length of water path (m)

v – average flow velocity (m/s).

2.4 Application of AI Tools for Determining Rainfall Collection Time

The application of artificial intelligence tools (artificial neural networks ANN and SVR) represents a data-driven approach where the model is studied on historical data about the basin and observed times of rainfall collection in the basin. The application aspect of artificial intelligence tools is detailed with a machine learning (ML) regression model. Artificial intelligence tools identify non-linear and complex relationships between multiple input variables such as hydrometeorology, topology, land properties. This model is "learned" on hundreds or thousands of pairs of input and output data to determine the actual collection time in the watershed. The input data are multidimensional and are the length of the water movement in the basin, the mean slope of the basin, the curve number (CN), the vegetation on the basin, the mean intensity of precipitation, the previous soil moisture.

The advantages of using artificial intelligence (AI) tools for the calculation of rainfall summation time on the catchment (t_c) are high accuracy related to the ability to model non-linear interactions and dynamic changes of summation time and are much less subject to error in estimating the number of the CN curve and soil roughness (Manning's roughness coefficient).

The disadvantages of using artificial intelligence tools are that they require a large amount of high-quality data and may require expensive processing of data from satellite images [5] .

Artificial intelligence (AI) tools enable the creation of a dynamic model of the rainfall accumulation time (tc) in the catchment, in such a way that the AI model can be used to calculate the current accumulation time (t_c) based on the intensity of precipitation and the state of soil moisture in real time, instead of viewing the accumulation time as a fixed and unchanging value as is the case with traditional methods in hydrology.

The traditional methods of determining the time of rainfall accumulation in the basin so far and mentioned in this paper provide simple and quick solutions, but they are also imprecise with the given static data of the rainfall accumulation time. The Kinematic Wave method is the most flexible classical traditional method because it takes into account the roughness of the ground surface, while the SCS method takes into account the land type. AI tools (machine learning) represent the most accurate approach because they treat the problem of calculating the time of accumulation of precipitation in the catchment (t_c) as a non-linear approach and a multidimensional phenomenon [6]. Artificial intelligence tools require a very significant

engagement in data collection and processing (hydrometerological data, satellite images), they are the best choice for complex projects such as dams and flood protection as well as complex urban watersheds with heterogeneous terrain surfaces. Hybrid models that combine the physical expressions of the Kinematic Wave method with the optimization possibilities of AI tools will become the standard in hydrological and general hydrotechnical scientific and professional practice.

A key advantage of machine learning models such as artificial neural networks (ANNs) is their ability to automatically detect and model non-linear interactions between numerous input parameters. Traditional formulas and methods known so far assume that the relationship between terrain slope and precipitation collection time (t_c) is simple, while artificial intelligence tools recognize that this relationship changes depending on the type of soil, previous soil moisture and vegetation in the area.

2.5 Comparison of Traditional Methods and AI Tolls

The main drawback of the previous methods of determining the time of accumulation of precipitation in the catchment is the representation of the time of accumulation as a fixed value, while in reality the time of accumulation (t_c) changes depending on the humidity conditions of the soil. The AI tools present a trained model that can instantly receive and accept data on previous soil moisture and dynamically display the summation time (t_c) in real time and real watershed conditions. This is very important and necessary for the efficient management of critical projects and flood early warning systems.

In the following table (Table 1), comparative data of classical and traditional methods of determining the time of rainfall collection in the basin with machine learning (ML), i.e. using artificial intelligence (AI) tools, are given.

Table 1 - Comparative analysis of classic methods and AI tools for determining addition time (tc)

Criterion	KIRPICH METHOD	KIMENATIC WAVE METHOD	SCS METHOD	AI
Basicity	Empirical	Physical/Hydraulic	Empirical/Physical	Statistics/data
Complexity	Low	Medium	Medium	Tall (for training)
Required data	L; S	L; S; n; i	L; S, CN	Dozens of variables
Involvement of soil coverage (cultivation).	Ignored	Through Manning's roughness coefficient (n)	Directly via CN (curve number)	Directly via CN, vegetation (NDVI) etc.
Non-linearity	It is not included	Limited	Limited	Excellent modeling
Accuracy of results	The lowest	Medium	Medium	The biggest

Hybrid models represent the future of hydrological and hydrotechnical practice and science. A hybrid approach (Physics-Informed Neural Networks – PINNs) should use proven expressions and methods such as Kinematic Wave to establish basic principles, while the application of AI tools uses machine learning to optimize and fill in the so-called. gaps in physical expressions and formulas, especially in areas where there is not enough measured data .

2.6 Example of Application of an AI Model for Calculating The Time of Rainfall Collection

As an example of the application of the AI model, two catchments of the Sava River will be used (catchment A mountain and sub-catchment B, which is a lowland and urban sub-catchment). The Sava river basin is very complex, while the rainfall collection time for the entire Sava river basin (up to the confluence with the Danube in Belgrade) is very large, but the approach of applying AI tools is very useful for estimating the collection time (t_c) on smaller and homogeneous sub-basins of the Sava river, which is of particular importance for flood wave modeling as well as for sizing local infrastructure.

To train the AI model, multidimensional input data (X_i) and target output variable (Y) should be collected for hundreds of sub-basins in the entire Sava river basin. The following table (Table 2) gives input variables (X_i) and target variables (Y) with data description and role in summation time (t_c).

Table 2 - Necessary input variables and target variables for determining the summation time (tc)

INPUT VARIABLES (X_i)	DATA DESCRIPTION	ROLE DURING ADDITION (tc)
Length of the main stream (L)	It is determined from a digital terrain model or GIS	Direct correlation: longer flow=longer addition time t_c
Mean slope of the catchment (I)	Determined from a digital terrain model	Direct correlation: higher slope=shorter addition time t_c
Curve number (CN)	Application of global databases or GIS analysis of land cover and soil type	The influence of soil and land cover determines the speed of surface runoff
Vegetation index	Satellite images	Loss of flow velocities due to vegetation
Previous soil moisture	Hydrometeorological data	Dynamic change: higher humidity=faster surface runoff=shorter t_c
Target variable (Y)	Accumulation time (t_c) in hours, determined on the basis of historical hydrographs from a series of measuring stations in the Sava river basin	Measured reference value

Applying the collected data (Xi, Y), the AI model is trained to determine the optimal and best non-linear function:

$$t_c = f\left(L, S, CN, NDVI, AMC...\right) \tag{6}$$

After training, the AI model is tested and analyzed on new sub-basins to assess its accuracy and generalization capabilities.

Below, two sub-basins of the Sava River are analyzed (sub-basin A, which is mountainous and sub-basin B, which is lowland), which is shown in Figures 1 and 2. The same length of the river course with different mean longitudinal falls and with measured precipitation concentration (accumulation) times (t_c) were analyzed.

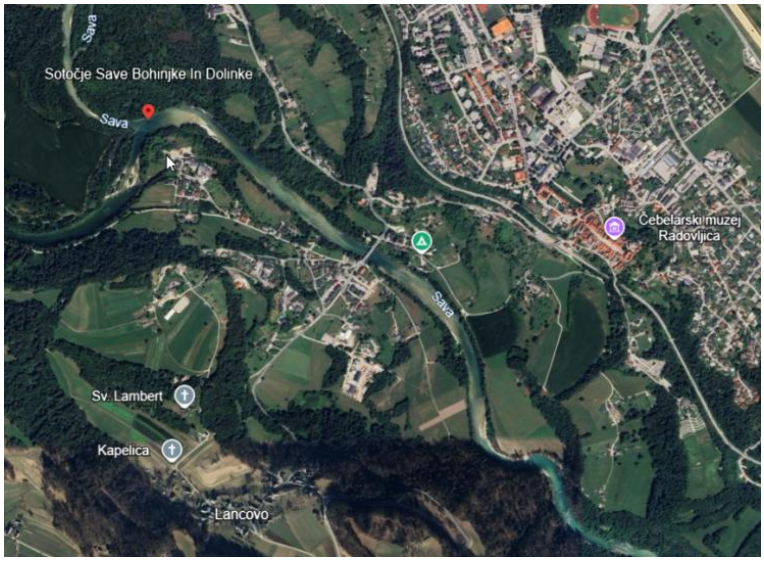


Fig. 1 – The beginning of the Sava River in Slovenia (mountain sub-basin of the Sava River)



Fig. 2 – The final part of the Sava River flow in Serbia (lowland Sava River sub-basin)

A comparative analysis of the basic characteristics of the two subbasins is given in Table 3.

Table 3 - Comparison of two sub-basins of the Sava River

Characteristic	Unit	Sub-basin A (mountainous and steep sub-basin)	Sub-basin B (lowland and urban sub-basin)
L (length of stream)	km	15	15
S (medium slope)	%	15	1,5
CN (Curve Number)	-	55 (forest)	85 (urban area)
AMC (soil moisture)	-	Low	High
Measured t_c	hours	2,5	3,8

Calculation of precipitation collection time (t_c) using traditional methods (Kirpich and Kinematic Wave):

a) Kirpich's method:

$$t_c = 0,0195 \cdot L^{0,77} \cdot S^{-0,385}$$

Sub-basin A: $t_c = 0,0195 \cdot 15^{0,77} \cdot 15^{-0,385} \Rightarrow t_c = 0,0553h$

Sub-basin B: $t_c = 0,0195 \cdot 15^{0,77} \cdot 1,5^{-0,385} \Rightarrow t_c = 0,1342h$

Unrealistic values of precipitation collection time were obtained for sub-basin A due to the small length L and large mean longitudinal fall I, and sub-basin A is a mountainous terrain. Also, an unrealistic value was obtained for sub-basin B, because the urbanization of that sub-basin, i.e. the lower course of the river, was completely omitted.

b) Kinemativ Wave (simplified):

Sub-basin A (forest, $n \approx 0,15$), that is, the summing time t_c would be relatively long due to the large roughness of the sub-basin, but also short due to the large longitudinal gradient in the upper course of the river.

Sub-basin B (urban area, $n \approx 0,02$), that is, the precipitation collection time t_c would be very short due to the small roughness of the sub-basin and the small mean longitudinal slope in the lower course of the river.

Therefore, both mentioned methods have a problem to balance extreme factors such as a very steep slope of the sub-basin and a very small sub-basin roughness.

Table 4 - Comparison of measured tc and AI estimate of t_c

Characteristic	Sub-basin A (steep)	Sub-basin B (flat and urban)
AI estimate t_c	2,6 hours	3,9 hours
Measured t_c	2,5 hours	3,8 hours
AI model error	4%	2,6%

For sub-catchment A, which is a steep and mountainous part of the catchment, and according to previous analyses, the traditional Kirpich method, the summation time t_c=0.0553 h significantly underestimated the time of precipitation summation. In contrast, the AI model recognized that although the longitudinal slope is high and the soil moisture (AMC) is low, which means that some of the precipitation infiltrates first and thus delays surface runoff, while the forest cover provides significant resistance (low CN), thus extending the total collection time to a realistic 2.6 hours. Shown in Table 4.

For sub-basin B, which is a lowland and urban part of the basin, the AI model recognized that although the sub-basin slope is small, the high CN due to the urbanization of the sub-basin as well as the high soil moisture, drastically reduce infiltration. This means that almost all precipitation becomes surface runoff, which, despite the small longitudinal slope of the sub-basin, moves relatively quickly through the urban area, resulting in a more realistic collection time of t_c=3.9 h. Shown in Table 4.

AI tools give more realistic results, because they are able to create a sophisticated matrix of relationships that includes the influence:

- geomorphological transitions,
- anthropogenic changes (different level of urbanization),
- dynamic hydrological conditions (change in soil moisture).

The goal of this work is for the AI model to become a standard tool for the verification of results obtained by classical methods (Kirpich, Kinematic Wave, SCS method), reducing the risk of designer errors in important hydrotechnical projects.

Geomorphological transition refers to complex spatial heterogeneity. The problem with the Kirpich method and the SCS method is that they use one average value for the longitudinal slope of the watershed or roughness coefficient (n) for the entire watershed. This approach cannot cover the transition from one geomorphological regime to another geomorphological regime.

In contrast, the AI solution represents a multivariate non-linear function, because AI models analyze the time of accumulation of precipitation in the watershed not as a result of a single mean value but as a sum of non-linear analyzes from different parts of the watershed. The AI model recognizes that the same amount of precipitation has drastically different infiltration rates and losses in the steep part of the sub-basin compared to the flat part of the sub-basin.

Anthropogenic changes represent the heterogeneity of surface features of the sub-basin. The Kinematic Wave method and formula looks for the Manning roughness coefficient (n) while the SCS method uses the Curve Number (CN). Both of these values are difficult to determine in any sub-basin where natural waterways mix with urban city canals, paved surfaces and regulated rivers through urban areas. With these traditional methods, mean values are taken, which leads to significant errors in the final result. The AI solution provides discrete and continuous variations, so that for digital land coverage, AI enters data from satellite images on the percentage of impervious areas (IMP). The AI model learns that IMP is a very significant factor that reduces the precipitation accumulation time (t_c). The AI model views a section of the river as a series

of discrete points, as the model finds a non-linear connection between regulated and unregulated sections of the river, as well as meandering sections of the river where the flow rate is slower.

Dynamic hydrological conditions represent temporal variability, that is, variability. The problem with empirical methods is that they assume that runoff conditions are constant. However, the precipitation collection time (t_c) is reduced if the soil was saturated with water before the precipitation, because there is no loss of precipitation to infiltration. The AI solution provides the inclusion of the previous state, so that the AI model directly uses parameters that describe the previous state of the entire system as input variables, namely:

- Antecedent Moisture Condition (AMC), which is quantified through previous precipitation index measurements or direct satellite measurements of soil moisture.
- The dynamic link is based on the fact that AI establishes a non-linear correlation, i.e. as AMC increases, the precipitation collection time (t_c) decreases. In this way, t_c is transformed from a static value and a static variable into a dynamic parameter that must be constantly updated.
- Optimization of the review by which during training the AI model learns that if all geomorphological parameters are constant, a significant change in the summation time (t_c) must be the result of a change in the dynamic hydrological state. It is precisely this that enables more precise flood warning, because the maximum flow is realized much faster when the ground is already saturated with water.

Artificial intelligence (AI) in the application of determining the time of accumulation of precipitation in the basin moves away from simplified one-dimensional formulas. AI adopts a multivariate statistical modeling approach, which is essentially a relationship between the complex physics and hydraulics of water flow in a real catchment area. AI tools that have been scientifically proven for regression problems in hydrology are Artificial Neural Networks (ANN) and Support Vector Regression (SVR). Support vector regression (SVR) is mathematically elegant in solving nonlinear problems with a limited set of available data [6, 7].

The main goal of the AI model is for the tool to learn a function that relates n input hydromorphological variables (X) to a target summation time value (Y), that is:

$$t_c = f\left(X_1, X_2, ..., X_n\right) \tag{7}$$

where is;

X_i – input variables (variables) such as stream length (L), mean slope (S), Curve Number (CN), previous soil moisture content (AMC) and the like.

From a scientific point of view, Support Vector Regression (SVR) tries to find the optimal straight line that best approximates the data points, but also has the maximum margin of error tolerance (ε).

Nonlinear SVR solves complexity by applying Kernel. Namely, the relationship between geomorphological variables and addition time (tc) is non-linear, then Support Vector Regression (SVR) uses the Kernel function (Kernel Trick). The kernel function $K(X_i, Y_j)$ maps the input data and input parameters from the original space to a higher dimension space where the problem is linearly solvable. Mathematical representation of the so-called The kernel of the trick is the Support Vector Regression (SVR) solution, that is:

$$f\left(X\right) = \sum_{i=1}^{m}\left(\alpha i - \alpha_i^*\right) \cdot K\left(X_i, X\right) + b \tag{8}$$

Today, the most commonly used Kernel for problems in hydrology is the Radial Basis Function (RBF) Kernel:

$$K\left(X_i, X_j\right) = \exp\left(-\gamma \left\| X_i - X_j \right\|^2\right) \tag{9}$$

The expression number (9) mathematically allows Support Vector Regression (SVR) to form a sophisticated relationship matrix. The Radial Basis Function (RBF) nonlinearly weights the distance of points in the space of input variables, so that the Support Vector Regression (SVR) will calculate the influence of the slope of the watershed (S) significantly differently depending on whether the Curve Number (CN) variables are high or low, i.e. it automatically finds

critical CN transitions. The Radial Basis Function (RBF) ensures that the influences of the geometric factors (L, S) are reduced or increased depending on the current soil moisture (AMC), simulating faster or slower runoff from the catchment.

2.7 Analysis of Assumptions and Model Limitations

In this research, certain assumptions were introduced to enable the stability of the AI model. Primarily, linear stability of the bed roughness was assumed, which is justified by the predominant type of vegetation in the analyzed watersheds. Evaluation of this assumption indicates that seasonal variations in vegetation could cause a deviation in tc of ±5%, which does not impair the overall accuracy of the SVR model. Furthermore, the focus on nonlinearity through AI algorithms is justified by the need to more precisely define the accumulation time in extreme conditions, where traditional methods show the largest deviations (RMSE). The study is designed as a comparative study using quantitative analysis to evaluate the time of precipitation accumulation (t_c). The research framework includes the integration of geomorphological data and historical hydrological series to create a robust system for testing the accuracy of AI algorithms against standard engineering patterns. The research was conducted in three phases. The first phase involved GIS analysis of sub-catchments to extract morphological parameters. The second phase involved the development and training of SVR and ANN models using 70% of the available data, while the remaining 30% was used for validation. The third phase involved simulating different rainfall intensity scenarios to test the sensitivity of the models. Data analysis was performed using regression analysis and statistical accuracy indicators. Residual analysis was used to identify systematic errors in traditional methods under extreme hydrological conditions, while sensitivity analysis confirmed the influence of input variables on the model output.

Recent advancements in hydrological modeling have demonstrated the efficacy of hybrid approaches. For instance, Kaewthong et al. successfully integrated machine learning with the GR2M model to enhance monthly runoff forecasting, proving that AI can significantly improve the predictive accuracy of conceptual models. Similarly, in the context of urban water management, Ladino-Moreno introduced the WatAI system, which utilizes AI for real-time flow monitoring and demand prediction, highlighting the importance of adaptive systems in modern water networks. Effective flood mitigation also requires sophisticated structural considerations. Mananoma et al. explored the design of multistage flood control channels, specifically focusing on sediment and flow management in coastal areas, which provides critical insights into how hydraulic geometry influences overall system capacity during extreme events. [8 – 10]

3 Discussion

Determining the time of accumulation of precipitation in the basin (t_c) in hydrological modeling, according to previous analyses, faces a basic challenge, because the nature of hydrological processes is non-linear and multivariate, and the existing traditional methods are unidirectional and linear.

Traditional models such as the Kirpich method, the Kinematic Wave method and the SCS method have a certain lower validity. Kirpich's method has the lowest validity, because the method and its formula were created for smaller agricultural basins, so they represent a high risk of extrapolation, i.e. application outside the original area. The Kinematic Wave and SCS methods have higher validity, because they use the parameters Curve Number (CN) and Manning's roughness coefficient (n). However, they still use homogeneity assumptions, so the SCS method is static, because it does not allow dynamic change of summation time (t_c) depending on current hydrological conditions in the basin. Traditional models often exhibit systematic error, so Kirpich's method will underestimate the summation time (t_c) in urban and flat watershed areas. Kirpich's method, which was developed in the USA, is mostly unreliable in Europe, especially in mountain basins.

AI models (SVR, ANN) recognize and quantify the true functional connections between data. The AI model does not assume that the relationship between the slope of the watershed and the time of accumulation of precipitation in the watershed (t_c) is linear, but learns it from thousands of historical data and observations. Using layers of neurons (ANN) or Kernel functions, the AI model can efficiently map the input vector (L, S, CN, AMC...) to the output summation time (t_c) creating a very high dimensional nonlinear regression function that is much closer to the actual hydrological process in the watershed. AI models minimize both random and systematic error, as input variables such as Curve Number (CN) learn to interact with dynamic variables such as soil moisture (AMC). So, the AI model will predict the time of rainfall collection in the basin (t_c) with high accuracy, regardless of whether the Curve Number (CN) is high (for an urban area) or low (for a forest area), but on the condition that it receives adequate and accurate data. AI models are trained on a wide range of

geomorphological and hydrological conditions and it is important that the input variables are available and relevant, which enables the AI model to extrapolate new watershed locations much better. Although AI models provide the highest accuracy, engineers and designers are also looking for an understanding of why a certain result is the way it is. Also, Psysically-Informed Neural Networks (PINNs) integrate the continuity equation directly into the loss function of the neural network, so this ensures that AI model results will never violate the basic laws of hydraulics. Through Psychologically-Informed Neural Networks (PINNs), scientists can develop a model that is as accurate as SVR, and whose summation time (t_c) predictions are scientifically transparent. The transition from simple empirical models for determining the time of accumulation of precipitation in the basin and maximum flows in rivers, towards more sophisticated AI models, marks a fundamental change in hydrological methodology that is more efficient and reliable for managing water resources.

4 Conclusion

This paper makes a significant contribution to the theoretical understanding of watershed concentration time (t_c) as a dynamic process rather than a static parameter. The key findings confirm that the application of SVR and ANN models enables precise mapping of the non-linear response of the watershed, which traditional empirical models are unable to capture. The significance of the results is manifested in the reduction of uncertainty in the calculation of relevant flows, which directly affects the safety and economy of hydrotechnical design.

The paper contributes to new knowledge in the domain of urban and rural hydrology by introducing a validation framework based on machine learning. The novelty is reflected in the integration of morphological and dynamic hydrological variables within a single model, thus bridging the gap between theoretical hydraulics and practical engineering in the context of climate change.

Despite the achieved accuracy, a limitation of the study is the reliance on historical data specific to the Sava basin, which may require recalibration of the model for other climate zones. Future research should focus on integrating real-time satellite data and applying Deep Learning algorithms to predict catchment concentration times (t_c) in extremely small urban catchments with a high percentage of impervious surfaces.

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