Research Article

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SWAT modelling and MCDM for spatial valuation in small hydropower planning

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Abstract: This study integrates the Soil and Water Assessment Tool (SWAT) modelling with multi-criteria decision-making (MCDM) analysis to assess and evaluate the spatial suitability for small hydropower development. The SWAT model is employed to perform a comprehensive hydrological analysis of the study area, which enables a precise characterisation of the hydrological dynamics within the catchment, ensuring that the derived data accurately reflects the physical realities of the region, which, in turn, enhances the reliability of subsequent spatial analyses. The outputs from the SWAT analysis are subsequently utilised as critical inputs for the MCDM analysis. This analysis integrated various spatial and environmental factors, including terrain slope, soil type, land cover, proximity to existing infrastructure, and potential ecological impacts. Integrating these diverse datasets allows the development of comprehensive grid and vector databases and maps delineating areas within the catchment most suitable for small hydropower development. These maps identify optimal locations and balance ecological sensitivity with socio-economic considerations, ensuring that growth is sustainable and beneficial to local communities. The findings from this integrated approach provide valuable insights for regional planners and policymakers, offering a scientifically grounded basis for the strategic development of small hydropower projects. This research significantly contributes to advancing spatial planning methodologies in Serbia, highlighting the importance of integrating advanced hydrological modelling with sophisticated decision-support tools in contemporary environmental management and infrastructure development.

Keywords: SWAT modelling, multi-criteria decision-making analysis, hydrological assessment, spatial valuation, small hydropower plants

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1 Introduction

Small hydropower development is crucial for the sustainable management of water resources and energy production. As an essential renewable energy source, establishing small hydropower plants (SHPs) requires a comprehensive understanding of catchment hydrology, environmental factors, and socio-economic impacts. The challenge is identifying suitable locations for SHP development while balancing ecological sensitivity with infrastructural needs. Combining hydrological modelling and Multi-Criteria Decision-Making (MCDM), an integrated approach is essential to achieving this goal.

Hydrological models, including the widely utilised Soil and Water Assessment Tool (SWAT), have been extensively employed to understand the hydrological dynamics of catchment areas [1–3]. The SWAT model is a physically based, semi-distributed model that simulates various processes, including water balance, sediment transport, erosion processes, and land use change impacts [4]. SWAT's ability to incorporate complex interactions within the hydrological cycle makes it particularly suitable for evaluating the viability of water resource management and development projects, such as SHPs. In the context of the Rasina River catchment in Serbia, previous research has demonstrated the effectiveness of SWAT in providing a detailed hydrological characterisation, encompassing parameters such as water balance, erosion, and sediment transport, which are critical for determining the potential of hydropower development [2,3].

Combining SWAT modelling with MCDM creates a strong methodological framework for assessing the spatial suitability for SHP development. The MCDM method systematically evaluates various spatial and environmental factors, including terrain slope, land cover, soil type, proximity to infrastructure, and potential ecological impacts. This methodology allows for creating detailed grid maps that identify the most appropriate areas for SHP development within a catchment, ensuring that environmental concerns are balanced with socio-economic factors related to energy production. Moreover, the MCDM framework has been effectively utilised in diverse ecological planning scenarios, such as assessing the renewable energy potential for wind and solar sources. By methodically integrating spatial, environmental, and socio-economic elements, these studies have yielded significant insights into site selection, resource optimisation, and the sustainability of renewable energy initiatives. This adaptability illustrates the framework's effectiveness in managing the complexities of energy planning in various contexts. These instances have demonstrated that the combination of hydrological modelling and MCDM analysis is a powerful decision-making tool that supports regional planners and policymakers in sustainable resource management [1,5–7]. In the context of Serbia, this integration exemplifies the advancement of spatial planning methodologies and the promotion of sustainable infrastructure development.

Deforestation and land-use change represent profound drivers of altered hydrological dynamics worldwide. At the global scale, deforestation significantly disrupts the water cycle by reducing evapotranspiration, increasing surface runoff, and impairing atmospheric moisture recycling, with consequences for precipitation patterns across distant continental interiors [8–10]. Studies in Europe document intensified drought following forest removal, particularly pronounced in northern regions where long-term deforestation has altered runoff regimes and exacerbated hydrological imbalance [11,12]. Within the regional context of the Western Balkans, land-use changes, including deforestation, have similarly destabilised watershed hydrology, increasing peak flows and erosion rates, though literature remains more fragmented [13]. The deforestation and land use changes in Southern Serbia have been identified as significant factors influencing surface runoff and water balance within catchments [14]. Such changes are essential in the hydrological analysis, as they directly impact the SWAT model outputs related to runoff and sediment transport. By incorporating these aspects, the model provides a more accurate representation of the current state and potential future changes in hydrological processes within the catchment, ensuring that SHP development is planned within a sustainable framework.

In regions experiencing rapid environmental changes, such as Zlatibor, the formation of surface urban heat islands (SUHI) and shifts in vegetation cover further complicate hydrological dynamics [15]. These changes necessitate careful analysis of climate variability and its latent impact on the hydropower potential of catchments. Consequently, SWAT modelling is used to simulate current conditions and project future climate change impacts on water resources and hydropower capacity.

This study builds on these principles by integrating SWAT modelling and MCDM to evaluate the spatial suitability of the Rasina catchment for SHP development. The SWAT model performs a comprehensive hydrological analysis validated against official data to ensure accuracy and applicability. The outputs from the SWAT analysis serve as critical inputs for the MCDM analysis, which considers multiple spatial factors to identify optimal locations for SHP development. This integrated approach offers a scientifically grounded framework that enhances the strategic planning and sustainable development of SHPs in Serbia.

The research subject is the application of an integrated SWAT–MCDM methodology for spatial evaluation of hydropower potential at the catchment scale. The objective is to determine priority locations for sustainable SHP development by combining hydrological modelling outputs with multi-criteria spatial analysis. The significance of the anticipated findings lies in providing a replicable, evidence-based decision-support framework that can be applied to similar catchments, contributing to environmentally responsible energy planning in Serbia and the wider region.

Accordingly, this research examines the accuracy of SWAT modelling in representing runoff and sediment transport dynamics within the study catchment when validated against observed hydrological data. It further investigates which spatial and environmental criteria significantly influence site suitability for SHP development. Finally, it explores how integrating SWAT outputs into MCDM can enhance the identification of optimal and sustainable locations for small hydropower projects.

2 Materials and methods

2.1 Study area overview

This study focuses on the Rasina River catchment in central Serbia, which has been identified as a potential area for small hydropower development due to its significant hydrological and geomorphological characteristics [16,17]. The Rasina catchment study area is a sub-basin of the Morava River, covering approximately 522 km^2 and several tributaries with notable hydropower potential. The catchment encompasses various physical, environmental, and socio-economic attributes critical for spatial valuation and suitability for SHPs [5].

The area is characterised by diverse topography, with elevations ranging from around 262 m to over 1,920 m a.s.l. This results in a mix of climatic conditions and land use patterns significantly influencing hydrological processes

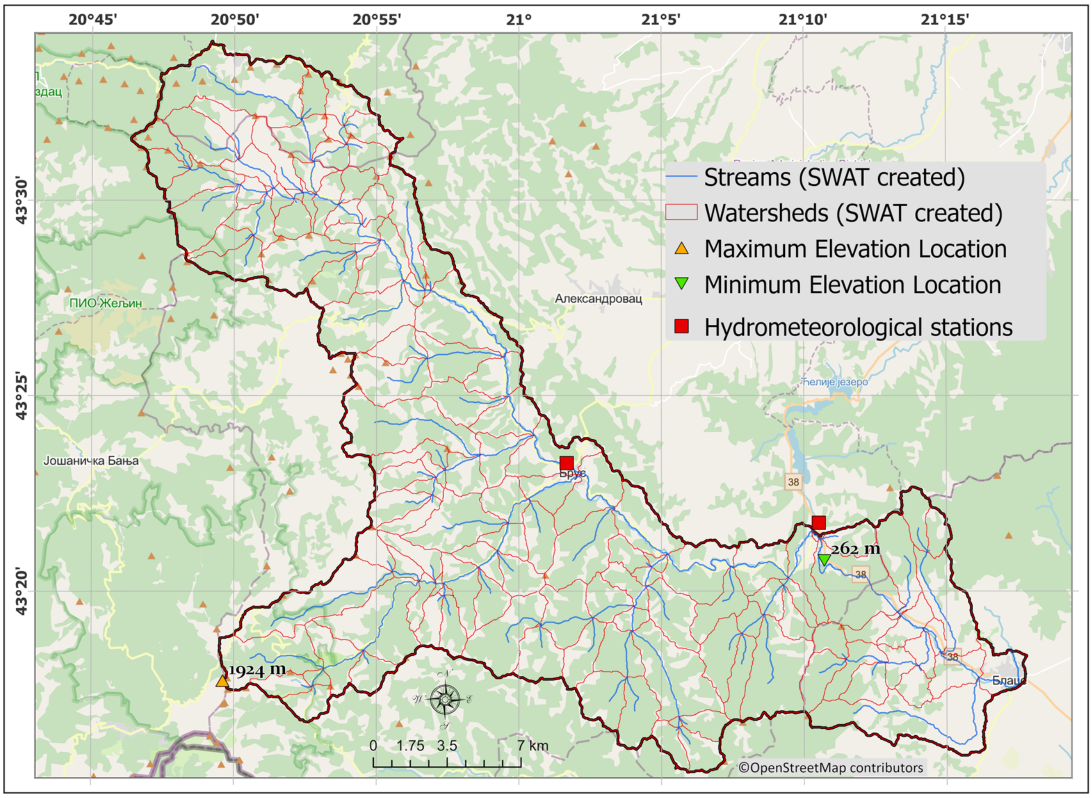

Figure 1: Study area of the Rasina watershed with hydrological and topographical characteristics. Source: background adapted from OpenStreetMap Contributors (2017) [19]. The data are available under the Open Database License. Copyright and License available at [https://www.openstreetmap.org/copyright].

(Figure 1). The geomorphology of the catchment includes mountainous regions with steep slopes and valleys that facilitate the natural flow of water, which is favourable for hydropower production [18]. The area has a mix of forested regions, agricultural land, and urban settlements, contributing to the complexity of the hydrological processes within the catchment.

The selected area offers a representative sample of the different hydrological conditions within the Rasina catchment (Figure 1). The detailed spatial analysis conducted in this study aims to detect the most appropriate locations for SHP installations while balancing environmental sustainability and socio-economic benefits, contributing to broader hydropower planning in Serbia.

2.2 SWAT methodology and input data

Consequently, the SWAT model accurately captures water flow dynamics and sediment transport. The methodology for assessing the suitability of the Rasina catchment for SHP development includes a comprehensive geosystemic analysis that integrates natural and anthropogenic factors, such as climate, hydrographic network, topography, soil types, and land cover. It also accounts for potential environmental stresses like deforestation and land use changes, which can significantly impact water resources and sediment transport [5,14,20].

The SWAT model further incorporates climate variability, a critical factor for the long-term planning of SHP development. This approach ensures that potential future changes in water availability are accounted for, providing a robust framework for sustainable hydropower development [21]. The research also evaluates existing environmental protections and regulations to ensure that the proposed SHP development aligns with sustainable practices.

SWAT is a semi-distributed, process-based model widely used to predict the impact of land use, land cover, and climate on hydrological processes within a watershed. Its structure allows it to simulate surface runoff, sediment transport, water quality, and catchment-scale hydrological processes. It employs several key input parameters, including a digital elevation model (DEM), land use/land cover maps, soil type data, and climate data, which facilitate the creation of basic hydrological units (hydrological response units [HRUs]). Each HRU is analysed for hydrological processes

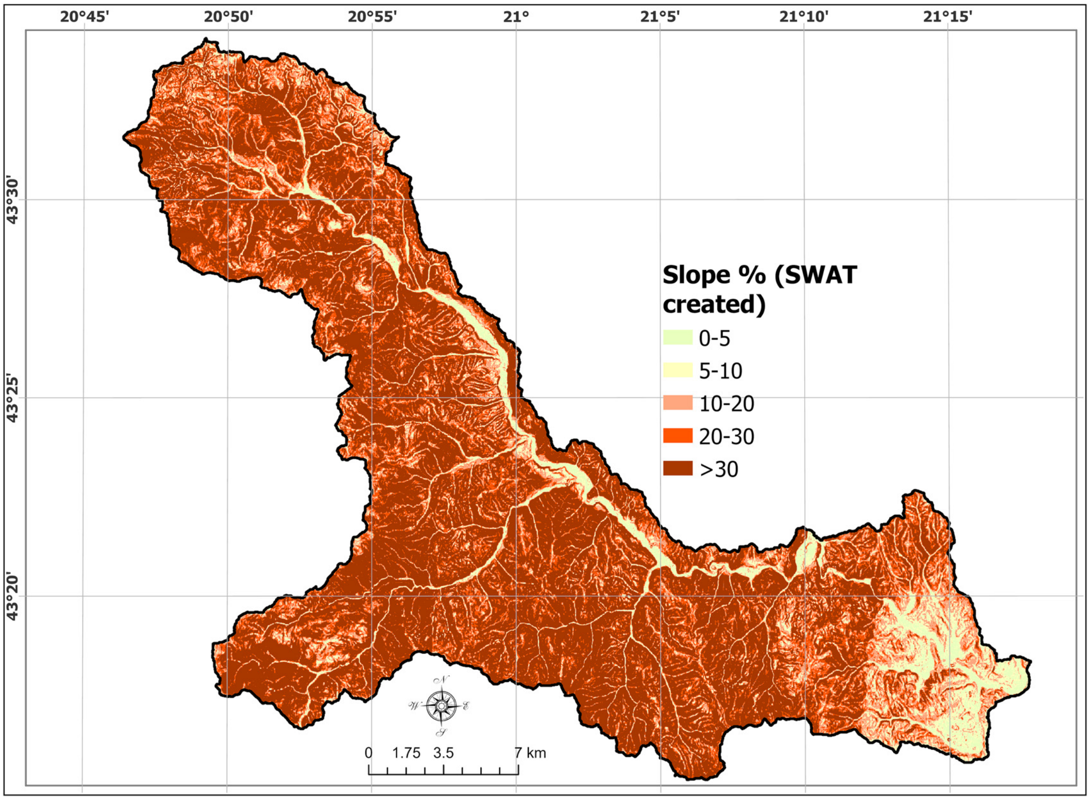

Figure 2: Slope of the study area created during SWAT step 2.

such as surface runoff, groundwater flow, and evapotranspiration [22–24].

2.2.1 SWAT input components

2.2.1.1 DEM

The DEM provides topographical information, determining the slope (Figure 2), flow direction, and other critical terrain characteristics influencing water flow and accumulation. A 22 m resolution DEM is used to achieve detailed topographical analysis. To determine the river network, watershed, and slope, the DEM from 2010 was developed by the Japan Aerospace Exploration Agency (JAXA) using data obtained from the ALOS satellite system [25].

The DEM used in this study initially has a 22 m resolution. However, it is standardised to a 10 m resolution through resampling to align with the land cover data, which also has a 10 m resolution. This standardisation ensures consistency across all raster input datasets used in the analysis. Additionally, all input raster datasets are resampled to a 10 m resolution and reprojected into the UTM 34N projection to maintain spatial compatibility and accuracy during spatial analysis.

This step is crucial for minimising potential errors associated with mismatched resolutions and projections, mainly when conducting hydrological modelling and weighted overlay analyses. By adopting a higher resolution for the DEM and aligning all datasets spatially, the study ensures that the results accurately represent the complex geomorphology of the Rasina River catchment and provide reliable insights for SHP development.

2.2.1.2 Land cover

The land use/land cover map plays a crucial role in understanding the contributions of various land types to runoff, sedimentation, and overall hydrological processes. To develop this map, supervised pixel-based classification was applied using the random forest algorithm, recognised for its robustness in handling complex datasets and high analytical accuracy. This method is widely adopted in land cover classification when training samples are carefully defined for algorithm optimisation [14,26–30]. Comparable approaches have also been discussed in recent literature. Various machine learning algorithms, such as support vector machines, *k*-nearest neighbour, and Bayesian classifiers, have been successfully employed in land cover classification [30–32]. However, several comparative studies highlight the superiority of RF due to its capacity to handle high-dimensional datasets, reduce overfitting, and deliver stable results even with limited training data [33–36]. These properties make RF particularly suitable for Sentinel-2 imagery, where many spectral bands and complex landscape heterogeneity require a robust and flexible classification approach.

The satellite imagery required for this analysis is sourced from the "Copernicus Open Access Hub" platform [37] and corresponds to Level 2A products. These Sentinel-2 datasets are atmospherically corrected and orthorectified, providing imagery representing the bottom of atmosphere reflectance. Sentinel-2 imagery has a spatial resolution of 10–60 m, a revisit time of 5 days, and a radiometric resolution of 12 bits across 13 spectral bands [38,39]. For supervised classification in this study, the visible (red, green, blue) and near-infrared bands with 10 m spatial resolution were utilised, as they provide the most relevant spectral information for distinguishing land cover types.

The Rasina River catchment area is covered by four different Sentinel-2 images, necessitating the creation of a mosaic for the study area. Three images – S2A_MSIL2A_20170701T093031_N0205_R136_T34: TDN, TEN, and TEP – were captured on July 1, 2017, while the fourth image, S2A_MSIL2A_20170711T093031_N0205_R136_T34TDP, was taken on July 11, 2017.

The software used for satellite image processing included different options. For mosaic creation, the European Space Agency's (ESA) free software, SNAP8, is utilised [40]. Subsequently, classification using machine learning algorithms is performed using the open-source software QGIS and the dzetsaka plugin [41,42].

Accuracy assessment was performed using a confusion matrix, a widely applied technique for evaluating supervised classifications [43]. This matrix calculated the overall accuracy (OA) as the proportion of correctly classified samples out of the total sample set. At the same time, the kappa coefficient (K) was used to account for agreement occurring by chance [44]. These indicators are considered robust metrics for assessing thematic accuracy in remote sensing classifications [45,46]. In this study, both OA and K confirmed satisfactory classification reliability. The resulting land cover map of the study area is presented in Figure 3.

2.2.1.3 Soil maps

Soil type data are integral to hydrological modelling as they influence critical processes such as infiltration capacity,

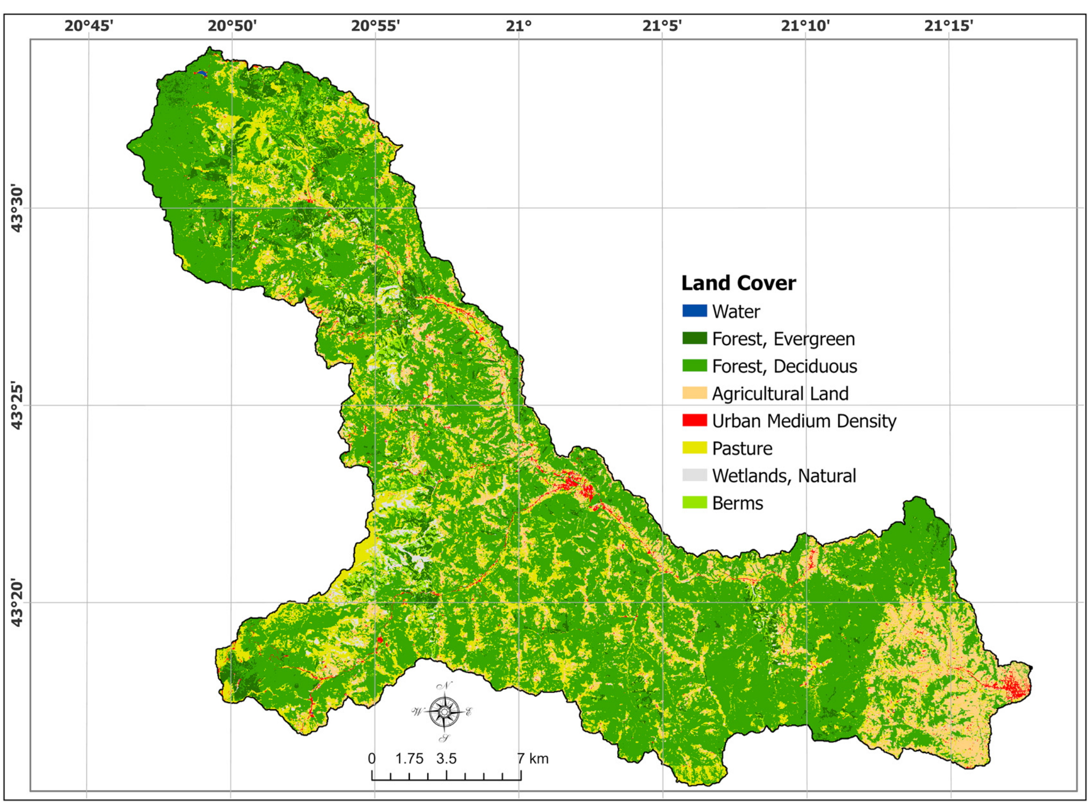

Figure 3: Land cover classification of the study area derived from multispectral analysis.

soil moisture retention, and erosion potential. These characteristics directly affect the water balance within the catchment, making accurate soil mapping essential for reliable SWAT model simulations.

For this study, the soil map is obtained from the Harmonized World Soil Database (HWSD), developed by FAO in collaboration with IIASA, ISRIC, the Institute of Soil Science of the Chinese Academy of Sciences, and the Joint Research Centre of the European Commission [47]. The database offers high-resolution global soil data, harmonised to ensure compatibility across different regions and scales. This resource provides detailed information on various soil properties, including texture, organic carbon content, pH levels, and water retention characteristics. It is well-suited for use in hydrological and land-use models.

The soil map data are pre-processed to align with the requirements of the SWAT model. This pre-processing step includes reclassifying soil types into SWAT-compatible categories, ensuring that all soil attributes are accurately represented. Soil parameters such as hydraulic conductivity, soil depth, and water holding capacity are linked to the catchment's corresponding HRUs to enable precise simulation of water–soil interactions.

Using HWSD ensures that the spatial variability of soil properties within the Rasina River catchment is accurately captured, enabling the model to account for localised differences in infiltration and runoff. Furthermore, the global standardisation of HWSD data allows for comparability with other studies, contributing to the broader applicability of the findings [5].

The SWAT model employed in this study incorporated several distinct soil types to simulate hydrological processes within the Rasina River catchment effectively. These soil types are inherent to the Rasina River catchment and are analysed based on their hydrological and physical properties, significantly influencing surface runoff, infiltration, and sediment transport (Figure 4). The primary soil types and their corresponding SWAT codes are as follows:

(a) Dystric Acid Brown Soil (SWAT code: Ao41-2ab-4271)

This soil type is characterised by its low fertility and high susceptibility to erosion. It is predominantly found in lower altitudes, up to 800 m above sea level, where thermophilous oak forests are typical. The acidic nature of the soil and its weak structure contribute to its limited agricultural potential and

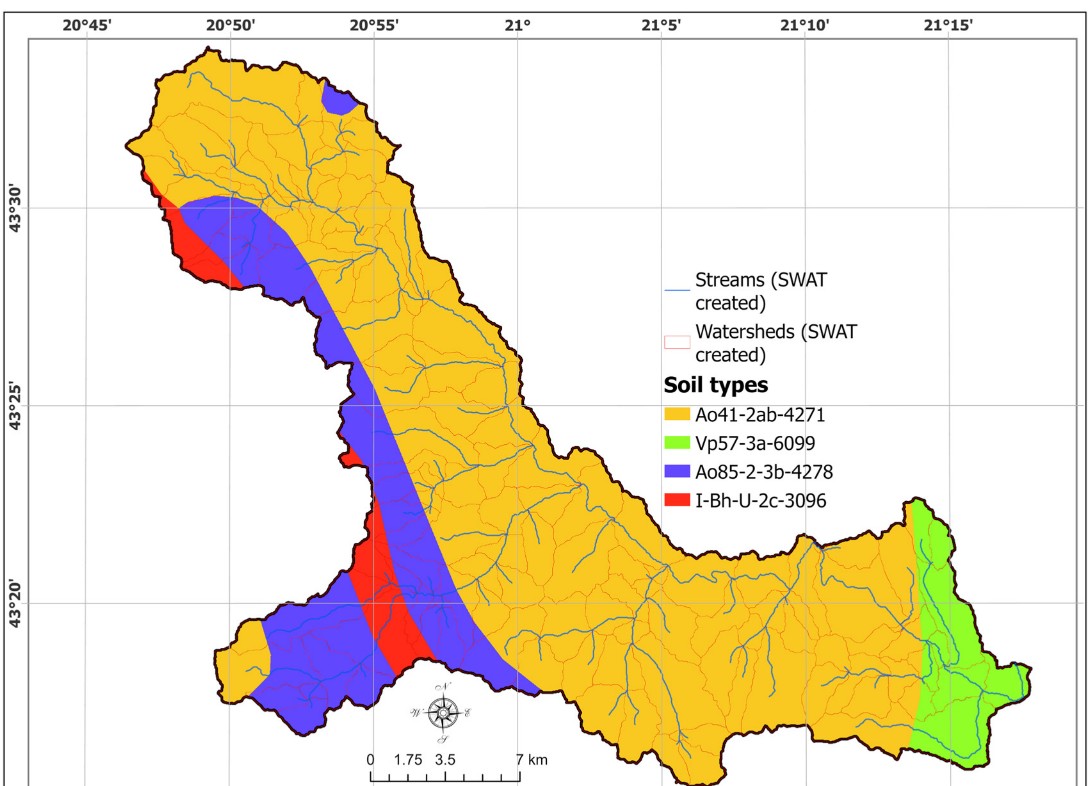

Figure 4: Soil types of the study area.

heightened vulnerability to surface runoff during precipitation events [48].

(b) Vertisol (SWAT code: Vp57-3a-6099)

Vertisols are highly plastic clay soils that are fertile and widely used for agriculture. However, their tendency to expand and contract due to moisture changes makes them prone to erosion, particularly in areas with intensive rainfall. These soils are critical in understanding the hydrological dynamics of agricultural lands within the catchment [49].

(c) Eutric Brown Soil (SWAT code: Ao85-2-3b-4278)

Eutric Brown Soil is primarily associated with agricultural zones because it contains nutrients and a moderate erosion risk. Its relatively stable structure supports vegetation growth, making it essential for analysing land use impacts on hydrological processes [48].

(d) Humus-Rich Siliceous Soil (SWAT code: I-Bh-U-2c-3096)

This soil type is distinguished by its high organic matter content and excellent infiltration capacity, which reduces surface runoff and erosion risks. It is predominantly found in higher altitudes, contributing significantly to the hydrological balance of the forested regions [50].

These soil types (Figure 4) provided critical input for the SWAT model, allowing for a detailed simulation of water-soil interactions and sediment transport dynamics within the catchment. Their incorporation ensured that the spatial variability of the catchment's physical and hydrological characteristics was accurately captured, thereby enhancing the reliability of the analysis.

2.2.1.4 Meteorological data

Meteorological data are essential for hydrological modelling as they provide the basis for simulating water cycle processes at a daily temporal resolution. These datasets enable the SWAT model to assess how climatic variations influence water availability, quality, and overall catchment dynamics. The key climate parameters required include precipitation, temperature, solar radiation, wind speed, and relative humidity.

This study's meteorological data are sourced from the "Global Weather Data for SWAT" repository [51]. These datasets encompass 10 weather stations distributed around the study area, covering the period from 1971 to 2014. The recorded parameters included air temperature (°C), precipitation (mm), wind speed (m/s), relative humidity (%), and solar radiation (MJ/m^2). The data originate from the archives of the National Centers for Environmental Prediction (NCEP) Climate Forecast System Reanalysis (CFSR), ensuring consistency and reliability in their application [52–54].

The geographical bounds of the Dataset extend from 42.9601° to 43.739° North latitude and 20.0552° to 21.6097° East longitude. The meteorological data were retrieved on August 4 2018, with files formatted explicitly for SWAT input.

The SWAT model run focused on the period from 2000 to 2014, using daily rainfall and temperature data from multiple gauges across the watershed. The Penman-Monteith method calculates potential evapotranspiration, ensuring robust estimations of water loss due to evaporation and plant transpiration. The rainfall–runoff relationship is modelled using the curve number method, while daily stream routing is executed through the Variable Storage routing method. These settings allow the model to account for the' temporal and spatial variability of hydrological processes [55].

The SWAT printout settings are configured for monthly outputs, with a 4-year warm-up period to initialise model conditions. The 15-year simulation run provided detailed insights into the hydrological behaviour of the catchment under varying climatic conditions, incorporating key processes such as daily runoff estimation, constant channel dimensions, and in-stream nutrient transformations modelled using the QUAL2E equations [56].

This methodology ensures a thorough representation of the climate's impact on the hydrology of the Rasina River catchment, providing a reliable basis for subsequent analyses and decision-making.

2.2.2 SWAT modelling process

The process begins with loading all input data into the model to define the physical properties of the watershed. Sub-basins are generated based on topographical data from the DEM, and these are further divided into HRUs according to land use and soil type. Once defined, the model simulates hydrological processes for each HRU, accounting for daily precipitation, temperature fluctuations, and soil characteristics to estimate runoff, evapotranspiration, and sediment transport [5,23].

2.2.3 Calibration and validation of SWAT

The calibration and validation process is crucial for ensuring the accuracy and reliability of the SWAT model. Calibration involves adjusting model parameters to match simulated data with observed hydrological data, while validation tests the model's predictive capability with independent datasets. In the study focusing on the Rasina catchment, calibration and validation are performed using daily streamflow data from two nearby hydrometeorological stations over 10 years (Figure 1).

During calibration, sensitive parameters are iteratively adjusted to minimise the discrepancies between observed and simulated streamflow, sediment yield, and other hydrological indicators. The Nash–Sutcliffe efficiency coefficient (NSE), coefficient of determination (R^2), and per cent bias (PBIAS) are among the metrics used to evaluate model performance and accuracy. Ensuring that the model replicates observed hydrological behaviour is essential for accurately predicting water balance, sediment transport, and the impact of land use changes on hydrology [4,57].

2.3 MCDM analysis

The MCDM methodology used in this study is based on a weighted overlay analysis performed in a GIS environment, specifically within ArcGIS Pro. This approach allows for integrating various spatial datasets to assess the suitability of different locations for small hydropower development. The main objective of the MCDM is to evaluate and rank areas based on multiple criteria that influence the potential for sustainable development.

2.3.1 Steps of the MCDM process

The MCDM process systematically identifies optimal locations for small hydropower development. The initial step involved selecting criteria and preparing data, with input datasets encompassing topographical features, hydrological features, land cover, and soil types datasets. Each dataset contributed to capturing the spatial characteristics relevant to hydropower potential. Specifically, the DEM with a 10 m resolution and its features, land cover information, hydrological features, and soil data are derived from the same sources utilised for the SWAT model, ensuring consistency in data use.

All input criteria are standardised onto a scale to facilitate comparability among diverse datasets. This standardisation process entailed reclassifying datasets into ranked categories based on their influence on hydropower suitability. For example, steeper slopes are attributed higher values due to their capacity to facilitate water flow accumulation and energy generation, highlighting their significance in determining site potential.

The criteria are weighted to indicate relative significance in hydropower site selection. Weights are appointed to each criterion based on expert judgement and a comprehensive literature review, aligning them with their relevance. For instance, topographical features and slopes are given higher weights due to their critical role in determining the energy potential of water flow. In contrast, land cover and soil types are weighted to account for their contributions to site accessibility and environmental considerations.

Following standardisation and weighting, a weighted overlay analysis is performed. This analytical step involved integrating all standardised criteria maps and combining them according to their weights. The resulting output is a composite suitability map, with each pixel assigned a score indicating its overall appropriateness for hydropower development [58].

The final stage of the MCDM process entailed evaluating and ranking areas based on their suitability scores. Regions with the highest scores are the most favourable for small hydropower development. This ranking balanced critical factors such as hydrological features, topography, land use, and environmental impact. This comprehensive approach enabled a spatially balanced evaluation that supports sustainable and efficient hydropower resource utilisation.

By employing a GIS-based MCDM approach, the study effectively integrated multiple datasets into a unified analytical framework. This methodology provides an objective means of identifying optimal sites for small hydropower development while simultaneously addressing diverse environmental and socio-economic considerations.

2.3.2 MCDM input data and coefficients

The MCDM analysis is performed using the Weighted Overlay tool in ArcGIS Pro, combining spatial datasets to identify the most suitable sites for SHP development. The selected input datasets reflect critical spatial and environmental criteria, each contributing uniquely to the assessment. The input parameters, their coefficients, and influence percentages are presented in Table 1.

(a) Land cover data

The LC dataset served as a fundamental input for the MCDM analysis. This dataset evaluated various land-use categories, including vegetation cover, built-up areas, and other land features, each significantly affecting the suitability of SHP development. Different land cover types are assigned MCDM coefficients based on their influence on hydropower

Table 1: MCDM input data and parameters

Land cover				MCDM % influence
Raster value	**SWAT code**	**Name**	**MCDM coefficient**	
1	WATR	Water	100	20
2	FRSE	Forest, evergreen	40	
3	FRSD	Forest, deciduous	50	
4	AGRL	Agricultural land	30	
5	URMD	Urban medium density	20	
6	PAST	Pasture	100	
7	SWRN	Wetlands, natural	100	
8	BERM	Berms	100	
Soil types				**MCDM % influence**
Raster value	**Swat code**	**Name**	**MCDM coefficient**	
2	Ao41-2ab-4271	Dystric Acid Brown Soil	50	10
3	Vp57-3a-6099	Vertisol	100	
4	Ao85-2-3b-4278	Eutric Brown Soil	10	
5	I-Bh-U-2c-3096	Humus-Rich Siliceous Soil	25	
Slope				**MCDM % influence**
Raster value	**–**	**Slope value (%)**	**MCDM coefficient**	
1	—	0–5	50	10
2	—	5–10	80	
3	—	10–20	90	
4	—	20–30	90	
5	—	>30	50	
Sedimentation (out of the watershed, total, annual)				**MCDM % influence**
Raster value	**–**	**Value (m^3/s)**	**MCDM coefficient**	
1	—	0–5,000	100	25
2	—	5,000–15,000	85	
3	—	15,000–50,000	60	
4	—	50,000–100,000	40	
5	—	100,000–250,000	20	
6	—	250,000–500,000	10	
Flow out (annual mean)				**MCDM % influence**
Raster value	**–**	**Value (m^3/s)**	**MCDM coefficient**	
1	—	0–0.25	5	35
2	—	0.25–0.5	20	
3	—	0.5–1.0	40	
4	—	1.0–3.0	70	
5	—	3.0–5.0	85	
6	—	>5.0	100	

potential. For example, water bodies (WATR), natural wetlands (SWRN), and pastures (PAST) received the highest coefficients (100), indicating their critical importance. At the same time, urban areas and agricultural lands are assigned lower coefficients due to their reduced compatibility with SHP development.

(b) Soil types

Soil type data are included in the MCDM analysis to account for their influence on hydrological processes such as infiltration and sediment retention. The coefficients assigned to each soil type reflect their hydrological significance and suitability for hydropower development.

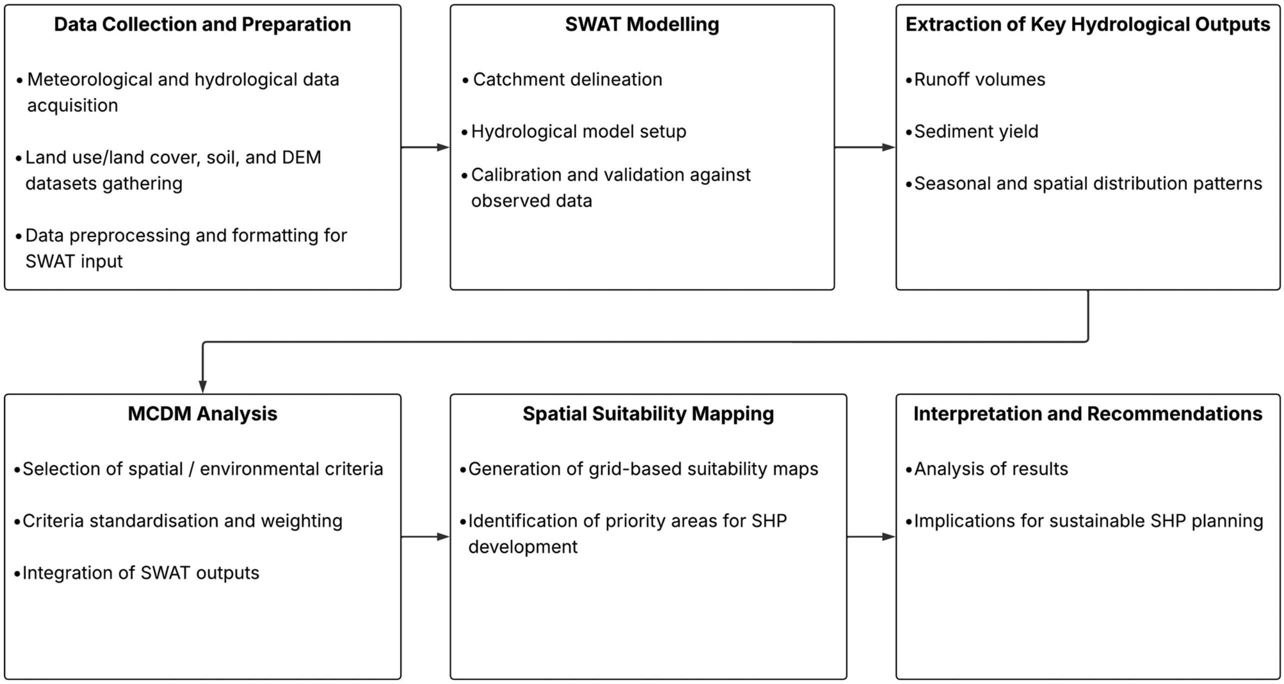

Figure 5: Workflow chart of the integrated SWAT–MCDM methodology for spatial suitability assessment of small hydropower development.

Vertisol (Vp57-3a-6099) is assigned the highest coefficient (100) due to its excellent water retention properties, while Eutric Brown Soil (Ao85-2-3b-4278) received the lowest coefficient (10), reflecting its limited impact on these processes. Other soil types, such as Dystric Acid Brown Soil (Ao41-2ab-4271) and Humus-Rich Siliceous Soil (I-Bh-U-2c-3096), are assigned coefficients of 50 and 25, respectively, based on their hydrological and physical characteristics.

(c) DEM

A 10 m resolution DEM, previously employed in the SWAT analysis, is utilised in the MCDM process to assess terrain characteristics, particularly slope. The slope is a critical factor influencing hydropower potential, directly affecting water flow accumulation and velocity. Slopes between 10 and 30% are identified as most favourable, receiving high coefficients (90), whereas slopes above 30% or below 5% are assigned lower coefficients, reflecting their limited suitability.

(d) SWAT-derived input data

Key outputs from the SWAT model, sedimentation and flow out, are incorporated as the most influential parameters in the MCDM analysis. Sedimentation data, representing the annual sediment yield at the watershed outlet, are categorised and weighted to prioritise areas with lower sediment transport, as excessive sedimentation could impact infrastructure and operational efficiency. Similarly, flow-out data, representing the annual mean flow rate, are weighted to prioritise areas with higher discharge rates, essential for hydropower generation. For instance, areas with flow rates above 5.0 m^3/s are assigned the highest coefficient (100), while regions below 0.25 m^3/s received minimal weight (5).

2.3.3 Weighted overlay and resulting analysis

The weighted overlay process integrated all standardised datasets according to their respective coefficients and influence percentages. Land cover contributed 20% to the overall analysis, soil types 10%, slope 10%, sedimentation 25%, and flow out 35%. These weights reflect the relative importance of each criterion in determining the suitability of SHP development. The result is a composite suitability map, identifying optimal locations that balance ecological and socio-economic considerations for sustainable hydropower development.

The combination of these datasets provides a robust framework for assessing the hydrological and spatial factors influencing the development of SHPs within the Rasina catchment. Integrating SWAT modelling and MCDM through a GIS-based approach ensures a comprehensive spatial valuation that balances hydrological potential with environmental sustainability and infrastructure considerations (Figure 5).

3 Results

The analysed study area encompasses a total surface of 522 km^2. The topography is characterised by a minimum elevation of 262 m and a maximum elevation of 1,924 m a.s.l., with a mean elevation of 739.52 m. Notably, over 58% of the area falls within the 500–1,000 m elevation range, classifying the region as predominantly mountainous. Slope analysis indicated that more than 50% of the terrain exhibits slopes greater than 30%, followed by 20–30% and 10–20% gradients. These steep slopes highlight the rugged nature of the landscape and its implications for hydrological modelling and watershed management. The land cover analysis revealed that deciduous forests constitute the dominant land cover type, followed by pastures and agricultural land. These findings underscore the ecological significance of forested areas in the hydrological and geomorphological dynamics of the region. Regarding soil distribution, Dystric Acid Brown Soil is the predominant soil type, covering over 71% of the total area. This soil type is known for its limited fertility and high susceptibility to erosion, making it a critical factor in assessing sediment transport and surface runoff (Table 2).

Table 2: Statistical overview of study area characteristics: Land use, soil types, slope, and elevation

	Area (km^2)	Watershed (%)
Land use		
WATR	2.50	0.48
FRSE	24.12	4.62
FRSD	304.12	58.31
AGRL	72.83	13.95
URMD	6.05	1.16
PAST	88.14	16.89
SWRN	9.08	1.74
BERM	14.87	2.85
Soil types		
Ao41-2ab-4271	375.59	71.95
Vp57-3a-6099	53.96	10.34
Ao85-2-3b-4278	74.99	14.37
I-Bh-U-2c-3096	17.46	3.34
Slope value (%)		
0–5	24.59	4.71
5–10	36.91	7.07
10–20	88.64	16.98
20–30	109.41	20.96
>30	262.45	50.28
Elevation (m a.s.l.)		
<500	121.52	23.3
500–1,000	306.74	58.76
1,000–1,500	86.43	16.57
>1,500	7.31	1.37

3.1 Calibration and validation of the SWAT model

The calibration and validation processes for the SWAT model are performed using daily discharge data from two hydrological stations, Brus and Ravni [59], located on the Rasina River (Figure 1). The calibration aimed to minimise the difference between observed and simulated streamflow, while validation assessed the model's predictive performance on an independent dataset [4].

3.1.1 Calibration process

The calibration is conducted using the SUFI-2 algorithm within SWAT-CUP, with 14 parameters identified as critical to hydrological processes [4,60]. The final parameter ranges and fitted values are presented in Table 3.

3.1.2 Validation process

The validation phase utilised an independent dataset to test the model's predictive capability without further parameter adjustments. The performance metrics achieved during calibration and validation for both stations are summarised in Table 4. Metrics such as the NSE, coefficient of determination (R^2), and percent bias (PBIAS) are used to evaluate the model's performance:

- During calibration, an NSE value of over 0.65 is achieved for both stations, indicating good agreement between observed and simulated values.

Table 3: Fitted calibration parameters for the stations "Brus" and "Ravni"

Parameter name	Fitted value (Brus)	Fitted value (Ravni)	Min. value	Max. value
r__CN2.mgt	0.094	0.102	−0.2	0.2
v__ALPHA_BF.gw	0.131	0.15	0	1
v__GW_DELAY.gw	205.14	190	30	450
v__GWQMN.gw	0.33	0.4	0	2
v__GW_REVAP.gw	0.1878	0.2	0	0.2
v__ESCO.hru	0.8178	0.85	0.8	1
v__CH_N2.rte	0.1773	0.2	0	0.3
v__CH_K2.rte	52.875	60	5	130
v__ALPHA_BNK.rte	0.033	0.045	0	1
r__SOL_AWC(..).sol	0.1762	0.19	−0.2	0.4
r__SOL_K(..).sol	0.6864	0.7	−0.8	0.8
r__SOL_BD(..).sol	−0.0699	−0.05	−0.5	0.6
v__SFTMP.bsn	2.25	2.5	−5	5
v__SURLAG.bsn	6.68415	6.5	0.05	24

Table 4: Performance metrics for calibration and validation

Station	Phase	NSE	R^2	PBIAS (%)
Brus	Calibration	0.67	0.7	−5.5
Brus	Validation	0.65	0.68	−6
Ravni	Calibration	0.69	0.72	−4.8
Ravni	Validation	0.68	0.71	−5.2

- Validation results are consistent with the calibration phase, demonstrating the model's reliability.

3.2 MCDM analysis results

The MCDM analysis for SHP site selection utilised a weighted overlay method in ArcGIS Pro. This method incorporated the input parameters listed in Table 1, where each parameter is weighted according to its significance in influencing hydropower suitability. Each dataset is assigned coefficients (Table 1) reflecting its specific contribution to the hydrological, environmental, and operational feasibility of SHP development.

The output of the MCDM analysis resulted in a range of suitability values between 11 and 72 from a possible range of 0–100. The spatial distribution of these values is categorised into intervals, as presented in Table 5 and Figure 6, which reflects the total area (km²) within each suitability range.

Suitability above 50: Areas with values exceeding 50 (categories 50–60, 60–65, and 65–100) are identified as optimal locations for SHP development. Although covering only a minor portion of the watershed (approximately 0.94 km²), these regions are characterised by favourable hydrological and environmental conditions.

Suitability below 50: Areas with values below 50 (categories <15, 15–40, and 40–50) dominate the watershed, accounting for the vast majority of the area (521.73 km²). These areas are less suitable due to economic and operational risks associated with low water availability, excessive sedimentation, or other limiting factors.

To further analyse and visualise the optimal SHP locations, the raster values representing the highest suitability scores (72, 71, 70, 69, 68, 67, 66, and 65) are extracted and converted into a vector format as points. Each point corresponds to a raster cell, retaining the associated value attribute to indicate its suitability score.

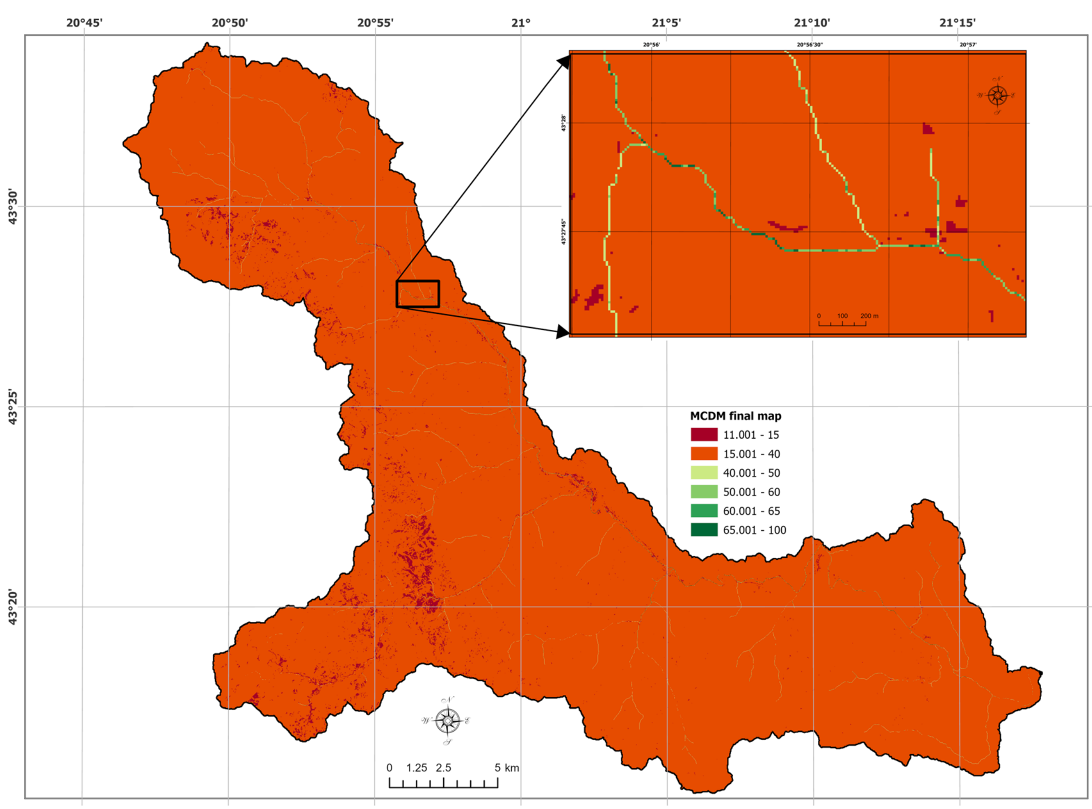

Figure 6: Spatial distribution of suitability classes for SHP development based on MCDM analysis.

Table 5: MCDM suitability ranges with corresponding area coverage

Value	Area (km^2)
7–15	8.47
15–40	511.26
40–50	1.13
50–60	0.70
60–65	0.15
65–100	0.09

The vectorised points are created using the Raster to Point tool in ArcGIS Pro, ensuring that only cells with the aforementioned high suitability values are included in the conversion process. This process resulted in 1,976 points, representing the most optimal locations for SHP development. Each point is georeferenced and contains attributes allowing further spatial analysis and integration into decision-making workflows. The most valuable locations, with suitability values ranging from 70 to 72, comprise a total of 128 points, which are distributed across the middle and lower sections of the Rasina River catchment.

The resulting points are overlaid onto the base stream map, clearly visualising high-priority locations. These locations align with areas characterised by favourable terrain, hydrological conditions, and environmental factors. The final suitability map, presented in Figure 7, illustrates the spatial distribution of these locations and highlights areas with the most significant potential for sustainable SHP development.

This map serves as a valuable decision-making tool, enabling the identification of priority areas for detailed feasibility studies and future SHP implementation. Focusing on the most suitable locations ensures that ecological, economic, and operational considerations are balanced in the planning and development.

4 Discussion

The proposed study successfully combined SWAT modelling and MCDM analysis to identify optimal locations for SHPs within the Rasina River catchment. The approach effectively integrates hydrological and spatial analyses, providing valuable insights into site suitability. Moreover, this study represents a pioneering effort in Serbia, being the first to integrate SWAT modelling with MCDM methodology for SHP site selection. Previous research in Serbia has not

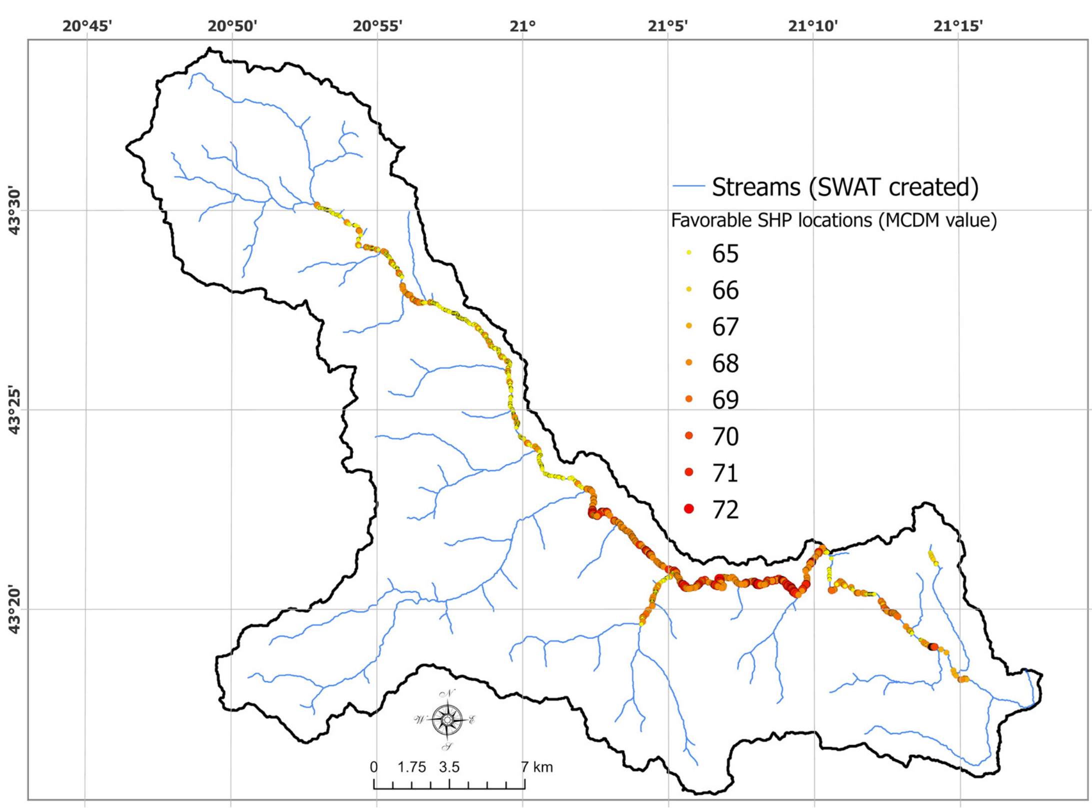

Figure 7: Suitability map for SHP locations based on weighted overlay analysis.

employed this specific combination of tools to assess hydropower suitability, making this study a significant contribution to renewable energy planning. The original aspect of this research lies in its application of SWAT modelling for detailed simulations of hydrological processes, including flow rates and sediment transport, combined with a systematic evaluation of spatial criteria using MCDM. This integrated approach provides a robust foundation for data-driven decision-making, which is vital for sustainable SHP development. As the first application of this methodology in Serbia, the study sets a benchmark for future research and offers a replicable model for similar analyses in other regions.

This research demonstrates several key improvements and advancements compared to similar studies, such as [1,61,62]. Unlike these studies, which utilise coarser datasets and focus on general hydrological parameters, this study employs higher-resolution input data, including a 10 m DEM and multispectral land cover analysis. These refinements enhance the spatial accuracy of suitability assessments, particularly in areas with complex geomorphological characteristics. Furthermore, incorporating sedimentation and flow parameters directly derived from SWAT outputs provides a region-specific analysis that more accurately reflects the hydrological dynamics of the Rasina River catchment. This approach bridges the gap between hydrological simulation and spatial decision-making, ensuring more precise site evaluations.

While [61,62] explored GIS-based hydropower assessments, neither integrated a calibrated and validated SWAT model, as presented in this study. This research ensures higher accuracy in hydrological predictions by incorporating robust calibration and validation processes, using metrics such as NSE and PBIAS at two hydrometric stations. Additionally, the alignment of all raster datasets at a 10 m resolution and their reprojection into UTM 34N further contributes to the reliability of the results, an aspect not explicitly addressed in the other studies.

The originality of this study lies in its application to Serbia, addressing region-specific challenges such as sediment control and the optimisation of less suitable areas for SHP development. While the aforementioned studies provide valuable frameworks, they lack strategies for improving low-suitability regions, a critical aspect addressed in this research. Moreover, the study lays the groundwork for integrating future climate change scenarios, a forward-thinking perspective that enhances its relevance for long-term hydropower planning.

A notable limitation of this study is the lack of integration of socio-economic factors. While the analysis focused primarily on hydrological and ecological parameters essential for determining SHP feasibility, socio-economic considerations such as cost–benefit analyses, land acquisition challenges, and community acceptance are not addressed. Including these factors in future studies could provide a more comprehensive framework for SHP site selection. Evaluating the economic viability of proposed sites, alongside their environmental suitability, would support more informed decision-making. Furthermore, assessing the impacts on local communities and suggesting strategies to mitigate potential adverse effects would contribute to socially sustainable hydropower development.

The MCDM analysis results indicate that most watersheds scored low in suitability (<50), suggesting that many areas face challenges such as limited water availability and excessive sedimentation. Addressing these challenges presents an opportunity to expand the range of viable SHP sites. Future research could explore measures such as implementing sediment control systems, including soil conservation practices and sediment traps, to reduce sedimentation levels in key areas. Optimising land use through controlled agricultural practices or reforestation in erosion-prone zones could also enhance hydrological conditions. Water management strategies such as constructing small reservoirs or retention systems could also help increase water availability in areas with low flow rates, improving their suitability for SHP development.

Another critical consideration is the impact of climate change on hydropower potential. Although this study accounted for climate variability, it did not incorporate future climate change scenarios. Given the anticipated effects of climate change on water resources, future studies should include scenario-based analyses to evaluate the long-term sustainability of SHP locations. Modelling changes in precipitation patterns, temperature increases, and extreme weather events using the SWAT model would provide valuable insights into the resilience of identified sites. Such analyses would also support the development of mitigation policies to address potential risks associated with climate change.

The study also highlighted the importance of aligning spatial datasets for accurate analysis. The resampling of the DEM to a 10 m resolution and its alignment with other datasets ensured consistency and improved the reliability of the results. However, further refinements of input data, such as employing higher-resolution DEMs or incorporating more detailed land cover and soil maps, could enhance the precision of future analyses. These improvements would help reduce uncertainties, particularly in areas with complex geomorphological characteristics.

By addressing these constraints, future research can build upon the framework established in this study, advancing methodologies for sustainable SHP development.

Integrating socio-economic factors, improving conditions in low-suitability areas, and incorporating climate change scenarios will ensure more robust and comprehensive planning for hydropower projects. Moreover, enhancing spatial data quality will further improve the reliability of site suitability assessments, ultimately contributing to more effective and sustainable hydropower development in similar catchments.

5 Conclusion

This study provides an initiating approach to SHP site selection within the Rasina River catchment by integrating the SWAT modelling with MCDM analysis. This integration offers a robust methodological framework that combines hydrological accuracy with spatial precision, making it an invaluable tool for renewable energy planning. The study achieves high spatial and hydrological reliability by employing a 10 m resolution DEM, resampled and aligned datasets, and SWAT-derived parameters such as sedimentation and flow out.

The originality lies in its region-specific approach. Unlike many global studies, this research incorporates sedimentation and flow parameters directly derived from hydrological modelling outputs, providing a nuanced understanding of the unique challenges and opportunities in the Rasina River catchment. The findings demonstrate the suitability of only 0.94 km^2 of the watershed for SHP development, highlighting the need for strategic interventions, such as sediment control measures and optimised land-use practices, to improve the suitability of less favourable areas.

This research is particularly significant for Serbia as it marks the first application of this integrated methodology in the country, setting a benchmark for future research. Its advanced hydrological modelling, detailed spatial analysis, and data-driven decision-making provide a replicable framework for other regions with similar geophysical characteristics.

Nevertheless, the study identifies areas for future improvement. These include incorporating socio-economic factors, such as cost–benefit analyses and community impact assessments, to enhance decision-making comprehensiveness. Additionally, including climate change scenarios in hydrological modelling would offer insights into the long-term viability of proposed SHP locations under evolving environmental conditions.

This research advances the methodologies for SHP planning and contributes to sustainable infrastructure development in Serbia, fostering a balance between energy production, environmental protection, and socio-economic considerations. Future studies can further refine this framework by addressing the outlined limitations, ensuring it remains an effective tool for achieving sustainable energy goals.

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