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Surface water runoff estimation: a review of methods incorporating terrain shape

Yessica Ramirez-Yara[1], Agnieszka A. Malinowska[2], Ryszard Hejmanowski[3]

[1] *AGH University of Krakow, Faculty of Geo-Data Science, Geodesy, and Environmental Engineering, Krakow, Poland, e-mail: yyara@agh.edu.pl (corresponding author), ORCID ID: 0000-0001-9634-5406*
[2] *AGH University of Krakow, Faculty of Geo-Data Science, Geodesy, and Environmental Engineering, Krakow, Poland, e-mail: amalin@agh.edu.pl, ORCID ID: 0000-0002-8492-9073*
[3] *AGH University of Krakow, Faculty of Geo-Data Science, Geodesy, and Environmental Engineering, Krakow, Poland, e-mail: hejman@agh.edu.pl, ORCID ID: 0000-0002-0269-0565*

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Abstract: Surface runoff is a key variable in the water balance, representing excess water that exceeds soil infiltration capacity and is not absorbed by drains. Accurate estimation of surface runoff is crucial for flood prevention, optimizing agricultural water use, and detecting irregular water capture. Various computational approaches, including machine learning, deep learning, statistical models, and hydraulic simulations, have been developed to estimate runoff. However, despite extensive research, many models overlook the influence of terrain characteristics – such as topography, slope, and surface roughness – leading to potential inaccuracies in runoff prediction. This study conducts a comprehensive bibliographic review of state-of-the-art research on surface runoff estimation, with a focus on methods that integrate digital terrain models (DTMs), remote sensing, and computational modeling techniques. Through this analysis, a specific research niche was identified and verified, highlighting the need for terrain-sensitive runoff models that better incorporate topographic variables into hydrological modeling. By evaluating and comparing existing methodologies, this review provides insights into the most effective approaches for runoff estimation and offers recommendations for selecting the appropriate models based on landscape and hydrological conditions. It also presents potential solutions that may pave the way for a better understanding of runoff processes.

Keywords: runoff, DEM, deep learning, machine learning, remote sensing

INTRODUCTION

Surface runoff is a critical hydrological variable that occurs globally when rainwater, snowmelt, or overflow from water bodies causes the soil to reach saturation, preventing further infiltration and leading to water flowing across the land surface into bodies of water such as rivers, streams, reservoirs, and lakes (Yang et al. 2015, Jehanzaib et al. 2022). Measuring runoff globally is theoretically possible but presents significant challenges due to the vast and complex nature of the Earth's surface (Chen et al. 2020). Estimating runoff and its parameters has consistently been a major challenge in hydrology, however, it can be measured locally using specialized equipment, globally via advanced remote sensing technologies and through the estimation of the hydrological balance equation and hydrometeorological models to enhance runoff estimates across varied geographical regions.

Globally, Liang and Greene (2020) calculated runoff using a simple water balance function,

$R = P - E$ (where R is the runoff, P is the precipitation and E is the evaporation). After analyzing runoff in China, the authors extrapolated their findings to the global continental area. The results suggest that global runoff volume is higher than reported in most prior studies, pointing to an underestimation of global surface runoff and underscoring the need for more detailed study of this variable. Similarly, Miao et al. (2023) demonstrated that over 70% of global land area shows an increase in projected runoff for the 5th and 6th Coupled Model Intercomparison Projects over the long term (2070–2099), relative to the reference period of 1970–1999. This increase highlights that model uncertainty in projected runoff changes accounts for over 60% of total uncertainty worldwide. Therefore, it is crucial to analyze surface runoff by considering both anthropogenic dynamics and intrinsic soil conditions. These conditions can vary geographically and include factors such as geomorphology, geology, and infiltration characteristics.

The variability of land surface features influence the movement, distribution, and storage of surface water across landscapes defining flow paths, infiltration rates, and sediment transport, which do not remain constant over time or across different regions, must be considered, as they are critical to accurately assessing flooding risk, climate change, ecological integrity, and land surface movements worldwide (Guzy et al. 2021, Angelakis et al. 2023). Incorporating terrain and topographical data into runoff modeling, through detailed digital elevation models (DEMs), enhances the precision of hydrological simulations and supports sustainable land-use planning. Failing to consider these aspects in runoff estimations can lead to significant inaccuracies in predicting runoff volumes and patterns, particularly in regions with complex geomorphology.

Runoff measurement techniques differ based on the source of water, such as rainfall, snowmelt, or glacier melt. Measuring runoff from rainfall events is essential for understanding how precipitation contributes to surface water flow (Zhu et al. 2023, VillabonaOrtíz et al. 2025). Snowmelt runoff is vital in cold regions, driven by seasonal temperatures. Glacier melt remains uncertain due to limited mass balance data, affecting long-term water and ecosystem forecasts (Liu L. et al. 2020, Łucka et al. 2022, 2024, Piwowar et al. 2023).

One of the earliest approaches to estimating runoff was introduced by Mulvaney (1851), who proposed the classical rational method, connecting rainfall intensity, catchment area, and runoff coefficient to predict peak discharge, although it is limited by its simplicity and general assumptions. The demand for more sophisticated models led to the catchment model by Dalrymple (1960), which offered a systematic approach to runoff estimation by accounting for catchment dynamics such as soil properties, vegetation cover, and land use, opening the possibilities for the implementation of more complex hydrological models. Following this, the Soil Conservation Service (SCS) curve number model (Ponce 1989), became one of the most widely used methods for estimating runoff. The SCS model calculates runoff based on factors such as land use, soil type, hydrological conditions, and precipitation, and has remained fundamental in flood management, hydrological studies, and land-use planning (Ajmal et al. 2020, Rao 2020, Gupta & Dixit 2022). Despite its broad application, traditional empirical models like the rational method and the SCS curve number model exhibit notable limitations. These methods often rely heavily on field observations which are not always accessible, creating challenges in calibration and validation. Additionally, they offer limited consideration of landscape morphology, potentially affecting accuracy in diverse terrain, working better for smaller areas (Tarate et al. 2024).

Numerous methods and technologies have emerged for the measurement of surface runoff. For example, conceptual methods that aim to obtain the relationship between hydrological cycle variables and runoff without considering the detailed physical processes (Okkan et al. 2021), include tank models (Phien & Pradhan 1983), TOPMODEL (Beven 2012), the HBV model (Lindström et al. 1997), the unit hydrograph (Gupta & Sorooshian 1983), and VIC (Liang et al. 1994). Each of these models simplifies the complex interactions within a catchment to produce runoff estimates based on a simplified, conceptual understanding of hydrological processes which are particularly useful in areas with limited observation networks, without accounting for detailed terrain shape (Fowler et al. 2020), and physical soil details.

The need for more advanced and accurate models for runoff modeling has been one of the main research topics in water resources planning, leading to the development of the Hydrologic Engineering Centre (HEC) model by the U.S. Army Corps of Engineers (USACE-HEC) in 1981. HEC simulates runoff and streamflow within a watershed by incorporating hydrological processes such as infiltration, evaporation, and surface runoff, making it a widely adopted tool for flood risk analysis and watershed management. Later, in the 1990s, the USDA Agricultural Research Service (ARS) developed the Soil and Water Assessment Tool (SWAT) (Neitsch et al. 2002). SWAT is designed to simulate the effects of land use, soil properties, climate, and topography on hydrological processes, including runoff, sediment transport, and nutrient cycling, based on watershed characteristics. Subsequently, the GR4J model, a hybrid conceptual-hydrological model developed in 1995 by France's National Institute of Agronomic Research (INRA), was introduced. GR4J does not consider spatial variability in hydrological processes; rather, it focuses on the overall behavior of a catchment. GR4J strikes a balance between complexity and computational efficiency, making it a popular choice for practical applications (Mo et al. 2024).

With rapid advancements in technology and computational capabilities, runoff estimation has increasingly shifted toward data-driven models that leverage large datasets and sophisticated algorithms to uncover relationships between input data, such as precipitation, temperature, and land characteristics with the runoff as an output (Al-Safi et al. 2020, Peel & McMahon 2020, Kan et al. 2024). As Jehanzaib et al. (2022) note, these models can provide more accurate runoff estimations without a heavy reliance on physical parameters, making them especially useful in regions with limited field data.

In recent years, machine and deep learning techniques have gained significant attention as promising alternatives to traditional mathematical models, achieving notable success across fields, including hydrology and meteorology (Bhusal et al. 2022). Zounemat-Kermani et al. (2020) emphasize that machine learning, artificial intelligence and physical-based models greatly improved the overall runoff dynamics modeling performance by identifying complex patterns in data, providing a reliable alternative to conventional models (Morales et al. 2021, Gichamo et al. 2024). This transition towards machine learning and data-driven models represents a milestone in runoff estimation, offering enhanced flexibility, accuracy, and applicability across diverse hydrological and topographical conditions (Singh et al. 2022).

However, with the advent of machine learning and deep learning structures, there is an opportunity to study runoff estimation by incorporating models that synthesize terrain shape in high spatial resolution, considering at least a three-dimensional representation. For example, the grid cell size of DEM significantly affects derived terrain variables such as slope, aspect, and curvature. Available runoff estimation methods can be improved by incorporating solutions from the perspectives of method optimization and runoff characterization (Yu et al. 2024). In the same way, the rainfall-runoff models should be made more flexible including additional input parameters that can incorporate land-use changes, land-use topographical dynamics and rainwater harvesting for flood management (Ali et al. 2024). Nagaveni et al. (2019) mention that the main factor causing uncertainty in runoff estimations is the low quality of DEMs, as features such as slope and aspect are crucial and heavily influence runoff flow and volume. These features direct the stream according to the shape and geological characteristics of the region, which are essential for obtaining a reliable runoff estimation based on the geomorphological features of the soil during runoff events.

In this article, we conduct a literature review following the methodology described by Barry et al. (2022), of the most used runoff estimation methods worldwide, highlighting how these methods incorporate terrain shape in their calculations and also how researchers are estimating runoff, as a punctual value (one-dimention), as a time series analysis (two-dimensions), as an interpolate surface (three-dimentions) or as a multidimensional approach in the space and in the time. We present the methodology used to analyze more than

200 scientific articles, classifying them based on whether they include terrain shape in their estimations and highlighting the necessity of proposing a new spatial-temporal runoff estimation model that incorporates detailed DEM data using deep learning techniques.

MATERIALS AND METHODS

This article presents a literature review on runoff estimation using terrain shape approaches, following Barry et al. (2022). A systematic search of databases including Scopus, WoS, Google Scholar, and ResearchGate focusing on articles published over the last 10 years was done. Articles were selected based on relevance, citations, and methodological innovation. The selection criteria targeted studies addressing the calculation of surface runoff across a range of disciplines, including engineering, hydrology, environmental sciences and atmospheric sciences. Figure 1 reflects the most emphasized technique in each study; in cases where multiple methods were used, only the primary approach was counted to avoid duplication.

Figure 1 shows a notable increase in runoff estimation publications since 2019 in studies applying machine learning and deep learning. ML has become the most widely used technique globally, offering robust tools for runoff estimation, prediction, and modeling. DL exhibits the steepest growth, highlighting its rising relevance in the field. In contrast, studies focusing on terrain shape maintain a steady trend, reflecting sustained but less accelerated interest.

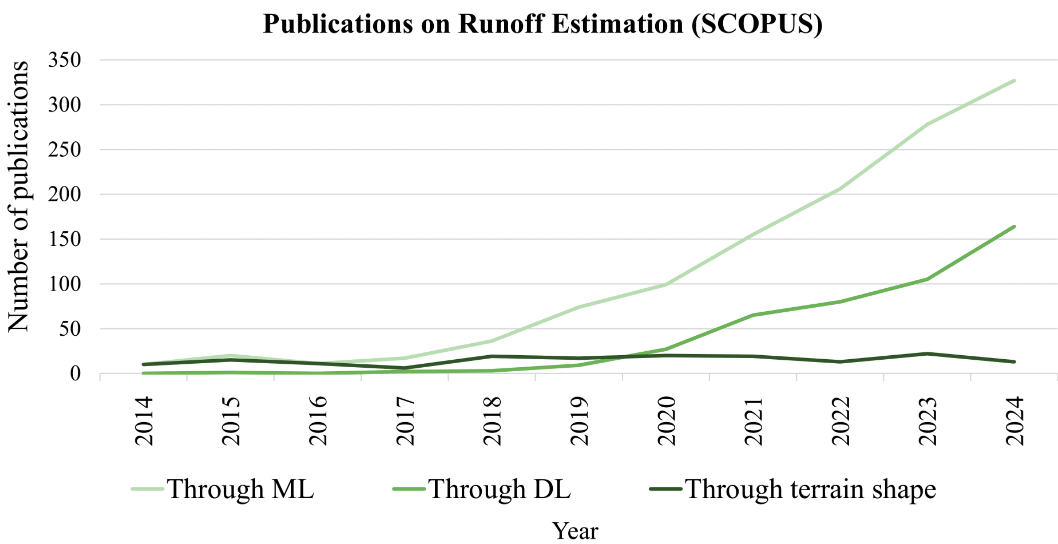

Fig. 1. *Graph of the number of literature positions published in the past 10 years of runoff estimation using ML, DL and terrain shape (data from https://www.scopus.com/)*

REVIEW OF METHODS FOR RUNOFF ESTIMATION INCORPORATING TERRAIN SHAPE

Following the methodology described by Barry et al. (2022), the reviewed articles were classified into three groups: those that did not consider the detailed shape of the terrain where runoff occurs, those that partially considered it, and those that included a detailed terrain layer for estimating runoff.

General findings on runoff modeling without terrain shape

Recent studies show that hybrid machine and deep learning models significantly improve runoff prediction by combining decomposition methods, ensemble learning, and neural networks. Wavelet-based models (Nourani et al. 2019) enhance time-frequency analysis, while ensemble methods like Ensemble-KNN (Yang et al. 2020) boost monthly forecasts. Advanced DL models such as CNN-RNNs (Shekar et al. 2024), BiLSTM-CNNs (Wu J. et al. 2023), and SD-GRU (He et al. 2024) improve spatial and temporal learning. Others use PCA (Zhang et al. 2021), EEMD (Niu et al. 2019), and kernel-based models (Safari et al. 2020) to increase accuracy. Overall, these approaches reflect a clear shift toward integrating preprocessing, decomposition, and advanced neural network structures to enhance the robustness and precision of runoff forecasting models without considering terrain features in the modeling.

Partially including terrain shape in runoff modeling

Terrain-based hydrological models

Recent research integrates hydrological models to assess runoff under climate and human activities. Budyko-elasticity approaches with HBV and BTOPMC (Al-Safi et al. 2020, Li H. et al. 2020) show HBV's superior performance in unregulated catchments. Remote sensing-enhanced models also proved effective in ungauged basins (Zhang et al. 2020). GIS-SWAT frameworks aid reservoir siting (Kalogeropoulos et al. 2020), and fine-resolution microtopography studies (Caviedes-Voullième et al. 2021) emphasize slope-driven infiltration effects. These models partially incorporate terrain shape through slope and watershed structure but often lack full spatial resolution of topographic complexity.

Studies using GIS and remote sensing with SCS-CN methods show that incorporating DEM-derived slope improves runoff estimation accuracy (Gupta & Dixit 2022). Additional research (Mekonnen & Melesse 2016, Rao 2020, Atharinafi & Wijaya 2021) confirms that slope consideration enhances results in high-runoff zones. Climate and forest coverage are also key runoff drivers (Liu W. et al. 2020), and ASMA-enhanced SCS-CN improves predictions for agricultural areas (Verma et al. 2020). These models incorporate terrain shape through slope and watershed delineation but often simplify its spatial variability.

Spatio-temporal analysis

Mo et al. (2023) and Miao et al. (2020) identified a declining runoff coefficient across 82 Chengbi River watersheds, attributed to human activity for 30 years, supported by land use changes (Luan et al. 2020). Hydrological simulations by Asadi et al. (2024) showed ensemble ML models (SVR, FFNN, LSTM) offered superior predictive accuracy in a network set. Remote sensing further enhanced runoff modeling: GRACE data (Chen et al. 2020) closely matched observed runoff; evapotranspiration and water storage improved calibration (Huang et al. 2020); and corrected precipitation data boosted accuracy in poorly gauged regions (Zhu et al. 2023). In fact, terrain shape is indirectly considered via watershed delineation, network data gathering and remotely sensed elevation, for a period, but its detailed morphological influence remains underrepresented.

Machine learning and deep learning

Machine learning (ML) models have shown superior performance in runoff prediction compared to traditional hydrological methods (Li M. et al. 2020, Wu H. et al. 2023, Xu et al. 2024). Ensemble approaches (Adnan et al. 2021) like ANFIS-PSO and MARS reduce uncertainty in ungauged basins, while hybrid models (Kwon et al. 2020) like Tank-LSSVM enhance daily runoff simulations. Techniques such as PCA-ANFIS (Bartoletti et al. 2018) simplify model structure without sacrificing accuracy. ML also aids in data gap-filling and improving simulations when integrated with physical models (Bhusal et al. 2022, Wahba et al. 2023). GARP modeling has been used for flood susceptibility via runoff depth estimation. While terrain shape is indirectly captured through input variables like DEM-derived slope or basin characteristics, its explicit treatment in ML frameworks remains limited and often underexploited.

Deep learning models, particularly hybrid approaches, have outperformed traditional hydrological methods in runoff estimation. CNNs combined with LSTM and GR4J (Kapoor et al. 2023) or MLP and SVM (Mohammadi et al. 2022) yielded higher predictive accuracy than standalone models. LSTM-based architectures, including sequence-to-sequence and vector-enhanced variants (Han et al. 2021), have proven effective for fine-resolution runoff and snowmelt prediction (Yokoo et al. 2022). Additionally, ensemble satellite-based models have improved accuracy in ungauged areas (Nourani et al. 2021, Gichamo et al. 2024). Despite leveraging spatial patterns through gridded data or sequence models, deep learning often only partially integrates terrain shape, typically through static inputs like DEM, without fully modeling topographic flow dynamics.

Including terrain shape in runoff modeling

Experimental approaches have been realized to try to understand the pattern of the runoff varying the landscape, for example, Chen et al. (2022), implement laboratory testing for analyzing the effects of topography on runoff, sediment yield and water and soil loss regulations over an open-pit coal mine dump in four different topographic scenarios varying according to the shape slope and angle of simulations considering soil hydrology and erosion dynamics. Tripathi et al. (2021), implement the estimation of the surface Soil Conservation Service-curve number (SCS-CN) runoff coefficient taking into consideration the DEM with a 15-meter pixel size, concluding that the results show that a higher resolution DEM can be used for effective and accurate runoff modeling: at areas located on high slopes, the runoff is lowest as the water quickly tends to rush down.

DISCUSSION

Topographic influence on runoff estimation

Some authors have analyzed the shape of the land as an important input in runoff estimation, leveraging hydrological modeling (e.g., SWAT). They compare different DEM layers at various spatial resolutions from different providers against real runoff data obtained from on-site stations (Bista et al. 2021, Hamdan et al. 2021, Fanta & Sime 2022). They found that when adding the DEM to the runoff estimation, the modeling results improve considerably compared to the same model without this additional layer. The conclusions drawn by the authors, even with slight changes in the methodology for including the DEM in the calculations, are quite similar: the inclusion of DEM aims to enhance runoff estimation and improve analyses for disaster mitigation approaches, climate change, agriculture, land management, and other applications.

Trends in runoff estimation research

The reviewed scientific articles in the current state-of-the-art, reveal that most of the research literature (62% of articles) does not consider terrain shape in the runoff calculation. This means that these studies allocate the punctual estimation, time series, runoff hydrological network or data-driven runoff in an empty space, disregarding the geomorphology of the ground where the runoff occurs. Typically, authors make inferences regarding the correspondence between rainfall-runoff events through complex and sophisticated data structures, obtaining valid results while ignoring the natural behavior and definition of this hydrological variable over the terrain.

Some authors, however, argue that runoff estimation should be geographically characterized within a defined space (20% of reviewed articles), for example, by calculating basins or water catchments (Bista et al. 2021), or by allocating the runoff network to identify trends varying spatially over time (Miao et al. 2020, Querales et al. 2022, Mo et al. 2023). This approach ranges from point-based observation to computing interpolated surfaces, sometimes incorporating topographical features such as land use, soil properties, or meteorological information to enhance calculations, often derived from remote sensing (Huang et al. 2020, Ghiggi et al. 2021, Nourani et al. 2021, Gulshad et al. 2024, Yu et al. 2024).

Finally, only 18% of studies directly consider terrain features in runoff estimation, particularly in analyses aimed at categorizing the DEM based on pixel values to model runoff streams according to slope and aspect (Mekonnen & Melesse 2016, Liu W. et al. 2020, Rao 2020, Kumar et al. 2021, Gupta & Dixit 2022), making comparisons between DEMs to identify the most accurate model for runoff estimation with minimal bias (Nagaveni et al. 2019), conducting experimental analyses across different terrain shapes (Chen et al. 2022), and include high-resolution DEMs as parameters in runoff modeling (Tripathi et al. 2021, Wagle & Smith 2024) (Fig. 2).

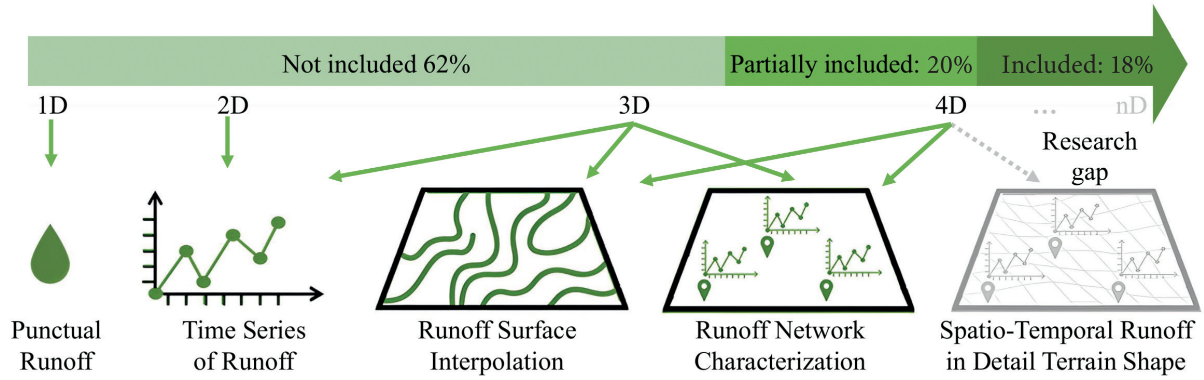

Fig. 2. *Distribution of the most common runoff estimations methods including terrain shape features according to the state of the art, varying over the runoff estimation dimension: 1D – punctual estimation, 2D – time series runoff analysis, 3D – runoff surface interpolation and runoff network characterization, 4D – estimation of runoff, including detailed terrain features where runoff occurs*

RESEARCH GAPS AND LACUNAE

While significant advancements have been made in runoff estimation, several research gaps, lacunae, and limitations persist, hindering the development of more accurate and comprehensive models. The identified gaps emphasize firstly, the integration of terrain-derived hydrological indices for water storage features and runoff flow path modeling through remote sensing and high-resolution DEM's (33.3% of the reviewed literature), and secondly, the inability to integrate terrain features such layer, parameters, inputs, etc., into artificial intelligent models such as machine learning and deep learning (66.6% of the reviewed literature) (Fig. 3).

While remote sensing technologies have significantly advanced our understanding of runoff processes, several research gaps remain, particularly in integrating terrain-derived features and improving model precision. Addressing these gaps is essential to enhance the accuracy and reliability of runoff predictions, as terrain plays a pivotal role in hydrological dynamics:

Despite significant advancements in runoff estimation using machine learning and deep learning techniques, a crucial research gap persists in the integration of terrain-based features, such as elevation, elevation gradients, slope, curvature, hydrological indices, and DEM-derived attributes. This limitation hinders the models' ability to fully capture the complex topographical influences on runoff dynamics.

A graphical summary of the research gaps is presented in Figure 4, providing a visual representation of the identified limitations and areas for improvement. This illustration highlights the key challenges in integrating terrain features into AI models and the need for enhanced utilization of terrain-derived hydrological indices in remote sensing and high-resolution DEMs for more accurate runoff estimation.

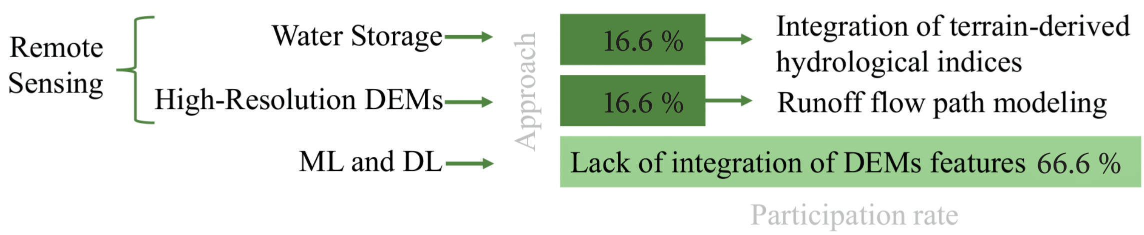

Fig. 3. *Research gaps approach for runoff estimation including terrain shape*

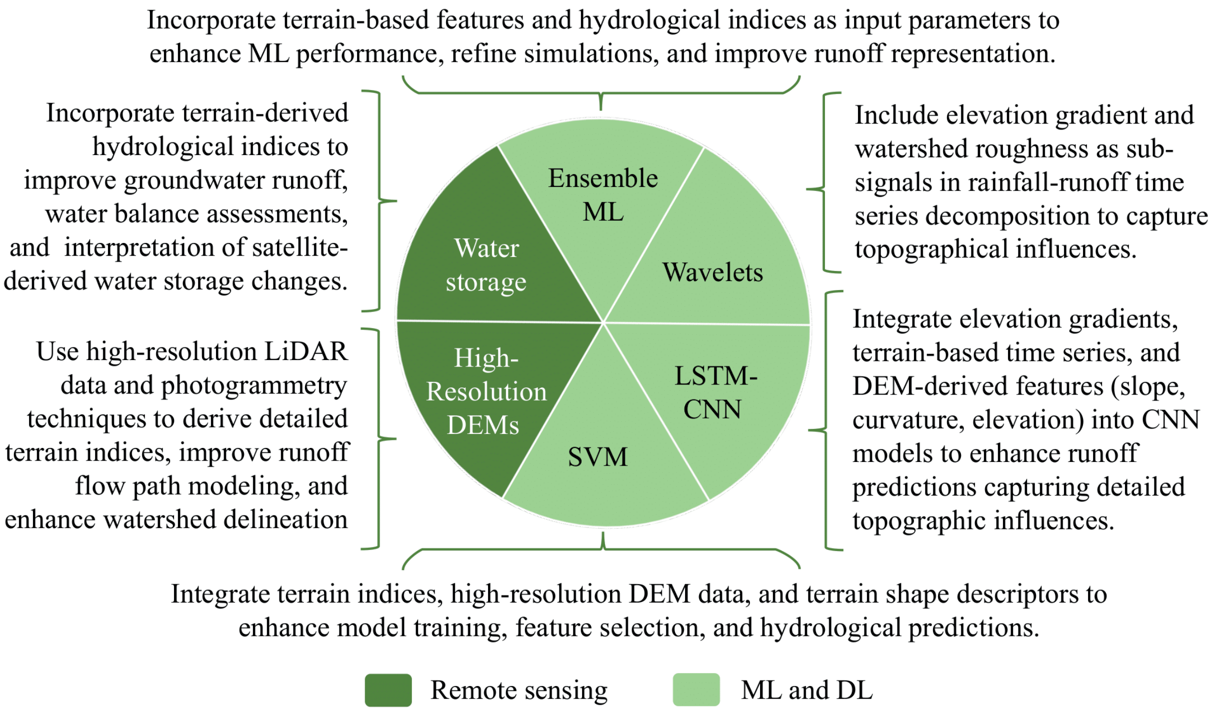

Fig. 4. *Research gaps in ML, DL and remote sensing for runoff estimation including terrain shape*

CONCLUSIONS

This literature review highlights a significant gap between the inclusion of terrain shape in runoff estimation and the use of more common techniques such as machine learning and deep learning. This gap underscores the importance of considering terrain shape as a critical factor in runoff studies. By incorporating a multi-dimensional spatial analysis where runoff takes place, researchers can better understand the dynamics of runoff across detailed landscapes. This approach addresses the limitations of current methods by providing a spatial perspective that enhances the accuracy and applicability of runoff models. Bridging this gap has the potential to advance the field significantly, offering more robust and comprehensive solutions to challenges in hydrological modeling and water resource management.

Conceptual models are simple and widely used, but they often lack the precision needed for complex environments because they rely on general assumptions. Empirical methods, which are more data-driven, can provide valuable insights but are limited by the quality and availability of data. Machine learning ML has shown great promise in estimating runoff by capturing non-linear relationships and adapting to different datasets. However, the success of ML models depends heavily on the amount and quality of training data. Deep learning DL, a more advanced form of ML, offers even greater potential by automating the process of feature extraction and handling large datasets, but it comes with the challenge of being computationally expensive and requiring large volumes of data to avoid overfitting. Each method has its place: conceptual and empirical models are simpler and more efficient, while ML and DL offer higher accuracy and flexibility in complex scenarios.

Limited research on soil and topographical conditions affecting water retention further complicates accurate runoff assessments, as models often fail to differentiate between water that infiltrates the soil and water that remains as surface runoff.

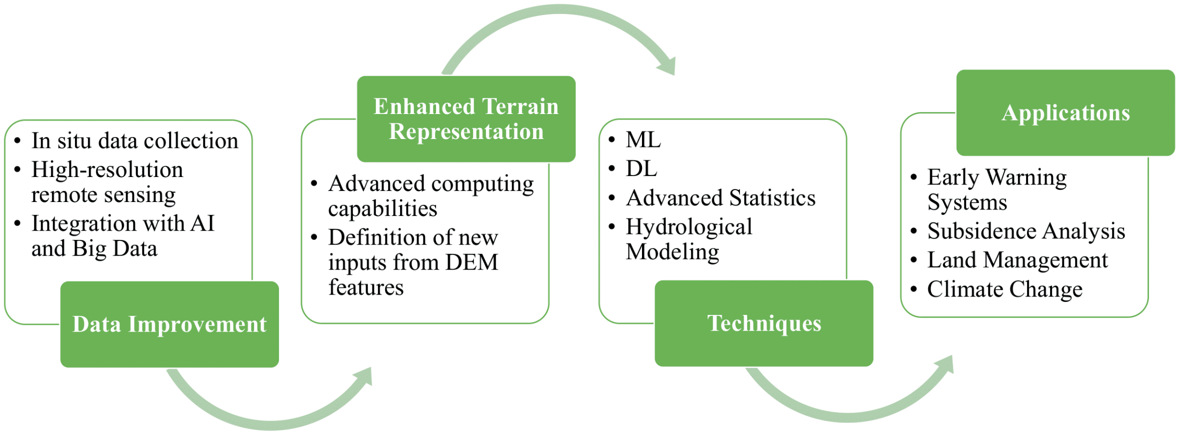

Fig. 5. *Future research and applications*

Another key challenge is the integration of sediment transport into runoff models, which is essential for understanding erosion and water quality but is frequently oversimplified or omitted. Addressing these limitations through improved terrain representation and integrating sediment transport dynamics is crucial for enhancing the accuracy and applicability of runoff models in flood management, land-use planning, and sustainable water resource management.

Future research on runoff estimation should focus on leveraging cutting-edge technologies to improve the accuracy and applicability of models in fields such as statistical analysis, machine learning, deep learning, meteorology, remote sensing, and hydrological modeling, based on broad cross-disciplinary collaboration (Fig. 5).

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